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Research Article

Predicting Non-Life Insurers' Financial Distress: Evidence from Bangladesh

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Abstract
This study aims to develop an interpretable early-warning framework to predict financial distress among non-life insurers in Bangladesh. The research addresses the question of which financial and operational indicators most accurately signal early signs of distress in the insurance sector. Using a firm-year panel covering 2014–2024, the study applies penalized logistic regression, random forests, and gradient-boosted trees, combined with class-balancing remedies and SHAP-based interpretability techniques, to identify the key determinants of insurer distress. The results show that gradient-boosted trees achieve the highest out-of-time recall performance. At the same time, SHAP analysis consistently identifies the management expense ratio, lagged underwriting performance, and reinsurance intensity as the most influential predictors. Robust tests across alternative sampling and feature reduction methods confirm the stability of these findings. The study concludes that monitoring expense efficiency, underwriting results, and reinsurance practices provides the most reliable early warning signals of financial distress in thin-premium markets. The originality of this research lies in integrating explainable machine learning with operational financial indicators in a developing-market insurance context, producing a transparent and policy-ready predictive model that balances accuracy and interpretability.

Keywords: financial distress prediction; non-life insurance; explainable machine learning; early-warning systems

JEL Classification: C53, G22, G33

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1. Introduction
Financial distress prediction has become a critical issue in the modern insurance industry, especially in emerging markets where limited capital reserves and volatile underwriting conditions amplify systemic vulnerability. The collapse or distress of insurance companies can trigger severe economic and social consequences, including delayed claim settlements, erosion of consumer confidence, and fiscal burdens on governments (Ayinaddis & Tegegne, 2023; Kebede, Tesfaye, & Erana, 2024). In many developing economies, insurance firms operate on thin premium bases and limited reinsurance coverage, leaving them more exposed to operational inefficiencies and market shocks.

As the insurance sector plays a vital role in risk pooling and financial stability, the early detection of financial distress through predictive modeling is indispensable to ensure the industry's sustainability (Grize, Fischer, & Lützelschwab, 2020; Lokanan & Ramzan, 2024).

In recent years, technological advances and data availability have encouraged researchers to apply machine learning (ML) to financial distress prediction, improving accuracy and providing earlier warnings compared to traditional statistical approaches (Abrahamsen, Nylén-Forthun, Møller, de Lange, & Risstad, 2024; Dhamo, Gjeçi, Zibri, & Prendi, 2025). Traditional models such as Altman's Z-score and Ohlson's O-score, while foundational, rely heavily on linear relationships and are limited in their ability to capture complex interactions among financial ratios (Altman, 1968; Ohlson, 1980). In contrast, ensemble and boosting algorithms can capture nonlinear patterns, address data imbalance, and enhance sensitivity to rare events such as insurer distress without compromising interpretability when integrated with explainable AI tools (Bussmann et al., 2024; Kuizinienė, 2022). This advancement provides a strong rationale for applying ML-based frameworks in the insurance sector, particularly in emerging markets where data irregularities and limited historical distress events present unique challenges.

Despite the progress in financial distress modeling, most existing studies focus on banking, manufacturing, or publicly listed firms, with limited evidence from the insurance industry (Shetty, Musa, & Brédart, 2022). The insurance business exhibits distinctive operational structures, such as underwriting cycles, reserve management, and reinsurance dependency, which differentiate its distress dynamics from those of other industries (Bragoli et al., 2021; Valaskova, Kliestik, Svabova, & Adamko, 2018). Furthermore, studies targeting developing economies often overlook contextual factors such as data scarcity, weak governance, and market concentration that affect the robustness and applicability of prediction models (Ashraf & Vincent, 2021; Kebede et al., 2024). This gap underscores the need for context-specific research that balances predictive accuracy and interpretability, enabling regulators to make informed, data-driven decisions.

Another pressing issue is the limited interpretability of many ML-based distress models, which restricts their practical adoption by regulators and policymakers. While complex algorithms achieve superior statistical performance, they often operate as “black boxes,” providing little insight into which financial indicators trigger distress warnings (El Madou, Marso, El Kharrim, & El Merouani, 2023; Hajek & Munk, 2023). Explainable Artificial Intelligence (XAI) frameworks, such as SHAP (Shapley Additive Explanations), offer a promising solution by translating algorithmic outputs into understandable financial indicators (Bussmann et al., 2024). This interpretability bridges the gap between academic innovation and regulatory usability, enabling supervisory agencies to act swiftly and confidently when early warning signals appear (Petropoulos, Siakoulis, Stavroulakis, & Vlachogiannakis, 2020).

