IJAMESC, Vol. 4 No. 4, August 2026
DOI: https://doi.org/10.61990/ijamesc.v4i4.828
e-ISSN 2986-8645

FINANCIAL DISTRESS PREDICTION USING THE DECISION TREE METHOD IN MANUFACTURING COMPANIES IN INDONESIA

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Abstract

This study aims to predict financial distress in Indonesian manufacturing companies using the Decision Tree method. A quantitative predictive design was applied to secondary data from the annual financial statements of manufacturing companies listed on the Indonesia Stock Exchange during 2020–2024, yielding 612 firm-year observations. Financial distress was measured as a binary outcome (financially distressed versus non-financially distressed), with Current Ratio, Debt to Asset Ratio, Return on Assets, Total Asset Turnover, Sales Growth, and Firm Size as predictors. Using Python, a pruned Decision Tree achieved 84.6% accuracy, 64.7% precision, 75.9% recall, and a 69.8% F1-score for the financially distressed class. Return on Assets was the most influential predictor, followed by Debt to Asset Ratio and Current Ratio. The resulting rules show that distress reflects interacting conditions of weak profitability, high leverage, low liquidity, inefficient asset utilization, and declining sales growth. Theoretically, the study extends financial distress prediction research by demonstrating the value of interpretable machine learning in an emerging-market manufacturing context. Practically, its transparent rules provide an actionable early-warning tool for investors, creditors, managers, and regulators to identify financial vulnerability and support timely intervention.

Keywords: Decision Tree, Financial Distress, Manufacturing Companies, Machine Learning, Financial Ratios

1. Introduction

Financial distress prediction has become an increasingly important issue for manufacturing companies in Indonesia because the pressure faced by the sector is no longer merely cyclical, but structural, multidimensional, and closely related to both macroeconomic uncertainty and firm-level financial vulnerability. Manufacturing firms operate under the combined pressure of changing export demand, exchange rate volatility, rising input costs, tightening liquidity, supply chain disruption, and increasing competition in both domestic and global markets. S&P Global reported that Indonesia's Manufacturing Purchasing Managers' Index experienced contractionary pressure in recent periods, reflecting weakening output and export orders in the manufacturing sector (S&P Global, 2026). This condition shows that financial distress should not be understood only as an accounting symptom before bankruptcy, but as an early warning signal of declining liquidity, profitability, solvency, and operational resilience. Therefore, the prediction of financial distress is urgent because it provides an analytical basis for identifying financial vulnerability before it develops into corporate failure.

Manufacturing remains strategically important to Indonesia through its contribution to value added, employment, industrial linkages, exports, and economic resilience. Statistics

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DOI: https://doi.org/10.61990/ijamesc.v4i4.828
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Indonesia reported economic growth of 5.11% in 2025, following 5.03% in 2024, amid global trade uncertainty and uneven external demand (BPS, 2026). Because financial weakness in manufacturing firms can spread through supply chains, employment, and production capacity, early distress detection has implications beyond individual companies.

The specific problem underlying this study is that many financial distress prediction models in Indonesia still rely heavily on conventional approaches, such as Altman Z-Score, Springate, Zmijewski, discriminant analysis, and logistic regression. These approaches remain useful because they provide structured and relatively simple tools for identifying corporate failure risk. However, classical models often assume a relatively linear relationship among financial ratios, while the actual financial condition of manufacturing firms is often shaped by complex and non-linear interactions among liquidity, leverage, profitability, activity, growth, and firm size. Early studies such as Beaver (1966), Altman (1968), Ohlson (1980), and Zmijewski (1984) laid the foundation for financial distress prediction, but more recent literature shows that machine learning models may offer better predictive ability because they can capture complex relationships among financial indicators (Barboza et al., 2017; Chen, 2011; Olson et al., 2012).

In the Indonesian context, previous studies have examined financial distress using financial ratios such as liquidity, activity, leverage, profitability, and sales growth. However, many of these studies emphasize the statistical effect of financial ratios rather than developing a practical classification model that can be used as an early warning system. Bukhori et al. (2022) and Rahayuningtyas and Yanti (2023), for example, show that financial ratios are relevant in explaining financial distress among listed firms, but such studies do not fully address how financial ratios can be transformed into transparent decision rules for classifying firms into distressed and non-financially distressed categories. This limitation is important because investors, creditors, managers, and regulators require not only statistical significance, but also a model that is understandable, operational, and useful for decision-making.

Failure to predict financial distress at an early stage may create serious consequences for both internal and external stakeholders. For firms, undetected distress may lead to declining operating capacity, liquidity shortages, delayed debt payments, asset restructuring, loss of creditor confidence, and eventually bankruptcy. For investors and creditors, late detection increases the risk of mispricing, lending losses, and delayed portfolio adjustment. The Indonesia Stock Exchange has introduced special notations for listed companies with certain risk indicators, such as negative equity, bankruptcy petitions, debt moratorium, and problematic audit opinions (IDX, 2026). However, such market signals usually appear when financial risk has already become publicly visible. Therefore, predictive models are needed to identify financial distress patterns before formal market warnings emerge.

Theoretically, this study is grounded in signaling theory, agency theory, and corporate failure theory. Signaling theory explains that financial statements contain information signals that can be interpreted by external stakeholders in assessing a firm's financial health (Spence, 1973; Ross, 1977). Strong profitability, adequate liquidity, and efficient asset utilization may signal financial strength, while declining earnings, increasing leverage, weak liquidity, and negative growth may signal potential distress. Agency theory further explains that financial distress may arise when managerial decisions related to financing, investment, and working capital management do not fully align with the interests of shareholders and creditors (Jensen & Meckling, 1976). Thus, financial distress prediction is not merely a technical classification exercise, but also a mechanism for reducing information asymmetry and monitoring managerial performance.

The development of machine learning has encouraged researchers to move beyond conventional statistical models in predicting financial distress. Barboza et al. (2017) show that machine learning models can improve bankruptcy prediction accuracy compared to traditional models. Alaka et al. (2018) also emphasizes that model selection in bankruptcy prediction should consider predictive performance, data characteristics, interpretability, and practical applicability. Similarly, Qu et al. (2019) note that financial distress prediction has developed from traditional discriminant and regression models toward machine learning and deep learning techniques. These developments indicate that financial distress prediction increasingly requires models that can process complex patterns in financial data while still producing results that are useful for decision-making.

Although machine learning offers promising predictive accuracy, not all algorithms are equally suitable for accounting and finance research. Some algorithms, such as neural networks, deep learning, and complex ensemble models, may produce high accuracy but are often difficult to explain to users. In high-stakes financial decisions, interpretability is important because stakeholders need to understand why a firm is classified as distressed. Decision Tree has a methodological advantage because it produces explicit decision rules and threshold-based classification paths. Chen (2011) shows that Decision Tree models can be integrated with logistic regression for corporate financial distress prediction, while Kim and Upneja (2014) demonstrate the usefulness of Decision Tree and AdaBoosted Decision Tree models in predicting financial distress. Therefore, Decision Tree is relevant because it balances predictive ability and interpretability.

