Predicting Financial Distress in Indonesian Companies using Machine Learning

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Received: 26 July 2024 | Revised: 15 August 2024 and 13 September 2024 | Accepted: 15 September 2024

 DOI: https://doi.org/10.48084/etasr.8520

ABSTRACT

Predicting financial distress is essential in Indonesia's rapidly evolving economy, characterized by diverse business environments and regulatory challenges. This study evaluates four machine learning classifiers, XGBoost, Random Forest (RF), Support Vector Classification (SVC), and Long Short-Term Memory (LSTM), to predict financial distress among Indonesian companies. Two sampling methods, Random Under-Sampling (RUS) and Synthetic Minority Over-Sampling Technique (SMOTE), were used to address class imbalance. Empirical results indicate that the RF model trained with SMOTE sampling was the most effective, achieving an F1 score of 0.9632 and an accuracy of 0.96, while the XGBoost classifier with RUS sampling achieved a precision of 0.9716. These findings provide valuable insights into Indonesia's financial sector, guiding the selection of appropriate models for timely financial distress prediction and intervention.

Keywords-financial distress prediction; machine learning models; Indonesian companies; SMOTE sampling; random forest

I. INTRODUCTION

Financial distress, often defined as the difficulty of a corporation in meeting its financial obligations, has historically been subjectively evaluated, leading to inconsistent results [1, 2]. Consequently, novel methods have been proposed to address the issue. In [3, 4], financial ratios were used to predict bankruptcy, forming the foundation for current predictive models. Over the years, this topic has attracted much interest and enthusiasm. Several recent research models have examined special treatment indicators in the Chinese stock market, such as in [5]. Classification strategies can be employed to address issues related to consistency and accuracy, which can be classified into two distinct categories: statistical methods and machine learning methods. Statistical techniques have straightforward structures and high clarity. However, several stringent assumptions, such as the presence of linear relationships, homogeneity of variance, and the assumption of independence, limit their applicability in real-life scenarios. A breach of such assumptions has the potential to decrease the level of predictability. Statistical methods include several types, such as discriminant analysis, logistic regression, and Cox hazard survival models.

According to [6, 7] the occurrence of financial distress not only results in significant economic losses for the company but also directly affects its growth and long-term viability. Recognizing the importance of financial difficulties for a company underscores the need to accurately predict the occurrence of financial distress [8]. In [9], it was observed that companies in the Chinese market often experience financial distress within four years of their Initial Public Offering (IPO), typically requiring an additional 2-4 years for recovery. In [3, 4], extensive research on bankruptcy was conducted, and this topic has garnered increasing interest and attention over time. Many research models have emerged, such as those proposed by [5] and [10] for investigating the Chinese stock market's special treatment indicator. Numerous studies have observed that financial distress often arises from the mismanagement of funds derived from third parties that do not align with expectations, leading to long-term effects. In many cases, around 52% of these companies return to normal after undergoing reconciliation through management changes [11]. This process also involves reestablishing good corporate governance practices within the company [12], asset restructuring, and cost reduction efforts to mitigate substantial losses [13]. Furthermore, many companies with high leverage opt for smaller investments in underperforming projects as a strategic move [14]. In [15], the Spanish hospitality sector was explored during the 2008 crisis, when all companies faced financial distress. This study showed that Kaplan-Meier analysis could help predict outcomes for companies by reorganizing profitability, corporate capital structure, operational ratios, and employee composition. In [16], the effective implementation of good corporate governance was identified as a solution to financial distress in Spain. In [17], building on this, the importance of operating cash flow ratios and short-term debt ratios was emphasized in addressing financial distress issues in SMEs in the Czech Republic. This study aims to develop a financial distress model for Indonesian companies spanning from 2013 to 2022, encompassing a total of 236 companies, using machine learning methods to analyze and identify nominal variables from a set of 20 variables.

