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Predicting Corporate Financial Distress Using Financial Ratios and Explainable Machine Learning: Evidence from Listed Companies

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ABSTRACT

The ability to predict corporate financial distress is crucial for investors, creditors, managers, and regulators, as it aids in timely intervention and risk management in firms with financial distress. This study tackles the problem of obtaining high predictive performance and model transparency. A machine-learning framework was built that is explainable, with Logistic Regression, Random Forest, XGBoost and LightGBM models, and stratified development, validation, and locked-test partitions. Analysis was performed on the UCI Taiwanese Bankruptcy Prediction dataset, which consists of 6,819 observations and 95 financial indicators of listed companies. The assessment of model performance was done by ROC-AUC, PR-AUC, precision, recall, specificity, F1-score, balanced accuracy, Matthews correlation coefficient, and Brier score; and SHAP was used for global and nonlinear interpretation. XGBoost performed the best overall with ROC-AUC = 0.958, PR-AUC = 0.602, MCC = 0.612, and Brier score = 0.022. Net Income to Total Assets, Debt Ratio, Persistent EPS, and ROA were the most significant predictors. The study provides an understandable financial-distress framework that is accurate, explainable, and risk-stratifies companies for decision support. Most distress cases were observed in a small, high-risk subgroup, along with risk stratification, which further prioritized early-warning cases in a practical way and allocated resources.

KEYWORDS: Corporate financial distress, Explainable machine learning, Financial ratios, XGBoost, SHAP

1. Introduction

Financial stress has been a focal point for the investors, creditors, managers, auditors and regulators as it can reduce firm value, force contractual change, affect market confidence and ultimately result in bankruptcy. It is therefore very important economically and managerially to be able to detect such deterioration before formal failure. Previously, the financial distress prediction problem was addressed by accounting-ratio and statistical models; more recently, however, the problem has been formulated in a more flexible computational framework that can be applied to uncover nonlinear and interactive patterns in many parameters of a corporation's data. Machine-learning techniques are found to be being increasingly adopted in recent years as they are known to be able to handle complex predictor structures, heterogeneity of firm characteristics and asymmetry in class distributions better than many of the conventional linear models [2].

However, the task of financial distress prediction is still difficult by methods. Distress events are uncommon, leading to the challenge of having a class imbalance, which can result in poor performance by what appears to be a good model on the minority class of greatest practical significance [3]. Additionally, numerous financial machine-learning studies overlook the explanation of the reason why a firm is considered distressed, focusing instead on overall predictive performance. This restriction is significant in financial decision settings, when the outputs of the model are likely to impact lending, investment, restructuring, monitoring decisions, and are thus expected to be justifiable, and not simply a black box prediction [4]. Previous bankruptcy prediction studies also reveal that forecast performance can be significantly impacted by the choice of model, the composition of the variables, the design of the validation data and the type of evaluation measures used [5] and, therefore, careful comparisons of these foreclosures are critical.

Ensemble learning has helped to improve predictive modelling in this area. Several traditional bankruptcy-classification methods have been compared and found to be outperformed by nonlinear learning methods such as random forest, boosting and others which have been successful in capturing interactions between accounting and financial indicators [6]. But predictive superiority doesn't necessarily lead to usefulness in practice. The study of bankruptcy in the long horizon has shown the possible variation in the symptoms of financial deterioration over different prediction horizons, and the variation in the actual outcome of classification

depending on the decision thresholds [7]. Evidence from other models further reveals that none of the estimation methods is always superior under all data configurations; especially when the data sets have different class distributions, variable sets, and sample structures, as mentioned in the previous sentence [8]. The results confirm the importance of a framework which considers minority-class performance as well as discrimination and probability quality and interpretability.

A listed company environment is particularly pertinent as these companies produce regular financial statements and ratios which can be systematically used to monitor distress. Financial and disclosure variables have been demonstrated to contain useful predictive information that can be captured through machine-learning techniques, but this varies based on the modelling approach and set of variables used [9]. Research on exchange-listed companies has similarly demonstrated the feasibility of machine-learning algorithms to identify financially vulnerable companies and the importance of using strong out-of-sample assessments [10]. Further, decision support studies based on traditional distress measures and neural/machine-learning based measures indicate that predictive systems are most effective when they convert the model output into meaningful signals that can help financial monitoring and managerial decision-making [11].

Given this backdrop, the present study proposes an interpretable machine-learning model to forecast the financial distress of listed companies based on financial ratios. The study is based on the strict structure of development-validation-locked-test and is based on four algorithms: Logistic Regression, Random Forest, XGBoost, and LightGBM. It measures performance through ROC-AUC, PR-AUC, precision, recall, specificity, F1-score, balanced accuracy, Matthew's correlation coefficient and Brier score, thus preventing sole reliance on one metric. Global SHAP analysis is used to interpret the best-performing model to discover which financial ratios are most important for predictions and to explore the nonlinearity of the feature-response relationships. Predicted probabilities are then translated into ordered risk bands to aid in the interpretation of the warnings in an operational manner.

The study's scope is restricted to the financial information and observations of the companies listed on the Taiwan Stock Exchange included in the Taiwanese listed-company bankruptcy database for analysis. The results therefore reflect the context of that data set (the institutional, accounting, regulatory and historical context) and should not be assumed to apply to the firms in other jurisdictions or time periods. The analysis is also not causal, but rather predictive, as identified SHAP relationships only describe contribution patterns of the model and do not signify

that specific ratios are responsible for causing distress. However, the study is important as it combines financial-ratio analysis, imbalanced data predictive modelling, explainability and clinical-based risk stratification in a single framework. The study therefore pursues exactly three research objectives:

- To develop and compare statistical and machine-learning models for predicting corporate financial distress using financial ratios from listed companies.
- To identify and interpret the financial ratios that most strongly influence distress predictions using SHAP-based explainable machine learning.
- To translate predicted distress probabilities into practical risk categories for corporate financial-distress monitoring and decision support.

