International Journal of Digital Entrepreneurship and Business (IDEB)
Vol. 6, No. 2, October 2025 ISSN 2723-5432
pp. 1 – 18 https://ejournal.jic.ac.id/ideb/

PREDICTING FINANCIAL DISTRESS IN A TURBULENT WORLD: A COMPARATIVE MACHINE LEARNING ANALYSIS ACROSS NATIONS

Syahril Ramadhan [1], Pedro J Trujillo T[2*]
Department of Accounting, Universitas Jakarta International, Indonesia [1], and
Faculty of Information System, Universidad Industrial de Santander, Bucaramanga, Colombia [2]
*Corresponding Author: syahril.ramadhan@uniji.ac.id

ABSTRACT

This study evaluates the performance of six machine learning models in predicting financial distress, with a primary focus on Indonesia and comparative insights from other countries. Using evaluation metrics such as accuracy, AUC Macro, F1 Macro, F1 Weighted, and Log Loss, the results indicate that the Random Forest model combined with a Standard Scaler wrapper achieves the best overall performance across most metrics. However, the LightGBM model with a MaxAbs Scaler is identified as the most suitable for deployment due to its robustness and scalability in real-world applications. Furthermore, feature importance analysis reveals that key determinants of financial distress include investment growth, GDP growth, and economic uncertainty. These findings underscore the critical role of machine learning in enhancing economic forecasting and supporting policymaking. In particular, the study highlights the importance of digital optimization and AI-driven decision-making in addressing challenges related to global financial stability.

Keywords: Financial Distress Prediction, Machine Learning, Comparative Analysis, Economic Stability, Feature Scaling, Investment Growth, GDP Growth

ABSTRAK

Studi ini mengevaluasi kinerja enam model pembelajaran mesin dalam memprediksi kesulitan keuangan, dengan fokus utama pada Indonesia dan wawasan komparatif dari negara lain. Menggunakan metrik evaluasi seperti akurasi, AUC Macro, F1 Macro, F1 Weighted, dan Log Loss, hasilnya menunjukkan bahwa model Random Forest yang dikombinasikan dengan wrapper Standard Scaler mencapai kinerja keseluruhan terbaik di sebagian besar metrik. Namun, model LightGBM dengan MaxAbs Scaler diidentifikasi sebagai yang paling cocok untuk diterapkan karena kekokohan dan skalabilitasnya dalam aplikasi dunia nyata. Lebih lanjut, analisis kepentingan fitur mengungkapkan bahwa penentu utama kesulitan keuangan meliputi pertumbuhan investasi, pertumbuhan PDB, dan ketidakpastian ekonomi. Temuan ini menggarisbawahi peran penting pembelajaran mesin dalam meningkatkan peramalan ekonomi dan mendukung pembuatan kebijakan. Secara khusus, studi ini menyoroti pentingnya optimasi digital dan pengambilan keputusan berbasis AI dalam mengatasi tantangan yang terkait dengan stabilitas keuangan global.

Kata Kunci: *Prediksi Kesulitan Keuangan, Pembelajaran Mesin, Analisis Komparatif, Stabilitas Ekonomi, Peningkatan Skala Fitur, Pertumbuhan Investasi, Pertumbuhan PDB.*

ARTICLE INFO

Article History:
Received: November 9, 2025
Revised: April 14, 2025
Published Online: May 7, 2026

How to cite:
Ramadhan, S. & Trujillo, P. J. (2026). Predicting Financial Distress in A Turbulent World: A Comparative Machine Learning Analysis Across Nations. *Journal of Digital Entrepreneurship and Business (IDEB)*, *6*(2), 1-18. https://doi.org/10.52238/ideb.v6i2.292

Conflict of interest statement: The author(s) reported no conflict of interest.

INTRODUCTION

The global financial landscape is undergoing a profound metamorphosis driven by the convergence of digital currencies and algorithmic trading with traditional financial systems (Cohen, 2023). This convergence marks the onset of a new era characterized by innovation and disruption, presenting unprecedented opportunities and challenges for policymakers, regulators, and market participants worldwide. At the core of this transformation lies the complex challenge of navigating monetary policy amidst global uncertainty, exacerbated by geopolitical tensions and trade disputes.This challenge emerges at the intersection of various factors, each contributing to the complexity and uncertainty of the financial environment. The digitalization of currency, propelled by the rise of cryptocurrencies like Bitcoin and the emergence of stablecoins, poses a fundamental challenge to conventional monetary policy frameworks (Barrdear and Kumho, 2022). Concurrently, algorithmic trading, powered by artificial intelligence and machine learning algorithms, introduces new dynamics into financial markets, prompting concerns about market stability and in tegrity (Chaboud et al., 2014). Moreover, geopolitical tensions and trade disputes loom large over economic prospects, introducing further volatility into aalready tumultuous landscape (Bouri, 2023; Jha 2024). Additionally, the interconnectedness of financial systems amplifies the repercussions of disruptions in one part of the world on global markets, heightening the complexity of policy responses (Salim et al., 2023). In the face of this global uncertainty and interconnectedness, policymakers must navigate a swiftly evolving financial landscape while safeguarding financial stability and economic resilience (Pedauga et al., 2023).

