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A COMPARATIVE STUDY OF ANN AND LOGISTIC REGRESSION FOR FINANCIAL DISTRESS PREDICTION IN INDONESIAN MANUFACTURING FIRMS

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Abstract

This study aims to compare the predictive performance of the Logistic Regression (LR) model and the Artificial Neural Network (ANN) in forecasting financial distress among manufacturing firms listed on the Indonesia Stock Exchange (IDX) during 2022–2024. Financial distress represents a deterioration in a company's financial condition and serves as an early warning of potential bankruptcy; therefore, accurate prediction models are crucial for investors, creditors, and corporate decision-makers. The sample comprises manufacturing companies selected through purposive sampling, based on the availability and completeness of financial statements for the observation period. The variables used include financial ratios such as Return on Assets (ROA), Debt-to-Assets Ratio (DAR), and Current Ratio (CR). Two predictive models were developed: Logistic Regression, a conventional statistical approach, and an Artificial Neural Network, a nonlinear machine learning method. The results indicate that the Logistic Regression model achieves a higher recall rate than the Artificial Neural Network model (55.56%), suggesting that Logistic Regression provides better predictive performance in identifying companies experiencing financial distress.

Keywords: *Artificial Neural Network, Financial Distress, Logistic Regression, Manufacture, Recall*

1. Introduction

According to Statistics Indonesia (BPS, 2025), the Indonesian economy experienced a slowdown compared to previous years. In 2023, the country's Gross Domestic Product (GDP) declined by 0.26%, followed by a smaller decrease of 0.02% in 2024. The deceleration of Indonesia's economic growth from 2022 to 2024 has intensified companies' financial pressures, thereby increasing the likelihood of financial distress. During periods

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of economic instability or stagnation, firms face greater challenges in sustaining growth and achieving expected profitability. Conversely, when the economy expands, market demand tends to rise, leading to improved corporate performance and higher investment value (Said & Pangestuti, 2024).

The protracted economic pressures increasingly amplify the risk of default, thereby rendering legal instruments such as the PKPU (Suspension of Debt Payment Obligations) ever more pivotal in averting further financial deterioration. PKPU (Suspension of Debt Payment Obligations) is a legal mechanism introduced to address situations of potential bankruptcy. It is a process that allows financially distressed companies to restructure their debts without immediately declaring bankruptcy. Through PKPU (Suspension of Debt Payment Obligations), firms can negotiate with creditors to reach mutually beneficial agreements that support business continuity and prevent further financial deterioration (Raharja & Gunardi, 2023).

The salience of PKPU (Suspension of Debt Payment Obligations) in a weakening economic climate is also evident in the data reported by CRIF Indonesia. There were 624 cases of Suspension of PKPU (Suspension of Debt Payment Obligations) recorded in 2024, averaging 156 cases per quarter. This figure was slightly lower than the 677 cases in 2023 and 636 cases in 2022, indicating potential improvements in corporate debt management, operational efficiency, or the effectiveness of government policies aimed at sustaining economic stability. However, the upward trend from 126 cases in the second quarter of 2024 to 162 cases in the third quarter and 171 cases in the fourth quarter suggests that liquidity challenges remain unresolved. In addition, CRIF Indonesia (2025) also identified the specific industries most affected by PKPU (Suspension of Debt Payment Obligations) during the fourth quarter of 2024. This pattern further underscores the growing vulnerability of firms under tightening economic conditions, thereby providing a clearer conceptual bridge to the broader notion of financial distress.

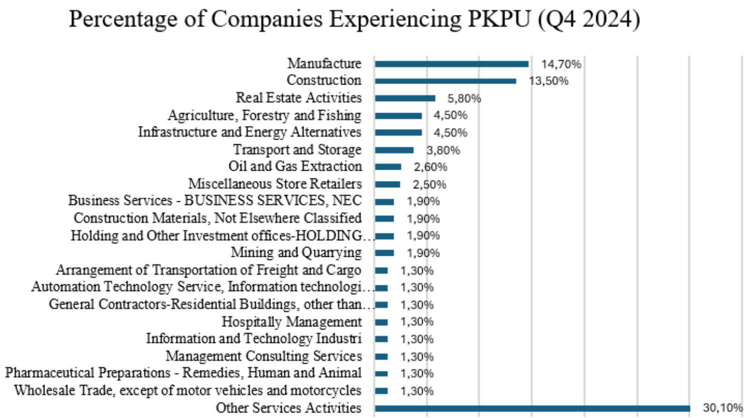

Figure 1 Percentage of Companies Experiencing Suspension of Debt Payment Obligations

Financial distress refers to a condition in which a company experiences financial instability or deteriorating performance. A firm is considered to be in financial distress when it faces internal problems that hinder its operations. This situation often arises from several factors, including excessive debt obligations and sustained operational losses. Such circumstances require firms to closely monitor their financial condition, as prolonged financial distress may ultimately lead to bankruptcy (Sari et al., 2020).