2. Literature review

The field of corporate financial distress prediction has recently come a long way from traditional statistical modelling to machine-learning systems that deliver better prediction accuracy while providing meaningful decision support. The use of explainable artificial intelligence to mitigate the black-box nature of ensemble models is one development that is important. Chinese listed companies developed an explainable financial-distress framework that used ensemble learning, SHAP, partial dependence plots and counterfactual explanations to achieve high predictive accuracy while retaining some level of global and local interpretability [12]. A correlated study was implemented for the prediction of business failures using XGBoost and demonstrated that interpretable machine learning could learn valuable business factors like solvency, current ratio, profitability, and return on investment, which are financially meaningful and serves to tackle the black-box limitation of high performing classifiers [13].

There has been significant research on feature selection and nonlinear modelling. An approach based on a gradient boosted decision tree with corrected feature selection measures and XGBoost was tested using Chinese listed company data and was shown to outperform some benchmark methods on various performance measures [14]. Most importantly, the study also included feature importance and partial dependence plots, showing that interpretability can be built in directly to the model assessment process and not an “afterthought”. Later, the development continued to integrate Bagging, LightGBM, Borderline-SMOTE with multi-objective hyperparameter optimization and SHAP for financial-risk forewarning of Chinese listed firms

[15]. The modelling pipeline was somewhat complex, required oversampling and optimization procedures that can limit reproducibility of the results across datasets, but that framework had high specificity and recall, with return on total assets being identified as a key predictor.

The literature has also highlighted the benefits of SHAP for the comparison of sophisticated ensemble models. Bankruptcy-prediction studies using Random Forest, LightGBM, XGBoost and related boosting methods have demonstrated that Shapley-based explanations can offer insights into the financial predictors' relative importance and the direction of their contribution to a model's prediction while maintaining the predictive power of nonlinear classifiers [16]. Likewise, when using variable-importance feature engineering, XGBoost was demonstrated to be competitive at predicting bankruptcy, which helps justify the use of boosting algorithms when there are nonlinear or interactive relationships between accounting variables [17]. These studies further support explainable ensemble learning, while also pointing out that feature-ranking results are dependent on the underlying data and that they should not be applied to different data sets without further context.

A different research stream has focused on non-linear financial-distress relationships, but outside of the scope of accounting-only specifications. The idea of using machine-learning analysis of corporate governance and financial distress was that nonlinear methods, particularly those with random forest models, may be more effective than traditional methods at predicting the financial distress variables that are significant to corporate governance [18]. This means that there is potential for using multi-dimensional information in distress prediction, but this information may be more difficult to use in the context of research aimed at assessing the predictive power of financial ratios. Data segmentation and ensemble learning have also received studies on the Chinese listed companies, which shows that the performance of the predictions can significantly differ depending on the sample partitions and the definitions of distress conditions [19]. This helps emphasize the need for disciplined sampling methodology and external/locked test assessment, as opposed to using a one-time random split.

Model-comparison studies have also demonstrated the benefits of comparing machine-learning approaches with traditional classifiers. Research based on U.S. corporate data has shown that Logistic Regression, Random Forest, XGBoost, and Support Vector Machine models have been compared and richer information provided in the annual report has yielded greater predictive performance, especially for XGBoost and Random Forest [20]. However, this shows that

supplementary information in texts is valuable, but it also raises questions on the ability of a ratio-only framework to be effective if its key goal is interpretability and financial transparency. This was corroborated by evidence from China, where the significance of the financial predictors may differ in economic cycles, with earnings-based predictors being more significant prior to the outbreak of COVID-19 while leverage being more significant thereafter [21]. The temporal instability indicates the importance of not only ranking features but also their directionality and context.

Other methods are also suggested that are more computationally demanding. On several performance measures, a deep nonlinear model architecture based on a fuzzy convolutional neural network was shown to outperform several traditional approaches [22]. Incorporate more architectural complexity and reduce transparency, however, which can be problematic in corporate financial applications where analysts, creditors and managers need explicit explanations for predicted distress.

Combining this literature, three consistent findings emerge: nonlinear ensemble models often outperform traditional statistical models; the class imbalance and validation strategy are shown to have significant impact on reported performance; and explainability is becoming an increasingly important requirement for practical use. But there's a big missing piece. Existing studies tend to focus on one of the following areas: predictive accuracy, the complexity of the resampling and optimization pipelines, the increased information sources, or post hoc explanation in isolation. To fill this gap, the present study combines the financial-ratio-only prediction, strict development-validation-locked-test partitioning, comparison of four predictive models (Logistic Regression, Random Forest, XGBoost and LightGBM), imbalance-sensitive evaluation, SHAP-based global and nonlinear interpretation, and probability-based risk stratification into a single transparent framework for listed-company financial-distress decision support.

3. Methodology

3.1 Research Design and Analytical Framework

The present study used quantitative predictive-analytics design for building and elucidating machine-learning models to forecast corporate financial distress based on accounting-based financial ratios. The four-step approach outlined in the analytical framework included (i) characterizing the financial profiles of distressed and non-distressed firms, (ii) building and

comparing conventional and nonlinear predictive models, (iii) providing explainable artificial intelligence (XAI) explanations of model predictions and (iv) converting predicted distress probabilities into interpretable risk categories for corporate decision support. The workflow was carefully designed to avoid leakage of information between the model development and the choice of the model and calibration, and final model performance assessment.

