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Artificial Neural Network (ANN): An Artificial Intelligent (AI) Tool to Predict Fraudulent Financial Reporting and Financial Distress

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Abstract-- *Artificial Neural Network (ANN) is an Artificial Intelligence (AI) tool to predict Fraudulent Financial Reporting and Financial Distress. This paper explores the effectiveness of the (AI) tool in accomplishing the task of management fraud detection; auditors could be facilitated in their work by using Artificial Neural Network technique. The input vector of ANN study is composed of financial ratios from the firm's financial statements such as the working capital, total assets, total liability, inventories, and cost of sales, sales and net income. Based on Bursa Malaysia, the sample data taken is based on PN17 companies means the companies which currently facing FD and companies committed financial fraud. This research employs seven proxy variables from 240 observations for quantitative analysis and also investigates the usefulness of Neural Networks in Predicting Fraudulent Financial Reporting and Financial Distress. The results reflect that the ANN model used is accurate.*

Keywords-- *Artificial Neural Network (ANN), Artificial Intelligence (AI), Fraudulent Financial Reporting (FFR), Financial Distress (FD), Financial Ratios.*

I. INTRODUCTION

Fraud embraces the various means that human skill can formulate or force to achieve a gain over others, using false recommendation to destruct the truth. There are many definitions of fraud, however, it is often depicted as any wrongful act that intentionally deceives or misrepresents facts to others (Mugala, 2013).

For a firm, there are two types of fraud; internal and external. Internal fraud is also known as occupational fraud. The Association of Certified Fraud Examiners (ACFE) defines occupational fraud as a violation of a position of trust to the detriment of the firm. In their annual Report to the Nations, the ACFE has classified occupational fraud into Financial Statement Fraud, Bribery & Corruption and Asset Misappropriation. Financial Statement Fraud, also known as Fraudulent Financial Reporting (FFR), is describedas the deliberate misrepresentation of the financial condition of an enterprise. This could include an intentional misstatement or omission of amounts or disclosure in the financial statements to deceive financial statement users (Hawariah et al., 2014) or contains falsifications of figures, which do not represent the true scenario (Spathis, 2002).

The increasing levels of FFR among listed companies in the past decade has accelerated public attention. A distinctive characteristic of FFR is the definite involvement of the firm's management. Management fraud is defined

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as a “deliberate fraud committed by management that injures investors and creditors through misleading financial statements” **(R. Elliot, and J. Willingham, 2013).** Regulations and increasing knowledge of management fraud has emphasised more stringent controls and penalties. Regardless, these atrocities still happen since a particular weakness of governance and controls, is the ability of management to override controls and bully employees, whilst still keeping an outward good governance culture. It has also been noted that the increased emphasis on system assessment is at odds with the profession’s position regarding fraud prediction, since most material frauds originate at the top levels of the organization, where controls and systems are least prevalent and effective **(Cullinan & Sutton, 2002).**

A crucial question to be asked is why would key executives risk their status and perhaps, even face the risk of a jail term to fraudulently report a firm’s performance and position. This research then refers to the work of Donald Cressey, the famous Fraud Triangle to assess this using the three components of pressure or motivation, rationalisation and opportunity. The Fraud Triangle Model is widely used by audit professionals and standards-setters as a tool for predicting fraud. For instance, the Treadway Commission (1987) concludes FFR is caused by a combination of situational pressures and opportunity. The Treadway Commission defines pressures as ‘red flags’, which are associated with the risk of FFR increases. Meanwhile, (**AICPA ,2002)** through ‘**AU Section 316: Consideration of Fraud in a Financial Statement Audit’** has specifically mentioned the three factors of the Fraud Triangle Model **(Cressey, 1953)** in the Standards: “Three conditions generally are present when fraud occurs. First, management or other employees have an incentive or are under pressure, which provides a reason to commit fraud. Second, circumstances exist - for example, the absence of controls, ineffective controls, or the ability of management to override controls that provide an opportunity for a fraud to be perpetrated. Third, those involved can rationalise committing a fraudulent act. Some individuals possess an attitude, character, or set of ethical values that allow them to knowingly and intentionally commit a dishonest act. However, even otherwise honest individuals can commit fraud in an environment that imposes enough pressure on them. The greater the incentive or pressure, the more likely an individual will be able to rationalise the acceptability of committing fraud” (**AU Section 316).** FFR or misappropriation of assets, involves incentive or pressure to commit fraud, a perceived opportunity to do so and some rationalisation of the act”. Based on the standard example, incentive or pressure to commit FFR may exist when management is under pressure, from sources outside or inside the entity, to achieve an expected (and perhaps unrealistic) earnings target or financial outcome. A perceived opportunity to commit fraud may exist when the trust violator is in a position of trust or has knowledge of specific deficiencies in internal control **(Kassem & Higson, 2012).**

Past studies suggest that managers may have incentives to manipulate financial statements to meet specific goals, both internal and external. For instance, a study by **(Ettredge, 2010)** found evidence that managers manipulate their financial statements to meet a specific accounting target. According to **(Fung, 2015),** manipulating financial results is a risky way to improve a firm’s financial appearance. Therefore, the current practice of mapping the executive’s performance to their compensation (variable components of remuneration) may just increase the firm’s risk of FFR. Therefore, **(Khanna ,2015)** suggest that regulators, investors and governance experts pay attention to the appointment of the Chief Executive Officer that will potentially increase or decrease the likelihood

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of fraud activity. However, in most of these cases, the Chief Financial Officer must be involved together with the Chief Executive Office since it revolves around the Financial Report of the firms. Therefore, it would seem logical to focus the red flags of the firm's downward performance on its ratios or indicators.