Bankruptcy can be viewed as a consequence of a company's inability to sustain its performance, which ultimately weakens its competitiveness in a dynamic market environment. When a firm's performance continues to deteriorate, it may eventually be forced out of the business landscape (Ungkari et al., 2023). To ensure long-term survival, management must formulate effective strategies and make sound decisions, particularly those that influence the company's future direction (Sitorus & Yulita, 2023). Before reaching bankruptcy, a company typically enters a phase of financial distress, a state of deteriorating financial health that serves as an early warning of potential insolvency. To prevent bankruptcy, firms can identify and analyse early signs of distress by evaluating their financial statements and assessing indicators of declining performance (Suryani & Mariani, 2022).

Assessing financial distress is essential for anticipating potential bankruptcy and ensuring the continuity of a company's operations. Prior studies have shown that financial ratios such as ROA, CR, and DAR are useful indicators of a firm's overall financial condition. Studies by (2023), Kristanti et al. (2023), and Tumpach et al. (2020) further support the relevance of these ratios in identifying early signs of financial distress among companies. Their findings suggest that ROA, CR, and DAR are meaningful variables for constructing models to predict financial distress. To assess financial distress, logistic regression is commonly used. Logistic regression is an analytical method used to model how one or more predictor variables influence an outcome with two possible categories (Situngkir & Sembiring, 2023). However, this method has a notable limitation: it is susceptible to underfitting when handling imbalanced datasets, which can reduce prediction accuracy (Umat et al., 2024). Previous studies by Kristanti & Dhaniswara (2023) and Zizi et al. (2021) found that logistic regression outperformed the Artificial Neural Network (ANN) in predicting financial distress.

In addition to logistic regression, the Artificial Neural Network (ANN) model can also be utilised to predict financial distress. ANNs are recognised as nonparametric statistical approaches capable of addressing complex, unstructured problems. One of the key strengths of ANN lies in its ability to capture highly nonlinear relationships among variables, which enables it to achieve superior predictive performance compared with simpler machine learning techniques (Alamsyah et al., 2021). Empirical findings from (2024), Lokanan & Ramzan (2024), Song et al. (2023), Kristanti et al. (2023), and Alamsyah et al. consistently indicate that ANN provides the highest predictive accuracy and the lowest error rate.

This study aims to evaluate and compare the predictive performance of Artificial Neural Networks (ANNs) and logistic regression for identifying financial distress, using ROA, CR, and DAR as key financial indicators. The novelty of this research lies in its direct examination of performance differences between the two models and its application to the most recent data from manufacturing firms listed on the IDX, thereby addressing gaps in earlier studies that typically relied on a single method or did not conduct an empirical comparison. Through this comparative approach, the study assesses the effectiveness of each predictive technique in detecting early signals of financial difficulties. The findings are expected to offer deeper empirical insights and serve as a valuable reference for corporate decision-makers in supporting evaluation, control, and strategic financial planning to maintain the firm’s financial stability.

2. Literature Review

2.1 Signaling Theory

The signalling theory suggests that the information holder, or signal sender, conveys indicators that reflect the firm’s actual condition, providing valuable insights to the information receiver (Spence, 1973). A signal can be understood as an action or individual attribute within the market that, either intentionally or unintentionally, influences perceptions or conveys information to other market participants (Spence, 1974). Signalling theory posits that corporate management acts as an agent responsible for communicating financial reporting information to external parties. The theory further emphasises that companies intentionally transmit information to external stakeholders, such as investors and other interested parties. The information disclosed by the firm serves as an indicator of its prospects, and management typically seeks to project a more favourable outlook than that of other firms in the market (Goh, 2023).

2.2 Financial Distress

Financial distress refers to a condition in which a business faces a severe financial crisis. This situation typically arises when an entity is unable to meet its debt obligations due to insufficient funds to sustain its operations (Sitorus et al., 2022). A company's distress can ultimately lead to bankruptcy, which may manifest as economic, business, or financial failure. Economic failure occurs when a firm is unable to generate revenues sufficient to cover its total costs and the capital invested in its operations (Weo et al., 2022).