In Bangladesh, the non-life insurance sector provides a particularly suitable environment to study financial distress due to its concentrated premium base, evolving regulatory structure, and exposure to macroeconomic instability. Many insurers operate on narrow margins and exhibit uneven underwriting performance, which makes the identification of distress-prone firms a regulatory priority (Abrahamsen et al., 2024; Kebede et al., 2024). The absence of prior empirical studies focused on Bangladesh’s insurance sector further justifies this research. Examining how operational indicators such as management expense ratio, reinsurance intensity, and combined ratio contribute to early-warning detection will fill a crucial knowledge and policy gap (Ayinaddis & Tegegne, 2023; Grize et al., 2020).

This study, therefore, aims to develop an interpretable early-warning framework to predict financial distress among non-life insurers in Bangladesh using machine learning techniques. Specifically, it seeks to (1) evaluate the performance of several predictive algorithms logistic regression, K-nearest neighbors, support vector machines, random forest, and gradient-boosted trees in detecting distress; (2) address class imbalance through oversampling methods; and (3) employ SHAP analysis to identify the most influential accounting indicators driving distress predictions (Lokanan &

Ramzan, 2024; Dhamo et al., 2025). The combination of predictive performance and interpretability ensures that the results are both academically rigorous and operationally relevant for regulators.

The main issue this research addresses is the high financial vulnerability of non-life insurance companies in emerging markets such as Bangladesh, driven by capital constraints, operational inefficiencies, and reliance on reinsurance, which increases the risk of financial distress and systemic failure. This research highlights that traditional prediction methods (such as the Altman Z-score and Ohlson O-score) are less able to capture the nonlinear patterns and complexity of relationships between financial ratios in the insurance context. Therefore, the novelty offered is the development of an explainable machine learning-based early-warning system framework using a gradient-boosted trees algorithm integrated with the SHAP (Shapley Additive Explanations) interpretation method. This approach not only improves prediction accuracy but also provides regulators with transparency into key indicators of financial distress such as management expense ratios, underwriting performance, and reinsurance intensity thereby offering high practical value for insurance sector supervision and policy in developing countries.

2. Literature Review and Hypothesis

Literature Review

Financial Distress

Financial distress theory explains a firm's inability to meet financial obligations without restructuring or external assistance. It arises from persistent operational inefficiency, declining profitability, and excessive leverage (Altman, 1968; Ohlson, 1980). The classical Altman Z-score model introduced discriminant analysis to predict bankruptcy using accounting ratios. In contrast, Ohlson's O-score model employed a probabilistic framework, highlighting solvency, liquidity, and performance indicators as key predictors. Later extensions of these models integrated multidimensional perspectives, emphasizing that distress evolves through both short-term liquidity pressures and long-term solvency erosion (Shumway, 2001; Wang, Gong, Li, & Wang, 2025). These frameworks collectively underscore that financial distress is not a single-point failure but a gradual process measurable through accounting ratios and operational efficiency indicators.

Capital Structure

Capital structure theory posits that a firm's mix of debt and equity affects its risk of distress due to differences in financial leverage and cost of capital. Highly leveraged firms face increased insolvency risk because fixed obligations magnify losses during downturns (Bragoli et al., 2021; Valaskova, Kliestik, Svabova, & Adamko, 2018). In insurance firms, capital adequacy reflects both solvency and regulatory compliance, while contingent claims theory interprets solvency as the outcome of option-like payoffs on assets and liabilities (Wang et al., 2025; Grize, Fischer, & Lützelschwab, 2020). These theories suggest that variables such as equity ratio and leverage serve as structural indicators of financial resilience or vulnerability to distress.

Underwriting Cycle Theory

Underwriting cycle theory explains periodic fluctuations in insurance profitability, driven by market competition, claim trends, and pricing strategies. During “soft” market phases, insurers reduce premiums to gain market share, increasing future claims exposure and reducing solvency margins (Grize et al., 2020; Bragoli et al., 2021). Firms with weak cost controls and aggressive growth strategies face an increased risk of financial distress when premium revenue fails to cover claims and expenses (Kebede, Tesfaye, & Erana, 2024; Ayinaddis & Tegegne, 2023). The combined ratio, reinsurance dependency, and management expense ratio thus become essential measures of underwriting efficiency and key predictors of early warning systems.

Resource-Based View (RBV) and Organizational Resilience Theory

The resource-based view (RBV) and organizational resilience theory emphasize the role of internal capabilities, governance, and operational efficiency in ensuring long-term financial stability (Valaskova et al., 2018; Liang et al., 2020). Firms that manage resources effectively such as human capital, underwriting expertise, and risk management systems are better equipped to withstand external shocks. In contrast, operational inefficiencies, weak governance, and poor expense management increase the risk of financial distress. These theories explain why managerial competence, cost control, and adaptive capacity are critical internal determinants of financial sustainability in the insurance industry (Kebede et al., 2024; Bussmann et al., 2024).

Hypothesis

Return on Assets (ROA) on Financial Distress.

Return on Assets (ROA) reflects a company's ability to generate profits from its total assets. Based on profitability and signaling theory, the higher the ROA, the better the company's financial condition because it indicates the efficiency of asset utilization in generating revenue (Ohlson, 1980; Abrahamsen et al., 2024). A decline in ROA is an early signal of financial distress, as insufficient profits fail to cover short-term liabilities.

