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Early Detection of Financial Distress in Islamic Banking Using Explainable Artificial Intelligence

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ABSTRACT

This paper examines the effectiveness of an explainable machine learning–based Early Warning System (EWS) in detecting financial distress in Islamic banking. Following recurrent episodes of financial instability, regulators and bank managers increasingly require predictive tools that are not only accurate but also interpretable. This study aims to develop a transparent and reliable distress prediction framework for Indonesian Islamic banks. Conventional early warning models can signal which banks are at risk but fail to explain why distress occurs at the variable level, limiting their usefulness for supervisory intervention. This study introduces an integrated Explainable Artificial Intelligence (XAI) framework that combines ensemble tree-based machine learning with SHAP and LIME to uncover non-linear threshold effects in the risk–stability relationship an aspect largely overlooked in prior Islamic banking studies. Using panel data from Indonesian Islamic banks over the period 2014–2024, financial distress is modeled as a binary outcome based on asset quality and profitability thresholds. Predictive performance is evaluated using Random Forest algorithms and benchmarked against conventional logit models, while interpretability is achieved through SHAP and LIME analyses. The results show perfect predictive separation (AUC = 1.00), with operational inefficiency (BOPO), profitability (ROA), and asset quality (NPF Gross) emerging as dominant risk drivers, exhibiting clear non-linear threshold effects. The study concludes that explainable machine learning significantly enhances both predictive accuracy and supervisory interpretability, offering a robust and policy-relevant tool for early intervention in Islamic banking stability.

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INTRODUCTION

Financial system stability constitutes a fundamental pillar in sustaining economic growth and maintaining public confidence in the banking industry (Barra & Zotti, 2021; Ullah et al., 2024; Ijaz et al., 2020; Oino, 2021). The experience of the global financial crisis and various episodes of post-crisis systemic stress demonstrate that the failure of a single banking institution can trigger widespread contagion effects across the entire financial system (T. Sun, 2025; B. Sun & Liu, 2025; Chen et al., 2021). In examining this, the main argument of this study is that conventional and Islamic banks both face limitations in predicting financial distress, and the incorporation of explainable AI methods is essential for improving risk assessment and supervisory interventions. In this context, Islamic banking, which normatively emphasizes prudence, risk sharing, and the prohibition of speculation, is often assumed to possess a higher level of resilience compared to conventional banking (Majid et al., 2025; Abasimel, 2022; Faizulayev, 2025; Butt & Chamberlain, 2025). However, recent empirical evidence indicates that Islamic banks remain vulnerable to liquidity pressures, deterioration in asset quality, and trade-offs between stability and profitability, particularly during periods of economic turbulence (Safdar et al., 2024; Bouheni et al., 2021; Mohammad et al., 2020; Paltrinieri et al., 2020).

Along with the increasing complexity of risks and nonlinear dynamics in the financial industry, conventional approaches to detecting financial distress are facing growing limitations (Liu, 2025; Yin, 2025; Gao et al., 2025). Traditional Early Warning Systems (EWS) based on financial indicators generally provide only probabilistic signals of bank failure risk, without explaining the specific mechanisms underlying such risks (Purnell et al., 2024; Alshareefi & Alshamari, 2024; Filippopoulou et al., 2020). These limitations are becoming increasingly critical for regulators and bank management, who require not only accurate predictions but also actionable insights at the variable and policy levels (Wang et al., 2021; Kovalenko & Petruk, 2025).

In recent years, ensemble tree–based machine learning (ML) algorithms such as Gradient Boosting (XGBoost and LightGBM) have demonstrated superior performance in predicting financial distress due to their ability to capture nonlinear patterns, complex interactions, and data imbalance (Qian et al., 2021; J. Liu et al., 2022). However, these predictive advantages are overshadowed by a major criticism related to their black-box nature, which undermines the legitimacy of ML adoption in public policy and financial supervision contexts (Carmona et al., 2022; Amirshahi & Lahmiri, 2024). Therefore, the integration of Explainable Artificial Intelligence (XAI) has emerged as a strategic research agenda to bridge the gap between predictive accuracy and the need for interpretability.

The primary challenge in the early detection of financial distress in Islamic banking does not lie in the availability of data or financial indicators, but rather in the inability of conventional models (Mehreen et al., 2020; Asutay & Othman, 2020) and traditional EWS to explain why a bank is at risk. Most econometric approaches, such as logit or probit regressions, assume linear and stable relationships among variables, thereby failing to capture threshold effects and regime shifts that are inherently nonlinear. On the other hand, although machine learning is capable of improving predictive accuracy, these models often produce outputs that lack transparency for regulators. In supervisory practice, information stating that "Bank A is at risk of distress," without detailed explanations of variable contributions such as NPF Net, CAR, impairment reserves, or operating efficiency ratios, is insufficient for designing well-targeted policy interventions. Consequently, there is an inherent tension between the need for predictive precision and the demands for accountability and policy interpretability.

The literature on the application of Machine Learning (ML) and Explainable Artificial Intelligence (XAI) in the financial sector has developed rapidly over the past decade, particularly in areas such as credit risk, financial distress prediction, and fraud detection. However, this development remains characterized by fragmented research focuses in terms of study objects, methodological approaches, and the depth of integration with economic theory and financial stability frameworks. Broadly, the financial distress prediction literature can be classified into three major streams: econometric approaches based on financial ratios that excel in statistical significance but are limited in capturing nonlinearity and complex interactions; machine learning approaches that emphasize predictive accuracy but often overlook interpretability and theoretical implications; and Islamic banking studies that remain relatively limited in adopting advanced analytical approaches.

A recent study by Gafsi (2025) represents an important effort to integrate tree ensemble–based ML algorithms with explainability analysis using SHAP to predict credit risk in both participation banks and conventional banks in the United Kingdom. The main findings of the study highlight the dominance of bank-specific microeconomic variables over macroeconomic factors in predicting non-performing loans. Nevertheless, the study remains limited to credit risk and does not explicitly examine financial distress as a systemic phenomenon involving the simultaneous interaction of operational efficiency, capitalization, and bank stability.

On the other hand, the conceptual literature on XAI in finance has advanced significantly through various systematic reviews and meta-surveys, such as those conducted by Martins et al. (2024), Arsenault et al. (2024), Weber et al. (2023), Dwivedi et al. (2022), Hassija et al. (2023), Saeed & Omlin (2021), and Černevičienė & Kabašinskas (2024). These studies emphasized the urgency of transparency, accountability, and trust in the application of AI within high-risk sectors such as banking. However, the predominantly conceptual nature of these studies results in limited empirical evidence directly linking XAI to the dynamics of banking stability, particularly within the context of Islamic banking in developing countries. At the micro-empirical level, Nallakaruppan et al. (2024) and De Lange et al. (2022) demonstrated that the combination of ML and XAI could enhance both accuracy and interpretability in credit risk assessment. Nevertheless, their focus is confined to the level of individual borrowers rather than institutional bank distress as a systemic entity. Meanwhile, studies by Ghosh (2025), Awosika et al. (2023), Aljunaid et al. (2025), and Leelavathi et al. (2025) develop XAI-based models for fraud detection and cybersecurity with remarkably high accuracy, yet they do not examine the relationship between banking financial ratios and the risk of failure or financial system stability.

