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Detecting Fraudulent Financial Reporting Using Artificial Neural Network

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Abstract: This research aims to examine whether Artificial Neural Network (ANN) method can detect fraudulent financial reporting and whether firms are indicated to commit fraudulent financial reporting. The population in this research are firms listed on the Indonesia Stock Exchange in 2019 and companies that are confirmed to have committed fraudulent financial reporting. In total, 506 data sets were obtained through the purposive sampling technique. The data used in this research were obtained from financial statements. ANN method is used as the data analysis method in this research. Ten variables were used as fraud risk indicators to detect fraudulent financial reporting using ANN. Findings indicate that the developed ANN model can detect fraudulent financial reporting in financial statements. The findings of this research contribute to the literature on methods of detecting indications of financial statement fraud and that it can also be used to assist the auditor's role in detecting material misstatements attributable to fraud.

Keywords: *fraudulent financial reporting, artificial neural network, fraud risk, indicators, fraud detection models*

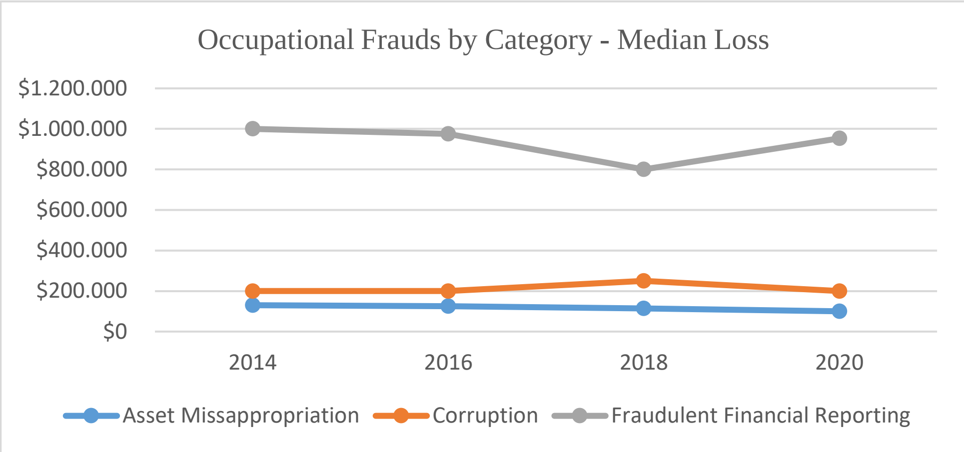
Introduction

Financial statements that should guide decisions may mislead investors when fraud occurs in the financial reporting processes (referred to as fraudulent financial reporting). Financial statements that have been modified or constructed may convey erroneous and invalid information, decreasing the quality of financial reporting (Denziana, 2015). According to the results of the Association of Certified Fraud Examiners (ACFE) survey published in the 2020 Report to the Nations, corruption and asset misappropriation are the most common fraud in the Asia Pacific, while fraudulent financial reporting accounts for only 10 per cent of the total cases with an average loss of $954,000. When comparing the total losses caused by fraudulent financial reporting to fraud cases such as corruption and asset misuse, Figure 1 shows that fraudulent financial reporting causes the most damages. Compared to the survey results in 2018, the average total loss caused by fraudulent financial reporting was $800,000, implying that losses due to fraudulent financial reporting increased by $154,000.

One of the cases of fraudulent financial reporting in Indonesia is the case experienced by PT. Garuda Indonesia. According to the online media of CNBC Indonesia, PT. Garuda Indonesia is regarded as inappropriate to formerly recognise revenue from the cooperation contract with Mahata Aero Technology as the provider of Wi-Fi services on aeroplanes, which is the amount of revenue recognised by PT. Garuda Indonesia was US$ 239 million as revenue in 2018.