A key weakness in previous studies is the tendency to prioritize numerical accuracy without sufficient attention to the interpretability and usability of the model. A highly complex model may perform well statistically, but it may not clearly indicate which financial ratio threshold should trigger managerial concern or which combination of financial indicators reflects higher distress risk. Abrahamsen et al. (2024) highlight the importance of explicable early warning machine learning models, while Dasilas and Rigani (2024) emphasize that bankruptcy prediction research increasingly requires broader evaluation metrics, such as precision, recall, and F1-score, rather than relying solely on accuracy. This argument is particularly relevant in financial distress prediction because failing to detect distressed firms may create greater risk than incorrectly flagging healthy firms.

Based on this condition, the research gap addressed in this study lies in the limited development of a financial distress prediction model that simultaneously focuses on manufacturing companies in Indonesia, applies the Decision Tree method, and emphasizes interpretable decision rules. Recent studies have expanded machine learning-based distress prediction across different countries and industries, but the specific characteristics of Indonesian manufacturing firms remain underexplored. Manufacturing companies have distinctive financial structures, including fixed asset intensity, inventory dependence, working capital needs, production cost exposure, and sensitivity to demand fluctuations. Therefore, a general prediction model across sectors may obscure the financial distress patterns that are specific to manufacturing companies.

This study aims to predict financial distress in manufacturing companies in Indonesia using the Decision Tree method. Specifically, this study examines whether financial ratios can be used to classify firms into financially distressed and non-financially distressed categories, identifies the most important financial indicators in the classification process, and evaluates the usefulness of Decision Tree as an interpretable early warning model. The novelty of this study lies in the use of Decision Tree not only to generate predictive performance, but also to produce decision rules that explain how profitability, leverage, liquidity, activity, sales growth, and firm size interact in determining financial distress classification.

This study makes distinct theoretical and practical contributions. Theoretically, it extends financial distress prediction evidence in an emerging market and demonstrates how signaling theory, agency theory, and the dynamic view of corporate decline can be operationalized through interpretable, non-linear classification rules. Methodologically, it shows how a Decision Tree can bridge predictive performance and explainability in a sector-specific setting. Practically, investors can use the model to screen portfolio risk, creditors to support lending and monitoring decisions, managers to identify combinations of deteriorating ratios that require corrective action, and regulators to prioritize surveillance of vulnerable listed firms.

2. Theoretical Background

2.1 Financial Distress and Corporate Failure Prediction

Financial distress refers to a condition in which a company experiences financial pressure that weakens its ability to meet short-term and long-term obligations. This condition does not always immediately lead to bankruptcy, but it reflects deterioration in liquidity, profitability, solvency, cash flow, and operational performance. In corporate finance literature, financial distress is generally regarded as an early stage of corporate failure, where the company begins to experience difficulties in maintaining financial stability and sustaining business operations. Beaver (1966) explains that financial ratios can be used as predictors of business failure, while Altman (1968) develops a discriminant model to predict corporate bankruptcy using financial ratios. Ohlson (1980) and Zmijewski (1984) further expand the prediction literature by introducing probabilistic and methodological perspectives in bankruptcy prediction.

Manufacturing firms were selected because their fixed-asset intensity, inventory dependence, working-capital requirements, production cost exposure, and sensitivity to demand and raw-material fluctuations create distinctive pathways into financial distress. Weak profitability may therefore combine with inefficient asset utilization, high leverage, poor liquidity, and declining sales. Moreover, distress is dynamic rather than a single static event: firms may move through successive stages of deterioration, recovery, or failure as financial indicators interact over time (du Jardin, 2017). This sector-specific and dynamic perspective supports the use of a flexible classification method capable of identifying conditional patterns in financial ratios.

Financial distress prediction has traditionally relied on accounting-based models such as Altman Z-Score, Springate, Ohlson, Zmijewski, and logistic regression. Their simplicity is useful, but fixed coefficients, cut-off values derived from other periods or jurisdictions, and predominantly linear or additive specifications may not transfer reliably to Indonesian firms with different reporting environments, capital structures, and sectoral conditions. These models may also understate interactions—for example, leverage may be manageable when profitability and liquidity are strong but critical when both deteriorate. Decision Tree addresses these limitations by learning sample-specific, non-linear thresholds and interactions while retaining transparent decision rules (Barboza et al., 2017; du Jardin, 2017).

2.2 Signaling Theory, Agency Theory, and Financial Distress

This study is grounded in signaling theory and agency theory. Signaling theory explains that firms communicate information to the market through observable signals, including financial statements, profitability, liquidity, leverage, and other financial indicators (Spence, 1973; Ross, 1977). In the context of financial distress, weak financial ratios may function as negative signals that indicate declining financial health. Investors and creditors may interpret declining ROA, high DAR, weak CR, and negative sales growth as signals of increasing financial risk. Therefore, financial ratios are not merely accounting numbers, but information signals that reflect the firm's ability to maintain financial stability.

Agency theory provides another important perspective in understanding financial distress. Jensen and Meckling (1976) explain that the separation between ownership and control creates potential conflicts between shareholders and managers. Managers may make financing and investment decisions that increase risk, delay corrective actions, or prioritize short-term interests. When managerial decisions increase debt burden, reduce profitability, or weaken liquidity, the firm becomes more vulnerable to financial distress. Thus, financial distress prediction can also be understood as a monitoring mechanism that helps reduce information asymmetry and supports corporate governance.

From these theoretical perspectives, financial distress prediction serves two main functions. First, it provides signals regarding the firm's financial condition. Second, it supports governance mechanisms by helping stakeholders evaluate whether managerial decisions have placed the firm under financial pressure. The use of financial ratios as predictor variables is therefore theoretically justified because ratios summarize the outcome of managerial decisions related to liquidity, leverage, profitability, activity, growth, and asset management.

2.3 Financial Ratios as Predictors of Financial Distress

Financial ratios are commonly used in financial distress prediction because they reflect the firm's financial structure, operating efficiency, and ability to sustain business activities. Liquidity ratios indicate the company's ability to meet short-term obligations. A firm with weak liquidity is more vulnerable to payment delays, working capital shortages, and operating disruption. Leverage ratios describe the extent to which the company relies on debt financing. High leverage increases fixed financial obligations and exposes the firm to repayment risk. In manufacturing firms, excessive leverage may become more problematic because production activities require continuous expenditure on raw materials, inventories, machinery, and labor.

