Journal of Economics
AND MANAGEMENT SCIENTIES
https://jems.ink
ISSN 2655-1934 (print), 2655-6685 (online)

Implementation of Artificial Neural Network (ANN) to Predict Financial Distress (A Case Study on Metal and Mineral Industry Companies Listed on IDX 2019–2023 Period)

Wardanianti Sari Rahayu[1], *and Khairunnisa*[2*]

[1,2] *Telkom University, Indonesia*

ARTICLE HISTORY

Received: 06 July 25
Final Revision: 11 July 25
Accepted: 13 July 25
Online Publication: 30 September 25

KEYWORDS

Artificial Neural Network, Data Mining, Financial Distress, Financial Ratios, Metals and Minerals Industry Companies

KATA KUNCI

Artificial Neural Network, *Data Mining*, *Financial Distress*, Rasio Keuangan, Perusahaan Industri Logam dan Mineral

CORRESPONDING AUTHOR

khairunnisa@telkomuniversity.ac.id

DOI

10.37034/jems.v7i4.184

A B S T R A C T

This research utilizes data mining techniques, specifically the Artificial Neural Network (ANN) model, to predict financial distress. In this ANN model, five financial ratios serve as the main input variables, namely Return on Assets (ROA), Debt to Assets Ratio (DAR), Current Ratio, Total Assets Turnover, and Operating Cash Flow Ratio. The selection of these ratios is based on evidence that they are effective in predicting financial distress. This study aims to develop a financial distress prediction model for metal and mineral industry companies listed on the Indonesia Stock Exchange during the 2019-2023 period, using a data mining approach with Artificial Neural Network (ANN). The study results show that the financial ratios of companies experiencing financial distress tend to be lower than companies that do not experience it, so these ratios are effective as input variables for the model. The best ANN architecture, found through training using a sample of 26 companies, has a configuration of 25 neurons in the input layer, 10 neurons in the hidden layer, and 1 neuron in the output layer. Further analysis revealed that 12 out of 26 energy companies were predicted to experience financial distress, with the model achieving the highest accuracy of 84.62%.

A B S T R A K

Penelitian ini memanfaatkan teknik *data mining*, khususnya model *Artificial Neural Network* (ANN), untuk memprediksi *financial distress*. Dalam model ANN ini, lima rasio keuangan berfungsi sebagai variabel *input* utama, yaitu *Return on Assets* (ROA), *Debt to Assets Ratio* (DAR), *Current Ratio*, *Total Assets Turnover*, dan *Operating Cash Flow Ratio*. Pemilihan rasio-rasio ini didasarkan pada bukti bahwa mereka efektif dalam memprediksi kondisi *financial distress*. Penelitian ini bertujuan untuk mengembangkan model prediksi *financial distress* pada perusahaan industri logam dan mineral yang terdaftar di Bursa Efek Indonesia selama periode 2019-2023, menggunakan pendekatan *data mining* dengan *Artificial Neural Network* (ANN). Hasil studi menunjukkan bahwa rasio keuangan perusahaan yang mengalami *financial distress* cenderung lebih rendah dibandingkan perusahaan yang tidak mengalaminya, sehingga rasio-rasio ini efektif sebagai variabel *input* model. Arsitektur ANN terbaik, yang ditemukan melalui pelatihan menggunakan sampel 26 perusahaan, memiliki konfigurasi 25 neuron pada lapisan *input*, 10 neuron pada lapisan tersembunyi, dan 1 neuron pada lapisan *output*. Analisis lebih lanjut mengungkapkan bahwa 12 dari 26 perusahaan energi diprediksi mengalami *financial distress*, dengan model mencapai akurasi tertinggi sebesar 84.62%.

1. Introduction

The Indonesia Stock Exchange (IDX), also known as *Bursa Efek Indonesia* (BEI), is a Self-Regulatory Organization (SRO) that operates as the official marketplace organizer for securities trading in Indonesia. It plays a crucial role in ensuring that securities transactions are conducted in an orderly, fair, and efficient manner accessible to all stakeholders, as mandated by Law No. 8 of 1995. Since 1996, IDX utilized the Jakarta Stock Industrial Classification (JASICA) system; however, beginning in 2021, it adopted a new industrial classification system known as the IDX Industrial Classification (IDX-IC). This updated framework categorizes companies into twelve sectors: Energy, Basic Materials, Industrials, Non-Cyclical Consumer, Cyclical Consumer, Healthcare, Financials, Properties & Real Estate, Technology, Infrastructure, Transportation & Logistics, and Listed Investment Product. Within the Basic Materials sector, the Metal and Mineral Industry constitutes a vital pillar of the Indonesian economy, contributing significantly to national GDP and employment. However, firms within this industry often face considerable financial risk due to commodity price volatility, regulatory changes, and global economic uncertainty. External shocks such as trade wars and the COVID-19 pandemic have notably driven up metal prices, directly impacting the performance and stability of companies operating in this sector.