In addition to the case of PT Garuda Indonesia, PT Tiga Pilar Sejahtera Food Tbk (AISA) also has management issues. Based on a fact-based investigation report by Ernst&Young (EY) Indonesia to the new management of AISA on March 12, 2019, the alleged inflation was suspected of having occurred in the accounts receivable, inventories and fixed assets of PT AISA. The prior board of directors was found to have inflated funds worth IDR 4 trillion and IDR 662 billion in alleged mark-ups on income items and IDR 329 billion in other inflations in the Earning Before Interest Taxes, Depreciation, and Amortization (EBITDA) account.

Figure 1. Losses Due to Fraud



According to the results of a survey conducted by ACFE in 2020, external audits contributed only 7 per cent to detecting fraud cases. A variety of fraud detection methods have been implemented to assist auditors to detect fraudulent financial reporting. Several methods are commonly used to detect fraudulent financial reporting, including the Altman Z-Score, Beneish M-Score, and, more recently, data mining techniques. Data mining is a data processing tool that finds patterns and connections in massive amounts of data using data search capabilities and good statistical algorithms (Omar et al., 2017). Data mining is believed to have high classification abilities and the ability to generate predictions, which can be used to assist and facilitate the role of auditors in detecting fraud (Ravisankar et al., 2011; (Soeprajitno, 2019). Many data mining methods have been developed to detect fraudulent financial reporting, including logistic regression, probit regression, decision trees, Bayesian Networks and Artificial Neural Networks (ANN). Based on the advantages, this research focused on data mining techniques with the Artificial Neural Network method in detecting the indications of fraudulent financial reporting in firms listed on the Indonesia Stock Exchange in 2019.

Literature Review

Agency Theory

Agency theory was firstly introduced by Michael C. Jensen and Willian H. Meckling in 1976. According to agency theory, a firm can be seen as a loosely defined contractual relationship between two parties: the shareholders and the company's operations. As an investor or owner, the principal has access to and desires to know more about the firm's state. In contrast, as a real actor in carrying out the firm's operational activities, the agent certainly has access to various information related to the firm's operation and overall performance. The term "information asymmetry" refers to a situation where one party knows more about a particular situation and information than the other. Based on the fraud triangle theory proposed by Cressey in 1953, fraud can be caused by three factors: pressure, opportunity, and rationalisation. Agency theory is a factor in the formation of the traits described by the fraud triangle theory (Purniati & Heryana, 2018)

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Fraud Theory

We adopted the fraud triangle theory as the basis for selecting input variables in order to develop a fraudulent financial reporting model using an artificial neural network. This theory was chosen because it is used in fraud standards, such as ISA 240 and SA 240, which deals with "Auditor Responsibilities Related to Fraud in Financial Statements Audit". Fraud triangle theory is a model that describes the factors that lead to a person committing fraud. The fraud triangle theory was proposed by Donald Cressey in 1953, with pressure, opportunity and rationalisation as fraud risk indicators.

Fraudulent Financial Reporting

The American Institute Certified Public Accountant (AICPA) defines financial statement fraud as an intentional act or omission that results in a material misstatement that misleads financial statements (Moeller, 2009). Financial statement fraud includes several modes, including (1) falsification, alteration, or manipulation of financial records, supporting documents or business transactions, (2) intentional omission of significant events, transactions, accounts, or other information as policies and procedures for measuring, recognising, reporting and disclosing economic events and business transactions, (3) intentional omission of information that should be presented and disclosed regarding the principles and accounting policies used in compiling financial statements (Wells, 2011; Yesiariani & Rahayu (2017)).

Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a type of Artificial Intelligence (AI) that uses data mining techniques. ANN is a mathematical model based on biological neural networks. Unlike traditional systems where knowledge must always follow the rules, ANN generates its own rules by learning and practising from the given examples, implying that this method has been trained to operate according to the sample (Koskivaara 2000; Omar et al., 2017). ANN is a tool that uses the same pattern and structure and parallels processing techniques as the human brain to analyse sample data repeatedly. The structure of the Artificial Neural Network is depicted in the diagram below (Cerullo & Cerullo, 1999).

