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Sustainability of Transport Sector Companies: Bankruptcy Prediction Based on Artificial Intelligence

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Abstract: Understanding business failure within the transport industry is crucial for formulating an effective competitive policy. Acknowledging the pivotal role of financial stability as a cornerstone of sustainability, this study undertakes a comparative investigation between statistical models forecasting business failure and artificial intelligence-based models within the context of the transport sector. The analysis spans the temporal period from 2014 to 2021 and encompasses a dataset of 4866 companies from four South European countries: Portugal, Spain, France, and Italy. The models created were linear support vector machines (L-SVMs), kernel support vector machines (K-SVMs), k-nearest neighbors (k-NNs), logistic regression (LR), decision trees (DTs), random forests (RFs), extremely random forests (ERFs), AdaBoost, and neural networks (NNs). The models were implemented in Python using the scikit-learn package. The results revealed that most models exhibited high precision and accuracy, ranging from 71% to 73%, with the ERF model outperforming others in both predictive capacity and accuracy. It was also observed that artificial intelligence-based models outperformed statistical models in predicting business failure, with particular emphasis on the AdaBoost and ERF models. Thus, we conclude that the results confirm the hypothesis that the artificial intelligence models were superior in all metrics compared to the results obtained by logistic regression.

Keywords: artificial intelligence; forecasting; business failure; financial sustainability; financial indicators; transport sector

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1. Introduction

In the intricate web of global economies, the transport sector is a linchpin, facilitating the seamless movement of goods, services, and people. There is extensive literature on sustainable transportation, covering various topics from planning and engineering to policy and environmental considerations. For instance, Black [1] presents a comprehensive overview of sustainable transportation issues, covering ecological impacts, energy consumption, and policy solutions. Rodrigue [2] provides a solid foundation for understanding the spatial aspects of transportation systems, which is crucial for sustainable transport planning. Gudmundsson [3] offers insights into the development and application of indicators for measuring and managing the sustainability performance of transportation systems.

Amidst this dynamic landscape, the importance of financial sustainability in the transport sector cannot be overstated (Kockelman [4] and Delmon [5]). It is the bedrock upon which transportation systems' efficiency, reliability, and resilience rest. Moreover, financial sustainability is pivotal in fostering innovation within the transport sector. Investments in research and development of sustainable technologies, such as electric vehicles and alternative fuels, are imperative to mitigate the environmental impact of transportation. Embracing these innovations not only aligns with global efforts to combat climate change but also positions the transport sector as a key player in sustainable development.

Predicting business failure represents a topic of paramount significance that has garnered increasing attention in recent decades. According to Borchert et al. [6], the prognostication of business failure offers researchers and stakeholders a highly pertinent tool for assessing a company's fiscal well-being. The financial health of enterprises has evolved into one of the most pressing societal concerns for economic agents. Consequently, many models for business failure prediction have been developed to distinguish between failed and non-failed entities. Therefore, this subject necessitates ongoing study and adaptation to the evolving economic milieu for more precise results.

In a succinct definition, business failure can be understood as the incapacity of a company to meet all of its financial obligations, potentially leading to bankruptcy. Business failure prediction models are designed to help companies recognize impending failure through indicators, enabling proactive measures.

Numerous studies have been undertaken to engender novel models for predicting business failure and enhance each model's predictive capacity. The seminal work of Beaver [7] is noteworthy as the pioneering exploration of business failure prediction models employing financial ratios for model estimation. Subsequent models have been introduced, such as the multiple discriminant analysis model developed by Altman [8] and Deakin [9], the logit model presented by Ohlson [10], and the probit model proposed by Hoetker [11]. More recently, artificial intelligence-based models have emerged, including neural networks (Altman et al. [12] and Neves and Vieira [13]), decision trees (Gepp et al. [14] and Chiang et al. [15]), support vector machines (Alaka et al. [16] and Shetty et al. [17]), and genetic algorithm (Gordini [18]). The bankruptcy prediction and artificial intelligence literature reflects a shift towards more sophisticated data-driven approaches. Machine learning and AI techniques offer the potential to enhance the accuracy and reliability of bankruptcy prediction models. Still, challenges related to data quality, model interpretability, and adapting to dynamic market conditions persist. Thus, ongoing research, namely Aly and Salem [19], Chi and Shen [20], and Zhang et al. [21], focuses on addressing these challenges and refining methodologies to improve the effectiveness of bankruptcy prediction models.