Previous research has shown that ROA is negatively related to financial distress in various industry contexts, including the insurance and banking sectors (Kebede et al., 2024; Ayinaddis & Tegegne, 2023; Wu, Yang, & colleagues, 2022; Shetty, Musa, & Brédart, 2022). Thus, a high level of profitability reduces the likelihood that a company will experience financial distress.

H1: Return on Assets (ROA) has a negative and significant effect on financial distress.

Equity Ratio to Financial Distress.

The equity ratio indicates the proportion of equity capital to total assets and serves as an indicator of solvency. According to capital structure theory, companies with a strong capital base are more resilient to economic shocks and the risk of loss (Altman, 1968; Bragoli et al., 2021). A low equity ratio indicates a high reliance on debt, thus increasing the potential for default.

Previous research confirms a negative relationship between the equity ratio and financial distress in the financial and insurance sectors. Petropoulos et al. (2020) found that capital adequacy is a key predictor of bank solvency, while Valaskova et al. (2018) and Kebede et al. (2024) showed that a low equity ratio accelerates the risk of bankruptcy. Furthermore, Liang et al. (2020) emphasized that good corporate governance can strengthen the protective effect of equity capital.

H2: The equity ratio has a negative and significant effect on financial distress.

Management Expense Ratio: Financial Distress.

According to agency theory, high management expenses reflect operational inefficiency and weak oversight of managerial behavior (Bussmann et al., 2024; Liang et al., 2020). In the insurance industry, a high management expense ratio indicates inefficient resource use and poor internal controls, which can worsen financial performance.

Empirical studies support the important role of this ratio in detecting financial distress. Kebede et al. (2024) found that the management expense ratio was a key predictor of financial distress in Ethiopian insurance companies. Similar findings were also demonstrated by Grize, Fischer, and Lützelschwab (2020), who found that unmanageable management expenses were an early signal of a company's inability to pay claims. Furthermore, Ayinaddis and Tegegne (2023) and Lokanan and Ramzan (2024) confirmed that operational efficiency is a key indicator of financial health in the insurance sector.

H3: The Management Expense Ratio has a positive and significant effect on financial distress.

Reinsurance Ratio to Financial Distress.

The reinsurance ratio measures a company's dependence on reinsurance to transfer underwriting risk. According to contingent claims theory and the underwriting cycle theory, excessive reliance on reinsurance can indicate internal capital weakness and reduce potential net income (Grize et al., 2020; Bragoli et al., 2021).

Empirically, Kebede et al. (2024) found that high reliance on reinsurance increases the likelihood of financial distress by reducing premium retention. Ayinaddis and Tegegne (2023) added that companies with a high proportion of reinsurance are more vulnerable to external shocks and the

risk of default by reinsurance counterparties. Furthermore, research by Shetty et al. (2022) and Petropoulos et al. (2020) also shows that excessive reinsurance strategies weaken a company's financial stability.
H4: The reinsurance ratio has a positive and significant effect on financial distress.

Lagged Combined Ratio on Financial Distress.
The lagged combined ratio reflects underwriting efficiency in the previous period. Based on underwriting cycle theory, poor underwriting performance has a lasting effect on solvency because past losses can reduce a company's ability to cover future claims (Ayinaddis & Tegegne, 2023; Grize et al., 2020).

Previous research indicates that this ratio is a leading indicator of financial distress in the insurance sector. Kebede et al. (2024) found that a high combined ratio reflects underwriting losses and is an early signal of distress. Wu et al. (2022) and Abrahamsen et al. (2024) also confirmed that historical underwriting performance influences long-term financial stability. Therefore, this ratio is used as a primary predictor in early warning models.
H5: The lagged combined ratio has a positive and significant effect on financial distress.

Conceptual Framework
The conceptual framework illustrates the relationship between five independent variables—Return on Assets (ROA), Equity Ratio, Management Expense Ratio, Reinsurance Ratio, and Lagged Combined Ratio and the dependent variable, Financial Distress. Each independent variable has an arrow pointing toward Financial Distress, indicating a direct influence. This model shows that profitability and capital strength can reduce the risk of financial distress, while management inefficiency, reinsurance dependence, and poor underwriting performance increase the likelihood of financial distress in non-life insurance companies.