The policy dilemma inherent in addressing this challenge revolves around striking a balance between innovation and risk management (Keisler et al., 2021). On one hand, digital currencies and algorithmic trading hold the potential to revolutionize the financial industry, enhancing efficiency, and broadening access to financial services. On the other hand, regulating these technologies poses a formidable challenge, with policymakers contending with issues of consumer protection, market integrity, and systemic stability amidst geopolitical tensions, trade disputes, and the interconnectedness of financial systems. The rapid pace of technological advancement further complicates regulatory efforts, as regulators endeavor to keep pace with innovation while ensuring effective oversight and risk mitigation. In this context, the need for agile and adaptive policy frameworks is more pressing than ever. These frameworks must respond swiftly to geopolitical developments and market changes while leveraging technological advancements in digitalization and artificial intelligence (Ozgur & Akkoc, 2022; Richardson et al., 2021). Effectively integrating digitalization and AI capabilities into policy frameworks is essential for addressing emerging risks and opportunities. Traditional models may fall short in capturing the complexity of modern challenges, but the new framework presents an opportunity to enhance policy effectiveness.

To demonstrate the efficacy of this new approach, our study examines the application of machine learning models to detect signs of impending financial distress that could lead to severe economic and financial impacts, allowing policymakers to take proactive measures to mitigate the effects or prevent the crisis altogether. Using post-event data, we assess the performance of machine learning classifiers in predicting and mitigating potential risks. Furthermore, we investigate the impact of heterogeneous environments on policy outcomes, highlighting the need for tailored approaches to address specific challenges. By deploying machine learning techniques and feature scaling, we evaluate the effectiveness of different classifiers in capturing the nuances of complex policy landscapes.

LITERATURE REVIEW

The exploration of monetary policy dynamics remains a cornerstone of economic literature (Gnabo and Moccero, 2015). Recent scholarship has increasingly focused on the challenges posed by the convergence of digital currencies and algorithmic trading with traditional financial systems (Cohen, 2021; Cohen and Qadan, 2022). This convergence has sparked discussions on the need for innovative policy responses and risk management strategies to navigate the evolving financial landscape. The critical role of digital currencies in financial stability is underscored by their potential to disrupt traditional systems. Digital currencies, particularly those based on distributed ledger technologies, are perceived as resilient but face increased susceptibility to fraud and cyber risks compared to traditional central bank payment systems (Financial Stability Oversight Council, 2023). The literature primarily examines digital currencies' investment potential rather than their function as currency (Badev & Chen, 2014). The recent surge in Bitcoin's value and debates surrounding its potential bubble status highlight the challenges in determining the fundamental value of digital assets (Shiller, 2000). Financial stability concerns revolve around the size and usage patterns of digital currencies, emphasizing potential risks in economies with significant adoption (Nelson, 2018). Monetary policy implications in a digital currency landscape are complex, focusing on issues like economic volatility and the efficacy of traditional policy tools (Bordo & Levin, 2017). The fixed or exogenous supply of digital currency amplifies economic and financial volatility, challenging traditional monetary policy mechanisms (Bordo & Levin, 2017). While central bank digital currencies offer potential solutions, such as overcoming the zero lower bound on nominal interest rates, political hurdles may impede their implementation. Despite debates on potential benefits, digital currencies are unlikely to significantly disrupt central banks' ability to manage the economy and control inflation (Nelson, 2018). Nonetheless, the ongoing mania surrounding digital currencies underscores the need for continued vigilance and analysis of potential risks and implications (Shiller, 2000).

Geopolitical factors also play a significant role in shaping the modern financial landscape. The impacts of conflict and peace have long been subjects of study, with early 20th-century economists like Keynes (1919) and Pigou (1940) examining the economic effects of the World Wars. Research has also focused on the economic impacts of various conflicts, such as wars and terrorism (Collier and Sambanis, 2003; Blomberg et al., 2004). However, the broader macroeconomic consequences of increasing geopolitical tensions among nations have been less studied until recently. Jha et al. (2024) addresses this gap by analyzing how these tensions differently affect economic growth in advanced versus emerging economies. Geopolitics, according to Dijkink (2009), studies how geographical factors influence politics and international relations, a concept that has grown increasingly complex. Now, the term encompasses statecraft and various state assets, such as economic, military, and cultural factors, which states use to gain international influence (Al-Rodhan, 2009). Caldara and Iacoviello (2022) developed a Geopolitical Risk (GPR) index to measure the impact of international conflicts and violence on economic conditions, used as a proxy for geopolitical tensions in this study. The relationship between economic growth and GPR is significant. Higher GPR can lead to increased savings and reduced spending, as well as delayed investment decisions due to greater economic uncertainty (Bloom, 2009). These tensions disrupt supply chains and economic activities, causing business cycle fluctuations. Recent increases in GPR have negatively affected the global economy, resulting in higher inflation, stock market volatility, and changes in government spending (Das et al., 2019; Tiwari et al., 2019;

Cunado et al., 2020; Lee and Lee, 2020; Wang et al., 2023a, b). The Bank of England has recognized GPR as part of an "uncertainty trinity" that significantly affects economic activities (Carney, 2016).

Central banks need to understand the significant role of geopolitical risk in economic fluctuations and incorporate this understanding into their monetary policy frameworks. As geopolitical tensions disrupt supply chains and increase economic uncertainties, central banks should develop strategies to address the resulting inflation and investment hesitations. Bouri et al. (2023) highlights that geopolitical risk significantly impacts inflation spillovers, especially during crises like the Russo-Ukrainian war, which saw inflation spillover indices surpass previous peaks from the 1970s energy crisis. This underscores the necessity for central banks to adopt a coordinated approach to combat inflation caused by global geopolitical shocks (Bouri et al., 2023).