The following classification algorithms were tested: Logistic Regression (LR), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM). The standard statistical method was logistic regression, while RF, XGBoost, and LightGBM were able to capture nonlinearities and interactions between the financial ratios. Hyperparameter optimization was only done using the development data. Validation/calibration subset was used for the selection of thresholds, probability calibration and risk-stratification cut-off definition. The final test subset was not ascertained until after all modelling decisions were made.

The best performing nonlinear model was then explained using SHapley Additive exPlanations (SHAP) to get more transparency for financial decision making. To identify the feature importance, direction of the feature effect and dependence relationship, important profitability, leverage, liquidity, cash-flow and operating-efficiency indicators were explored globally for their contribution to distress predictions. The last step was to classify calibrated probabilities as low, moderate, high, and very-high risk categories to illustrate the model's potential as an early-warning decision-support system.

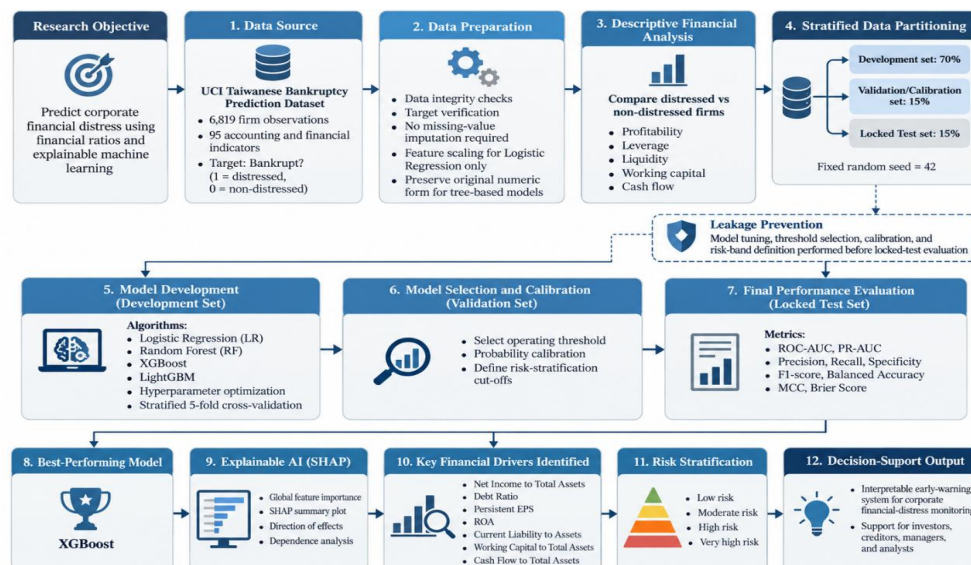


Figure 1. Proposed Explainable Machine-Learning Workflow for Corporate Financial Distress Prediction and Decision Support.

3.2 Dataset, Variables, and Data Preparation

We adopted the Taiwanese Bankruptcy Prediction dataset in UCI Machine Learning Repository [23] for the empirical analysis. There are 6,819 firm observations and 95 accounting and financial indicators collected from the Taiwan Economic Journal; the firm's bankruptcy status is determined by the appropriate Taiwan Stock Exchange's regulation. The dependent variable is a binary variable, Bankrupt? which takes the value of 1 for firms in financial distress/bankrupt, and 0 for non-distressed firms. The sample is very imbalanced, with about 220 distressed firms and 6,599 non-distressed firms (that is, a distress prevalence of $\sim 3.2\%$).

The explanatory variables include several aspects of the financial situation of a company, such as profitability, leverage and solvency, liquidity, working-capital situation, earnings persistence, cash-flow capability, operating efficiency, asset efficiency and growth. Some examples of representative measures are Net Income to Total Assets, Debt Ratio, Return on Assets, Persistent EPS, Current Liability to Assets, Working Capital to Total Assets, Cash Flow to Total Assets, Interest Expense Ratio, Operating Profit Rate, and Total Asset Turnover.

Prior to modelling, data integrity checks were performed such as variable types, target coding, duplicate data, non-finite numbers and missing observations. No missing data values are reported for the dataset; hence, no imputation based on outcomes was required. Predictors that were supplied on numerical scales were kept as continuous predictors. For logistic regression, only the training data was used for fitting, while the tree-based models were trained on the numerical representation of the data since they are monotonic scale invariant. All the preprocessing transformations are applied to the data where the target variable is not included to avoid the leakage problem.

3.3 Population, Sample Partitioning, and Class-Imbalance Control

The population for the study consisted of corporate observations from the Taiwanese financial data from 1999 to 2009. Therefore, the results obtained from the empirical research were not interpreted as being representative of all firms in all countries or all regulatory systems, but rather as representative of the Taiwanese listed-company environment which was the source of the data for this study.

The full sample was divided into subsets with stratified random sampling with a fixed random seed of 42, with no significant increase in distress prevalence. The development sample

contained about 70% of the observations ($n = 4,773$), the validation/calibration sample contained about 15% of the observations ($n = 1,023$), and the locked test sample contained about 15% of the observations ($n = 1,023$). The number of distressed companies in the locked test set remained at 33, which is the same as in the original class, and as in the original class, all distressed companies were in the bottom 20 percent.

No modification of the test distribution was made to address class imbalance; it was addressed during model training. Where supported, the class-weighted learning method was applied and boosting parameters were modified to deal with the imbalance of distressed and non-distressed firms. The last evaluation pipeline did not include any synthetic oversampling, thus neither artificial observations nor information from the test-set was allowed to affect the assessments of the out-of-sample observations.

