Predicting Business Vulnerability Using Neural Networks: Evidence From Brazilian SMEs

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Abstract: *Goal*: Analyze the performance of a business diagnosis prediction model. *Design / Methodology / Approach*: Business diagnostic interviews were carried out with 98 companies, using the IncubE methodology, to assess the level of maturity, based on six dimensions: general, management, business, market, technology and financial. The evaluations were discretized and used as input for a neural network model implemented with the Keras API from the Scikit-Learn library in Python. *Results*: The machine learning algorithm achieved an accuracy of 75%, enabling the identification of business failures that could lead to organizational vulnerability. *Limitations of the research*: The proposed model is applicable only to companies where consultants trained in the IncubE methodology have performed a prior organizational diagnostic assessment. *Practical implications*: This study supports consultants and business managers to anticipate critical business situations and prevent the occurrence of failure scenarios. *Social implications*: Possible reduction of organizational problems and consequent reduction in the number of companies in crisis or bankrupt. *Originality / value*: There are few works in literature that deal with prediction of business vulnerabilities and none were found that use a methodology which evaluates the five organizational dimensions of the CERNE methodology: entrepreneur, technology, market, management and financial.

Keywords: Business fault prediction, AI prediction, Business fault, Business failure, SMEs

1. Introduction

Brazil exhibits high annual demand for new business openings. In 2024, government data reported over 4.2 million new company registrations, yet the same period saw 2.4 million closures—97.6% of which were micro and small enterprises (Brasil, 2025). Consistent with the Brazilian Micro and Small Business Support Service's (Sebrae, 2020) Business Survival 2020 study, failure rates over five years remain stable: 29% of micro-entrepreneurs, 21.6% of micro-enterprises, and 17% of small enterprises discontinue operations.

Entrepreneurship serves as a critical income alternative during economic crises (Arantes, 2024; Fernandes & Braz, 2024) and for commercializing academic innovations (Cultri, 2024; Abreu, Lauricio & Baeta, 2023; Sousa & Florêncio, 2023). In both cases, founders often possess domain expertise and motivation. However, they often lack business management skills, which becomes the primary factor contributing to business failures, placing companies in a state of vulnerability (Leal, 2024; Pinto Junior, 2021c; Freitas, 2020; Kops, 2019; Drucker, 2007).

In a previous study, we developed the IncubE Methodology (Pinto Junior, Silvestro & Morais, 2021) to guide the incubation process of enterprises, from the initial business diagnosis and action plan development to the company's graduation with its problems solved. In this research, we will use entrepreneurial diagnostics conducted through the IncubE Methodology with 98 companies. An initial business diagnosis was carried out to assess the potentialities and challenges these companies faced across five dimensions: entrepreneurship, management, technology, financial, and market. Each of these dimensions was assigned a score according to the level of risk categorized in the methodology. Additionally, a sixth score was assigned by a senior consultant, reflecting the overall risk level in a category termed "general." This axis is the most critical, as it evaluates the likelihood of the business failing if no intervention is made to address the identified issues.

The current research applies machine learning techniques to this diagnostic dataset, focusing particularly on predicting general-axis assessments. This focus stems from two key factors: (1) while senior consultants provide rigorous evaluations (Mendonça, 2021), their expertise requires substantial training time and field experience (Oliveira, 2011), and (2) the prediction tool aims to enhance diagnostic accuracy for junior consultants who lack equivalent experience.

The predictive tool was developed using a Keras-based neural network model implemented in Python through the Scikit-Learn library. This framework enabled the development and evaluation of a deep learning model trained on business diagnostic data. Using a dataset of 98 companies representing various maturity levels, the model achieved a predictive accuracy of 75%, sufficient to identify companies at risk of business failure according to the general axis evaluation.

The paper proceeds as follows: Section 2 reviews relevant studies on business diagnostics and failure prediction. Section 3 details the research methodology, while Section 4 presents and discusses the results. Finally, Section 5 summarizes the key findings and provides concluding remarks.

2. Related Works

The integrative literature review, conducted across Scopus and Web of Science databases, identified six relevant studies contributing to this research field through diagnostic models or predictive techniques. To contextualize the discussion, we examine the work of Kasiki (2017), who traced the genesis and global development of business diagnostics. Focusing on the Czech Republic and Slovakia, Kasiki analyzed emerging trends, approaches, and diagnostic models.