Previous studies have extensively examined the application of machine learning techniques in predicting financial distress. The primary contribution of this study lies in its use of a comprehensive dataset that represents all listed companies in Indonesia, as well as the application of the Random Forest (RF) model. In particular, the results in [18] show that the RF model is much more accurate than other models, such as the dynamic hazard model and the random Decision Tree (DT). The results of this study have the potential to significantly enhance the understanding of Indonesia's financial distress framework and the wider field of corporate financial management. This study drew its sample from 11 distinct industry sectors listed on the Indonesia Stock Exchange (IDX). This deliberate selection of diverse data ensures that the sample accurately represents the entirety of companies registered on the IDX. A dataset was collected from 2013 to 2022, which reveals a total of 158 companies experiencing financial distress. The sample includes companies from 11 different industry sectors listed on the Indonesia Stock Exchange (IDX). As a result, the data used is heterogeneous and representative of the entire range of companies listed on the IDX.

Academics are actively developing effective models to improve prediction precision and minimize predicted discrepancies. In [18, 19], it was shown that the future of an organization can be predicted using market efficiency information and market prices. In [7], a study was conducted with a focus on improving corporate governance. The computational ratio is a critical aspect of a financial distress investigation. In addition to its development, various research methods have emerged, including the pioneering Multiple Discriminant Analysis (MDA) model, introduced in [4] and subsequently refined in [20, 21], and the logistic regression model. These approaches aim to establish a probability model, ultimately leading to the derivation of the Z-score. In [22, 23], Data Envelopment Analysis (DEA) was introduced. In [24, 25], neural network models were presented, using text data sourced from the Internet. In [18], Chinese companies were reported to use the RF model as the most effective machine learning model, followed by dynamic hazards and statistical models in terms of performance. In [6], logistic regression was determined as the most appropriate model to predict financial distress in Zimbabwe, which is an emerging market. In general, the predictive capacity of a machine learning model is significantly influenced by imbalanced data, characterized by diminishing trend results.

These studies collectively illustrate the evolution of machine learning techniques in predicting financial distress. In [26], the benefits of hybrid models were demonstrated, while subsequent research in [27] reinforced the superiority of advanced models such as neural networks and RF. In [1, 28], the practical applications and effectiveness of DT models were highlighted, whereas in [29], the adaptability of RF was showcased. In [17, 29], improved predictive accuracy was achieved with modern techniques such as XGB and the integration of machine learning models. In [30, 31], these findings were further validated, demonstrating the reliability of RF models and the impact of corporate governance variables on model performance.

II. RESEARCH METHODOLOGY

The financial and risk management capabilities of a company's management team significantly affect its success or failure. Therefore, predicting the risk of financial trouble is crucial because it allows investors and managers to implement appropriate risk mitigation strategies. It is important to engage in data preparation to eliminate extraneous data or substitute missing data. The next step accordingly involves scaling and transforming the data.

A. *Data Collection and Preprocessing*

This study uses secondary data, specifically business financial documents, selected through purposive sampling. IDX companies from 2013 to 2022 with complete data and two consecutive years of negative EBIT were considered. A crucial aspect of this phase involves the management of data through the application of filtering techniques to ensure the preservation of all values and the normalization of datasets. Before utilization, every variable undergoes normalization to ensure that it falls within the range of 0 to 1. The variable Y is assigned a value of 1 if the company has incurred negative Earnings Before Interest and Taxes (EBIT) over the past two years, indicating financial difficulty. If the company has not experienced financial distress, the Y variable is assigned a value of 0. Feature selection is used to determine the health of the company, and the financial ratio derived from the company's financial information is used.

TABLE I. DATASET DESCRIPTION

Variable	Note	Variable	Note
Y	Distress = 1 Non-Distress = 0	X10	Total Asset Turnover = Total Assets / Net Sales
X1	ROA = Net Income / Total Assets	X11	Turnover of Accounts Receivable = Net Credit Sales / Average Accounts Receivable
X2	Operating Margin = Operating Income / Revenue	X12	Operating Funds to Liability = Operating Cash Flow / Current Liabilities
X3	Operating Expense Ratio = Operating Expenses / Income	X13	Long-term Liability to Current Assets = Long-term Liabilities / Total Assets
X4	Cash Flow Ratio = Net Profit + Depreciation + Amortization	X14	Total Expense Ratio = Total Income / Total Expense
X5	Growth of Company Assets = Growth Rate / Total Assets	X15	Total Expense Ratio = Total Expense / Total Assets
X6	Leverage Ratio = Net Worth / Growth Rate	X16	Cash Flow Ratio = Cash Flow / Sales
X7	Debt Ratio = Current Ratio / Total Debt	X17	Investing Cash Flow Ratio = Cash Flow / Total Assets
X8	Total Net Worth = Total Assets - Total Liabilities	X18	Financing Cash Flow Ratio = Cash Flow / Total Liability
X9	Debt Ratio = Total Debt / Total Assets	X19	Interest Coverage Ratio Interest Expense to EBIT = EBIT / Interest Expense

