American Journal of Business and Operations Research

♦ ISSN: 2692-2967 Vol: 11, No. 01, 2025 ♦ PP. 14–18

Article DOI: https://doi.org/10.54216/AJBOR.110102

FULL LENGTH ARTICLE

An Improved Approach for Modeling Bank Loan Default in Pursuit of Sustainable Banking

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Received: May 15, 2023 Revised: August 13, 2023 Accepted: December 03, 2023 ⋆ Corresponding author

ABSTRACT

This article presents our research effort to explore the convergence of sustainable banking practices and predictive modeling for bank loan defaults, with a primary emphasis on addressing the pressing need for resilient financial systems. To this end, an applied methodology is presented in this study to model bank loan defaults, emphasizing the incorporation of sustainability criteria into predictive analytics. Given the temporal nature of loan data, our approach leverages Long Short-Term Memory (LSTM) networks as its backbone process for predictive modeling. The empirical results of the public case study underscored the enhanced predictive accuracy accomplished through this approach, emphasizing the pivotal function of integrating sustainability metrics in predicting mortgage defaults inside the banking area.

Keywords: Loan Default ▪ Sustainable Finance ▪ Credit Risk Modeling ▪ Banking Sustainability ▪ Machine Learning ▪ Financial Stability ▪ Default Probability Estimation ▪ Risk Management ▪ Econometric Modeling ▪ Banking Practices

1. INTRODUCTION

The worldwide economic panorama continues to evolve, prompting a vital evaluation of banking structures to foster sustainability and resilience. Within this realm, the predictive modeling of bank loan default stands as a pivotal region influencing financial stability and sustainable practices [1, 2, 3]. This paper delves into an imperative pursuit: the refinement of a technique geared toward modeling financial institution mortgage default, looking to reinforce the basis of sustainable banking. In a generation in which economic volatility intertwines with environmental and social considerations, the enhancement of predictive models becomes imperative to mitigate dangers and nurture a sustainable monetary environment [4, 5]. At the heart of sustainable banking lies the project of efficiently managing credit risks while aligning operations with ethical, social, and environmental principles [6, 7]. The inherent complexity of predicting mortgage defaults needs sophisticated modeling strategies that not only investigate financial aspects but also integrate broader sustainability metrics. Embracing this project, this paper endeavors to provide a modern framework that amalgamates strong statistical methodologies and contemporary machine-learning algorithms [8, 9, 10]. Such an integrative method aims not only to enhance predictive accuracy in loan-default modeling but also to embed sustainability standards into the center of banking decision-making approaches [11].

This research embarks on an exploration of methodologies that go beyond traditional hazard-assessment paradigms, acknowledging the multidimensional nature of sustainable banking [12, 13, 14, 15, 16]. By bridging the space between quantitative modeling and sustainability imperatives, this paper aspires to contribute to a nuanced understanding of how advanced modeling strategies can bolster the resilience of economic institutions. Furthermore, it seeks to elucidate

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how the amalgamation of those methodologies fosters a more holistic approach to risk control, one which fosters the long-term viability of banks within a framework of societal and environmental stewardship [17, 18, 19].

In essence, this study sets out to redefine the contours of predictive modeling for financial institution loan defaults by emphasizing the integration of sustainability concerns. By doing so, it aims not only to enhance the predictive power of models but also to cultivate a banking ethos rooted in responsible lending practices and a commitment to sustainable development goals [13]. Through an in-depth exploration of this intersection between monetary modeling and sustainability, this paper strives to offer insights that will resonate in the banking sector and contribute to the wider discourse on fostering sustainability inside economic structures [20, 21].

This paper is structured to provide a complete understanding of the pursuit of sustainable banking via an improved method for modeling financial institution mortgage default. Section 2 navigates through the prevailing literature and empirical studies shaping the panorama of mortgage-default modeling. Section 3 unveils the innovative framework developed in this study. Section 4 details the methodologies used in testing and validating the proposed approach. Section 5 presents the empirical findings and conducts a rigorous evaluation of the consequences. Finally, Section 6 synthesizes the key insights gleaned from this study.