Hernández-Díaz et al. (2021) investigated SME sustainability through a Puerto Rican case study. Their study conceptualized business sustainability as maintaining organizational health across all dimensions, extending beyond environmental considerations. The researchers employed a 106-item questionnaire aligned with the 5 MOPSE dimensions, administered to 108 SMEs to generate their analytical framework.

Hoa and Tuyen (2021) developed an assessment model for digital transformation readiness in Vietnamese SMEs. Their approach applied linear and non-linear regression algorithms combined with fuzzy methods to analyze data from 510 SMEs.

The authors Santos and Martinho (2020) created a maturity model specifically designed to evaluate Industry 4.0 integration in enterprises. The model's validation involved case studies with two major Brazilian automotive companies, using questionnaire-based assessments.

The relationship between resistance to change and organizational performance was the theme of the work conducted by Metz (2017). The research implemented an organizational diagnostic framework applied to a multinational ICT company in Romania. The comprehensive diagnostic tool evaluated 14 organizational dimensions, encompassing: purpose and values, structure, relationships, conflicts, communication, decision-making processes, benefits, motivation, leadership, change resistance, support mechanisms, personal dynamics, operational transparency, and performance metrics. The study collected data through questionnaires administered to 776 employees, followed by statistical analysis to determine correlations between change resistance and performance outcomes.

Advancing predictive methodologies, Le et al. (2021) introduced a hybrid approach combining oversampling techniques with cost-sensitive learning for business failure prediction. Their analysis focused exclusively on financial indicators, leveraging the Korean bankruptcy database containing 307 failed companies and 120,048 solvent firms. Notably, their methodology incorporated multiple technologies: HAOC (hybrid approach using oversampling and cost-sensitive learning), CBoost (bankruptcy prediction algorithm), Python programming language, and the Scikit-learn library. This study stands out as the only reviewed research that implemented both statistical analysis and machine learning algorithms for scenario prediction.

Beyond the systematic review, additional relevant studies were identified through expert recommendations. Agrawal et al. (2024) complement our machine learning approach by demonstrating predictive modeling applications for employee turnover. While our research focuses on neural networks for business vulnerability prediction, their work explores machine learning algorithms for attrition pattern identification, illustrating predictive analytics' adaptability across organizational contexts.

The study by Dhar et al. (2022) established the critical relationship between leadership styles and strategic diagnosis in emerging markets. Their findings demonstrate how leadership heterogeneity directly impacts strategic flexibility and execution, highlighting strategic adaptation as a key success factor in dynamic environments. The study emphasizes that effective diagnostic tools must incorporate both quantitative metrics and qualitative assessments.

3. Methodology

Creswell (2010) asserts that projects require a philosophical design structure, research strategies, and research methods, which are interconnected and give substance and legitimacy to the research. This study adopts a pragmatic approach, which seeks to solve real-world problems using both scientific and non-scientific knowledge and methods to find solutions.

The study employs a mixed-methods design with sequential strategy, selected for its capacity to integrate qualitative data collection with quantitative analysis while aligning with the researchers' expertise. This methodological choice enables the application of predictive techniques while maintaining theoretical consistency. Following Cupani's (2006) classification, the research qualifies as technological, as it applies existing knowledge to develop practical solutions.

This work represents an extension of previous studies that examined critical challenges facing micro, small, and medium-sized enterprises (SMEs), particularly the mediating role of business incubators. Building on findings from Morais et al. (2021) and Silvestro, Pinto Junior, and Duncke (2021), we developed the IncubE methodology (Pinto Junior, Silvestro & Morais, 2021) to standardize business diagnostics for vulnerable enterprises.

The methodology incorporates a comprehensive evaluation system based on five core business dimensions recognized by the Brazilian National Association of Entities Promoting Innovative Enterprises (Anprotec, 2018): entrepreneur, management, technology, financial/capital, and market. Each dimension receives a discrete maturity score according to standardized assessment criteria. Complementing these, a sixth comprehensive risk evaluation is provided by senior consultants. Figure 1 illustrates the diagnostic framework's six evaluation domains and their respective scoring criteria.