2.3 Financial Statement

A financial statement is a record that presents a series of financial information about a company within a specific accounting period, providing a clear depiction of the firm’s performance regardless of its size or industry, whether in services or trading (Manik et al., 2023). The primary objective of financial statements is to deliver reliable financial information concerning a company's economic resources, obligations, and changes in those resources, as well as data that assist in estimating potential income and other relevant disclosures (Siswanto, 2021). Financial statements generally comprise several key reports, including the balance sheet, income statement, statement of changes in equity, and cash flow statement. Although these reports appear as sheets of paper filled with numerical data, they ultimately reflect the underlying assets and economic activities that define the company's true financial condition (Daeli et al., 2024).

2.4 Return on Asset (ROA)

The Return on Assets (ROA) ratio indicates how much profit a company earns per unit of total assets, reflecting the return generated from the assets it controls. It reflects a company's ability to generate earnings by effectively utilising its available resources. The primary purpose of ROA is to assess how efficiently a firm employs its assets to generate profits. Additionally, ROA is an indicator of the firm's overall return on investment, measured against its total assets. A higher ROA indicates greater efficiency in generating returns for investors, implying stronger operational performance. Conversely, a decline in ROA indicates that the company's profitability is weakening, which may suggest potential financial difficulties or operational inefficiencies (Pratama et al., 2024). ROA formula is as follows :

$$\mathrm{ROA} = \frac{\text{Net Income}}{\text{Total Asset}}$$

2.5 Current Ratio (CR)

The Current Ratio (CR) shows how well a company's short-term assets can absorb its immediate liabilities. An elevated CR indicates that the firm is better positioned to meet its near-term financial commitments. CR is a valuable metric for assessing a company's liquidity position, as it reveals how effectively the firm's current assets can guarantee the repayment of its short-term debts (Hikmah & Muniarty, 2024). Moreover, the CR serves as a margin of safety for short-term creditors, demonstrating the degree to which their claims are secured by assets expected to be converted into cash within the same period as the maturity of those liabilities (Rahayu, 2020). CR formula is as follows:

$$\mathrm{CR} = \frac{\text{Current Asset}}{\text{Current Liabilties}}$$

2.6 Debt to Asset Ratio (DAR)

The Debt-to-Asset Ratio (DAR), often classified as a leverage or solvency indicator, measures the extent to which a firm's assets are financed with borrowed capital (Jurlinda et al., 2022). This ratio reflects the degree of financial risk a firm faces: a higher DAR indicates greater reliance on borrowed funds and, consequently, a higher likelihood of default. Conversely, a lower DAR suggests that the company is less dependent on external debt, implying a stronger solvency position and reduced financial risk (Silvia & Yulistina, 2022). DAR formula is as follows:

$$\text{DAR} = \frac{\text{Total Liabilities}}{\text{Total Asset}}$$

3. Research Methods

Logistic regression is a statistical method used to model how one or more predictors influence an outcome with two possible categories (Situngkir & Sembiring, 2023). It is a data analysis technique that models the association between a binary response variable and one or more continuous or categorical explanatory variables. In this context, the binary response variable Y typically takes two possible values, denoted Y=1 and Y=0, corresponding to "yes" and "no," respectively (Rivanda & Muslim, 2021). However, a key limitation of logistic regression is its susceptibility to underfitting, particularly when applied to imbalanced datasets, which can lead to low predictive accuracy (Umat et al., 2024).

The Artificial Neural Network (ANN) is a machine learning algorithm capable of modelling complex nonlinear relationships among variables, thereby achieving higher predictive accuracy than simpler machine learning techniques (Alamsyah et al., 2021). The architecture of an ANN generally comprises three types of network structures: the Single-Layer Network, the Multilayer Network, and the Competitive Network. A single-layer network consists only of an input layer and an output layer, whereas a multilayer network includes an additional hidden layer between the input and output layers. Meanwhile, a competitive network incorporates feedback loops in which output neurons send signals back to input neurons, thereby forming a dynamic learning structure. Based on the learning paradigm, Artificial Neural Networks (ANNs) are generally classified as supervised or unsupervised. In supervised learning, the model is trained using inputs paired with known target outputs, enabling it to improve by comparing its predictions with the correct results. In contrast, unsupervised learning operates on datasets without target outputs, enabling the network to identify underlying patterns and relationships autonomously (Kurniati et al., 2024).

This research utilises secondary data obtained from the financial reports of manufacturing firms listed on the Indonesia Stock Exchange (IDX) for the years 2022–2024. The research population comprises 271 companies. The samples were selected through purposive sampling, taking into account the accessibility and completeness of the required data and their relevance to the study criteria. The final sample comprises 183 companies, yielding 549 observations over the three years. The detailed sampling criteria are presented in Table 1.