Figure 2. Artificial Neural Network Structure (Chen and Du, 2009)

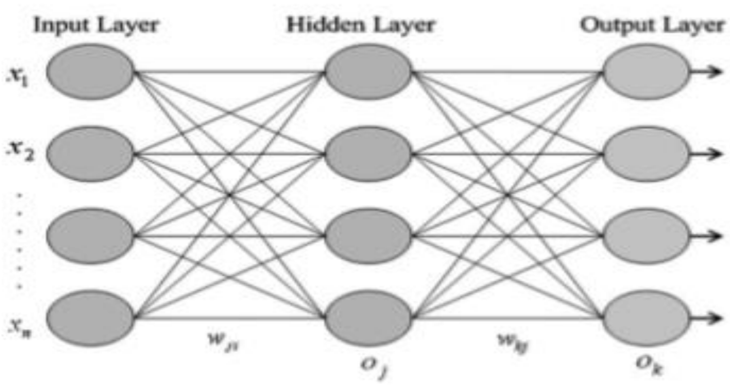

Figure 2 is an architectural depiction of a back-propagation network with three layers: input, hidden, and output. The input layer stimulates or encourages the model, whereas the output layer results from the stimulation of the input layer. The hidden layer determines the mapping relationship between the input and output layers, while the relationship between neurons is stored as the weight of the connecting link. In comparison to logistic regression, ANN has the advantage of requiring less formal statistical training. Because ANN is rarely used as a strategy or model to identify fraudulent financial reporting, we have decided to use it as a model to predict indications of

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fraudulent financial reporting within the research.

ANN and Fraudulent Financial Reporting

This research replicates a study conducted by Omar et al., 2017. Variables were selected based on the fraud triangle theory and the criteria for fraud risk indicators found in ISA 240 regarding "Auditor's Responsibility to Consider Fraud in Financial Statements Audit".

Pressure. The first factor that causes fraudulent financial reporting, according to ISA 240, is pressure. The threat of bankruptcy represents an indication of pressure, according to ISA 240 in this study. When a company experiences a solvency issue, managers are concerned that investors may discover the issue and withdraw their investment, prompting managers to engage in fraudulent financial reporting to conceal the issue. In other words, the threat of bankruptcy is motivation and indicator of pressure to commit fraudulent financial reporting (Omar et al., 2017). A high debt structure increases the possibility of fraudulent financial reporting, where managers can manipulate financial statements because of their need to fulfil debt agreements (Kirkos et al., (2007)). One way to estimate the threat of bankruptcy is to calculate the solvency ratio. The solvency ratio, often known as financial leverage, measures the firm's ability to meet long-term and short-term obligations. The debt-to-equity ratio and total debt to total asset ratio are the ratios used to measure pressure elements.

*Opportunity***.** The subsequent risk that leads to fraudulent financial reporting, according to ISA 240 regarding "Auditor's Responsibility to Consider Fraud in Financial Statements Audit", is opportunity. Accounts that are difficult to authenticate and lack proper supervision from stakeholders and the firm size are elements that constitute the opportunity. Asset turnover ratios are used as a proxy to reflect accounts that are difficult to verify and lack adequate oversight from stakeholders. The reason for choosing this ratio is that accounts from financial statements such as accounts receivable, inventory, sales, gross profit, and total assets are frequently used to calculate asset turnover ratios and are most often manipulated by fraudsters (Omar et al., 2017). Accounts receivable, inventory and sales are accounts with subjective estimations that are difficult to audit, making it easier to conduct fraud against them (Kirkos et al., (2007)). Receivable to sales, gross profit to total assets and inventories to sales are used to represent accounts that are difficult to confirm in an opportunity.