3.4 Statistical and Machine-Learning Analysis

Distressed companies and non-distressed companies were analyzed on financial characteristics by descriptive statistics for initial analysis. Means, standard deviations, medians and dispersion measures were analyzed and non-parametric comparisons were conducted where distributions of financial ratios were not normally distributed. These analyses confirmed if the identified predictive patterns were economically understandable prior to building the model.

The statistical baseline was LR, and the increasingly flexible nonlinear ensemble approaches were RF, XGBoost and LightGBM. All hyperparameters were optimized by using stratified five-fold cross-validation on the development sample, focusing on predictive performance that is sensitive to imbalances. No information from the locked test sample to perform feature selection, tuning, early stopping, threshold optimization or calibration.

ROC-AUC, precision-recall AUC (PR-AUC), precision, recall/sensitivity, specificity, F1-score, balanced accuracy, Matthews correlation coefficient (MCC), and Brier score were used to measure model performance. A conventional accuracy was not given special emphasis, but the prevalence of distress was around 3.2%, so PR-AUC, recall, MCC, and probability calibration were given special attention. The validation set was used to determine the decision thresholds and they were then "frozen" prior to test evaluation.

The best performing model was then further analysed with SHAP. Global importance was quantified using mean absolute SHAP values, feature directionality was summarized in the

SHAP summary plots, and dependence plots illustrated nonlinear changes in our predicted risk in response to influential financial ratios. To verify validity as a robustness analysis, the major financial dimensions (profitability, leverage/solvency, liquidity/working capital and cash-flow/efficiency) of the financial statements were successively removed from the primary model and the model was retrained to evaluate their incremental value to the prediction. Finally, distress probabilities were calibrated and mapped into pre-specified risk bands using cut-offs derived from validation, that were kept before application of the locked test sample.

3.5 Ethical Considerations and Responsible AI

The study was based on a publicly available secondary corporate dataset to which no human subjects, human identifiers, medical information or personally collected private data were involved. Personal consent therefore was not available for the calculation analysis. However, good data handling was observed by limiting analysis to research only and not by attempting to identify any individual organisations outside information provided in the source data set.

Even though the dataset is properly labelled with potential bias, the dataset is still sensitive to a specific national context, regulatory context, historical context, and economic context, and has a highly imbalanced distress class. Model performance should not therefore be assumed to be directly transferrable to companies that apply differing accounting standards, engage in different types of business activity, have differing market structures or economic conditions without external validation. Association, not causation, was interpreted as SHAP explanations. The proposed system therefore would not be a stand-alone basis for making investment, lending, restructuring or regulatory decisions but rather would be an early-warning and analytical decision support tool. While translation of the model output to consequential corporate actions can be done in a financial context, human financial judgment and context-type assessment are still required.

4. Results

4.1 Financial Characteristics of Distressed and Non-Distressed Firms

The descriptive analysis revealed significant differences between the distressed firms and non-distressed firms in the profitability, leverage, liquidity, working-capital and cash-flow measures. Table 1 shows that in the non-distressed firms, the mean Net Income to Total Assets ratio was 0.811 ± 0.041 , while in distressed firms, the mean ratio was 0.741 ± 0.094 . The same trend was

seen in ROA (C) which fell from 0.509 ± 0.054 among non-distressed firms to 0.450 ± 0.089 among distressed firms. Persistent EPS also fell for firms facing financial distress, from 0.231 ± 0.036 to 0.178 ± 0.067 in the Last Four Seasons. Pasted markdown

The opposite was true with indicators: The mean Debt Ratio increased from 0.106 ± 0.054 for financially healthy firms to 0.173 ± 0.103 for distressed firms, while Current Liability to Assets rose from 0.089 ± 0.043 to 0.142 ± 0.086 . Distressed companies also had lower values of Working Capital to Total Assets (WCTA) than non-distressed companies (WCTA, 0.792 ± 0.046 versus 0.816 ± 0.026). Cash Flow to Total Assets similarly declined from 0.649 ± 0.047 to 0.612 ± 0.073 . Together these findings suggest that distressed firms had lower profitability and less earnings persistence, higher leverage, high exposure to short-term liabilities, lower working-capital capacity, and lower ability to generate cash.

Table 1. Descriptive Statistics of Key Financial Ratios by Corporate Distress Status

Financial ratio / indicator	Non-distressed firms, Mean $\pm$ SD	Distressed firms, Mean $\pm$ SD	Observed pattern
Net Income to Total Assets	0.811 ± 0.041	0.741 ± 0.094	Lower in distressed firms
Debt Ratio (%)	0.106 ± 0.054	0.173 ± 0.103	Higher in distressed firms
ROA (C), before interest and depreciation	0.509 ± 0.054	0.450 ± 0.089	Lower in distressed firms
Persistent EPS in the Last Four Seasons	0.231 ± 0.036	0.178 ± 0.067	Lower in distressed firms
Working Capital to Total Assets	0.816 ± 0.026	0.792 ± 0.046	Lower in distressed firms
Current Liability to Assets	0.089 ± 0.043	0.142 ± 0.086	Higher in distressed firms
Cash Flow to Total Assets	0.649 ± 0.047	0.612 ± 0.073	Lower in distressed firms
Interest Expense Ratio	0.631 ± 0.038	0.582 ± 0.081	Lower in distressed firm