Research that directly examined XAI-based financial distress prediction remains relatively limited. Zhang et al., (2022) provide an important contribution through the development of an explainable ensemble learning framework for publicly listed non-financial firms in China; however, differences in risk characteristics between the non-financial sector and the banking industry particularly Islamic banking constrain the generalizability of these findings. Moreover, most prior studies continue to treat the relationship between financial indicators and risk as linear or monotonic, while rarely exploring threshold effects and nonlinear tipping points that may transform banking soundness indicators from stabilizing mechanisms into sources of vulnerability. These limitations are further reinforced by the scarcity of studies employing long-span datasets across multiple economic eras, including pre-crisis, COVID-19 crisis, and post-crisis periods. Building on these research gaps, there remains substantial room for studies that systematically integrate high-performance machine learning with Explainable AI in the context of Islamic banking, uncover nonlinearities and threshold effects in banking soundness indicators, and situate empirical findings within the Fragility Risk Stability Nexus framework with adequate temporal coverage.

This study offers a solution through the development of an Explainable AI (XAI)-based Early Warning System that integrates ensemble tree-based machine learning algorithms with model interpretation techniques such as SHAP (SHapley Additive exPlanations) and LIME. This approach enables highly precise financial distress prediction while providing a decomposition of each financial variable’s contribution to distress probability, both globally and locally. By defining financial distress based on critical ratio thresholds such as NPF Net and CAR the proposed model not only identifies risky conditions but also reveals tipping points at which certain ratios shift their role from stability safeguards to sources of vulnerability. The primary motivation of this research stems from the urgent need for banking supervision systems that are intelligent, transparent, and adaptive to modern risk complexities. For regulators such as the Financial Services Authority (OJK), an in-depth understanding of risk formation mechanisms is more valuable than merely aggregate warning indicators. For bank management, information regarding which variables serve as leading indicators of distress enables more proactive and efficient risk mitigation strategies. Academically, this study is motivated to transcend linear approaches and “open the black box” of ML to produce theory-informed evidence that enriches the literature on financial stability and Islamic banking.

This study aims to develop a precise and transparent early warning system for predicting financial distress risk in Indonesian Islamic banks during the period 2014 to 2024, while simultaneously disentangling the nonlinear mechanisms underlying these risks using an Explainable Artificial Intelligence approach. Specifically, it seeks to compare predictive performance between conventional econometric models and ensemble tree-based machine learning algorithms; identify dominant determinants and the relative importance of Islamic banking soundness indicators; and uncover nonlinear relationships and threshold effects through Shapley Additive Explanations. In addition, this study evaluates the robustness and stability of prediction models across different economic eras including changes in risk structure during the COVID-19 pandemic and provides an interpretability framework based on Local Interpretable Model-Agnostic Explanations to support more precise, evidence-based, and accountable supervisory policymaking.

This research offers several key contributions. Theoretically, it enriches the Fragility–Risk–Stability Nexus by demonstrating that indicators normatively perceived as "safe", such as high impairment reserves may turn into signals of hidden insolvency or managerial inefficiency once they exceed certain thresholds, consistent with the Bad Management Hypothesis. This finding underscores that banking stability is nonlinear and contextual. Methodologically, this study addresses the principal criticism of ML in economics by integrating XAI, thereby generating models that are not only accurate but also explainable and accountable. Practically, the findings provide strong empirical grounds for regulators and bank management to implement more targeted evidence-based supervision. Overall, this study positions Explainable AI as a strategic bridge between methodological innovation and policy needs in safeguarding Islamic banking stability amid increasingly complex risk dynamics.

METHOD, DATA, AND ANALYSIS

This study used a quantitative predictive analytics approach, which involved applying statistical and mathematical techniques to identify patterns based on data, with machine learning methods that enabled models to learn from data and improve predictions over time. Its main goal is to develop an Early Warning System (EWS) to identify financial distress in Islamic banking. It also interprets machine learning models—often considered complex or opaque—by using an Explainable Artificial Intelligence (XAI) framework, which helps clarify how these models make decisions.

This study used secondary balanced panel data from Islamic Commercial Banks (Bank Umum Syariah/BUS) in Indonesia, covering 2014 to 2024. The data came from quarterly and annual financial reports by the Financial Services Authority (OJK) and bank websites. The dataset included key financial ratios for capital adequacy, asset quality, earnings, and operational efficiency. Data cleaning is applied to fix missing values and reporting inconsistencies. The dependent variable is Financial Distress status (Y). Instead of a binary approach based only on legal bankruptcy, this study built a Composite Distress Index using regulatory thresholds and operational criteria. A bank was Distressed (Y = 1) if it met either:

(1) Net NPF ratio > 5% (exceeds OJK's credit risk threshold), or (2) ROA ratio < 0.5% (shows profitability inefficiency or possible losses). The target function is defined as follows:

$$Y_{it} = \begin{cases} 1, if\ NPF_{net,it} > 5\%\ or\ ROA_{it} < 0.5\% \\ 0, if\ others\ (healthy) \end{cases}$$

The predictor variables (X) included eight key financial ratios: Capital Adequacy Ratio, NPF Gross, NPF Net, Operating Expense to Operating Income Ratio (BOPO), Return on Assets, Non-Performing Assets Ratio, and Loan Loss Provision (CKPN). To prevent overfitting and evaluation bias, the dataset (D) was divided into two mutually exclusive subsets using a stratified sampling. Eighty percent was for model training (D_{train}) and the remaining 20% for model testing (D_{train}). This method kept the proportions of Distressed and Healthy classes balanced in both datasets.

$$D = D_{train} \cup D_{test}, \qquad D_{train} \cap D_{test} = \emptyset$$

This study employed the Random Forest Classifier algorithm, an ensemble learning method that constructs multiple decision trees during the training phase and produces a class prediction based on the mode of the classes (for classification) or the average of predictions (for regression) generated by individual trees. The tree-building mechanism applied a splitting criterion based on Gini Impurity. For a given node t with a class distribution p, the Gini Impurity is calculated as follows:

$$Gini(t) = 1 - \sum_{j=1}^{C} p(j/t)^2$$

Where C denotes the number of classes (in this case, 2: Healthy and 1: Distressed). The algorithm selected the feature and split point that minimizes the Gini Impurity value at the child nodes. The advantages of this method included its robustness to noise, its ability to handle non-linear relationships, and its immunity to multicollinearity among independent variables. Model performance was evaluated using the test dataset (D_{train}) through several metrics derived from the Confusion Matrix. Accuracy was employed to describe the proportion of correct predictions relative to the total number of observations. Sensitivity or recall reflected the model's ability to correctly identify banks that were truly in financial distress. In addition, the model's discriminatory capability was assessed using the Area Under the Curve–Receiver Operating Characteristic (AUC-ROC), which measured the model's ability to distinguish between positive and negative classes, where an AUC value of 1.0 indicated perfect class separation.

To further interpret the complex Random Forest model, this study applies a cooperative game theory approach using SHAP values. These values quantify the marginal contribution of each feature (financial ratio) to the predicted probability of distress. The SHAP value (Øi) for a feature is defined as the weighted average of its marginal contribution across all possible combinations of features:

$$\emptyset_i(f,x) = \sum_{z' \subseteq x'} \frac{|z'|!\,(M - |z'| - 1)!}{M!}\left[f_x(z') - f_x(z' \backslash \{i\})\right]$$

This analysis enables the presentation of several complementary forms of visualization. Global importance visualization identifies macro-level determinants that shape overall banking risk. Dependence plots reveal non-linear relationships among variables and detect threshold effects influencing risk shifts. At a more micro level, local waterfall plots diagnose specific factors contributing to financial distress on an individual basis. This provides a deeper understanding of each bank's conditions.