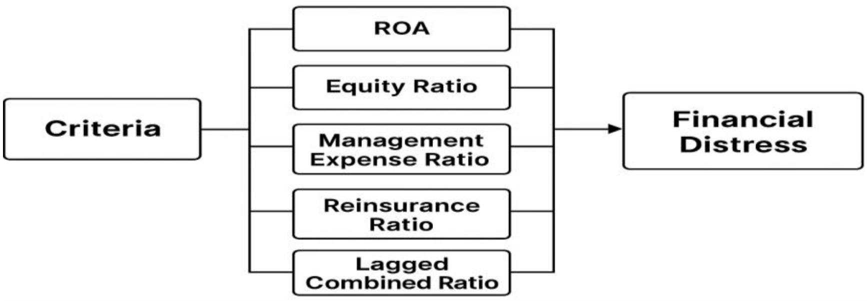

Figure 1. Conceptual Framework

3. Data and Method
We developed a predictive framework to classify financial distress among general insurance companies in Bangladesh using firm-level accounting ratios and supervised machine learning. This section outlines our labeling strategy, feature selection, model set, evaluation protocol, and robustness checks. We designed the workflow to reflect regulatory requirements, emphasizing out-of-time validation, interpretable predictors, and sensitivity analyses that inform operational implementation.

This dataset covers all general insurance companies operating in Bangladesh from 2014 to 2024. Financial data were collected from each insurance company's annual report and the Bangladesh Insurance Association (BIA) yearbook. The final dataset consists of 506 company-year observations across 46 companies, including 45 private insurers and one public insurer. However, data for three companies were unavailable for 2024, as their annual reports had not been published as of 31 August 2025. The number of missing values was less than 1% of the total observations.

Data Splitting, Preprocessing, and Balancing

We divided the panel into two sets: a training set (2014-2022) and a test set (2023-2024). We used the training set for learning from observations and the testing set for out-of-sample prediction simulations. Due to the inherent class imbalance caused by the small number of catastrophe insurance companies, we applied the Synthetic Minority Oversampling Technique (SMOTE) to the training dataset to balance the classes and improve the model's ability to learn from limited catastrophe observations without introducing data leakage bias. Furthermore, we standardized all features using StandardScaler from the scikit-learn library in Python to ensure fair and consistent model training. Using this normalization process, we set all features to zero and their standard deviations to 1. This step is crucial for models sensitive to feature scale.

Furthermore, we excluded the current-year combined ratio from the feature set to prevent target leakage. Instead, we used the one-period lagged combined ratio as a predictor of financial distress in the main models. Therefore, this adjustment reduces the total number of observations to 460, covering the period 2015 to 2024.

Hyperparameter Tuning and Cross-Validation

We optimized hyperparameters using a 5-fold cross-validation grid search on the training data to improve model performance. This approach divides the training data into five folds, trains the model on four folds, and evaluates the model's performance on the remaining fold. This process is repeated across all combinations within the specified hyperparameter grid to identify the best hyperparameters based on the F1 score. We then retrained each model with optimal hyperparameters on the full training set using a similar processing pipeline, including mean imputation, feature scaling, and SMOTE.

Robustness Checks

To assess the reliability of the best predictive models, we applied several robustness checks. First, we used alternative resampling methods on the best-performing models. Here, we tested Adaptive Synthetic Sampling (ADASYN) and no resampling, in addition to SMOTE, to assess the impact of different class imbalance handling techniques. Second, we performed feature reduction based on SHAP values. We train the model on the reduced set of features to examine its results after excluding low-importance and highly correlated variables. Third, we maintained consistent time-based validation. We compared performance across these variations using standard metrics, with the results discussed in the results section and visualizations provided in the appendix.

4. Results

Summary Statistics and Preliminary Analyses

The dataset comprises 506 company-year observations from 46 non-life insurers in Bangladesh over the period 2014 to 2024. Among 506 observations, three of the company's 2024 data were imputed with mean values due to missing values. Using the criterion of a combined ratio greater than 1, Table 6 shows that 404 observations (79.84%) correspond to non-distressed insurers, while 102 (20.16%) correspond to distressed insurers. Moreover, the yearly distribution of distress shows notable year-to-year fluctuations in the proportion of the distressed insurers in Bangladesh from 2014 to 2024. Table 1 presents the percentage of distress company-year observations and their actual counts for the combined ratio criteria.

Table 1. Yearly Distribution of Financial Distress

Year	Non-distressed	Distressed	Distressed (%)
2014	31	15	32.61
2015	34	12	26.09
2016	38	8	17.39
2017	41	5	10.87
2018	34	12	26.09
2019	36	10	21.74

2020	37	9	19.57
2021	43	3	6.52
2022	36	10	21.74
2023	36	10	21.74
2024	38	8	17.39
Total	**404**	**102**	**100%**

Source: Processed data 2025

Yearly distributions of distress show that 2014 had the highest proportion (32.61%), followed by 2015 and 2018. In contrast, 2021 had the lowest distress rate (6.52%). This variability over time underscores the impact of several drivers, including macroeconomic shifts, regulatory changes, and company-level management strategies, on financial outcomes. Moreover, it justifies the inclusion of time-variant factors (a lagged combined ratio) in the prediction of financial distress.

