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Bankruptcy Prediction with Explainable Artificial Intelligence for Early-Stage Business Models

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Abstract

Bankruptcy is a significant risk for start-up companies, but with the help of cutting-edge artificial intelligence technology, we can now predict bankruptcy with detailed explanations. In this paper, we implemented the Category Boosting algorithm following data cleaning and editing using OpenRefine. We further explained our model using the Shapash library, incorporating domain knowledge. By leveraging the 5C's credit domain knowledge, financial analysts in banks or investors can utilize the detailed results provided by our model to enhance their decision-making processes, even without extensive knowledge about AI. This empowers investors to identify potential bankruptcy risks in their business models, enabling them to make necessary improvements or reconsider their ventures before proceeding. As a result, our model serves as a "glass-box" model, allowing end-users to understand which specific financial indicators contribute to the prediction of bankruptcy. This transparency enhances trust and provides valuable insights for decision-makers in mitigating bankruptcy risks.

Keywords: *Explainable Artificial Intelligence, Bankruptcy Prediction, Shapley value, LIME, Ensemble Learning methods, ADASYN, OpenRefine*

1. Introduction

In today's increasingly advanced Artificial Intelligence (AI) landscape, the ability to predict bankruptcy for start-up companies has assumed vital importance in domains such as the stock market, bank loan approval, and business planning. The advent of Explainable Artificial Intelligence (XAI) tools enables start-up companies to gain a comprehensive understanding of their financial situation and evaluate their risk of bankruptcy with detailed explanations. Additionally, these tools facilitate comparisons between start-ups and their competitors, shedding light on the likelihood of bankruptcy within the industry. By assessing their financial indicators prior to commencing operations, start-up companies can proactively identify potential risks and mitigate them effectively.

When collecting bankruptcy datasets from real-life sources, they often exhibit a highly imbalanced nature.

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To address this issue, we employed the use of Adaptive Synthetic (ADASYN) [1], ADASYN resampling technique, to mitigate the imbalanced data problem. Additionally, we utilized OpenRefine [2] to clean and edit the data for our experiment, ensuring its quality and reliability. For our bankruptcy prediction experiment, we selected the Category Boosting method, which is a widely used Ensemble Learning algorithm. This method combines multiple base learners to create a powerful predictive model for bankruptcy prediction. By leveraging the strengths of ensemble learning, we aimed to enhance the accuracy and robustness of our predictions.

Furthermore, the Shapash library can be employed to provide explanations for the aforementioned model. The Shapash library utilizes Shapley value and Local Interpretable Model-Agnostic Explanations (LIME) techniques for generating explanations. The incorporation of Explainable Artificial Intelligence methods enhances the credibility of bankruptcy prediction models, instilling trust among both users and developers. Consequently, our model becomes a "glass-box" model [3], allowing us to identify the specific features that contribute to bankruptcy predictions. This paper is organized into five sections: Section 2 provides the background information, Section 3 describes the algorithm used and the dataset employed, Section 4 presents the experimental procedures and results, and finally, Section 5 concludes the paper.

2. Background

Since 2017, there has been a significant development of Explainable Artificial Intelligence tools based on the concept of Shapley value. Shapley value is an XAI approach inspired by game theory [4]. It is worth noting that Shapley value is the only theory that satisfies fairness axioms, which include symmetry, efficiency, dummy player, and group additivity. This concept was originally formulated by Lloyd Shapley, an American mathematician and Nobel laureate, in 1951. Another technology utilized in the Shapash library is Local Interpretable Model-Agnostic Explanations (LIME) [5]. The central idea behind LIME is to create surrogate explanation models for machine learning algorithms. This technique allows for the interpretability of Machine Learning (ML) algorithms, enhancing our understanding of their predictions and decisions.

Bankruptcy prediction models typically analyze data using financial ratios. In a paper titled "Corporate Bankruptcy Prediction Model for Internet Startup Companies" [6], published in 2020, the authors employed the Logistic Regression Analysis method to predict bankruptcy for internet startup companies. Additionally, in another paper published in 2020, titled "Predicting startup survival using first-year financial statements" [7], the authors analyzed data from 6,167 Spanish startup companies during an economic crisis. The study focused on predicting the survival of these startups based on their financial statements in the initial years of operation.

