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Financial Risk Classification Using Machine Learning Models: Evidence from Listed Maritime Shipping Firms in Vietnam

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Abstract: Financial risk is among the most significant challenges faced by firms in the maritime shipping industry due to its high capital intensity and strong exposure to market fluctuations, particularly in emerging economies such as Vietnam. Therefore, the classification of financial risk plays a crucial role in providing early warning signals, enabling firms to respond proactively and enhance their resilience to potential financial distress. This study employs machine learning techniques, including Random Forest, Extreme Gradient Boosting, and Linear Support Vector Machine, to classify the financial condition of listed maritime shipping firms in Vietnam, using a panel dataset of 25 firms over the period 2015 - 2025. The empirical results confirm the effectiveness of machine learning approaches in financial risk classification, particularly their capability to model nonlinear relationships and complex interactions among financial variables. These findings not only support the early identification of financial distress risk in maritime shipping firms but also provide a scientific basis for the development of early warning systems and the strengthening of financial risk monitoring mechanisms within the industry.

Keywords: Machine learning; classification; financial risk; maritime shipping firms; Random Forest; Support Vector Machine; Extreme Gradient Boosting.

I. Introduction

Maritime shipping is widely regarded as one of the most efficient models of large scale freight transportation worldwide. According to the International Maritime Organization (IMO, 2024), approximately 90% of global trade volume is transported by sea. In Vietnam, the maritime shipping industry plays a critical role in fostering economic growth and facilitating international trade integration. However, due to its capital intensive nature and high sensitivity to volatile factors such as exchange rates, freight rates, fuel prices, and global trade demand, maritime shipping firms are particularly vulnerable to financial distress. Consequently, the early classification of financial risk is of crucial importance, not only for safeguarding firms' operational performance but also for maintaining macroeconomic stability.

In this study, financial risk is defined as the probability that a firm is unable to meet its financial obligations. If financial risk is not identified and addressed in a timely manner, it may lead to a significant deterioration of financial capacity and ultimately result in firm bankruptcy. Therefore, the early identification of financial distress is essential for firms and stakeholders including investors, creditors, and regulatory authorities in assessing risk exposure and implementing appropriate intervention measures.

Traditional financial distress prediction models, such as Altman's Z-score model (Altman, 1968), Ohlson's O-score model (Ohlson, 1980), and Zmijewski's model (Zmijewski, 1984), are primarily based on accounting indicators and assume linear relationships among variables. However, in practice, financial data often exhibit nonlinear relationships and complex interactions, which constrain the predictive capability of conventional models in many cases. In contrast, machine learning offers a data driven approach with strong pattern recognition and adaptive learning mechanisms, thereby significantly enhancing predictive accuracy. Machine learning algorithms have demonstrated superior performance in financial distress prediction across various domains such as banking, manufacturing, and healthcare (Kristanti et al., 2024; Patra & Khuntia, 2024; Rahman & Zhu, 2024). Nevertheless, empirical studies applying machine learning techniques in the maritime shipping sector remain relatively limited. Moreover, only a small number of studies integrate machine learning classifiers with industry specific financial risk indicators in the context of emerging economies, particularly Vietnam.

This study aims to address this research gap by applying three machine learning algorithms, including Random Forest (RF), Linear Support Vector Machine (Linear SVM), and Extreme Gradient Boosting (XGBoost), to classify the financial status of listed maritime shipping firms in Vietnam over the period 2015–2025. The binary dependent variable is determined based on the Z″-score model (Altman & Hotchkiss, 1993). The independent variables consist of financial indicators grouped into five categories: financial leverage, liquidity, operational efficiency and profitability, cash flow quality, and firm size. Model performance is evaluated using four major classification metrics: accuracy, precision, recall, and F1-score.

By combining traditional financial distress indicators with advanced machine learning techniques, this study provides significant methodological and practical contributions. It enhances financial risk prediction in an under researched sector in Vietnam and offers a valuable early warning tool for investors, regulators, and financial managers in an environment characterized by high market volatility and data limitations.

The remainder of the paper is organized as follows: Section 2 reviews the relevant literature on financial distress classification and the application of machine learning techniques; Section 3 outlines the research methodology, including the data collection process, variable construction, and model implementation; Section 4 reports the empirical findings and evaluates the comparative performance of the models; Finally, section 5 concludes the study by discussing key implications and suggesting directions for future research.