The transport sector assumes a position of paramount importance and indispensability within human needs, facilitating the transboundary movement of individuals and goods (Eurostat [22]). Enterprises within the freight transport sector hold substantial weight in the business landscapes of Portugal, Spain, France, and Italy. The yearly revenue of the transportation and storage industry within the European Union witnessed a continual rise until the year 2020. During that period, the combined transportation and storage activities across the 27 European Union member states generated a turnover exceeding EUR 1.3 trillion (Carlier [23]). Based on the statistics of the revenue of the industry "transportation and storage" in Portugal, Spain, France, and Italy, between 2012 to 2018, it was projected (Statista Research Department [24]) that the revenue of transportation and storage in these countries, by 2025, will amount to approximately EUR 9.375 billion in Portugal, EUR 58.942 billion in Spain, EUR 112.735 billion in France, and EUR 83.064 billion in Italy. According to the authors, these projections were automatically generated utilizing the well-established Statista forecast algorithm, which relies on similarity parameters to existing analyst forecasts. The foundation for the initial forecasts comprises a blend of time series forecasts and driver forecasts (such as GDP, population, etc.) gathered from reputable sources like the World Bank or the International Monetary Fund, as well as insights from business surveys.

Given the significance of the transport sector, this research aims to compare statistical business failure models with artificial intelligence-based models within the transport sector. As the prediction of business success stands as a pivotal factor for organizations, particularly in the wake of the global financial crisis in 2008, as underscored by Shi and Li [25], the relevance of this study is unquestionable. The study utilizes data from 2014 to 2021, encompassing a sample of 4866 companies from four South European countries (Portugal, Spain, France, and Italy). This timeframe enables the assessment of the potential impact of the COVID-19 pandemic on organizational failure.

The intersection of sustainability, bankruptcy prediction, and artificial intelligence (AI) has gained attention in recent years. Still, a noticeable gap exists in the existing literature regarding the seamless integration of these domains. The existing literature treats sustainability and financial risk as distinct domains, overlooking the potential synergies between environmental, social, and governance (ESG) factors and bankruptcy indicators.

This article begins with the premise that financial sustainability is a crucial dimension within the broader concept of sustainability. It aims to address the following research questions: (i) What are the most salient indicators for predicting business failure? (ii) Do artificial intelligence-based business failure prediction models outperform statistical models? The rest of the paper is structured as follows. Part two reviews the literature on business failure prediction. Part three explains the research methodology, namely the procedures applied in sample selection and data analysis. In part four, we present, interpret, and discuss the results. Finally, we provide the main conclusions and the direction for future research in part five.

2. Literature Review

2.1. Failure Definitions

The concept of failure, specifically business failure, has been the subject of diverse definitions and scholarly exploration due to the ongoing concern with predicting organizational demise. Grounded in the insights of Walsh and Cunningham [26], research into business failure dates back to the 19th century, but it has witnessed intensified and comprehensive investigation in recent years. Beaver [7] defines failure as an organization's inability to fulfill its financial obligations, signifying its incapacity to meet creditor obligations, distribute dividends to shareholders, or avoid bankruptcy. Furthermore, Beaver et al. [27] characterize failure as the non-fulfillment of financial obligations, encompassing financial difficulties, which entails the failure to meet obligations on time and, on the other hand, the organization's bankruptcy. Conversely, following the perspective advanced by Altman and Hotchkiss [28], a company can find itself in a state of economic failure for an extended period without defaulting on its obligations. In this view, the quality of managerial stewardship by the board of directors emerges as the primary determinant of failure. In concordance with Amankwah-Amoah et al. [29], business failure materializes when a company cannot recover from a period of decline, ultimately leading to its collapse. In a more general sense, business failure can be delineated as the cessation of operations due to an inability to adapt to external changes (Amankwah-Amoah and Wang [30]). However, as Pereira et al. [31] noted, it is essential to recognize that no singular concept of business failure exists, encompassing a spectrum ranging from legal bankruptcy to insolvency, suspension of payments, or persistent financial losses.