The development and implementation of Adaptive Early Warning Systems (AEWS) for detecting signs of impending financial distress are crucial. The literature on EWS has evolved significantly, expanding to encompass more sophisticated methodologies for predicting extreme financial events. Initially introduced by Kaminsky, Lizondo, & Reinhart (1998), the 'signals' approach pioneered the use of statistical methods to monitor economic and financial variables for signs of impending financial distress. Subsequent advancements by Kaminsky (1999) and Goldstein, Kaminsky, & Reinhart (2000) extended this approach to include the detection of banking and currency crises. Building on this foundation, Davis & Karim (2008) refined the EWS framework in response to the U.S. Subprime Crisis, employing advanced econometric techniques for banking crisis detection. Recent contributions by Sarlin (2013) and Alessi & Detken (2014) emphasize policymakers' loss functions in enhancing EWS frameworks, with a focus on forecasting accuracy. Following the inception of the signals approach, there has been a surge in research aimed at bolstering EWS frameworks, particularly within central banking institutions. Alessi & Detken (2014) and Sarlin (2013) have introduced novel methodologies, while Liu & Moench (2016) and Ng (2014) have improved datasets. Concurrently, efforts to update crisis definitions have been evident, as seen in studies by Babecky et al. (2012) and Frankel & Saravelos (2012). Bhimjee (2022) contributes to this discourse with the proposition of an AEWS protocol, addressing operational aspects overlooked in existing EWS literature. The AEWS protocol integrates fundamental principles and outlines a universal template for an AEWS surveillance platform, delineating various stages of AEWS implementation.

The discussion on how digitalization and artificial intelligence (AI) impact monetary policy evaluation and forecasting has advanced significantly due to recent technological developments. For example, Karocha et al. (2013) highlighted the potential of data mining techniques in creating an early warning system for predicting currency crises. This system provides critical insights for researchers and managers by offering a comprehensive understanding of financial instabilities. In parallel, machine learning techniques have shown great promise in enhancing the accuracy of economic forecasts. Ozgur and Akkoc (2022), for instance, demonstrated significant improvements in inflation forecasting, while Richardson et al. (2020) highlighted the efficacy of machine learning in predicting real GDP growth, outperforming traditional econometric methods. Vrontos et al. (2021) further supported the application of machine learning over standard econometric techniques in recession prediction. In addition to these advancements, more sophisticated metrics and methods have proven effective in monetary policy prediction. Li (2023) utilized the XGBoost approach with genetic algorithms to forecast inflation over different horizons, comparing it with six other forecasting models. Similarly, Bluwstein et al. (2023) concluded that decision-tree-based ensembles, such as extremely randomized trees and random forests, are among the most accurate models available.

Moreover, the benefits of machine learning methods extend beyond monetary policy to other predictive tasks. For example, Chatterjee and Byun (2022) demonstrated that an ensemble voting classifier outperformed existing methods in Alzheimer's disease classification, excelling in accuracy, sensitivity, specificity, and AUC. Gautam (2024) similarly found improvements in accuracy for seismic vulnerability assessments of RCC bridges using a voting ensemble method. Recent studies have also demonstrated the exceptional capabilities of LightGBM in predictive modeling, particularly in complex engineering applications, such as estimating the Rapid Chloride Penetration Test (RCPT) values in metakaolin-containing concrete (Abdulalim et al., 2022) and predicting the interfacial bond strength (IBS) of fiber-reinforced polymer (FRP) laminates on concrete prisms (Nasir et al., 2022). These successes suggest that combining high-performing models leverages their unique strengths, enhancing predictive performance by reducing overfitting, improving generalization, and capturing a broader range of data patterns. Additionally, feature scaling and selection techniques play a crucial role in achieving high performance in predictive modeling. Paepae (2022) emphasized the importance of feature scaling, such as using the MinMax scaler, while Reddy (2021) discussed the impact of feature selection techniques in producing the best results. By integrating these advanced methods, we can significantly enhance the accuracy and reliability of economic forecasting and monetary policy evaluation.

METHODS

1. Data Sources

The data utilized in this study are sourced from a variety of comprehensive and reputable databases, ensuring a robust and diverse dataset for analysis. These sources include:

- Archival Federal Reserve Economic Database (ALFRED): Provides historical economic data that allows for analysis of economic trends over time (https://alfred.stlouisfed.org).
- World Bank Data (World Development Indicators): Offers a wide range of economic, social, and environmental indicators (https://data.worldbank.org).
- GPR Data from Matteo Iacoviello's website: Contains the Geopolitical Risk (GPR) index, which measures the impact of geopolitical events on economic conditions. (https://www.matteoiacoviello.com/gpr.htm).
- Economic Freedom Data from the Fraser Institute: Provides data on the economic freedom of various countries, useful for understanding economic policy impacts (https://www.fraserinstitute.org/economic-freedom).
- World Uncertainty Index (WUI) data: Tracks uncertainty across the globe based on reports from the Economist Intelligence Unit (https://worlduncertaintyindex.com).
- Bitcoin Dataset: Contains data on Bitcoin transactions and prices, useful for analyzing the impact of digital currencies (https://public.opendatasoft.com/explore/dataset/bitcoin/api/).
- Statistik Ekonomi dan Keuangan Indonesia (SEKI) and Sistem Keuangan Indonesia (SSKI) from Bank Indonesia: (https://www.bi.go.id).
- Badan Pusat Statistik (BPS) data: (https://www.bps.go.id).