	1. ENTREPRENEURSHIP
5	No entrepreneurial training/knowledge.
4	Has an entrepreneurial profile, limited knowledge, and little time to dedicate.
3	Has an entrepreneurial profile, limited knowledge, but enough time to dedicate.
2	Has an entrepreneurial profile, good knowledge, but little time to dedicate.
1	Has an entrepreneurial profile, good knowledge, and adequate time.
	2. MANAGEMENT
5	Has no management control.
4	Knows some management variables, but does not control them.
3	Knows and controls some management variables.
2	Knows and reasonably controls all management variables of the business.
1	Knows and fully controls all management variables of the business.
	3. TECHNOLOGICAL
5	Has not implemented digital transformation and does not use any digital/technological resources for management or production flow.
4	Uses some resource to digitally structure the business OR uses some digital/technological resource for management or production flow.
3	Uses some resources to digitally structure the business AND uses some digital/technological resource for management or production flow.
2	The business is based on a digital platform and uses digital/technological resources for management or production flow.
1	Has implemented digital transformation and uses digital/technological resources for management or production flow.
	4. MARKET
5	Has a prototype and/or business model ready, but does not sell.
4	Is starting commercialization and needs to create/adjust pricing and sales strategies.
3	Has market insertion, but needs to increase it. The pricing policy may need adjustments and may require better strategies for customer and/or supplier relationships.
2	Has good market insertion, a mature pricing policy, and needs improvements in customer and/or supplier relationship strategies.
1	Has good market insertion, a mature pricing policy, and good strategies for customer and supplier relationships.
	5. CAPITAL
5	Has overdue debts, and monthly closures are in deficit.
4	Has debts in order, but monthly closures are in deficit.
3	Has lines of credit in order, and monthly closures are in surplus.
2	Does not have debts, and monthly closures are in surplus.
1	Does not have debts, has cash reserves and/or investments, and monthly closures are in surplus.
	6. GENERAL RISK (of closing)
5	The macro analysis of the company's problems/vulnerabilities indicates a HIGH risk of closure if no immediate intervention is made.
4	The macro analysis of the company's problems/vulnerabilities indicates a MEDIUM risk of closure if no immediate intervention is made.
3	The macro analysis of the company's problems/vulnerabilities indicates a LOW risk of closure if no immediate intervention is made.
2	The macro analysis of the company's problems/vulnerabilities indicates a possibility of entering a vulnerability zone.
1	The macro analysis of the company's problems/vulnerabilities indicates business stability (sustainability).

Source: Authors (2025)

Figure 1: Evaluation domains and scoring criteria

The research employed the IncubE Methodology along with its evaluation framework (Figure 1) to assess participating companies. For machine learning purposes, each company's diagnostic profile was represented as a 6-dimensional vector comprising scores from all evaluation areas.

Trained senior consultants conducted business diagnostic interviews with 98 companies. Following data collection, all evaluations were standardized through discrete scoring, enabling both risk-level ranking and subsequent machine learning analysis. The resulting dataset served as input for predictive modeling of business diagnostics.

3.1 Experiment Setup

To leverage historical business diagnostic data and enable predictive capabilities for new assessments, we developed an artificial intelligence system based on neural network architecture. The technical implementation details, including programming language, platform, libraries, and network configurations, are summarized in Table 1. This final configuration was determined through extensive parameter optimization, resulting in the highest predictive performance.

Table 1: Technical Specifications of the Experiment

Technical Specifications of the Experiment	
Programming Language	Python
Development Platform	Google Colab
Libraries Used	Scikit-Learn and TensorFlow
Data Balancing	Unbalanced
Training and Test Set Split	70% training / 30% testing
Type of Neural Network	Sequential, implemented by the Keras model
Layers and Neurons	Layer 1: 30 neurons, with ReLU activation function Layer 2: 10 neurons, with ReLU activation function Layer 3: 2 neurons, with Sigmoid activation function
Compilation	For model compilation, the parameters were set as loss="mean_squared_error", optimizer="adam", and metrics="accuracy".
Epochs / Batch Size	100 epochs, with batch size of 10

Source: Authors (2025)

The study employed Python for its robust scientific programming capabilities, extensive machine learning libraries, and comprehensive online support resources. Key libraries included Scikit-Learn for data loading and preprocessing, and TensorFlow to implement the Keras deep learning framework (Keras, 2025). The Keras Sequential model was selected for its ability to stack linear layers and provide integrated training and inference functionalities.

The dataset comprised diagnostic evaluations from 98 companies, as detailed in previous sections. All records were anonymized and assigned unique identification numbers for experimental control, with company identities remaining confidential. The data was structured in a CSV file where each row represented a company and columns contained:

- Scores (1-5) for five diagnostic dimensions (1 = lowest risk, 5 = highest risk)
- A binary label for the General axis (0 = "at risk", 1 = "not at risk")

This structured format enabled efficient preprocessing and model training while maintaining data integrity and confidentiality.