2.2. Financial Distress Prediction Models

In alignment with the diversity of failure definitions, a variety of models and methodologies exist for predicting business failure. This spectrum begins with the seminal univariate analysis model introduced by Beaver [7] and extends to multivariate discriminant analysis, logit, and probit models, as expounded by Pereira et al. [31]. Moreover, recent developments have given rise to models rooted in artificial intelligence techniques. Corroborating the assertion of Korol and Spyridou [32], establishing a financial early warning system is critical for organizations, leveraging reasonable forecasting models that empower stakeholders to evaluate financial risks capable of shaping organizational success or failure. It is imperative to recognize that each of the discussed models has advantages and drawbacks. Consequently, there is no universally superior technique, and selecting an appropriate model hinges on individual circumstances and one's conception of business failure, aligning with Pereira et al. [33].

The development of business failure models gained momentum in the 1960s, catalyzed by the imperative to scrutinize business failure and the ensuing economic and social ramifications for all stakeholders. The initial techniques employed encompassed statistical methodologies applied to companies' financial data, involving the utilization of a set of financial ratios (Maricica and Georgeta [34]). Pioneering contributions, such as those of Beaver [7] and Altman [8], played pivotal roles in this analytical domain. Regarding the most frequently employed technique for predicting business failure, multiple discriminant analysis is the prevailing approach in the corpus of analyzed studies (Alaka et al. [16]), Hausser and Booth [35], and Lenox [36].

Statistical techniques have historically served as the prevailing method for predicting business failure. These techniques, founded on a predefined threshold, classify companies as failures if their scores fall below the specified threshold or as non-failures if not. Nevertheless, as posited by Ooghe and Spaenjers [37], statistical techniques may yield specific errors, imposing costs on companies, such as type I errors (where failed companies are erroneously classified as non-failed) or type II errors (the converse situation). Pereira et al. [38] note that initial research sought to ascertain whether datasets contained sufficient information to forecast impending insolvency or aimed to discern the most effective predictive models. Subsequently, with more comprehensive models, such as artificial intelligence-based techniques, a quest for enhanced accuracy and reduced error rates in business failure prediction emerged.

Following Yeh et al. [39], the limitations of early business failure prediction models are twofold. Firstly, these models exclusively relied on financial ratios as independent variables. Secondly, they overlooked the significance of a company's managerial effectiveness as a critical variable for classifying failures. While widely adopted, statistical techniques often entail restrictive assumptions such as linearity, normality, and independence among variables (Wu [40]). Alternative methods rooted in artificial intelligence have been introduced to circumvent these limitations.

According to Shetty et al. [17], the 1990s ushered in a new phase in the evolution of business failure prediction models, introducing innovative methods, particularly artificial intelligence algorithms, including neural networks (Špiler et al. [41]) and decision trees. These artificial intelligence-based techniques offer promising alternatives to traditional statistical models, addressing their principal shortcomings (Dong and Chen [42]).

Neural networks (NN), as defined by Neves and Vieira [13], represent a prominent artificial intelligence-based method for business failure prediction. These networks, inspired by the architecture of the human brain, can learn directly from examples without prior knowledge of specific problems. A neural network comprises interconnected processing units, each with a calculation function (Tam and Kiang [43]). The learning process involves iterative adjustments to minimize errors until the network attains equilibrium, resolving the problem (Altman et al. [12]).

Neural networks offer several advantages over statistical models. They eliminate the need for a pre-established functional relationship among variables, as they can direct knowledge acquisition through the learning process. Furthermore, the collective behavior of multiple units, rather than individual units, contributes to their efficiency (Altman et al. [12]). Despite their advantages, neural networks are relatively slow learners and may yield complex, challenging-to-interpret results (Altman et al. [12]). Understanding the final rules neural networks acquire can also be challenging (Shin and Lee [44]). Numerous studies have compared the performance of neural networks with statistical techniques, revealing that neural networks may exhibit superior predictive capacity in specific scenarios (Altman et al. [12] and Gámez et al. [45]). It has been suggested that combining neural networks with multiple discriminant analyses may yield more accurate and comprehensible results (Altman et al. [12]). Noh [46] compared the bankruptcy prediction performance of the long short-term memory (LSTM), logistic regression (LR), k-nearest neighbors (k-NN), decision tree (DT), and random forest (RF) models. For the author, the results of this study provide useful information for selecting a suitable bankruptcy prediction model when the dataset has relatively few bankrupt companies.