The growth trajectory of the metal and mineral industry has been notably influenced by multifaceted factors, including the COVID-19 pandemic, global demand for base metals, commodity price fluctuations, and government policy interventions. Based on data, the growth rate of the basic metal industry exhibited a downward trend in 2019, reaching its lowest point in Q3 (-4.51%). A significant recovery was observed in 2021, with a peak growth of 18.03% in Q2, driven by post-pandemic economic recovery and rising metal demand. In 2022, the industry recorded its highest growth rate in the past five years, reaching 20.16% in Q3, which can be attributed to increased production and export activities, particularly under Indonesia's downstream industrialization policy. However, in 2023, the growth rate showed a declining trend again, reflecting the cyclical nature of the metal industry, shaped by global price dynamics and international policy shifts. As of the latest data, there are 35 metal and mineral companies listed under the Basic Materials sector on the Indonesia Stock Exchange.

Financial distress refers to a condition in which a company is experiencing significant financial difficulties. Financial distress arises when a company fails to manage its finances properly, resulting in operational losses and, ultimately, financial hardship [1]. Financial distress is an undesirable state that can lead to business failure [2]. Financial distress occurs when a firm struggles to fulfill its debt obligations, often with varying degrees of severity, which may ultimately diminish firm value and lead to bankruptcy in the absence of external intervention [3]. The causes of financial distress are commonly grouped into internal and external factors. Internal factors include poor human resource quality, substandard product quality, unrealistic pricing strategies, inadequate technological adaptability, ineffective marketing strategies, and flawed distribution processes. On the other hand, external factors encompass a company's inability to adapt to socio-cultural changes, macroeconomic fluctuations such as inflation, changes in regulatory policies, and natural disasters that could disrupt business continuity [4].

Forecasting financial distress is a crucial preventive measure to detect and mitigate potential financial failures within firms. It serves as an early warning system by identifying signs of financial instability enabling stakeholders to evaluate a company's future financial condition [3]. This aligns with signaling theory, which posits that companies must communicate relevant information to external parties to convey their financial soundness. Financial distress predictions offer valuable insights into a company's fiscal status, aiding both internal and external stakeholders in decision-making to minimize financial losses [5]. One of the tools used in this analysis is financial ratio assessment derived from financial statements. A common indicator is Earnings Per Share (EPS), which reflects a company's profitability. A negative EPS indicates corporate losses, serving as a red flag for financial distress [6], [7]. Numerous studies have utilized negative EPS as a predictive metric for identifying financially distressed firms [8], [9], [10]. Data from 2019 to 2023 on EPS in metal and mineral sector firms listed on the Indonesia Stock Exchange reveals a peak in negative EPS occurrences in 2023, a trend closely linked to weakening export markets and declining commodity prices [11].

Non-Tax State Revenue (PNBP) from the mineral and coal (minerba) sector has shown volatility but remains a critical contributor to national income, with coal alone accounting for 75% to 85% of total minerba PNBP over the past four years [12]. After a slight decline in both target and realization in 2020 (Rp36 trillion target vs. Rp35 trillion actual), PNBP soared in 2022 to Rp183.5 trillion—far exceeding the target of Rp102 trillion—primarily due to a 54% surge in coal production. However, this oversupply led to market saturation. In 2023, average coal prices fell from US$25,000 per ton in 2022 to US$21,521 per ton, compressing corporate profit margins and reducing PNBP to Rp172.96 trillion [13]. Similarly, the metal industry was adversely affected as oversupply of nickel—driven by increased domestic smelter capacity—pushed global prices down, with expectations of continued pressure through 2025. This downturn is compounded by the global shift toward renewable energy and an economic slowdown in China, a key consumer, reducing demand for nickel and other metals [14]. Furthermore, Indonesia's mineral downstreaming policy, intensified since 2019, mandates the prohibition of raw material exports in favor of domestic processing, requiring significant capital investment in smelter infrastructure. Although this initiative is intended to increase national revenue and employment, it presents financial challenges for firms transitioning from raw material exporters to refined product manufacturers. The high capital requirements, technological risks, and fluctuating global prices for refined products can erode profitability and increase debt burdens—factors that heighten the risk of financial distress. The net profit/loss values reported by metal and mineral companies listed on the Indonesia Stock Exchange from 2019 to 2023—of which only 27 consistently submitted financial reports—further reflect the volatility and financial fragility experienced by the sector during this period.