RESULTS AND DISCUSSION

Figure 1 presents the trend of Return on Assets (ROA) for each Islamic bank during the period 2014–2024, with a red dashed line at the 0.5% level indicating the minimum profitability health threshold. The graph demonstrates substantial heterogeneity in profitability performance across banks, both in terms of average levels and annual volatility. Several banks exhibit relatively stable ROA patterns that consistently remain above the regulatory threshold, reflecting a sustained ability to generate profits. Conversely, other banks display sharp fluctuations, with multiple episodes of negative ROA or values falling below the threshold during specific periods, indicating persistent operational and profitability pressures.

Figure 1 also illustrates the trend of Non-Performing Financing (NPF Net), with a 5% threshold line in accordance with supervisory regulations. The graph reveals that financing risk is not uniformly distributed across banks or over time. Some banks consistently maintain NPF Net below the threshold, while others experience episodic or recurrent spikes in NPF. Together, these two time-series graphs indicate that profitability pressures and financing risks vary significantly among banks and across years, highlighting the need for ongoing monitoring of bank performance. Notably, these risks are specific to individual banks and do not necessarily occur simultaneously across all banks in the same period.

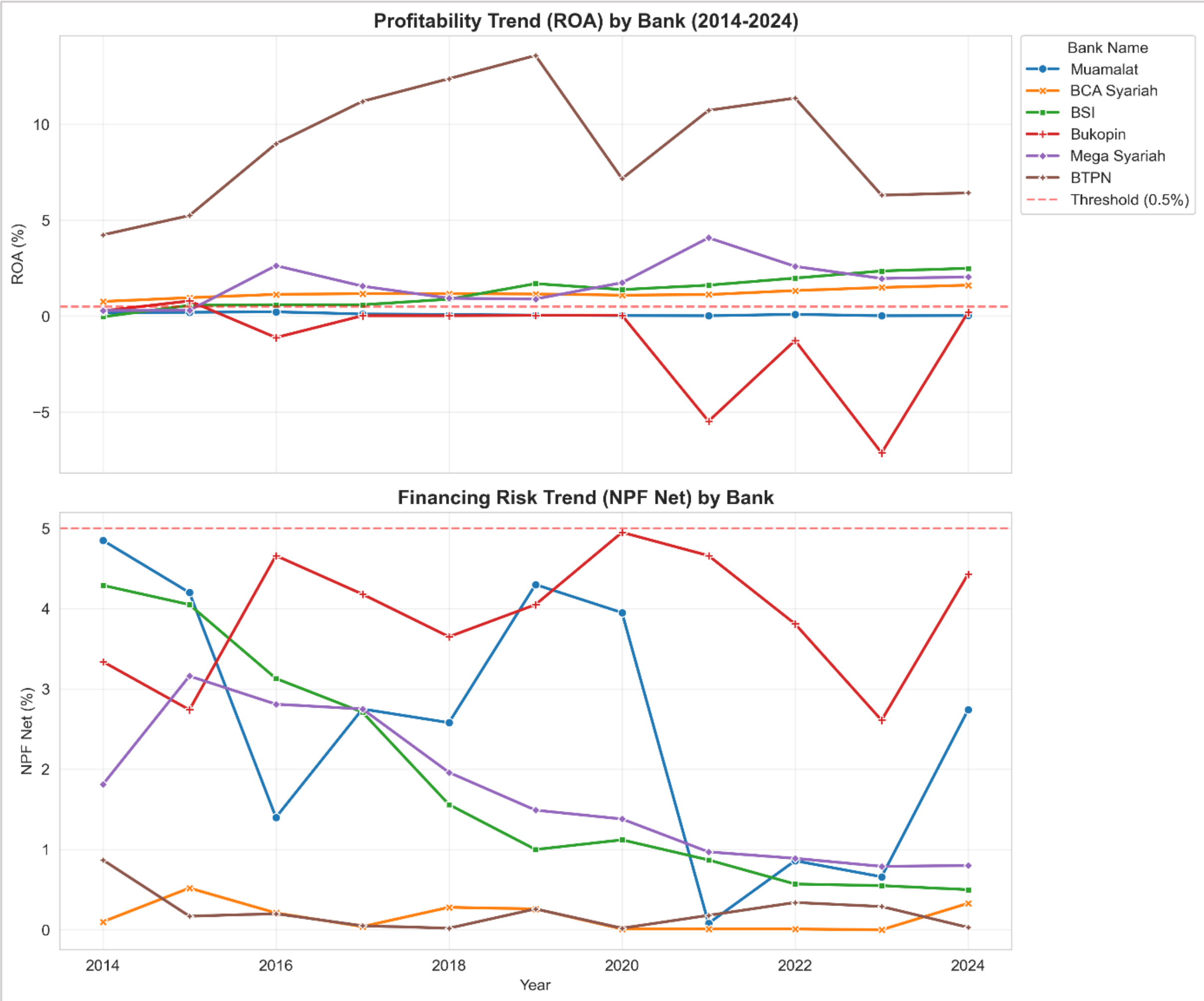

Figure 1. Profitability & Financial Risk Trend by Bank

Source: Python data processing, 2026

Following the assessment of ROA and NPF trends, Figure 2 presents a comparison of the ten-year mean values for key indicators BOPO, CAR, and Gross NPF across Islamic banks. This visualization provides a concise overview of the relative position of each bank in terms of efficiency, capitalization, and asset quality over the medium to long term. The results indicate clear disparities in operational efficiency, as reflected by the BOPO ratio, with several banks exhibiting relatively low and stable levels, while others demonstrate substantially higher values. Overall, capital adequacy ratios appear relatively high; however, notable variation persists across banks due to differences in capital strategies and risk absorption capacity.

Meanwhile, Gross NPF displays wider dispersion, indicating that financing risk management remains a primary source of performance heterogeneity among Islamic banks. Descriptively, this graph directly identifies banks that are, on average, the most efficient and those most exposed to risk over the past decade.