The anonymized company dataset used in this study, along with the implementation code, are available upon reasonable request from the corresponding author.

4. Results and Discussion

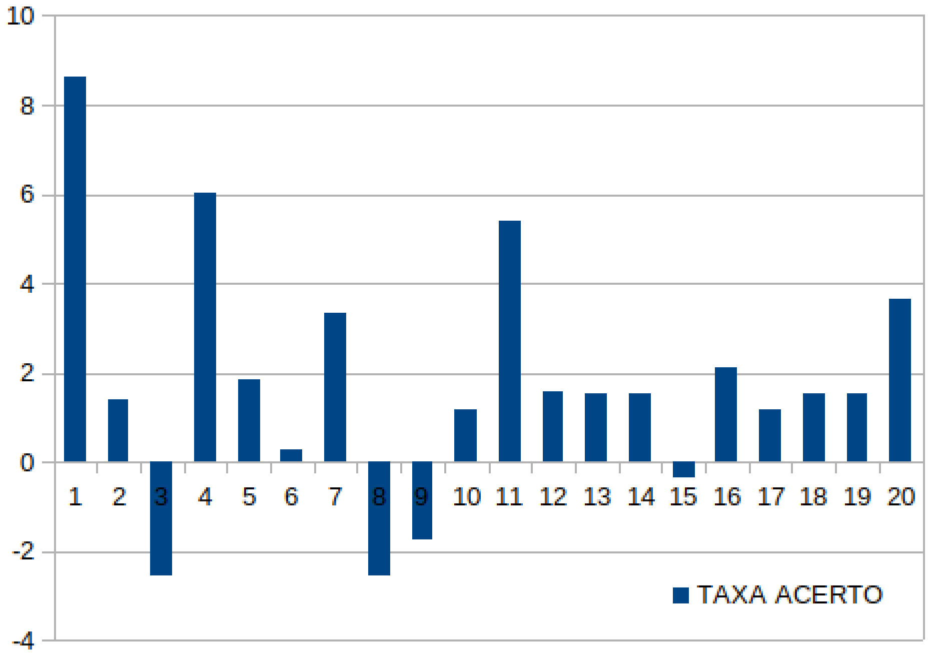
The experimental results identified optimal performance using data partitioning of 70% of the data for training and 30% for testing, with 3 network layers:

- Layer 1: 30 neurons with ReLU activation;
- Layer 2: 10 neurons with ReLU activation;
- Output layer: 2 neurons with sigmoid activation.

This architecture achieved convergence after processing 100 epochs with a batch size of 10.

The output of the network showed a total processing time of 70ms/step. The loss generated by the network was 28.7%, and the accuracy was 75%. We analyzed the 25% error caused at the output and observed that the margin of error was at most less than 4 percentage points. In Figure 2, it is possible to visualize the membership rates obtained for 20 elements of the test set. For each element, there is a probability distribution that, from the learning process, indicates how much an element belongs, percentage-wise, to the value 0 (in general risk) or 1 (not at risk), assigned to the label attribute, which determines if it is at risk.

On the 'y' axis, the value zero is the decision threshold, meaning that the positive values on the 'x' axis indicate correct predictions of the company's risk status, and the value specified on this axis corresponds to the difference between the value of the corresponding label column and the value of the non-corresponding column. In the same logic, negative values also correspond to the difference between these two columns, but they represent predictions that failed.



Source: Authors (2025)

Figure 2: Membership Rate

The machine learning framework presented in this study offers valuable decision-support capabilities for both junior consultants and entrepreneurs. It is important to emphasize that business risk assessment represents a complex analytical process that cannot be adequately performed through isolated diagnostic examinations alone. Effective evaluation requires contextual knowledge of vulnerability indicators, comparative analysis of multiple diagnostics, and informed interpretation of organizational data.

The implementation of this neural network allows learning from a series of previously conducted diagnostics, providing the consultant or manager with this knowledge as machine learning and offering a reasonably reliable business risk diagnosis, considering the algorithm's 75% accuracy rate. Therefore, consultants can use this tool to support their consulting efforts and combine the results of the algorithm with their personal analyses.