Profitability ratios measure the company's ability to generate earnings from its assets, equity, and sales. Weak profitability indicates that the company may not generate sufficient internal funds to support operations and repay obligations. Activity ratios, such as total asset turnover, reflect how efficiently the company uses its assets to generate sales. Low asset turnover may indicate underutilized production capacity, inefficient asset management, or weak market demand. Sales growth reflects changes in business expansion and market performance. A decline in sales may indicate weakening competitiveness, lower demand, or operating inefficiency. Firm size is also relevant because larger firms generally have better access to external financing, stronger bargaining power, and more stable business operations.

Previous studies support the relevance of financial ratios in predicting financial distress. Chen and Du (2009) show that financial indicators can be used in data mining

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DOI: https://doi.org/10.61990/ijamesc.v4i4.828
e-ISSN 2986-8645

models for financial distress prediction. Lin et al. (2011) emphasize the importance of selecting appropriate financial ratios for business crisis prediction. Barboza et al. (2017) also show that financial ratios remain useful in machine learning-based bankruptcy prediction. Therefore, liquidity, leverage, profitability, activity, sales growth, and firm size are used in this study as predictor variables for financial distress classification.

2.4 Decision Tree Method in Financial Distress Prediction

Decision Tree is a supervised machine learning method that classifies observations by splitting data into branches based on predictor variables. Each branch represents a decision rule, while each terminal node represents the final classification result. In financial distress prediction, Decision Tree can classify firms into distressed and non-financially distressed categories based on financial ratio patterns. The main advantage of this method is interpretability. Unlike black-box algorithms, Decision Tree produces explicit rules that can be understood by users. For example, the model may classify a firm as financially distressed when ROA is low, DAR is high, and CR is weak.

Decision Tree is particularly suitable for accounting and finance because it combines non-linear classification with interpretability. Compared with black-box methods such as neural networks, it produces visible split thresholds, hierarchical decision paths, and auditable if-then rules. These characteristics allow investors, creditors, managers, and regulators to understand not only which classification is produced but also why it is produced, a requirement for accountable financial decisions. Evidence from Chen (2011), Kim and Upneja (2014), and Olson et al. (2012) supports the use of tree-based and data-mining methods in corporate distress prediction.

Recent literature also emphasizes the importance of explainable and interpretable machine learning models in financial distress prediction. Abrahamsen et al. (2024) propose an explicable early warning machine learning model for listed Nordic companies, while Dasilas and Rigani (2024) show that machine learning techniques in bankruptcy prediction have developed rapidly but still require careful evaluation of interpretability and performance metrics. Therefore, this study uses Decision Tree to build a model that is not only predictive but also understandable and practically applicable.

2.5 Previous Studies and Research Gap

Research on financial distress prediction has developed from traditional accounting-based models to machine learning-based approaches. Earlier models such as Altman Z-Score, logistic regression, and discriminant analysis are widely used because they are simple and interpretable. However, the increasing availability of financial data and computational tools has encouraged researchers to apply machine learning techniques such as Decision Tree, Random Forest, Support Vector Machine, Neural Network, XGBoost, and deep learning. Barboza et al. (2017) show that machine learning models can improve bankruptcy prediction accuracy compared to traditional models. Qu et al. (2019) also show that bankruptcy prediction research has moved toward machine learning and deep learning techniques.

Several studies have examined financial distress prediction using different machine learning models. Chen (2011) applies Decision Tree and logistic regression to predict corporate financial distress. Kim and Upneja (2014) use Decision Tree and AdaBoosted Decision Tree models to predict financial distress. du Jardin (2017) emphasizes that financial distress should be understood as a dynamic process of firm financial evolution. Mai et al. (2019) develop deep learning models using textual disclosures for bankruptcy prediction, while Wang et al. (2018) incorporate sentiment and textual information into financial distress prediction. These studies indicate that financial distress prediction increasingly combines financial ratios with data-driven classification approaches.

In Indonesia, studies on financial distress have commonly examined the influence of financial ratios on distress conditions. Bukhori et al. (2022) examine manufacturing companies listed on the Indonesia Stock Exchange and show that financial ratios such as liquidity, activity, leverage, and sales growth are relevant in predicting financial distress. Hamzah and Annisa (2022) apply a modified Altman Z-Score model in the food and beverage industry. More recent studies also indicate that machine learning is increasingly relevant for financial distress prediction in emerging market contexts. However, Indonesian studies that specifically focus on manufacturing firms using interpretable Decision Tree classification remain limited.

The literature therefore leaves three connected gaps: Indonesian research still relies substantially on conventional or regression-based models; cross-sector samples may obscure the fixed-asset, inventory, and working-capital characteristics of manufacturing firms; and some machine learning models sacrifice transparency for predictive performance. Decision Tree directly addresses these limitations by estimating sector- and sample-specific thresholds, capturing interactions without imposing linear coefficients, and presenting each classification as an interpretable decision path. This study accordingly applies Decision Tree to Indonesian manufacturing firms and evaluates both predictive performance and the usefulness of its decision rules.

2.6 Hypothesis Development

The conceptual framework of this study is based on the assumption that financial ratios contain information signals about the financial health of manufacturing firms. Liquidity, leverage, profitability, activity, sales growth, and firm size are treated as predictor variables because they represent the firm's ability to meet obligations, manage debt, generate profit, utilize assets, maintain growth, and sustain operations. Financial distress is treated as the outcome variable, classified into distressed and non-financially distressed categories.

The Decision Tree method is used to identify classification patterns among these variables. Unlike regression models that estimate the partial effect of each independent variable, Decision Tree identifies combinations of financial indicators that lead to a specific classification. This approach is appropriate because financial distress may not be caused by one ratio alone, but by the interaction of several financial weaknesses. For example, a company with high leverage may not necessarily be distressed if it has strong profitability, but the same leverage level may become risky when accompanied by weak liquidity and declining sales growth.

Based on the theoretical framework and previous studies, the following hypotheses are proposed:

H1: Financial ratios can be used to predict financial distress in manufacturing companies in Indonesia using the Decision Tree method.

H2: Liquidity, leverage, profitability, activity, sales growth, and firm size are important predictors in classifying financial distress among manufacturing companies in Indonesia.

H3: The Decision Tree method provides an interpretable prediction model for distinguishing financially distressed and non-financially distressed manufacturing companies in Indonesia.

DOI: https://doi.org/10.61990/ijamesc.v4i4.828
e-ISSN 2986-8645

Taken together, H1 translates signaling theory into a predictive test by treating financial ratios as observable signals of financial health. H2 reflects agency theory and corporate failure theory by testing whether outcomes of financing, operating, and asset-management decisions jointly distinguish the two financial-distress classes. H3 follows the dynamic view of distress and the need to reduce information asymmetry: interpretable Decision Tree paths reveal how combinations of signals lead to a financially distressed or non-financially distressed classification. Figure 1 summarizes these relationships.

