Implementation of Artificial Neural Network with Particle Swarm Optimization Algorithm for Financial Distress Prediction of Private Banks in Indonesia

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Abstract

Banking stability, particularly the risk of financial distress in private commercial banks, remains a critical issue that requires accurate and reliable prediction models. This study aims to analyze the characteristics of financial distress in Indonesian private commercial banks and to evaluate the effectiveness of Artificial Neural Networks (ANN) and ANN optimized with Particle Swarm Optimization (ANN-PSO) in predicting financial distress. Using financial data from 59 private commercial banks over the 2020–2023 period, this research employs five financial ratios as input variables and applies ANN and ANN-PSO models, with parameter selection conducted through a trial-and-error and optimization process. The results show that financial distress peaked in 2022–2023 with 32 distressed banks, while descriptive statistics indicate differences between distress and non-distress banks, including average NPLs of 1.40% versus 1.04%, ROA of 0.36% versus 0.75%, and LDR of 93.89% versus 92.39%, respectively. In predictive performance, both ANN and ANN-PSO achieved identical test accuracy of 95.74%, sensitivity of 93.75%, specificity of 96.77%, and an F1 score of 93.75%, although ANN-PSO demonstrated better model stability with lower training accuracy (98.40%) compared to ANN (99.47%), indicating reduced overfitting. Despite these promising results, this study is limited to a relatively short observation period and a fixed set of financial ratios; therefore, future research is recommended to incorporate longer time horizons, additional macroeconomic variables, and alternative optimization techniques to further enhance prediction robustness and generalizability.

Keywords: *Artificial Neural Network, Financial Distress, Particle Swarm Optimization*

I. INTRODUCTION

The banking sector is one of the main pillars in a country's financial system, including Indonesia. Bank stability and health are essential to maintain public trust in the financial system and encourage economic growth. Given its main function as intermediary finance, banks have a strategic role in managing public funds and distributing them to productive sectors. Therefore, maintaining banking stability is a top priority for the government and related authorities. However, threats to banking stability, such as Financial distress, remains a major concern, especially in private commercial banks [1]. Financial distress is a financial condition that experiences a continuous decline and causes the stability of an institution's financial performance to suffer losses. This condition not only affects the profitability of banks, but also the trust of customers and investors in the banking system as a whole. Therefore, strategic steps are needed to identify and prevent Financial distress Early [2].

Preventing financial distress can be effectively achieved through early and accurate financial distress forecasting, which enables banks and regulators to take proactive corrective actions before financial problems escalate. In this context, artificial intelligence–based approaches, particularly Artificial Neural Networks (ANN), represent a relevant and powerful choice for financial distress prediction due to their ability to model complex, dynamic, and non-linear relationships among financial variables that are often difficult to capture using traditional statistical or econometric methods. ANNs can process large volumes of financial ratio data simultaneously and learn hidden patterns that reflect early warning signals of deteriorating bank conditions. Nevertheless, the predictive performance of ANN models is highly dependent on the selection of optimal parameters, such as learning rate, network architecture, number of hidden neurons, and training epochs, as inappropriate parameter settings may lead to overfitting or poor generalization [3]. To address this limitation, optimization algorithms such as Particle Swarm Optimization (PSO) can be integrated with ANN to systematically search for optimal parameter combinations. PSO, inspired by the collective behavior of social organisms, is effective in exploring complex solution spaces and improving convergence toward optimal solutions. By optimizing ANN parameters, PSO enhances model stability, predictive accuracy, and generalization capability, making ANN-PSO a more robust approach for forecasting financial distress in dynamic and uncertain banking environments [4].

The integration of Artificial Neural Networks (ANN) with Particle Swarm Optimization (PSO) in this study is intended to provide a reliable and robust predictive solution for identifying potential financial distress in private commercial banks by enhancing model accuracy and stability. This study employs five key financial ratios as input variables, namely Non-Performing Loan (NPL), Return on Assets (ROA), Return on Equity (ROE), Loan to Deposit Ratio (LDR), and Current Ratio (CR), which are widely recognized indicators of bank financial performance and resilience. NPL reflects credit risk and asset quality, ROA and ROE represent the bank's profitability and efficiency in utilizing assets and equity, LDR captures liquidity management and the balance between lending activities and funding sources, while CR indicates the bank's short-term liquidity and ability to meet immediate obligations. The selection of these variables is grounded in their strong theoretical and empirical relevance in banking and financial distress literature, as together they provide a comprehensive representation of risk, profitability, and liquidity dimensions. By incorporating these five variables into the ANN-PSO framework, the model is expected to capture complex interrelationships among financial indicators and generate more accurate early warning signals of financial distress.