2. Analysis Period and Feature Engineering

The analysis covers the period from 1961 to 2024. A critical step in our methodology was feature engineering, which involved creating new features and normalizing existing ones to enhance the predictive power of our models. Utilizing domain knowledge, we derived features that could potentially predict financial distress. While digital currencies and algorithmic trading are recent innovations heralded as revolutionary forces in the financial sector, their impact on global economic uncertainty is difficult to conclude. This is largely due to the limited availability of comprehensive data for these innovations. Machine learning techniques require massive datasets to be effective, and the current data for digital currencies and algorithmic trading cannot yet be matched with the extensive historical data available for other economic factors and geopolitical tensions. Based on the findings of Ng (2014), we utilized a comprehensive list of real and financial indicators improve our predictive models. We also incorporated insights from Liu & Moench (2016), Bouri et al. (2023), and Jha et al. (2024) to identify and engineer relevant features.

3. Econometric and Machine Learning Models

To gain insights into the dynamic behavior of economic variables and generate forecasts, we employed the Time-Varying Parameter Vector Autoregression (TVP-VAR) model. This model provides a robust econometric framework for understanding and predicting economic conditions (Primiceri, 2005). The forecasts generated by the TVP-VAR model were used as features in our machine learning models to explore complex relationships and enhance prediction accuracy.

4. Predictive Framework for Financial Distress

Our framework for predicting financial distress is grounded in the work of Bhimjee (2022), utilizing variables from Karocha et al. (2013) and Bluwstein et al. (2023), and applying calculation methods from Liu & Moench (2016). Key indicators considered include:

- Negative GDP Growth: A sustained period of negative GDP growth, indicative of economic recession and financial distress.
- Increase in Unemployment Rate: Rising unemployment rates, signaling deteriorating labor market conditions and potential financial instability.
- Decrease in Industrial Production: A decline in industrial production, especially significant in manufacturing-dependent economies.
- Currency Depreciation: Sharp depreciation in the national currency's exchange rate, indicating currency instability and potential financial crises.
- Increase in Sovereign Debt Yield Spreads: Widening yield spreads between the central bank rate and deposit rate, reflecting increased perceived risk of default.
- Banking Sector Distress: Indicators such as rising non-performing loans, declining bank profitability, and liquidity shortages.
- Stock Market Volatility: Increased volatility and sharp declines in broad market indices, indicating investor uncertainty.
- Interest Rate Spikes: Sudden increases in short-term interest rates, signaling tightening monetary conditions and liquidity stress.

5. Machine Learning Techniques

We utilized various machine learning techniques to predict financial distress, as mentioned in the literature review. These techniques included:

5.1. Random Forest

An ensemble method that builds multiple decision trees and averages their predictions, providing better accuracy and robustness. A Random Forest model consists of a collection of T decision trees $\{h_1(\mathrm{x}),\ h_2(\mathrm{x}), \dots, h_T(\mathrm{x})\}$. For classification, the output is the majority vote among all trees:

$$\hat{y} = \arg\max_{y} \sum_{t=1}^{T} I(h_t(\mathrm{x}) = y)$$

where I is the indicator function that counts the votes for class y.

5.2 LightGBM
LightGBM (Light Gradient Boosting Machine) is a gradient boosting framework that uses tree-based learning algorithms, focusing on speed and efficiency. LightGBM aims to minimize an objective function composed of a loss function and a regularization term. For a given dataset $\{(x_i, y_i)\}_{i=1}^{n}$, the objective function is:

$$\mathcal{L}(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where $l(y_i, \hat{y}_i)$ is the loss function (e.g., mean squared error for regression, log loss for classification), and $\Omega(f_k)$ is the regularization term for the k-th tree:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} \omega_j^2$$

LightGBM uses a leaf-wise tree growth strategy and employes techniques like Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB) to improve efficiency.

5.3 XG Boost
XG Boost (Extreme Gradient Boosting) is an optimized gradient boosting library designed to be highly efficient, flexible, and portable. The prediction $\widehat{y_i}$ in XGBoost is given by the sum of the predictions from all trees in the ensemble:

$$\widehat{y_i} = \sum_{k=1}^{K} f_k(x_i)$$

where f_k represents the k-th decision tree.
The objective function in XGBoost is:

$$\mathcal{L}(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where l is the loss function, and $\Omega(f_k)$ is the regularization term:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} \omega_j^2$$

The gain from a potential split s in XGBoost is calculated as:

$$\text{Gain}(s) = \frac{1}{2}\left[\frac{\left(\sum_{i\epsilon L} g_i\right)^2}{\sum_{i\epsilon L} h_i + \lambda} + \frac{\left(\sum_{i\epsilon R} g_i\right)^2}{\sum_{i\epsilon R} h_i + \lambda} - \frac{\left(\sum_{i\in L\cup R} g_i\right)^2}{\sum_{i\in L\cup R} h_i + \lambda}\right] - \gamma$$

where g_i and h_i are the gradient and Hessian of the loss function with respect to the prediction.