Decision trees (DTs) constitute another machine-learning technique for business failure prediction. Decision trees map a hierarchy of classes or values based on conditional logic rules, leading to a classification. The main goal is to uncover relationships and dependencies between the variables, usually presented in the form of rules (e.g., "X $\rightarrow$ Y").

Decision trees offer versatility and a high comprehension rate, facilitating the identification of critical factors for accurate company classification (Pereira et al. [31]). Moreover, they do not necessitate the transformation of variables or the imposition of constraints and can incorporate the costs of incorrect classification, ultimately reducing financial burdens (Gepp et al. [14]). However, decision trees have some drawbacks, including the arbitrary assignment of prior probabilities, rendering them less precise than statistical models. Additionally, they merely indicate the relative importance of variables, unlike statistical models that provide detailed significance levels (Gepp et al. [14]). Challenges include creating decision trees, which can be time-consuming, difficulty handling incomplete information, and the possibility of unexpected values (Pereira et al. [31]).

Support vector machines (SVMs) are an artificial intelligence-based method for business failure prediction. These machines employ a linear model to create an optimal separator for binary classification. The variables closest to this separator, referred to as support vectors, define the outcome, classifying companies as failures or non-failures (Alaka et al. [16]). SVMs excel in minimizing structural risk, offer a higher predictive capacity, and are adept at handling overlapping data (Yeh et al. [39] and Shetty et al. [17]). SVMs are lauded for their precision and stability in predicting business failure. Their simplicity facilitates integration with traditional statistical techniques, leveraging the strengths of both approaches (Min and Lee [47]). Kernel-based support vector machines (K-SVMs) enhance classification accuracy and outperform other prediction models (Shaw and Routray [48]). Genetic algorithms (GAs), a stochastic search technique inspired by natural genetics and evolution, also contribute to business failure prediction. GAs transform complex problems into simpler ones that can be treated as discriminant functions as mentioned by Gordini [18]. GAs excel in optimizing objective functions subject to rigid and flexible constraints and can explore non-linear solution spaces without prior information about the model (Shin and Lee [44] and Wu et al. [49]). GAs entail four key stages: initialization, selection, crossover, and mutation. In the initialization phase, a population of genetic structures, or chromosomes, is distributed in the solution space. The best-performing chromosomes are selected and copied to the next generation, gradually occupying a more significant portion.

As explained above, the burgeoning field of business failure prediction has witnessed a paradigm shift with the advent of artificial intelligence (AI) technologies. This study aims to investigate and compare the efficacy of business failure prediction models based on AI against those grounded in traditional statistical approaches. Based on the literature in the field, this study posits that AI-driven models outperform their statistical counterparts in accurately forecasting business failures.

AI-based models, particularly machine learning algorithms, offer a distinct advantage in handling complex and dynamic datasets. These models exhibit a capacity for nuanced pattern recognition, leveraging vast amounts of data to identify subtle indicators of financial distress that may elude conventional statistical methods. Moreover, AI models can adapt and evolve with changing market conditions, providing a more robust and responsive framework for business failure prediction. By harnessing the power of deep learning and neural networks, these models can uncover intricate relationships within financial data, offering a more comprehensive understanding of the multifaceted factors contributing to business failure.

Contrastingly, traditional statistical models often rely on predefined assumptions and linear relationships, limiting their ability to capture the intricacies of modern business dynamics. Statistical methods may struggle with non-linearity and fail to adapt to the evolving nature of markets, leading to diminished predictive accuracy.

Thus, our research hypothesis is that AI-driven business failure prediction models surpass statistical models.

3. Methodology

The principal aim of this research project is to undertake a comparative analysis of the performance of statistical business failure prediction models against artificial intelligence-based prediction models. The methodological framework is structured around two primary approaches: firstly, statistical methods, specifically logistic regression (LR), and secondly, artificial intelligence-based methods, including neural networks (NNs), support vector machines (SVMs), and decision trees (DTs).

