Journal of
Risk and Financial Management

MDPI

Systematic Review

Challenges of Artificial Intelligence for the Prevention and Identification of Bankruptcy Risk in Financial Institutions: A Systematic Review

Luis-Javier Vásquez-Serpa *, Ciro Rodríguez, Jhelly-Reynaluz Pérez-Núñez and Carlos Navarro

Facultad de Ingeniería de Sistemas e Informática, Universidad Nacional Mayor de San Marcos (UNMSM), Lima 15081, Peru; crodriguezro@unmsm.edu.pe (C.R.); jhelly.perez@unmsm.edu.pe (J.-R.P.-N.); cnavarrod@unmsm.edu.pe (C.N.)
* Correspondence: luis.vasquez2@unmsm.edu.pe

Abstract: The identification and prediction of financial bankruptcy has gained relevance due to its impact on economic and financial stability. This study performs a systematic review of artificial intelligence (AI) models used in bankruptcy prediction, evaluating their performance and relevance using the PRISMA and PICOC frameworks. Traditional models such as random forest, logistic regression, KNN, and neural networks are analyzed, along with advanced techniques such as Extreme Gradient Boosting (XGBoost), convolutional neural networks (CNN), long short-term memory (LSTM), hybrid models, and ensemble methods such as bagging and boosting. The findings highlight that, although traditional models are useful for their simplicity and low computational cost, advanced techniques such as LSTM and XGBoost stand out for their high accuracy, sometimes exceeding 99%. However, these techniques present significant challenges, such as the need for large volumes of data and high computational resources. This paper identifies strengths and limitations of these approaches and analyses their practical implications, highlighting the superiority of AI in terms of accuracy, timeliness, and early detection compared to traditional financial ratios, which remain essential tools. In conclusion, the review proposes approaches that integrate scalability and practicality, offering predictive solutions tailored to real financial contexts with limited resources.

Keywords: bank bankruptcy risk; financial institution; bank; artificial intelligence; prediction; machine learning; random forest; CNN; LSTM; XGBoost; accuracy; precision

Academic Editors: Mohamed Chaouch and Thanasis Stengos

Received: 2 November 2024
Revised: 26 December 2024
Accepted: 8 January 2025
Published: 10 January 2025

Citation: Vásquez-Serpa, L.-J., Rodríguez, C., Pérez-Núñez, J.-R., & Navarro, C. (2025). Challenges of Artificial Intelligence for the Prevention and Identification of Bankruptcy Risk in Financial Institutions: A Systematic Review. *Journal of Risk and Financial Management*, *18*(1), 26. https://doi.org/10.3390/jrfm18010026

1. Introduction

In the contemporary financial world, the identification and prevention of bankruptcy risks have become a critical task to ensure the stability and sustainability of financial institutions. The bankruptcy of a financial institution is a complex event with significant repercussions for the economy in general and for the individuals who deposit their money in the affected institution. With the increasing complexity and volume of financial data, traditional risk analysis techniques have limitations in addressing emerging challenges. (Radovanovic & Haas, 2023). In this context, artificial intelligence (AI) has emerged as a powerful tool, offering advanced and efficient solutions to predict and mitigate the risk of bankruptcy (Ren et al., 2024).

The global financial sector has faced significant challenges in recent years, marked by bank bankruptcy across various regions. In the United States, prominent institutions like Silicon Valley Bank (SVB), Signature Bank, and First Republic Bank collapsed in 2023 due to poor risk management, interest rate hikes, and structural issues, with losses comparable to those of the 2008 crisis (Erer & Erer, 2024). Europe witnessed the downfall of Credit Suisse, a symbol of Swiss financial stability, primarily due to mismanagement and corruption scandals (Economics Observatory, 2023). Similarly, Zhongzhi Enterprise Group of China declared insolvency in 2024, exposing regulatory gaps (Reuters, 2024). Latin America has experienced diverse financial struggles: Mexico averted a bank run caused by fake news about Banco Azteca in 2023 (El-Economista, 2024), and in Peru, deficiencies in credit and risk management have led to significant financial instability, with worrying losses at several financial institutions. By early 2024, half of the financial institutions, six municipal savings and loan associations, four rural savings associations, and three banks in the country had recorded substantial combined losses (SBS, 2014, 2015, 2019, 2023, 2024a, 2024b, 2024c, 2024d). These findings highlight systemic vulnerabilities and emphasize the need for enhanced risk management and regulatory frameworks in the banking sector.

Of the cases mentioned in the previous paragraph, it can be said that the most common causes of bankruptcy of a financial institution are: (a) Poor risk management, encompassing credit risk, market risk, and operational risk; (b) inadequate lending practices, such as lending to clients with a high risk of default; (c) external economic factors, comprising events such as economic recessions, financial crises, or sudden changes in interest rates, which can negatively affect the profitability and solvency of a financial institution; and (d) fraud or irregularities, including acts such as embezzlement of funds or manipulation of financial statements (Fox, 2022; Jia et al., 2020).

In addition, the bankruptcy of a financial institution can have serious consequences for the economy in general, and for the individuals who deposit their money in the affected institution. Some of the main consequences include: (a) loss of deposits, wherein savers may lose part or all of the money they had deposited in the failed institution (Birchler, 2000); (b) a domino effect on the economy, generating panic in financial markets and provoking a broader financial crisis (Yadav et al., 2023; Erer & Erer, 2024); (c) an economic recession, reflected through a reduction in the availability of credit in the economy, which can negatively affect consumption, investment, and economic growth (Chorafas, 2014); (d) layoffs of employees, which increases unemployment in the country (Evans & Borders, 2014); and (e) damage to the country's reputation with international investors, which can make it difficult to obtain external financing (Citterio, 2024).

To prevent the bankruptcy of financial institutions, several measures can be implemented by the authorities and by the institutions themselves: (a) financial regulations can oblige financial institutions to maintain an adequate level of capital and reserves to cover possible losses; (b) financial supervision can detect problems in time and take corrective measures; (c) good risk management practices can identify, evaluate, and mitigate the risks institutions face; and (d) depositor protection mechanisms established by governments can ensure that savers recover part of their money in the event of bankruptcy of a financial institution (Kou et al., 2022). On the other hand, because banks are large from a business point of view, they are less likely to fail (Zikri et al., 2024).

On the other hand, artificial intelligence (AI) has become a fundamental component in various sectors, including the financial sector. The ability of AI to analyze large volumes of data quickly has opened up new opportunities and challenges in identifying and predicting critical financial situations, such as bankruptcies of financial institutions. This phenomenon has aroused growing interest in the academic and business community, as the ability to anticipate and effectively manage these situations can have a significant impact on the stability of the global financial system (Celik & Jain, 2024).

Several research studies have explored the potential of artificial intelligence and machine learning to improve bankruptcy prediction models in financial institutions (Tadaaki

Hosaka, 2019). These studies have shown that advanced AI techniques can identify patterns and early signs of financial deterioration, allowing institutions to take preventive measures and mitigate risks proactively. However, despite significant advances, there are still important challenges that limit the full adoption of AI in this context.

According to the cases of bank bankruptcy that have occurred, a major problem is in the need for stakeholders to identify, in a timely manner, the existing and updated risks regarding financial institutions in order to make an immediate decision. The early identification of the risk of bankruptcy is fundamental for the supervisory body to take measures relating to the institution involved (Parra et al., 2021). Microeconomic and macroeconomic factors have a direct impact on bankruptcy risk. The study of macroeconomic factors reveals the impact of macroeconomic variables (such as interest rates, inflation, and GDP growth) on bank stability. Similarly, the analysis of microeconomic factors entails an evaluation of how internal bank factors (such as management, capitalization, and asset quality) influence the risk of bankruptcy (Erer & Erer, 2024).

This article contributes to the field by systematically reviewing recent developments in the use of AI for the prevention and detection of insolvency risk in financial institutions. The following novel aspects are highlighted: (1) a critical assessment of the metrics used to validate AI techniques, and their adaptability to different financial contexts; (2) a detailed classification of the datasets used, and the approaches to their collection; and (3) an identification of the gaps in the literature that limit the practical applicability of current models.

In doing so, this article not only provides an updated perspective on AI techniques, but also proposes a framework for future research to optimize the effectiveness of these tools in bankruptcy prediction, thereby contributing to the strengthening of the global financial system.

The remainder of this paper is organized as follows: Section 2 explores traditional and modern methods employed in assessing bankruptcy risk in financial institutions, highlighting their relevance as a foundation for integrating AI-based approaches. Section 3 details the AI methods used to identify bank bankruptcy risk. Section 4 describes the methodology applied for the literature review, including the objectives, research questions, and search strategies employed. Section 5 constitutes the core of the paper, providing a thorough analysis of the historical background and the selected articles. Section 6 presents a critical discussion of the findings, while Section 7 presents the main conclusions. Section 8 addresses the limitations of the study, and finally, in Section 9, directions for future research are proposed.

2. Assessment to Identify the Risk of Bankruptcy of a Financial Institution

The assessment of the bankruptcy risk of a financial institution is a process that integrates the analysis of financial indicators, predictive models, and qualitative assessments (Citterio, 2024; Nießner et al., 2022). This approach employs a combination of both traditional and contemporary tools to address a complex problem that carries significant implications for financial stability. While statistical techniques have been extensively utilized to predict the probability of bankruptcy, recent advancements in artificial intelligence and machine learning have demonstrated significant potential in enhancing the accuracy and efficiency of these methods (Shrivastav & Ramudu, 2020). By leveraging structured data derived from traditional approaches, these techniques facilitate the identification of patterns and early signals of financial deterioration (Radovanovic & Haas, 2023). The methods and procedures commonly used in the diagnosis of bankruptcy risk are detailed below, highlighting their relevance as a basis for the development of more advanced predictive models.

(a) *Financial Indicators Analysis*

Capitalization is an assessment of the bank's level of capital, which is a key indicator of its ability to absorb losses. Liquidity measures the bank's ability to meet its short-term obligations (M. Wang, 2022). Asset quality analysis reveals the quality of the bank's assets, including the delinquency rate and bad loans. The profitability of a bank or financial institution is assessed through indicators such as the return on assets (ROA), return on equity (ROE), and earnings before interest, taxes, depreciation, and amortization (EBITDA) (Parra et al., 2021). Leverage involves evaluating the level of indebtedness in relation to an institution's capital. Financial indicators are inputs for the CAMELS index or system, which evaluates the possible risks of financial institutions (Song & Shahbudin, 2023). In general, all financial ratios are important variables for bankruptcy risk prediction (Tadaaki Hosaka, 2019; Affes & Hentati-Kaffel, 2019a; Pavlicko et al., 2021; Hamdi et al., 2024). Fiscal arrears are a very important variable for bankruptcy risk prediction, and it is more efficient to combine them with financial ratio variables (Lukason & Andresson, 2019).

(b) *Predictive Models*

Z-score models use models such as Altman's Z-score, which combines several financial ratios to predict the probability of bankruptcy (Vukčević et al., 2024; Isaac-Roque & Caicedo-Carrero, 2023; Valverde & Ortiz, 2022). The CAMELS model is widely used to analyze the performance of financial institutions, focusing on analyzing the variables of capital, asset quality, management efficiency, earnings, liquidity, and sensitivity (Nguyen et al., 2020). Logistic regression models utilize financial and non-financial variables to estimate the probability of insolvency (Gavurova et al., 2022). Discriminant analysis uses statistical techniques to classify banks into risk categories (Gajdosikova & Valaskova, 2023; Valverde & Ortiz, 2022).

(c) *Qualitative Assessment*

Corporate governance involves analyzing a bank's governance structure and the quality of its management (Alzayed et al., 2023). Risk exposure measurement assesses a bank's exposure to various risks, such as market risk, credit risk, and operational risk (Fiordelisi & Marqués-Ibañez, 2013). The impact of the economic environment and regulatory framework on a bank's stability should also be considered (Erer & Erer, 2024).

(d) *Stress Testing*

Stress tests are essential for financial institutions to evaluate and analyze the behavior and impact of adverse scenarios on financial stability and prevent possible bankruptcies. These scenarios occur through extreme simulations, for example, economic crises, interest rate increases, and market crashes (Hu et al., 2014).

(e) *Continuous Monitoring*

In financial institutions, continuous monitoring is crucial for the early detection of possible bankruptcy, and the implementation of artificial intelligence can significantly improve this process. The objective of such monitoring is to detect early signs of financial problems, such as decreases in deposits, increases in delinquency rates, or a deterioration in asset quality (Al-Araj et al., 2022).

(f) *Review of External Reports and Audits*

For the prediction of the possible bankruptcy of any financial entity, it is important to review and analyze audited financial reports and external audit reports to identify any concerns or discrepancies that may indicate financial problems (Muñoz-Izquierdo et al., 2019).

(g) Market Indicators

It is important to monitor market signals, and analyze how fluctuations in market indicators influence the price of the financial institution's shares, changes in credit ratings, and the behavior of bond spreads (De Moraes Souza et al., 2024).

3. Artificial Intelligence Methods to Identify Bank Bankruptcy Risk

Artificial intelligence (AI) offers a variety of advanced methods and techniques for the identification of bank or financial institution bankruptcy. Some of the most widely used methods are detailed below, indicating their operation, application, advantages, and disadvantages of each.

(a) Artificial neural networks (ANNs) work by mimicking the structure of the human brain, using layered artificial neurons to process information. In predicting the risk of bankruptcy of a financial institution, ANNs analyze large volumes of financial data to identify complex patterns that could indicate a high risk of bankruptcy (Gavurova et al., 2022). The advantages of ANNs include their ability to handle nonlinear data, their high prediction accuracy, and their ability to improve over time through learning. However, the disadvantages include the need for large amounts of data to be properly trained, the high associated computational cost, and the complexity of interpreting their results (Oberoi & Banerjee, 2023). Including more layers in multilayer neural network (MLP) algorithms does not imply efficiency in model prediction (Jencova et al., 2021). Additionally, one can convert financial ratios as a grayscale image and then apply a convolutional neural network (CNN) model to generate results (Tadaaki Hosaka, 2019).

(b) Support vector machines (SVMs) work by classifying data by finding the optimal hyperplane that separates different classes in a high-dimensional space. In predicting the bankruptcy risk of a financial institution, SVMs analyze financial data and determine whether an institution is prone to fail or not based on selected features (Shrivastav & Ramudu, 2020). The advantages of SVMs include their effectiveness in high-dimensional spaces and their ability to handle nonlinear classification cases by using kernels. However, the disadvantages are their high computational requirement for large datasets and the difficulty in selecting the optimal kernel and parameters for good performance.

(c) Decision trees (DTs) work by iteratively dividing a dataset into subsets based on the most significant characteristics, creating a tree-like structure where each node represents a characteristic, and each branch represents a possible outcome. In predicting the risk of bankruptcy of a financial institution, decision trees use historical financial data to classify institutions as bankruptcy-prone or non-bankruptcy-prone. The advantages of decision trees include their simplicity, interpretability, and ability to handle categorical and numerical data. However, the disadvantages include a propensity for overfitting, especially with small datasets, and their instability, as small variations in the data can result in significantly different trees (Fan, 2021).

(d) Random forest (RF) works by combining multiple decision trees to improve accuracy and reduce the risk of overfitting. Each tree in the forest is trained on a random sample of the dataset, and in the end, the model makes a final decision by averaging the predictions of all the trees. In predicting the risk of bankruptcy of a financial institution, RF is used to analyze historical financial data and determine the probability of bankruptcy. The advantages of RF include its high accuracy, robustness to overfitting, and ability to handle large datasets with many characteristics. However, the disadvantages are its complexity, higher consumption of computational resources, and lower interpretability compared to simpler models (Gurnani et al., 2021).