2. RELATED WORKS

In terms of sustainable banking and forecasting models for loan defaults, this section presents a comprehensive review of the relevant literature and empirical research underpinning this study. Ahmed [22] examined the implications of the global financial crisis through the lens of Islamic finance, including its views and responses to economic policy and sustainability in the Islamic framework. Pisano et al. [23] examined the complex relationship between finance and sustainable development, emphasizing the role of the financial sector in promoting or constraining sustainable practices. Betz et al. [24] contributed significantly to the discussion by providing a predictive model of distress in European banks, enhancing the understanding of risk assessment in banking institutions. Calomiris and Gorton [25] examined the origins of banking panics by providing insights into models, facts, and bank regulation. Ng [26] emphasized the role of institutional legitimacy and market heterogeneity in the global economic environment. In addition, Nizam et al. [27] conducted a comprehensive global study assessing the impact of social and environmental sustainability on the financial performance of the banking sector and providing empirical evidence for the interplay between sustainability and financial outcomes.

Sanusi [28] scrutinized the aftermath of the global economic meltdown in the Nigerian banking sector, focusing on the reforms instituted to mitigate systemic dangers. Poledna and Thurner [29] proposed a systemic-risk transaction tax to remove systemic risk in financial networks, contributing to the discourse on systemic-risk management. Furthermore, Gennaioli et al. [30] introduced a model of shadow banking, offering insights into the complexities and implications of this monetary mechanism. Bolton and Freixas [31] investigated the connection between corporate finance and the monetary transmission mechanism, shedding light on the links between economic decision-making and the broader economy. Weber et al. [32] contributed to the integration of sustainability standards into credit-risk management, emphasizing its significance in contemporary risk-evaluation practices. Bihari and Pradhan [33] explored the relationship between Corporate Social Responsibility (CSR) and performance in the Indian banking sector, highlighting the effect of CSR initiatives on financial institutions' performance metrics.

Ozili and Outa [34] carried out a comprehensive review of bank loan-loss-provision studies, providing a detailed analysis of the factors influencing those provisions within banking establishments. Yap et al. [35] explored the application of data-mining techniques to improve credit-scoring models, emphasizing their importance in assessing creditworthiness. Arafah and Nugroho [36] examined the application of Maqhashid Sharia in a clean-water financing business model at an Islamic bank, offering insights into the intersection of Islamic standards and sustainable financing. Finally, Behr et al. [37] analyzed the financial constraints faced by private firms and their implications for bank-lending behavior, contributing to the understanding of lending practices concerning constrained corporations.

3. METHODOLOGICAL DESIGN

This section presents the methodology used in this study and provides a systematic framework for developing an advanced approach to modeling bank loan defaults in sustainable banking.

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture designed to process and model sequential information while mitigating the limitations associated with vanishing and exploding gradients in traditional RNNs. LSTM networks are characterized by their ability to capture and retain long-term dependencies within sequential information through specialized memory cells. These memory cells include input, forget, and output gates that regulate the flow of information, enabling LSTMs to selectively retain or discard information over varying time steps. By leveraging these gating mechanisms, LSTMs efficiently manage and retain relevant information across sequential inputs, making them particularly appropriate for modeling and predicting temporal patterns, trends, and dependencies within dynamic datasets such as financial time series.

In this study, we used an LSTM network as a sophisticated deep-learning technique to identify and understand the complex structure embedded in the loan database. The inherent ability of LSTM to model temporal dependence made it a suitable candidate for capturing the complex sequential relationships in financial data, especially when forecasting loan defaults. In particular, after fitting the loan dataset to the LSTM system, the network automatically identified temporal patterns and dependencies embedded in the data. Through iterative and optimized training, the LSTM model successfully indexed the sequences, extracted latent factors, and found complex temporal relationships between variables. It thereby allowed us to harness the power of deep learning to reveal regular patterns and subtle relationships in the loan dataset, providing a more accurate and comprehensive model for predicting bank loan defaults in a sustainable banking system.

The following equations articulate the working mechanism of the LSTM cell:

$$f_t = \sigma\left(W_f[h_{t-1}, X_t] + b_f\right), \quad (1)$$
$$i_t = \sigma(W_i[h_{t-1}, X_t] + b_i), \quad (2)$$
$$N_t = \tanh(W_N[h_{t-1}, X_t] + b_N), \quad (3)$$
$$C_t = C_{t-1} f_t + N_t i_t, \quad (4)$$
$$O_t = \sigma(W_O[h_{t-1}, X_t] + b_O), \quad (5)$$
$$h_t = O_t \tanh(C_t). \quad (6)$$

The output generated by the LSTM layers progresses to fully connected layers (FCLs) with sigmoid activation, expressed as

$$\text{Output}_{\text{FCL}} = \sigma(Wx + b). \quad (7)$$

Here, $\text{Output}_{\text{FCL}}$ denotes the output of the FCL, W represents the weight matrix, x signifies the input vector from the LSTM output, and b symbolizes the bias vector.