3.1. Why the Transport Sector?

The transport sector plays a paramount role in the daily lives of individuals, facilitating the movement of people, goods, and services between nations. It is a fundamental component of European businesses and global supply chains (European Commission [50]). The significance of this sector has rapidly increased for the European economy over the last six decades (Ali et al. [51]). Kliestik et al. [52] emphasize that the modern development of a country's economy is impossible without creating a highly efficient transport sector. Shafique et al. [53] stress that the transport sector is crucial for economic development and accelerates economic activities, making a fundamental contribution to economic growth. The economic influence of the transport sector on the economy is also analyzed by Vukic et al. [54]. Michalikova et al. [55] highlight its significance during the COVID-19 pandemic based on a review of contributions published between 2020–2022.

Moreover, it is instrumental for international and national trade, contributing to economic development by ensuring efficient, safe, and cost-effective goods transport (Eurostat [56]). As part of the national economy, this sector constitutes a substantial portion of the GDP (Murta [57]). As noted by the European Commission [58], approximately 5% of the European Union's GDP is attributed to the transport sector, employing over 10 million individuals across Europe. In a country like Portugal, the transport sector employed around 136,000 people in 2021, with a majority engaged in road haulage (Corselli-Nordblad et al. [59] and Eurostat [60]).

As the economy expands, the transport sector also prospers, catalyzing economic development and exhibiting a pre-cyclical nature (Murta [57]). The continuous growth of freight transport within the European Union is propelled by expanding global trade and economic practices like economies of scale and just-in-time deliveries (Eurostat [56]). Nevertheless, the sector confronts pressing environmental concerns, accounting for a substantial share of greenhouse gas emissions in the European Union. The European Green Deal has set the ambitious target of reducing emissions by 90% (European Commission [58]), necessitating the adoption of sustainable and environmentally friendly transportation methods (Ala et al. [61] and European Commission [62]).

The transport sector confronts several challenges, including noise, road accidents, congestion, and fluctuating fuel prices due to geopolitical events (European Commission [50]). As emphasized by Nastisin et al. [63], effective reputation management stands out as a crucial tool for achieving sustainable performance within the business domain. Consequently, the sustainability of the transport sector is intricately linked to the implementation of smart city initiatives and pollution reduction measures. It is imperative to recognize that these challenges not only hinder the sector's progress but also present significant threats to its overall development.

In conclusion, the transport sector encompasses land, maritime, and air transport, which is pivotal for exchanging goods between countries and guaranteeing people mobility. While land transport is dominant in facilitating cross-border interest transport, it is also the most polluting mode. On the other hand, rail and maritime transport offer more environmentally friendly alternatives (Banco de Portugal [64]).

The dynamic nature of the transport sector is shaped by global economic integration and evolving market dynamics. However, the industry faces numerous challenges, particularly regarding congestion, governance, and environmental concerns. The choice of transportation mode is influenced by cost, environmental impact, and safety. A financially robust transportation sector fosters economic growth, societal well-being, and sustainability. Its vitality is a linchpin of economic prosperity, enabling the efficient flow of goods and services, enhancing trade, and facilitating access to essential resources. This, in turn, bolsters economic development, creates employment opportunities, and fortifies the overall quality of life for a society's inhabitants. A robust transportation sector also often contributes to adopting sustainable practices, reducing environmental impacts, and promoting long-term resilience. A financially sound transport sector is a cornerstone of economic, social, and ecological progress.

3.2. Data Selection and Preparation

The empirical investigation in this research centers on predicting a company's success or failure through a supervised learning framework. This is accomplished by constructing a dataset comprising various financial indicators of companies and their corresponding success/failure status. These indicators serve as the independent explanatory variables in building predictive models. These models are then evaluated for their ability to predict success or failure on previously unseen data.

The predictive performance of each model is assessed through commonly used classification metrics in machine learning, which include precision, recall, F1 score, and accuracy. It is essential to note that all data were sourced from the Bureau Van Dijk—ORBIS database and encompass accounting data from companies from 2014 to 2021.

Without a theoretical framework guiding the selection of explanatory variables for business failure, this empirical research adopts financial indicators as the independent variables. These financial ratios were chosen based on their prevalence and significance in prior studies. Financial ratios were selected for modeling due to their capacity to reveal a company's efficiency and allow for comparing relationships between various accounting figures. Furthermore, analyzing a company's financial information is crucial for assessing its financial health and prospects for sustainability. Consequently, these ratios play a pivotal role in predicting the success or failure of organizations (Lacher et al. [65], Idrissi and Taouab [66], and Altman [8]).