Based on the importance of banking stability and the need for early detection of financial problems, this study aims not only to develop an accurate and reliable financial distress prediction model but also to provide practical insights for key stakeholders, including bank management, regulators, and investors, in formulating preventive and corrective strategies. By generating early warning signals through an optimized ANN–PSO model, bank management can strengthen internal risk management, improve financial performance, and implement timely restructuring or policy adjustments before distress conditions worsen. For regulators, the model can serve as a supportive analytical tool for supervisory monitoring and macro prudential oversight, enabling more effective intervention to maintain systemic stability and public confidence in the banking sector. Meanwhile, investors can utilize the prediction results as an objective reference in assessing bank risk profiles and making informed investment decisions. Therefore, the outcomes of this study are expected to contribute not only to methodological advancement in financial distress prediction but also to practical decision-making processes aimed at mitigating financial distress risks and ensuring the long-term stability of private commercial banks in Indonesia.

II. METHOD

A. Financial Distress

Financial distress is the condition of a company's inability to meet its financial obligations on time, which is usually seen from a significant deterioration in financial ratios. This condition can lead to bankruptcy, reorganization, or liquidation if the company does not take adequate corrective action. Financial distress be phase deterioration of financial conditions experienced by the company, which occurred before bankruptor liquidation. This condition is generally characterized by EBIT, EBITDA and net income experiencing negative for 2 consecutive years. According to the main factors of the cause [5]. According to the Otoritas Jasa Keuangan (OJK), a bank is declared bankrupt or liquidated when it starts experiencing financial problems and cannot be rehabilitated. OJK determines the status of a bank based on the OJK Regulation (POJK) Number 5 of 2024 concerning the determination of supervisory status and handling of issues in commercial banks.

Banks can be classified into two conditions based on their financial health and supervisory status. The first category consists of banks under normal supervision, commonly referred to as non-distress banks, which are able to maintain business continuity and comply with regulatory requirements. The second category includes banks undergoing rehabilitation, or distress banks, which are identified as having potential financial difficulties that threaten their business sustainability, particularly when their Statutory Reserves Ratio (Giro Wajib Minimum/GWM) falls below the regulatory threshold of 7.5% as stipulated by the Financial Services Authority (OJK). Financial distress in banks generally arises from several key factors, including financial management mistakes such as poor control of working capital, debt, and investment decisions, which can place significant pressure on financial stability. In addition, an excessive debt burden may become a serious problem when banks are unable to generate sufficient cash flow to meet their obligations. A decline in operational performance, caused by inefficiencies or loss of market share, can further reduce revenue and weaken financial conditions. Moreover, external economic factors, such as economic recessions, exchange rate volatility, and changes in regulatory policies, can exacerbate financial difficulties and accelerate the onset of financial distress [6].

B. Financial Ratios

Financial ratio is one of the financial analysis tools that can be a benchmark or parameter in assessing the performance of a company, especially in the efficient use of resources and financial management. Financial ratios are calculated through several important components present in financial statements, such as profit and loss, cash flow, balance sheet, and so on. In addition to being a benchmark in assessing the performance of a company or business, financial ratios, also known as financial ratios, are often used as supporting data in decision-making.

With this data, the management can predict the right steps and if it happens in the future. Financial ratios are divided into several types, which are as follows:[7]

1. *Non-Performing Loan (NPL)*

Non-Performing Loan (NPL) is a ratio used to measure the level of non-performing loans owned by banks. This non-performing loan includes loans that no longer generate interest or principal that are not repaid by the customer according to the payment schedule, usually after 90 days. NPLs are an important indicator of the quality of a bank's assets, where a high NPL ratio reflects large credit risk and less effective risk management. NPLs are used to assess the potential difficulty of banks in collecting their receivables that can jeopardize the bank's business operations. The ideal NPL according to the OJK is below 5%, in accordance with banking standards in Indonesia. NPLs can be calculated by Equation 1.[8]

$$NPL = \frac{kredit\ bermasalah}{total\ kredit} \tag{1}$$

2. *Return on Asset (ROA)*

Return on Asset (ROA) is a profitability indicator that measures a bank's ability to generate net profit from its assets. ROA is an important indicator for regulators, such as OJK, to assess management efficiency in managing bank resources. ROA can be calculated using Equation 2 [9].