(e) Principal component analysis (PCA) works by reducing the dimensionality of a dataset while preserving as much variation as possible. In predicting the risk of bankruptcy of a financial entity, PCA is applied to transform highly correlated financial variables into a smaller set of uncorrelated variables, called principal components, that capture the essence of the original data. The advantages of PCA include simplifying the model, reducing noise, and improving the interpretability of the data. However, the disadvantages are that it can lose important information if too many components are removed, and that it is not suitable for nonlinear data. In addition, the transformation of the data can make it difficult to directly interpret the principal components in terms of the original variables (Adisa et al., 2019).

(f) Deep learning (DL) works by using deep neural networks that automatically learn complex features and patterns from large volumes of data. Predicting the risk of bankruptcy of a financial institution is achieved using historical financial and non-financial data to identify signals of potential bankruptcy. The advantages of deep learning include its high predictive capacity, the ability to handle large datasets, and the ability to learn complex features without the need for manual feature engineering. However, its disadvantages are the need for large volumes of data and computational power, its complexity and opacity, which makes it difficult to interpret the results, and the risk of overfitting if not handled properly (Elhoseny et al., 2022; Jabeur & Serret, 2023; Hamdi et al., 2024).

- **(f.1)** **Long short-term memory models (LSTMs)** are a type of recurrent neural network (RNN) designed to learn and remember long-term information. An LSTM works through the use of "memory cells" and gating mechanisms that regulate the flow of information, allowing the model to maintain and update memories effectively. Their applications are broad, most notably in time-series prediction, natural language processing, and speech recognition, where sequence and context are crucial. The advantages of LSTM include its ability to handle long-term dependencies and its effectiveness in complex sequential tasks. However, disadvantages include a higher computational requirement and greater difficulty to train compared to simpler RNNs due to their complex architecture. They are widely used for time-series estimation and perform well in estimating the risk of corporate bankruptcy (Vochozka et al., 2020; Noh, 2023).
- **(f.2)** **Bayesian networks (BNs)** function by representing probabilistic relationships between variables by means of an acyclic directed graph. In predicting the risk of bankruptcy of a financial institution, they are used to model the interdependencies between various financial and non-financial variables. These networks allow the incorporation of expert knowledge and historical data to calculate the probability of bankruptcy. The advantages of BNs include their ability to handle uncertainty, their flexibility in incorporating new data, and the clear interpretability of the contained causal relationships. However, the disadvantages are the complexity of their construction and the need for a large volume of data for a correct estimation of probabilities, in addition to the fact that they can be computationally intensive for large networks (Bidyuk et al., 2020).

(g) Extreme Gradient Boosting (XGBoost) is a machine learning algorithm based on decision trees which optimizes the boosting process by using regularization techniques and missing data handling, improving both the speed and accuracy of predictions. It is widely applied in classification and regression problems, excelling in data science scenarios and applications in finance, marketing, and bioinformatics. Its advantages include high computational efficiency, the ability to handle large datasets, and flexibility with various loss functions. However, the disadvantages of XGBoost include the need for careful tuning of hyperparameters and the possibility of overfitting if regularization is not handled properly (Shetty et al., 2022; Yotsawat et al., 2023).

(h) Natural language processing (NLP) works by analyzing and understanding human language to extract valuable information from unstructured text. In predicting the risk of bankruptcy of a financial institution, NLP is applied to analyze financial reports, news, and legal documents, identifying patterns and signals of financial risk. The advantages of NLP include the ability to handle large volumes of textual data, uncover hidden information, and provide a deeper understanding of financial context. However, disadvantages include the need for large amounts of data to train models, the complexity of interpreting the results, and the challenge of handling ambiguities and variations in natural language (Khan et al., 2024). In addition, NLP models can be sensitive to biases in the training data (Iqbal & Riaz, 2022).

(i) Sentiment analysis works by evaluating the emotional tone of texts to determine whether the expressed sentiment is positive, negative, or neutral. Predicting the risk of bankruptcy of a financial institution is performed by analyzing news, financial reports, and social networks to detect early signs of financial distress. The advantages of sentiment analysis include the ability to capture changes in public and market perception, providing early warnings of potential risks. However, its disadvantages lie in the difficulty of interpreting sarcasm and complex contexts, the need for advanced language processing to maintain accuracy, and the susceptibility to biases present in the analyzed data sources (De Jesus & Besarria, 2023).

(j) Hybrid models combine multiple artificial intelligence algorithms and machine learning techniques to improve accuracy and robustness in predicting events, such as financial bankruptcy. They work by integrating various approaches, such as neural networks, decision trees, and ensemble methods, to take advantage of the individual strengths of each technique and compensate for their weaknesses. They are applied in areas such as fraud detection, bankruptcy prediction, and credit risk assessment. The advantages of hybrid models include greater accuracy, generation capacity, and resistance to data biases. However, they have disadvantages such as greater complexity in their implementation, higher computational demand, and difficulty in interpreting the results due to the combination of multiple algorithms. In Affes and Hentati-Kaffel (2019a), they apply the hybrid MARS model.

(k) Ensemble methods combine multiple models to increase the accuracy and robustness of predictions. Their application includes techniques such as bagging, boosting, and stacking, which optimize the ability to predict bankruptcies. Advantages include improved accuracy and reduced risk of overfitting. However, they have disadvantages, such as greater difficulty in interpretation and longer training times (Siswoyo et al., 2022).

(l) The Synthetic Minority Over-sampling Technique (SMOTE) is a data balancing technique used to address the problem of class disproportionality in datasets, especially in scenarios where the instances of one class are significantly smaller than those of another, as in the case of bankruptcy prediction in financial institutions. SMOTE generates new synthetic samples of the minority class by interpolating between existing instances of that class rather than simply duplicating them. It is commonly applied in the field of bank bankruptcy prediction, as failed banks are few in number compared to non-failed banks. SMOTE is used to create a more balanced dataset, allowing machine learning models to learn more representative patterns and reduce bias towards the majority class. The advantage of the SMOTE technique is that it improves the predictive ability and accuracy of models by addressing the class imbalance problem and can increase the detection of (minority) bankruptcy events (Aljawazneh et al., 2021; Garcia, 2022). However, it has disadvantages in generating noise and duplicating information excessively if not properly configured, and does not consider the possible temporal relationship between instances in financial time series (Soltanzadeh & Hashemzadeh, 2021). In Jain et al. (2021), the authors mention that there are several factors that influence the performance of machine learning algorithms: class imbalance, irrelevant or redundant variables, and proper selection of the learning algorithm. To optimally balance the data, they use the SMOTE technique, eliminating irrelevant and redundant features by the fuzzy method.

4. Methodology

In this section, in accordance with existing research studies, the literature review and future trends in artificial intelligence challenges for identifying potential bankruptcies of financial institutions are presented.

4.1. Objectives and Research Questions

In this study, using the PICOC strategy (Population, Intervention, Comparison, Outcome, Context) (Petticrew & Roberts, 2006), a literature review was conducted surrounding the causes that generate the bankruptcy of banks, financial institutions, and some influential companies in the financial system. Additionally, studies that apply machine learning algorithms, neural networks, and other artificial intelligence models to predict the bankruptcy of a financial institution were analyzed. For this systematic review, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method was applied in order to identify, select, compile, and analyze the most relevant methods and research results (Moher et al., 2009).

Based on what was presented in the introduction, in order to explore the latest contributions of AI in the prevention, identification, and prediction of bankruptcy risk in financial institutions, four research questions with their respective objectives were posed (see Table 1). To answer these questions, the following steps were followed: definition of objectives; establishment of selection criteria; identification of sources of information; planning the search; selecting studies; and collecting data and results.

Table 1. Research questions.

	Research Questions	Objectives
RQ1.	Which Artificial Intelligence (AI) techniques or models are the most widely used for bankruptcy risk analysis in financial institutions and related companies?	Explore the latest developments and most widely used artificial intelligence approaches used for bankruptcy risk identification and prevention in financial institutions and related companies.
RQ2.	Which models implemented for bankruptcy prediction of a bank, financial institution, or related company show the best performance?	Evaluate and compare the different bankruptcy prediction models in terms of their accuracy, adaptability, predictive ability, datasets, and application.
RQ3.	What datasets and balancing techniques are used to apply AI models in predicting and identifying the risk of bankruptcy of financial institutions?	Identify the datasets used, consider the different ways of capturing information, apply bankruptcy prediction models, and analyze the data balancing techniques used to address class mismatch in these datasets.
RQ4.	What are the most commonly used variables in AI bankruptcy prediction models, and how do they relate to variables in other prediction models?	Identify and analyze the variables most commonly used in bankruptcy prediction models using AI and see how they relate to variables in other prediction models.

4.2. Search Strategy

For the exhaustive literature review and obtaining AI techniques, datasets, variables, and prediction results, the main repositories of scientific studies and their respective search engines were used: SCOPUS, Web of Science (WoS), and IEEE. Table 2 shows the search criteria: peer-reviewed academic papers in English, in the area of computer science, engineering, and mathematics, published during the period from January 2019 to June 2024.

Table 2. Search criteria and queries.

	Criteria			
Restrictions	Academic papers (peer-reviewed); Publication date: Jan 2019 to Jun 2024; Language: English; Area of study: computer science, engineering, and mathematics. Filter by keyword: "artificial intelligence" AND "bankruptcy" AND ("bank" OR "financial institution" OR "financial entities").			
Enlargements	Apply to equivalent words.			
	Search Query	**Scopus**	**WoS**	**IEEE**
Query 1 15 June 2024	TITLE (("Artificial intelligence" OR "machine learning" OR "deep Learning" OR "meta learning" OR "ANN" OR "CNN" OR "Neural Networks" OR "modelling" OR "ensemble" OR "bank" OR "Financial institutions" OR "Financial entities" OR "Ratios" OR "Analysis" OR "prediction") AND ("bankruptcy"))	1033	641	23
Query 2 15 June 2024	TITLE (("Artificial intelligence" OR "machine learning" OR "deep Learning" OR "meta learning" OR "ANN" OR "CNN" OR "neural networks" OR "modelling" OR "ensemble" OR "bank" OR "Financial institutions" OR "financial entities" OR "ratios" OR "financial" OR "Analysis" OR "prediction" OR " techniques" OR "resources" OR "validation" OR " evaluate") AND ("bankruptcy" AND "financial"))	245	162	11
Query 3 15 June 2024	TITLE (("Artificial intelligence" OR "machine learning" OR "deep learning" OR "meta-learning" OR "ANN" OR "CNN" OR "neural networks" OR "modeling" OR "assembly" OR "bank" OR "finance institutions " OR "financial entities" OR "ratios" OR "prediction") AND ("bankruptcy" AND ("bank" OR "financial institution" OR "financial entities")))	102	36	7

In Figure 1, following the criteria in Table 2, the methodological process carried out for the systematic review is illustrated, following the PRISMA framework and using the PICOC approach, guaranteeing the transparency, reproducibility, and rigor of the research by identifying, evaluating, and selecting relevant articles on the prediction of bankruptcy risk in financial institutions. Due to the reduced number of articles on bank bankruptcies, it was decided to incorporate in the review articles on the prediction of bankruptcy of companies directly linked to the financial system. The steps applied in the systematic review are explained in detail below.

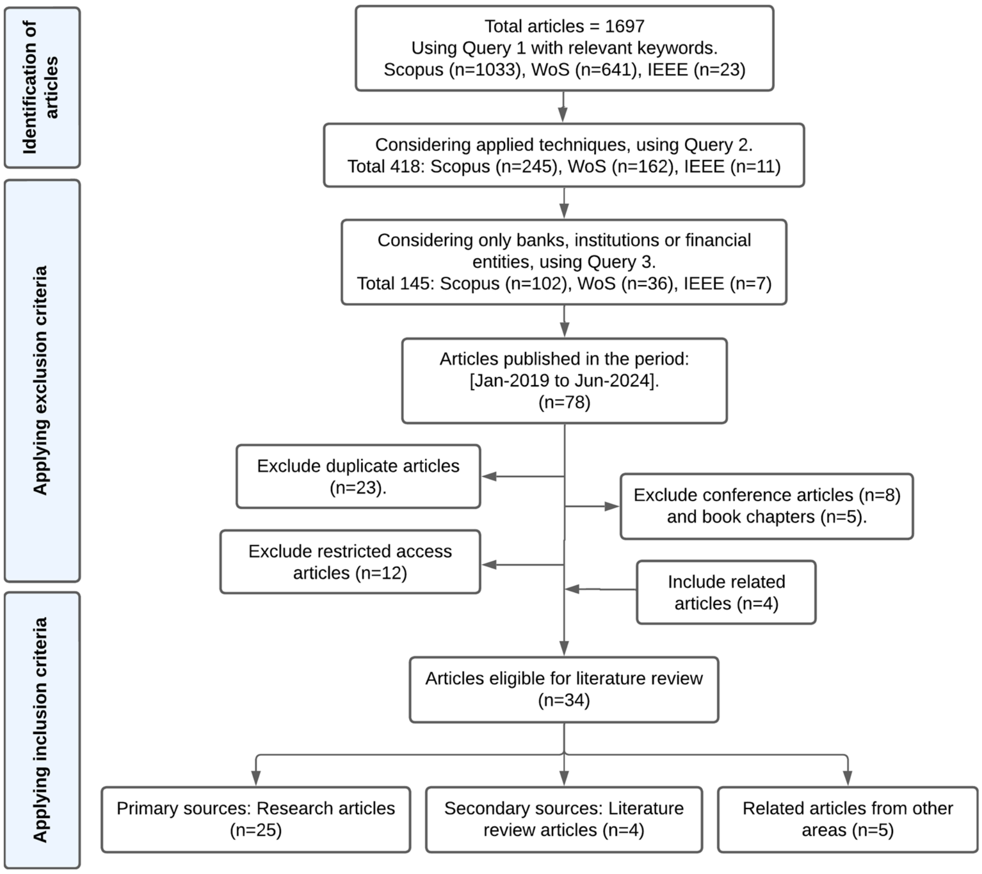

Figure 1. Flowchart for systematic review.

4.2.1. Identification of Articles

First stage: An initial search for articles was carried out using Query 1 (see Table 2) using relevant keywords related to the topic: artificial intelligence, machine learning, deep learning, meta learning, modeling, bank, financial entities, financial institutions, ratios, analysis, prediction, bankruptcy, techniques, and ensemble. These searches covered three main databases: Scopus (n = 1033), Web of Science (WoS, n = 641), and IEEE Xplore (n = 23), yielding a total of 1697 articles.

Application of Query 2: Subsequently, the results were refined by selecting only articles that applied specific techniques relevant to bankruptcy risk analysis, which reduced the total number to 418 articles (Scopus: n = 245; WoS: n = 162; IEEE: n = 11).

4.2.2. Application of Exclusion Criteria

At this stage, the articles were filtered considering only those that addressed financial institutions, such as banks and related entities, using Query 3. This resulted in 145 articles being selected (Scopus: n = 102; WoS: n = 36; IEEE: n = 7).

Only articles published between January 2019 and June 2024 were considered, further reducing the results to 78 articles.

Duplicate articles (n = 23), articles that were restricted access (not open access) (n = 12), book chapters (n = 5), and conference articles (n = 8) were then excluded.

4.2.3. Application of Inclusion Criteria

After the exclusion process, related studies were evaluated, and although they did not belong to the specific domain of financial bankruptcy prediction, they provided contextual value to the analysis. Four additional related articles were included.