Table 1. Sample Criteria

Sample Criteria	Total
Manufacturing companies listed on the Indonesia Stock Exchange (IDX) during the period 2022-2024	271
Manufacturing companies that did not publish their financial statements consecutively for the years 2022-2024 were excluded.	(59)
Manufacturing companies that did not present their financial statements in Indonesian Rupiah (IDR) during the period 2022-2024 were excluded.	(29)
Total Sample	183
Year of Observation	3
Total Data	549

Source: Data processed (2025)

Based on the collected data, this study identifies predictive indicators, as presented in Table 2, for both Logistic Regression and Artificial Neural Network (ANN) models. These indicators are subsequently processed using Python software to develop the prediction models. The analysis produces an output for each firm, ranging from 0 to 1, indicating the likelihood of financial distress. An output value approaching 0 indicates that the company is financially healthy, whereas a value approaching 1 indicates financial distress.

Table 2. Operational Definition of Variables

Variable	Definition	Measurement
Financial Distress	Financial distress refers to a condition in which a business faces a severe financial crisis. This situation typically arises when an entity is unable to meet its debt obligations due to insufficient funds to sustain its operations (Sitorus et al., 2022)	The values of 1 for the distressed company and 0 for the non-distressed company.
Debt to Asset Ratio	This ratio reflects the degree of financial risk a firm faces: a higher DAR indicates greater reliance on borrowed funds and, consequently, a higher likelihood of default. Conversely, a lower DAR suggests that the company is less dependent on external debt, implying a stronger solvency position and reduced financial risk (Silvia & Yulistina, 2022)	$Assets \frac{\text{Total Liabilities}}{\text{Total Asset}}$

Current Ratio	Valuable metric for assessing a company's liquidity position, as it reveals how effectively the firm's current assets can guarantee the repayment of its short-term debts (Hikmah & Muniarty, 2024)	$, AssetsAssets \frac{\text{Current Asset}}{\text{Current Liabilities}}$
Return on Asset	a metric that shows how effectively a company's assets contribute to generating net income (Yulianti et al., 2025)	$\frac{\text{Net Income}}{\text{Total Asset}}$

Source: Kristanti & Dhaniswara, (2023)

To ensure that the empirical analysis yields reliable and interpretable results, this study applies several data-processing procedures as follows.

a. Data Collection

Before conducting the financial distress prediction, this study first defined financially troubled firms as those that reported losses for three consecutive years and/or were flagged with a special notation by the Indonesia Stock Exchange (IDX). Using these criteria, financial statements of manufacturing companies listed on the IDX for the 2022–2024 period were gathered. Of the initial population of 271 firms, 183 met the required conditions and were retained in the final sample, whereas 88 were excluded for inconsistent publication of financial reports or for using currencies other than the Indonesian rupiah during the observation window.

b. Data Balancing

During the data collection stage, the researcher identified an imbalance between classes, a condition that can compromise the effectiveness of predictive models. To address this issue, an oversampling strategy was employed to increase the representation of the minority class and achieve a more proportional distribution relative to the majority class. In this study, the SMOTE algorithm was employed to generate synthetic minority samples rather than simply replicating existing observations.

Table 3. Class Distribution Before and After Resampling

Before Resampling		After Resampling	
0	1	0	1
0.817518	0.182482	0.5	0.5

Source: Data Processing Result (Python) (2025)

c. Training-Test Set Split

The dataset was partitioned into two subsets: the first, designated as the training sample, comprised 75% of the observations (137 firms), while the second, serving as the validation or test sample, consisted of the remaining 25% (46 firms). Predictive models were subsequently developed using the training subset, and their performance was assessed on the test subset.

d. Variable Analysis

As outlined in the previous section, financial distress is the primary variable of interest in this study. It is a qualitative, dichotomous, and binary variable. In this research, a value of 1 is assigned to firms that report losses for three consecutive years and/or receive a special notation from the Indonesia Stock Exchange (IDX), indicating that the firm is experiencing financial distress. Conversely, a value of 0 is assigned to firms that do not meet either condition, indicating the absence of financial distress. Before incorporating these variables into the modelling process, the dataset was assessed for normality, the correlation matrix examined, and multicollinearity evaluated.

e. Stepwise and LASSO Selection Techniques

1) Stepwise Logistic Regression Selection

The stepwise method is a procedure for selecting the most suitable variables in a regression model by alternately adding (forward) and removing (backward) predictors, to identify the combination that yields the most effective and efficient model (Zizi et al., 2021). The underlying principle of the stepwise approach is to minimise one of the following criteria:

Akaike Information Criterion (AIC):

$$AIC = -2\ln(L) + 2(K + 1)$$

Bayesian Information Criterion (BIC):

$$BIC = -2\ln(L) + (K + 1)\ln(n)$$

2) LASSO Logistic Regression Selection

The Least Absolute Shrinkage and Selection Operator (LASSO) is a technique for shrinking regression coefficients (Zizi et al., 2021). This approach has been extended to a variety of statistical models, including generalised linear models, M-estimators, and proportional hazard models. LASSO offers the advantage of producing parsimonious and consistent variable selection by identifying a limited subset of predictors, thereby enhancing the interpretability of the model. Consequently, the selected subset of variables is employed for predictive purposes

f. Prediction Models

1) Logistic Regression

In this model, the dependent variable to be predicted is denoted as Y, while the independent or explanatory variables are represented by $X = (X_1, X_2, \ldots, X_j)$. Within the framework of binary logistic regression, Y can take only two possible values: 1 or 0. The conditional distribution of X given Y = 1 is expressed as $P(X|1)$, whereas the conditional distribution of X given Y = 0 is represented as $P(X|0)$. The logit term for p(1|X) is formulated as follows:

$$ln = (\frac{p(1|X)}{1 - p(1|X)})_{+}\beta 0 + \sum_{i=1}^{j} \beta iX1$$

2) Artificial Neural Network

An Artificial Neural Network (ANN) is a system whose concept was initially schematically inspired by the function of biological neurons. This network comprises interconnected formal neurons that enable the solution of complex problems, such as pattern recognition and natural language processing, by adjusting their weights during the learning phase. A formal neuron is a model characterised by an internal state s ∈ S, input signals X = (X1, X2,…XJ)T, and an activation function:

$$s = \mathrm{h}(\mathrm{X1}, \mathrm{X2}, \dots \dots \mathrm{Xj}) = g(\alpha 0 + \sum_{i=1}^{j} \alpha iXi\ )$$

g. Metrics

In this study, the performance of predictive models is evaluated using machine learning metrics summarised in a confusion matrix, including accuracy, precision, sensitivity, specificity, F1-score, and the Area Under the Curve (AUC). The researcher employed sensitivity (also referred to as recall) to compare the effectiveness of Logistic Regression and Artificial Neural Network models in predicting financial distress. Sensitivity was chosen because it quantifies the proportion of true positive cases correctly identified by the model, highlighting its capability to detect positive instances. This metric is particularly critical because failing to recognise positive cases (false negatives) can have significant consequences (Sethi & Mahadik, 2025).

4. Results and Discussion

4.1 Result

4.1.2 Feature Selection Results

Table 4 displays the financial ratios identified through the Stepwise and LASSO selection procedures. The Stepwise logistic regression method identifies the most relevant variables by minimising the Bayesian Information Criterion (BIC). In contrast, the LASSO logistic regression approach identifies relevant ratios based on the optimal penalty coefficient. In this analysis, the optimal BIC value is 131.8631, whereas the optimal penalty coefficient (λ) is 0.359381.

Table 4. Selected Variables with Stepwise and LASSO LR

Model	Selected Variable	Criterion Value
Stepwise Logistic (BIC)	ROA	BIC = 131.8631
LASSO Logistic Regression	ROA, DAR, and CR	penalty λ = 0.359381

Source: Data Processing Result (Python) (2025)

The Stepwise Logistic Regression produced the best-fitting model with only one significant variable, ROA, and a BIC value of 131.8631. This finding indicates that ROA is the dominant indicator of financial distress. In contrast, the LASSO Logistic Regression, with a penalty value (λ) of 0.359381, retained three significant variables: DAR, ROA, and CR, demonstrating that LASSO tends to include more contributing variables while simultaneously controlling model complexity through regularisation. These differences indicate that Stepwise emphasises model simplicity, whereas LASSO prioritises a balance between predictive accuracy and model stability.

4.1.2 Descriptive Statistics

Tables 5 and 6 summarize the descriptive characteristics of the variables selected through the LASSO and Stepwise methods. The tables present descriptive statistics, normality tests, correlation matrices, and multicollinearity diagnostics.