II. Literature Review

2.1. Overview of Traditional Financial Distress Prediction Models

In this study, financial distress is defined as a state in which a firm faces substantial difficulty in maintaining financial stability, typically reflected in weak liquidity, excessive leverage, and a sustained decline in profitability. This risk is especially pronounced for maritime shipping firms, which depend heavily on debt financing and operate in a highly volatile market environment. Exposure to fluctuations in fuel prices and shifts in global trade cycles further increases their vulnerability to financial distress.

Statistical models for financial distress prediction have been developed since the late 1960s, with prominent examples including the Z-score model (Altman, 1968), the O-score model (Ohlson, 1980), and the model proposed by Zmijewski (1984). These approaches have remained widely used due to their transparency and ease of implementation, as they rely primarily on firms' financial ratios. Among them, the Z-score model (Altman, 1968) is the most extensively applied. The original Z-score model was developed for publicly traded manufacturing firms in the United States and employed five weighted financial ratios capturing liquidity, profitability, leverage, solvency, and operating efficiency. To extend its applicability beyond manufacturing industries, Altman and Hotchkiss (1993) introduced a revised version, the Z″-score, which removes the sales to total assets ratio to better suit service industries and capital-intensive sectors.

In recent years, the Z″-score has been increasingly applied across different industries and countries, particularly in emerging economies. Al-Najjar and Jawad (2023) employed both the Z-score and the Z″-score to evaluate the financial health of an industrial firm in Iraq from 2016 to 2022. Their findings show that the firm was classified as financially distressed in several years under the Z-score, whereas the Z″-score indicated a more stable financial condition. This difference underscores the importance of selecting a model that is appropriate to the specific institutional and industrial context, especially in developing and volatile markets. Similarly, Yuningsih and Suherman (2025) used the Z-score to assess the financial condition of cosmetic and household manufacturing firms listed on the Indonesian Sharia Stock Index (ISSI), providing evidence that the model remains applicable even in sectors subject to distinctive financial regulations.

Although the maritime shipping industry shares financial characteristics with other sectors that require substantial capital investment, the Z″-score has rarely been applied directly to this industry, particularly in Southeast Asia. Existing studies typically examine broader industrial sectors or aggregate heterogeneous firms without considering the distinctive financial features of shipping companies. This gap highlights the need for financial distress assessment frameworks that are tailored to the specific context of maritime shipping firms.

To address this issue, this study applies the Altman Z″-score to classify the financial condition of listed maritime shipping firms in Vietnam from 2015 to 2025. The classifications obtained from the Z″-score are then used as the dependent variable in the machine learning models. By integrating a well established financial distress measure with machine learning techniques, the study contributes both empirically and methodologically to the literature on financial risk assessment in an industry that remains relatively unexplored despite its considerable financial risk.

2.2. Overview of Machine Learning Models in Financial Risk Classification

Although traditional approaches such as the Z-score remain useful for distinguishing financially distressed firms from healthy ones, they typically rely on linear relationships between explanatory variables and outcomes. In reality, financial conditions are often driven by complex and nonlinear interactions. Accordingly, recent studies have increasingly adopted machine learning techniques to improve predictive performance in corporate financial distress analysis. Advances in computing technology and data processing capabilities have enabled the development of intelligent predictive systems for bankruptcy assessment (Goldstein et al., 2019). Empirical evidence further suggests that machine learning methods often outperform conventional statistical approaches (Florez-Lopez, 2007), largely because they can capture nonlinear patterns and handle complex relationships without imposing restrictive statistical assumptions.

Machine learning has been widely applied in numerous fields, ranging from finance and medicine to data science. In the field of information systems and data science, Boonprapapan et al. (2024) combined the SMOTE technique with Support Vector Machine to address data imbalance in text classification, achieving an accuracy of 94.37%, significantly higher than traditional TF-IDF-based methods. In intelligent transportation, Li et al. (2024) proposed VehiClassNet, a machine learning-based model integrating multi level feature extraction, attention mechanisms, and cross modal fusion, achieving high accuracy on the Stanford Cars 196 dataset, thereby demonstrating its effectiveness for intelligent transportation systems and autonomous vehicles. In healthcare, Patra and Khuntia (2024) applied algorithms such as logistic regression, KNN, and Random Forest to predict diabetes, cancer, and cardiovascular diseases with high accuracy.