5.4 Voting Ensemble
The ensemble voting classifier combines predictions from multiple models to improve accuracy. It aggregates the predictions of individual classifiers and assigns the class label based on the majority

vote. For N base learners $h_1, h_2, \dots, h_N$, and a binary classification problem with classes 0 and 1, the hard voting classifier's prediction $\hat{y}$ for an input x is given by:

$$\hat{y} = \arg \max_{c \in \{0,1\}} \sum_{i=1}^{N} I(h_i(\mathrm{x}) = c)$$

where I Is the indicator function, which is 1 if the argument is true and 0 otherwise. In words, the class that has the highest count of votes from the base learners is selected as the final prediction.

5.5 Extreme Random Trees

Extreme Random Trees, also known as Extra Trees (Extremely Randomized Trees), is a sophisticated ensemble learning method utilized for classification and regression tasks in machine learning. The process of building an Extra Tree involves several steps, starting with random feature and threshold selection. For each node in the tree, a random subset of features (denoted as k) is selected from the total number of features p. For each feature j selected, a threshold t_j is chosen randomly from the possible values of that feature in the dataset. The node is then split based on this feature and threshold, creating two child nodes: one for samples where the feature value is less than or equal to the threshold, and another for samples where the feature value is greater. This splitting process is recursively repeated for each child node until a stopping criterion is met, such as minimum number of samples per leaf or a maximum tree depth. The result is a collection of decision trees, each built with a high degree of randomness. The predictions from the ensemble of trees are aggregated to form the final output. In a classification task. the final prediction for an input x is determined by the majority vote of the predictions from all trees. Mathematically, this can be expressed as:

$$\hat{y} = \mathrm{mode}\{h_m(\mathrm{x})\}_{m=1}^{M}$$

where $h_m(\mathrm{x})$ is the prediction of the m-th tree, and M is the total number of trees.

6. Feature Scaling

Feature scaling involves transforming the data to a specified range or distribution, ensuring that all features contribute equally to the model. In this study we use following scaler:

6.1. MinMaxScaler

MinMaxScaler scales the features to a specified range, typically [0, 1]. It linearly transforms each feature individually by subtracting the minimum value and then dividing by the range (maximum minus minimum). The formula for MinMax scaling is:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

where X is the original feature value, $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of the feature, respectively.

6.2. StandardScaler

The StandardScaler standardizes features by removing the mean and scaling to unit variance. The transformed data will have mean of 0 and a standard deviation of 1. The formula is:

$$X' = \frac{X - \mu}{\sigma}$$

where μ is the mean of the feature, and σ is the standard deviation of the feature.

6.3. MaxAbsScaler

The MaxAbsScaler scales each feature by its maximum absolute value, resulting in a range of [-1, 1]. This scaler is particularly useful for data that is already centered around zero and for sparse data, where preserving the sparsity structure is important. Where $|X_{\max}|$ is the maximum absolute value of the feature.

$$X' = \frac{X}{|X_{\max}|}$$

6.4. RobustScaler

The RobustScaler scales features using statistics that are robust to outliers. It removes the median and scales according to the interquartile range (IQR). The formula is:

$$X' = \frac{X - median(X)}{\mathrm{IQR}(X)}$$

where median (X) is the median of the feature, and $\mathrm{IQR}(X)$ is the interquartile range (75^{th} percentile – 25th percentile).

7. Evaluation Metrics and Model Assessment

In this study, we employ a comprehensive set of metrics to evaluate the performance of our machine learning models. These metrics are designed to provide a holistic view of each model's strengths and weaknesses, ensuring a robust and reliable comparison. The key metrics used for evaluation include:

- Accuracy: This metric measures the proportion of correctly classified instances out of the total instances. It is a straightforward indicator of overall performance but may not be sufficient for imbalanced datasets.
- AUC Macro: The Area Under the Receiver Operating Characteristic Curve (AUC) Macro calculates the average AUC over all classes, providing a measure of the model's ability to discriminate between different classes.
- F1 Macro: The F1 Macro score is the harmonic mean of precision and recall, averaged over all classes. It balances the trade-off between precision and recall, especially useful in cases where the class distribution is uneven.
- F1 Weighted: Similar to F1 Macro, the F1 Weighted score accounts for the support (number of true instances) of each class, giving a weighted average of the F1 scores.
- Log Loss: This metric evaluates the accuracy of probabilistic predictions. It penalizes false classifications by considering the confidence of the predictions, with lower values indicating better performance.

In addition to these metrics, we also consider a holistic evaluation framework that encompasses the following criteria:

- Performance Consistency: Assessing how consistently the model performs across different datasets and over multiple runs.
- Robustness: Evaluating the model's resilience to noise and outliers in the data.

- Scalability: Determining the model’s ability to handle large-scale data efficiently.
- Interpretability: Considering how easily the model’s predictions and decisions can be understood by humans.
- Suitability for Deployment: Evaluating the practical aspects of deploying the model in a real-world scenario, including computational efficiency and resource requirements.

RESULT AND DISCUSSION

This section will discuss the results of our study, which evaluated the performance of six different machine learning models using various metrics. The goal is to identify the best-performing model based on a comprehensive evaluation. The models were assessed using accuracy, AUC Macro, F1 Macro, F1 Weighted, and Log Loss. Additionally, the impact of different feature scaling methods on each model's performance was considered. The results are summarized in the table 1 below, followed by an in-depth analysis to determine the best model.