Finally, 34 eligible articles were selected based on the identification and prediction of the bankruptcy of financial institutions or related companies using artificial intelligence techniques: twenty-five were sourced from Scopus, five from WoS, and four from IEEE. For the final review, the selected articles were divided into primary sources, comprising twenty-five empirical or applied research articles, secondary sources, comprising four related literature review articles, and related articles from other areas, comprising five relevant studies that complement the analysis from different perspectives.

The selected articles were then studied, and the proposed techniques and prediction results were analyzed.

4.2.4. Explanation of the Selection Criteria

The criteria for the selection of articles were based on the PICOC principles as follows:

Population: Financial institutions (banks, financial institutions, rural banks, municipal banks, etc.) and companies directly linked to the financial system.

Intervention: Using statistical methods, predictive models, and artificial intelligence techniques to address bankruptcy risk.

Comparison: Comparison between traditional methods and AI-based approaches.

Outcome: Improvement in the accuracy and timeliness of bankruptcy risk prediction.

Context: Articles focused on the global financial field, with emphasis on recent periods of financial and economic instability.

4.3. Study Extraction and Synthesis

Three independent researchers (L-J. V-S., C. R., and J-R. P-N.) screened each study based on the title and abstract to determine its eligibility for the full-text review stage. In addition, the reference list of the selected articles was reviewed to identify studies that might have been missed in the initial search. Any conflicts in selection were resolved by a third reviewer (C. R.). For each study, the following data were extracted: author(s), year, study design, and relevant findings. Data extraction was performed by one reviewer (L-J. V-S.), with collaboration from the other authors (C. R., J-R. P-N., and C. N.). Studies published in languages other than English, narrative or systematic reviews, meta-analyses, and conference proceedings were excluded due to the high risk of bias. The systematic review was not registered on any public platform.

5. Results and Findings

The implementation of artificial intelligence (AI) in the financial and banking sectors has evolved since the 1980s, when rule-based expert systems such as PROLOG and LISP were used for fraud detection and credit assessment (Russell & Norvig, 2003). In the 1990s, more advanced techniques such as decision trees and support vector machines (SVM) emerged, improving the accuracy of default detection and the discernment of patterns in large volumes of financial data (Witten et al., 2011; Altman et al., 1977). With the rise of Big Data in the 2000s, machine learning made it possible to manage high-dimensional data using multi-layer neural networks and models such as random forest, optimizing customer segmentation and anomaly detection in real time (Bishop, 2006).

Over the past decade, the development of deep neural networks, such as convolutional neural networks (CNNs) and long-short-term memory (LSTM), has revolutionized financial risk prediction, achieving accuracies of over 90% in certain cases (Goodfellow et al., 2016; Gavurova et al., 2022). Hybrid approaches combining traditional models, such as CAMELS, with advanced AI algorithms are now widely used to assess risk, while real-time analytics using unstructured data, such as social media and financial news, has expanded predictive capabilities in dynamic markets (Nguyen et al., 2020; Erer & Erer, 2024). These advances have transformed financial management, but pose challenges, such as the need for significant computational resources and the integration of diverse data.

In this section, an exhaustive analysis of the 34 articles selected according to the search strategy shown in the previous section is carried out. This analysis is presented in Table 3, which shows the techniques or models applied, the datasets (number of banks and firms), variables, periods, countries, and the main results with respect to the bank bankruptcy prediction performance of banks or firms linked to the financial system of the selected articles. Table 3 is the fundamental input to answer the research questions of this paper.

Table 3. Analysis of selected articles.

Authors	Techniques	Dataset, Period, and Variables	Results
(Idhmad et al., 2024)	SVM, KNN, LR, RF, NB, DT, AdaBoost, GBT, and SMOTE	Financial and corporate governance indicators of 6915 companies listed on the Taiwan Stock Exchange from 1999 to 2009, using 95 variables.	Accuracy with SMOTE and 70 characteristics: SVM 98.90%, LR 90.19%, RF 97.54%, NB 69.02%, DT 95.08%, AdaBoost 95.76%, GBT 98.14%, KNN 95.68%.
(Da Silva Mattos & Shasha, 2024)	XGBoost, AdaBoost, RF, Bagging, SVM, and logistic regression (LR)	Financial indicators, institutional factors, and collateralizable assets of 503 private companies in Brazil from 2007 to 2020, using 26 variables.	Accuracy: XGBoost 76.80%, AdaBoost 77.10%, RF 78.25%, Bagging 77.47%, SVM 77.76%, LR 75.47%.
(Chandok et al., 2024)	RBF Algorithm, RF, MLP, DBN, CNN, GRU, WSODL-BPFCA, ALSTM, and min-max normalisation technique	Financial, accounting, and market indicators of 690 Australian companies in 1992, using 14 variables.	Accuracy: RBF Algorithm 74.00%, RF 86.00%, MLP 90.90%, DBN 91.29%, CNN 90.08%, GRU 91.16%, WSODL-BPFCA 97.61%.
(Khan et al., 2024)	GNB, Hybrid LSTM- CNN, Vader NLTK, and NLP	Social network data (Twitter) of 279,779 tweets from Silicon Valley Bank (SVB) in the United States, using five variables.	Accuracy: GNB 63%, Hybrid LSTM- CNN 60%, Vader NLTK 51%.
(Hamdi et al., 2024)	LDA, LR, DT, RF, SVM, and DNN	Income statements of 732 Tunisian companies from different sectors of activity for 2011–2017, using 25 variables.	Accuracy: LDA 80.9%, LR 85.8%, DT 74.3%, RF 88.2%, SVM 84.8%, DNN 93.6%.
(X. Wang et al., 2023)	LR, RF, LightGBM, MLP, and DeepFM	Financial statements of 35,879 Luxembourg mercantile companies from 2011–2021, using 18 variables.	Accuracy: LR 75%, RF 79%, LightGBM 87%, MLP 77%, DeepFM 64%.
(Gabrielli et al., 2023)	RF and ML techniques	Dataset of active and bankrupt companies, financial ratios, and gross accounting data.	The accuracy of RF with the use of financial ratios was 98%, 13.95% higher than that without the use of ratios.
(Noh, 2023)	LR, K-NN, DT, RF, RNN, and LSTM	Financial statements and ratios of 1020 companies in Korea from 2012 to 2021, 13 variables.	Accuracy: LR 75.70%, SVM 72.36%, RF 98.99%, RNN 97.89%, LSTM 99.36%, Ensemble 98.26%.
(Gajdosikova & Valaskova, 2023)	MDA	Financial information of 3783 Slovak companies in 2020 and 2021, 12 variables.	The model developed had a correct classification rate of 93%.
(Oberoi & Banerjee, 2023)	LR, RF, AdaBoost, ANN, DL, Relief algorithm, and SMOTE	Data from 59 Indian public and private sector banks from March 2001 to March 2018, 26 financial variables.	Techniques, type-II error: LR 64.34%, RF 58.25%, AdaBoost 1.74%, ANN 0.87%.
(Jabeur & Serret, 2023)	DA, LR, SVM, PLS-DA, NN, CNN, and FCNN	Financial information of 266 French companies from 2014 to 2016, 17 financial variables.	Accuracy: FCNN 78.56%, CNN 73.04%, NN 77.34%, PLS-DA 77.07%, LR 77.81%, DA 68.11%, SVM 74.20%.

Table 3. *Cont.*

Authors	Techniques	Dataset, Period, and Variables	Results
(Radovanovic & Haas, 2023)	LR, LDA, SVM, boosting, RF, NN, and bagging	Financial datasets and social costs of 18,858 companies listed in North America from 1985 to 2020, 19 financial variables.	Altman variables, accuracy: LDA 68%, LR 68%, RF 73%, NN 71%, Bagging 74%, Boosting 78%, SVM radial 77%. Altman plus variables, accuracy: LDA 69%, LR 71%, RF 78%, NN 78%, Bagging 77%, Boosting 80%, SVM radial 75%. Accuracy: LDA 64%, LR 65%, RF 78%, NN 79%, Bagging 76%, Boosting 77%, SVM radial 76%.
(Valverde & Ortiz, 2022)	MDA of the Altman Z model with the harmonic mean	Financial datasets of 26 Peruvian financial institutions from 2015 to 2021, five variables.	20% are in the safe zone, while 13% are at risk of bankruptcy.
(Shah et al., 2022)	RF and linear regression	A dataset of Polish companies with 10,000 records and 64 variables.	Accuracy: RF 97.35%. Incorporated a linear regression model to determine the variables.
(Gavurova et al., 2022)	NN, MLP, and LR	Financial indicators of 2384 companies in the Slovak Republic from 2018 to 2019, nine variables.	Accuracy: NN 99.7%, RL 89.4%.
(Siswoyo et al., 2022)	LR, SVM, RF, NN, and BELM (new method combining LR, SVM, RF, and NN)	Financial ratios of the Indonesian banking industry in 2010–2016, four variables.	Accuracy: LR 81%, SVM 81%, RF 90%, BELM 97%.
(Garcia, 2022)	LR, BLR, LDA, PLS-DA, NB, KNN, NN, SVM, Extreme GBM, RF, RF-Ensemble, SMOTE and extensions, ADASYN, BL, DB, SL, and SMOTE-CBU	Financial dataset of 1824 US companies with 41,933 observations, 2010–2018, five variables.	AUC with SMOTE: LR 86.8%, BLR 91.5%, LDA 90.4%, PLS-DA 52.4%, NB 74.5%, KNN 73.3%, NN 76.3%, SVM 88.4%, Extreme GBM 78%, RF 84.6%, RF-Ensemble 100%.
(Elhoseny et al., 2022)	AWOA-DL, LR, RBF Network, TLBO-DL, and DNN; adjustment of hyperparameters with AWOA	Four financial datasets comprising 690, 50, 10,503, and 6819 firms from Australia, China, Poland, and Taiwan, respectively, in the average period 1999–2012, with 14, 5, 64, and 94 variables in each set.	AWOA-DL achieved an average accuracy of 95.77%, surpassing other techniques: TLBO-DL 93.87%, DNN 89.67%, LR 84.57%, and RBF Network 78.22%.
(Shetty et al., 2022)	XGBoost, SVM, and DNN	Financial data of 3128 Belgian companies in 2002–2012, five variables.	Accuracy: XGBoost 83%, SVM 83%, NN 82%.
(Jain et al., 2021)	RF, SMO, IBK, JRip, PART, J48, and SMOTE	Financial statements of banks and companies from five datasets: 7027, 10,173, 10,503, 9792, and 5910 cases, 64 variables.	Accuracy: RF 95.1%, SMO 79.4%, IBK 58.6%, JRip 92.8%, PART 92.7%, J48 91.8%.AUC: RF 98.8%, SMO 79.4%, IBK 58.8%, JRip 95.2%, PART 96.6%, J48 92.9%.
(Chen et al., 2021)	Z-Score, NB, LG, KNN (IBK), BAG, DT, J48 algorithm of DT, and linear regression	Financial statements and ratios of 2946 companies operating in Taiwan in the period 2000 to 2019, 22 variables.	Accuracy: NB 93.89%, LG 98.98%, IBK 99.49%, BAG 99.32%, J48 99.32%. Accuracy with cross-validation 10 times: NB 93.99%, LG 92.52%, IBK 99.59%, BAG 99.46%, J48 99.59%.

Table 3. *Cont.*

Authors	Techniques	Dataset, Period, and Variables	Results
(Jencova et al., 2021)	MLP with backpropagation	Financial ratios of 754 and 233 companies in the Slovak Republic for the years 2017 and 2018, respectively, 12 variables.	Accuracy 93.2%.
(Pamuk et al., 2021)	NN, LR, DT, XGBoost, cross validation and training, and SMOTE and extensions SMOTE-TOMEK and SMOTE-ENN	Financial reports of German companies from 2000 to 2012, consiting of 3,309,007 entries with 74 variables and 2040 insolvent companies with 13 variables.	Accuracy with oversampling SMOTE: NN 82.8%, XGBoost 98.2%, LR 65.1%, DT 81.8%. Accuracy with oversampling SMOTE-TOMEK: NN 81.6%, XGBoost 98.2%, LR 65.1%, DT 82.3%. Accuracy with oversampling SMOTE-ENN: NN 86.2%, XGBoost 99%, LR 63.7%, DT 82.9%.
(Muslim & Dasril, 2021)	KNN, DT, GB, RF and SM; feature selection with XGBoost with weight value filter of 10	Dataset of 42,625 Polish companies from 2000 to 2012, 65 variables.	Accuracy: KNN 95.6%; DT 94.8%; GB 96.9%; RF 96.9%; Stacking Model (SM) 97%.
(Aljawazneh et al., 2021)	LSTM, DBN, MLP (six layers), RF, SVM, KNN, AdaBoost, XGBoost, and SMOTE and extensions	Financial datasets of companies from Spain, Taiwan, and Poland: 471, 6819, and 10,000 records, respectively, from 1988–2003, 37 variables.	Accuracy: DBN 75.57%, LSTM 98.97%, MLP-6L 99.45%, RF 99.32%, SVM 86.6%, KNN 94.56%, AdaBoost 89.76%, XGBoost 99.42%.
(Pavlicko et al., 2021)	RobustBoost, CART, KNN, simple voting, average model, and proposed model (hybrid combining RobustBoost, CART, and K-NN)	Data from over 550,000 companies in Central Europe from 2017 to 2018, 27 variables.	Accuracy: RobustBoost 94.25%, CART 92.11%, KNN 91.65%, Simple Voting 92.69%, Average Model 92.8%, Proposed Model 94.25%.
(Vochozka et al., 2020)	LSTM and NN	Historical financial data for 5500 firms in the Czech Republic from 2014 to 2018, 15 variables.	Efficiency: LSTM 97.8%, NN 75%.
(Xhindi & Shestani, 2020)	Altman Z-Score and LR	Financial data of 367 companies in Albania from 2018 to 2019, five variables.	Prediction: Altman Z-Score 48.5%, LR 61%.
(Shrivastav & Ramudu, 2020)	SVM with linear kernel (SVMLK) and radial kernel (SVMRK)	Data from 58 banks in India from 2000 to 2017, 16 variables.	Accuracy: SVMLK 92.86%, SVMRK 71.43%.
(Du et al., 2020)	CUS, GBDT, XGBoost, and hybrid model; five feature selection methods were applied	The financial dataset of 670 firms from China unbalanced in 2018, 21 variables.	Accuracy: Hybrid CUS-GBDT-XGBoost 91.53%, CUS-GBDT 99.54%, XGBoost 94.44%, CUSBoost 99.39%, RUBoost 20.47%.
(Tadaaki Hosaka, 2019)	CNN, CART, LDA, SVM, MLP, AdaBoost, and Altman Z-Score.	Financial statements of 2063 companies listed on the Tokyo Stock Exchange from January 2002 to June 2016, 133 variables.	AUC: CART 77.7%, LDA 85.1%, SVM 87.2%, MLP 84.8%, AdaBoost 90.7%, Altman Z-Score 71.5%, CNN 92%.
(Lukason & Andresson, 2019)	LR and MLP	The tax arrears and financial ratios dataset of 4515 Estonian companies from 2013 to 2017, 13 variables.	Accuracy (financial ratios only): LR 79.9%, MLP 80.6%. Accuracy (financial ratios with tax arrears): LR 90.2%, MLP 87.6%.

Table 3. *Cont.*

Authors	Techniques	Dataset, Period, and Variables	Results
(Affes & Hentati-Kaffel, 2019b)	CDA, logistic regression (Logit)	The financial data of 1247 US banks from 2008 to 2013, 10 variables.	LOGIT: sensitivity 95.58%, specificity 91.22%, correct classification 91.57%. CDA: sensitivity 86.86%, specificity 96.39%, correct classification 95.72%.
(Affes & Hentati-Kaffel, 2019a)	CART, MARS, and K-MARS (hybrid model combining K-Means and MARS)	The financial data of 1247 US banks from 2008 to 2013, 10 variables.	Accuracy: CART 94.76%, MARS 96.06%, K-MARS 98.84%.