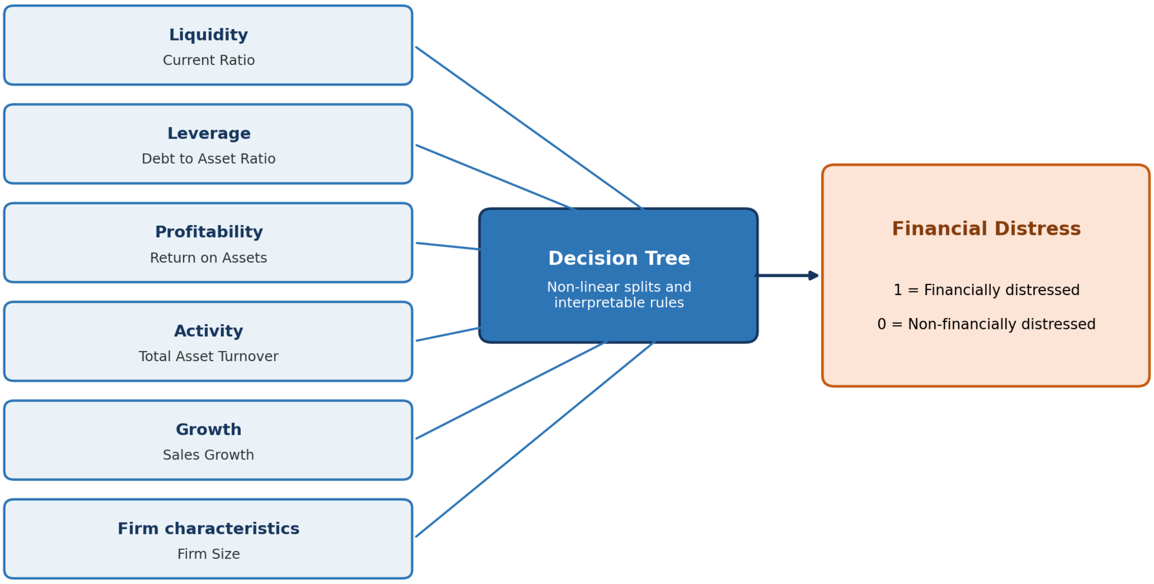

Figure 1. Conceptual Framework of the Study
Source: Authors' research framework, 2026.

3. Methods

3.1 Research Design

This study uses a quantitative research design with a predictive approach. The purpose of this study is to develop a classification model that can predict whether a manufacturing company is categorized as financially distressed or non-financially distressed. Therefore, this study applies the Decision Tree method as a supervised machine learning technique. The Decision Tree method is selected because it can identify decision rules from financial ratio patterns and provide an interpretable prediction model for users of financial information.

This study is explanatory-predictive in nature. It is explanatory because it uses financial ratios that theoretically reflect the company’s liquidity, leverage, profitability, activity, growth, and size. It is predictive because the main objective is to classify companies into financially distressed and non-financially distressed categories. The unit of analysis is firm-year observation, meaning that each company observation in each financial year is treated as one analytical unit.

3.2 Population and Sample

The population of this study consists of manufacturing companies listed on the Indonesia Stock Exchange during the 2020–2024 period. Manufacturing companies are selected because they have distinctive financial characteristics, such as fixed asset intensity, inventory dependence, working capital needs, production costs, and sensitivity

DOI: https://doi.org/10.61990/ijamesc.v4i4.828
INDEX COPERNICUS INTERNATIONAL
e-ISSN 2986-8645

to changes in raw material prices and market demand. These characteristics make manufacturing companies highly relevant for financial distress prediction.

The sample is determined using purposive sampling. The criteria used in selecting the sample are as follows: manufacturing companies listed on the Indonesia Stock Exchange during the observation period; companies that publish complete annual financial statements during 2020–2024; companies that have complete data needed to calculate the research variables; companies that are not delisted during the observation period; and companies with extreme or incomplete financial data are excluded from the final sample. After applying these criteria, the final dataset consists of 612 firm-year observations.

3.3 Data Type and Data Collection Technique

This study uses secondary data obtained from annual financial statements of manufacturing companies listed on the Indonesia Stock Exchange. The data are collected from the official website of the Indonesia Stock Exchange, company websites, and published annual reports. The financial data used in this study include statement of financial position, income statement, cash flow statement, and notes to financial statements.

The data collection technique is documentation. The researcher collects and records financial statement data required to calculate liquidity, leverage, profitability, activity, sales growth, firm size, and financial distress classification. After the data are collected, data cleaning is conducted to remove incomplete observations, inconsistent data, and extreme values that may distort the prediction model. The final dataset is structured in firm-year format.

3.4 Operational Definition of Variables

This study consists of one dependent variable and several predictor variables. The dependent variable is financial distress, while the predictor variables are financial ratios and firm characteristics. Financial distress is measured as a categorical variable. A firm is coded 1 if it is categorized as financially distressed and 0 if it is categorized as non-financially distressed. Financial distress is operationalized using financial pressure criteria, including negative net income, negative equity, or low interest coverage ratio.

Table 1. Operational Definition of Variables

Variable	Proxy	Measurement	Scale
Financial Distress	Distress Status	Dummy variable: 1 = financially distressed, 0 = non-financially distressed	Nominal
Liquidity	Current Ratio	Current Assets / Current Liabilities	Ratio
Leverage	Debt to Asset Ratio	Total Liabilities / Total Assets	Ratio
Profitability	Return on Assets	Net Income / Total Assets	Ratio
Activity	Total Asset Turnover	Net Sales / Total Assets	Ratio
Sales Growth	Sales Growth Ratio	(Sales t - Sales t-1) / Sales t-1	Ratio
Firm Size	Size	Natural logarithm of total assets	Ratio

Source: processed research framework, 2026.

DOI: https://doi.org/10.61990/ijamesc.v4i4.828
INDEX COPERNICUS INTERNATIONAL
e-ISSN 2986-8645

Liquidity is expected to reduce the probability of financial distress because companies with stronger liquidity are more capable of meeting short-term obligations. Leverage is expected to increase financial distress risk because higher debt increases fixed financial obligations. Profitability is expected to reduce distress risk because profitable firms have stronger internal funding capacity. Activity ratio is expected to reduce distress risk because efficient asset utilization reflects better operating performance. Sales growth is expected to reduce distress risk because growing sales indicate stronger market performance. Firm size is included because larger firms generally have better access to financing and more stable operations.