Several companies within the metal and mineral industry have exhibited weak financial performance, with some experiencing substantial declines in net income, even to the point of reporting negative earnings. One of the most severe cases involves PURE, which reported negative earnings for five consecutive years, culminating in a staggering loss of IDR 98.747 trillion in 2020. This situation indicates a strong signal of financial distress. A company is considered financially distressed if it incurs losses over two consecutive fiscal years [15]. The onset of financial distress is marked by a continuous decline in profitability, particularly when net income turns negative [4]. Such conditions suggest that the company is no longer able to sustain its operational efficiency and may be at risk of insolvency or bankruptcy without timely intervention.

Artificial Neural Networks are a subset of machine learning algorithms capable of modeling complex nonlinear relationships between variables, thereby offering higher predictive accuracy than simpler methods [8]. ANNs are computer-based systems that simulate neural structures and learning mechanisms of the human brain by replicating intuitive reasoning and adaptive learning [16]. Prior research has widely utilized ANN in financial distress prediction. For instance, a study reported that ANN achieved 80% accuracy across 90% of the cases analyzed [17]. Another study compared Multiple Discriminant Analysis, Logit models, and ANN in evaluating three telecommunication companies listed on the Indonesia Stock Exchange, finding equal accuracy levels of 94.33% for both the Logit and ANN models [18]. Different study also concluded that ANN outperformed the Z-score model in accuracy, scoring 99.4% compared to 86.54% [5]. Researcher, in their study on Spanish banks, demonstrated that multilayer perceptron-based ANN models achieved over 97% accuracy in predicting financial distress using training and testing datasets [3].

Previous research has predominantly utilized financial ratios as key indicators in forecasting corporate bankruptcy. Certain study incorporated five financial ratios: Current Ratio (CR), Return on Assets (ROA), Debt to Assets Ratio (DAR), Total Asset Turnover, and Cash Flow from Operations [19]. Liquidity is represented by the Current Ratio, which measures the firm's capacity to meet short-term liabilities. Profitability is indicated by ROA, reflecting the company's ability to generate profits from its asset base. Leverage is assessed through DAR, which evaluates the firm's reliance on debt to finance its assets [20]. Asset utilization efficiency is captured by Total Asset Turnover, while the Cash Flow from Operations to Total Debt ratio reflects the firm's ability to repay obligations using operational cash flow. Motivated by these findings, this research investigates the prediction of financial distress in metal and mineral industry firms to anticipate financial instability and mitigate bankruptcy risks. Utilizing a data mining approach, this study applies the Artificial Neural Network model, selected for its superior accuracy. The research uses five input parameters—CR, ROA, DAR, Total Asset Turnover, and Cash Flow from Operations—to assess financial health and classify companies into financially distressed or non-distressed categories.

2. Research Method

Research is a scientific process aimed at systematically obtaining data for specific objectives and applications [21]. This study adopts a quantitative research method. Quantitative research refers to the collection and analysis of data expressed in numerical form, either originally gathered as numerical data or derived from qualitative data transformed into measurable variables [21]. The unit of analysis in this study is the organization, as the research focuses on companies operating within the metal and mineral industry listed on the Indonesia Stock Exchange (IDX), with data sourced from corporate-level financial disclosures. The research is descriptive in nature, aligned with the objective of forecasting financial distress conditions. Descriptive research aims to systematically and accurately describe a phenomenon based on factual data, and is typically used to explore and clarify specific social or economic realities by providing analytical insight into the interrelated variables of the subject and unit of study [22].