Table 5. Descriptive Statistics for Variables Selected by LASSO

Variable	ROA	DAR	CR
Entire Data			
Mean	0.041477	0.438090	3.003533
Std	0.086597	0.271163	3.671530
Normality Test (Kolmogorov-Smirnov)	0.001000	0.014705	0.001000
Normality Test (Shapiro-Wilk)	0.000018	0.000000	0.000000
Distressed SMEs			
Mean	-0.050408	0.600550	3.686570
Std	0.083779	0.416005	6.881649
Non-Distressed SMEs			
Mean	0.062444	0.401018	2.847673
Std	0.072626	0.210680	2.426094
Correlation Matrix			
ROA	1.0000	-0.3362	-0.0062
DAR	-0.3362	1.0000	-0.5058
CR	-0.0062	-0.5058	1.0000
Multicollinearity Test			
VIF	1.1831	1.5898	1.4102
TOL	0.8452	0.6290	0.7091

Source: Data Processing Result (Python) (2025)

Based on descriptive analysis using the LASSO method, firms experiencing financial distress tend to exhibit lower profitability, as reflected in negative ROA values, and higher leverage than their non-distressed counterparts. This condition implies that financially constrained companies rely more heavily on external financing and face greater default risk. Although distressed firms exhibit a higher Current Ratio (CR), this may indicate an accumulation of current assets—such as receivables or inventory—that are not readily converted into cash, thereby weakening their actual liquidity position. The normality test indicates that all variables are not normally distributed, whereas the correlation analysis shows that inter-variable relationships remain below the multicollinearity threshold ($|r| <$

0.7). The negative correlations between DAR–CR and DAR–ROA suggest that as debt levels increase, the firm's ability to meet short-term liabilities and generate returns diminishes. Conversely, the weak negative association between CR and ROA indicates that changes in liquidity have minimal influence on profitability. Moreover, the multicollinearity assessment indicates that all variables have VIF values below 5 and TOL values above 0.1, confirming that the model is free of multicollinearity and is suitable for further analysis.

Table 6. Descriptive Statistics for Variables Selected by Stepwise

Variable	ROA
Entire Data	
Mean	0.041477
Std	0.086596
Normality Test (Kolmogorov-Smirnov)	0.022869
Normality Test (Shapiro-Wilk)	0.000018
Distressed SMEs	
Mean	-0.050408
Std	0.083779
Non-Distressed SMEs	
Mean	0.062444
Std	0.072626
Correlation Matrix	
ROA	1.0
Multicollinearity Test	
VIF	1.0
TOL	1.0

Source: Data Processing Result (Python) (2025)

ROA emerges as a key differentiator between companies experiencing financial distress and those operating normally. Firms under financial strain exhibit negative ROA, indicating limited capacity to generate returns on their assets. In contrast, financially healthy companies show positive ROA, indicating efficient asset utilisation and operational effectiveness. Furthermore, the relatively high standard deviation highlights notable variations in financial performance across firms, which is reasonable given differences in industry sectors, managerial practices, and market competition. Normality tests reveal that the data do not follow a normal distribution (p-value < 0.05), suggesting that subsequent predictive analyses require more robust statistical approaches. Regarding multicollinearity, because only ROA is included as a predictor, the VIF equals 1, and the TOL exceeds 0.1, confirming that the model is free of multicollinearity. Overall, ROA is the most influential variable and is suitable for use as a predictor in models of financial distress.

4.1.3 Estimation Results of the Stepwise and Lasso Logistic Regression Models

Table 6 reports the estimation results for the logistic regression models estimated using the Stepwise approach. The stepwise logistic regression indicates that ROA is significantly negatively associated with the likelihood of financial distress at the 1% significance level (p-value = 0.000). This implies that an increase in ROA reduces the probability of financial distress. The ROA coefficient of –22.7188 suggests that each one-unit increase in ROA lowers the log-odds of financial distress by 22.7188. The negative coefficient indicates that higher ROA is associated with a lower probability of the firm entering a distressed state. The constant term of –1.1932 is also significant (p-value = 0.000), indicating that even when ROA equals zero, the probability of financial distress remains relatively low. Additionally, the large absolute value of the z-statistic (–5.136) further supports the conclusion that ROA is a strong and influential predictor of financial distress.

Table 7. Stepwise Logistic Regression Results

	coef	std. err	z	p>|z|
const	-1.1932	0.232	-5.136	2.80×10^{-7}
ROA	-22.7188	4.424	-5.136	2.80×10^{-7}

Source: Data Processing Result (Python) (2025)

Table 8 presents the estimated results from logistic regression models fitted via LASSO. The LASSO logistic regression analysis identified three variables as significant predictors of financial distress: DAR, ROA, and CR. Both DAR (Debt to Asset Ratio) and CR (Current Ratio) exhibit a positive association with the likelihood of a firm encountering financial difficulties, indicating that higher values of these ratios correspond to an increased probability of distress. The coefficients for DAR and CR, 0.569178 and 0.516414, respectively, quantify the increase in the log-odds of financial distress per one-unit increase in these ratios. Although an elevated CR may suggest a higher risk of distress, it does not necessarily imply efficiency, as it can reflect underutilised assets. In contrast, ROA shows a negative relationship, with a coefficient of –1.634655, implying that higher asset profitability reduces the likelihood of financial distress. In essence, firms that are more effective at generating returns from their assets face a reduced likelihood of experiencing financial strain.