Table 2 presents a comparative analysis of group means, along with the results of the t-test comparing the feature means between distressed and non-distressed insurers. The distressed insurers exhibit lower ROA, Equity ratios, and premium growth, as well as smaller company size. Moreover, they have a high management expense ratio, greater reliance on reinsurance transfers, high leverage, and a higher lagged combined ratio. Additionally, the t-test results indicate that ROA, reinsurance ratio, and management expense ratio exhibit statistically significant differences in their mean values between distressed and non-distressed insurers. The results suggest that poor profitability and high operational costs, coupled with a high reliance on reinsurance facilities, can be associated with financial distress.

Table 2. Comparative Analysis of Group Means

Feature	Mean (Distressed)	Mean (non-distressed)	Mean Difference	P-value
ROA	0.0585	0.0708	-0.0123	**0.0046***
Equity Ratio	0.3294	0.3335	-0.0042	0.8528
Reinsurance Ratio	0.4645	0.4010	0.0635	**0.0000***
Mgt. Exp Ratio	0.6203	0.4192	0.2011	**0.0000***
Investment Yield	0.499	0.4461	0.0528	0.3346
URR Ratio	0.4181	0.4055	0.0126	0.2105
Company Size	3.1922	3.1961	-0.0038	0.9119
Leverage	0.6706	0.6665	0.0042	0.8528
Premium Growth	0.0626	0.1299	-0.0674	0.1136
Lagged Combined Ratio	0.8198	0.7843	0.0355	0.4581

Source: Processed data 2025

We conduct a Variance Inflation Factor (VIF) analysis to assess multicollinearity among the features selected for predicting financial distress. Table 3 shows that two important features, Leverage and Equity ratio, exhibit high VIF values. However, we retain these variables because our goal is to achieve predictive accuracy in modeling financial distress rather than to interpret coefficients. Additionally, we use logistic regression as a benchmark model, and the three-based models (Random Forest and XGBoost) are robust to multicollinearity by design. As these models form the core of our analysis, multicollinearity does not adversely affect their predictive performance.

Table 3. Multicollinearity

Feature	VIF
ROA	1.109765
Equity Ratio	15.72185
Reinsurance Ratio	1.172303
Mgt Exp Ratio	1.236439
Investment Yield	1.090808
URR Ratio	1.14585

Company Size	1.644624
Leverage	89.15425
Premium Growth	1.015793
Lagged Combined Ratio	1.020458

Source: Processed data 2025

In summary, these descriptive statistics and preliminary analyses provide a solid foundation for subsequent predictive modeling with benchmark, classical, and ensemble models.

Model Performance Using Default Settings

After preliminary data analysis and preprocessing, we employ five supervised machine learning models. The models include Logistic regression, KNN, SVM, Random Forest, and XGBoost. We implement all models with their default hyperparameters. We imply missing values through their mean values. We apply SMOTE to address class imbalance, as distressed companies are a minority here (20.12%). Therefore, we train the models on the 2014-2022 dataset and evaluate them on the 2023-2024 test set. Table 4 summarizes the results of the models with their default hyperparameters. We present detailed classification results in the form of a Confusion Matrix for all models in Figure OA1 of the Online Appendix.

Table 4. Default Model Performance Summary

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.7065	0.3714	0.7222	0.4906	0.7538
K-Nearest Neighbors	0.7609	0.4231	0.6111	0.5000	0.7395
Support Vector Machine	0.7935	0.4815	0.7222	0.5778	0.8071
Random Forest	0.8152	0.5238	0.6111	0.5641	0.8431
XGBoost	0.7717	0.4545	0.8333	0.5882	0.8468

Source: Processed data 2025

The results in Table 4 show that Logistic regression, as a benchmark model, achieves a test accuracy of 70.65% and a recall of 72.22% for detecting financially distressed insurers. The ROC score of 0.75 and limited precision (0.37) indicate moderate discriminatory power in detecting financial distress, with the potential to misclassify some healthy insurers as distressed.

Among the KNN and SVM models, the Support Vector Machine achieves balanced performance with 79% accuracy and 72% recall. Moreover, the ROC-AUC of 0.81 signifies strong sensitivity to distressed cases. In comparison, K-Nearest Neighbors (KNN) demonstrated slightly lower performance than SVM, with an accuracy of 76% and a recall of 61%. The ROC-AUC also indicates moderate predictive performance for the KNN model.

Between two ensemble models, Random Forest exhibits robust performance, reaching 82% accuracy, with precision and recall of 0.52 and 0.61, respectively. The ROC-AUC of 0.84 suggests effective distinction between distressed and non-distressed insurers. However, XGBoost outperforms other models, achieving the highest recall of 0.83 and an accuracy of 77%. As shown in the ROC curves in Figure OA3 of the Online Appendix, the ensemble models, Random Forest and XGBoost, achieve higher accurate positive rates across a range of thresholds than the default models.

Overall, the models exhibit reasonable predictive capacity, with ROC-AUC values above 0.70. Notably, all the models have lower precision than recall, which is expected given the dataset's small number of distressed firms. According to the F1 score and ROC-AUC, the XGBoost model outperforms other models with its default settings.