The researcher's involvement in this study is categorized as minimal, indicating no direct engagement with the research subjects. Consequently, the researcher does not interfere or manipulate the data, as it is obtained from archival financial reports. The research takes place in a natural setting, where the observed conditions are unaltered by the presence of the researcher, qualifying it as a non-contrived setting. The study applies a time series approach, utilizing data from multiple time periods—spanning from 2019 to 2023—for trend analysis and inference development. The population is defined as all companies within the metal and mineral industry listed on the IDX during the observed period, comprising 35 companies. Population, in this context, is not limited to the number of units but encompasses all relevant characteristics inherent to those units. The sampling technique employed is purposive sampling, wherein specific criteria are used to select representative firms. The criteria used include (1) consistent IDX listing from 2019 to 2023 and (2) availability of required financial data. Based on these criteria, 26 companies qualified as the final research sample, resulting in 130 observations over five years.

The data set used for this study includes a final sample of 25 firms and 125 observations, following the elimination of companies that did not consistently meet inclusion criteria. Before conducting the financial distress prediction on the testing data set, the Artificial Neural Network (ANN) model must be trained using a separate training data set consisting of distressed and non-distressed firms. The distressed companies were selected based on confirmed bankruptcy filings, as financial distress typically precedes bankruptcy. The training data comprises publicly listed companies worldwide, in accordance with the criteria established [23]. These criteria specify that non-distressed firms must: (a) not experience financial distress or bankruptcy as of 2023, (b) have published financial statements from 2018–2022, (c) maintain a current ratio above 100%, (d) show a positive return on assets, (e) have a debt-to-asset ratio below 50%, and (f) demonstrate total asset turnover above 45%. Conversely, distressed firms must: (a) be declared distressed or bankrupt in 2023, (b) have published financial statements for 2018–2022, (c) show a current ratio below 100%, (d) report a negative return on assets, (e) have a debt-to-asset ratio exceeding 50%, and (f) display total asset turnover below 45% during the same period.

This study relies on secondary data obtained from corporate annual reports and publicly accessible databases. Secondary data refers to information not collected directly by the researcher, but acquired from third-party documents and archives. Financial statements published by the companies themselves, the Indonesia Stock Exchange, and respective official websites served as key data sources for both training and testing sets. For data processing and analysis, financial ratios were calculated using Microsoft Excel. The Artificial Neural Network model was implemented using Python programming to carry out both the financial distress prediction and the descriptive data analysis. The analysis process began with model training using the predefined training data, followed by prediction testing on the sample firms. This methodological approach ensures a rigorous and replicable framework for assessing the financial health of metal and mineral industry firms listed on the Indonesia Stock Exchange between 2019 and 2023.

3. Result and Discussion

3.1. Descriptive Analysis

Descriptive statistical analysis in this study involved the use of mean, minimum, maximum, range, and standard deviation to measure data dispersion. The sample comprises all companies within the metal and mineral industry listed on the Indonesia Stock Exchange during the 2019–2023 period. A total of 26 companies fulfilled the sample criteria, yielding 130 firm-year observations across five years. The variables used in this study include the Current Ratio, Return on Assets (ROA), Debt to Assets Ratio (DAR), Total Assets Turnover (TATO), and Cash Flow from Operation to Total Current Debt (CFOTDC). Table 1 presents the descriptive statistical output, indicating a wide range and variability across all variables, reflecting significant heterogeneity in financial conditions among the sampled firms. The analysis provides insight into the overall liquidity, profitability, leverage, operational efficiency, and cash flow management of companies operating in this sector.

Table 1. Descriptive Analysis

Variable	N	Mean	Min	Max	Std. Deviation
Current Ratio	130	3.8950	0.0600	170.66	16.268
Return On Assets	130	0.0136	-0.1900	0.21	0.079
Debt to Assets Ratio	130	0.5230	0.0010	1.44	0.292
Total Assets Turnover	130	0.8060	0.0037	5.38	0.860
Cash Flow from Operation to Total Debt Current	130	0.2730	-5.7700	19.87	1.890

The descriptive analysis indicates that the average Current Ratio for the sampled firms is 3.895, suggesting that, on average, companies possess adequate current assets to cover their short-term liabilities. However, the high standard deviation of 16.268 and the extremely wide range (from 0.06 to 170.66) reflect considerable variation in short-term liquidity across the firms. The maximum Current Ratio, recorded at 170.66 by PT Optima Prima Metal Sinergi Tbk (OPMS) in 2021, indicates that the company had Rp48,298 million in current assets against only Rp283 million in current liabilities—implying potential inefficiency in managing excess liquidity. In contrast, the lowest Current Ratio, 0.06, was observed in PT Wilton Makmur Indonesia Tbk in 2020, where current assets of Rp32,014 million were significantly insufficient to meet current liabilities of Rp539,913 million. This low liquidity ratio serves as an early warning sign of potential financial distress and the firm's inability to meet short-term obligations.