In the financial domain, machine learning techniques such as Random Forest, XGBoost, and Support Vector Machine have been increasingly employed to predict corporate financial distress in different institutional settings. Kristanti et al. (2024) compared several algorithms, including Random Forest, XGBoost, SVM, and LSTM, for Indonesian firms and reported that Random Forest provided the most reliable early warning performance. Dewi and Susilaningrum (2024) combined K-means clustering with SVM to evaluate non-financial firms listed on the Indonesia Stock Exchange from 2018 to 2021, showing that the hybrid approach improved predictive accuracy relative to the standalone classifier. Similarly, Rahman and Zhu (2024) applied ensemble methods such as CUSBoost, CART, and AdaBoost to listed construction companies in China and found that these approaches performed more effectively than traditional Z-score–based classifications. Collectively, these studies indicate that machine learning methods can enhance financial distress prediction by capturing complex relationships in corporate financial data.

Although the literature on machine learning applications in financial distress prediction has grown rapidly across countries and industries, empirical evidence from emerging markets remains limited, particularly for Vietnam's maritime shipping sector. Existing studies often rely on traditional statistical methods or qualitative evaluation, while the use of advanced techniques such as Random Forest, XGBoost, and Support Vector Machine is still relatively limited in this context. The shipping sector requires substantial capital investment and is highly cyclical, with strong exposure to fuel price movements and fluctuations in global trade. These characteristics motivate the development of predictive models capable of capturing nonlinear relationships and potential class imbalance. Accordingly, this study develops a machine learning framework for listed maritime shipping firms in Vietnam and highlights its implications for early warning systems and financial decision making.

III. Research Methodology

3.1. Research Data and Variables

The dataset consists of 275 firm-year observations for 25 listed maritime shipping companies in Vietnam from 2015 to 2025. Financial information was collected from audited financial statements disclosed on company websites and from mandatory public disclosure reports. To ensure reliability, the data were verified and supplemented using the Vietstock database and official filings submitted to the State Securities Commission of Vietnam (SSC).

The dependent variable is a binary indicator of financial distress derived from the revised Altman Z″-score, which is generally regarded as more appropriate for non-manufacturing firms and emerging market settings. The Z″-score is computed as follows:

$$Z'' = 6.56T_1 + 3.26T_2 + 6.72T_3 + 1.05T_4 \qquad (1)$$

where:

T_1 = Working capital / Total assets

T_2 = Retained earnings / Total assets

T_3 = Earnings before interest and taxes / Total assets

T_4 = Market value of equity / Total liabilities

Following Altman & Hotchkiss (2006), firms are classified as financially distressed when $Z'' < 1.8$ (coded as 1) and financially stable when $Z'' \geq 1.8$ (coded as 0). This threshold has been shown to be suitable in emerging market settings, particularly for industries that require substantial capital investment, such as maritime shipping. In corporate failure prediction, the number of distressed firms is typically much smaller than that of healthy firms, leading to class imbalance. In the present dataset, however, the imbalance ratio is moderate and does not warrant the use of resampling techniques. After data cleaning, the observations were randomly divided into training and testing samples in an 80:20 ratio. The training sample was used to estimate the models, and the testing sample to evaluate out-of-sample predictive performance.

The independent variables comprise financial indicators grouped into five categories: (i) leverage, (ii) liquidity, (iii) operating performance and profitability, (iv) cash flow quality, and (v) firm size and market characteristics. The leverage group includes ratios reflecting the use of debt in the capital structure, such as total debt to equity and total debt to total assets, which represent financial obligations and exposure to leverage risk. Liquidity is proxied by payment capacity measures, including current ratios and operating cash flow relative to short term debt, indicating the firm's ability to meet near term obligations. Operating performance and profitability are measured using ROA, ROE, and profit margins, reflecting earnings capacity and efficiency in asset utilization. Cash flow quality is evaluated through ratios of operating cash flow to revenue, net income, and total debt, which assess the sustainability and reliability of reported profits. Finally, firm size and market characteristics are represented by variables related to total assets and market capitalization, capturing corporate scale and market position.