RQ1: What Artificial Intelligence (AI) techniques or models are most commonly used for bankruptcy risk analysis in financial institutions and related companies?

As a result of the review (see Table 3), a diversity of models and techniques employed was revealed. Figure 2 shows that logistic regression (LR) was used most frequently, appearing in 17 studies, followed by random forest (RF) with 15 studies and SVM with 11. Other commonly implemented models include neural networks (NN) and KNN, both in eight studies, and MLP with decision tree (DT), used in seven and six studies, respectively.

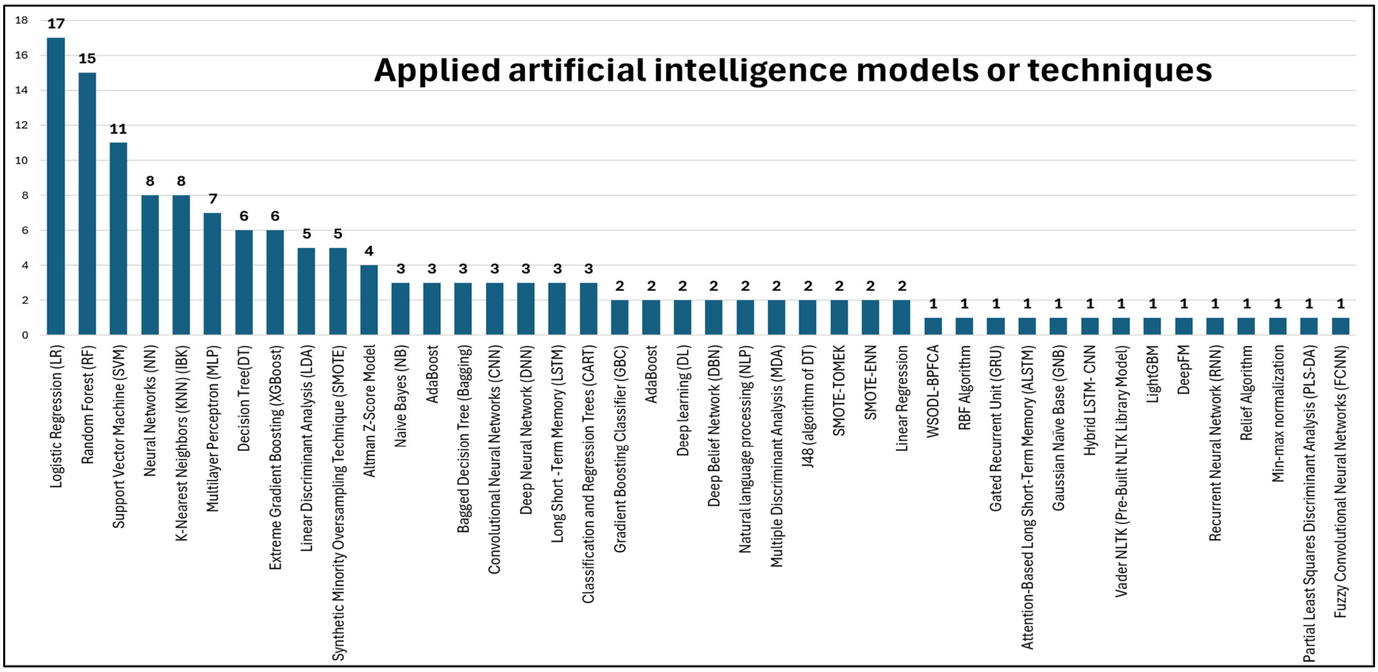

Figure 2. The most commonly used techniques according to selected articles (see Table 3).

In addition, the XGBoost model was also mentioned in six studies, while the linear discriminant analysis (LDA) model and the Synthetic Minority Oversampling Technique (SMOTE) were cited in five cases each. The Altman Z-Score model appeared in four studies, and other approaches such as naive Bayes (NB), AdaBoost, Bagging, convolutional neural network (CNN), deep neural network (DNN), long short-term memory (LSTM), and classification and regression trees (CART) were mentioned in 3 studies each.

Additionally, techniques such as gradient boosting classifier (GBC), deep learning (DL), deep belief network (DBN), natural language processing (NLP), and multiple discriminant analysis (MDA) have been used less frequently according to the review, each appearing in two studies. Other unique techniques mentioned include algorithms such as SMOTE-TOMEK, SMOTE-ENN, WSODL-BPFCA, radial basis function (RBF) based algorithms, gated recurrent unit (GRU), attention-based long short-term memory (ALSTM), hybrid models, and hyperparameter optimization techniques, among others (see Figure 2 and Table A1 in Appendix A).

The most-used techniques correspond to the classical machine learning models. This result is because most articles used a basic prediction model to compare the results with other techniques or proposed models. Figure 2 shows some of the many techniques used once or twice, because they are hybrid models calibrated for a certain dataset of banks or companies in a certain country in a certain period. On the other hand, the SMOTE technique was used in most papers to balance the amount of data, since the number of failed banks or firms is always from smaller than the number of non-failed banks or firms.

Jabeur and Serret (2023) proposed a combined method using fuzzy convolutional neural networks for the prediction of bankruptcy of companies using financial information and comparing their results with all of the classical machine learning techniques. In some articles, apart from using artificial intelligence models, they used statistical and economic methods to analyze the effects of bank bankruptcy (Erer & Erer, 2024). Likewise, some econometric models contribute to predicting variables; however, in many cases, ML outperforms them. It is best to combine traditional methods with ML (Pérez-Pons et al., 2022).

RQ2: Which models implemented for bankruptcy prediction of a bank, financial institution, or related companies perform best?

Figure 3 shows the prediction performances of the models applied in each of the articles selected, according to Table 3. These results are presented in ascending order, from least to most accurate, together with the model applied, the number of variables, and the author of the article analyzed.

According to the selected articles (see Figure 3), the NN model presented the best performance, with nine variables and an accuracy of 99.70% obtained in Gavurova et al. (2022); however, this study was focused on the study of bankruptcy risk in companies. The second-best model was KNN with cross-validation 10 times with 22 variables and 99.59% accuracy, obtained in Chen et al. (2021). Another notable model is CUS-GBDT, with 32 variables and 99.54% accuracy obtained in Du et al. (2020). The XGBoost model with SMOTE also showed a high accuracy of 99.42% using 37 variables in Aljawazneh et al. (2021). Finally, the LSTM model in Noh (2023) with 13 variables reached 99.36% accuracy. These models, with accuracies above 99%, stand out for their effectiveness, robustness, and reliability in bankruptcy prediction.

There was also a group of outstanding models with accuracies between 97% and 99%. This group contains the XGBoost model with oversampling SMOTE-ENN with 13 variables and 99% accuracy, obtained in Pamuk et al. (2021); the hybrid K-MARS model with 10 variables and 98.84% accuracy, obtained in Affes and Hentati-Kaffel (2019b); the GBT model with 95 variables and 98.14% accuracy, obtained in Idhmad et al. (2024); LSTM with 15 variables and 97.80% accuracy, obtained in Vochozka et al. (2020); and the WSOLD-BPFCA model with 14 variables and 97.51% accuracy, given in Gunita Arun Chandok et al. (2024). Likewise, the random forest (RF) model has shown good performance, with 97.35% and 98% accuracy obtained in Shah et al. (2022) and Gabrielli et al. (2023), respectively.

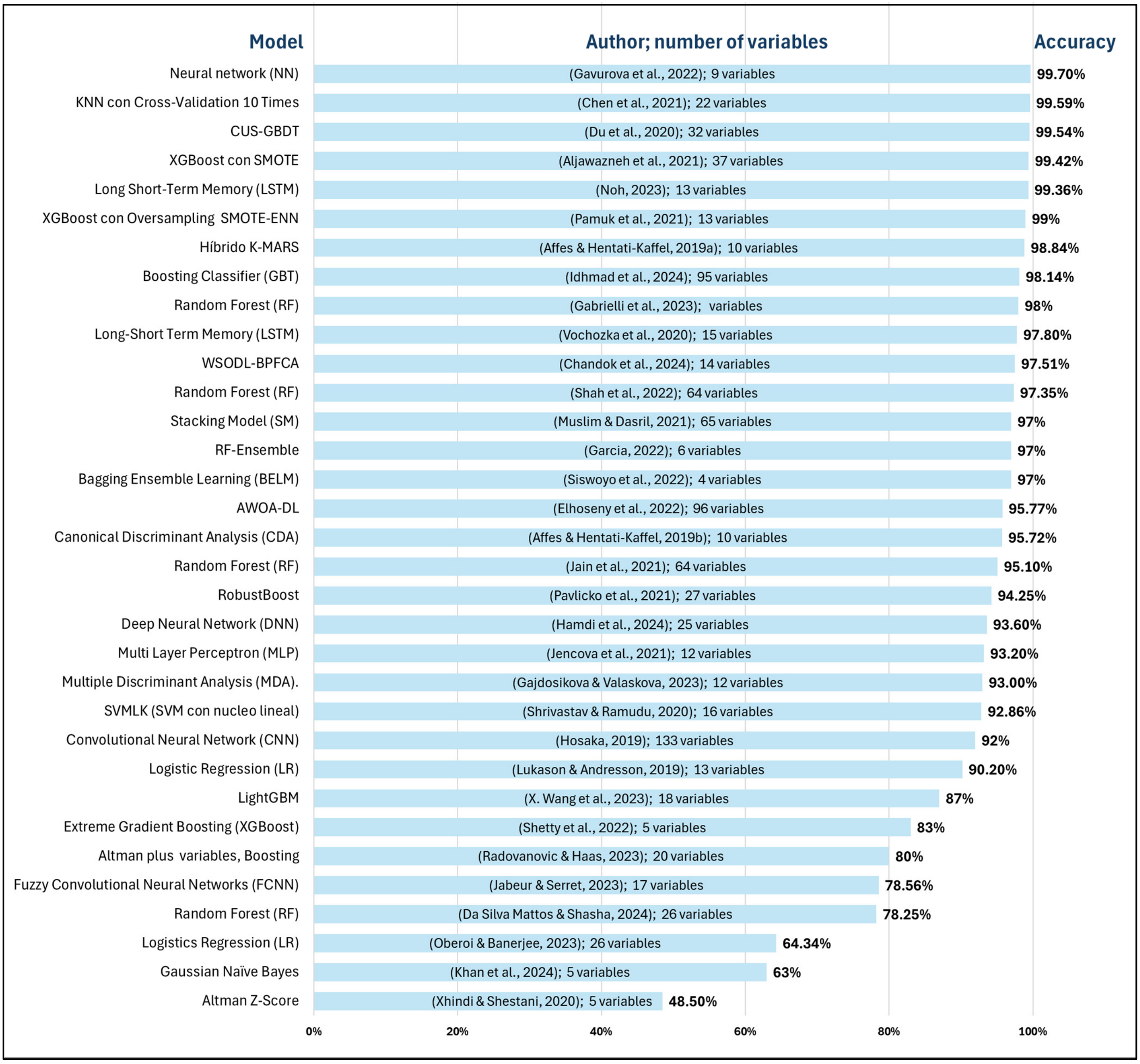

Figure 3. Predictive performance of the models applied in the articles reviewed (see Table 3); (Affes & Hentati-Kaffel, 2019a, 2019b; Aljawazneh et al., 2021; Chandok et al., 2024; Chen et al., 2021; Da Silva Mattos & Shasha, 2024; Du et al., 2020; Elhoseny et al., 2022; Gabrielli et al., 2023; Gajdosikova & Valaskova, 2023; Garcia, 2022; Gavurova et al., 2022; Hamdi et al., 2024; Tadaaki Hosaka, 2019; Idhmad et al., 2024; Jabeur & Serret, 2023; Jain et al., 2021; Jencova et al., 2021; Khan et al., 2024; Lukason & Andresson, 2019; Muslim & Dasril, 2021; Noh, 2023; Oberoi & Banerjee, 2023; Pamuk et al., 2021; Pavlicko et al., 2021; Radovanovic & Haas, 2023; Shetty et al., 2022; Shrivastav & Ramudu, 2020; Siswoyo et al., 2022; Valverde & Ortiz, 2022; Vochozka et al., 2020; X. Wang et al., 2023; Xhindi & Shestani, 2020).

Among the models with moderate accuracy were the following: RF with 64 variables achieved an accuracy of 95.10% in Jain et al. (2021); CDA with 10 variables and an accuracy of 95.72% was given in Affes and Hentati-Kaffel (2019b); and AWOA-DL with 96 variables and 95.77% accuracy was given in Elhoseny et al. (2022). There exists also a subgroup of three outstanding models with 97% accuracy each: a stacking model, RF-Ensemble, and BELM, with 65, 6, and 4 variables, respectively, obtained in Muslim and Dasril (2021), Garcia

(2022), and Siswoyo et al. (2022), respectively. While not reaching the highest figures, these models still showed considerable accuracy, and are thus feasible for financial forecasting.

Finally, some models presented relatively low accuracy compared to those mentioned above. The Altman Z-Score model with five variables presented a limited performance of 48.50% prediction, obtained by Xhindi and Shestani (2020). Likewise, a Gaussian naïve Bayes model with five variables, logistic regression with twenty-six variables, and a fuzzy convolutional neural network (FCNN) with 17 variables exhibited relatively weak performances, exhibiting 63%, 64.34%, and 78.56% accuracy, respectively, obtained in Khan et al. (2024), Oberoi and Banerjee (2023), and Ben Jabeur and Serret (2023), respectively. With significantly lower accuracy, these models may not be as effective in predicting financial bankruptcies compared to other more advanced methods.

RQ3: What datasets and balancing techniques are used to apply AI models in predicting and identifying the risk of bankruptcy of financial institutions?

According to the selected articles in Table 3, the datasets used were financial statements, financial ratios, comments in social networks (tweets), and economic and social indicators. Financial statements are essential inputs to obtain datasets through nominal data or financial ratios. The main financial statements are balance sheets, profit and loss statements, and cash flow statements. Figure 4 summarizes the characteristics of the papers selected in this literature review, highlighting the number of variables used in the datasets, the number of banks or firms analyzed, the countries of study, and the corresponding period. These data, derived from the articles in Table 3, provide a comparative overview of the approaches used for predicting bankruptcy risk.

In this review, there was a wide variation in the number of variables used, which influenced the accuracy of the models (see Figures 3 and 4). The model that used the most significant number of variables was CNN (Tadaaki Hosaka, 2019), which used 133 variables and achieved an accuracy of 92.00% on a set of 1063 companies working in Tokyo in the period from 2002 to 2016. This is followed by the AWOA-DL model (Elhoseny et al., 2022), with 96 variables and an accuracy of 95.77% on a large set of 690, 50, 10,503, and 6819 companies from the countries of Australia, China, Poland, and Taiwan, respectively, in the average period 1999–2012. Thirdly, there is the GBT model with 95 variables and 98.14% accuracy, obtained in Idhmad et al. (2024), applied to a set of 6915 Taiwanese companies from 1999 to 2009. These models show how using a large number of variables can significantly improve prediction accuracy, although it also implies greater complexity in data processing.

There is a group of three models that used almost the same amount of variables, obtaining similar results: a stacking model (SM) with 65 variables and 97% accuracy given in Muslim and Dasril (2021), applied to a set of 42,625 Polish companies; and two random forest (RF) models, both with 64 variables, and with accuracies of 95.10% (applying SMOTE) and 97.35%, given in Jain et al. (2021) and Shah et al. (2022) for 10,503 banks and 10,000 Polish companies, respectively. These models demonstrate that a larger number of variables can improve accuracy, highlighting their applicability in complex bankruptcy prediction scenarios.