A diverse range of financial ratios is available for business failure analysis. These can be grouped into categories such as return on investment, financial leverage, capital turnover, short-term liquidity, cash position, inventory turnover, and accounts receivable turnover (Lacher et al. [65]). However, this research focuses on financial structure ratios, profitability, solvency, liquidity, and indebtedness, as these are the most commonly used and of significant interest to researchers (Idrissi and Taouab [66]). In this particular dataset, 14 financial indicators were chosen as independent variables and are presented in Table 1.The selection of the independent variables was based on the literature (Bellovary et al. [67] and Kušter et al. [68]).

Table 1. Independent variables.

Independent Variable	Variable Name
ROEBT	ROE using P/L before tax
ROABT	ROA using P/L before tax
ROENI	ROE using net income
ROANI	ROA using net income
Profit	Profit margin
EBITDA	EBITDA margin
EBIT	EBIT margin
CF/OpRev	Cash flow/Operating revenue
NetAssets	Net assets turnover

Table 1. *Cont.*

Independent Variable	Variable Name
CurrentRatio	Current ratio
Liquidity	Liquidity ratio
Solvency	Solvency ratio (Asset-based)
Gearing	Gearing
CostsEmpl/OpRev	Costs of employees/Operating revenue

Author's elaboration.

When consulting the database, we looked for direct and indirect indicators of the sustainability policies followed by the companies. However, the lack of coherent data made it impossible to include any sustainability indicators in the study. The landscape of sustainability performance indicators for companies remains notably limited, with a paucity of firms actively publishing comprehensive sustainability reports. This scarcity is further compounded by the absence of a well-established and universally accepted metric for gauging company sustainability performance. Consequently, researchers aiming to integrate sustainability indicators into business failure prediction models encounter significant challenges in obtaining sufficient and standardized data.

The reluctance of many companies to disclose detailed sustainability information hampers the availability of pertinent data necessary for robust predictive modeling. Without a standardized indicator, the heterogeneous nature of sustainability reporting makes it challenging for researchers to aggregate and compare data across diverse industries and business sectors. This absence of data not only impedes the inclusion of crucial sustainability metrics in predictive models but also underscores the pressing need for industry-wide efforts to establish universally recognized indicators, fostering transparency and enabling more accurate assessments of companies' sustainability performance.

The dataset includes a total of 5854 companies from four different countries: Italy (1580 companies), Spain (1949 companies), Portugal (1216 companies), and France (1109 companies). Within the dataset, 3869 companies are classified as successful (66%), while 1985 companies are categorized as failed (34%). The independent variables consist of financial indicators and the country of origin. Although the country of origin was initially considered an independent variable, its inclusion had minimal impact on the results, leading to its removal.

The dataset structure allows for the construction of discriminant functions for both the statistical models and artificial intelligence-based models. These functions facilitate the assessment of whether the companies are failures or not and enable a comparison of predictive capabilities between the two model categories.

The initial dataset showed an overall completeness rate of about 95.9%. In order to enhance the number of usable data points and standardize the dataset, we opted to exclude a specific financial indicator—the solvency ratio based on liabilities. This decision was made due to the prevalence of missing data in this particular indicator, since it was the most commonly absent data point in the analysis.

Subsequently, the final dataset comprised 4866 companies, with 592 from Italy, 1949 from Spain, 1216 from Portugal, and 1109 from France. The sample was further divided into 1985 failed companies and 2881 non-failed companies. To facilitate model development and evaluation, the dataset was randomly split into training and test sets, with an 80–20% stratified division, maintaining the ratio of successful to failed companies in both sets. The same training/testing split was consistently applied to all models developed. Finally, the dataset was normalized through standardization, subtracting the mean and dividing by the standard deviation for each independent variable within the training set.

4. Results Presentation and Discussion

The financial indicators selected above were used to build various machine learning models to predict the success or failure of companies and make it possible to compare statistical models with models based on artificial intelligence. The methods implemented were linear support vector machines (L-SVMs), kernel support vector machines (K-SVMs), k-nearest neighbors (k-NN), logistic regression (LR), decision trees (DTs), random forests (RFs), extremely random forests (ERFs), AdaBoost and neural networks (NNs). The models were implemented in Python using the scikit-learn package. We applied all AI classifiers that were readily available in free implementations, including neural networks, which are the most popular approach for applying AI to data analysis in recent years.