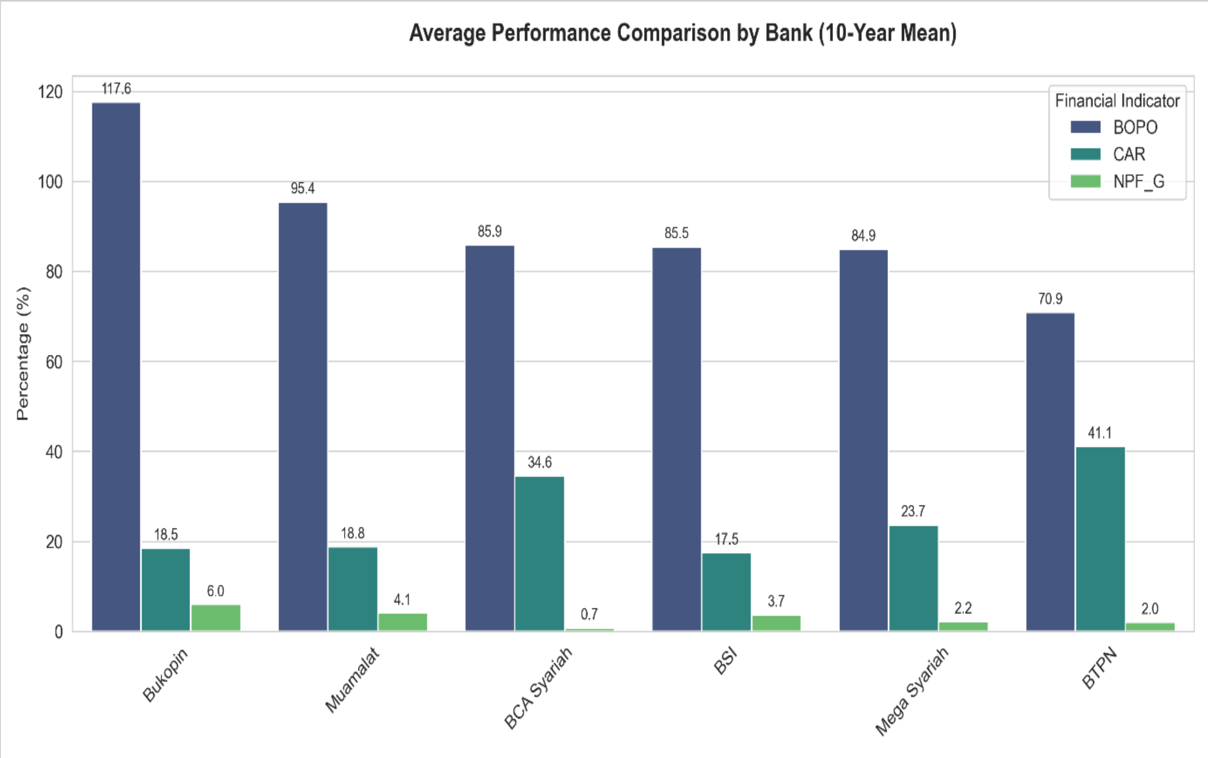

Figure 2. Average Performance Comparison by Bank

Source: Python data processing, 2026

Expanding upon this overview, Figure 3 presents boxplots of the distributions for the key variables (ROA, Net NPF, CAR, and BOPO), complemented by strip plots indicating the positions of individual observations. This visualization enables an assessment of data dispersion, the degree of volatility, and the potential presence of extreme values (outliers). The distribution of ROA exhibits a relatively wide range with a concentration of observations at low to moderate levels, along with several extreme negative values. This indicates that the profitability of Islamic banks is not only structurally low but also vulnerable to sharp fluctuations. The distribution of Net NPF displays a right-skewed pattern, with most observations concentrated at low levels but accompanied by a long right tail due to spikes in NPF during certain periods. This pattern reflects the episodic yet significant nature of credit risk. The distribution of CAR is relatively more concentrated with a high median, indicating a tendency toward strong capitalization, although variation across observations remains. Meanwhile, the distribution of BOPO shows a wide and asymmetric spread, indicating pronounced differences in operational efficiency across banks and over time.

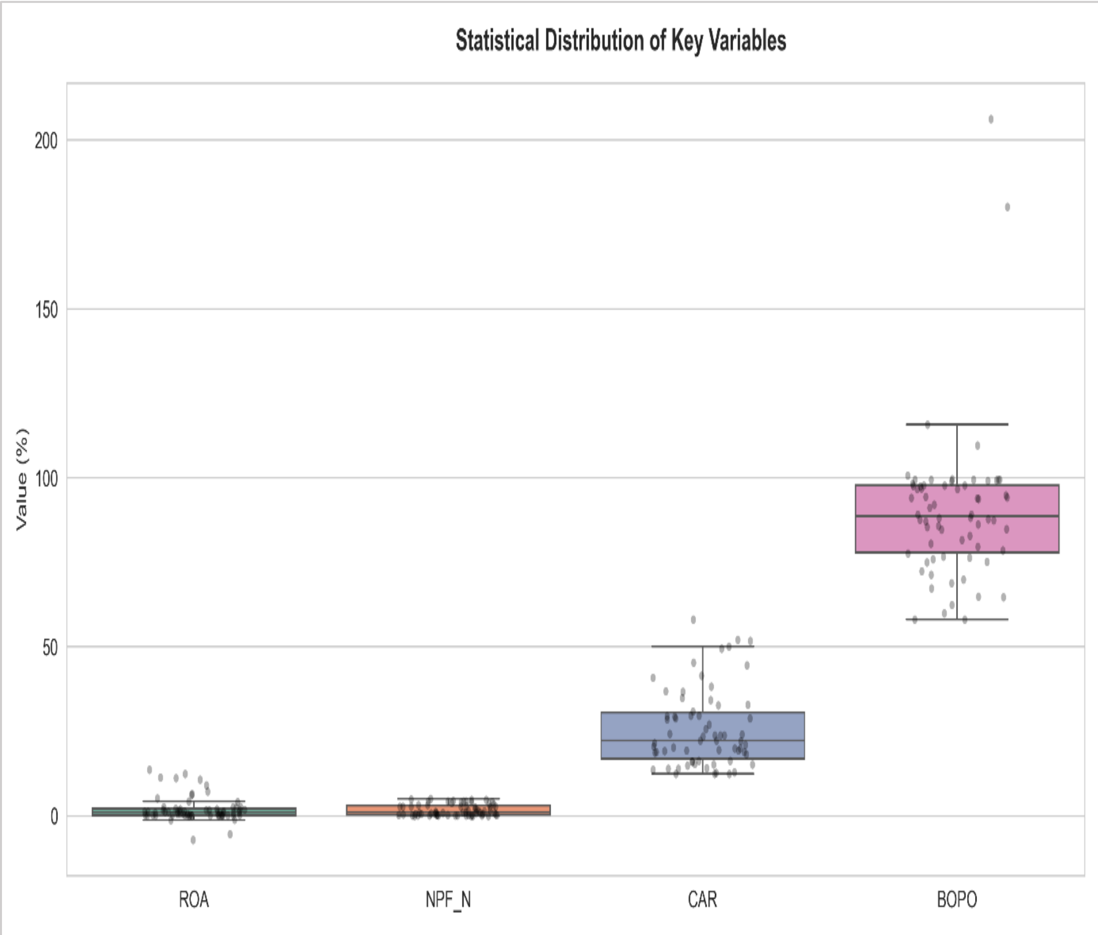

Figure 3. Statistical Distribution of Key Variables

Source: Python data processing, 2026

Figure 4 presents a Health Map of Islamic banking in the form of a color matrix visualization for the period 2014 to 2024. Green indicates a healthy condition, while red signifies financial distress based on the established criteria. The visualization reveals, first, that bank health conditions are temporally dynamic, with some banks experiencing isolated episodes of distress, while others exhibit recurrent distress patterns. Second, there are temporal clusters in which indications of distress simultaneously appear across multiple banks, particularly during periods of economic turbulence. Finally, several banks demonstrate relatively consistent resilience, as reflected by the dominance of green throughout the observation period. Descriptively, this health map provides an intuitive chronological depiction of the evolution of Islamic banking stability and serves as an important foundation for further analyses of the determinants and mechanisms of distress.