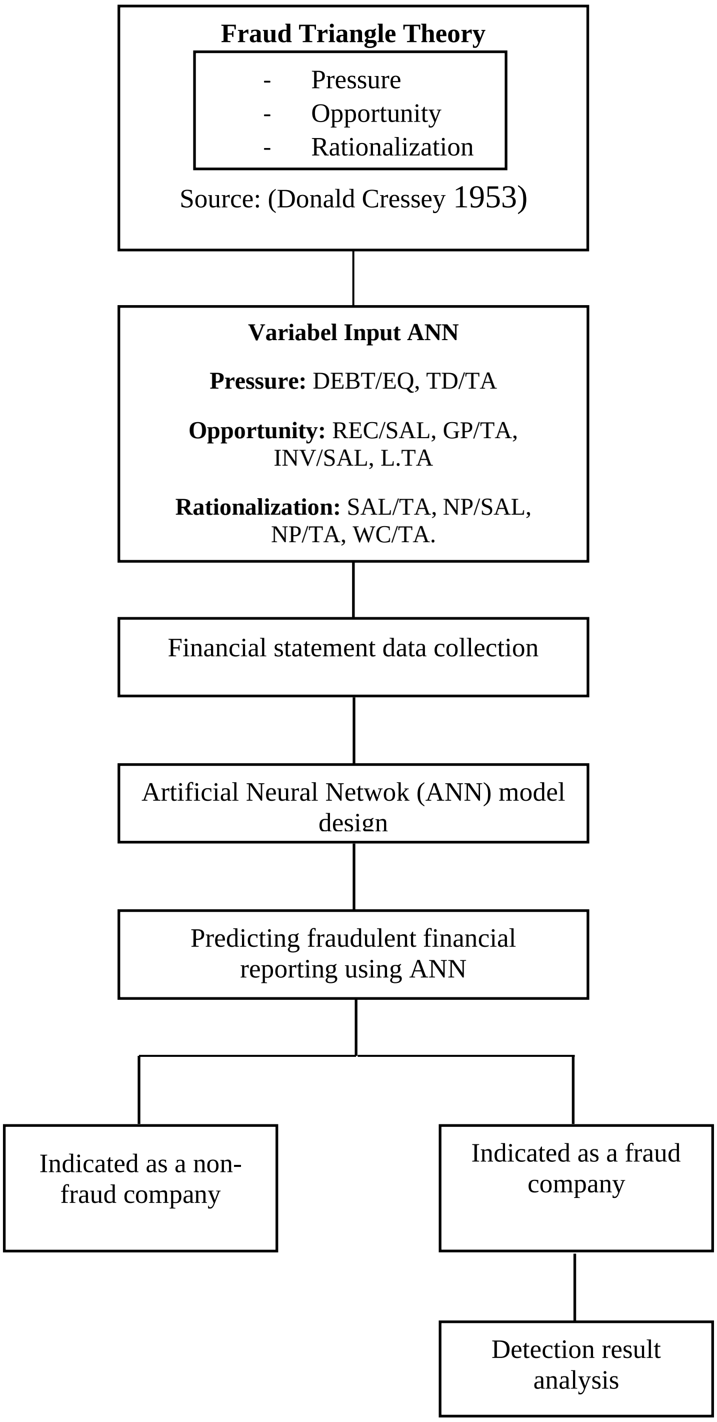
A financial statement restatement is described as an adjustment to financial statements due to a failure to comply with GAAP (Generally Accepted Accounting Principles) regulations (Hasnan et al., 2020). There is a relationship between firm size and financial restatement (Rezaei and Mahmoudi, 2013; Hasnan et al., (2020)). Financial restatement occurs when there is a material misstatement. Large firms are more likely to be detected lying in stating the amount of their income (Dechow et al., (2011)). The reason is that large firms are more well-known among investors and are scrutinised more closely by the press and experts. Firm size is calculated through the logarithm of total assets.