In the case of global models and, similar to what was seen in da Silva et al. [69], for each of the methods, we tried various perfect combinations of parameters for the specific algorithm. Then, we used the best combination to build the rest of the models. In the case of the L-SVM model, we tried various weights and different losses and numbers of interactions. For the decision trees, we tried different depths and different criteria for measuring a split at each node. As for the neural networks, we tried different numbers of hidden layers and different numbers of neurons in each layer.

As mentioned, the models were trained and trialed on companies in Italy, Spain, Portugal, and France. The results of the models chosen for each type of classifier are summarized in Table 2 below. The results in red are the best results for each metric considering all models. Results in bold are the second-best results for each metric.

Table 2. Model results for each type of classifier.

Model	Accuracy	Precision C0	Recall C0	F-Score C0	Precision C1	Recall C1	F-Score C1
L-SVM	60.0% ± 0.0%	50.9% ± 0.0%	49.9% ± 0.0%	50.4% ± 0.0%	66.0% ± 0.0%	66.9% ± 0.0%	66.4% ± 0.0%
K-SVM	71.6% ± 0.0%	66.9% ± 0.0%	**59.9% ± 0.0%**	**63.2% ± 0.0%**	**74.3% ± 0.0%**	79.5% ± 0.0%	76.8% ± 0.0%
KNN	68.5% ± 0.0%	63.7% ± 0.0%	52.6% ± 0.0%	57.7% ± 0.0%	70.9% ± 0.0%	79.4% ± 0.0%	74.9% ± 0.0%
LR	58.4% ± 0.0%	49.1% ± 0.0%	58.2% ± 0.0%	53.3% ± 0.0%	67.1% ± 0.0%	58.6% ± 0.0%	62.5% ± 0.0%
DT	72.1% ± 0.0%	69.0% ± 0.1%	57.2% ± 0.0%	62.5% ± 0.0%	73.6% ± 0.0%	82.3% ± 0.1%	77.8% ± 0.0%
RF	**72.8% ± 0.3%**	**71.1% ± 0.6%**	56.0% ± 0.5%	62.7% ± 0.4%	73.6% ± 0.2%	**84.3% ± 0.5%**	**78.6% ± 0.3%**
ERF	**73.4% ± 0.6%**	70.5% ± 1.1%	**59.6% ± 0.8%**	**64.6% ± 0.8%**	**74.9% ± 0.4%**	82.8% ± 0.9%	**78.6% ± 0.6%**
AdaBoost	71.8% ± 0.0%	**77.7% ± 0.0%**	43.1% ± 0.0%	55.4% ± 0.0%	70.0% ± 0.0%	**91.5% ± 0.0%**	**79.3% ± 0.0%**
NN	71.9% ± 0.7%	68.7% ± 2.2%	57.5% ± 2.3%	62.5% ± 0.8%	73.7% ± 0.6%	81.9% ± 2.5%	77.6% ± 0.9%

Author's elaboration.

The results in Table 1 show the average and standard deviation of the metrics for 10 runs of each method. This indicates that most of the methods were fairly stable over different runs, with the exception of the neural networks, which had a standard deviation of more than 0.5%, which can be explained by the different random initialization of the network parameters in the different runs. However, this was a significantly stable behavior.

The precision, recovery and *f*-score metrics were calculated for each class. Thus, given the imbalance in the data set, i.e., the imbalance between non-failed and failed companies, the metrics were calculated for failed companies (C0) and non-failed companies (C1).

In line with the above, the L-SVMs were developed based on balanced class weights, with C = 10, 10,000 interactions and a loss of articulation. The K-SVMs were trained with an RBF kernel, with C = 10, balanced class weights and a scaling kernel coefficient. The K-NN was developed based on five neighbors, the ball tree algorithm, uniform weights and the Manhattan metric. Logistic regression was trained using the IBFGS solver, balanced class weights and no regularization. The DTs were developed with a tree depth of 6 with all characteristics, an entropy criterion and uniform class weights. The RF was developed with 1000 estimators using $\log^2$ of the number of features for each estimator, balanced class weights and the Gini index criterion. The ERF was trained with 100 estimators using all of the features, uniform class weights and an entropy criterion similar to that used in decision trees. AdaBoost was trained with 10 estimators and the SAMME.R algorithm using a learning rate of 0.5. Finally, the NNs were developed with 3three hidden layers and a softmax output, 100 neurons in the first layer and 10 neurons in the second and third layers, a sparse categorical cross entropy loss without class weights, the Adam optimizer with a learning rate of 10*e*-4, a batch size of 64 and 100 training epochs.