A comprehensive study [8] conducted across 53 countries reveals that the financial responsibility of start-up companies is significant, with the average cost in the range of 30,000 to 40,000 US dollars during the first year. Given these substantial costs, accurately predicting the failure of a start-up in its early stages is of paramount importance for the overall economy. When investors are aware of the potential risks of bankruptcy associated with a particular business model, they have the opportunity to make improvements or decide against proceeding with the venture before committing significant resources. The application of XAI technology empowers these investors to identify the key factors contributing to bankruptcy and address any weaknesses or vulnerabilities in their business model proactively. By leveraging XAI, start-ups can gain valuable insights, make informed decisions, and improve their chances of long-term success.

3. Methodology

3.1 Algorithm

CatBoost or Category Boosting, developed by Yandex, the largest technology entity in Russia, is a newly developed and widely used library. The first version of CatBoost was released as an open-source library to the public in 2017. This library offers several advantages, including efficient handling of categorical features, compatibility with GPUs, and the ability to achieve good results without extensive parameter tuning. CatBoost is primarily based on Gradient Boosting on Decision Trees, and it is known for its fast performance compared to other ensemble learning methods, as highlighted in a research paper by Yandex [9]. CatBoost was preferred for the bankruptcy prediction task over other Boosting algorithms like Random Forest, XGBoost, and AdaBoost. Its selection was based on its exceptional capabilities, including effective handling of categorical features, robustness to overfitting, efficient performance, adaptive learning rate, excellent accuracy, and built-in visualization tools. These advantages made CatBoost the ideal choice for achieving accurate and interpretable predictions in the context of bankruptcy prediction.

CatBoost is primarily designed to tackle the overfitting problem commonly associated with Gradient Boosting. However, it does have a limitation when dealing with sparse matrices, which typically occur in datasets containing a large number of missing values. To address this limitation, we meticulously cleaned and examined our dataset using OpenRefine. During the data preparation process, we identified a column named "Liability-Assets Flag" that contains only "0"s. Since "Liability-Assets Flag" serves as a flag indicator and not a value attribute, we have made the decision to remove this particular instance from the dataset. Additionally, we observed that the "Net Income Flag" column is also a flag indicator, containing only "1"s. Therefore, we have similarly chosen to remove this instance from the dataset. By carefully managing these specific instances, we aim to ensure the dataset is well-prepared for training with CatBoost, optimizing its performance and mitigating any potential overfitting issues.

3.2 Data

The dataset utilized in our experiment was sourced from the Taiwan Economic Journal, encompassing data from 1999 to 2009. It consisted of 6,819 companies, among which 220 companies were officially declared bankrupt, following the regulations set by the Taiwan Stock Exchange. To address the challenge of class imbalance in our dataset, we employed the ADASYN technique to facilitate hyperparameter tuning. Class imbalance arises when the instances in different classes are significantly disproportionate, resulting in an imbalanced distribution. This can cause machine learning models to exhibit bias towards the majority class, leading to suboptimal performance on the minority class. ADASYN serves as a solution to this issue by generating synthetic samples for the minority class, effectively balancing the class distribution. By doing so, ADASYN enhances the model's ability to learn from the underrepresented class, leading to improved performance and more accurate predictions in scenarios where rare events or positive instances are critical. Thus, ADASYN proves to be an effective approach in mitigating the effects of class imbalance during the hyperparameter tuning process.

The dataset consists of 93 features, which are financial ratios. For our experiment, we split the dataset into 70% for training and 30% for testing purposes. Calculating Shapley values with real numbers can be time-consuming. To address this, we utilized OpenRefine to truncate the values to three decimal places using General Refine Expression Language (GREL) codes. Additionally, we converted our data into UTF-8 formatting.

OpenRefine, previously known as GoogleRefine, is a web-based application developed by Google for data cleaning and transformation. It provides a scripting language called GREL for expressing formulas and manipulating data. In our data cleaning process, we used the GREL command "value.toNumber().toString("%.3f")" to shorten the lengthy real number financial ratios.

4. Experiment and Results

To address the imbalanced data problem, we implemented the Adaptive Synthetic (ADASYN) algorithm. ADASYN is a technique that generates virtual minority class data along a straight line between existing minority class data points. The algorithm selects data points randomly from the K-nearest neighbors of each minority class data point. By applying ADASYN, we were able to increase the number of instances in the training set to 4,619 for Class 0 (non-bankrupted companies) and 4,591 for Class 1 (bankrupted instances). Initially, there were only 154 instances for Class 1, representing approximately 3% of the target class in the dataset. We used a Workstation equipped with an i7 processor and RTX 2080ti GPU for main experiment. First step is to apply the CatBoost algorithm for a binary classification task. Performance metric result is shown below in Table 1.