This framework, based on five groups of financial indicators, allows the machine learning models to incorporate information on capital structure, liquidity, operating performance, cash flow strength, and firm size, thereby improving the classification of financial distress among listed maritime shipping firms operating in volatile market environments. The selected indicators are also consistent with the core determinants used in traditional financial distress prediction models, including the Z-score (Altman, 1968), the O-score (Ohlson, 1980), and the model proposed by Zmijewski (1984).

3.2. Model Selection and Hyperparameter Optimization

This study evaluates the predictive performance of three machine learning models: Random Forest (RF), Linear Support Vector Machine (Linear SVM), and Extreme Gradient Boosting (XGBoost).

Random Forest is an ensemble method that constructs multiple decision trees using bootstrap samples and aggregates their predictions through majority voting. At each split, only a randomly selected subset of predictors is considered, which increases model diversity and helps reduce overfitting. Owing to its ability to model nonlinear relationships and interactions among variables, Random Forest has been widely used in financial risk prediction.

Linear SVM is a supervised classification algorithm that identifies a linear hyperplane separating observations into two groups by maximizing the margin between classes. The penalty parameter (C) controls the trade-off between margin width and classification error. Its generalization ability and computational efficiency make Linear SVM suitable for high-dimensional financial datasets and binary classification tasks such as financial distress identification.

XGBoost is an implementation of gradient boosting based on decision trees (Friedman, 2001). The model builds trees sequentially, with each new tree correcting the prediction errors of the previous ones. Regularization is incorporated to control model complexity and improve predictive stability, which makes XGBoost effective for structured financial data.

Prior to model estimation, the data were preprocessed according to standard machine learning procedures. The dependent variable is a binary indicator of financial distress (Risk), and the remaining financial variables serve as predictors. The observations were randomly divided into training and testing samples in an 80:20 ratio to evaluate out-of-sample predictive performance. A fixed random seed was used to ensure reproducibility.

To mitigate differences in measurement scales among financial indicators and improve the performance of linear algorithms, all predictors were standardized using Z-score normalization. To avoid data leakage, the scaling parameters (mean and standard deviation) were estimated from the training sample only and then applied to the testing sample. The standardized data were subsequently used for hyperparameter tuning and model evaluation.

To determine the optimal model specification, hyperparameters were selected using a grid search procedure combined with six-fold cross-validation. Recall was adopted as the primary optimization criterion in order to prioritize the correct identification of financially distressed firms. For the Random Forest model, the tuning process considered the number of trees, the splitting criterion, and the maximum tree depth. For the Support Vector Machine, the penalty parameter and the use of class weighting were examined under a linear kernel specification to account for potential class imbalance. For XGBoost, the tuning procedure included the number of trees, maximum depth, learning rate, and sampling ratios for both observations and predictors. The selected hyperparameters were then used to estimate the final models on the training sample.

After model estimation, predictive performance is assessed using the confusion matrix, which compares predicted classifications with the actual values in the testing sample. The matrix summarizes both correctly and incorrectly classified observations and forms the basis for calculating performance metrics.

In this binary classification setting, firms are categorized as distressed or non-distressed, and model predictions are evaluated accordingly. Table 1 presents the structure of the confusion matrix used for performance evaluation.

Table 1. Confusion matrix for evaluating classification performance.

Actual / Predicted	Positive	Negative
Positive	TP	FN
Negative	FP	TN

In this framework, True Positive (TP) and True Negative (TN) denote correctly classified distressed and non-distressed firms, respectively, whereas False Positive (FP) and False Negative (FN) indicate incorrect classifications. Based on the confusion matrix, classification performance is evaluated using several standard metrics, including Accuracy, Precision, Recall, and the F1-score.

Accuracy is defined as the proportion of correctly classified observations (TP and TN) relative to the total number of observations. However, this measure can be misleading in imbalanced datasets, where one class substantially outnumbers the other.

Accuracy = (TP + TN) / (TP + TN + FP + FN) (2)

Precision measures the proportion of correctly predicted positive cases among all observations classified as positive, indicating the reliability of positive predictions.

Precision = TP / (TP + FP) (3)

Recall measures the proportion of actual positive cases that are correctly identified, reflecting the model's ability to detect financially distressed firms.

Recall = TP / (TP + FN) (4)

The F1-score, defined as the harmonic mean of Precision and Recall, provides a balanced measure that accounts for both false positives and false negatives. It is particularly informative in imbalanced classification settings where both metrics are important. Higher values of the F1-score indicate better classification performance.