Model Tuning and Evaluation

We perform 5-fold cross-validation and hyperparameter tuning using a grid search as part of the robustness check. Grid search allows us to systematically test different combinations of hyper-parameters for each model to find the best-performing combinations. Whereas the 5-fold cross-validation splits the training data into five parts, the model trains on four and validates on the 5th. With five repeating processes, we use the average F1 score to select the hyper-parameters to ensure the most reliable performance. Table 5 summarizes the best hyperparameters of the models, along with their average F1 scores.

Table 5 Model Performance and Best Hyper-parameters

Model	Best Hyper-parameters	CV F1 Score	Default Model F1 Score	Tuned Model F1 Score
Logistic Regression	Regularization strength (C) = 0.01, Penalty type (L1/L2) = L2, Solver choice = *lbfgs*	0.5095	0.4906	0.4815
K-Nearest Neighbors	Number of neighbors = 9, Distance metric = Manhattan, Weight function = Distance	0.5601	0.5000	0.5833
Support Vector Machine	Regularization parameter (C) = 1, Gamma = Scale, Kernel type = RBF	0.5215	0.5778	0.5000
Random Forest	Number of trees = 200, Maximum tree depth = None, Minimum samples per split = 2	0.5724	0.5641	0.5714
XGBoost	Learning rate = 0.01, Maximum tree depth = 3, Number of Estimator = 50, Subsample ratio =1	0.6300	0.5882	0.5614

Source: Processed data 2025

Table 6 presents mixed yet meaningful results for the model's performance after tuning with the best hyperparameters. Logistic regression maintains almost similar accuracy around 70% and ROC-AUC of 0.75. This indicates that, despite tuning, the benchmark model shows only limited improvement in predictive capacity. The tuned KNN model achieves 78% accuracy, 78% recall, and an ROC-AUC value above 0.80. The overall gain demonstrates that a tuned KNN model gains better predictive power in detecting distress. However, the tuned SVM model underperforms the default SVM models, achieving an accuracy of 72% and a similar recall of 72%.

Table 6. Tuned Model Performance Summary

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.6957	0.3611	0.7222	0.4815	0.7515
K-Nearest Neighbors	0.7826	0.4667	0.7778	0.5833	0.8078
Support Vector Machine	0.7174	0.3824	0.7222	0.5000	0.7538
Random Forest	0.8043	0.5000	0.6667	0.5714	0.8296
XGBoost	0.7283	0.4103	0.8889	0.5614	0.8641

Source: Processed data 2025

Hyper-parameters tuning improves the performance of both three-based models. On the one hand, the Random Forest model achieves better recall and F1 scores at the cost of a slight drop in ROC-AUC. On the other hand, the post-tuned XGBoost model achieves strong results, with the highest recall and ROC-ACU, confirming its effectiveness. The confusion matrices after tuning present additional insights into how hyperparameter optimization affected the classification outcomes, particularly improving the identification of distressed firms (see Figure OA2 in the Online Appendix).

Overall, tuning with hyperparameters has a varying effect across models: an increase in recall and precision with a slight drop in accuracy. After tuning, the ensemble models maintain strong performance across all evaluation measures, while XGBoost maintains its supremacy in detecting financial distress as reflected in its ROC-AUC. The ROC curves for the tuned models (see Figure OA4 in the Online Appendix) demonstrate the improved discriminatory power of XGBoost and KNN models, especially in detecting distressed insurers. Therefore, these findings emphasize the need to optimize hyperparameters to increase the reliability and accuracy of predicting financial distress in the Bangladesh non-life insurance market.

Feature Importance in Predictive Analysis

The XGBoost model shows better consistency in both the default and tuned models across all evaluation measures. Subsequently, we examine feature importance using an XGBoost model to identify the key financial drivers of financial distress prediction in non-life insurers in Bangladesh. To identify feature importance, we use SHAP, a widely used method for explaining the output of machine learning models. Table 7 shows the Mean SHAP values, whereas Figure OA5 in the Online Appendix presents the feature-importance plot generated by the XGBoost model, highlighting the management expense ratio, reinsurance ratio, and lagged combined ratio as leading predictors.

Table 7. Shapley Additive Explanations

Feature	Mean SHAP Value	Importance %
Management Expense Ratio	0.89	43.53
Reinsurance Ratio	0.32	15.63
Lagged Combined Ratio	0.25	12.25
ROA	0.20	9.82
URR Ratio	0.12	6.03
Company Size	0.10	4.84
Premium Growth	0.08	3.78
Investment Yield	0.07	3.45
Equity Ratio	0.01	0.65
Leverage	0.00	0.02

Source: Processed data 2025

The sorted mean SHAP values indicate that the management expense ratio is the most powerful indicator of financial distress in the Bangladesh non-life insurance market, accounting for nearly 44% of the model's decision. This suggests that higher operating costs are positively related to financial distress. Further, the reinsurance ratio and the combined ratio, with a one-period lag, together account for almost 28% of the model's decision. This indicates that, in the non-life insurance market, risk management practice and past underwriting performance play a critical role. These three indicators dominate approximately 70% of the decisions made by the XGBoost model. However, profitability measures and reserve adequacy ratio also improve the model performance in identifying distressed firms. Other variables, such as company size, premium growth, and investment yield, have a moderate influence, while two indicators equity ratio and leverage have minimal impact on model performance. To further interpret the model's decisions, we present SHAP value-based feature importance in Figure OA6 of the Online Appendix, showing how each feature influences the model’s output in predicting distress.