The average Return on Assets across the sample is 0.0136, reflecting relatively low profitability among the firms in utilizing their total assets. The ROA values range from -0.19 to 0.21 with a standard deviation of 0.079, indicating diverse operational outcomes—from firms with strong asset utilization to those experiencing losses. PT Archi Indonesia Tbk (ARCI) posted the highest ROA in 2020, at 0.21, having earned Rp1,070,847 million in net income from Rp8,465,180 million in total assets. This suggests strong managerial efficiency in generating returns from asset investment. On the other hand, PT Alumindo Light Metal Industry Tbk (ALMI) recorded the lowest ROA, -0.19, in the same year, reflecting substantial net losses of Rp266,800 million against total assets of Rp1,426,607 million. Such a negative return suggests inefficiencies and potential profitability issues, placing the firm at a higher risk of entering financial distress.

The average Debt to Assets Ratio is 0.523, indicating that 52% of a firm’s assets, on average, are financed through debt. A standard deviation of 0.292 suggests significant variation in capital structure strategies among firms. The highest DAR of 1.44 was recorded by

PT Wilton Makmur Indonesia Tbk in 2020, where liabilities exceeded assets, signaling a highly leveraged and financially unstable position. In contrast, the lowest DAR of 0.001 was held by PT Optima Prima Metal Sinergi Tbk in 2021, indicating near-complete reliance on equity financing and very minimal use of debt. The Total Assets

Turnover (TATO) averaged at 0.764, with a broad range from 0.0037 to 5.38 and a standard deviation of 0.860, reflecting disparities in operational efficiency. PT Tembaga Mulia Semanan Tbk (TBMS) led with a TATO of 5.38 in 2022, demonstrating exceptional efficiency in asset utilization, while PT Alaska Industrindo Tbk (ALKA) trailed with a TATO of 0.0037 in 2019, indicating a poor ability to convert assets into revenue.

The mean value of CFOTDC is 0.273, suggesting that, on average, operating cash flows cover approximately 27% of current debt obligations. However, the values vary dramatically from -5.77 to 19.87, with a standard deviation of 1.89, highlighting substantial differences in cash flow management among firms. The highest value of 19.87 was recorded by PT Optima Prima Metal Sinergi Tbk in 2019, signifying exceptionally strong cash flow performance, where operational cash was nearly twenty times the company's short-term liabilities. Conversely, the same company reported the lowest CFOTDC, -5.77, in 2023, reflecting a negative operational cash flow nearly six times the amount of its current debt. This dramatic shift between years suggests volatility in financial performance and highlights concerns regarding the firm's cash-generating capacity from core business operations. The contrast between the maximum and minimum values—both belonging to the same company—emphasizes a pattern of financial instability over time.

3.2. Artificial Neural Network

The results presented in Table 2 illustrate the performance of various Artificial Neural Network (ANN) architectures tested in this study, specifically varying the number of neurons in the hidden layer while keeping the input layer fixed at 25 neurons. The initial architecture, consisting of 25 input neurons and 5 hidden neurons, yielded an accuracy of only 0.2500 and a Mean Squared Error (MSE) of 0.7500. This low accuracy and high error suggest that the model's complexity was insufficient to capture the underlying patterns within the dataset. A significant improvement was observed when the number of hidden neurons was increased to 10, resulting in an accuracy of 0.7500 and a notable decrease in MSE to 0.2500. This outcome indicates that increasing the model's capacity by adding hidden neurons enhanced its ability to learn the nonlinear relationships between input variables and the target output effectively.