Rationalisation. A rationalisation is a mindset that leads to dishonesty among management or employees of a firm and makes those who commit the dishonesty rationalise their actions (Her, 2016; Rahma and Suryani, 2019). Based on the fraud risk indicator in ISA 240 (Omar et al., 2017), rationalisation can be proxied into an aggressive and unrealistic profit trend. It is because fraudsters may manipulate financial statements to show a high level of profitability to attract investors. Because firms threatened with bankruptcy will not go bankrupt when many investors invest their capital, the firm reputation may eventually improve (Omar et al., 2017). As a result, the profitability ratio is measured using the following measurements: (1) sales to total assets; (2) net profit to sales; (3) net profit to total assets; and (4) working capital to total assets.

Method, Data and Analysis

This research uses quantitative data to examine the financial statements of firms listed on the Indonesia Stock Exchange in 2019 that commit fraudulent financial reporting using the artificial neural network method. Purposive sampling was used in the sampling process. A total of 506 financial statements from firms listed on the Indonesia Stock Exchange in 2019 were gathered as part of the sample.

Figure 3. Research Framework



Fraudulent Financial Reporting Detection Model Using ANN

Training Process. The modelling stage is the ANN architectural design. This stage includes sharing data, determining the modelling structure and internal rules such as selecting the number of neurons in the hidden layer, training functions, and transfer functions.

After the data is ready to be used, we develop the ANN model by first preparing the data for training and testing. 506 financial statement data is used, and these data are then divided into two parts. Four hundred four data

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(80%) is used as training data, while the other 102 data (20%) is used for testing. For training data, 402 financial report data are used as examples of financial statements that do not commit fraudulent financial reporting and two financial report data as examples of reports with fraudulent financial reporting. The two reports used as examples of reports with fraudulent financial reporting are financial statements that the Financial Services Authority has sanctioned because of discrepancies in the preparation of the report, and investors and shareholders rejected the report that has alleged fraud and the financial statements. While the other 102 data is used in the testing stage are not categorised as fraud or non-fraud.

To obtain optimal model results in detecting the indications of fraudulent financial reporting, numerous factors must be tested during the training process. The model used in this research is based on the Mean Square Error (MSE) value achieved throughout the training process, with the selected model produces a small MSE value. MSE is an overall measure indicator to determine the success of running results of the training. When the optimal model is obtained at the training stage, the model is used to predict fraudulent financial reporting using testing data that could account for up to 20 per cent of the total data. Number '1' in the output indicates that a firm has not committed fraudulent financial reporting. Number 2, on the other hand, indicates that a firm has committed fraudulent financial reporting. The factors and parameters that will be tested in order to construct a prediction model for fraudulent financial reporting are as follows:

Table 1. Factors and Parameters Proposed

Factors	Types of Parameters	Description
Transfer function	Trial-error	1. Log-sigmoid (*logsig*) 2. Tan-sigmoid (*tansig*)
Training function	Trial-error	1. Gradient descent back propagation (*traingd*) 2. Gradient descent with adaptive learning rule back propagation (*traingdm*) 3. Levenberg-Marquardt back propagation (*trainlm*)
Hidden neuron number	Trial-error	5-30
Epoch number	1000	

Result and Discussion

Training Process

We created the ANN model during the training process by conducting trials on the predetermined parameters using training data with a known distribution, accounting for up to 80 per cent of the total data. Therefore, 36 ANN architectures were tested within this experiment, and each architecture produced a different MSE value. Five sequence models yield the least MSE, based on the results of trials of various parameter models or ANN architectural options (see Table 2 below).

Table 2. List of Optimal Factors and Values

Transfer Function	Training Function	Hidden Neuron Number	Perform MSE
Traingd	Tansig	15	0.0018
Trainlm	Tansig	10	0.0048
Trainlm	Logsig	10	0.0049
Trainlm	Logsig	20	0.005
Trainlm	Logsig	30	0.0051