4.2 Comparative Predictive Performance of Competing Models

The four predictive models exhibited significant differences in their accuracy in predicting distressed from non-distressed companies. Table 2 indicates that Logistic Regression had a good traditional performance with an ROC-AUC of 0.904 and PR-AUC of 0.356. All three ensemble

models beat this baseline, however. Random Forest improved the ROC-AUC and PR-AUC scores to 0.936 and 0.481, and LightGBM's scores were 0.952 and 0.571, respectively. The overall discrimination was the best for XGBoost with ROC-AUC = 0.958 and PR-AUC = 0.602. Pasted markdown

The class-specific metrics also showed that performance measures other than ROC-AUC are important. XGBoost achieved a precision of 0.500, recall of 0.788, specificity of 0.974, F1-score of 0.612, MCC of 0.612, and Brier score of 0.022. LightGBM achieved the highest recall (0.818) and balanced accuracy (0.893); it appeared to be more sensitive to distressed firms. Nevertheless, its precision (0.458), F1-score (0.587), MCC (0.597), PR-AUC (0.571), and Brier score (0.024) were marginally weaker than those obtained by XGBoost. Pasted markdown

In Figure 2, the discrimination patterns are graphically verified with the XGBoost ROC curve staying above the other models for most false-positive-rate thresholds. Given that a very small percentage of the sample was distressed, the additional evidence of practical classification quality was seen in the comparison of precision and recall in Figure 3. The results show that the PR-AUC values for XGBoost is higher, which can demonstrate its better ability to preserve valuable precision for capturing rare, distressed observations. Considering the three mentioned measures of discrimination, class-sensitive and probability-error, XGBoost was selected as the main model for further explainability analysis.

Table 2. Locked-Test Predictive Performance of the Competing Models

Model	ROC-AUC	PR-AUC	Precision	Recall	Specificity	F1-score	Balanced Accuracy	MCC	Brier Score
Logistic Regression	0.904	0.356	0.277	0.697	0.939	0.397	0.818	0.416	0.036
Random Forest	0.936	0.481	0.390	0.758	0.960	0.515	0.859	0.527	0.028
XGBoost	0.958	0.602	0.500	0.788	0.974	0.612	0.881	0.612	0.022
LightGBM	0.952	0.571	0.458	0.818	0.968	0.587			