An interesting case is the XGBoost model with SMOTE, given in Aljawazneh et al. (2021), which employed 37 variables and achieved a high accuracy of 99.42% over 17,290 companies, showing that using oversampling techniques combined with many variables can result in very accurate models. Similarly, the CUS-GBDT model (Du et al., 2020) using 32 variables achieved an accuracy of 99.54% over 670 companies listed on the Chinese stock exchange, reaffirming the importance of an adequate number of variables to improve model accuracy.

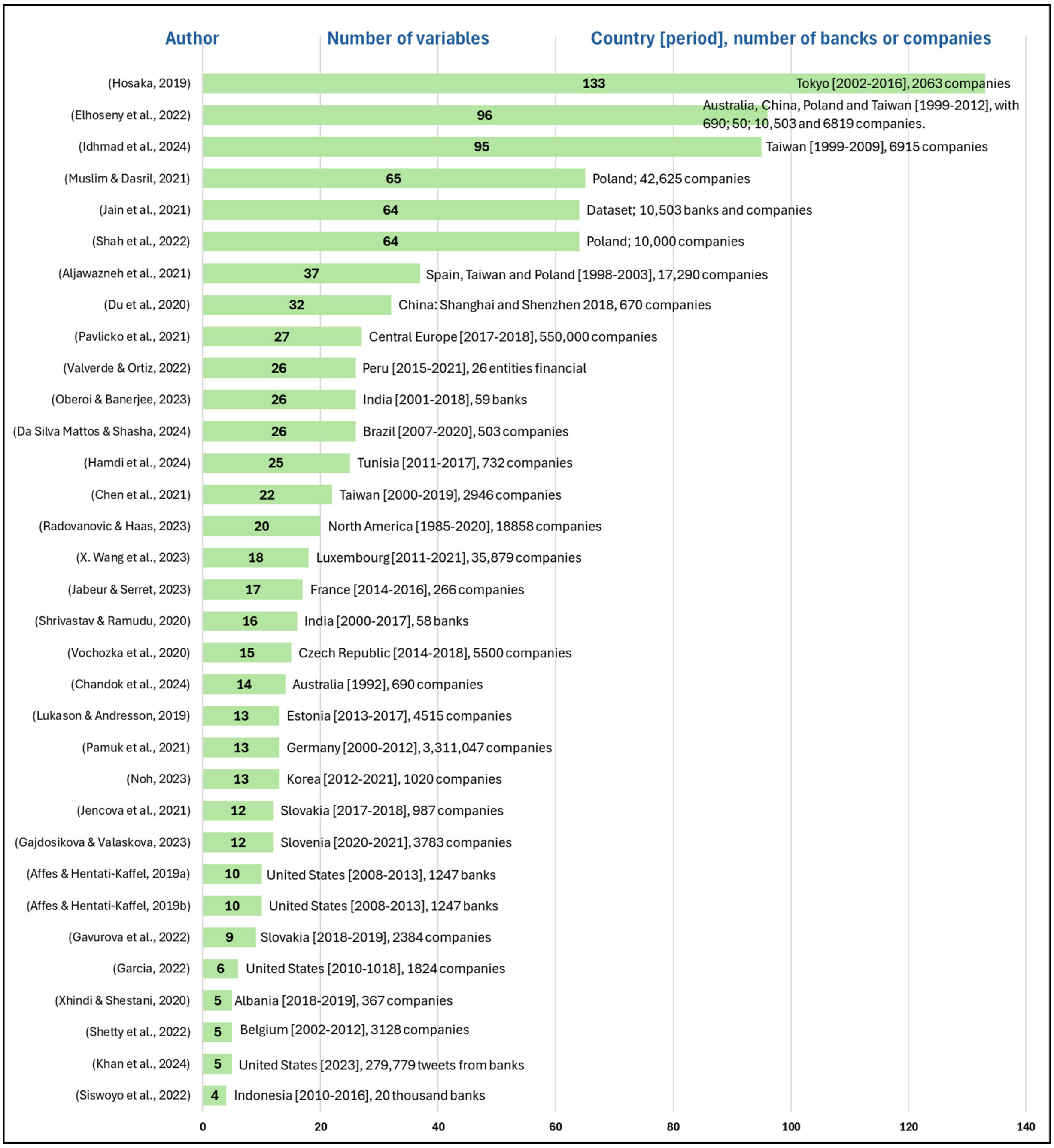

Figure 4. Datasets and number of variables used in the articles reviewed (see Table 3); (Affes & Hentati-Kaffel, 2019a, 2019b; Aljawazneh et al., 2021; Chandok et al., 2024; Chen et al., 2021; Da Silva Mattos & Shasha, 2024; Du et al., 2020; Elhoseny et al., 2022; Gajdosikova & Valaskova, 2023; Garcia, 2022; Gavurova et al., 2022; Hamdi et al., 2024; Tadaaki Hosaka, 2019; Idhmad et al., 2024; Jabeur & Serret, 2023; Jain et al., 2021; Jencova et al., 2021; Khan et al., 2024; Lukason & Andresson, 2019; Muslim & Dasril, 2021; Noh, 2023; Oberoi & Banerjee, 2023; Pamuk et al., 2021; Pavlicko et al., 2021; Radovanovic & Haas, 2023; Shah et al., 2022; Shetty et al., 2022; Shrivastav & Ramudu, 2020; Siswoyo et al., 2022; Valverde & Ortiz, 2022; Vochozka et al., 2020; X. Wang et al., 2023; Xhindi & Shestani, 2020).

In terms of models with a moderate use of variables, the RF model, given by Da Silva Mattos and Shasha (2024), used 26 variables and obtained an accuracy of 78.25% over 503 Brazilian companies from 2007–2020. The LR model with the SMOTE technique to balance the data, given in Oberoi and Banerjee (2023), also with 26 variables, achieved an accuracy of 64.34% over 59 Indian banks from 2001 to 2018. FCNN, given in Jabeur and Serret (2023), employed 17 variables and exhibited an accuracy of 78.56% over 266 French companies from 2014 to 2016, while LightGBM (X. Wang et al., 2023) used 18 variables to obtain an accuracy of 87.00% over 35,879 Luxembourg companies from 2011 to 2021. These models show that a smaller number of variables can still provide competitive results.

Finally, at the other extreme, some models have employed fewer variables, with mixed results. The NN model, given in Gavurova et al. (2022), used only variables, and obtained the maximum performance of 99.70% accuracy over 2384 Slovak companies in 2018–2019. It is also remarkable that the LSTM model given in Noh (2023) using 13 variables achieved 99.36% accuracy over a set of 1020 companies listed on the Korea Stock Exchange from 2012 to 2021. Similarly, the XGBoost model with oversampling SMOTE-ENN given in Pamuk et al. (2021) with 13 variables obtained 99% accuracy over a set of 3,311,047 German companies in the period 2000–2012.

However, some models that used a few variables obtained low accuracy performance. The Altman Z-Score model, given in Xhindi and Shestani (2020), employed only five variables and obtained 48.50% accuracy over 367 companies in Albania 2018–2019. Similarly, the Gaussian naïve Bayes model, given in Khan et al. (2024), also with five variables, obtained a low accuracy of 63% over a set of 279,779 tweets in the year 2023. Conversely, the XGBoost model given in Shetty et al. (2022), also with five variables, obtained a reasonable accuracy of 83% on a set of 3128 Belgian small and medium-sized companies from 2002 to 2012.

In conclusion, the number of variables used in bankruptcy prediction models for financial institutions has tended to vary considerably, directly influencing the accuracy and complexity of the model. Models with a more significant number of variables tend to offer greater accuracy, although they require more computational resources. On the other hand, efficient models with fewer variables can also achieve high levels of accuracy if appropriate techniques and algorithms are applied. Likewise, the SMOTE technique has been the most widely used technique to balance and generate bias in the prediction.

Figure 5 shows the datasets studied according to the countries where firms and banks were analyzed for bankruptcy prediction. It shows that the United States, Taiwan, and Poland have the most articles resulting from studies on banks and firms in these countries, followed by Slovakia, Australia, India, and China.

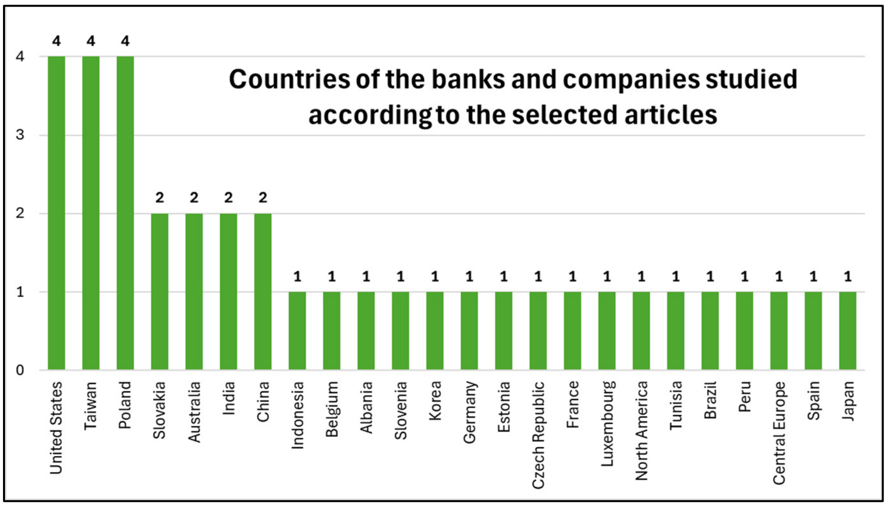

Figure 5. Countries of the banks and companies studied according to the selected articles (see Table 3).

Likewise, Figure 6 shows that of the articles selected in Table 3, 21% correspond to the prediction of bankruptcy of banks or financial institutions. In comparison, 79% correspond to companies linked to the financial system, as they are corporate companies that work closely with banks.

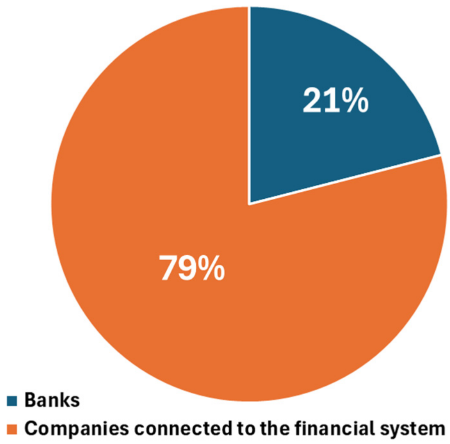

Figure 6. Type of entities studied on the risk of bankruptcy according to selected articles.

RQ4: What are the most commonly used variables in AI bankruptcy prediction models, and how do they relate to variables in other prediction models?

Figure 7 shows the main variables used in the different models used in each of the selected articles, according to Table 3. The financial statements of the banks or related companies are the base documents for obtaining the financial ratios and the accounting, financial, and economic indicators. The main financial statements used, according to the review, were the balance sheet, profit and loss statement, and cash flow statement.

To select relevant information as variables, different methods were employed across studies. In Du et al. (2020), they used five feature selection methods based on different theoretical backgrounds and obtained reasonable performance results in predicting financial difficulties. In Muslim and Dasril (2021), they also used techniques to select information, showing that the stacking model performed better. In Issa et al. (2024), they used financial indicators (variables) such as liquidity, profitability, debt composition, and operating effectiveness to analyze whether a set of 20 financial institutions was likely to fail. The result was that excessive indebtedness was shown to have a negative influence on profitability, which leads to a decrease in the profitability of shares and a higher probability of bankruptcy.

As for leverage variables, the most frequent was the debt ratio, used 19 times. This variable is also classified under solvency and capital structure, reflecting its multifaceted importance. Debt to equity ratio and long-term debt to equity ratio were also recurring variables in this category, with 16 and 14 mentions, respectively. Likewise, the interest coverage ratio appeared 12 times, standing out in its ability to assess both the leverage and solvency of a company.

Solvency variables followed a similar pattern, with debt ratio and debt equity ratio topping the list with 19 and 16 mentions each. Equity ratio, long-term debt to equity ratio, and cash flow to debt ratio were also prominent in this category, with 15 and 14 mentions, respectively.

In the capital structure category, debt ratio and debt to equity ratio were again the most frequently mentioned. Equity ratio and interest coverage ratio had 15 mentions each, while long-term debt to equity ratio and cash flow to debt ratio were mentioned 14 times each. These variables have been shown to be crucial in assessing a company's financial health and ability to manage its debts.

Profitability variables were also widely used, with return on assets (ROA) and return on equity (ROE) leading with 18 mentions each. Net profit margin and gross profit margin were other key variables in this category, appearing 16 and 15 times, respectively. Operating profit margin and return on investment (ROI) also stand out, with 14 and 12 mentions each, indicating their relevance in assessing a company's operating efficiency and profitability.

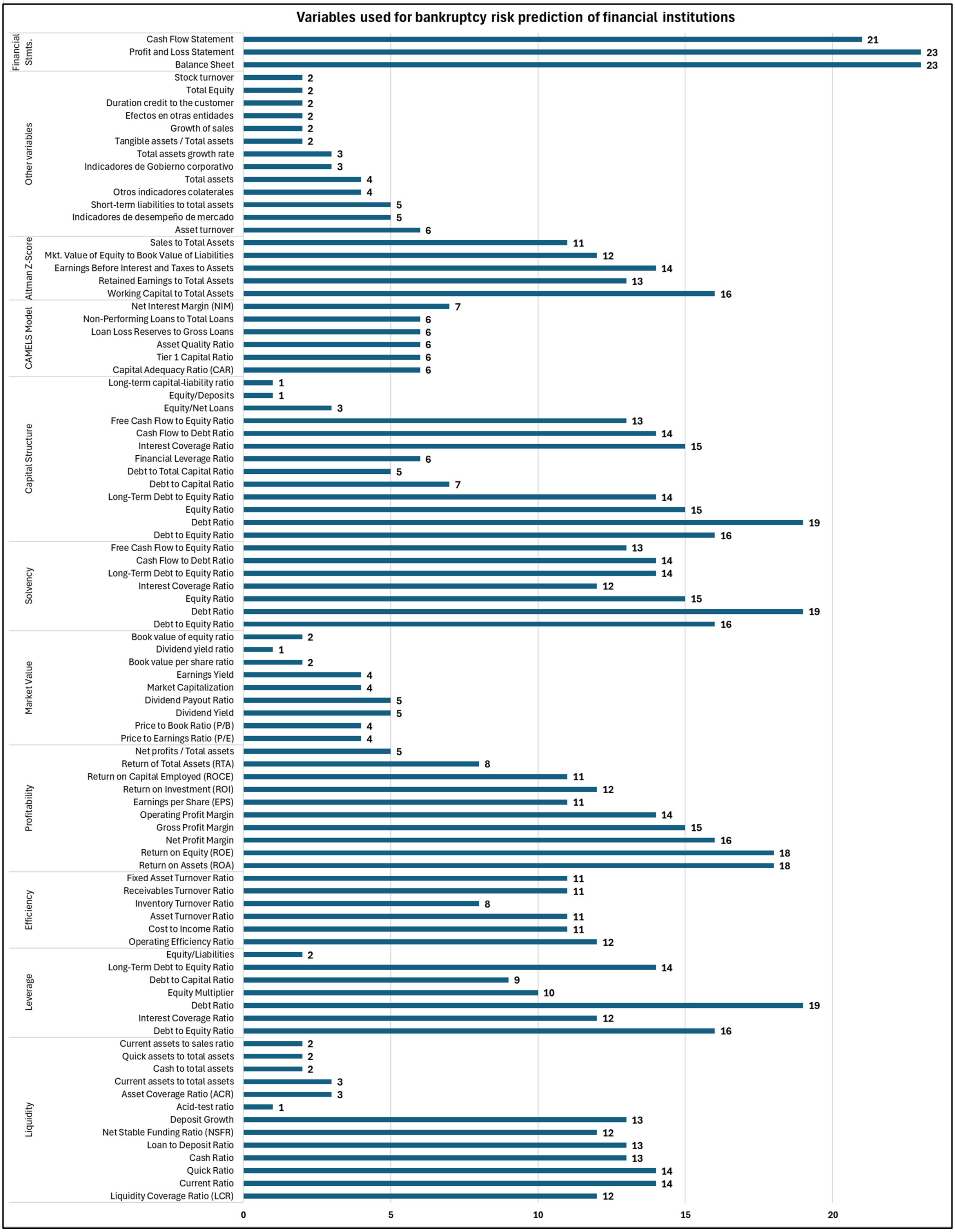

Figure 7. The most commonly used variables according to the literature reviewed.