F1-score = (2 × Precision × Recall) / (Precision + Recall) (5)

IV. Research Findings

Table 4 presents the optimal hyperparameter settings and the corresponding model performance across the evaluation metrics.

Table 4. Performance evaluation results of the models

Model	Accuracy	Precision (Risk=1)	Recall (Risk=1)	F1-score (Risk=1)	Execution time (s)	Optimal hyperparameters
Random Forest	0,91	0,90	0,86	0,88	0.18	criterion = gini; max_depth = None; n_estimators = 50
Linear SVM	0,55	0,45	0,90	0,60	0.01	kernel = linear; C (optimized via GridSearchCV); class_weight = balanced
XGBoost	0,95	0,96	0,90	0,93	0.08	n_estimators = 300; max_depth = 3; learning_rate = 0,05; subsample = 0,8; colsample_bytree = 0,8

The Random Forest (RF) classifier was estimated after hyperparameter tuning using a grid search with six-fold cross-validation. Recall was adopted as the optimization criterion in order to prioritize the identification of financially distressed firms. The selected specification includes 50 trees, the Gini splitting criterion, and unrestricted tree depth.

On the testing sample, the RF model achieved an overall accuracy of 0.91, indicating strong classification performance across firm groups. For financially stable firms (Risk = 0), the model recorded a recall of 0.94 and an F1-score of 0.93, suggesting that most stable firms were correctly identified. For financially distressed firms (Risk = 1), recall reached 0.86 with an F1-score of 0.88, indicating that the majority of distressed firms were successfully detected, although a small number of cases remained misclassified.

Figure 1 presents the confusion matrix for the RF model. The classifier correctly identified 32 stable firms and 18 distressed firms. Two stable firms were incorrectly classified as distressed, while three distressed firms were classified as stable. The relatively small number of missed distressed cases supports the model's effectiveness as an early warning tool for financial risk.

Overall, the Random Forest model demonstrates balanced performance across both classes and appears well suited to financial distress classification for listed maritime shipping firms in Vietnam. These findings provide a benchmark for comparison with the other machine learning models considered in this study.

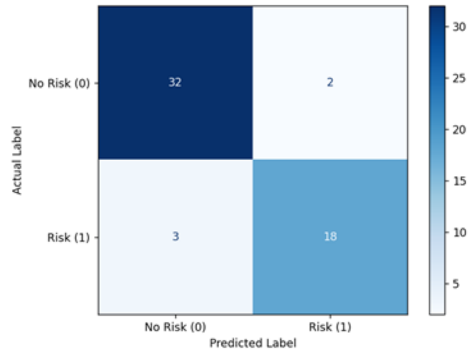

Figure 1. Confusion matrix of the Random Forest model

For the Extreme Gradient Boosting (XGBoost) model, hyperparameter tuning selected a configuration with 300 trees, a maximum depth of 3, a learning rate of 0.05, and sampling ratios of 0.8 for both observations and predictors.

On the testing sample, XGBoost achieved an overall accuracy of 0.95, indicating improved classification performance relative to the other models. For financially stable firms (Risk = 0), recall reached 0.97 with an F1-score of 0.96. For financially distressed firms (Risk = 1), the model obtained a recall of 0.90 and an F1-score of 0.93, suggesting that most distressed firms were successfully identified with few missed cases.

Figure 2 presents the confusion matrix for the XGBoost model. The classifier correctly identified 33 stable firms and 19 distressed firms, while only one stable firm was classified as distressed and two distressed firms were classified as stable. The small number of missed distressed observations supports the suitability of the model for early detection of financial distress.

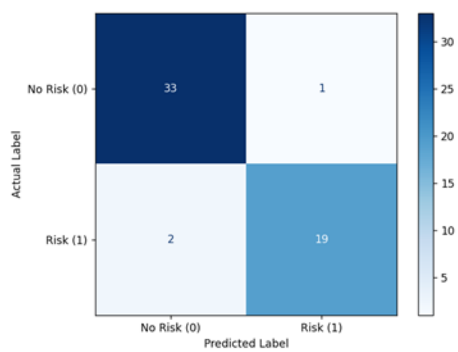

Figure 2. Confusion matrix of the XGBoost model

The Linear Support Vector Machine (Linear SVM) model is included to provide a benchmark from a linear classification approach and to evaluate whether nonlinear methods offer performance gains in financial distress prediction. As with the other models, hyperparameters were selected using a grid search with six-fold cross-validation, with recall used as the optimization criterion to prioritize the identification of distressed firms.