Table 1. Performance metrics

	Precision	Recall	F1-score	Support	Accuracy
All				2,046	0.87
0	0.99	0.88	0.93	1,980	
1	0.16	0.70	0.26	66	
Macro avg	0.57	0.79	0.60	2,046	
Weighted avg	0.96	0.91	0.91	2,046	

After evaluating our model's performance, we obtained an accuracy score of 0.87 and a recall score of 0.88 for class 0, as well as a recall score of 0.70 for class 1. These results indicate that our model training was successful, considering the total of 93 features used in the process. To gain deeper insights into our model and better understand its predictions, we applied the Shapash model interpretation tool. Shapash enables us to interpret the model's behavior and provides valuable explanations for individual predictions, shedding light on the factors contributing to each outcome. With the help of Shapash, we can gain more transparency into our model's decision-making process, ensuring greater trust and understanding of its performance.

Table 2. Comparison with other methods

Method name	Accuracy score
CatBoost	0.87
RandomForest	0.83
Extreme Gradient Boosting	0.86
AdaBoost	0.86
Multilayer Perceptron	0.65
Logistic Regression	0.59
Support Vector Machines	0.46

In Table 2, it is evident that our selected CatBoost algorithm outperforms other methods, demonstrating the best performance. While Extreme Gradient Boosting and AdaBoost perform well, CatBoost slightly surpasses them. Conversely, Logistic Regression and Support Vector Machines show poor performance, with accuracy scores of 0.59 and 0.46, respectively. The superiority of CatBoost highlights its effectiveness in handling the complexities of our dataset and achieving superior predictive performance.

Top 20 features from Shapash WebApp output are shown below in Figure 1.

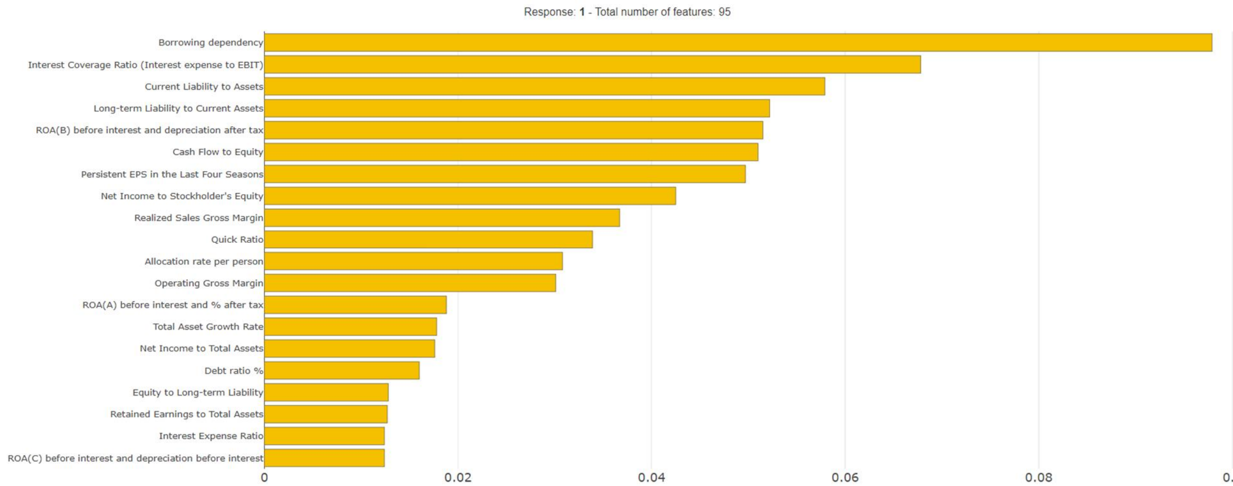

Figure 1. Result from Shapash

The top three features responsible for the bankruptcy prediction task are Borrowing dependency, Interest Coverage Ratio, and Current Liability to Assets. The picture displays the top 20 financial ratios. Other features with contributions below 0.0124 were excluded from interpretation to focus on the most significant factors using the Shapash model interpretation tool. This approach provides clearer insights into our model's decision-making process.