Liquidity variables included the current ratio and the quick ratio, both mentioned 14 times. Cash ratio and loan to deposit ratio followed closely, with 13 mentions each. The liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR) had 12 mentions each, underlining their importance in liquidity management and long-term financial stability.

Within the scope of the Altman Z-Score model, the most recurrent variables were working capital to total assets with 16 mentions, and earnings before interest and taxes to assets and retained earnings to total assets, with 14 and 13 mentions, respectively. These variables are essential to evaluate the solvency and capacity of a company to cover its short and long-term financial obligations.

Efficiency variables such as the operating efficiency ratio, cost to income ratio, and asset turnover ratio appeared 12 and 11 times each. These variables are crucial in measuring a company's ability to use its assets efficiently and generate income.

Finally, in the category of CAMELS model variables, net interest margin (NIM) was the most frequent with seven mentions, followed by the capital adequacy ratio (CAR) and tier 1 capital ratio, each mentioned six times. These variables are fundamental for assessing the stability and risk of financial institutions.

In summary, basic financial variables such as the balance sheet and the profit and loss statement were the most widely used in the reviewed studies, reflecting their importance in financial analysis. Variables related to profitability and leverage, such as return on assets (ROA), return on equity (ROE), and debt ratio, were also frequently used, underlining their relevance in the evaluation of the financial health of companies.

6. Discussion

The literature review revealed that artificial intelligence models applied to bankruptcy prediction of financial institutions present both significant advantages and disadvantages.

According to the review, it is not clear which AI model has better predictive performance, nor is it clear with respect to the type of variables to be used. What is noted is that there is no direct relationship between the predictive accuracy of the models and the number of variables applied. For example, the review showed that the NN model had the highest accuracy of 99.7% using only nine variables; however, in Pamuk et al. (2021), it reached 82.8% accuracy with thirteen variables, in Shetty et al. (2022) it reached 82% with five variables, in Radovanovic and Haas (2023) it reached 79% with twenty variables, in Ben Jabeur and Serret (2023) it reached 77.34% with seventeen variables, and in Garcia (2022) it reached 73.6% with six variables. Similarly, with respect to the KNN model, Chen et al. (2021) reached the second-best accuracy of 99.59% with 22 variables. However, in Idhmad et al. (2024) the accuracy with KNN reached 95.68% with 95 variables; in Muslim and Dasril (2021), it was 95.6% with 65 variables; in Aljawazneh et al. (2021), it was 94.56% with 37 variables; in Pavlicko et al. (2021), it was 91.65% with 27 variables; in Garcia (2022), it was with 73.3% with 6 variables; and in Jain et al. (2021), it was 58.6% with 64 variables. In addition, apart from the financial indicators that the articles used, some authors took into account other indicators, as in Chen et al. (2021) and Aljawazneh et al. (2021), with 99.59% and 99.42% accuracy, respectively.

It is worth considering the use of almost all the financial indicators in order to capture the relevant variables for prediction; however, the number of variables decreases the performance. For example, Tadaaki Hosaka (2019) used 133 variables, the maximum number of variables in this review, in the CNN model, obtaining an acceptable result of 92% accuracy. Similarly, in Idhmad et al. (2024), the authors used 95 variables in the boosting classifier (GBT) model, obtaining an outstanding 98.14% accuracy; however, this study did not describe or show the details of the selected variables, as in Khan et al. (2024).

On the other hand, according to the review, the most used technique was LR, followed by RF; however, these methods did not guarantee the best performance in terms of accuracy. For example, the LR model, in Lukason and Andresson (2019), Idhmad et al. (2024), Gavurova et al. (2022), Hamdi et al. (2024), Elhoseny et al. (2022), Siswoyo et al. (2022), Jabeur and Serret (2023), Noh (2023), Da Silva Mattos and Shasha (2024), X. Wang et al. (2023), Radovanovic and Haas (2023), and Pamuk et al. (2021), returned accuracy rates of 90.2%, 90.19%, 89.4%, 85.8%, 84.57%, 81%, 77.81%, 75.70%, 75.47%, 75%, 71%, and 65.1, respectively. However, the RF model fared better in accuracy performance in Aljawazneh et al. (2021), Noh (2023), Idhmad et al. (2024), Muslim and Dasril (2021), Jain et al. (2021), Hamdi et al. (2024), X. Wang et al. (2023), and Da Silva Mattos and Shasha (2024), with 99.32%, 98.99%, 97.54%, 96.9%, 95.1%, 88.2%, 79%, and 78.25%, accuracy, respectively. The good performance of the XGBoost model in Aljawazneh et al. (2021), Pamuk et al. (2021), Du et al. (2020), Shetty et al. (2022), and Da Silva Mattos and Shasha (2024), with 99.42%, 98.2%, 94.44%, 83%, and 76.8% accuracy, respectively, was also noteworthy.

With respect to advanced models such as LSTM and CNN, these have shown a remarkable improvement in predictive accuracy. For example, the LSTM models in Noh (2023), Aljawazneh et al. (2021), and Vochozka et al. (2020) achieved 99.36%, 98.97%, and 97.8% accuracy, respectively. Additionally, the CNN models in Tadaaki Hosaka (2019), Chandok et al. (2024), and Jabeur and Serret (2023) achieved 92%, 90.08%, and 73.04% accuracy, respectively. However, these models also have disadvantages, such as the need for large amounts of labelled data and their computational complexity, which can make them difficult to implement in resource-constrained environments.

With respect to hybrid models, it is not clear as to precisely how to implement them in their execution; however, some have shown high levels of accuracy. For example, the CUS-GBDT model in Du et al. (2020) was 99.54% accurate; the K-MARS model in Affes and Hentati-Kaffel (2019a) exhibited 98.84% accuracy; and the WSODL-BPFCA model in Chandok et al. (2024) had 97.51% accuracy. These models take advantage of the strengths of multiple algorithms to provide more accurate and reliable predictions. As for the classical machine learning models, almost all the reviewed articles applied these as a prediction reference and for comparison with other advanced models.

6.1. Applicability of the Findings in the Real World

The results of this study show that the implementation of advanced AI techniques in financial institutions can significantly improve bankruptcy risk prediction, providing a powerful tool for strategic decision making. For example, models such as LSTM and XGBoost offer practical solutions for overcoming the limitations of traditional methods, such as logistic regression, by handling large volumes of data and capturing non-linear and dynamic relationships in financial data (Vukčević et al., 2024; Shrivastav & Ramudu, 2020). However, the adoption of these techniques faces several challenges in the real world. One of the main obstacles is data quality, as many financial institutions lack robust data management systems or access to clean and complete datasets (Isaac-Roque & Caicedo-Carrero, 2023). Moreover, integrating these models requires investments in technological infrastructure and staff training, which could be especially challenging for small or emerging institutions (Parra et al., 2021).

Phased implementation and collaboration with AI experts could mitigate these challenges. Institutions such as banks and municipal savings banks could start with the adoption of more accessible models, such as random forest or XGBoost, before moving towards more complex solutions such as LSTM, which require more computational capacity and technical expertise (Radovanovic & Haas, 2023).

6.2. Contribution to Advancing the Use of AI in the Financial Sector

This study provides strong evidence on how advanced AI techniques can overcome the limitations of traditional approaches to bankruptcy risk prediction. For example, the results confirm that machine learning models, such as XGBoost, achieve superior accuracy in heterogeneous and complex data scenarios, while LSTM excels in capturing temporal patterns in sequential data (Nguyen et al., 2020). Furthermore, the integration of these techniques is shown to identify early signs of financial deterioration, such as changes in liquidity ratios or increases in delinquency rates, which could give institutions time to implement corrective measures (Affes & Hentati-Kaffel, 2019a). These capabilities not only improve forecasting accuracy, but also enable a proactive approach to risk management, a critical advantage in contexts of high economic volatility (Hamdi et al., 2024). By incorporating metrics such as sensitivity and accuracy, this study also provides a basis for evaluating and comparing the performance of different models in real-world contexts, which represents an advance on the existing literature (Tadaaki Hosaka, 2019).

6.3. Model Comparison: LSTM and XGBoost

Model comparison suggests that LSTM and XGBoost consistently outperform other techniques due to their unique capabilities. LSTM is particularly effective for analyzing time-series data, as it can capture long-term relationships and non-linear dynamics in financial data, which is essential for forecasting deteriorating trends (Gavurova et al., 2022; Radovanovic & Haas, 2023). On the other hand, XGBoost excels in its ability to handle complex, multidimensional datasets with high computational efficiency, which makes it ideal for scenarios in which multiple interdependent variables are analyzed (Vukčević et al., 2024). This model also offers advantages in terms of interpretability, as it allows identification of which variables contribute most to bankruptcy risk, such as capitalization ratios or asset quality (Parra et al., 2021). Simpler models, such as logistic regression, tend to have limitations in that they do not adequately capture non-linear relationships and are less robust to incomplete or noisy data (Song & Shahbudin, 2023). In contrast, advanced models not only offer greater accuracy, but also provide practical insights that can be used directly by decision-makers in financial institutions.

Finally, some gaps and potential future research directions have been evidenced through this paper, such as the variables and datasets employed, and the ways in which to apply the advanced neural network models. Furthermore, the scarcity of the literature with regards to the application of these models in financial entities and the scarce consideration of non-financial factors, such as sentiment analysis or macroeconomic events, represent areas for future research.

7. Conclusions

This study addresses a critical problem in the financial sector: the identification and prevention of the risk of bankruptcy of financial institutions using advanced artificial intelligence (AI) techniques. The results obtained offer several key insights in terms of comparison between traditional financial ratio-based methods and AI-based predictive approaches. This literature review highlights the increasing relevance and effectiveness of AI models in the prediction and identification of bankruptcy risks in financial institutions. It also finds that AI models predict financial bankruptcies more accurately and robustly than traditional methods. It is concluded that basic models such as RF, LR, KNN, and NN and advanced models such as CNN, LSTM, XGBoost, and hybrid models stand out for their high accuracy, taking into account that they require large amounts of data and computational resources, which makes them difficult to implement in resource-constrained environments. It is also suggested to use all variables involved in the main financial statements and to use various variable filtering techniques in order to select the most influential variables in bankruptcy risk prediction performance.

7.1. Advantages of Using AI Compared to Traditional Financial Ratios

Financial ratios, such as those related to profitability, liquidity, leverage, and asset quality, have long been fundamental tools for assessing the financial health of institutions. Their simplicity and ease of calculation have made them effective and widely adopted monitoring mechanisms. However, this study demonstrates that AI techniques, such as LSTM and XGBoost, offer significant advantages over traditional financial ratios.

First, AI methods allow for the analysis of large volumes of data with multiple interdependent variables, capturing non-linear relationships and complex patterns that financial ratios cannot identify. Moreover, AI has the ability to incorporate dynamic data, such as time series, and to generate real-time forecasts, improving the ability to anticipate emerging financial risks.

Additionally, AI integration can address challenges related to the quality and integrity of financial data, using pre-processing techniques and handling noisy data to ensure more reliable predictions. This represents a significant competitive advantage for institutions seeking to adopt more adaptive and robust approaches in the face of economic volatility.

7.2. Benchmarking: Financial Ratios Versus AI Methods

One of the most salient contributions of this study is the empirical comparison between the results obtained using traditional financial ratios and those generated by AI models. AI-based predictive models, such as XGBoost and LSTM, consistently outperformed traditional approaches in terms of accuracy, sensitivity, and early bankruptcy detection capability. For example, results show that AI models achieved accuracies of over 90% in scenarios with complete historical data, while traditional financial ratios had an average pre-accuracy of 75–80%.

In addition, AI methods exhibited a better ability to identify early signals of financial deterioration, such as fluctuations in liquidity patterns and increases in default rates, before these variables were reflected in standard financial ratios. This highlights the ability of AI to complement and, in many cases, enhance traditional risk assessment mechanisms.

However, it is important to note that financial ratios remain valuable tools, especially in scenarios where data availability or technological resources are limited. The results suggest that an integration of both approaches could offer a more comprehensive and effective solution, combining the interpretability and accessibility of ratios with the advanced accuracy of AI models.

8. Limitations

This review highlights that artificial intelligence (AI) models have significant strengths, but also limitations in predicting bankruptcy risks in financial institutions. One of the main limitations is the variability in the datasets and financial indicators used in the reviewed studies, which affects the comparability of the results and poses challenges in assessing the performance of the models in different contexts. In addition, the lack of transparency in the description of variables and factors contributing to the predictions hinders the interpretation and practical application of the findings in real-world settings.

Another critical aspect is the limited availability of data. Many studies rely on restricted or region-specific datasets, which can introduce biases and limit the generalizability of results. The studies reviewed also exhibited inconsistencies in the metrics for assessing model performance, which makes standardized and comprehensive comparison difficult. The lack of consistency in measures of accuracy, sensitivity, and specificity underlines the need to develop uniform assessment frameworks to ensure more robust and comparable results.

In terms of the methodological process, limitations include the exclusion of articles in languages other than English and the reliance on open access publications. These methodological choices could have reduced the diversity of perspectives and applications included in the review. In addition, the focus on recent publications may have omitted important contributions at earlier stages in the development of AI-based predictive models.

From a practical perspective, the scalability of advanced models remains a challenge, especially in contexts with limited computational resources. Advanced AI models, while accurate, require large amounts of data and computational processing, which may be unattainable for smaller financial institutions or in emerging markets.

9. Future Work

For the continuation of this research, several lines of work are proposed to strengthen and extend the current findings. A key priority is to investigate the integration of additional data sources, such as macroeconomic variables, market indicators, and qualitative data from financial reports in order to provide a more holistic view of bankruptcy risk. Furthermore, the development of hybrid models that combine traditional machine learning techniques with advanced algorithms, such as deep learning and convolutional neural networks, could increase both the accuracy and robustness of predictions.

Another promising direction lies in the implementation of continuous learning techniques, which allow models to adapt in real time to changes in the financial and business environment. This adaptive capability would be particularly valuable in markets characterized by volatility and dynamism. Moreover, integrating approaches that combine traditional financial ratios with artificial intelligence models could maximize predictive capabilities by leveraging the strengths of both paradigms.

It is also essential to explore the inclusion of qualitative factors, such as corporate governance and macroeconomic risks, in predictive models. Incorporating contextual data, such as sentiment analysis derived from news or social media, could capture dynamics that are not reflected in conventional financial data. In parallel, assessing and mitigating potential biases in models and training data is critical to ensure the applicability of predictions in diverse geographical and economic contexts.