This feature analysis highlights that expense management, prior underwriting outcomes, and risk transfer strategies serve as critical early warning signals for predicting financial distress among non-life insurers in Bangladesh.

Robustness Check

We conduct several robust checks to ensure the reliability and stability of the XGBoost model. The reliability test evaluates model performance under varying class-imbalance handling strategies using a reduced feature set, eliminating financial indicators with lower mean SHAP values. Table 8 shows the result of the robustness check.

Table 8. Robustness Check

Re-sampling	Feature Set	Accuracy	Precision	Recall	F1-Score	ROC-AUC
SMOTE	Full Features	0.793	0.485	0.889	0.627	0.865
ADASYN	Full Features	0.783	0.471	0.889	0.615	0.865
None	Full Features	0.837	0.571	0.667	0.615	0.856

SMOTE	Reduced Features	0.761	0.444	0.889	0.593	0.884
ADASYN	Reduced Features	0.750	0.429	0.833	0.566	0.860
None	Reduced Features	0.837	0.579	0.611	0.595	0.843

Source: Processed data 2025

We compare the model's performance across three resampling strategies: SMOTE, ADASYN, and no resampling. Both SMOTE and ADASYN improved recall (around 88.89%) at the expense of low precision. In contrast, no resampling method achieves the highest accuracy and precision, with a low recall (61%). These trade-offs demonstrate the challenges of identifying minor events in a limited dataset and thereby support the use of SMOTE in our models to identify the distressed companies.

Further, we tested the XGBoost model with a reduced set of eight features, removing the equity ratio and leverage due to their low SHAP values. The results show a minimal drop in performance, confirming that these two features have low predictive power.

Overall, these robustness checks confirm the stability and predictive validity of the XGBoost model across various preprocessing scenarios, reinforcing its suitability for early warning systems in Bangladesh's non-life insurance sector to predict financial distress.

5. Discussion

Effect of Return on Assets (ROA) on Financial Distress

The finding that Return on Assets (ROA) negatively affects financial distress indicates that more profitable firms are less likely to experience financial instability. This aligns with profitability theory, which suggests that efficient asset utilization enhances earnings and liquidity, enabling firms to meet financial obligations successfully. The result reinforces the perspectives of Ohlson (1980) and Altman (1968) that profitability serves as a buffer against financial shocks. Similar findings by Kebede, Tesfaye, and Erana (2024) and Ayinaddis and Tegegne (2023) showed that higher ROA significantly reduces the likelihood of financial distress in insurance firms. In the context of non-life insurers in Bangladesh, this relationship underscores the importance of operational efficiency and effective investment management in maintaining solvency. Profitability thus serves as an early indicator of resilience, underscoring that sustained earnings power is vital for long-term financial health.

Effect of Equity Ratio on Financial Distress

The negative relationship between equity ratio and financial distress suggests that stronger capitalization enhances the financial stability of non-life insurers. According to capital structure theory, firms with greater equity financing capacity exhibit greater shock absorption capacity and lower debt-service pressure (Bragoli et al., 2021). The results are consistent with previous studies by Petropoulos, Siakoulis, Stavroulakis, and Vlachogiannakis (2020) and Valaskova, Kliestik, Svabova, and Adamko (2018), which found that adequate capital reduces insolvency risk in financial institutions. This implies that the equity ratio is a critical indicator of risk-bearing capacity and regulatory solvency. In developing markets such as Bangladesh, where financial systems are often undercapitalized, maintaining a robust equity base is essential to mitigate exposure to market volatility and unexpected claims. The findings confirm that a firm's capital adequacy plays a central role in reducing the probability of distress.

Effect of Management Expense Ratio on Financial Distress

The positive and significant effect of the management expense ratio on financial distress demonstrates that operational inefficiency and excessive administrative spending increase the risk of financial instability. From an agency theory perspective, this result indicates misalignment between managerial actions and shareholder interests, as inefficient cost management erodes profitability and solvency (Liang, Tsai, Lu, & Chang, 2020). Empirical evidence from Kebede et al. (2024) and Grize, Fischer, and Lützelschwab (2020) supports this finding, emphasizing that higher management expenses reflect weak internal controls and poor governance practices. In the context of non-life insurance, excessive management costs may also signal ineffective underwriting strategies or misallocation of resources. Thus, firms that fail to optimize their operational expenditure are more vulnerable to liquidity shortages and long-term financial distress. The results underline the importance of efficient managerial control systems in ensuring organizational sustainability.