Table 2. Confusion Matrix

Input Layer	Hidden Layer	Accuracy	MSE
25	5	0.2500	0.7500
25	10	0.7500	0.2500
25	15	0.5000	0.5000
25	20	0.5000	0.5000
25	30	0.5000	0.5000
25	50	0.5000	0.5000

However, further increasing the number of hidden neurons beyond 10 produced diminishing returns. When the hidden layer was expanded to 15, 20, 30, and even 50 neurons, the model's accuracy consistently plateaued at 0.5000, while the MSE stabilized at 0.5000. These results suggest that additional neurons beyond the optimal configuration introduced unnecessary complexity without improving predictive performance, potentially due to overfitting or increased noise sensitivity. Consequently, the ANN architecture with 25 neurons in the input layer, 10 neurons in the hidden layer, and one neuron in the output layer (25-10-1) was identified as the optimal model. This configuration achieved the highest observed accuracy and lowest error, striking a balance between model complexity and generalization capability. As such, it was selected as the best-performing architecture for predicting financial distress in this study.

3.3. Confusion Matrix and Classification Report

Table 3 presents the confusion matrix illustrating the performance of the Artificial Neural Network (ANN) model in classifying companies into distress and non-distress categories based on actual financial conditions. The matrix reveals that 12 companies classified as Non-Distress were correctly predicted as such by the model, representing the true negatives. Similarly, 10 companies experiencing financial distress were accurately predicted as Distress, indicating the true positives and reflecting the model's ability to correctly identify companies at risk of financial failure. However, the model also made classification errors: 2 Non-Distress companies were incorrectly classified as Distress (false positives), and 2 Distress companies were misclassified as Non-Distress (false negatives).

Table 3. Artificial Neural Network

Confusion Matrix			
		Predicted	
		Non-D	Distress
Actual	Non-D	12	2
	Distress	2	10

Table 4 presents the classification report, providing a detailed evaluation of the ANN model's performance across the two classes: Non-Distress and Distress. For the Non-Distress class, the model achieved a precision of 0.86, which means that 86% of companies predicted to be in a healthy financial condition were correctly classified. The recall score, also at 0.86, indicates that the model successfully identified 86% of the actual Non-Distress companies in the dataset. The F1-score, which represents the harmonic mean of precision and recall, further supports this balanced performance at 0.86. These metrics suggest that the model was highly effective in minimizing false positives and capturing the majority of non-distressed firms, thereby maintaining a strong predictive capability for healthy financial conditions.

Table 4. Classification Report

Classification Report				
	precision	recall	f1-score	support
Non-Distress	0.86	0.86	0.86	14
Distress	0.83	0.83	0.83	12
accuracy			0.85	26
macro avg	0.85	0.85	0.85	26
weighted avg	0.85	0.85	0.85	26

In the case of companies experiencing financial distress, the model demonstrated a precision of 0.83, implying that 83% of companies identified as Distress were indeed facing actual financial difficulties. The recall for the Distress class was also 0.83, showing the model's effectiveness in detecting a substantial portion of the actual distressed firms. The corresponding F1-score of 0.83 confirms a balanced performance between precision and recall for this class. Overall, the ANN model attained an accuracy of 84.62%, a strong indication of its predictive reliability. Moreover, the macro average and weighted average for all three metrics—precision, recall, and F1-score—stand uniformly at 0.85. This consistency underscores the model's balanced treatment of both classes and affirms its suitability for predicting financial distress within the context of this study.

3.4. Discussion

Following the determination of the optimal model architecture for the Artificial Neural Network (ANN)—which includes the appropriate number of neurons in the input, hidden, and output layers—and the successful training process yielding accurate weights and error values, the next stage involves conducting predictions. This prediction process utilizes testing data comprising metal and mineral industry companies listed on the Indonesia Stock Exchange during the 2019–2023 period. The pre-trained ANN model, configured with 25 neurons in the input layer, 10 neurons in the hidden layer, and a single output neuron, is applied to the testing dataset. The model generates a single output value for each firm, which is interpreted as an indicator of the company's financial condition. Output values approaching or equal to 1 indicate a prediction of financial distress, whereas values approaching or equal to 0 suggest a prediction of non-distress. The prediction results are presented in tabular form, summarizing the probability scores and the binary classification outcomes for each company evaluated.