Source: Data processed by the authors

The variable Y is calculated under the assumption that if it equals 1, the company has incurred negative EBIT for the past two periods, else it is assumed to be 0.

To address class imbalance, Random Under-Sampling (RUS) and Synthetic Minority Over-Sampling Technique (SMOTE) were used. Financial distress occurs when a company cannot meet its obligations, indicated by a negative EBIT. The financial data used in this investigation were imbalanced, which means that there were few instances in which companies experienced financial distress. The dataset was divided into training and testing.

B. Model Selection and Evaluation

Choosing the ideal model for the suitable environment requires comparing different models. This study employed DT, RF, Support Vector Classification (SVC), and Long Short-Term Memory (LSTM) models. Classification can use several performance measures, including:

TABLE II. CONFUSION MATRIX

Table Head	Type 1 facts	Type 2 facts
Type 1 predictions	True Positive (TP)	False Positive (FP)
Type 2 predictions	False Negative (FN)	True Negative (TN)

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

F score is the harmonic average of precision and recall.

$$F\ score = 2x\ \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

$$F\ score = \frac{TP}{TP+\frac{1}{2}(FP+FN)} \quad (5)$$

Machine learning algorithms often give possibilities rather than yes/no results (such as still working or bankrupt). A threshold was used to determine which class the sample would be classified into. For example, any company that is expected to have financial difficulties above 90% will be considered bankrupt. The result of this threshold increase is expected to result in a lower False Positive Rate (FPR) while also increasing the real positive.

- TPR = FPR = 0: Set the threshold to 100% will yield TPR = FPR = 0.
- TPR = FPR = 1: Setting the threshold to 0% will result in TPR = FPR = 1.

The ROC curve connects the two values (Figures 1 and 2). Performance can be evaluated using the ROC curve. The algorithm result is a solid line, while a split line shows what would be received through random guessing. A good value is the one closest to the upper left corner. A value near the upper left corner has a higher TPR and a lower FPR. Area Under the Curve (AUC) is the area located below the receiver ROC curve. The random approach is expected to have a yield of 0.5. AUC can be conceptualized as the aggregate of potential algorithms that offer a range of scenarios, each of which may require different measures.

III. RESULTS AND DISCUSSION

The choice of method in model development often relies heavily on data sampling during the model-building process. This is because the selection of the method plays a crucial role in optimizing the model to be constructed. This occurs because the choice of the machine learning method can significantly affect the quality and performance of the model to be developed. This study carried out four experiments using RF, XGB, SVC, and LTSM. The aim was to identify the most suitable method for constructing a machine-learning model for the prediction of financial distress in Indonesian companies. From the four experiments conducted, a comparison of the accuracy values was performed to determine the most suitable method for building a machine-learning model in this context. The evaluation of various machine learning models applied to a binary classification problem offers insightful observations about the effectiveness of different algorithms and sampling techniques. Among the algorithms tested, XGB and RF stand out for their high performance across multiple metrics, including accuracy, precision, recall, and F1-score, in similar studies. The robustness of these algorithms appears to make them favorable for handling complex classification tasks.