Table 8. LASSO Logistic Regression Results

Variable	**Coefficient**
DAR	0.569178
ROA	-1.634655
CR	0.516414

Source: Data Processing Result (Python) (2025)

4.1.4 Performance of Logit Models

Table 9 presents a performance comparison between two logistic regression approaches, Stepwise Logistic Regression and LASSO Logistic Regression, for predicting a company's financial condition as distressed or non-distressed. In the Stepwise model, while the high specificity (97.30%) reflects a strong ability to identify financially healthy firms correctly, the sensitivity is relatively low (44.44%), indicating that a considerable portion of truly distressed companies go undetected. The Type I error is substantial (55.56%), indicating that some healthy firms were incorrectly flagged as distressed. Overall accuracy is 86.96%, precision is 72.73%, F1-score is 80.00%, and AUC is 0.928, indicating good overall discrimination, albeit with limitations in detecting distressed firms. In contrast, LASSO Logistic Regression exhibits superior performance, maintaining the same high specificity (97.30%) but achieving higher sensitivity (55.56%), lower Type I error (4.44%), higher accuracy (89.13%), precision (80.00%), F1-Score (84.21%), and AUC (0.934). These results indicate that LASSO more effectively identifies companies truly experiencing financial distress, confirming its overall advantage over Stepwise Logistic Regression in predictive performance.

Table 9. Confusion Matrices For Logit Models

Stepwise Logistic Regression			**LASSO Logistic Regression**		
	0	**1**		**0**	**1**
0	36 (97.30%) a	1 (2.70%) b	**0**	36 (97.30%) a	1 (2.70%) b
1	5 (55.56%) c	4 (44.44%) d	**1**	4 (44.44%) c	5 (55.56%) d
Overall Accuracy		86.96%	Overall Accuracy		89.13%
Precision		72.73%	Precision		80.00%
F1-Score		80.00%	F1-Score		84.21%
AUC		0.928	AUC		0.934

Source: Data Processing Result (Python) (2025)

4.1.5 Performance of Artificial Neural Network

Table 10 presents a performance comparison between stepwise and LASSO ANN. The comparison between Stepwise ANN and LASSO ANN reveals distinct performance characteristics. Stepwise ANN demonstrates an exceptional ability to correctly identify non-distressed companies, achieving 100% specificity and virtually no type II errors (0%). However, it frequently misclassifies healthy companies as distressed (type I error rate of 77.78%) and exhibits low sensitivity (22.22%), limiting its effectiveness in detecting genuinely distressed firms. In contrast, LASSO ANN shows a modest reduction in specificity to 97.30% but substantially reduces misclassification of non-distressed companies (type I error rate of 55.56%). Its sensitivity increases to 44.44%, indicating improved detection of companies that are truly experiencing financial distress. Additionally, the accuracy, precision, F1-score, and AUC metrics for the LASSO ANN demonstrate more balanced performance in both prediction accuracy and distress identification. Overall, LASSO ANN outperforms Stepwise ANN, providing a more reliable tool for recognising firms in actual financial distress, even though its specificity is slightly lower.

Table 10. Confusion Matrices For ANN

Stepwise ANN	**LASSO ANN**

	0	1		0	1
0	37 (100.00%) a	0 (0.00%) b	**0**	36 (97.30%) a	1 (2.70%) b
1	7 (77.78%) c	2 (22.22%) d	**1**	5 (55.56%) c	4 (44.44%) d
Overall Accuracy		84.78%	Overall Accuracy		86.96%
Precision		72.73%	Precision		58.33%
F1-Score		80.00%	F1-Score		66.67%
AUC		0.928	AUC		0.850

Source: Data Processing Result (Python) (2025)

4.2 Discussion

The key outcomes of this research reveal that the LASSO logistic regression model outperforms LASSO artificial neural network, stepwise logistic regression, and stepwise artificial neural network in predicting corporate financial distress, as evidenced by its higher sensitivity (recall) of 55.56%. This demonstrates that the model is better able to accurately identify companies that are truly experiencing financial distress, leading to the rejection of H_0 in this study. The selection of sensitivity as the primary metric aligns with the imbalanced nature of the data (19% distress and 81% non-distress), where model success is evaluated not by accuracy but by its ability to detect the minority class, consistent with the literature on classification model evaluation under imbalance (Salmi et al., 2024). Sensitivity, also known as recall, is the proportion of true positive cases that the model successfully detects, making it especially important in situations where missing positive instances could have serious implications (Sethi & Mahadik, 2025).