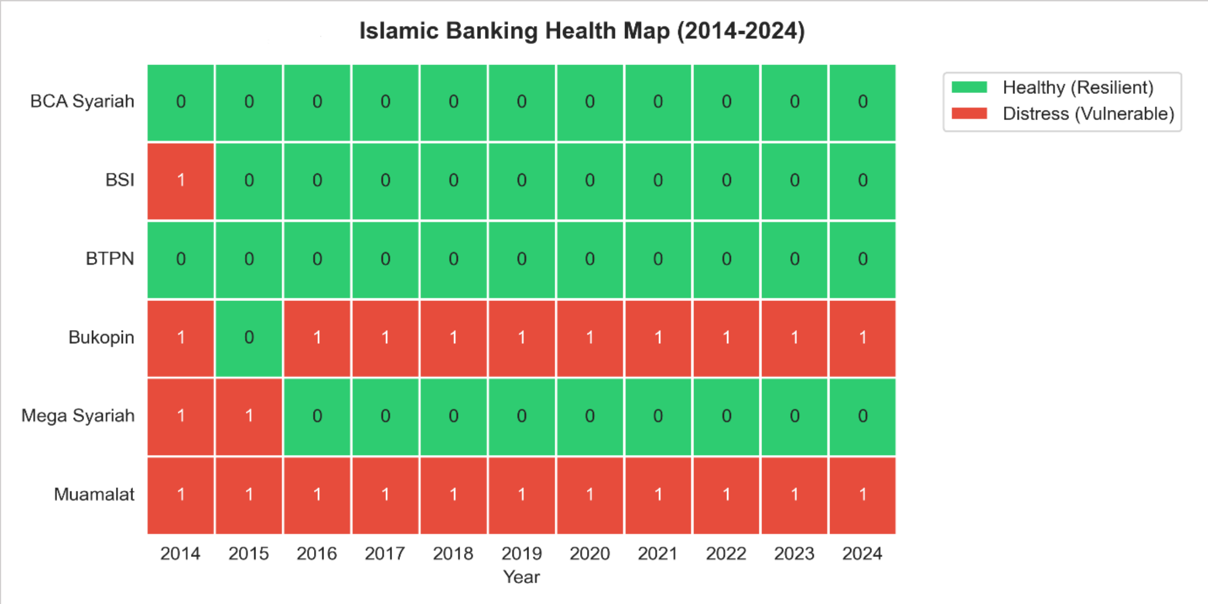

Figure 4. Islamic Banking Health Map (2014-2024)

Source: Python data processing, 2026

The model performance was evaluated using a testing set comprising 20% of the total 66 observations. The target variable (Distress) was defined compositely, whereby a bank was categorized as experiencing financial distress if it recorded an NPF Net greater than 5% or an ROA below 0.5%, thus reflecting simultaneous pressure on asset quality and profitability. Based on the Confusion Matrix presented in Figure 5, the machine learning model demonstrated perfect classification performance (perfect separation). Of the 14 observations in the testing set, all samples were correctly predicted with no misclassification. In detail, the True Negative cases (nine banks) indicated that all banks in a healthy condition were accurately identified, while the True Positive cases (five banks) showed that all banks experiencing financial distress were successfully detected by the model. Both False Positive and False Negative values were zero, indicating the absence of prediction errors. The model achieved an accuracy rate of 100%, implying exceptionally strong discriminatory capability in distinguishing between healthy and distressed banks within the dataset.

The robustness of the model is further reinforced by the Area Under the Receiver Operating Characteristic Curve (AUC–ROC) value of 1.0000, indicating perfect discriminatory power in differentiating between the two classes of observation. In the context of an Early

Warning System, this achievement is particularly significant, as the model not only exhibits high sensitivity and specificity, but also produces no false alarms, an issue that commonly undermines traditional early warning systems reliant on single indicators.

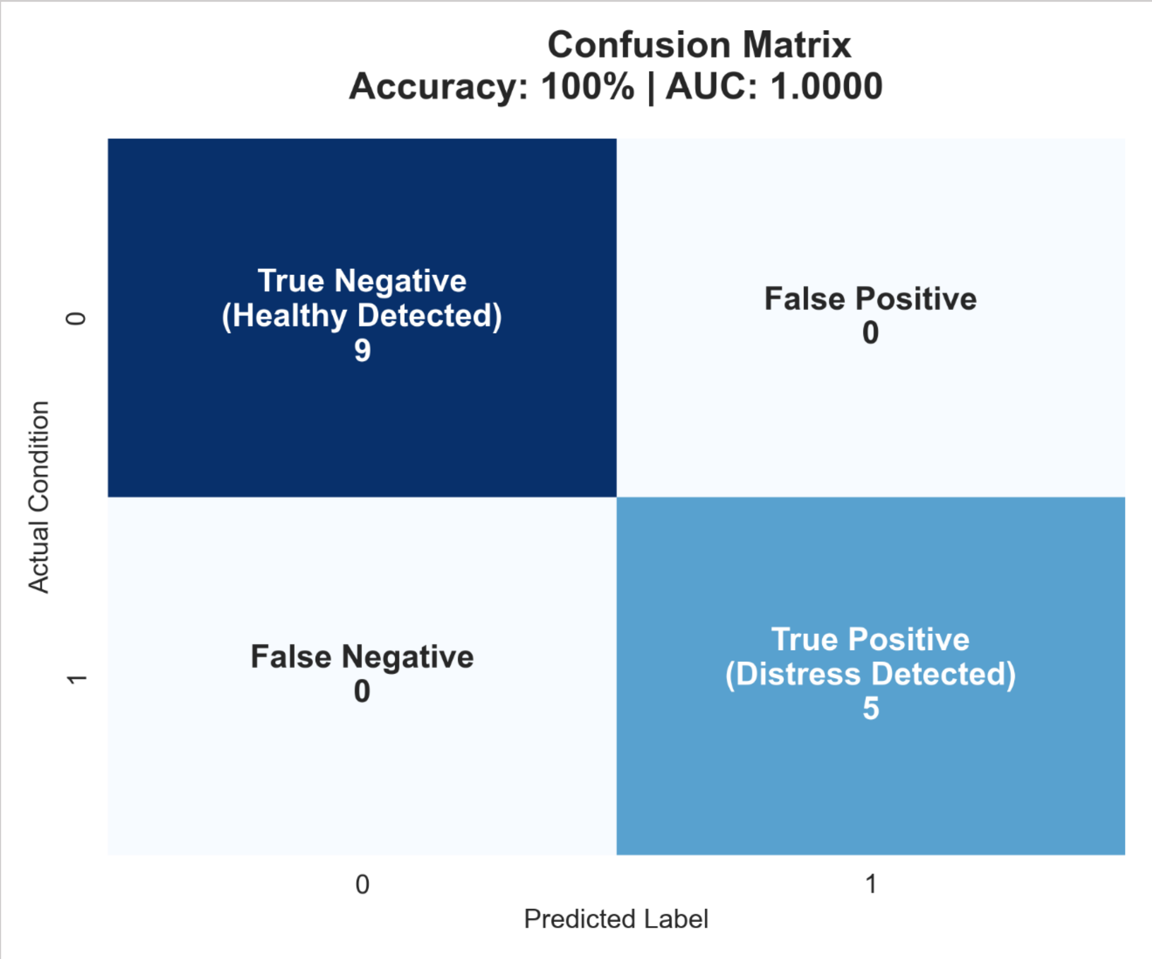

Figure 5. Confusion Matrix

Source: Python data processing, 2026

The identification of the key determinants of financial distress was conducted through a Feature Importance analysis derived from the ensemble tree-based machine learning model. The estimation results are presented in Figure 6, illustrating the relative marginal contribution of each financial variable to the prediction of distress. The BOPO ratio emerges as the most dominant determinant, with a contribution weight of 25.8%. This finding indicates that operational inefficiency represents the strongest signal in detecting the potential failure of Islamic banks. The substantial role of BOPO suggests that persistent operational cost pressure, when not matched by sufficient operating income, directly accelerates the deterioration of banks' financial health, even before credit risk or capital indicators exhibit significant stress.