TABLE III. ACCURACY AND PRECISION COMPARISON

Sampling	Methods	Accuracy	Precision
RUS	XGB	0.9510	0.9716
SMOTE	XGB	0.9600	0.9693
RUS	RF	0.9530	0.9704
SMOTE	RF	0.9600	0.9711
RUS	SVC	0.9260	0.9622
SMOTE	SVC	0.9430	0.9403
RUS	LSTM	0.9360	0.9649
SMOTE	LSTM	0.9490	0.9539
RUS	XGB	0.9510	0.9716

The RUS and SMOTE sampling methods have different impacts on model performance. Generally, SMOTE yields slightly better or comparable results across all models, aligning with existing literature that recommends oversampling techniques for imbalanced datasets. However, RUS also produces competitive results, suggesting its suitability in scenarios where computational complexity or time is constrained. The metrics reveal the specific strengths and limitations of each model. While precision is higher in XGB and RF models, recall is generally well-maintained across all classifiers. This raises questions about the trade-off between false positives and false negatives, which depends on the application context. For instance, in medical diagnosis, maximizing recall could be more critical, whereas in e-mail filtering, high precision could be more desirable.

Figures 1 and 2 show a comparison of the ROC curves. These results indicate that the models constructed using each method performed effectively. This can be deduced from the curves approaching the value of 1 or the AUC of nearly 1. In other words, these models can perfectly distinguish between data with positive and negative classes.

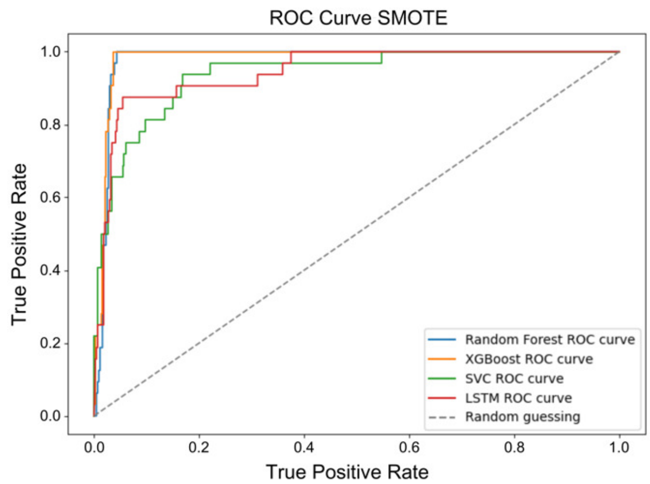

Fig. 1. ROC curve comparison for each method using SMOTE sampling.

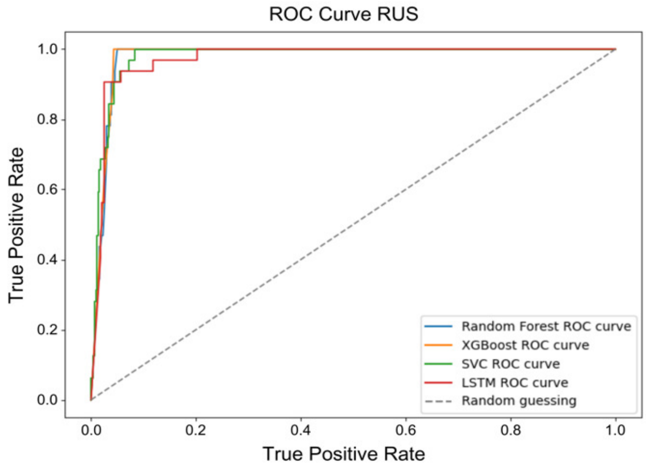

Fig. 2. ROC curve comparison for each method using RUS sampling.

Figures 3 and 4 display a comparison of the precision-recall results for each method. Precision measures the number of true positive predictions, providing information about the efficacy of the model in classifying positive outcomes. On the other hand, recall measures the model's ability to find positive instances within the dataset.

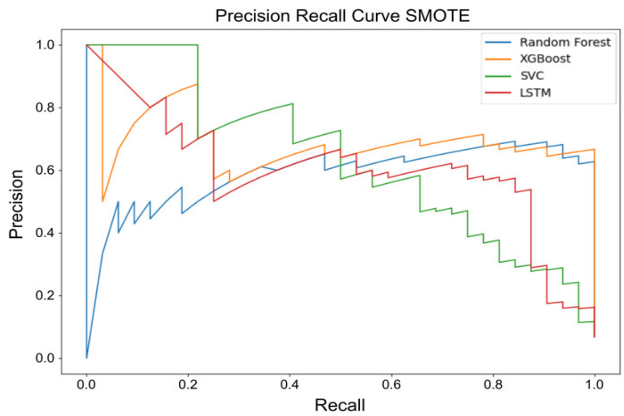

Fig. 3. Precision-recall curve comparison for each method using SMOTE.