On the testing sample, Linear SVM achieved an overall accuracy of 0.5455, indicating limited classification performance. For financially stable firms (Risk = 0), the model produced high precision (0.8462) but low recall (0.3235), suggesting that predictions of stability were reliable but many stable firms were incorrectly flagged as distressed.

For financially distressed firms (Risk = 1), recall reached 0.9048, indicating that most distressed firms were detected. However, precision was relatively low (0.4524), implying that the model generated frequent false distress signals by classifying a considerable number of stable firms as distressed. The F1-score for distressed firms (0.6032) exceeded that for stable firms, confirming that the model was more effective at detecting distress than at accurately classifying the full sample.

Figure 3 presents the confusion matrix for the Linear SVM model on the testing sample. Of the 34 stable firms, only 11 were correctly classified, whereas 23 were incorrectly labeled as distressed. Conversely, among the 21 distressed firms, the model correctly identified 19 cases and missed only 2. These results indicate that Linear SVM is effective in detecting distressed firms but generates a substantial number of false alarms among stable firms.

Overall, Linear SVM behaves as a conservative early warning classifier that prioritizes minimizing missed distress cases. However, its relatively low overall accuracy and high false positive rate limit its usefulness as a standalone predictive model. Compared with nonlinear approaches such as Random Forest and XGBoost, the linear specification provides weaker classification performance, suggesting that nonlinear methods are better suited to financial distress prediction in this context.

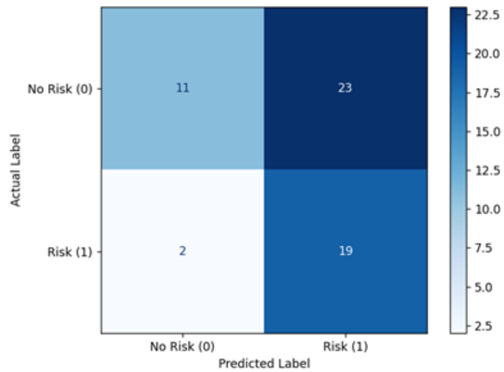

Figure 3. Confusion matrix of the Linear SVM model

The comparative results suggest that nonlinear and ensemble approaches, particularly XGBoost and Random Forest, provide better performance in financial distress classification for maritime shipping firms. In financial risk management, the cost of failing to identify distressed firms is typically higher than the cost of false alarms; therefore, models with higher recall and F1-score for the distressed class are generally preferred. Although Linear SVM does not achieve the highest overall accuracy, it may still serve as a supplementary early warning indicator when minimizing missed distress cases is the primary concern.

V. Conclusion

This study applies machine learning techniques to classify financial distress among listed maritime shipping firms in Vietnam using financial indicators related to leverage, liquidity, operating performance, cash flow quality, and firm size. A comparative framework is employed to evaluate the performance of Random Forest, XGBoost, and Linear Support Vector Machine models.

The empirical results show that XGBoost provides the strongest classification performance, reflected in high accuracy and a strong F1-score for distressed firms. Random Forest also demonstrates stable and balanced results, indicating good generalization capability. In contrast, although Linear SVM achieves high recall for distressed firms, it tends to over-predict distress, leading to lower overall accuracy. These findings indicate that nonlinear and ensemble approaches are more effective in capturing complex relationships among financial indicators.

From a methodological perspective, the results emphasize the importance of aligning model selection with the objectives of financial risk management. When the cost of failing to identify distressed firms exceeds the cost of false alarms, models such as XGBoost and Random Forest are more suitable for early warning analysis. The comparison between linear and nonlinear specifications also provides additional insight into the classification behavior of different algorithms.

Nevertheless, several limitations should be acknowledged. The analysis focuses on binary distress classification and does not examine the relative importance of individual financial variables. In addition, the sample is restricted to listed maritime shipping firms in Vietnam, a sector with distinctive financial characteristics, which may limit the generalizability of the findings. Future research may extend the dataset to other industries and incorporate feature-importance analysis to better understand the determinants of financial distress.

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