$$ROA = \frac{laba\ bersih}{total\ aktiva} \times 100\% \tag{2}$$

3. *Return on Equity (ROE)*

Return on Equity ROE shows the bank's ability to utilize shareholder capital to generate profits. ROE is used to measure the rate of return on net profit that a bank earns from shareholder equity. ROE can be calculated by Equation 3 [10].

$$ROE = \frac{laba\ bersih}{ekuitas} \times 100\% \tag{3}$$

4. *Loan to Deposit Ratio (LDR)*

LDR is a liquidity indicator that measures the extent to which third-party funds raised by banks are used to distribute credit. If the LDR is too high, banks can face liquidity risks. On the other hand, if it is too low, the bank is considered not to utilize the funds to the fullest. LDR can be calculated by Equation 4 [9].

$$LDR = \frac{kredit}{dana\ pihak\ ketiga} \times 100\% \tag{4}$$

5. *Current Ratio (CR)*

Current Ratio (CR) is used to measure a bank's ability to meet its short-term obligations using its current assets. Although CR is more commonly used in the corporate sector, banks also use this ratio to ensure their liquidity is maintained. A high CR indicates that the bank has sufficient liquidity to meet its short-term obligations. CR can be calculated by Equation 5 [11].

$$CR = \frac{aset\ lancar}{kewajiban\ lancar} \times 100\% \tag{5}$$

C. *Artificial Neural Network (ANN)*

Artificial Neural Network (ANN) is a computational model inspired by the way the human brain works in processing information. The ANN is made up of a number of artificial neurons that are interconnected and organized. Each neuron functions as a processing unit that receives input, processes it through activation functions, and produces output that is passed on to other neurons. The ANN learning process is carried out by adjusting the weights and biases on each connection between neurons using learning algorithms, such as backpropagation, which aims to minimize errors in network output. ANNs have the ability to handle complex and non-linear data, so they are widely used in a variety of applications, including pattern recognition, prediction, classification, and system control. However, ANNs also have some drawbacks, such as requiring large training data, high computing time, and the risk of overfitting if not designed properly. Overall, ANN is a very flexible tool for solving difficult computing problems and has been widely adopted in various fields, such as image recognition, speech recognition, recommendation systems, and data analysis [12].

The way ANNs work is the information that comes in (Input) will be sent to the neuron with a certain weight and then processed by a function that will add up the values of the existing weights. The sum result will be compared to the threshold value through the activation function of each neuron. If the input crosses a certain threshold value, then the neuron will be activated, if not, then the neuron will not be activated. An activated neuron will transmit output through its output weights to all the neurons associated with it. ANN consists of three main components, namely the input layer, the hidden layer, and the output layer [13].

1. ***Input Layer***
   Also known as Input Nodes, this layer contains input/information from the outside world that the model uses to learn and draw conclusions. The input node sends data to the next layer, the Hidden layer.

2. ***Hidden Layer***
   A hidden layer is a group of neurons that perform all calculations on the input data. There can be a number of hidden layers in a neural network. The most basic network has one hidden layer.

3. ***Output Layer***
   The output layer contains the output/conclusion of the model generated from all calculations. The output layer can have one or more nodes.

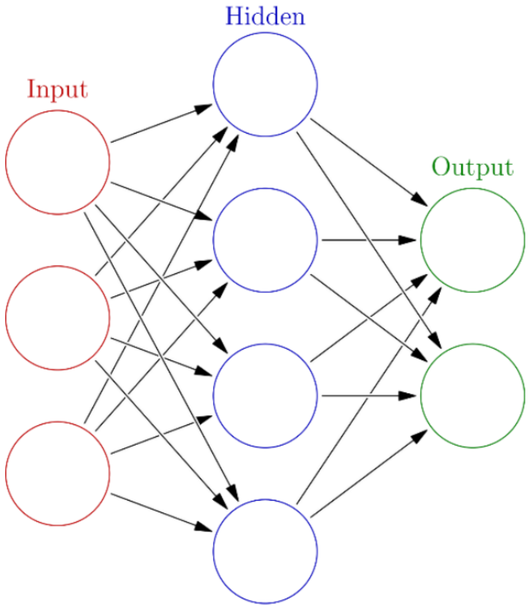

Figure 1 Simple Artificial Neural Network

Figure 1 is an example of a simple Artificial Neural Network with 3 layers. There are basically three types of layers. The first layer that connects to the input variable is called the input layer. The last layer that connects to the output variable is called the output layer. The layer between the input layer and the output layer is called the hidden layer. Hidden layers can be more than one. Information is transmitted through connections between nodes. In a simple situation, information is passed forward.