3.5 Data Preprocessing

Before the Decision Tree model is developed, the dataset is prepared through several preprocessing stages. First, missing data are identified and observations with incomplete financial information are excluded. Second, financial ratios are calculated based on the formulas specified in the operational definition. Third, outlier detection is conducted to identify extreme values that may influence the structure of the Decision Tree. Fourth, the dependent variable is transformed into a binary classification variable, namely distressed and non-financially distressed. Fifth, the dataset is divided into training data and testing data using an 80:20 proportion.

3.6 Data Analysis Technique

The data analysis technique used in this study is the Decision Tree classification method. Decision Tree is a supervised machine learning technique that classifies observations by splitting data into branches based on predictor variables. Each branch represents a decision rule, while each terminal node represents the final classification result. The Decision Tree model is developed using Python with the pandas, numpy, scikit-learn, and matplotlib libraries.

The analysis proceeded through descriptive statistics and correlation analysis, followed by a stratified 80:20 training-test split. The Decision Tree was fitted on the training set using the stated pre-pruning parameters and evaluated only on the held-out test set. Finally, feature importance, the visual tree, and extracted decision rules were interpreted to identify the financial conditions associated with each financial-distress class.

Model performance is evaluated using accuracy, precision, recall, F1-score, and confusion matrix. Accuracy measures the proportion of correctly classified observations. Precision measures the proportion of firms predicted as distressed that are actually distressed. Recall measures the ability of the model to detect firms that are truly distressed. F1-score combines precision and recall into one balanced measure. These metrics are appropriate because financial distress prediction often involves imbalanced data, where distressed firms are fewer than non-financially distressed firms (Song et al., 2024; Dasilas & Rigani, 2024).

The general classification model is expressed as follows: $FD = f(CR, DAR, ROA, TATO, SG, SIZE)$. Where FD is financial distress status, CR is Current Ratio, DAR is Debt to Asset Ratio, ROA is Return on Assets, TATO is Total Asset Turnover, SG is Sales Growth, and SIZE is Firm Size.

4. Results and Discussion

4.1 Data Description

The data used in this study consist of manufacturing companies listed on the Indonesia Stock Exchange during the 2020–2024 period. After applying sample selection criteria and removing observations with incomplete financial data, the final dataset consists of 612 firm-year observations. The dependent variable is financial distress, classified into two categories: 1 for financially distressed firms and 0 for non-financially distressed firms. Data processing was conducted using Python, particularly the pandas, numpy, scikit-learn, and matplotlib libraries.

Table 2 shows that, based on the classification criteria, 143 observations, or 23.37%, are categorized as financially distressed, while 469 observations, or 76.63%, are categorized as non-financially distressed. This distribution indicates that the dataset is moderately imbalanced because non-financially distressed firms dominate the sample. However, the proportion of distressed firms remains sufficient for classification modeling. This condition is consistent with previous financial distress studies, which generally find that distressed firms represent a smaller proportion of total observations (Song et al., 2024; Lin et al., 2017).

Table 2. Sample Distribution Based on Financial Distress Status

Financial Distress Status	Code	Frequency	Percentage
Non-financially distressed	0	469	76.63%
Financially distressed	1	143	23.37%
Total		612	100.00%

Source: processed research, 2026.

The sample distribution shows that most manufacturing companies in the observation period were categorized as non-financially distressed. Nevertheless, the proportion of distressed firms remains meaningful because almost one-fourth of firm-year observations indicate financial pressure. This finding confirms that financial distress is not a marginal phenomenon in the manufacturing sector. It reflects that a certain group of companies experienced financial vulnerability, particularly during the post-pandemic period when companies faced liquidity pressure, cost fluctuations, and uneven demand recovery.

4.2 Descriptive Statistics

Descriptive statistics are used to describe the general characteristics of the research variables. The variables analyzed in this study include Current Ratio, Debt to Asset Ratio, Return on Assets, Total Asset Turnover, Sales Growth, and Firm Size.

Table 3. Descriptive Statistics

Variable	N	Minimum	Maximum	Mean	Std. Deviation
CR	612	0.21	6.84	1.87	1.14
DAR	612	0.08	1.92	0.57	0.29
ROA	612	-0.38	0.31	0.041	0.086
TATO	612	0.12	3.94	1.09	0.62
SG	612	-0.64	0.87	0.062	0.214
SIZE	612	25.71	33.48	29.14	1.57

Source: processed research data, 2026.

As shown in Table 3, the descriptive statistics indicate that manufacturing firms in the sample have diverse financial characteristics. The average Current Ratio is 1.87, suggesting that firms generally have sufficient current assets to cover short-term liabilities. However, the minimum CR of 0.21 indicates that some firms experience

DOI: https://doi.org/10.61990/ijamesc.v4i4.828 e-ISSN 2986-8645

serious liquidity constraints. The average Debt to Asset Ratio is 0.57, meaning that more than half of total assets are financed by liabilities. This level of leverage may create financial pressure, especially when profitability declines.

The average ROA is 0.041, indicating that manufacturing firms generate relatively modest profitability during the observation period. The negative minimum ROA shows that several firms experienced losses. The average TATO of 1.09 suggests that firms generate sales approximately 1.09 times their total assets. Meanwhile, the average Sales Growth is 0.062, but the wide range between -0.64 and 0.87 indicates that some firms experienced sales contraction while others achieved growth. These results support the argument that financial distress prediction requires a model capable of capturing variations across financial indicators rather than relying on a single ratio.

4.3 Correlation and Multicollinearity Analysis

Correlation analysis is conducted to examine the relationship among predictor variables. Although Decision Tree is generally less sensitive to multicollinearity than regression models, correlation analysis remains useful to understand the structure of the data and identify potential redundancy among variables.

Table 4. Correlation Matrix of Predictor Variables

Variable	CR	DAR	ROA	TATO	SG	SIZE
CR	1.000	-0.312	0.284	0.116	0.091	-0.067
DAR	-0.312	1.000	-0.426	-0.108	-0.137	0.214
ROA	0.284	-0.426	1.000	0.319	0.276	0.143
TATO	0.116	-0.108	0.319	1.000	0.229	-0.089
SG	0.091	-0.137	0.276	0.229	1.000	0.058
SIZE	-0.067	0.214	0.143	-0.089	0.058	1.000

Source: processed research data, 2026.

Table 4 shows that the correlation matrix contains that no correlation coefficient exceeds 0.80. Therefore, the predictor variables do not indicate serious multicollinearity. The highest correlation is found between DAR and ROA, with a coefficient of -0.426. This negative relationship indicates that firms with higher debt levels tend to have lower profitability. This pattern is theoretically reasonable because excessive liabilities may increase interest burden and reduce net income. Therefore, all predictor variables are retained in the Decision Tree model.