The cross-entropy loss function, $\mathscr{L}_{\text{CE}}$, is employed to evaluate the disparity between the predicted values and the actual labels and is defined as

$$\mathscr{L}_{\text{CE}} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right]. \quad (8)$$

Here, N signifies the total number of samples in the dataset, y_i denotes the actual label (either 0 or 1) for the ith sample, and $\hat{y}_i$ represents the predicted probability produced by the sigmoid function for that sample.

4. EXPERIMENTAL SETUP

In this part of the manuscript, the experimental setup used to validate and test the proposed technique for modeling bank mortgage default within the context of sustainable banking is comprehensively detailed. This section delineates the design and execution of empirical experiments orchestrated to evaluate the efficacy and performance of the modeling method presented above.

Table 1 presents a comprehensive compilation of precise information derived from the mortgage dataset, encapsulating key quantitative measures that provide a descriptive overview of the data's characteristics. The table includes important statistical metrics such as the mean, standard deviation, minimum, maximum, and quartile values for applicable variables or features within the mortgage dataset. It is notable that the mean values of different features lie in different ranges, which necessitates normalizing the features to a uniform range before fitting them into the model. In addition, the tabulated count values imply that some columns contain missing values, necessitating appropriate imputation techniques.

Table 1. Summary Statistics of Loan Dataset Variables

Variable	Count	Mean	Std.	Min.	25%	50%	75%	Max.
loan_amount	148664.0	331115.1	183909.9	16500.0	196500.0	296500.0	436500.0	3576500.0
rate_of_interest	112226.0	4.0	0.6	0.0	3.6	4.0	4.4	8.0
interest_rate_spread	112026.0	0.4	0.5	-3.6	0.1	0.4	0.8	3.4
upfront_charges	109023.0	3225.1	3251.1	0.0	581.9	2596.8	4812.5	60000.0
term	148623.0	335.1	58.4	96.0	360.0	360.0	360.0	360.0
property_value	133566.0	497915.5	359928.4	18000.0	268000.0	418000.0	628000.0	16508000.0
income	139520.0	6957.3	6496.6	0.0	3720.0	5760.0	8520.0	578580.0
Credit_Score	148664.0	699.8	115.9	500.0	599.0	699.0	800.0	900.0
LTV	133566.0	72.5	18.9	1.0	60.5	75.1	86.2	263.5
Status	148664.0	0.2	0.4	0.0	0.0	0.0	0.0	1.0
dtir1	124549.0	37.7	10.5	5.0	31.0	39.0	45.0	61.0

5. EXPERIMENTAL RESULTS

In this phase of our work, we evaluated the empirical results derived from applying the modeling method described in the previous sections. This phase provides a comprehensive exploration of the findings obtained through the experimental setup, aiming to scrutinize the efficacy and sustainability implications of the proposed method for modeling financial institution mortgage default within sustainable banking frameworks.

Figure 1 presents a dendrogram showing the ranked features in the loan dataset. This representation illustrates the relationships and proximity among the various factors used in the study. Through hierarchical clustering, the features are organized according to their similarities, revealing groups or clusters based on shared characteristics or patterns. Examining this dendrogram provides insight into the underlying structure and relationships among features.

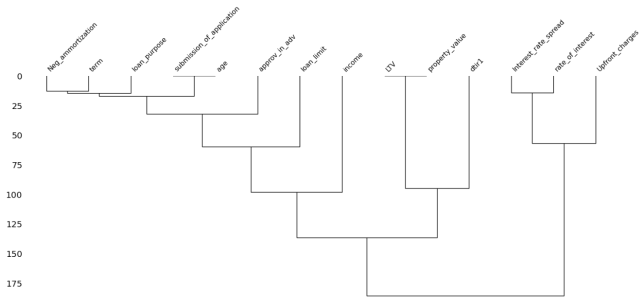

Figure 1. Dendrogram visualization of features in the loan dataset.

Figure 2 presents box-and-whisker plots that offer a comprehensive visual representation of the distribution and variability of variables within the mortgage dataset. These plots depict statistical measures such as the median, quartiles, and outliers for each variable, providing a clear illustration of their central tendency, spread, and potential extreme values.