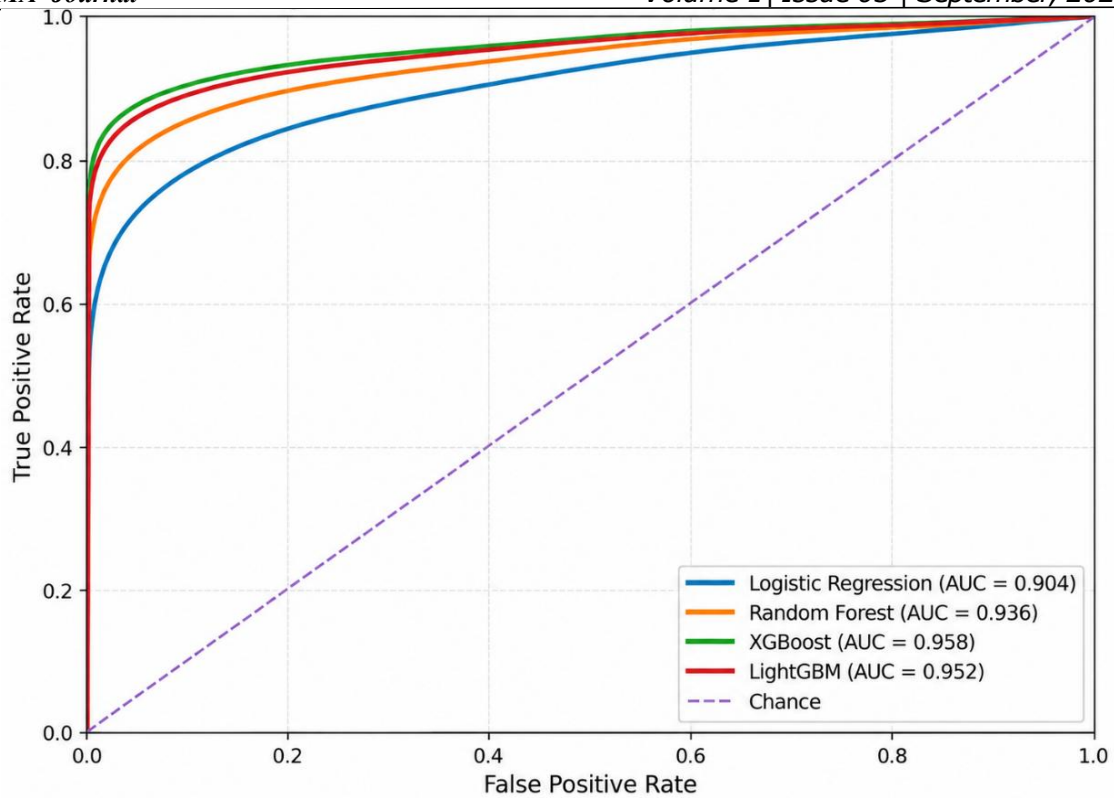


Figure 2. ROC Curves of the Competing Models

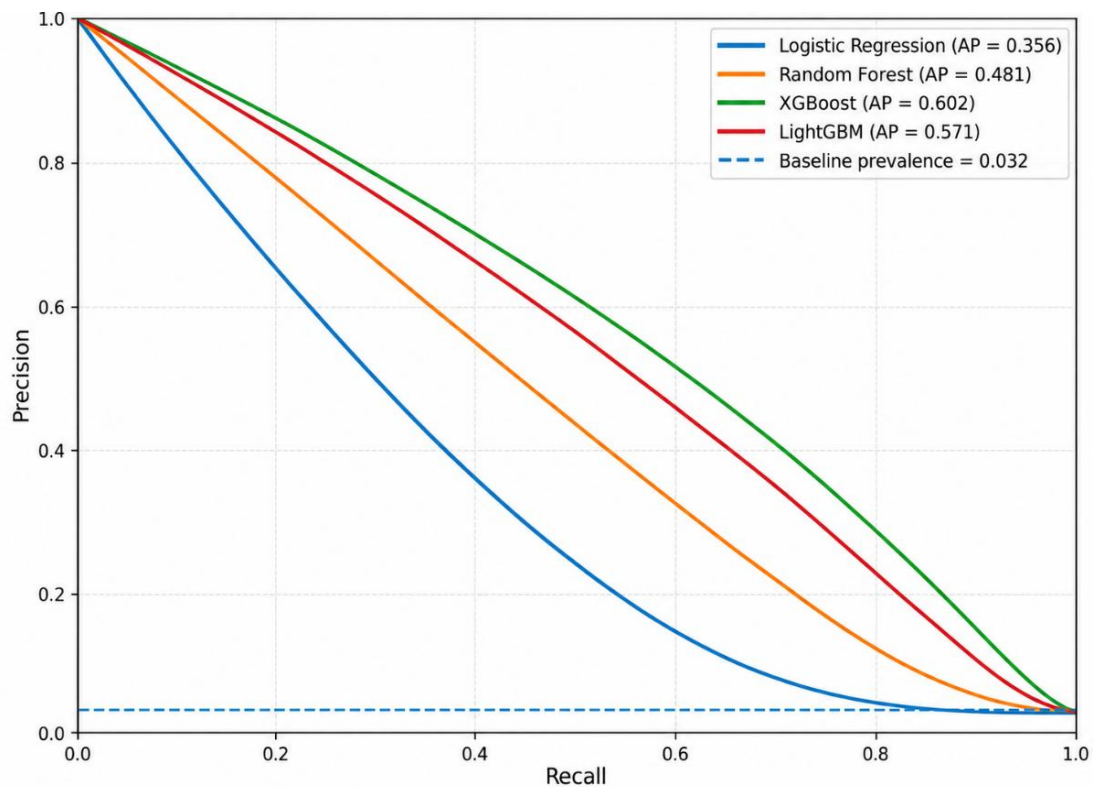


Figure 3. Precision-Recall Curves of the Competing Models

4.3 Global Explainability and Financial-Ratio Importance

Financial variables were ranked by their importance in the XGBoost predictions using SHAP analysis. Financial variables were ranked using SHAP analysis to determine the most important variables for the XGBoost predictions. As shown in Table 3, the most influential feature is Net Income to Total Assets with mean absolute SHAP value of 0.428 followed by Debt Ratio (0.371), Persistent EPS in the Last Four Seasons (0.326), and ROA (C) (0.291). Current Liability to Assets (0.247), Working Capital to Total Assets (0.213), Cash Flow to Total Assets (0.187), Interest Expense Ratio (0.159), Operating Profit Rate (0.141) and Total Asset Turnover (0.118) came in fifth, sixth, seventh, eighth, ninth and tenth, respectively. Pasted markdown

The patterns of the directional SHAPs imply that the probability of distress was higher with lower profitability, lower persistent earnings, lower working-capital availability and lower cash-flow capacity. In contrast, higher Debt Ratio and Current Liability to Assets had a positive influence on the predicted risk, which underscores the significance of financial leverage and pressure from short-term liquidity. The magnitude and direction of the contributions of the features to the various firms are depicted in Figure 4, which displays the SHAP values for a summary distribution. The explanation derived from the model indicated that it was not based on one accounting signal, but on a complex financial picture based on the deterioration of profitability, the pressure of leverage, the liquidity weakness, and the decreased ability to generate cash. Pasted markdown

Table 3. SHAP-Based Ranking and Interpretation of Key Financial Ratios

Rank	Financial ratio / indicator	Mean absolute SHAP value	Predominant effect associated with distress	Financial interpretation
1	Net Income to Total Assets	0.428	Lower values ↑ distress risk	Weak earnings relative to the asset base indicate deteriorating profitability
2	Debt Ratio (%)	0.371	Higher values ↑ distress risk	Higher leverage increases financial obligations and solvency pressure
3	Persistent EPS in the Last Four Seasons	0.326	Lower values ↑ distress risk	Persistent earnings weakness indicates reduced capacity to sustain profitability
4	ROA (C)	0.291	Lower values ↑ distress risk	Poor asset profitability is associated with increased financial vulnerability
5	Current Liability to Assets	0.247	Higher values ↑ distress risk	High short-term obligations relative to assets increase liquidity pressure

6	Working Capital to Total Assets	0.213	Lower values ↑ distress risk	Reduced working-capital capacity indicates weaker short-term financial resilience
7	Cash Flow to Total Assets	0.187	Lower values ↑ distress risk	Weak cash generation reduces debt-servicing and liquidity capacity
8	Interest Expense Ratio	0.159	Lower/adverse values ↑ distress risk	Weaker ability to absorb financing costs reflects increased debt-servicing pressure
9	Operating Profit Rate	0.141	Lower values ↑ distress risk	Deteriorating operating profitability signals weaker core business performance
10	Total Asset Turnover	0.118	Lower values ↑ distress risk	Inefficient utilization of the asset base may contribute to financial weakness