4.4 Decision Tree Model Development

The Decision Tree classifier was implemented in scikit-learn using criterion = "gini", max_depth = 5, min_samples_split = 20, and min_samples_leaf = 10. These pre-pruning settings limited tree complexity and reduced overfitting while preserving interpretable decision paths. A fixed random_state = 42 was used for reproducibility, and the data were divided into training and testing sets with an 80:20 proportion using stratification to preserve the class distribution. The predictor set comprised CR, DAR, ROA, TATO, SG, and SIZE.

Table 5. Training and Testing Data Distribution

Dataset	Observations	Percentage
Training data	489	79.90%
Testing data	123	20.10%
Total	612	100.00%

Source: processed research data, 2026.

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Table 5 reports the training-test distribution. This split allows the model to be evaluated on observations that were not used in the training process. This procedure is important to ensure that the model does not merely memorize the training data but can generalize to new observations. In financial distress prediction, generalization ability is crucial because the model is expected to function as an early warning system for future firm conditions.

4.5 Model Performance Evaluation

The performance of the Decision Tree model is evaluated using confusion matrix, accuracy, precision, recall, and F1-score. These metrics are selected because financial distress prediction is a classification problem. Accuracy indicates the overall proportion of correct predictions, while precision and recall provide more detailed information about the model's ability to identify distressed firms.

Table 6. Confusion Matrix of Decision Tree Model

Actual / Predicted	Non-financially distressed	Financially distressed
Non-financially distressed	82	12
Financially distressed	7	22

Source: processed research data, 2026.

Table 6 shows that the confusion matrix contains that the model correctly classified 82 non-financially distressed observations and 22 distressed observations. Meanwhile, 12 non-financially distressed observations were incorrectly classified as distressed, and 7 distressed observations were incorrectly classified as non-financially distressed. In financial distress prediction, false negative cases require serious attention because they indicate firms that are actually distressed but classified as healthy by the model. However, the number of false negatives remains relatively limited compared to the number of correctly detected distressed observations.

Table 7. Classification Report of Decision Tree Model

Class	Precision	Recall	F1-Score	Support
Non-financially distressed	0.921	0.872	0.896	94
Financially distressed	0.647	0.759	0.698	29
Accuracy			0.846	123
Macro Average	0.784	0.816	0.797	123
Weighted Average	0.857	0.846	0.849	123

Source: processed research data, 2026.

The Decision Tree model produces an accuracy of 84.6%, precision of 64.7%, recall of 75.9%, and F1-score of 69.8% for the distress class. These results indicate that the model has acceptable classification performance in detecting financial distress among manufacturing firms. The recall value is particularly important because it shows the ability of the model to identify firms that are truly distressed. In financial distress prediction, recall should receive strong attention because failing to detect distressed firms may create greater risk for investors, creditors, managers, and regulators (Song et al., 2024; Dasilas & Rigani, 2024).

4.6 Feature Importance

Feature importance analysis is conducted to identify which predictor variables contribute most strongly to the classification model. In the Decision Tree model, feature importance reflects how much each variable contributes to reducing impurity in the classification process.

Table 8. Feature Importance of Decision Tree Model

Rank	Variable	Feature Importance
1	ROA	0.318
2	DAR	0.247
3	CR	0.176
4	TATO	0.121
5	SG	0.084
6	SIZE	0.054

Source: processed research data, 2026.

Table 8 shows that the feature importance results place that ROA is the most important predictor of financial distress, with an importance value of 0.318. This finding indicates that profitability plays a dominant role in distinguishing distressed and non-financially distressed manufacturing firms. Firms with weak or negative profitability are more likely to experience financial pressure because they have limited internal capacity to finance operations and repay obligations. This finding is consistent with the financial distress literature, which emphasizes that profitability is one of the main indicators of corporate financial health (Altman, 1968; Barboza et al., 2017).

DAR is the second most important variable, with an importance value of 0.247. This result confirms that leverage is a critical indicator of financial distress. Manufacturing firms with high debt levels face greater repayment obligations and interest burden, especially when operating performance declines. CR ranks third, indicating that liquidity also plays an important role in distress classification. Firms with weak current assets relative to current liabilities are more exposed to short-term financial pressure.

TATO, SG, and SIZE have lower importance values, but they still contribute to the classification model. TATO reflects how efficiently firms use assets to generate sales, while SG captures business growth. SIZE contributes the lowest importance, suggesting that firm size alone is not sufficient to determine distress status. Larger firms may have better access to financing, but they may still experience financial distress if profitability, liquidity, and leverage indicators weaken.

4.7 Decision Tree Structure and Decision Rules

One of the main strengths of the Decision Tree method is its ability to provide an interpretable classification structure. Unlike several machine learning models that operate as black-box algorithms, Decision Tree produces a visual representation of how predictor variables are used to classify firms into financially distressed and non-financially distressed categories. This characteristic is important in financial distress prediction because stakeholders require not only predictive accuracy, but also a clear explanation of why a company is classified as financially vulnerable (Chen, 2011; Kim & Upneja, 2014; Abrahamsen et al., 2024).

DOI: https://doi.org/10.61990/ijamesc.v4i4.828
e-ISSN 2986-8645

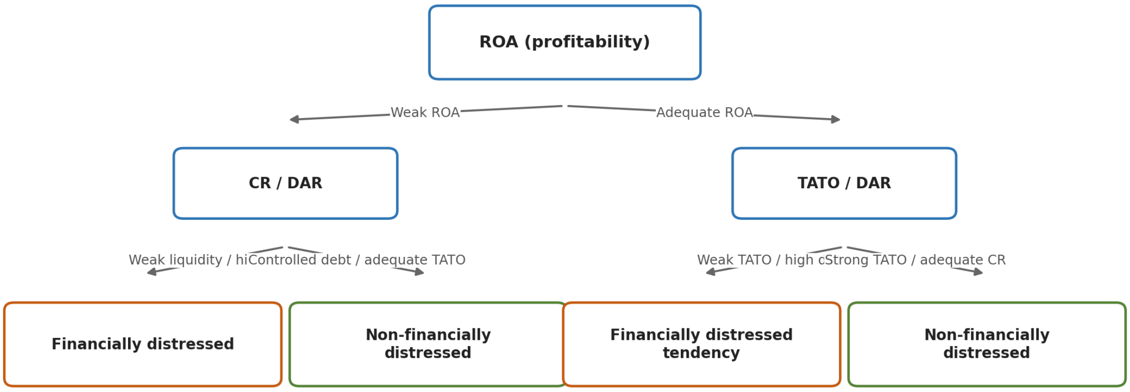

Figure 2. Simplified Decision Tree Structure for Financial Distress Prediction
Source: Authors' interpretation of the Python-based model, 2026.