Table 5. Financial Distress Predictions Result

No	Company Code	Prediction	Prob	Output
1	ALKA	Non-Distress	0.319	0
2	ALMI	Distress	0.984	1
3	ANTM	Non-Distress	0.451	0
4	ARCI	Non-Distress	0.067	0
5	BAJA	Distress	0.546	1
6	BRMS	Distress	0.676	1
7	BTON	Non-Distress	0.058	0
8	CITA	Non-Distress	0.001	0
9	CTBN	Non-Distress	0.498	0
10	DKFT	Distress	0.976	1
11	GDST	Non-Distress	0.070	0
12	GGRP	Non-Distress	0.367	0
13	IFSH	Non-Distress	0.000	0
14	INAI	Distress	0.899	1
15	INCO	Non-Distress	0.001	0
16	ISSP	Non-Distress	0.197	0
17	KRAS	Distress	0.836	1
18	LMSH	Distress	0.708	1
19	MDKA	Distress	0.683	1
20	NIKL	Distress	0.590	1
21	OPMS	Non-Distress	0.005	0
22	SQMI	Distress	0.635	1
23	TBMS	Non-Distress	0.000	0
24	TINS	Non-Distress	0.267	0
25	ZINC	Distress	0.953	1
26	PURE	Distress	0.998	1

The data processing results using the ANN model demonstrate that the most optimal predictive architecture is the 25-10-1 configuration. This model structure was found to be the most effective, achieving the lowest prediction error with a Mean Squared Error (MSE) of 0.2500 and a relatively high accuracy rate of 84.62%. Although some prediction errors occurred in the testing phase—specifically in the form of false positives and false negatives—no misclassifications were found during the training phase. Based on the ANN prediction results, twelve companies in the metal and mineral industry were identified as experiencing financial distress, indicated by output values close to 1. Conversely, fourteen companies were classified as non-distressed, based on output values approaching 0. These findings highlight the ANN model’s ability to provide a meaningful classification of corporate financial health, thereby offering valuable insights for early warning systems in the financial evaluation of publicly traded companies.

4. Conclusion

This study concludes that predicting financial distress among Indonesian retail companies using Artificial Neural Networks (ANN) requires initial calculation of key financial ratios—such as current ratio, return on assets, debt to assets ratio, total assets turnover, and cash flow to current debt—as model inputs. After training the model with historical financial data from distressed and non-distressed firms, the ANN with a 25-10-1 architecture (25 input, 10 hidden, 1 output neuron) achieved an accuracy of 84.62%, indicating strong predictive performance. When applied to metal and mineral companies listed on the Indonesia Stock

Exchange, the model identified 12 out of 26 firms as likely to experience financial distress, highlighting ANN's potential as a reliable tool for early detection and proactive financial risk management.

References

[1] Wulandari, E. W., & Jaeni, J. (2021). Faktor-Faktor Yang Mempengaruhi Financial Distress. *Jurnal Ilmiah Universitas Batanghari Jambi*, *21*(2), 734. https://doi.org/10.33087/jiubj.v21i2.1495

[2] Sidhu, A. V., Jain, P., Singh, S. P., Kanoujiya, J., Rawal, A., Rastogi, S., & Bhimavarapu, V. M. (2023). Impact of financial distress on the dividend policy of banks in India. *Journal of Risk and Financial Management*, *16*(2), 107. https://doi.org/10.3390/jrfm16020107

[3] Paule-Vianez, J., Prado-Román, C., & Gómez-Martínez, R. (2020). Monetary policy uncertainty and stock market returns: influence of limits to arbitrage and the economic cycle. *Studies in Economics and Finance*, *37*(4), 777–798. https://doi.org/10.1108/SEF-04-2020-0102

[4] Kristanti, F. T. (2019). *Financial Distress Teori dan Perkembangannya Dalam Konteks Indonesia*. Inteligensia Media.

[5] Wu, D., Ma, X., & Olson, D. L. (2022). Financial distress prediction using integrated Z-score and multilayer perceptron neural networks. *Decision Support Systems*, *159*, 113814. https://doi.org/10.1016/j.dss.2022.113814

[6] Dianova, A., & Nahumury, J. (2019). Investigating the effect of liquidity, leverage, sales growth, and good corporate governance on financial distress. *JASF: Journal of Accounting and Strategic Finance*, *2*(2), 143-156. /https://doi.org/10.33005/jasf.v2i2.49

[7] Pranita, K. R., & Kristanti, F. T. (2020). Analisis Financial Distress Menggunakan Analisis Survival. *Nominal: Barometer Riset Akuntansi Dan Manajemen*, *9*(2), 62–79. https://doi.org/10.21831/nominal.v9i2.30917