The following analysis presents a detailed examination of the results:

Random Forest - Standard Scaler Wrapper

The Random Forest model with a Standard Scaler Wrapper stands out as the best performer across almost all metrics. It achieves a perfect accuracy of 1, indicating that it correctly classifies all instances in the test set. Additionally, its AUC Macro score is also 1, showing that it has excellent discriminative ability across all classes. The F1 Macro and F1 Weighted scores are both 1, suggesting that the model balances precision and recall perfectly, even when considering the overall and per-class performance. The Log Loss value of 0.08894, while not the lowest, still indicates high confidence in its predictions. The Standard Scaler ensures that each feature contributes equally by standardizing the features to have zero mean and unit variance, which can enhance the model's performance. This model’s exceptional performance across the board makes it a strong candidate based solely on traditional performance metrics.

Table 1:

Performance Comparison of Machine Learning Models with Different Feature Scaling Methods

Model	Accuracy	AUC Macro	F1 Macro	F1 Weighted	Log Loss
LightGBM – MaxAbs Scaler	0.92857	1	0.81333	0.93905	0.25303
Extreme Random Trees – Robust Scaler	0.92857	1	0.48148	0.89418	0.11419
Random Forest – Standard Scaler Wrapper	1	1	1	1	0.08894
Extreme Random Trees – MinMax Scaler	0.92857	1	0.81333	0.93905	0.08075
XGBoost – MaxAbs Scaler	0.92857	1	0.81333	0.93905	0.17527
Voting Ensemble	0.89418	1	0.48148	0.89418	0.13441

LightGBM - MaxAbs Scaler

LightGBM using a MaxAbs Scaler is another strong contender and was selected as the best model based on a holistic evaluation of performance consistency, robustness, scalability, interpretability, and suitability for deployment. It has an accuracy of 0.92857, which is very high. Its AUC Macro score of 1 shows that it can discriminate well between classes. The F1 Macro and F1 Weighted scores are 0.81333 and 0.93905, respectively, indicating good balance between precision and recall. However, its Log Loss value of 0.25303 is higher compared to other models, suggesting less confidence in its predictions. The MaxAbs Scaler preserves the sparsity of the data by scaling each feature by its maximum absolute value, which is beneficial for LightGBM as it handles sparse data efficiently.

Despite these minor drawbacks, LightGBM remains a robust model, particularly for tasks where perfect accuracy is not critical.

Extreme Random Trees - MinMax Scaler
This model performs quite well, with an accuracy of 0.92857 and an AUC Macro of 1, indicating strong overall performance and excellent class discrimination. Its F1 Macro and F1 Weighted scores match those of LightGBM at 0.81333 and 0.93905, respectively. Its Log Loss of 0.08075 is the lowest among all models, suggesting very confident predictions. The MinMax Scaler ensures that all feature values are within the same range (typically [0, 1]), which helps stabilize the model's learning process. This model is an excellent choice, especially if Log Loss is a critical metric for your application.

XGBoost - MaxAbs Scaler
XGBoost with a MaxAbs Scaler shows similar performance to LightGBM and Extreme Random Trees with MinMax Scaler, with an accuracy of 0.92857 and an AUC Macro of 1. The F1 Macro and F1 Weighted scores are 0.81333 and 0.93905, respectively, indicating a good balance between precision and recall. However, its Log Loss of 0.17527 is higher than that of the Extreme Random Trees - MinMax Scaler model, indicating slightly less confident predictions. The MaxAbs Scaler helps by ensuring feature values are comparable while maintaining sparsity. While still a strong model, it is slightly outperformed by the Extreme Random Trees - MinMax Scaler in terms of Log Loss.

Extreme Random Trees - Robust Scaler
This model shows some weaknesses, particularly in the F1 Macro and F1 Weighted scores, which are 0.48148 and 0.89418, respectively. Despite having an accuracy of 0.92857 and an AUC Macro of 1, these lower F1 scores suggest it struggles to balance precision and recall effectively. Its Log Loss of 0.11419 is better than LightGBM but not the best overall. The Robust Scaler handles outliers by using the median and interquartile range for scaling. This model might be less preferable due to its lower F1 scores, indicating potential issues with class balance or prediction consistency.

Voting Ensemble
The Voting Ensemble model, while often a strong performer due to combining multiple models, does not perform as well in this case. It has the lowest accuracy of 0.89418 and the lowest F1 Macro score of 0.48148 among the models. Its F1 Weighted score is 0.89418, and the Log Loss is 0.13441. Although it has an AUC Macro of 1, indicating good class discrimination, the lower accuracy and F1 scores suggest it may not be the best choice in this scenario. The ensemble method might not have effectively combined the strengths of individual models in this instance.