The results further suggest that, in datasets with limited observations and a relatively small number of features, parametric models such as logistic regression offer greater stability than artificial neural networks, which tend to overfit without sufficient regularisation or large datasets (Wang et al., 2025). LASSO effectively selects the most relevant variables, thereby improving model interpretability and predictive performance (Zizi et al., 2021), addresses multicollinearity, performs automatic variable selection, and reduces the risk of overfitting (Yan et al., 2020). This finding supports signal theory, which posits that companies in poor condition tend to emit negative signals through deteriorating financial indicators such as low CR, high DAR, and negative ROA (Spence, 1973). Firms exhibiting low ROA, elevated DAR, and insufficient CR are at heightened risk of financial distress. The model enables these companies to recognise such vulnerabilities at an early stage, allowing for the proactive implementation of preventive measures. Preventive measures that companies can adopt include practising sound financial management, conducting thorough analyses of financial statements, implementing comprehensive risk management strategies, and upholding strong corporate governance practices. According to the LASSO Logistic Regression analysis, Return on Assets (ROA) emerged as the most influential variable in predicting financial distress. This is evidenced by its largest absolute coefficient of –1.634655, indicating that ROA exerts the strongest effect among all predictors. The negative coefficient indicates that a decline in ROA increases the likelihood of a firm entering financial distress. Meanwhile, the Debt-to-Asset Ratio (DAR) and Current Ratio (CR) also exhibit positive associations with financial distress, with coefficients of 0.569178 and 0.516414, respectively. However, their statistical influence is comparatively weaker than that of ROA. These findings underscore that profitability, as measured by ROA, is the primary determinant of a firm's financial health.LASSO logistic regression captures these signals by identifying the most relevant variables, whereas artificial neural networks are often considered "black boxes" due to their complexity, making predictions difficult to interpret (Moss et al., 2022).

These results are consistent with studies by Kristanti & Dhaniswara (2023) and Zizi et al. (2021), which found logistic regression superior to other models in predicting financial distress, with accuracies of 98.00% and 95.00%, respectively. However, they contrast with Mishra et al. (2024), who reported higher accuracy for artificial neural networks (86.66%), likely due to differences in the number of predictors, observations, and class distribution. Theoretically, the findings indicate that financial distress can be predicted from measurable financial signals, suggesting that information in financial statements serves as a signal of potential distress. In practice, the study shows that LASSO logistic regression is an effective early-warning tool for regulators, auditors, and investors. Overall, the study demonstrates that logistic regression is more suitable than artificial neural networks in contexts with limited and imbalanced data, enriches the literature on selecting appropriate predictive models for financial distress, and emphasises the importance of dataset characteristics, interpretability, and informed decision-making in financial risk management.

5. Conclusion

From a theoretical perspective, this study strengthens signalling theory by demonstrating that financial ratios such as Return on Assets (ROA), Debt to Asset Ratio (DAR), and Current Ratio (CR) can serve as reliable indicators of a firm's likelihood of financial distress. From a practical standpoint, the findings indicate that a logistic regression model enhanced with LASSO outperforms other models in predictive accuracy, making it a valuable early-warning tool for regulators, auditors, and investors in assessing and monitoring corporate financial stability. The findings of this study carry important practical implications for both companies and policymakers. For companies, the superior performance of the LASSO logistic regression model in detecting financial distress underscores the need to strengthen internal early-warning systems by closely monitoring key financial indicators, such as ROA, CR, and DAR, which have been shown to signal deteriorating financial conditions. Firms with declining profitability, inefficient liquidity management, or high leverage should promptly implement corrective measures, such as improving asset utilisation, restructuring debt, or optimising working capital, to mitigate the risk of entering into deeper financial distress. For policymakers and regulators, these results provide a valuable foundation for developing sector-wide monitoring tools to identify vulnerable firms before distress escalates into broader financial instability. Nevertheless, this research is subject to several limitations, including the use of only three primary financial variables, a relatively small number of observations, and an imbalanced dataset in which non-distressed firms significantly outnumber distressed firms.

Furthermore, the study period, which spans only 2022-2024, may not adequately capture long-term financial and economic fluctuations. For future research, it is recommended to incorporate a wider range of financial indicators, expand the analysis beyond the manufacturing sector to include industries such as banking, mining, and infrastructure, and extend the observation period to provide more comprehensive insights. Additionally, comparing Artificial Neural Networks with other advanced machine learning algorithms, such as Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting (XGBoost), and Decision Tree (DT), could enhance the robustness and generalizability of future predictive models.

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