Finally, future research should address practical barriers to the implementation of advanced models, such as simplifying their design and optimizing computational requirements, in order to facilitate their adoption across a wide range of financial institutions. These strategies would not only improve the accuracy of models, but also their accessibility and usefulness in real-world scenarios.

The adoption of artificial intelligence in bankruptcy risk prediction has the potential to revolutionize financial management. However, it must be approached with a holistic approach that combines methodological rigor, transparency, and practical applicability, which will allow progress towards more reliable, inclusive, and effective predictive systems for the early detection of financial risks.

Author Contributions: Conceptualization, L.-J.V.-S., C.R., J.-R.P.-N. and C.N.; methodology, L.-J.V.-S., C.R. and J.-R.P.-N.; formal analysis, L.-J.V.-S., C.R. and J.-R.P.-N.; investigation, L.-J.V.-S., C.R., J.-R.P.-N. and C.N.; writing—original draft preparation, L-J.V-S.; writing—review and editing, L.-J.V.-S., C.R., J.-R.P.-N. and C.N. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No processing data has been generated, only a literature review has been performed.

Acknowledgments: The authors extend their gratitude to the Universidad Nacional Mayor de San Marcos, Lima-Peru, for their invaluable contributions and support throughout this research.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. AI models applied in the literature review.

Models	Total Articles	Articles
Logistic Regression (LR)	17	(Idhmad et al., 2024; Da Silva Mattos & Shasha, 2024; Hamdi et al., 2024; X. Wang et al., 2023; Noh, 2023; Oberoi & Banerjee, 2023; Jabeur & Serret, 2023; Radovanovic & Haas, 2023; Gavurova et al., 2022; Siswoyo et al., 2022; Garcia, 2022; Elhoseny et al., 2022; Chen et al., 2021; Pamuk et al., 2021; Xhindi & Shestani, 2020; Lukason & Andresson, 2019; Affes & Hentati-Kaffel, 2019b)
Random Forest (RF)	13	(Idhmad et al., 2024; Da Silva Mattos & Shasha, 2024; Chandok et al., 2024; Hamdi et al., 2024; X. Wang et al., 2023; Gabrielli et al., 2023; Noh, 2023; Oberoi & Banerjee, 2023; Radovanovic & Haas, 2023; Shah et al., 2022; Siswoyo et al., 2022; Garcia, 2022; Jain et al., 2021; Muslim & Dasril, 2021; Aljawazneh et al., 2021).
Support Vector Machine (SVM)	11	(Idhmad et al., 2024; Da Silva Mattos & Shasha, 2024; Hamdi et al., 2024; Jabeur & Serret, 2023; Radovanovic & Haas, 2023; Siswoyo et al., 2022; Garcia, 2022; Shetty et al., 2022; Aljawazneh et al., 2021; Shrivastav & Ramudu, 2020; Tadaaki Hosaka, 2019).
Neural Networks (NN)	8	(Chandok et al., 2024; Oberoi & Banerjee, 2023; Radovanovic & Haas, 2023; Gavurova et al., 2022; Siswoyo et al., 2022; Garcia, 2022; Pamuk et al., 2021; Vochozka et al., 2020)
K-Nearest Neighbors (KNN) (IBK)	8	(Idhmad et al., 2024; Noh, 2023; Garcia, 2022; Jain et al., 2021; Chen et al., 2021; Muslim & Dasril, 2021; Aljawazneh et al., 2021; Pavlicko et al., 2021)
Multilayer Perceptron (MLP)	6	(Chandok et al., 2024; X. Wang et al., 2023; Gavurova et al., 2022; Aljawazneh et al., 2021; Tadaaki Hosaka, 2019; Lukason & Andresson, 2019; Jencova et al., 2021)
Decision Tree (DT)	6	(Idhmad et al., 2024; Hamdi et al., 2024; Noh, 2023; Chen et al., 2021; Pamuk et al., 2021; Muslim & Dasril, 2021)
Extreme Gradient Boosting (XGBoost)	6	(Da Silva Mattos & Shasha, 2024; Shetty et al., 2022; Pamuk et al., 2021; Muslim & Dasril, 2021; Aljawazneh et al., 2021; Du et al., 2020)
Linear Discriminant Analysis (LDA)	5	(Hamdi et al., 2024; Jabeur & Serret, 2023; Radovanovic & Haas, 2023; Garcia, 2022; Tadaaki Hosaka, 2019)
Synthetic Minority Oversampling Technique (SMOTE)	5	(Oberoi & Banerjee, 2023; Garcia, 2022; Jain et al., 2021; Pamuk et al., 2021; Aljawazneh et al., 2021)
Altman Z-Score Model	4	(Valverde & Ortiz, 2022; Chen et al., 2021; Xhindi & Shestani, 2020; Tadaaki Hosaka, 2019)
Naive Bayes (NB)	3	(Idhmad et al., 2024; Garcia, 2022; Chen et al., 2021)
AdaBoost	3	(Idhmad et al., 2024; Aljawazneh et al., 2021; Tadaaki Hosaka, 2019)
Bagged Decision Tree (Bagging)	3	(Da Silva Mattos & Shasha, 2024; Radovanovic & Haas, 2023; Chen et al., 2021)
Red Neuronal Convolucional (CNN)	3	(Chandok et al., 2024; Jabeur & Serret, 2023; Tadaaki Hosaka, 2019)
Deep Neural Network (DNN)	3	(Hamdi et al., 2024; Elhoseny et al., 2022; Shetty et al., 2022)
Long Short-Term Memory (LSTM)	3	(Noh, 2023; Aljawazneh et al., 2021; Vochozka et al., 2020)

Table A1. *Cont.*

Models	Total Articles	Articles
Classification and Regression Trees (CART)	3	(Pavlicko et al., 2021; Tadaaki Hosaka, 2019; Affes & Hentati-Kaffel, 2019a)
Gradient Boosting Classifier (GBC)	2	(Idhmad et al., 2024; Muslim & Dasril, 2021)
AdaBoost	2	(Da Silva Mattos & Shasha, 2024; Oberoi & Banerjee, 2023)
Deep learning (DL)	2	(Chandok et al., 2024),
Deep Belief Network (DBN)	2	(Chandok et al., 2024),
Natural language processing (NLP)	2	(Khan et al., 2024; Jencova et al., 2021)
Multiple Discriminant Analysis (MDA)	2	(Gajdosikova & Valaskova, 2023; Valverde & Ortiz, 2022)
J48 (algorithm of DT)	2	(Jain et al., 2021; Chen et al., 2021)
SMOTE-TOMEK	2	(Pamuk et al., 2021; Aljawazneh et al., 2021).
SMOTE-ENN	2	(Pamuk et al., 2021; Aljawazneh et al., 2021).
Linear Regression	1	(Shah et al., 2022; Chen et al., 2021)
WSODL-BPFCA	1	(Chandok et al., 2024)
RBF Algorithm	1	(Chandok et al., 2024)
Gated Recurrent Unit (GRU)	1	(Chandok et al., 2024)
Attention-Based Long Short-Term Memory (ALSTM)	1	(Chandok et al., 2024)
Gaussian Naïve Base (GNB)	1	(Khan et al., 2024)
Hybrid LSTM- CNN	1	(Khan et al., 2024)
Vader NLTK (Pre-Built NLTK Library Model)	1	(Khan et al., 2024)
LightGBM	1	(X. Wang et al., 2023)
DeepFM	1	(X. Wang et al., 2023)
Recurrent Neural Network (RNN)	1	(Noh, 2023)
Relief Algorithm	1	(Oberoi & Banerjee, 2023)
Min-max normalization	1	(Chandok et al., 2024)
Partial Least Squares Discriminant Analysis (PLS-DA)	1	(Jabeur & Serret, 2023)
Fuzzy Convolutional Neural Networks (FCNN)	1	(Jabeur & Serret, 2023)
Boosted Decision Tree (Boosting)	1	(Radovanovic & Haas, 2023)
Bagging Ensemble Learning (BELM)	1	(Siswoyo et al., 2022)
Boosted Logistic Regression (BLR)	1	(Garcia, 2022)
PLS-Discriminant Analysis	1	(Garcia, 2022)
Extrem GBM	1	(Garcia, 2022)
RF-Ensemble	1	(Garcia, 2022)
SMOTE-CBU	1	(Garcia, 2022)
Adaptive Whale Optimization Algorithm with Deep Learning (AWOA-DL)	1	(Elhoseny et al., 2022)

Table A1. *Cont.*

Models	Total Articles	Articles
RBF Network	1	(Elhoseny et al., 2022)
Teaching-Learning-Based Optimization-DL (TLBO-DL)	1	(Elhoseny et al., 2022)
Hyperparameter tuning with AWOA	1	(Elhoseny et al., 2022)
Sequential Minimization Optimization (SMO)	1	(Jain et al., 2021)
JRip	1	(Jain et al., 2021)
Decision Tree Partial (PART)	1	(Jain et al., 2021)
Multilayer Perceptron (MLP) and Backpropagation Algorithm	1	(Jencova et al., 2021)
Stacking	1	(Muslim & Dasril, 2021)
BL-SMOTE	1	(Aljawazneh et al., 2021)
SVM-SMOTE	1	(Aljawazneh et al., 2021)
ADASYN	1	(Aljawazneh et al., 2021)
K-means SMOTE	1	(Aljawazneh et al., 2021)
RobustBoost	1	(Pavlicko et al., 2021)
Simple Voting	1	(Pavlicko et al., 2021)
Average Model	1	(Pavlicko et al., 2021)
Hybrid Model Combining RobustBoost, CART and K-NN.	1	(Pavlicko et al., 2021)
Clustering-Based Subsampling (CUS)	1	(Du et al., 2020)
Gradient Boosting Decision Tree (GBDT)	1	(Du et al., 2020)
Canonical Discriminant Analysis (CDA)	1	(Affes & Hentati-Kaffel, 2019b)
Multivariate Adaptative Regression Splines (MARS)	1	(Affes & Hentati-Kaffel, 2019a)
Hybrid model that combines K-Means and MARS clustering	1	(Affes & Hentati-Kaffel, 2019a)

References

Adisa, J. A., Ojo, S. O., Owolawi, P. A., & Pretorius, A. B. (2019). Financial distress prediction: Principle component analysis and artificial neural networks. In *Proceedings—2019 international multidisciplinary information technology and engineering conference, IMITEC 2019*. IEEE. [CrossRef]

Affes, Z., & Hentati-Kaffel, R. (2019a). Forecast bankruptcy using a blend of clustering and mars model: Case of us banks. *Annals of Operations Research*, *281*(1–2), 27–64. [CrossRef]

Affes, Z., & Hentati-Kaffel, R. (2019b). Predicting us banks bankruptcy: Logit versus canonical discriminant analysis. *Computational Economics*, *54*(1), 199–244. [CrossRef]

Al-Araj, R., Haddad, H., Shehadeh, M., Hasan, E., & Nawaiseh, M. Y. (2022). The effect of artificial intelligence on service quality and customer satisfaction in jordanian banking sector. *WSEAS Transactions on Business and Economics*, *19*, 1929–1947. [CrossRef]

Aljawazneh, H., Mora, A. M., Garcia-Sanchez, P., & Castillo-Valdivieso, P. A. (2021). Comparing the performance of deep learning methods to predict companies' financial failure. *IEEE Access*, *9*, 97010–97038. [CrossRef]

Altman, E. I., Haldeman, R. G., & Narayanan, P. (1977). Zeta analysis: A new model to identify bankruptcy risk of corporations. *Journal of Banking & Finance*, *1*(1), 29–54. [CrossRef]

Alzayed, N., Eskandari, R., & Yazdifar, H. (2023). Bank failure prediction: Corporate governance and financial indicators. *Review of Quantitative Finance and Accounting*, *61*(2), 601–631. [CrossRef]

Bidyuk, P., Petrenko, L., Savina, N. B., Ivchenko, T., & Voronenko, M. (2020). Assessing risk of enterprise bankruptcy by indicators of financial and economic activity using bayesian networks. In S. W. Pickl, V. Lytvynenko, M. Zharikova, & V. Sherstjuk (Eds.), *CEUR workshop proceedings* (Vol. 2805, pp. 59–73). CEUR-WS. Available online: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85100905558&partnerID=40&md5=d6d06d7d6274d19f63c2ce56d2b1957d (accessed on 27 September 2024).

Birchler, U. W. (2000). Bankruptcy priority for bank deposits: A contract theoretic explanation. *Review of Financial Studies*, *13*(3), 813–840. [CrossRef]

Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer. [CrossRef]

Celik, D., & Jain, S. (2024). Implementation of machine learning and deep learning in finance. In *Advanced sciences and technologies for security applications*. (Part: 59–80). Springer. [CrossRef]

Chandok, G. A., Rexy, V. A. M., Basha, H. A., & Selvi, H. (2024). Enhancing bankruptcy prediction with white shark optimizer and deep learning: A hybrid approach for accurate financial risk assessment. *International Journal of Intelligent Engineering and Systems*, *17*(1), 140–148. [CrossRef]

Chen, Y.-S., Lin, C.-K., Lo, C.-M., Chen, S.-F., & Liao, Q.-J. (2021). Comparable studies of financial bankruptcy prediction using advanced hybrid intelligent classification models to provide early warning in the electronics industry. *Mathematics*, *9*(20), 2622. [CrossRef]

Chorafas, D. (2014). *Banks, bankers, and bankruptcies under crisis: Understanding failure and mergers during the great recession. banks, bankers, and bankruptcies under crisis: Understanding failure and mergers during the great recession*. Palgrave Macmillan. [CrossRef]

Citterio, A. (2024). Bank failure prediction models: Review and outlook. *Socio-Economic Planning Sciences*, *92*, 101818. [CrossRef]

Da Silva Mattos, E., & Shasha, D. (2024). Bankruptcy prediction with low-quality financial information. *Expert Systems with Applications*, *237*, 121418. [CrossRef]

De Moraes Souza, J. G., de Castro, D. T., Peng, Y., & Gartner, I. R. (2024). A machine learning-based analysis on the causality of financial stress in banking institutions. *Computational Economics*, *64*, 1857–1890. [CrossRef]

De Jesus, D. P., & da Nóbrega Besarria, C. (2023). Machine learning and sentiment analysis: Projecting bank insolvency risk. *Research in Economics*, *77*(2), 226–238. [CrossRef]

Du, X., Li, W., Ruan, S., & Li, L. (2020). CUS-heterogeneous ensemble-based financial distress prediction for imbalanced dataset with ensemble feature selection. *Applied Soft Computing*, *97*, 106758. [CrossRef]

Economics Observatory. (2023, April 13). *Why did credit suisse fail and what does it mean for banking regulation?* Economics Observatory. Available online: https://www.economicsobservatory.com/why-did-credit-suisse-fail-and-what-does-it-mean-for-banking-regulation (accessed on 17 September 2024).

El-Economista. (2024, April 7). *Banco azteca: Campaña de desprestigio en redes provocó salida de depósitos que se logró contener y revertir*. Available online: https://www.eleconomista.com.mx/sectorfinanciero/Banco-Azteca-campana-de-desprestigio-en-redes-provoco-salida-de-depositos-que-se-logro-contener-y-revertir-20240407-0050.html (accessed on 15 September 2024).