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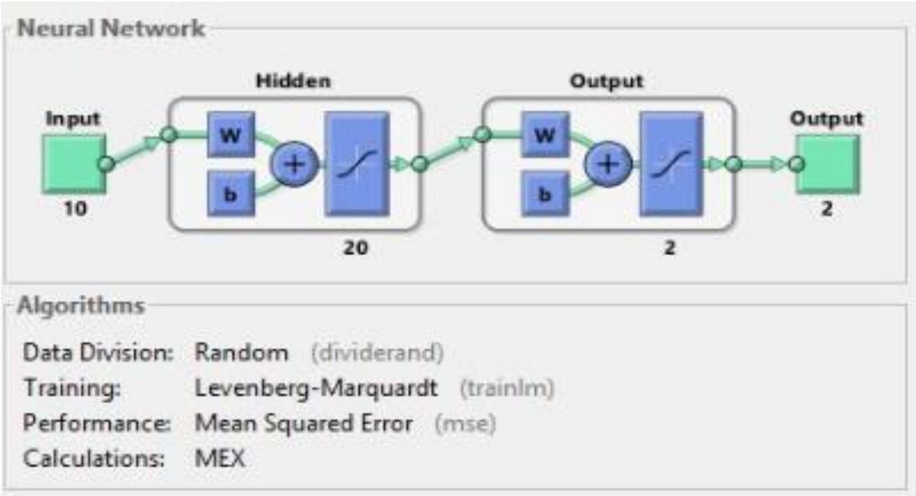
Based on the experimental results and the MSE value, we choose to use the trainlm logsig 20 model, which means that the training function factor will use the Levenberg-Marquardt parameter type (trainlm), the transfer function factor will use the log-sigmoid (logsig) parameter type, and there will be as many as 20 neural on hidden layers. Although the selected architectural model does not produce the smallest MSE value, the selected architecture can detect the example of financial statements with fraudulent financial reporting during the training process, namely the financial statements of PT. Garuda Indonesia.

Figure 4. Selected Multilayer Feed Forward Neural Network Architecture



Testing proses

Following the training phase, the next step is to use the ANN architecture chosen during the training process to predict fraudulent financial reporting. Based on the prediction results of fraudulent financial reporting using data testing, three firm's financial statements indicated that they were committing fraudulent financial reporting based on the ANN method using the selected parameters. The company is engaged in the goods and consumption industry, trade, services and investment sectors. The last ANN method also detects financial statements of firms engaged in the infrastructure, utilities and transportation sectors which are the financial statements used as examples of companies that commit fraudulent financial reporting. As a result, it can be inferred that the chosen ANN architecture can detect indicators of fraudulent financial reporting in financial statements.

Analysis of the Fraud Triangle Element

As explained in the literature review, the fraud indicator analysis used within the research was taken based on the fraud triangle theory, which was then proxied into dimensions. Ten financial ratios were used as input variables to build the ANN architectural model.

Table 3. Pressure Measurement

Firms	Pressure (Bankruptcy Threats)	
	Total Debt/Total Equity	Total Debt/Total Asset
TGKA	115,2%	53,5%
GIAA	380,3%	79,2%
MPMX	31,6%	24,2%

Pressure. The findings of data collection acquired from the financial statements of PT TGKA in 2019 yielded a solvency ratio of 1,115 or 115.2 per cent. Before the restatement in 2018, PT GIAA obtained a solvency ratio of 3,803 or 380.3 per cent, likewise a high figure. A good industry standard debt to equity ratio is 35 per cent, so there is a possibility that PT TGKA and PT GIAA are in a state of facing solvency issues and under pressure (Kasmir, 2008)(See Table 3 above).

According to ANN, the two firms identified for fraudulent financial reporting are in a state of the threat of bankruptcy, which is reflected in the solvency ratio value exceeding 100 per cent, indicating that there is a possibility that the firm may commit fraudulent financial reporting due to pressure. A high debt structure may lead to the possibility of fraudulent financial reporting. Therefore managers may manipulate financial statements because of their need to fulfil debt agreements (Kirkos et al., (2007)). While PT. MPMX is relatively good because the calculation results indicate results below 35 per cent, PT. MPMX is not in a condition of the threat of bankruptcy and under pressure.

