Artificial Neural Networks: A Deep Learning Approach in Financial Distress Prediction

Ni Wayan Dewinta Ayuni[1],
Wayan Hesadijaya Utthavi[2], and Ni Nengah Lasmini[3]

[1,2,3]Accounting Department, Politeknik Negeri Bali, Bali, Indonesia
dewintaayuni@pnb.ac.id

Abstract. Predicting financial distress is a crucial thing in company management, so researchers are competing to develop methods that can produce high accuracy in predicting financial distress. One method that is being widely developed is Machine Learning. Machine Learning, which is a branch of artificial intelligence, is a method that applies learning to machines so that machines are not only able to behave in making decision but can also adapt to changes that occur. The branch of Machine Learning that has high power in prediction is Deep Learning. Artificial Neural Networks (ANN) is one of the most important and reliable parts of deep learning. ANN is a model inspired by how neurons in the human brain work. Every neuron in the human brain is interconnected and information flows from each neuron. In the ANN architecture, the stimulus will enter a neuron called the input layer, be processed in one or several hidden layers which will be weighted according to the activation function, then the results will be passed on to the output layer. ANN is predicted to have many advantages compared to other machine learning methods in predicting financial distress. This research applies ANN to predict Financial Distress for Property and Real Estate Sector Companies listed on the IDX. The research results show that ANN produces higher prediction accuracy, namely 88.88% compared to other Machine Learning methods such as SVM at 80.47% and PSO-SVM at 83.16%.

Keywords: Deep Learning, Artificial Neural Networks, Financial Distress Prediction.

1 Introduction

The company's financial condition is a crucial topic for various parties and stakeholders. Whether the Company's finances are healthy or not can affect the survival of many parties. For this reason, companies must be able to analyze the company's financial health. The financial distress of a company usually refers to the situation in which the operating cash flow of the company cannot supersede the negative net assets of the company (Andreou et al., 2021; Ghasemzadeh et al., 2021). This condition can lead the company into bankruptcy. Company bankruptcy will cause economic disruption for company management, investors, creditors, suppliers,

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and employees, and can even disrupt the economic stability of a country (Li & Wang, 2018). For this reason, researchers have made financial distress prediction an important topic worthy of development (Liahmad et al., 2021; Sun et al., 2021; Abdu, 2022; Qian et al., 2022; Tarighi et al., 2022).

Various statistical methods have been developed to predict company financial distress, such as Altman Z-Score (Altman, 1968), Logistic Regression (Ohlson, 1980), and Factor Analysis (West, 1985). Then in the 1990s, statistical methods began to be combined with artificial intelligence, including machine learning (Li & Wang, 2018).

Machine learning is a subfield of artificial intelligence that involves training computers to exhibit human-like intelligence and enhance their understanding through automated experience (Kusuma, 2020). Machine learning is a field that aims to create self-learning machines capable of making decisions without the need for constant human programming (Retnoningsih & Pramudita, 2020). This enables machines to perform not only make decisions but also to adapt to occurring changes.

In the field of machine learning, there exist two types of data: training data and testing data. Training data is used to teach machine learning algorithms while testing data is employed to evaluate the performance of these taught algorithms. Specifically, testing data is used to assess how well the algorithms can handle new data that was not included in the training data (Fikriya et al., 2017).

Deep learning is a subfield of machine learning that utilizes neural networks, which are computational models inspired by the structure and function of the human brain's neurons (Abambres & Ferreira, 2019). The human brain structure consists of over 100 billion neurons, with each neuron forming 1,000 to 10,000 connections with other neurons. Information in the human brain is stored to allow for parallel processing and multiple repetitions. It is accurate to state that the human brain possesses an exceptionally potent processor.

Artificial neural networks (ANN), are an important foundation in deep learning. In artificial neural networks, stimulation is received from neurons called the input layer and then processed in one or several hidden layers whereas in the hidden layers, there is an activation function. This activation function will give weight to the input layer and then forward the results to the final neuron, namely the output layer (Dube et al., 2021).