Elhoseny, M., Metawa, N., Sztano, G., & El-hasnony, I. M. (2022). Deep learning-based model for financial distress prediction. *Annals of Operations Research*, 1–23. [CrossRef]

Erer, E., & Erer, D. (2024). The domino effect of Silicon Valley Bank's bankruptcy and the role of FED's monetary policy. *Borsa Istanbul Review*, *24*(3), 573–591. [CrossRef]

Evans, J., & Borders, A. L. (2014). strategically surviving bankruptcy during a global financial crisis: The importance of understanding chapter 15. *Journal of BUSINESS Research*, *67*(1), 2738–2742. [CrossRef]

Fan, Z. (2021). The evaluation of bank credit based on the improved decision tree model. In *ACM international conference proceeding series* (pp. 2603–2606). Association for Computing Machinery. [CrossRef]

Fiordelisi, F., & Marqués-Ibañez, D. (2013). Is bank default risk systematic? *Journal of Banking and Finance*, *37*(6), 2000–2010. [CrossRef]

Fox, M. (2022). Mechanism and methods of early prevention of bank insolvency. *DLSU Business and Economics Review*, *31*(2), 25–33.

Gabrielli, G., Melioli, A., & Bertini, F. (2023). High-dimensional data from financial statements for a bankruptcy prediction model. In *Proceedings-2023 IEEE 39th international conference on data engineering workshops, ICDEW 2023* (pp. 1–7). Institute of Electrical and Electronics Engineers Inc. [CrossRef]

Gajdosikova, D., & Valaskova, K. (2023). Bankruptcy prediction model development and its implications on financial performance in slovakia. *Economics and Culture*, *20*(1), 30–42. [CrossRef]

Garcia, J. (2022). Bankruptcy prediction using synthetic sampling. *Machine Learning with Applications*, *9*, 100343. [CrossRef]

Gavurova, B., Jencova, S., Bacik, R., Miskufova, M., & Letkovsky, S. (2022). Artificial intelligence in predicting the bankruptcy of non-financial corporations. *Oeconomia Copernicana*, *13*(4), 1215–1251. [CrossRef]

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning* (pp. 1–23). The MIT Press. Available online: https://mitpress.mit.edu/9780262035613/deep-learning/ (accessed on 24 September 2024).

Gurnani, I., Vincent, Tandian, F. S., & Anggreainy, M. S. (2021). Predicting company bankruptcy using random forest method. In *2021 2nd international conference on artificial intelligence and data sciences, AiDAS 2021*. IEEE. [CrossRef]

Hamdi, M., Mestiri, S., & Arbi, A. (2024). Artificial intelligence techniques for bankruptcy prediction of tunisian companies: An application of machine learning and deep learning-based models. *Journal of Risk and Financial Management*, *17*(4), 132. [CrossRef]

Hosaka, T. (2019). Bankruptcy prediction using imaged financial ratios and convolutional neural networks. *Expert Systems with Applications*, *117*, 287–299. [CrossRef]

Hu, D., Yan, J., Zhao, J. L., & Hua, Z. (2014). Ontology-based scenario modeling and analysis for bank stress testing. *Decision Support Systems*, *63*, 81–94. [CrossRef]

Idhmad, A., Kaicer, M., Nejjar, C., & Benjouad, A. (2024). Intelligent bankruptcy prediction models involving corporate governance indicators, financial ratios and smote. *Indonesian Journal of Electrical Engineering and Informatics*, *12*(1), 233–244. [CrossRef]

Iqbal, J., & Riaz, K. (2022). Predicting future financial performance of banks from management's tone in the textual disclosures. *Quality and Quantity*, *56*(4), 2691–2721. [CrossRef]

Isaac-Roque, D., & Caicedo-Carrero, A. (2023). Relationship between the altman z-score model and the z-score financial indicators [Relación entre los indicadores financieros del modelo altman z y el puntaje z]. *Retos*, *13*(25), 127–146. [CrossRef]

Issa, S., Bizel, G., Jagannathan, S. K., & Gollapalli, S. S. C. (2024). A comprehensive approach to bankruptcy risk evaluation in the financial industry. *Journal of Risk and Financial Management*, *17*(1), 41. [CrossRef]

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

Jain, P., Tiwari, A. K., & Som, T. (2021). Improving financial bankruptcy prediction using oversampling followed by fuzzy rough feature selection via evolutionary search. In *Modeling and optimization in science and technologies* (Vol. 18, pp. 455–471). Springer Science and Business Media Deutschland GmbH. [CrossRef]

Jencova, S., Petruska, I., Lukacova, M., & Abu-Zaid, J. (2021). Prediction of bankruptcy in non-financial corporations using neural network. *Montenegrin Journal of Economics*, *17*(4), 123–134. [CrossRef]

Jia, Z., Shi, Y., Yan, C., & Duygun, M. (2020). Bankruptcy prediction with financial systemic risk. *European Journal of Finance*, *26*(7–8), 666–690. [CrossRef]

Khan, M. H., Hasan, A. B., & Anupam, A. (2024). Social media-based implosion of silicon valley bank and its domino effect on bank stock indices: Evidence from advanced machine and deep learning algorithms. *Social Network Analysis and Mining*, *14*(1), 110. [CrossRef]

Kou, G., Chao, X., Peng, Y., & Wang, F. (2022). Network resilience in the financial sectors: Advances, key elements, applications, and challenges for financial stability regulation. *Technological and Economic Development of Economy*, *28*(2), 531–558. [CrossRef]

Lukason, O., & Andresson, A. (2019). Tax arrears versus financial ratios in bankruptcy prediction. *Journal of Risk and Financial Management*, *12*(4), 187. [CrossRef]

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: The prisma statement. *PLoS Medicine*, *6*(7), e1000097. [CrossRef] [PubMed]

Muñoz-Izquierdo, N., Camacho-Miñano, M. D. M., Segovia-Vargas, M. J., & Pascual-Ezama, D. (2019). Is the external audit report useful for bankruptcy prediction? evidence using artificial intelligence. *International Journal of Financial Studies*, *7*(2), 20. [CrossRef]

Muslim, M. A., & Dasril, Y. (2021). Company bankruptcy prediction framework based on the most influential features using xgboost and stacking ensemble learning. *International Journal of Electrical and Computer Engineering*, *11*(6), 5549–5557. [CrossRef]

Nguyen, A. H., Nguyen, H. T., & Pham, H. T. (2020). Applying the CAMEL model to assess performance of commercial banks: Empirical evidence from Vietnam. *Banks and Bank Systems*, *15*(2), 177–186. [CrossRef]

Nießner, T., Gross, D. H., & Schumann, M. (2022). Evidential strategies in financial statement analysis: A corpus linguistic text mining approach to bankruptcy prediction. *Journal of Risk and Financial Management*, *15*(10), 459. [CrossRef]

Noh, S.-H. (2023). Comparing the performance of corporate bankruptcy prediction models based on imbalanced financial data. *Sustainability*, *15*(6), 4794. [CrossRef]

Oberoi, S. S., & Banerjee, S. (2023). Bankruptcy prediction of indian banks using advanced analytics. *Ikonomicheski Izsledvania*, *32*(4), 22–41. Available online: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85159879914&partnerID=40&md5=228578e9a115f31afe76d5f2d8455299 (accessed on 25 September 2024).

Pamuk, M., Grendel, R. O., & Schumann, M. (2021). Towards ML-based platforms in the finance industry—An ML approach to generate corporate bankruptcy probabilities based on annual financial statements. In *ACIS 2021-australasian conference on information systems, proceedings*. Association for Information Systems. Available online: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85140473569&partnerID=40&md5=d0cd7c283b2daeb1ee79b7a9da6a59bc (accessed on 26 September 2024).

Parra, J., Pérez-Pons, M. E., & González, J. (2021). The importance of bankruptcy prediction in the advancement of today's businesses and economies. *Advances in Intelligent Systems and Computing*, *1242*, 175–181. [CrossRef]

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

Pérez-Pons, M. E., Parra-Dominguez, J., Omatu, S., Herrera-Viedma, E., & Corchado, J. M. (2022). Machine learning and traditional econometric models: A systematic mapping study. *Journal of Artificial Intelligence and Soft Computing Research*, *12*(2), 79–100. [CrossRef]

Petticrew, M., & Roberts, H. (2006). *Systematic reviews in the social sciences: A practical guide*. Available online: https://books.google.com.pe/books?hl=es&lr=&id=ZwZ1_xU3E80C&oi=fnd&pg=PR5&ots=w_R1AOKRPp&sig=mRfK0vr7wB_-WeV7kYQjdHQqw1Q&redir_esc=y#v=onepage&q&f=false (accessed on 28 September 2024).

Radovanovic, J., & Haas, C. (2023). The evaluation of bankruptcy prediction models based on socio-economic costs. *Expert Systems with Applications*, *227*, 120275. [CrossRef]

Ren, T., Li, S., & Zhang, S. (2024). Stock market extreme risk prediction based on machine learning: Evidence from the american market. *North American Journal of Economics and Finance*, *74*, 102241. [CrossRef]

Reuters. 2024 September 10. *At China's Zhongzhi, Risky Practices Preceded Shadow Bank's Collapse*. Reuters. Available online: https://www.reuters.com/world/china/chinas-zhongzhi-risky-practices-preceded-shadow-banks-collapse-2024-09-11/ (accessed on 4 October 2024).

Russell, S., & Norvig, P. (2003). *Artificial intelligence: A modern approach*. Prentice Hall/Pearson Education. Available online: http://www.amazon.com/dp/0137903952 (accessed on 12 September 2024).

Shah, J., Rao, B., Mehta, Y., & Kurhade, S. (2022). Predicting bankruptcy and suggesting improvements on financial attributes using machine learning models. In *3rd international conference on electronics and sustainable communication systems, ICESC 2022-proceedings* (pp. 807–812). Institute of Electrical and Electronics Engineers Inc. [CrossRef]

Shetty, S., Musa, M., & Brédart, X. (2022). Bankruptcy prediction using machine learning techniques. *Journal of Risk and Financial Management*, *15*(1), 35. [CrossRef]

Shrivastav, S. K., & Ramudu, P. J. (2020). Bankruptcy prediction and stress quantification using support vector machine: Evidence from indian banks. *Risks*, *8*(2), 52. [CrossRef]

Siswoyo, B., Abas, Z. A., Pee, A. N. C., Komalasari, R., & Suyatna, N. (2022). Ensemble machine learning algorithm optimization of bankruptcy prediction of bank. *IAES International Journal of Artificial Intelligence*, *11*(2), 679–686. [CrossRef]

Soltanzadeh, P., & Hashemzadeh, M. (2021). RCSMOTE: Range-controlled synthetic minority over-sampling technique for handling the class imbalance problem. *Information Sciences*, *542*, 92–111. [CrossRef]

Song, L., & Shahbudin, A. S. M. (2023). To anticipate the bankruptcy of baoshang bank based on CAMELS rating system. *Bank i Kredyt*, *54*(1), 65–88. Available online: https://ideas.repec.org/a/nbp/nbpbik/v54y2023i1p65-88.html (accessed on 3 September 2024). [CrossRef]

Superintendencia de Banca, Seguros y AFP (SBS). (2014). *Caja municipal de ahorro y crédito de pisco en liquidación*. Available online: https://www.sbs.gob.pe/supervisados-y-registros/entidades-en-liquidacion/liquidaciones-concluidas/sistema-financiero-liquidacion/cajas/caja-municipal-de-ahorro-y-credito-de-pisco-en-liquidacion (accessed on 5 September 2024).

Superintendencia de Banca, Seguros y AFP (SBS). (2015). *Caja rural de ahorro y crédito señor de luren en liquidación*. Available online: https://www.sbs.gob.pe/supervisados-y-registros/entidades-en-liquidacion/empresas-en-liquidacion/sistema-financiero/cajas-de-ahorro-y-credito-en-liquidacion/caja-rural-de-ahorro-y-credito-senor-de-luren-en-liquidacion (accessed on 5 September 2024).

Superintendencia de Banca, Seguros y AFP (SBS). (2019). *Financiera tfc en liquidación*. Available online: https://www.sbs.gob.pe/supervisados-y-registros/entidades-en-liquidacion/financiera-tfc-en-liquidacion (accessed on 5 September 2024).

Superintendencia de Banca, Seguros y AFP (SBS). (2023). *CRAC raiz en liquidación*. Available online: https://www.sbs.gob.pe/crac-raiz-en-liquidacion (accessed on 5 September 2024).

Superintendencia de Banca, Seguros y AFP (SBS). (2024a, June). *Información estadística de banca múltiple*. Available online: https://www.sbs.gob.pe/app/stats_net/stats/EstadisticaBoletinEstadistico.aspx?p=1# (accessed on 5 September 2024).

Superintendencia de Banca, Seguros y AFP (SBS). (2024b, June). *Información estadística de cajas municipales*. Available online: https://www.sbs.gob.pe/app/stats_net/stats/estadisticaboletinestadistico.aspx?p=3 (accessed on 5 September 2024).

Superintendencia de Banca, Seguros y AFP (SBS). (2024c, June). *Información estadística de cajas rurales*. Available online: https://www.sbs.gob.pe/app/stats_net/stats/EstadisticaBoletinEstadistico.aspx?p=4# (accessed on 5 September 2024).

Superintendencia de Banca, Seguros y AFP (SBS). (2024d, June). *Información estadística de empresas financieras*. Available online: https://www.sbs.gob.pe/app/stats_net/stats/EstadisticaBoletinEstadistico.aspx?p=2# (accessed on 5 September 2024).

Valverde, R. M. R., & Ortiz, R. G. R. (2022). Bankruptcy risk analysis of peruvian financial institutions, 2015-2021 [Análisis Del Riesgo de Quiebra de Instituciones Financieras Peruanas, 2015–2021]. *Revista Mexicana de Economia y Finanzas Nueva Epoca*, *17*(3), e735. [CrossRef]

Vochozka, M., Vrbka, J., & Suler, P. (2020). Bankruptcy or success? The effective prediction of a company's financial development using lstm. *Sustainability*, *12*(18), 7529. [CrossRef]

Vukčević, M., Lakićević, M., Melović, B., Backović, T., & Dudić, B. (2024). Modern models for predicting bankruptcy to detect early signals of business failure: Evidence from montenegro. *PLoS ONE*, *19*(5), e0303793. [CrossRef]

Wang, M. (2022). Research on the bankruptcy tendency of China's commercial banks—Based on the data experience of bankrupt banks in the united states during the 2008 financial crisis. In *ACM international conference proceeding series* (Vol. Par F180470). Association for Computing Machinery. [CrossRef]

Wang, X., Kräussl, Z., Zurad, M., & Brorsson, M. (2023). Effective automatic feature engineering on financial statements for bankruptcy prediction. In *International conference on electrical, computer, communications and mechatronics engineering, ICECCME 2023*. Institute of Electrical and Electronics Engineers Inc. [CrossRef]

Witten, I. H., Frank, E., & Hall, M. A. (2011). *Data mining: Practical machine learning tools and techniques* (3rd ed., pp. 1–629). Morgan Kaufmann Publishers. [CrossRef]

Xhindi, T., & Shestani, K. (2020). Financial distress and bankruptcy prediction: An empirical analysis of the manufacturing industry in albania. *WSEAS Transactions on Business and Economics*, *17*, 33–40. [CrossRef]

Yadav, M. P., Rao, A., Abedin, M. Z., Tabassum, S., & Lucey, B. (2023). The domino effect: Analyzing the impact of silicon valley bank's fall on top equity indices around the world. *Finance Research Letters*, *55*, 103952. [CrossRef]

Yotsawat, W., Phodong, K., Promrat, T., & Wattuya, P. (2023). Bankruptcy prediction model using cost-sensitive extreme gradient boosting in the context of imbalanced datasets. *International Journal of Electrical and Computer Engineering*, *13*(4), 4683–4691. [CrossRef]

Zikri, M., Shams, S., Rashid, A., & Krishnamurti, C. (2024). Does size matter? Examining the probability of firm emergence from bankruptcy. *International Review of Finance*, *24*, 669–713. [CrossRef]