ROA ranks as the second most influential variable, with a contribution weight of 24.7%. The high contribution of ROA reflects the internal consistency of the model, given that this indicator is also incorporated in defining distress status. Nevertheless, the substantial weight attributed to ROA further reinforces that declining profitability capacity constitutes a critical warning signal in the dynamics of financial distress among Islamic banks. The group of asset quality variables collectively contributes approximately 24%. Specifically, Total NPA accounts for 14.1%, Gross NPF contributes 9.9%, while Net NPF provides only 7.4%. This difference indicates that problematic financing indicators before provisioning (gross measures) possess stronger explanatory power than net ratios, thereby reflecting latent risks that have not been fully absorbed by loan-loss reserves.

CAR demonstrates a relatively small contribution, at approximately 2.8%. This result suggests that although capital adequacy remains essential from a regulatory perspective, it is not the primary determinant of distress within the context of this dataset, particularly when not accompanied by sufficient efficiency and asset quality.

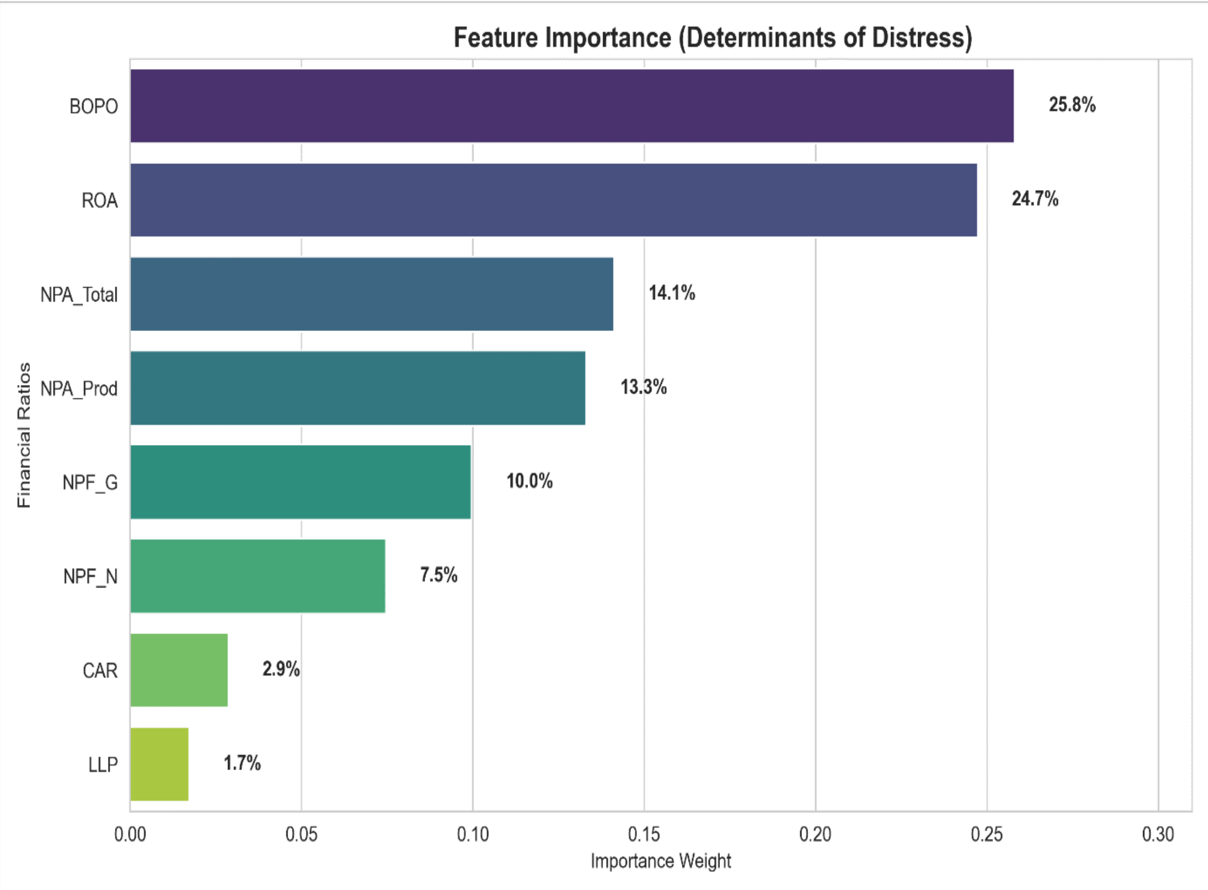

Figure 6. Feature Importance (Determinants of Distress)

Source: Python data processing, 2026

The analysis of mean differences in financial indicators between healthy and distressed banks reveals sharp, non-linear thresholds, as Figure 7 shows. Healthy banks record an average BOPO ratio of 80.77%. Distressed banks escalate to 106.17%. This rise signals a BOPO threshold of 100%, above which costs surpass operating income. Beyond this point, the probability of distress rises dramatically and approaches certainty. For the Gross NPF indicator, healthy banks average 1.96%, while distressed banks hit 5.09%. This gap suggests that an NPF ratio above 5% is not just typical variance, but marks the stage where credit risk erodes profitability and stability rapidly.

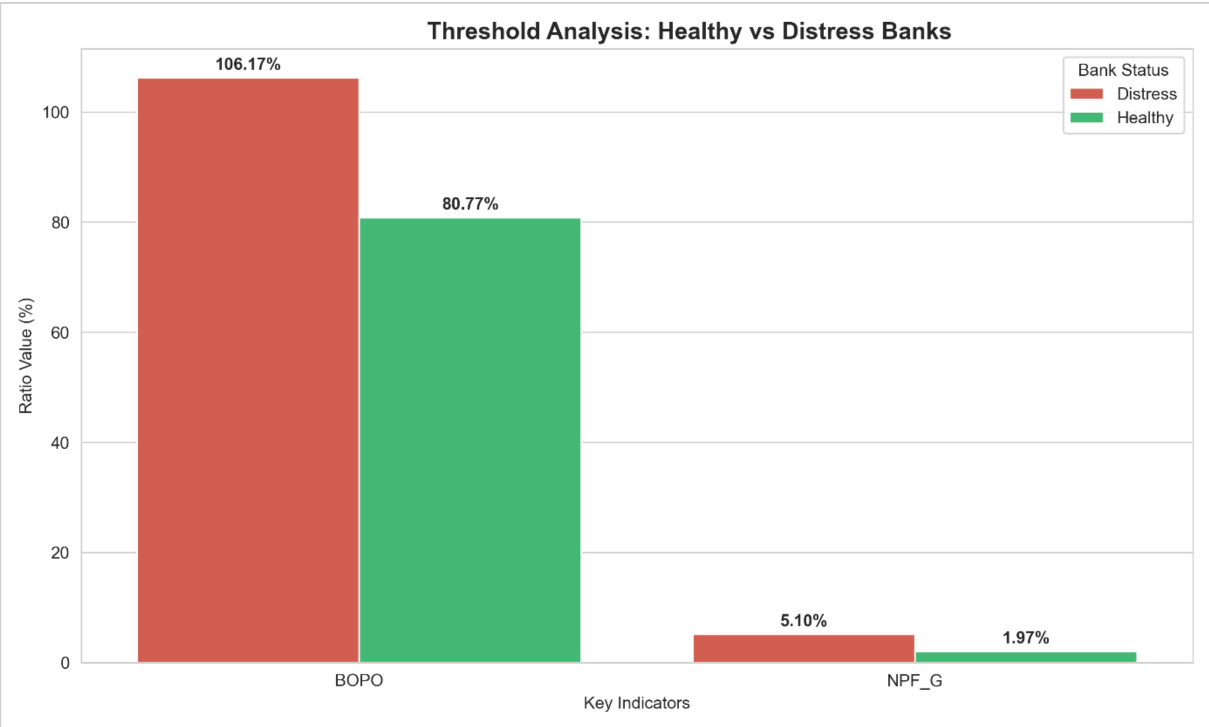

Figure 7. Threshold Analysis: Healthy vs Distress Bank

Source: Python data processing, 2026

The interrelationships among financial indicators were examined using a Correlation Matrix, as presented in Figure 8. The results reveal strong and consistent patterns throughout the observation period of 2014–2024. There is a very strong negative correlation between BOPO and ROA, with a coefficient of –0.74, indicating that increases in operational inefficiency directly and significantly erode banks' ability to generate profits. Meanwhile, the correlation between Gross NPF and Distress status is recorded at 0.69, reflecting a strong positive association. This finding reinforces that problematic financing serves as a primary trigger of financial pressure in Islamic banks.