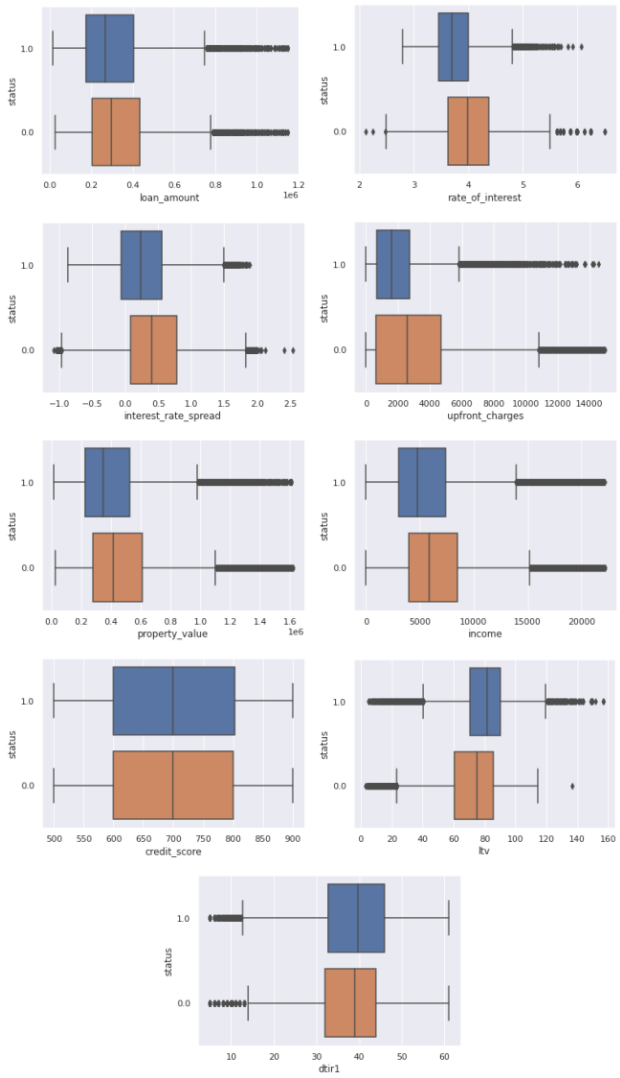

Figure 2. Visualization of box-and-whisker plots for loan-data variables.

Figure 3 presents the confusion matrix derived from evaluation of the model. The matrix summarizes the true positives, true negatives, false positives, and false negatives. This visualization serves as a pivotal tool for assessing the model's overall performance, facilitating a deeper understanding of its strengths, weaknesses, and areas for potential development in optimizing predictive outcomes.

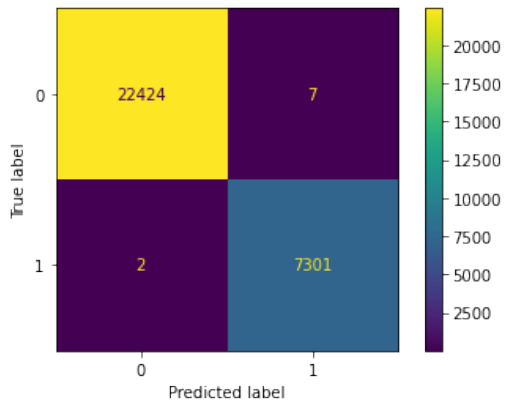

Figure 3. Confusion matrix representation of model evaluation.

6. CONCLUSION

This study spans the terrain of sustainable banking by taking a new approach based on advanced modeling techniques for forecasting bank loan defaults. Through the use of Long Short-Term Memory (LSTM) networks and comprehensive loan-data analysis, this study reveals nuanced understandings of the complex relationship between economic volatility and banking behavior. In addition to emphasizing the importance of predictive accuracy in identifying potential credit failures through complex patterns, the study emphasizes the importance of incorporating sustainability considerations into predictive-modeling efforts, paving the way for responsible lending practices and enabling resilience in monetary policy.

Specifically, this study integrates economic and developmental data and advocates a paradigm shift toward a more robust and conscientious banking system. The findings presented here not only highlight the effectiveness of LSTM-based modeling in increasing the accuracy of loan-default predictions but also highlight the important role of data-driven methods that emphasize sustainable development in the economic environment.

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