ANN has been widely applied in various fields for both prediction and classification (Arbabi et al., 2020; Raj et al., 2021). This method has also been applied by researchers in the field of financial distress (Nur & Panggabean, 2019; Alamsyah et al., 2021; Wu et al., 2022; Awalia & Kristanti, 2023; Pratiwi et al., 2023; Sabek, 2023). Prior studies have highlighted the benefits of Artificial Neural Networks (ANN) in the domain of financial distress prediction, with (Terzi et al., 2012) asserting that Neural Networks exhibit superior accuracy compared to other statistical approaches. In their study, (Geng et al., 2015) determined that artificial neural networks (ANN) outperformed the Support Vector Machine, Majority Voting, and Decision Tree models in terms of model accuracy. Gregova conducted research that demonstrated the superiority of the ANN model in predicting Financial Distress (Gregova et al., 2020). The accuracy of the ANN model surpassed that of the Logistic Regression and Random Forest models. Marso and Merouni found that, like earlier research, the Neural Network model was more successful than the Logistic Regression model in predicting Financial Distress in the Manufacturing Sector in Poland (Marso & Merouani, 2020). Dube utilized financial crisis prediction models to analyze the financial services sector and the manufacturing industry in South Africa (Dube et al., 2021). The research findings indicate that Artificial Neural Network (ANN) is the most suitable approach for predicting financial difficulties due to its exceptional accuracy rates of 81.3% and 96.6%. Alamsyah have additionally supported this claim, stating that artificial neural networks (ANN) are capable of modeling complex non-linear relationships between variables, resulting in a more precise prediction model (Alamsyah et al., 2021). Aydin asserted that artificial neural networks (ANN) are assumption-free, applicable to both linear and non-linear model architectures, possess strong predictive capabilities, and are user-friendly (Aydin et al., 2022).

This research utilizes Artificial Neural Networks (ANN) to forecast financial hardship for companies in the property and real estate industry in Indonesia, taking advantage of the superior benefits of ANN over other machine learning techniques. The accuracy of the artificial neural network (ANN) prediction findings in this study will be compared to the accuracy of the Support Vector Machine (SVM) and Particle Swarm Optimization Support Vector Machine (PSO-SVM) models that previous researchers have used.

2 Methodology

The research utilizes secondary data sourced from the Indonesia Stock Exchange (BEI) regarding companies in the property and real estate sector throughout the period of 2018-2022. The independent variables applied to the analysis are financial ratios in Table 1.

Table 1. Financial ratios

Financial ratios	Sub ratios
Liquidity ratio	Working Capital to Total Asset (X1), Current Ratio (X2), Quick Ratio (X3), Account Receivable Turnover (X4), and Inventory Turnover (X5)
Solvency ratios	Debt-to-Equity (X6) and Leverage Ratio (X7)
Profitability ratios	Gross Profit Margin (X8), Net Profit Margin (X9), Operating Profit Margin (X10), Return on Equity (X11), and Return on Assets (X12)
Asset utilization ratios	Asset Turnover Rate (X13), Working Capital Turnover Rate (X14), and Fixed Asset Turnover Rate (X15)
Investor ratios	Earning Per Share (X16), Price Earning Ratio (X17), and Book Value Per Share (X18)

The research focuses on predicting financial distress, with the dependent variable being categorized as either financial distress occurring (coded as 1) or financial distress not occurring (coded as 0). The financial distress category is determined based on whether the company fits one or more of the following criteria in its financial statements (Kasgari et al., 2013): a) Negative working capital; b) Negative operating profit; or c) Negative net profit. The research utilizes the t-1 period as the prediction period.

Preprocessing. Data cleaning and data standardization were carried out during the pre-processing step. Following that, the process of feature/variable selection was conducted using Principal Component Analysis (PCA). The variables used for feature selection are those with an eigenvalue greater than 0.3.

Modeling. The modeling stage starts by partitioning the data into separate sets for testing and training. There are three forms for dividing the training and testing data in this research: a ratio of 70:30, 80:20, and 90:10. There are two types of ANN architecture that will be constructed at this modeling stage:

Type 1: ANN architecture consists of 1 input layer (number of neurons depends on PCA result), 1 hidden layer (number of neurons varying between 5-15), and 1 output layer (with a single neuron).

Type 2: ANN architecture consists of 1 input layer, (number of neurons depends on PCA result), 2 hidden layers (number of neurons varying between 5-15), and 1 output layer (with a single neuron).