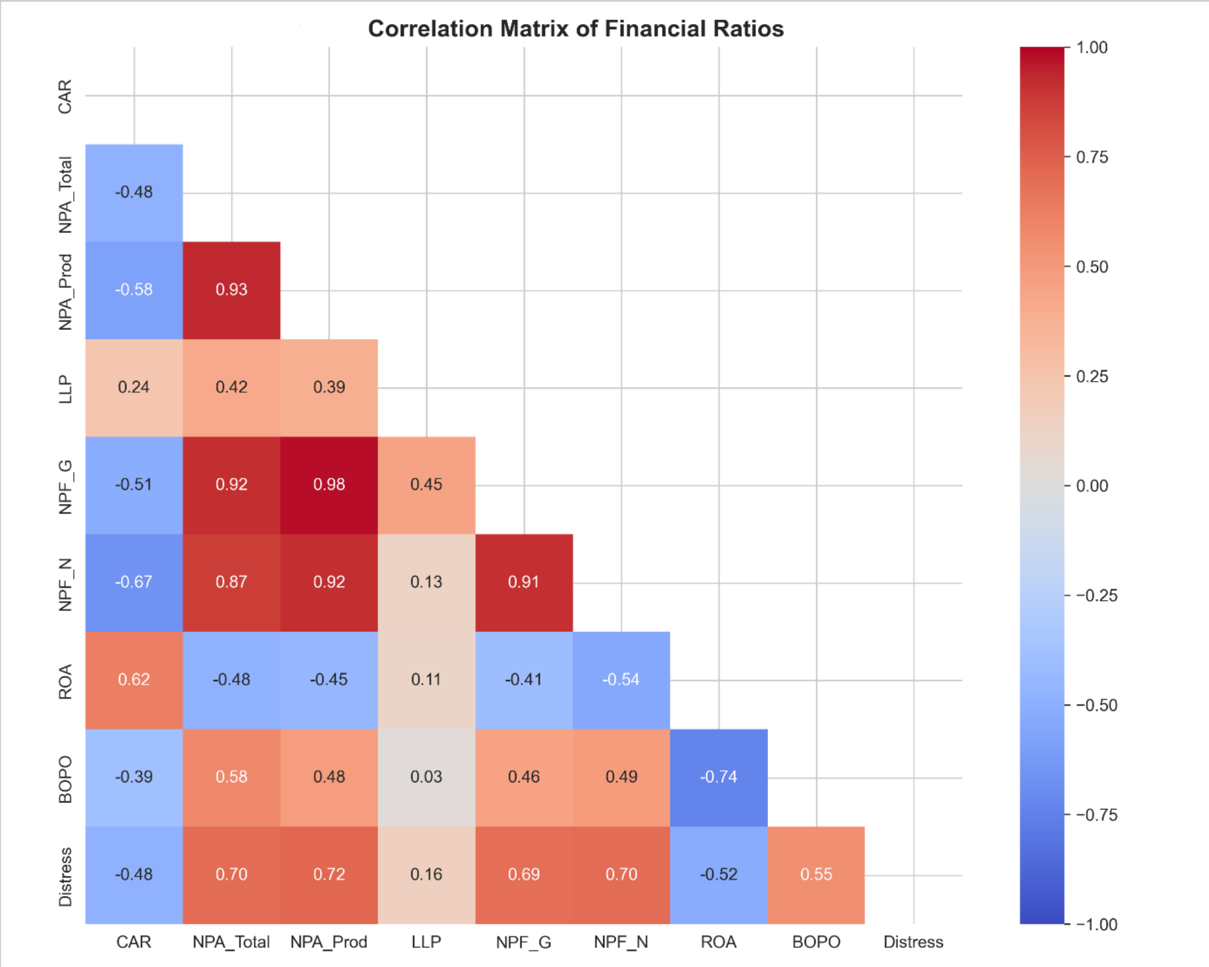

Figure 8. Correlation Matrix of Financial Ratios

Source: Python data processing, 2026

The Local Diagnosis analysis was conducted by comparing the average profiles of financial indicators between healthy banks and distressed banks, as illustrated in Figure 9. Healthy banks are characterized by high operational efficiency (BOPO of approximately 80%), strong capitalization (CAR approaching 29%), and well-maintained asset quality with low NPF and NPA ratios. This profile indicates a high capacity to absorb shocks arising from operational and credit risks. Conversely, banks classified as distressed exhibit BOPO values exceeding 100%, reflecting a negative operating margin; total NPA above 4.5%, indicating severe pressure on asset quality; and a substantial decline in profitability. These contrasting profiles underscore that financial distress in Islamic banking is heterogeneous in nature and requires diagnosis approaches that are specifically tailored at the level of individual banks.