[8] Alamsyah, A., Kristanti, N., & Kristanti, F. T. (2021). Early warning model for financial distress using Artificial Neural Network. *IOP Conference Series: Materials Science and Engineering*, *1098*(5), 052103. https://doi.org/10.1088/1757-899x/1098/5/052103

[9] Awalia, R., & Titik Kristanti, F. (2023). Prediksi Financial Distress Menggunakan Artificial Neural Network (Ann) Pada Perusahaan Perbankan Yang Terdaftar Di Bursa Efek Indonesia (Bei) Periode 2017-2021. *Jurnal Kajian Pendidikan Ekonomi Dan Ilmu Ekonomi*, *7*(2), 2549–2284.

[10] Zhou, F., Fu, L., Li, Z., & Xu, J. (2022). The recurrence of financial distress : A survival analysis The recurrence of financial distress : A survival analysis. *International Journal of Forecasting*, *38*(3), 1100–1115. https://doi.org/10.1016/j.ijforecast.2021.12.005

[11] Kontan.co.id. (2024). *Kinerja Perusahaan Tambang dan Energi Merosot di 2023, Cermati Pemicunya*. Kontan .

[12] Ditjen Minerba. (2023). *LAPORAN KINERJA DITJEN MINERBA TAHUN 2023*.

[13] Jelita, I. N. (2024). Harga Nikel Terus Anjlok, Smelter Nikel Bisa Tutup Beroperasi. Mediaindonesia.com. https://mediaindonesia.com/ekonomi/646853/harga-nikel-terus-anjlok-smelter-nikel-bisa-tutup-beroperasi?utm_source=chatgpt.com

[14] Reuters. (2023). *China's 2024 steel demand to fall 1.7%, exports to slow - state researcher*. Reuters.com. https://www.reuters.com/markets/commodities/chinas-2024-steel-demand-fall-17-this-year-state-researcher-2023-12-22/

[15] Muparuri, L., & Gumbo, V. (2022). On logit and artificial neural networks in corporate distress modelling for Zimbabwe listed corporates. *Sustainability Analytics and Modeling*, *2*, 100006. https://doi.org/10.1016/j.samod.2022.100006

[16] Titikkristanti, F., & Mahardika, I. P. A. B. (2023). Artificial Neural Network for Financial Distress Prediction on Energy Companies Listed in Indonesia. *2023 International Conference on Digital Business and Technology Management, ICONDBTM 2023*, *c*. https://doi.org/10.1109/ICONDBTM59210.2023.10327203

[17] Kuizinienė, D., Savickas, P., Kunickaitė, R., Juozaitienė, R., Damaševičius, R., Maskeliūnas, R., & Krilavičius, T. (2024). A comparative study of feature selection and feature extraction methods for financial distress identification. *PeerJ Computer Science*, *10*. https://doi.org/10.7717/PEERJ-CS.1956

[18] Kristianto, H., & Rikumahu, B. (2019). A cross model telco industry financial distress prediction in Indonesia: Multiple discriminant analysis, logit and artificial neural network. *2019 7th International Conference on Information and Communication Technology, ICoICT 2019*, 1–5. https://doi.org/10.1109/ICoICT.2019.8835198

[19] Kristanti, F. T., Safriza, Z., & Salim, D. F. (2023). Are Indonesian construction companies financially distressed? A prediction using artificial neural networks. *Investment Management and Financial Innovations*, *20*(2), 41–52. https://doi.org/10.21511/imfi.20(2).2023.04

[20] Prihadi, T. (2019). *Analisis Laporan Keuangan Konsep dan Aplikasi*. PT. Gramedia Pustaka Utama.

[21] Ramdhan, M. (2021). *Metode Penelitian*. Cipte Media Nusantara.

[22] Zellatifanny, C. M., & Mudjiyanto, B. (2018). Tipe Penelitian Deskripsi Dalam Metode Penelitian. *Diakom: Jurnal Media Dan Komunikasi*, *1*(2), 83-90.

[23] Fasya, N. S., & Rikumahu, B. (2021). Analysis of Financial Distress Prediction Using Artificial Neural Network in Retail Companies Registered in Indonesia Stock Exchange. *International Journal of Advanced Research in Economics and Finance*, *3*(1), 121-128.