Table 4. Opportunity Measurement

Firms	Opportunity			
	Accounts That Are Difficult to Confirm (Asset Turn Over Ratios)			Firm Size
	Receivable/Sales	Gross Profit/Total Assets	Inventories/Sales	Logarithm of Total Asset
TGKA	9,7%	446,3%	5,6%	28,728
GIAA	15,9%	104,7%	4%	31,737
MPMX	4,2%	175,9%	3,3%	29,889

Opportunity. According to the data collection and calculation (see Table 4), the asset turnover ratios of PT TGKA, PT GIAA, and PT MPMX were 446.3, 104.7 and 175.9 per cent, respectively. This figure compares gross profit to assets to determine the firm's ability to generate profits based on the number of assets owned. Significant figures indicate that these firms have a very high gross profit compared to their total assets.

Management may commit fraud by recording sales before they are achieved in order to boost accounts receivable (Persones, 1995; Stice, 1991; Feroz et al., 1991; Kirkos et al., (2007)) Furthermore, reporting inventory at a lower cost and recognising obsolete inventory are tactics that often occur in fraudulent financial reporting. Firms have the potential to commit fraudulent financial reporting by recording sales overstatement, increasing gross profit (Persones (1995); Stice (1991); Feroz et al. (1991); Kirkos et al., (2007)).

The finding of the data collection the logarithm of total assets of PT TGKA, PT GIAA and PT MPMX were 28.728 or RP. 2.995.872.438.975, 31.7371 or Rp. 60.709.063.193.094 and 29.889 or Rp. 9.563.681.000.000, respectively. According to the data collection result, all three firms had a large company size based on criteria company size from UUD RI No. 20 2008. Large companies appear to be relatively more likely to misstate their earnings since large firms have greater investor recognition and are under scrutiny by the press and analysts (Dechow et al., 2011).

Rationalisation. According to the results of the profitability ratio calculations, all three firms have a high profitability ratio value, with PT TGKA and MPMX having a profitability level of more than 100 per cent (see Table 5). PT GIAA has a value of 100 per cent in the ratio of sales to total assets. It can be indicated that the three companies have an aggressive and unrealistic profitability trend as a fraud risk indicator of the rationalisation element.

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Table 5. Rationalisation Measurement

Firms	Rationalisation (Aggressive and Unrealistic Profit Trends)			
	Sales/Total Assets	Net Profit/Sales	Net Profit/Total Assets	Working Capital/Total Asset
PT TGKA	446,3%	03,2%	14,3%	49,4%
PT GIAA	100%	0,1%	0,1%	-2,5%
PT MPMX	175,9%	2,8%	4,9%	81,6%

Conclusion

Three firms were identified as committing fraudulent financial reporting due to the ANN method's prediction results. Based on the results of descriptive analysis, two firms are suspected of engaging in fraudulent financial reporting due to pressure, opportunity and rationalisation. However, one firm is indicated to have committed fraudulent financial reporting due to the opportunity and rationalisation, but it is not under pressure, as evidenced by the solvency ratio, which shows that the firm does not have a large debt structure. With the result, this present study could contribute to the body of knowledge regarding the capability of ANN in detecting the phenomenon of fraudulent financial reporting, especially in firms listed on the Indonesia stock exchange in 2019. The present study also contributes to auditing and accounting research by examining the suggested variables to identify those that can detect fraudulent financial reporting. For the auditing profession, the result of this study could be beneficial in helping to address its responsibility of detecting fraudulent financial reporting.

This study's limitation was the lack of the data sample financial reporting who committed fraud used for data training in the learning process ANN. Based on the research and analysis findings, we suggest that future research increase the number of samples and balance the number of fraud and non-fraud firms samples so that the model can better identify fraud and minimise errors. This model can strengthen the role of auditors in detecting significant misstatements, as evidenced by the identification of PT GIAA's financial statements, which are used as samples of fraud firms. It is determined that the model constructed may detect fraudulent financial reporting based on the findings of the deployment of the model derived from the research of Omar et al. (2017).

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