The activation function used in the hidden layer is ReLu which is expressed in the equation:

$$f(x) = \max(0,x) \tag{1}$$

The ReLu function is applied due to its efficiency and ability to facilitate the learning of non-linear patterns and complicated data structures within the network. Meanwhile, the output layer adopts a sigmoid activation function, which is mathematically represented by the following equation:

$$f(x) = \frac{1}{1+e^{x}} \tag{2}$$

The sigmoid function is implemented in the output layer due to its simplicity and efficacy in facilitating smoother transitions in the output layer for binary classification. The data training procedure utilized the Adam Optimizer to attain convergent outcomes within the stipulated number of epochs, specifically 500 epochs.

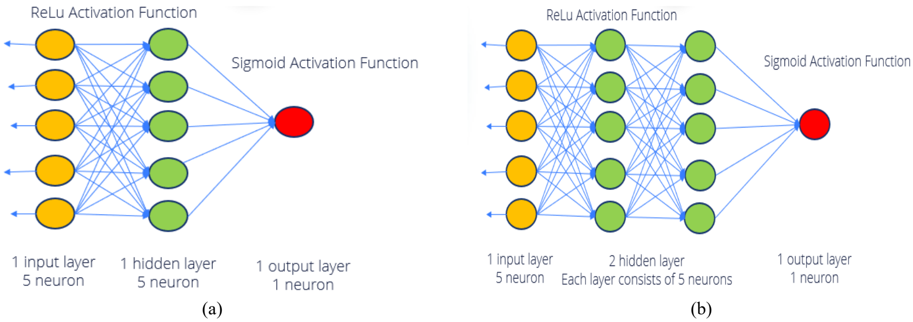

Figure 1. Types of ANN architecture built (a) 1 hidden layer (b) 2 hidden layers

Model evaluation. The model evaluation stage involves the utilization of a confusion matrix and the computation of the accuracy metric for the artificial neural network (ANN) model under construction. The optimal artificial neural network (ANN) model is the one that exhibits the highest accuracy value.

Table 2. Confusion matrix for model evaluation

Category		Actual Class	
		Positive	Negative
Prediction	Positive	TP (True Positif)	FP (False Positive)
Class	Negative	FN (False Negative)	TN (True Negative)

The accuracy value can be calculated using the following formula:

$$accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

3 Result and Discussion

3.1 Result

During the pre-processing stage, feature selection was performed using Principal Component Analysis (PCA). Five financial sub-ratios were chosen based on their eigenvector values, specifically selecting those with values greater than 0.3, which are Return on Assets (X12), Earning Per Share (X16), Book Value Per Share (X18), Operating Profit Margin (X10), and Net Profit Margin (X9). Afterward, these variables are used to build the ANN model.

ANN Architectures

Type 1 ANN architecture: The initial architecture of the ANN model contained a single input layer with 5 neurons, a hidden layer with a variety of neurons (varying from 5 to 15), and a single output layer. The accuracy results of the ANN model architecture are presented in Figure 2.

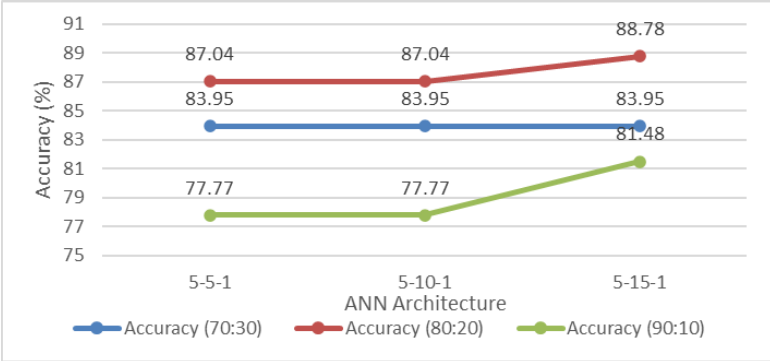

Figure 2. Results of ANN architecture type 1

Figure 2 demonstrates that all models within this artificial neural network (ANN) structure exhibit significantly high accuracy values. The ANN model achieved the highest accuracy of 88.78% when the training and testing data were divided in an 80:20 ratio, using a 5-15-1 architecture

Type 2 ANN architecture: The initial architecture of the ANN model contained a single input layer with 5 neurons, 2 hidden layers with a variety of neurons (varying from 5 to 15), and a single output layer. The accuracy results of the ANN model architecture are presented in Figure 3.