D. Backpropagation

Backpropagation (Backward Propagation of Errors) is an algorithm used to train Artificial Neural Network (ANN) by minimizing errors in tissue output through adjusting the weights on neurons. The predicted network value is compared to the expected output, and the error is calculated using the function. These errors are then propagated back into the entire network, one layer at a time, and the weights are updated according to the values that contributed to the errors [14].

E. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) optimizes objective functions by conducting population-based searches. The population is made up of a potential solution, named a particle, which is a metaphor for birds in a flock. These particles are randomly initialized and freely fly across the multidimensional search space. During flight, each particle updates its own velocity and position based on its own and the entire population’s best experience. The renewal policy encourages the particle swarm to move towards the region with a higher objective function value, and eventually all the particles will gather around the point with the highest objective value [15].

F. Synthetic Minority Oversampling Technique (SMOTE)

Synthetic Minority Oversampling Technique (SMOTE) is an approach *Over-sampling* where minority classes are oversampled by creating "synthetic" examples rather than by *Over-sampling* Replacement. This approach is inspired by techniques that have proven successful in handwritten character recognition [16]. SMOTE can address imbalances in the number of samples in a class by replicating minority class data, the results of which are known as synthetic data. If the proportion of the minority class sample is less than 35% of the total data, it is categorized as unbalanced data. On numerical data, SMOTE will work by looking for k-nearest neighbors for each data in the minority class using the Euclidean distance [17]. Synthetic data will be generated using the following equation.

$$X_{syn} = X_m + (X_{knn} - X_m)\gamma$$

Information:

X_{syn} : Synthesis data

X_m : ith data from minority classes

X_{knn} : Data from minorities that have the closest proximity

γ : A random number between the values 0 and 1

III. RESULTS AND DISCUSSION

A. Data Characteristics

Descriptive statistics have an important role in describing the characteristics of private commercial banks in Indonesia. Through this analysis, various information related to the bank's financial condition can be disclosed more clearly. This understanding is a strong foundation for decision-makers to formulate more effective strategies, improve financial performance, and face challenges arising from changing market conditions and regulations [19,20]. The discussion of the financial characteristics of private commercial banks in Indonesia will be explained as follows:

1. Financial Distress of Private Commercial Banks in Indonesia

The characteristics of commercial bank data in Indonesia are 59 banks. The analysis was carried out over the last 4 years of each bank. Every year, banks will be categorized into two based on the **value of reserve requirements** contained in the OJK bank's financial statements. If the **value of GWM>7.5%** then the bank will be categorized as non-distress, while if the value **of GWM<7.5%** then the bank will be categorized as distress. The characteristics of financial distress data will be presented with the aim of seeing the development of the number of banks experiencing financial distress every year, which can be seen in Figure 2 below:

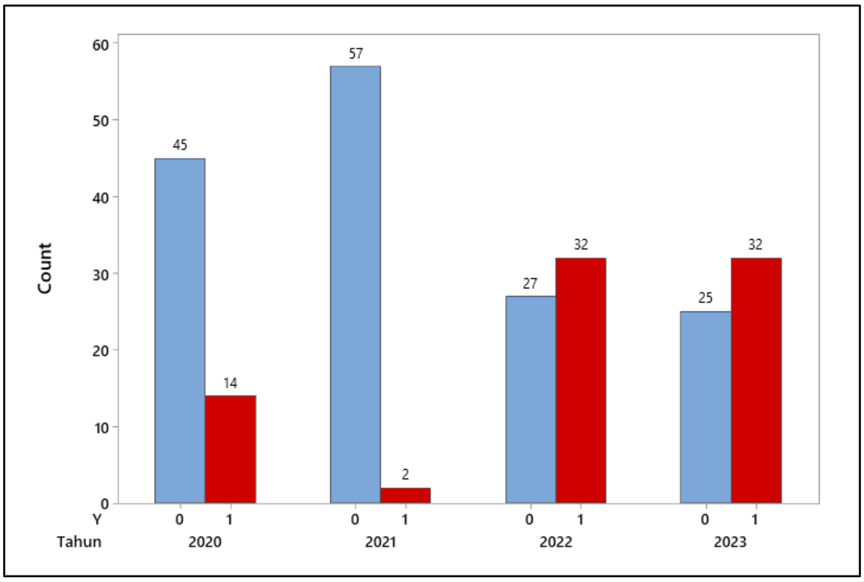

Figure 2 Financial Conditions of Private Commercial Banks in Indonesia

Based on Figure 2, it can be seen that the peak number of banks experiencing financial distress occurred in 2022 and 2023, with a total of 32 banks affected by financial distress and 25 other banks not experiencing financial distress. Meanwhile, in 2020, 14 banks experienced financial distress and 45 banks did not experience financial distress. In 2021, only 2 banks experienced financial distress and 57 banks did not experience financial distress.

2. Financial Ratios of Private Commercial Banks in Indonesia

Descriptive statistical analysis of financial ratio data of private banks in Indonesia is used to describe the characteristics of banks. The descriptive statistical analysis for each variable of the bank's financial ratios from 2020 to 2023 is explained as follows:

Table 1 Characteristics of Financial Ratios of Private Commercial Banks in Indonesia

Category	Financial Ratios	Average	Minimum	Maximum
Non-Distress	NPL	1.40%	0.00%	4.95%
	ROA	0.36%	-14.75%	5.12%
	ROE	-0.03%	-95.44%	27.55%
	LDR	93.89%	0.00%	527.91%
	CR	1.51%	0.65%	13.32%
Distress	NPL	1.04%	0.00%	4.83%
	ROA	0.75%	-14.11%	4.76%
	ROE	3.91%	-49.72%	23.49%
	LDR	92.39%	20.53%	316.89%
	CR	1.45%	0.63%	10.07%

Table 1 provides an overview of the characteristics of the financial ratios of private commercial banks in Indonesia which are grouped into two categories: non-distress and distress. In general, there are significant differences between the two categories in terms of profitability, liquidity, and non-performing credit risk. In the non-distress category, the average NPL (Non-Performing Loan) of 1.40% shows that non-performing loans are relatively under control, although there are several banks that have reached NPLs of up to 4.95%. A minimum value of 0.00% indicates that there are banks that have no non-performing loans at all. In terms of profitability, an average ROA (Return on Assets) of 0.36% indicates that the return on assets is still relatively small, with significant variability from a minimum of -14.75% (large losses) to a maximum of 5.12% (high returns). Meanwhile, ROE (Return on Equity) shows an average of -0.03%, which means that most banks in this category do not generate profits from their equity. A very low ROE minimum value (-95.44%) indicates a huge loss for some banks, although there are also banks that manage to achieve a maximum ROE of 27.55%. In terms of liquidity, the average LDR (Loan to Deposit Ratio) of 93.89% shows that most banks are quite aggressive in distributing credit to their deposits, although there is a large variation with a maximum value of 527.91%, which shows a large dependence on credit financing.

Furthermore, short-term liquidity measured through CR (Current Ratio) shows an average of 1.51%, indicating that the bank has sufficient current assets to meet short-term obligations, with a minimum value range of 0.65% to a maximum of 13.32%. In contrast, the distress category exhibits slightly different characteristics. The average NPL was 1.04% lower than that of the non-distress category, indicating that banks in this category tended to have more controlled non-performing loans. However, the maximum NPL value remains high, reaching 4.83%, which indicates the existence of credit risk for some banks in this category. In terms of profitability, distressed banks have an average ROA of 0.75%, which is higher than non-distressed banks, indicating a slightly better ability to generate profits from assets despite a minimum value of -14.11% indicating a loss. In addition, the ROE in the distress category reached an average of 3.91%, much better than in the non-distress category, indicating that banks in this category tend to be more effective in generating profits from their equity, despite the minimum value of -49.72%. In terms of liquidity, the average LDR of 92.39% is slightly lower than that of the non-distress category, with a maximum value of 316.89%, indicating that distressed banks tend to be slightly more cautious in distributing credit. The average CR in the distress category was 1.45%, slightly lower than non-distress, but still reflected quite good liquidity with a minimum range of 0.63% to a maximum of 10.07%.