Table 3. Shapley value of top 20 features

Feature	Shapley value
Borrowing dependency	0.0979
Interest Coverage Ratio	0.0678
Current Liability to Assets	0.0579
Long-term Liability to Assets	0.0522
ROA(B) before interest and depreciation after tax	0.0515
Cash Flow to Equity	0.0510
Persistent EPS in the Last Four Seasons	0.0497
Net income to Stockholder’s Equity	0.0425
Realized Sales Gross Margin	0.0367
Quick Ratio	0.0339
Allocated rate per person	0.0308
Operating Gross Margin	0.0301
ROA(A) before interest and % after tax	0.0188
Total Asset Growth Rate	0.0178
Net Income to Total Assets	0.0176
Debt ratio %	0.0160
Equity to Long-term Liability	0.0128
Retained Earnings to Total Assets	0.0127
Interest Expense Ratio	0.0124
ROA(C) before interest and depreciation after tax	0.0124

When banks evaluate loan applications, they typically assess them based on the 5C's of credit [10]. These are widely recognized factors that help determine the creditworthiness and risk associated with the borrower. The 5C's of credit include:

Capacity: This refers to the borrower's ability to repay the loan. It considers factors such as the borrower's income, employment stability, and debt-to-income ratio.

Capital: This refers to the borrower's own investment in the business or assets. It indicates the borrower's financial stake and commitment to the venture.

Collateral: Collateral refers to the assets or property that the borrower pledges as security for the loan. It provides the lender with a form of protection if the borrower fails to repay the loan.

Conditions: Conditions encompass the broader economic and industry-specific factors that may impact the borrower's ability to repay the loan. This includes market conditions, interest rates, and other external factors.

Character: Character refers to the borrower's reputation, integrity, and credit history. It considers factors such as credit scores, payment history, and past financial behavior.

By evaluating loan applications based on these 5C's of credit, banks can make informed decisions about lending money while assessing the potential risks associated with the borrower.

Table 3. Mapping into 5C's credit

5C's	Features	Description	Total Shapley value
Capacity	Borrowing dependency, Long-term Liability to Assets, Realized Sales Gross Margin, Debt ratio %	Ensure repay loan	0.2028
Capital	Interest Coverage Ratio, Cash Flow to Equity, Net income to Stockholder's Equity, Operating Gross Margin, Net Income to Total Assets	Savings and income	0.2090
Collateral	Total Asset Growth Rate, Equity to Long-term Liability	Secured loans and guarantee	0.0306
Conditions	Current Liability to Assets, Allocated rate per person, Interest Expense Ratio	Plan for using the loan and external factors	0.1011
Character	ROA(B) before interest and depreciation after tax, Persistent EPS in the Last Four Seasons, Quick Ratio, ROA(A) before interest and % after tax, Retained Earnings to Total Assets, ROA(C) before interest and depreciation after tax	Credit history and payment history	0.1790

We mapped top 20 features into 5C's credit categories and summed their Shapley values for allocated categories. Shapley value measures contribution of the feature for the decision. As in Table 4, we can see that the Shapley value of Capacity is 0.2028, Capital is 0.2090, Collateral is 0.0306, Conditions is 0.1011 and Character is 0.1790. Then we conclude that Capital is the main reason responsible for bankruptcy in our model with a score of 0.2090. Also, Capacity is the second category responsible for bankruptcy. Lastly, Collateral is the least important category of 5C's credit.

5. Conclusion

We have developed a bankruptcy prediction model for start-up companies using XAI technology. The utilization of the CatBoost algorithm has yielded excellent performance in training the model with a complex dataset. Our model is intended to assist business planners who are in the process of establishing start-up companies. One of the key advantages of our model is the integration of domain knowledge into the explanation process. By leveraging the Shapash library, we are able to understand the financial ratios within the dataset that are responsible for predicting bankruptcy. This allows us to provide detailed explanations for the situation of each company, aiding in their decision-making process. Overall, our model provides a valuable tool for business planners, empowering them to make informed decisions and mitigate the risks associated with establishing start-up companies.

Our model is considered a "glass-box" model, thanks to its interpretability using machine learning techniques. We have employed various data processing tools such as OpenRefine and ADASYN to mitigate potential issues in the dataset. The incorporation of domain knowledge, specifically the 5C's credit framework, enhances the usefulness of our model. Financial analysts in banks or investors can leverage our detailed results for their decision-making processes [11], even if they do not possess extensive knowledge about AI. This allows them to make informed judgments based on the insights provided by our model, thus improving the accuracy and reliability of their decisions.

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