In cases where the diagnosis indicates that the company is not at risk, the organization receives feedback indicating its healthy status. In such cases it would be wise to develop plans to explore its potential, boost the successful areas, and focus institutional goals on growth and expansion.

On the other hand, if the diagnosis indicates a risk situation, it suggests that the company seek more specific assistance to perform a detailed diagnostic, allowing the identification of areas and activities that are putting the organization into risk and need analysis and restructuring. Professionals with specific expertise may be sought to help build an action plan focused on business recovery.

A key benefit of this predictive tool is its ability to help both senior and junior consultants arrive at consistent conclusions regarding risk assessment. This shared understanding enables collaborative efforts to mitigate business risks and prevent potential bankruptcy scenarios.

It should be noted that the tool offers a scalable solution for business diagnostics; however, its implementation must consider ethical concerns. Junior consultants or non-expert users should not rely on this tool as a definitive diagnostic method, as missing contextual analysis or expert validation could lead to misjudgments. To mitigate this, public deployment of the model will include a recommendation to use it as a supplementary risk indicator, supported by human oversight. Future iterations may also integrate explainability features to enhance transparency in decision-making.

5. Final Considerations

This paper analyzed the contribution of a business diagnostic prediction model to assist business consultants in decision-making. We interviewed 98 companies using the diagnostic methodology advocated by IncubE and used the responses as input for a Keras neural network model in Python.

Regarding project management and strategic success, this study offers a data-driven approach to mitigate business risks and enhance decision-making in SME incubation programs. By predicting vulnerabilities across key organizational dimensions, the model enables consultants and managers to prioritize strategic interventions, allocate resources efficiently, and design targeted action plans during the incubation process. For instance, integrating this tool into project planning workflows could help incubators identify high-risk ventures early, tailor mentorship programs, and optimize resource distribution—ultimately increasing the success rate of these enterprises.

The machine learning results led to an output with 75% accuracy, which enabled us to determine whether a company has business failures that may put it at risk. This paper presents the initial findings of our ongoing research, which shows promising potential for further refinement. Future work will focus on several processing improvements, such as: conducting more consulting sessions to expand the database and enable learning from a larger and more diverse dataset; adapting the techniques and methodologies proposed here to learn from a larger database of business diagnostics; balancing the load of input data; and testing the assignment of weights to the diagnostic dimensions according to their importance in risk analysis.

We can implement changes in our algorithms to seek higher accuracy and/or a greater margin of error tolerance, with a broader decision threshold. Some possible changes include: 1. conducting more consulting sessions and using these diagnostics to expand the database and allow learning from a larger and more heterogeneous dataset; 2. testing the same technique developed here and adapting the methodology to learn from another business diagnostic database; 3. balancing the load of input data, assigning the same proportional number of companies at risk and not at risk to the learning and testing data groups; 4. testing the assignment of weights to the diagnostic dimensions, considering that each axis may have a different weight for business sustainability and, consequently, a different risk level in the business diagnosis.

In the format presented here, the research is limited to being applicable only to consultants and managers trained in the IncubE methodology. However, the incorporation of this machine learning tool enables consultants to anticipate critical business situations and prevent potential failure or vulnerability scenarios.

In the future direction of the research, we aim for our tool to provide the diagnosis directly to the company's manager, using text and speech analysis techniques to automate the diagnosis for each business axis. Thus, the business manager can use the tool to obtain the machine learning diagnosis and consider it when making decisions and setting priorities in management, functioning as a virtual benchmarking tool with a company database.

Future research will include benchmarking the neural network model against traditional methods (e.g., logistic regression, decision trees) and other machine learning approaches (e.g., SVM, Random Forest) to further validate its predictive performance. This expansion will provide a more comprehensive evaluation of the methodology and its applicability across diverse business contexts.

Finally, considering that there are few studies in the literature addressing the prediction of business vulnerabilities and none employing a methodology assessing all five critical organizational dimensions examined here (entrepreneurial, technological, market, management, and financial), we hope this paper and its future developments can contribute to reducing organizational issues and consequently reducing the number of companies in crises or bankruptcy.

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Ethics and AI Declaration: We declare that this research utilized the Keras neural network for machine learning. Furthermore, we affirm that the study did not involve the direct or indirect participation of human beings or animals at any stage. All methodologies applied were based on public data and previously published documents, ensuring compliance with ethical principles and good research practices. Therefore, the work fully respects the prevailing ethical guidelines for studies of this nature.

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