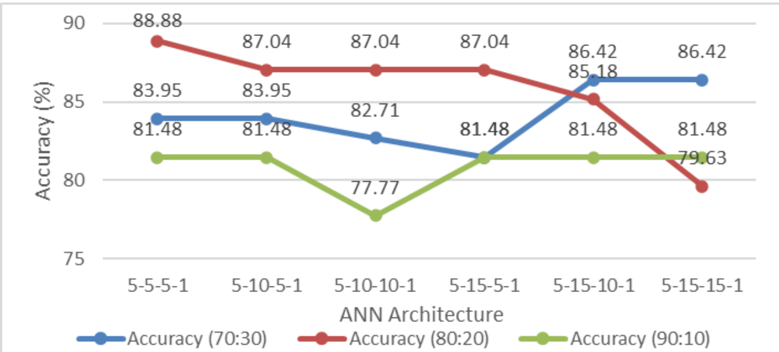

Figure 3. Results of ANN architecture type 2

Figure 3 shows that all models within this artificial neural network (ANN) structure exhibit significantly high accuracy values. The ANN model achieved the highest accuracy of 88.88% when the training and testing data were divided in an 80:20 ratio, using a 5-5-5-1 architecture

Comparison of Machine Learning Methods. The graph below displays the accuracy of the best models in Machine Learning research conducted in prior years, specifically the Support Vector Machine (SVM) and the Particle Swarm Optimization Support Vector Machine (PSO-SVM) (Ayuni et al., 2024).

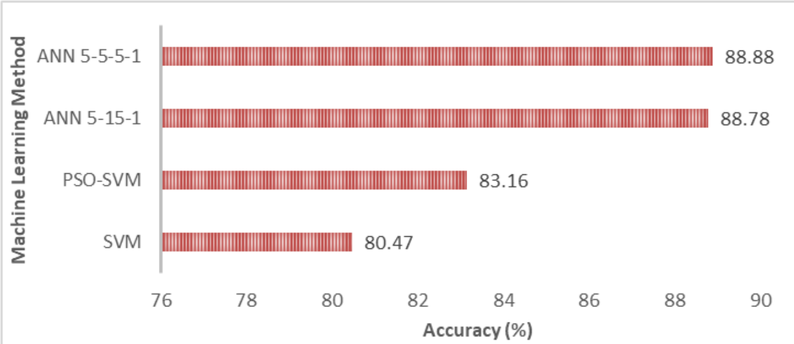

Figure 4. Comparison of Machine Learning Model in Predicting Financial Distress

The graph illustrates that the SVM model achieves an accuracy of 80.47% in predicting financial distress for companies in the Property and Real Estate sector. However, after parameter optimization using PSO, the model's accuracy improves to 83.16%. Nevertheless, the Artificial Neural Network (ANN) model surpassed both models by achieving the greatest accuracy rate of 88.88%. This demonstrates that employing the deep learning technique with the artificial neural network (ANN) model is an exceptionally effective method for forecasting a company’s financial distress. The best ANN architecture produces a confusion matrix as follows:

Table 3. Confusion matrix of the best ANN architecture type 2

Category		Actual FD	
		FD	Non-FD
Prediction FD	FD	32	1
	Non-FD	5	16

The artificial neural network (ANN) model, structured with a 5-5-5-1 architecture, accurately forecasted financial distress (FD) for 32 companies and correctly identified 16 companies without FD. However, there was a misclassification in predicting the development of financial distress (FD) in one firm that should not have been classified as FD. Additionally, there was a misclassification in predicting that five companies did not have FD when they actually did have FD

4 Conclusion

The analysis results indicate that the ANN model achieved the highest accuracy. The model was trained and tested using a proportion of 80:20 for training data and testing data, respectively. The model architecture consisted of 1 input layer with 5 neurons selected through feature selection with PCA, 2 hidden layers with 5 neurons each (using ReLu activation function and Adam Optimizer), and 1 output layer with 1 neuron and a sigmoid activation function. The accuracy of this model in predicting financial distress for companies in the property and real estate industry is 88.88%, surpassing previous ANN models in architecture. In comparison to other Machine Learning models examined in previous research, the ANN model demonstrates superior performance than the SVM model (with an accuracy of 80.47%) and the PSO-SVM model (with an accuracy of 83.16%) (Ayuni et al., 2024). Therefore, it can be inferred that utilizing the deep learning technique with the Artificial Neural Network (ANN) model may result in remarkable and precise results in predicting financial distress, particularly in Indonesian property and real estate companies.

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