B. Artificial Neural Network Method

One effective method to predict financial distress is through an Artificial Neural Network (ANN). In this study, the proposed ANN architecture consists of 1 input layer with 5 neurons, each representing 5 predictor variables or financial ratios used. The model also has 1 output layer with 1 neuron, which results in a binary classification, where financial distress (FD) is classified as 1 and non-financial distress (NFD) as 0. In addition, this model is equipped with hidden layers where in this study it is only limited to 1 which is explained as follows. The model selection was carried out by trial and error with a learning rate range between 0.01 to 0.001, a range of neuron counts between 5 and 8, and a range of iterations between 100 to 500. The best model results of the ANN method are shown in the following table2:

Table 2 Best ANN Models

Learning Rate	Hidden Neuron	Epochs	Train Accuracy	Test Accuracy	Sensitivity	Specificity	F1 Score
0,01	[5, 5]	500	99,47%	95,74%	93,75%	96,77%	93,75%

Based on Table 1, it can be seen that the best combination of ANN model parameters by handling data imbalances using SMOTE is a learning rate of 0.01, with 2 hidden sizes of [5.5] and the number of epochs of 500. This combination of parameters results in high accuracy, especially in the testing phase, as well as perfect precision. Overall this model is considered optimal for existing data, indicating that the hidden layer structure with two layers (5 and 5 neurons) is effective in extracting patterns in the data and minimizing prediction errors.

C. Artificial Neural Network Method Particle Swarm Optimization Algorithm

This subchapter will discuss the process of selecting the best model in the application of the PSO algorithm ANN to predict financial distress. The purpose of this model selection is to find the model configuration that produces the most accurate predictions with a good level of generalization, so as to minimize financial distress prediction errors and provide optimal results.

Table 3 ANN-PSO Best Model

Learning Rate	Hidden Neuron	Epochs	Train Accuracy	Test Accuracy	Sensitivity	Specificity	F1 Score
0,0075	[6, 7]	500	98,40%	95,74%	93,75%	96,77%	93,75%

Based on Table 1, it can be seen that the combination of ANN model parameters with PSO algorithm obtained the best value is a learning rate of 0.0075, with 2 hidden sizes of [6, 7] and the number of epochs of 500. The PSO-optimized ANN model shows good performance on test data with an accuracy of 95.74%. Balanced sensitivity and specificity show the model can recognize both positive and negative classes consistently.

D. Comparison of Prediction Results of ANN and ANN-PSO Methods

The ANN and ANN-PSO methods are used to model and predict the status of Financial Distress and Non-Financial Distress. The comparison of prediction results between the two methods is important to evaluate the reliability of the two models in processing financial variables as inputs and providing accurate predictions. The analysis was carried out by involving 5 financial ratios as input variables for each model, in order to see the performance and accuracy level generated from these two methods. By comparing the performance of the ANN and SVM models, it is hoped that it can identify which method is more effective in predicting Financial Distress, so that it can be used as a reference in better financial decision-making. The performance of both methods can be seen in Table 4.20 below:

Table 4 Comparison of ANN and ANN-PSO Models

Method	Train Accuracy	Test Accuracy	Sensitivity	Specificity	F1 Score
ANN	99,47%	95,74%	93,75%	96,77%	93,75%
ANN-PSO	98,40%	95,74%	93,75%	96,77%	93,75%

Based on Table 3, it can be seen that the comparison between the ANN (Artificial Neural Network) and ANN-PSO (Artificial Neural Network with Particle Swarm Optimization) methods, both methods show identical performance in the test data with the values of **Test Accuracy (95.74%), Sensitivity (93.75%), Specificity (96.77%),** and **F1 Score (93.75%)**. This shows that both methods have equal capabilities in predicting new data, detecting distress and non-distress cases in private commercial banks in Indonesia. However, ANNs have a higher training accuracy (99.47%) than ANN-PSO (98.40%), which can indicate the potential for overfitting in ANNs. In contrast, ANN-PSO shows a more stable model and avoids overfitting, with a smaller difference in training accuracy. Therefore, even though the test performance of both methods is the same, ANN-PSO is more recommended if model stability and generalization are priorities, especially in the face of new, more varied data.

IV. CONCLUSION

The characteristic analysis showed that there was a significant difference between *the non-distress* and *distress* categories, especially in terms of profitability, liquidity, and non-performing credit risk. Banks in *the non-distress* category tend to have a more stable performance, while banks in the distress category show higher profitability. In predicting *financial distress*, the ANN and ANN methods optimized with PSO show equivalent performance in processing data and providing prediction results. However, ANN-PSO is more recommended because it produces a more stable model and avoids *overfitting*. Therefore, even though the test performance of both methods is the same, ANN-PSO is more recommended if model stability and generalization are priorities, especially in the face of new, more varied data.

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