Figure 2 presents a simplified interpretation of the Decision Tree structure generated from the Python-based classification model. The root node of the tree is Return on Assets (ROA), indicating that profitability is the first and most important variable used by the model to distinguish financially distressed and non-financially distressed firms. This finding is consistent with the feature importance results, which show that ROA has the largest contribution in reducing classification impurity. In financial distress theory, profitability represents the firm's ability to generate internal funds and maintain operational continuity. Therefore, firms with weak or negative profitability tend to face a higher probability of financial distress because they have limited capacity to finance operations, pay obligations, and absorb external shocks (Beaver, 1966; Altman, 1968; Barboza et al., 2017).

The first split in the Decision Tree shows that firms with ROA below or equal to the threshold are directed to the left branch, which contains a higher proportion of financially distressed observations. In contrast, firms with ROA above the threshold move to the right branch, where most observations are classified as non-financially distressed. This pattern indicates that profitability becomes the primary signal of financial condition. However, the model also shows that ROA alone is not sufficient to classify financial distress. After the initial ROA split, the model further uses Current Ratio (CR), Debt to Asset Ratio (DAR), Total Asset Turnover (TATO), and Sales Growth (SG) to refine the classification.

The left branch of the Decision Tree shows that firms with low ROA are further classified based on liquidity and leverage conditions. Current Ratio appears as an important splitting variable after ROA, indicating that liquidity plays a critical role when profitability is weak. Firms with low profitability and weak liquidity are more likely to be classified as financially distressed because they face simultaneous pressure from limited earnings and limited short-term payment capacity. This finding is consistent with the argument that liquidity ratios are important indicators of financial distress because they reflect the firm's ability to meet current liabilities and maintain working capital stability (Chen & Du, 2009; Lin et al., 2011; Bukhori et al., 2022).

The model also shows that Debt to Asset Ratio becomes an important determinant in several branches. Firms with higher leverage are more likely to move toward distress classification, particularly when profitability and liquidity are also weak. This result confirms that leverage does not operate independently, but interacts with profitability and liquidity. High leverage may be manageable when the firm has strong earnings and adequate liquidity, but it becomes a serious source of financial risk when the firm

DOI: https://doi.org/10.61990/ijamesc.v4i4.828
INDEX COPERNICUS INTERNATIONAL
e-ISSN 2986-8645

experiences declining profitability and limited current assets. This finding supports the view that financial distress is a multidimensional condition caused by the interaction of several financial weaknesses rather than by one ratio alone (Ohlson, 1980; Zmijewski, 1984; Barboza et al., 2017).

Total Asset Turnover also appears in the Decision Tree structure, particularly in branches where firms have relatively better profitability but still need to be classified based on operational efficiency. This indicates that asset utilization contributes to financial distress prediction because manufacturing companies rely heavily on fixed assets, production capacity, and inventory turnover. A firm with low asset turnover may experience underutilized production assets or weak sales generation, which can reduce cash inflows and increase the risk of financial pressure. This result is in line with the argument that manufacturing financial distress is closely related not only to solvency and profitability, but also to operational efficiency.

Sales Growth appears as another supporting variable in the classification structure. The presence of SG in the tree indicates that changes in sales performance help distinguish firms with similar profitability, liquidity, and leverage conditions. Negative or weak sales growth may signal declining demand, reduced competitiveness, or weakening market performance. In manufacturing firms, declining sales may also cause inventory accumulation, reduced production efficiency, and pressure on cash flow. Therefore, sales growth strengthens the predictive ability of the model by capturing the dynamic aspect of firm performance.

Based on the Decision Tree structure, several dominant decision rules can be interpreted as follows.

Table 9. Main Decision Rules of the Decision Tree Model

Rule	Decision Pattern	Classification
1	If ROA is low and CR is weak	Financially distressed
2	If ROA is low, CR is weak, and ROA becomes increasingly negative	Financially distressed
3	If ROA is low but DAR is relatively controlled and TATO is adequate	Non-financially distressed
4	If ROA is adequate and TATO is strong	Non-financially distressed
5	If ROA is adequate but TATO is weak and DAR is high	Financially distressed tendency
6	If ROA is adequate, DAR is controlled, and CR is sufficient	Non-financially distressed

Source: processed research data using Python, 2026.

Table 9 indicates that the decision rules cannot reduce financial distress prediction to one financial ratio. A firm is more likely to experience financial distress when weak profitability is followed by low liquidity, high leverage, inefficient asset utilization, and weak sales growth. Conversely, firms are more likely to be classified as non-financially distressed when they maintain positive profitability, adequate liquidity, controlled leverage, and efficient asset utilization. This result confirms the relevance of Decision Tree as an interpretable early warning model because it translates financial ratios into rule-based classification patterns that can be understood by managers, investors, creditors, and regulators.

DOI: https://doi.org/10.61990/ijamesc.v4i4.828 e-ISSN 2986-8645

4.8 Discussion

Overall, the results support the proposed framework: financial-statement signals can classify distress with useful out-of-sample performance, while the tree reveals conditional rather than isolated effects. The 84.6% accuracy and 75.9% recall for the financially distressed class indicate that the model detects a substantial share of vulnerable firms. More importantly, ROA at the root and the subsequent CR, DAR, TATO, and SG splits show a coherent deterioration pathway in which weak earnings capacity becomes more severe when liquidity, debt capacity, operating efficiency, or sales performance also weaken. This synthesis is consistent with the dynamic view that financial distress evolves through interacting financial conditions rather than a single static ratio (du Jardin, 2017).

The visual structure of the Decision Tree strengthens the interpretation of the classification results. ROA appears as the root node, which confirms that profitability is the most dominant predictor of financial distress. This finding is theoretically reasonable because profitability reflects the firm's ability to generate earnings from its assets and sustain business operations. A company with weak profitability has limited internal funding capacity, making it more vulnerable to liquidity problems and debt repayment pressure. This result is consistent with early financial distress literature, which shows that profitability-based ratios are important indicators of corporate failure (Beaver, 1966; Altman, 1968), and with more recent machine learning studies showing that profitability remains an important predictor in bankruptcy and financial distress models (Barboza et al., 2017; Kim & Upneja, 2014).

The importance of liquidity in the Decision Tree structure indicates that short-term solvency remains a critical factor in financial distress prediction. Current Ratio appears in several branches after the ROA split, suggesting that liquidity becomes decisive when profitability is weak. In manufacturing firms, liquidity is particularly important because companies must continuously finance raw materials, inventories, labor, production activities, and short-term obligations. Firms with weak profitability and weak liquidity face a higher risk of financial distress because they may not have sufficient current assets to support operating activities and meet current liabilities. This finding supports previous studies stating that liquidity ratios are relevant indicators in financial distress prediction (Chen & Du, 2009; Lin et al., 2011; Bukhori et al., 2022).