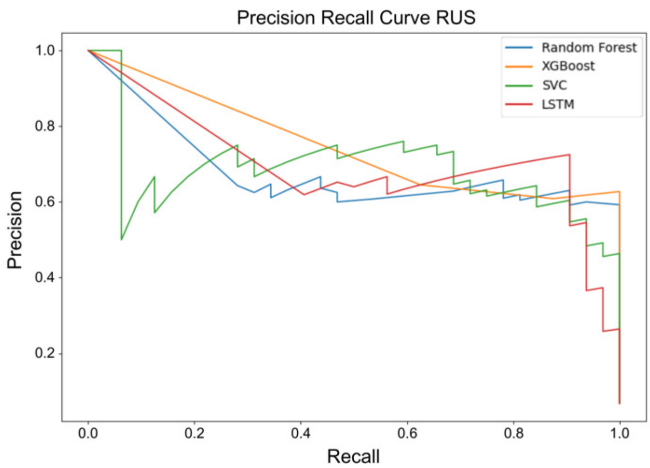

Fig. 4. Precision-recall curve comparison for each method using RUS.

As can be observed, the RF algorithm outperformed the DT model in terms of accuracy, which is consistent with the results in [32-34].

IV. CONCLUSION

This study explored the use of various machine learning algorithms to predict financial distress in Indonesian companies. The empirical results demonstrated that the RF model trained with SMOTE sampling achieved the highest performance, with an F1-score of 0.9632 and an accuracy of 0.96. These findings suggest that machine learning models, particularly RF, are effective tools for predicting financial distress in the context of Indonesian companies. However, several limitations must be acknowledged to provide a comprehensive understanding of the results and guide future research.

One significant limitation is the relatively small sample size and the inherent data imbalance. Although SMOTE and RUS techniques were employed to address class imbalance, their effectiveness can be limited by the sample size. Future studies should aim to collect larger and more balanced datasets to enhance the reliability and generalizability of the models. The complexity of some machine learning models used in this study, such as RF and LSTM, can sometimes lead to overfitting, particularly with smaller datasets. Although cross-validation was used to mitigate this risk, it remains crucial to explore simpler models or incorporate additional regularization techniques to ensure robust and reliable predictions. Simpler models may also provide better interpretability, which is valuable for stakeholders who need to understand the decision-making process of predictive models. The period of data collection (2013-2022) encompasses various economic cycles that may have influenced the financial distress patterns observed in the dataset. The economic conditions during this period, including the potential impacts of events such as the COVID-19 pandemic, may affect the generalizability of the findings. Future research should consider examining the impact of different economic cycles and including macroeconomic variables to improve the robustness of the model and capture broader economic influences on financial distress.

To address these limitations, future research should focus on several key areas. Efforts should be made to collect more extensive and balanced datasets and improve the robustness and accuracy of financial distress prediction models. Exploring simpler models and incorporating additional regularization techniques can help mitigate overfitting and enhance the interpretability of models. Furthermore, incorporating macroeconomic indicators and examining the impact of different economic cycles can provide a more comprehensive understanding of financial distress and improve the model's applicability across various economic contexts. In summary, while this study highlights the effectiveness of machine learning models in predicting financial distress among Indonesian companies, it also underscores the importance of addressing data limitations, model complexity, and economic conditions to enhance the robustness and generalizability of the models. Continued research in these areas can significantly contribute to the field of financial distress prediction and provide valuable insights to stakeholders in the financial sector.

ACKNOWLEDGMENT

This study was funded by PPM-PTM grants from the Ministry of Education, Culture, Research and Technology, Indonesia (KWR4.090/LIT07/PPM-LIT/2023).

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