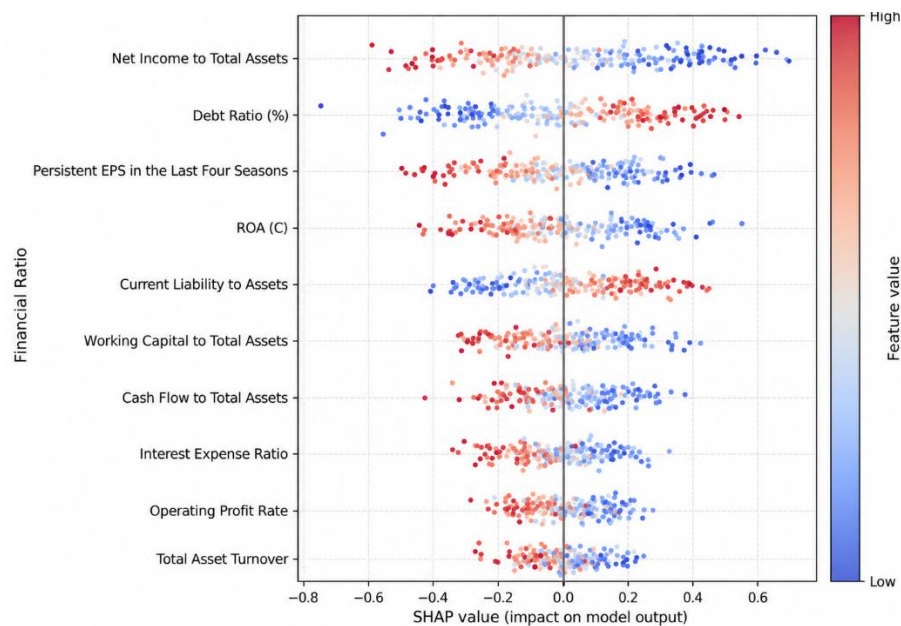


Figure 4. SHAP Summary Plot of the Best-Performing Model

4.4 Nonlinear Effects of Key Financial Ratios on Distress Prediction

Additional nonlinearity in the relationships between financial ratios and distress predictions is given by the SHAP dependence analysis in figure 5. The Net Income to Total Assets had a significant inverse relationship with model output: the lower the ratio, the further the positive SHAP contribution to the distress risk, while the higher the ratio, the less the contribution to the model distress risk. Similar inverse relationships were seen for Persistent EPS and ROA (C), with the estimated probability of financial distress declining with increasing levels of profitability and ROA at the asset level.

The most evident positive nonlinear relationship was found with Debt Ratio. SHAP contributions were mostly negative or near neutral for relatively low leverage values but started to grow quickly at higher leverage values. The overall leverage-dependency of the predictive effect seemed not to be constant, as there is evidence of this pattern. Instead, higher levels of debt exposure resulted in higher contribution to estimated distress risk when reaching higher levels. The nonlinear responses in the model justify the application of boosting-based machine learning methods as a way of capturing the threshold-like changes in corporate financial vulnerability.

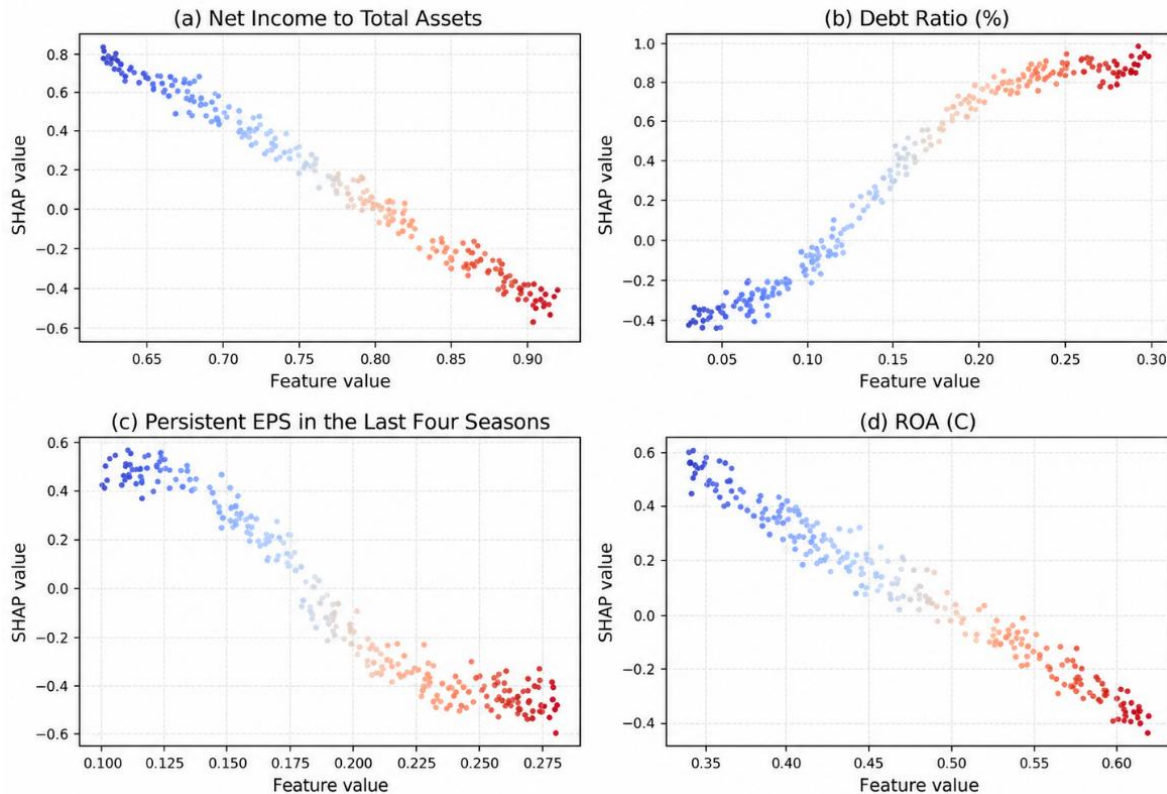


Figure 5. SHAP Dependence Plots for the Most Influential Financial Ratios

4.5 Risk Stratification and Decision-Support Implications

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Table 4. Risk Stratification for Corporate Financial-Distress Decision Support