Effect of Reinsurance Ratio on Financial Distress

The results showing a positive relationship between the reinsurance ratio and financial distress indicate that over-reliance on reinsurance can undermine a firm's financial stability. Although reinsurance is intended to transfer risk and stabilize earnings, excessive reliance can reduce retained premiums and profitability (Grize et al., 2020). This finding aligns with Ayinaddis and Tegegne (2023) and Kebede et al. (2024), who reported that insurance firms with high reinsurance ratios are more prone to financial distress due to reduced revenue retention and exposure to counterparty risk. Theoretically, contingent claims and underwriting cycle theories suggest that over-reinsurance may signal weak internal risk management and insufficient capital to absorb shocks. In emerging markets, such patterns often reflect limited underwriting capacity rather than prudent risk sharing. Therefore, while reinsurance remains an essential risk mitigation tool, its overuse may paradoxically amplify financial vulnerability if not balanced with sufficient retained earnings.

Effect of Lagged Combined Ratio on Financial Distress

The positive relationship between the lagged combined ratio and financial distress indicates that past underwriting performance significantly affects a firm's current solvency. Underwriting cycle theory explains that losses from prior periods create a cumulative financial burden that weakens liquidity and profitability over time (Grize et al., 2020). Consistent with Kebede et al. (2024) and Wu, Yang, and colleagues (2022), this study finds that firms with consistently high combined ratios face higher distress risks due to persistent inefficiencies in risk assessment and claims management. In the non-life insurance sector, underwriting discipline directly determines long-term financial health. The persistence of high combined ratios suggests that firms may be engaging in aggressive premium competition or underpricing, which eventually erodes financial reserves. The finding emphasizes the need for prudent underwriting strategies and accurate risk pricing to sustain profitability and avoid cumulative financial distress.

6. Conclusion

We set out to build an explainable, operationally viable early-warning framework for non-life insurer distress in a small, emerging market context. Motivated by the social costs of delayed claim settlement and the policy need for intelligible supervisory tools, this study evaluates a range of classifiers and experiments with class-imbalance remedies. It employs SHAP-based explanations to map predictions back to accounting indicators. The findings reveal that tuned gradient-boosted models deliver superior out-of-time recall. At the same time, SHAP explanations consistently identify management expense ratios, lagged underwriting performance, and reliance on reinsurance as key early-warning signals. Empirical evidence shows that operational ratios are more critical than traditional capital metrics for early detection in thin-premium insurance markets, refining theoretical expectations from capital-structure and underwriting-cycle perspectives.

Furthermore, this research contributes methodologically by offering a replicable pipeline that balances predictive performance with explainability, demonstrating how ensemble models combined with feature-attribution tools can be tailored to policy loss functions. It also bridges method and practice by showing that compact accounting-based models can remain robust under feature reduction and time-based validation, thereby enhancing feasibility for adoption in resource-constrained regulatory environments. Nevertheless, limitations remain in label construction, lag choice, cross-market generalizability, and governance aspects of model deployment. Future research should expand the pipeline to include stress scenarios, hybrid data integration, and pilot implementations with regulators to align model outputs with institutional capabilities and supervisory needs.

From a managerial standpoint, the study provides valuable insights for insurance executives and regulators in emerging markets. Managers should prioritize improving operational efficiency by controlling management expenses, enhancing underwriting discipline, and optimizing reinsurance dependency to mitigate early signs of financial distress. The explainable model framework can serve as a managerial decision-support tool to monitor solvency health and anticipate potential risks before they escalate. Regulators, in turn, can utilize these models as supervisory instruments to identify vulnerable insurers, allocate oversight resources efficiently, and design targeted interventions. By integrating predictive analytics with managerial and regulatory decision-making, this framework strengthens both organizational resilience and systemic stability in the non-life insurance sector.

Recommendation

Insurance managers should strengthen internal monitoring systems by regularly evaluating key operational ratios particularly management expense, underwriting performance, and reinsurance dependency to detect early signs of distress. Regulators are advised to adopt explainable machine learning based early-warning frameworks to enhance supervisory precision and transparency. Additionally, policymakers should promote standardized accounting disclosures and capacity-building programs to support model-driven supervision. Collaboration between insurers and regulators is essential to calibrate risk thresholds, ensure timely interventions, and maintain financial stability within the non-life insurance sector.

Limitations and avenues for future research

This study is limited by its reliance on standard accounting data and a distress labeling approach based solely on underwriting performance, which may not capture broader macro-financial dynamics. The analysis also focuses on a single market context, limiting generalizability. Future research should incorporate stress-testing scenarios, cross-country comparisons, and alternative data sources to enhance predictive accuracy and adaptability across diverse regulatory environments.

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