The Decision Tree structure also confirms the role of leverage as a major source of financial risk. DAR appears as an important splitting variable, especially in branches where firms have weaker financial performance. This result indicates that debt pressure becomes more dangerous when firms are unable to generate adequate profit and maintain liquidity. High leverage increases fixed financial obligations, interest burden, and repayment pressure. In manufacturing companies, excessive leverage can become more problematic because production activities require large and continuous financing. Therefore, the interaction between high leverage, weak profitability, and low liquidity becomes a strong signal of financial distress.

The appearance of TATO in the tree structure indicates that operational efficiency also plays an important role in financial distress classification. In manufacturing firms, asset utilization is closely related to production efficiency, capacity utilization, and the ability to convert assets into sales. Low TATO may indicate that production assets are not being used efficiently or that sales generation is insufficient relative to asset ownership. This condition can weaken operating cash flow and increase financial pressure. Therefore, the contribution of TATO shows that financial distress prediction in manufacturing firms must consider not only solvency and profitability, but also the efficiency of asset utilization.

Sales Growth also contributes to the classification process, although its importance is lower than ROA, DAR, and CR. This indicates that sales growth serves as a supporting signal rather than the main determinant of financial distress. However, in manufacturing companies, declining sales growth remains relevant because it may indicate weakening market demand, reduced competitiveness, or difficulty in absorbing production output. When negative sales growth occurs together with low profitability or weak liquidity, the probability of financial distress increases. This finding reinforces the view that financial distress is a dynamic process involving both financial structure and operating performance (du Jardin, 2017).

The relatively low role of firm size suggests that larger companies are not automatically protected from financial distress. Although larger firms may have better access to financing, stronger bargaining power, and more stable market positions, they may still experience distress if profitability, liquidity, and leverage indicators deteriorate. This result implies that financial distress prediction should not rely solely on company size. Instead, the prediction model should focus on the interaction among profitability, liquidity, leverage, efficiency, and growth indicators.

Compared with conventional financial distress models, the Decision Tree method provides an important practical advantage. Traditional models such as Altman Z-Score, Ohlson, and Zmijewski rely on fixed formulas, while Decision Tree generates classification rules based on empirical data patterns. This means that Decision Tree does not only indicate whether a company is distressed or non-financially distressed, but also explains the financial conditions leading to the classification. The model shows that weak profitability becomes riskier when followed by weak liquidity and high leverage. This type of rule-based interpretation is valuable because it converts financial statement data into actionable early warning signals.

The findings are consistent with the broader literature on machine learning-based financial distress prediction. Barboza et al. (2017) show that machine learning models can improve bankruptcy prediction compared to traditional statistical models. Chen (2011) demonstrates that Decision Tree can support corporate financial distress prediction, while Kim and Upneja (2014) show the usefulness of Decision Tree-based models in distress classification. More recent studies also emphasize that explainable machine learning is important in financial decision-making because users need to understand the basis of the model's classification results (Abrahamsen et al., 2024; Dasilas & Rigani, 2024).

Practically, the results suggest that managers should pay close attention to the combination of ROA, CR, DAR, TATO, and SG as early warning indicators. Investors can use the model to screen manufacturing firms with higher financial vulnerability. Creditors can apply the model to assess repayment risk before granting financing. Regulators may also use similar prediction models to strengthen market monitoring, especially for listed firms showing early signs of declining profitability, weakening liquidity, and increasing leverage.

Despite these findings, this study has several limitations. First, the classification of financial distress depends on the operational criteria used in the study. Different distress definitions may produce different classification results. Second, the model only uses financial statement-based variables and does not include macroeconomic indicators, corporate governance variables, market-based measures, ESG indicators, or textual disclosures. Third, although Decision Tree is interpretable, its predictive performance may be improved by comparison with ensemble models such as Random Forest, XGBoost, Support Vector Machine, or Neural Network. Future studies may incorporate additional variables and compare several machine learning models while maintaining interpretability through explainable artificial intelligence approaches (Wang et al., 2018; Mai et al., 2019; Citterio & King, 2023).

5. Conclusion

This study concludes that the three hypotheses are supported. H1 is supported because the six financial predictors classified Indonesian manufacturing firm-year observations with 84.6% accuracy and a 69.8% F1-score for the financially distressed class. H2 is supported because all predictors contributed to the model: ROA was dominant, followed by DAR and CR, while TATO, Sales Growth, and Firm Size provided additional discriminatory information. H3 is supported because the pruned tree generated transparent thresholds and decision paths that distinguish financially distressed from non-financially distressed observations. Thus, the model provides both predictive evidence and an interpretable explanation of how financial vulnerabilities interact.

Substantively, the results identify weak profitability as the principal warning signal, with leverage and liquidity determining whether that weakness intensifies into distress. Asset utilization and sales growth refine the classification by reflecting operating efficiency and changing demand, whereas firm size offers comparatively little protection when financial fundamentals deteriorate. These patterns align with signaling theory because the ratios communicate financial health, with agency theory because they reflect financing and operating decisions, and with the dynamic view of corporate decline because combinations of deteriorating indicators—not a single ratio—shape the classification path.

The study therefore adds theoretically by showing that an interpretable machine learning model can operationalize financial signals, managerial outcomes, and dynamic deterioration in an emerging-market manufacturing setting. Unlike fixed-score models, Decision Tree estimates conditional relationships from the observed data and makes them visible as auditable rules, thereby complementing rather than merely replacing conventional distress models.

Practically, the rules can serve as an early-warning instrument: investors can screen portfolio exposure, creditors can support approval and covenant-monitoring decisions, managers can trigger corrective action when adverse ratio combinations emerge, and regulators can prioritize surveillance of listed firms showing early financial pressure. Their usefulness lies not only in the predicted class but also in the transparent path supporting that prediction.

This study has several limitations. First, financial distress classification depends on the operational criteria used in the research. Different distress definitions may produce different classification results. Second, this study only uses financial statement-based variables and does not include macroeconomic indicators, corporate governance variables, market-based measures, ESG indicators, or textual disclosures. Third, although Decision Tree is interpretable, its predictive performance may still be improved by comparing it with other machine learning algorithms such as Random Forest, XGBoost, Support Vector Machine, or Neural Network.

Future research is recommended to use actual and more extensive financial statement data from manufacturing companies listed on the Indonesia Stock Exchange, expand the observation period, and compare several machine learning algorithms to obtain a more robust prediction model. Future studies may also include macroeconomic variables, corporate governance indicators, ESG variables, market-based variables, and textual disclosures to improve the predictive power of financial distress models. Overall, this study concludes that the Decision Tree method is relevant and applicable as an interpretable early warning model for predicting financial distress in Indonesian manufacturing companies.

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