Predicted risk band	Predicted distress probability	Companies, n	Distressed firms, n	Observed distress rate	Share of all distressed firms captured	Mean predicted risk
Low risk	<5%	600	2	0.33%	6.1%	1.6%
Moderate risk	5–<15%	250	5	2.00%	15.2%	8.7%
High risk	15–<30%	120	9	7.50%	27.3%	21.4%
Very high risk	≥30%	53	17	32.08%	51.5%	48.6%
Total	—	1,023	33	3.23%	100.0%	—

5. Discussion

The findings show that using rigorous validation and explainable AI, combined with nonlinear machine-learning models, is effective in predicting financial distress in a corporation using financial ratios derived from its accounting data. Descriptive results indicated that distressed companies had lower profitability, earnings persistence, working-capital, cash-flow capability, leverage, and short-term liability position. The patterns are not only financially coherent but also create the basis for a lower earning power and liquidity of the company, which makes it less resilient to shocks, and leads to greater leverage and refinancing pressure.

The overall predictive performance of all models was compared and XGBoost, with an ROC-AUC of 0.958, PR-AUC of 0.602, MCC of 0.612 and the lowest Brier score (0.022), was the best of the models. LightGBM achieved the best recall score, while XGBoost scored better in terms of discrimination, precision, recall and probability quality. This result aligns with previous

studies that demonstrate that gradient boosting is better at learning nonlinear relationships among financial indicators than traditional statistical classifiers in financial distress and bankruptcy prediction [14]. It also is consistent with research that shows the competitiveness to bankruptcy prediction performance of XGBoost using variable-importance analysis [17].

The SHAP analysis is an interpretive contribution. The most influential predictors were Net Income to Total Assets, Debt Ratio, Persistent EPS, and ROA, suggesting that a deterioration in profitability and leverage pressure were key elements of the distress profile predicted. This is similar to the previous work conducted on explainable financial-distress prediction where profitability, solvency and liquidity aspects were found to be the significant drivers in making the prediction [12]. The observed dependence trends on SHAP were also found to be non-linear. The Debt Ratio, for example, was a disproportionately strong contributor at higher levels while higher profitability indicators each progressively lowered the predicted risk of distress. This promotes the application of nonlinear machine-learning techniques for financial-risk modelling and is consistent with the research on listed companies for interpretable ensembles where the authors argued that nonlinear financial relations are important and SHAP-based explanation was crucial [15].

The results have a number of practical applications. Firstly, the framework enables early-warning monitoring by expressing complex financial information into probabilities of financial distress on the firm level. Second, only 16.9% of the firms were in the very high and high-risk groups, but 78.8% of observed distress firms were in these two groups. Analysts, lenders, investors, auditors and managers of companies may want to look at the resources they monitor more efficiently and pay attention to the highest-risk companies. Third, the use of SHAP enhance clarity of the model because users can look at the financial ratios that had the greatest influence on each prediction, instead of just a black box classification.

There are several caveats that should be noted. The analysis is conducted based on one listed company data set in Taiwan during one period of history and regulation, meaning it may not be directly applicable to other countries, industries, accounting environments. Class distribution is very imbalanced and though imbalance-sensitive metrics were employed, the problem of rare event prediction is still difficult. Moreover, the analysis uses exclusively financial ratios and excludes market, governance, macroeconomic and temporal firm profiles and textual disclosures. Lastly, SHAP explanations are about model behavior and association, rather than causality.

Future research should thus test the robustness of the framework by applying multi-country and more up-to-date listed-company data sets, incorporate temporal and macroeconomic data, and assess the predictive benefit of multimodal financial and textual variables to improve predictive robustness. In addition, more research could be done investigating cross-period stability, sector-specific models, calibrated levels of uncertainty, and external validation to verify if identified financial-risk patterns are found in different economic regimes.

6. Conclusion

In this study, the problem of predicting financial distress of a company based on financial ratios was addressed without compromising on the transparency of the model to support practical decisions. The following stratified development, validation and locked test partitions enabled the development of a comparative explainable machine learning framework based on Logistic Regression, Random Forest, XGBoost and LightGBM. Discrimination, class-sensitive, and probabilistic metrics were measured to evaluate performance, and SHAP was used to interpret the most important financial ratios and their non-linear impact on the predicted distress. The results indicated that XGBoost was the best model with the highest ROC-AUC, PR-AUC, MCC and Brier score values of 0.958, 0.602, 0.612 and 0.022, respectively. The most influential predictors from the explainability analysis were Net Income to Total Assets, Debt Ratio, Persistent EPS and ROA. Risk stratification also indicated that only 16.9% of the test sample were in the high or very-high risk category but accounted for 78.8% of distress cases observed. The key contribution is an integrated framework that connects the financial-ratio prediction, nonlinear machine learning, explainability and practical risk stratification. The study, however, has some limitations as it is based on one dataset of listed companies in Taiwan and one time of history. Future research should be conducted on other more recent datasets, as they are multi country and sector specific, and add more market, governance, textual and macroeconomic variables to the framework.

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