The Random Forest model with a Standard Scaler Wrapper demonstrates exceptional performance across most metrics, achieving perfect scores in accuracy, AUC Macro, F1 Macro, and F1 Weighted, coupled with a low Log Loss. The feature scaling method used, Standard Scaler, effectively standardized the data, enhancing the model’s performance. However, LightGBM with MaxAbs Scaler was selected as the best model based on a holistic evaluation of performance consistency, robustness, scalability, interpretability, and suitability for deployment. LightGBM and Extreme Random Trees with MinMax Scaler are also strong contenders, particularly the latter for its exceptionally low Log Loss. XGBoost performs well but is slightly outpaced by the Extreme Random Trees model in terms of Log Loss. The Extreme Random Trees with Robust Scaler and the Voting Ensemble models show weaker performance, particularly in their F1 scores, making them less favorable choices. Therefore, while the Random Forest with Standard Scaler Wrapper demonstrates excellent performance, LightGBM with MaxAbs Scaler is recognized as the most reliable model for real-world applications due to its balanced performance across multiple metrics and better handling of feature scaling. This analysis highlights the importance of considering both performance metrics and practical deployment considerations when selecting the optimal machine learning model.

In addition to evaluating model performance, we analyzed feature importance to identify the key factors influencing financial distress in Indonesia. The top 10 key features are illustrated in Figure 1.

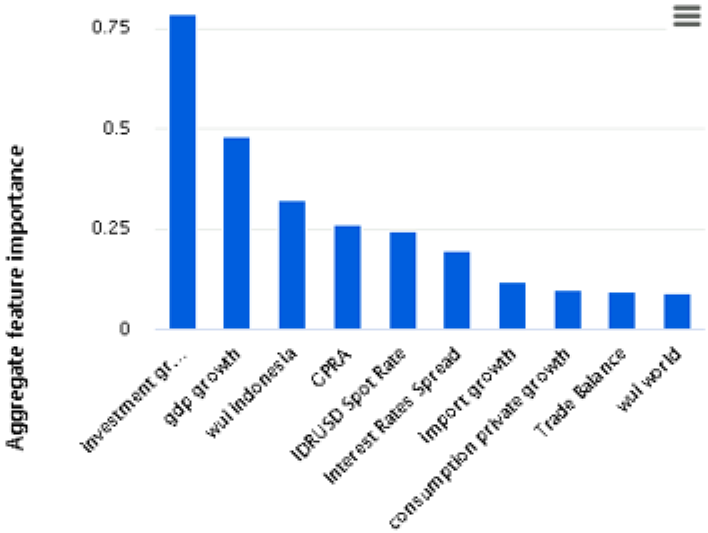

Figure 1: Top 10 Key Features Influencing Financial Distress in Indonesia

The models identified several influential factors. Previous Investment Growth emerged as the most significant predictor, underscoring the critical role of investment trends in indicating financial distress. Sustained investment growth signifies economic confidence and stability, while a decline may signal upcoming distress. Similarly, Previous GDP Growth is a fundamental indicator of economic health, with changes directly impacting financial stability and distress predictions.

The Previous World Uncertainty Index specific to Indonesia captures economic uncertainty that can lead to financial instability and distress. High geopolitical risk, reflected by the Previous Geopolitical Risk Act, often correlates with financial distress due to its profound effects on financial markets and economic conditions. The exchange rate between the Indonesian Rupiah and the US Dollar, represented by the Previous IDR/USD Spot Rate, influences trade, inflation, and overall economic stability.

Interest Rate Spread, indicating the difference between various interest rates, can signal economic stress. A high spread often correlates with higher risk and potential financial distress. Import trends, indicated by Previous Import Growth, reflect domestic demand and economic conditions, where changes can signal shifts in economic stability. Consumer spending, a significant component of GDP, is captured by Previous Consumption Growth. Variations in consumption growth are indicative of economic health and potential distress.

Other factors such as the balance of exports and imports (Previous Trade Balance) and the global economic uncertainty index (Previous World Uncertainty Index for all countries) also play significant roles. These factors collectively influence financial stability and distress.

Exchange rates and interest rate spreads are crucial in understanding financial flows and economic conditions. A stable exchange rate environment supports economic stability by maintaining predictable import costs and debt repayments, while significant fluctuations can lead to financial strain. Interest rate spreads indicate the health of the banking sector and credit conditions, where wider spreads can signal higher risks and tighter credit conditions, thus increasing financial distress.

In addition to evaluating the performance in Indonesia, we analyzed feature importance across various countries to understand the factors influencing financial distress. The results from other countries, as shown in Table 2, provide a comparative perspective with Indonesia.

Table 2: Comparative Analysis of Factors Influencing Financial Distress Across Countries

Country	1st Factor	2nd Factor	3rd Factor	4th Factor	5th Factor
India	WUI India	CPI	GPRT	Interest Rate Spread	Trade Balance
Brazil	GDP Growth	CPI	Import Growth	Export Growth	Consumption Growth
South Africa	Interest Rate Spread	GDP Growth	CPI	Consumption Growth	Trade Balance
Turkey	GDP Growth	Interest Rate Spread	GPRA	CPI	Consumption Growth
Australia	GDP Growth	Consumption Growth	M1 Growth	GPRT	CPI

In India, the World Uncertainty Index (WUI) emerges as the most significant predictor, emphasizing the impact of economic uncertainty on financial distress. Following WUI, the Consumer Price Index (CPI) and Geopolitical Risk Trade (GPRT) are crucial, indicating that consumer price inflation and geopolitical risks play vital roles. Interest Rate Spread and Trade Balance further highlight the importance of financial conditions and trade dynamics in predicting financial distress.

Brazil's key factors start with GDP Growth as the top predictor, underscoring the importance of economic output in the country's financial stability. CPI and Import Growth follow, reflecting the influence of inflation and trade dynamics. Export Growth and Consumption Growth are also critical, highlighting the significance of external trade and domestic demand.