The results of applying these models to the 4866 companies selected show that most of the methods achieved levels of precision and accuracy in the order of 71–73%, with the best precision being obtained by the ERF method.

To predict the failure of failed companies, represented in the table by the C0 metric, the best *f*-score was also obtained by the ERF model with the best balance between precision and recovery. However, in this case, the best precision was obtained using AdaBoost, and the best recovery was achieved using K-SVM.

In turn, for non-failed companies, metric C1 shown in Table 1, the best *f*-score was achieved using AdaBoost, which recorded the highest recovery in this case. The best precision was achieved using the ERF. Despite the frequent application of NNs in recent years for data analysis with artificial intelligence, the ERF and AdaBoost models performed better than NN.

The DT and SVM model results align with those found by Sue et al. [70]. Regarding the RF and KNN models, the accuracy was similar to that obtained by Noh [46] when using a small random sample. Amalia and Kartikasari [71] also achieved an accuracy rate of 75% for the ANN method. Nonetheless, Kušter et al. [68] obtained slightly better results than ours, with an overall predictive accuracy of 80.0% (Y-1) for the NN models and 73.3% (Y-2) for the testing dataset.

To summarize, we can say that the most suitable models for this study were ERF and AdaBoost, as they gave the best results in precision and recovery. Thus, the results confirm the hypothesis that AI-driven business failure prediction models surpass statistical models. Even so, the performance metrics were objectively modest and significantly worse than those obtained by Silva et al. [69], where accuracies were around 95%, with precisions and recall of 90%.

5. Conclusions

Through a meticulous evaluation of historical financial data and real-world business outcomes, this study endeavored to contribute empirical evidence supporting the hypothesis that AI-driven business failure prediction models surpass statistical models, thereby advocating for the adoption of cutting-edge technologies to enhance the resilience and precision of financial risk assessment in business contexts.

The dataset comprised 4866 companies (1985 failed companies and 2881 non-failed companies) distributed across four southern European countries: Italy, Spain, Portugal, and France. The models created were linear support vector machines (L-SVMs), kernel support vector machines (K-SVMs), k-nearest neighbors, logistic regression (LR), decision trees (DTs), random forests (RFs), extremely random forests (ERF), AdaBoost, and neural networks (NN). The models were implemented in Python using the scikit-learn package.

The results revealed that most models exhibited high precision and accuracy, ranging from 71% to 73%, with the ERF model outperforming others in both predictive capacity and accuracy. It was also observed that artificial intelligence-based models outperformed statistical models in predicting business failure, with particular emphasis on the AdaBoost and ERF models. Thus, we can conclude that the results confirm the hypothesis that the artificial intelligence models were superior in all metrics compared to the results obtained by logistic regression.

In evaluating the impact of the country of origin as a relevant variable in classifying companies, it was established that it did not exert a significant influence on the classification, as the results remained consistent. However, the fact that the study was restricted to the transport sector and encompassed data from only four countries is a critical limitation of the study. Additionally, the risk of data manipulation introduced significant study fragility. Another limitation may be the bias in the data due to the COVID-19 pandemic.

To deeply understand how sustainable practices and financial stability are intertwined and how incorporating sustainability metrics can enhance the accuracy of bankruptcy prediction models requires an in-depth analysis. While AI has shown promise in enhancing predictive capabilities, its application in the context of sustainable finance is underexplored. Research is needed to develop sophisticated AI algorithms that predict bankruptcy risk and consider the broader implications of sustainable business practices. This implies a holistic approach incorporating financial and non-financial indicators within AI models.

Future research should aim to develop frameworks that enhance predictive accuracy and contribute to the broader goal of promoting sustainable business practices within the financial domain. This interdisciplinary approach will fill existing research voids and provide valuable insights for practitioners, policymakers, and academics working at the intersection of sustainability, bankruptcy prediction, and artificial intelligence.

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