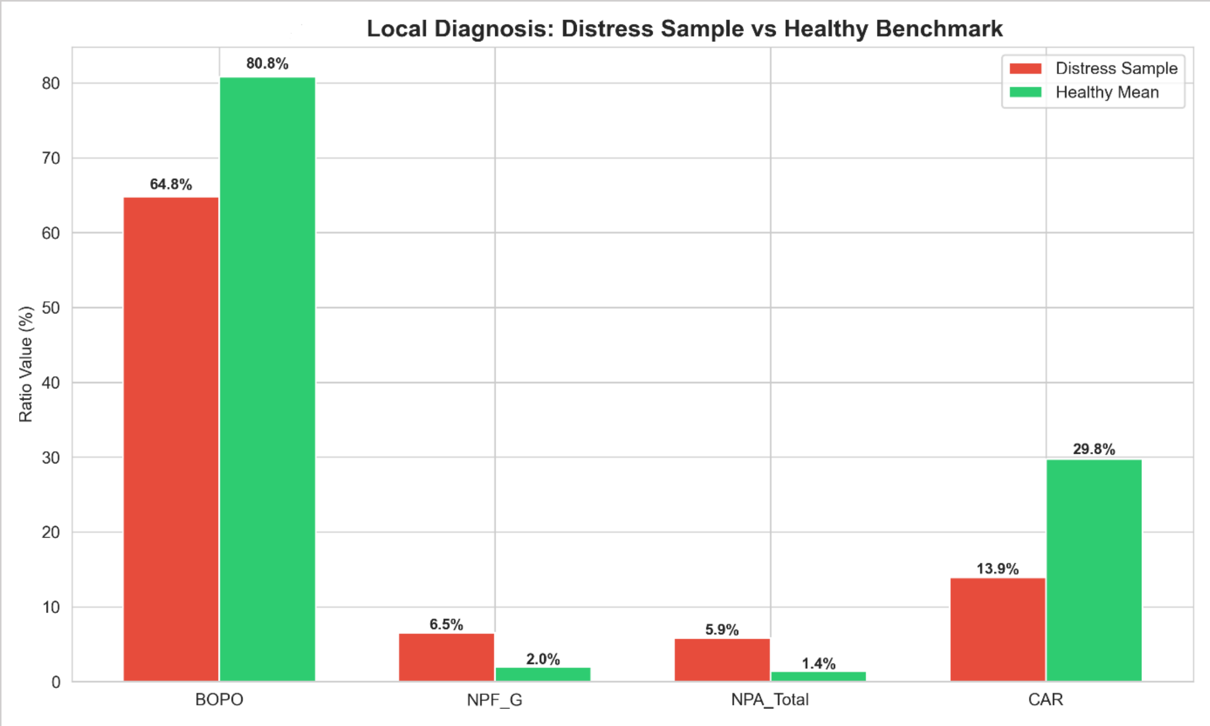

Figure 9. Local Diagnosis: Distress Sample vs Healthy Benchmark

Source: Python data processing, 2026

DISCUSSION

Prediction Accuracy and Superiority of Machine Learning Approaches

This study shows that the ensemble tree-based machine learning model achieves perfect accuracy and AUC-ROC values in detecting financial distress in Islamic banks. Machine learning models outperform conventional econometric models by better capturing complex and non-linear risk patterns.

This finding aligns with Gafsi, (2025), who found gradient boosting and random forest algorithms consistently outperform logistic-based approaches for credit risk prediction in UK participation banks. Likewise, Zhang et al., (2022) reported that LightGBM offers better performance in predicting corporate financial distress when paired with an explainable AI framework. This study advances the literature by highlighting Indonesian Islamic banking, defined by unique risk structures and regulations. These findings matter in Indonesia, where the Islamic banking sector is consolidating and expanding after the Bank Syariah Indonesia

(BSI) merger. The increasing complexity of business models, rising efficiency demands, and volatile financing quality make linear methods less suitable for early risk detection.

Primary Determinants of Financial Distress and the Bad Management Hypothesis

The findings identify BOPO (Operating Expenses to Operating Income) as the main cause of financial distress in Islamic banks. BOPO's predominance shows that managerial inefficiency is a more fundamental source of risk than capital adequacy or credit risk. This fits the Bad Management Hypothesis, which argues that bank failure begins with weak governance and inefficiency before it becomes visible as non-performing financing. Studies by Gafsi (2025) and De Lange et al., (2022) also show that internal bank performance variables have stronger predictive power than external factors.

In Indonesian Islamic banking, high BOPO levels result from suboptimal scale, high funding costs, and ongoing issues with digitalization and process efficiency. The fact that CAR has little impact shows that strong capitalization alone cannot ensure bank resilience; banks also need efficient operations.

Non-linearity and Threshold Effects within the Fragility Risk Stability Nexus

This study critically identifies non-linear relationships and threshold effects in Islamic bank soundness indicators, especially BOPO and NPF Gross. The analysis pinpoints critical points where increases in specific ratios cause an exponential surge in distress risk. This insight directly enriches the Fragility Risk Stability Nexus, long examined only in a linear framework. The study shows that indicators viewed as stable can shift function once past certain thresholds. For example, moderate operational inefficiency is manageable, but when BOPO exceeds 100%, banks become highly vulnerable in a negative carry phase.

This approach complements the XAI literature discussed by Martins et al. (2024) and Arsenault et al. (2024), who emphasize the importance of interpreting non-linear effects in financial models; however, such applications have rarely been implemented empirically in the context of Islamic banking.

Stability of Risk Determinants across Economic Eras

The time-series analysis demonstrates that the relationships between efficiency (BOPO), profitability (ROA), and credit risk (NPF) remain stable and consistent throughout the 2014–

2024 period, including during the COVID-19 pandemic shock. This finding indicates that the key determinants of financial distress in Islamic banking are structural rather than merely temporary. This phenomenon reinforces the argument that external crises such as the pandemic primarily function as stress amplifiers rather than the fundamental causes of distress. Banks entering crisis periods with high-cost structures and fragile asset quality tend to experience greater pressure compared to banks that were previously efficient and resilient.

Explainable AI and the Transformation of Islamic Banking Supervision

The integration of SHAP and LIME in this study transforms Early Warning Systems. EWS becomes policy diagnostic instruments, not just predictive tools. Traditional EWS only generate aggregate risk scores. The XAI approach lets regulators and bank management see specific reasons for distress predictions at the bank and year level. This finding aligns with Weber et al. (2023) and Černevičienė & Kabašinskas (2024), who state that AI sustainability in finance depends on transparency and accountability. For the Financial Services Authority (OJK) and Islamic banking supervision, XAI enables more precise, proactive risk-based supervision.

Implications and Contributions of the Study

The results suggest that regulators should not rely only on monitoring NPF Net or CAR. Instead, BOPO emerges as a leading indicator that must be closely supervised, and managerial intervention should begin when it approaches its critical threshold—even before credit risk indicators show significant stress. For Islamic bank management, these findings highlight the importance of sustained efficiency strategies and operational process optimization, while also positioning digital technology as a core risk management tool rather than merely for profitability. Furthermore, this study demonstrates that integrating machine learning and XAI enables richer, more accurate, and actionable risk analysis than conventional approaches.

This research contributes theoretically by extending the Fragility Risk Stability Nexus. It does this by providing empirical evidence of non-linearity and threshold effects in Islamic banking. Methodologically, it proposes an Explainable AI-based Early Warning System framework that combines predictive accuracy with interpretability. Contextually, it delivers contemporary empirical evidence on the determinants of Islamic banking distress in Indonesia across crisis cycles. It also offers an empirical foundation for transforming supervisory policy toward more explainable and data-driven approaches.

CONCLUSION AND SUGGESTIONS

This study finds that using machine learning with Explainable Artificial Intelligence (XAI) can offer an early warning system for financial distress in Islamic banks. This system is better at predicting problems and is also clear and easy to understand. The study shows that efficiency (BOPO), profit (ROA), and asset quality (NPF Gross) are the main factors influencing distress risk. These factors do not relate to risk in a straight line and show important tipping points. The results add to the understanding of the Fragility Risk Stability Relationship, mainly by showing that measures usually seen as keeping banks safe can turn into risks when limits are crossed. Using XAI tools (SHAP and LIME) helps reveal how the machine learning models work and what causes the risks, both for each factor and for each bank. For economics and policy, these findings help improve how Islamic banks in Indonesia are monitored. They make it possible for earlier, more accurate, and fact-based actions, especially around improving efficiency, which is still a big challenge in the industry.

Nevertheless, this study acknowledges several limitations that require critical consideration. First, the sample size is relatively limited due to the number of Islamic banks operating consistently during the observation period, which may constrain the generalizability of the findings. Second, while the exceptionally strong predictive performance reflects the robustness of pattern separation within the data, it also necessitates caution regarding potential overfitting, despite the application of training and testing data partitioning. These limitations do not stem from methodological shortcomings but rather from structural characteristics of the Islamic banking industry and the availability of public data. Therefore, future research is recommended to expand the dataset to a cross-country context, integrate macroprudential variables, and examine the stability of the findings using broader out-of-sample validation and stress-testing approaches, in order to strengthen the external validity and policy relevance of the proposed XAI framework.

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