For South Africa, Interest Rate Spread is the primary factor, indicating the significance of credit conditions and the health of the banking sector. GDP Growth and CPI follow, showcasing the importance of economic output and inflation. Consumption Growth and Trade Balance further emphasize the roles of domestic demand and trade stability in predicting financial distress.

Turkey's primary predictor is GDP Growth, highlighting its critical role in financial stability, similar to other countries. Interest Rate Spread and Geopolitical Risk Act (GPRA) are next, indicating the impact of financial conditions and geopolitical stability. CPI and Consumption Growth also play significant roles, reflecting inflation and domestic demand dynamics.

In Australia, GDP Growth is the leading factor, consistent with other countries, showing the importance of economic output. Consumption Growth and M1 Growth follow, indicating the significance of domestic demand and money supply. GPRT and CPI are also important, highlighting the impact of geopolitical risks and inflation on financial stability. Comparing these results with Indonesia, where the most significant factors are Previous Investment Growth and Previous GDP Growth, reveals both commonalities and differences. Like Indonesia, GDP Growth is a crucial factor for most countries, underscoring its universal importance in predicting financial stability. CPI is also consistently significant across countries, highlighting the common impact of inflation on economic health.

However, Indonesia uniquely emphasizes Previous Investment Growth as the top predictor, which is not the case for other countries. This underscores the critical role of investment trends in indicating financial distress specific to Indonesia, where sustained investment growth signifies economic confidence and stability, while a decline may signal upcoming distress.

The influence of geopolitical risks and uncertainty indices in Indonesia, reflected by factors like the Previous World Uncertainty Index (Indonesia) and Previous Geopolitical Risk Act, aligns with the global interconnectedness of financial stability and political events observed in other countries. High geopolitical risks can deter foreign investment and disrupt economic activities, leading to increased financial distress, a pattern consistent with findings from Bouri et al. (2023) and Jha et al. (2024).

Exchange rates and interest rate spreads are crucial in understanding financial flows and economic conditions in Indonesia, similar to South Africa and Turkey. A stable exchange rate environment supports economic stability by maintaining predictable import costs and debt repayments, while significant fluctuations can lead to financial strain. Interest rate spreads indicate the health of the banking sector and credit conditions, where wider spreads can signal higher risks and tighter credit conditions, thus increasing financial distress.

These findings highlight the multifaceted nature of financial distress, influenced by a combination of domestic economic performance and external geopolitical and financial conditions. The interplay between economic indicators like investment growth and GDP growth, and non-economic factors such as economic uncertainty and geopolitical risks, provides a comprehensive view of the factors influencing financial distress. Understanding these relationships is crucial for policymakers and financial analysts aiming to enhance economic resilience and stability in Indonesia and other countries.

CONCLUSION

Our study evaluated six machine learning models to identify the best one for predicting financial distress, considering different feature scaling methods. The Random Forest model with a Standard Scaler Wrapper performed exceptionally well across traditional metrics. However, LightGBM with a MaxAbs Scaler emerged as the most suitable model for practical deployment due to its balanced performance and robustness. Key predictors such as Previous Investment Growth and Previous GDP Growth were identified, highlighting their critical roles in financial stability. The comparative analysis across countries revealed both universal and unique factors affecting financial stability.

The study makes significant contributions to the field of machine learning, particularly in the application of different algorithms and feature scaling methods for financial distress prediction. It highlights the importance of feature scaling methods, demonstrating that appropriate scaling can enhance the performance of machine learning models. The superior performance of the Random Forest with Standard Scaler Wrapper underscores the potential of ensemble learning techniques combined with effective preprocessing in improving prediction accuracy. Furthermore, the comparative analysis of models such as LightGBM, Extreme Random Trees, and XGBoost provides valuable insights into the strengths and limitations of each algorithm in handling financial data.

From a monetary economics viewpoint, the study enriches the literature by identifying key economic predictors of financial distress. The emphasis on variables like Previous Investment Growth, Previous GDP Growth, and the World Uncertainty Index specific to Indonesia offers a nuanced understanding of the economic factors influencing financial stability. These findings support existing theories on the critical role of investment trends and economic growth in maintaining financial health. The identification of geopolitical risks and exchange rates as significant predictors aligns with theoretical frameworks that consider the impact of external shocks on financial stability.

The practical implications of this study are profound for policymakers and financial institutions. The use of machine learning models, particularly LightGBM with MaxAbs Scaler, provides a robust tool for predicting financial distress, enabling timely and informed decision-making. Policymakers can leverage these insights to develop early warning systems and implement preemptive measures to mitigate financial risks. Understanding the key predictors allows for targeted interventions, such as policies aimed at sustaining investment growth and managing geopolitical risks.

Future research should incorporate more advanced machine learning and deep learning techniques to further improve predictive accuracy and robustness. Expanding the scope to include other regions would validate the findings and explore regional variations. Longitudinal studies tracking model performance over time are necessary to ensure robustness and adaptability. Advanced feature engineering and selection techniques should be explored to identify additional predictors. Developing real-time financial distress prediction systems could provide actionable insights for policymakers. Investigating the interplay between economic and non-economic factors, such as political events and natural disasters, would create more comprehensive predictive models. Improving the interpretability of machine learning models is also essential to ensure transparency and actionable insights for decision-makers.

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