In 2002, the Auditing Standards Board issued the Statement on Auditing Standards **(SAS)** No. 99: Consideration of Fraud in a Financial Statement Audit. This Standard requires auditors to assess the risk of fraud during each audit and encourages auditors to consider both the internal control system and management's attitude toward controls, when making this assessment. Risk factors or ''red flags'' that relate to FFR may be grouped into the following three categories **(SAS No. 99)**: there are two types of fraud considered: misstatements arising from FFR (e.g. falsification of accounting records) and misstatements arising from misappropriation of assets (e.g. theft of assets or fraudulent expenditures). The International Auditing Practices Committee (IAPC) of the International Federation of Accountants approved the International Statement on Auditing (ISA) 240. This standard respect the auditor's consideration of the risk that fraud and error may exist and clarifies the arguments on the inherent limitations of an auditor's ability to predict error and fraud, particularly FFR. During the audit process, the auditors must estimate the possibility of management fraud. At present, some statistics and data mining methods have been applied successfully to predict FFR. However, predicting management fraud using normal audit procedures is a difficult task **(G. D. Coderre, 2009)**. First, there is a shortage of knowledge concerning the characteristics of FFR. Secondly, given its infrequency, most auditors lack the experience necessary to predict it. Finally, managers deliberately try to deceive auditors **(Fanning & Cogger, 1998; R. Elliot, and J. Willingham, 2013)**. These limitations suggest that there is a need for additional analytical procedures for the effective prediction of FFR.

Many analyses focus on more accrual based profitability analysis. This is insufficient as a possible cause of a firm's demise is its lack of cash flow. Hence, one significant indicator that used in this research is Financial Distress (FD). FD can be defined as "a condition where financial obligations are not met or are met with difficulty" by a firm **(Wu, Liang, & Yang, 2008).(Chan & Chen, 2011)** defined FD firms as those having poor performance, inefficient producers, and those with high financial leverage and cash flow problems due to which firms lose their market value. They are marginal in the sense that their prices tend to be more sensitive to changes in the economy and are less likely to survive adverse economic conditions. Due to this, investors demand a premium for holding such risky stocks and expect to be rewarded for bearing the risk. Typically, FD of the above nature is measured by the probability of failure (**Shumway, 2001).**

Recently, FD has become a famous topic in finance and financial health of firms as a crucial indicator for interested users to know more about company's performance. Many stakeholders such as creditors, suppliers, investors, customers as well as employees are reluctant to deal with financially distressed firms **(Cornell & Shapiro, 1987).** According to **(Beaver, 2006 ;Betker ,2007)**, FD plays a significant role in a firm's operations and profitability through its cost implications, such as administrative and legal costs associated with the bankruptcy process (i.e., direct FD costs) or increased costs for debt service and supplies (i.e., indirect FD costs). These costs may reduce the value of the company and thus it is important to determine the FD level among companies in Malaysia **(Abdul Rahman et al., 2016).**

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Since both FFR and FD may insinuate reflect similar outcomes, it would be combined in this research. The use of Data Mining techniques to predict FFR and FD is increasing, especially with the use of Artificial Intelligence. Recent research has paid more attention on how to propose appropriate model for effectively predicting FFR and FD by using a firm's internal data (financial ratios). Many models have been developed for the prediction of FFR because of numerous empirical studies **(Ravisankar ,2011; Kuçuksozen, 2004).** The main purpose of this paper is to select similarly relevant financial ratios and propose appropriate predicting model for FFR and FD of listed companies in Malaysia.

II. ARTIFICIAL NEURAL NETWORK TO DETECT FRAUDULENT FINANCIAL REPORTING AND FINANCIAL DISTRESS

Firms are relying more on data mining for business decisions. Data mining is defined as "a process that uses statistical, mathematical, artificial intelligence and machine learning techniques to extract and identify useful information and subsequently gaining knowledge from a large database" **(Parviz et al., 2019)**, to gain insights and patterns that are statistically reliable, previously unknown, and actionable. This can be applied to FFR and FD detection models as well. Data mining plays an important role in FFR and FD as it often applied to extract and discover the hidden patterns in very large collection of data **(Soheil Hassanipour et al., 2019)**. An auditor can never become certain about the legitimacy of and intention behind a fraudulent transaction due to its secretive nature. Data mining offers a more cost effective and accurate solution. Some of the proposed data mining algorithms that can be used to predict FFR are Linear Regression, Logistic Regression, Probit Regression, Decision Trees and Bayesian networks and Artificial Neural Networks **(ANNs)(Kirkos et al., 2007)** Nevertheless, the use of these newer techniques is either limited or not adequately reported and documented in literature.

ANN is the most prominent fraud prediction model preferred by professional compared to the other models, with reported successful applications. ANN is able predict FFR with an accuracy rate of 90% **(Coleman, 1991)** and is a superior Discriminant Analysis model that predicts the risk of bankruptcy in firms**(Odom and Sharda,1990)**, performing better than the models using Logit **(Salchenberger, 1992)**.

The ANN is a method that has many advantages compared to other techniques **(Trippi and Turban, 1996; Schalkof, 2007)**. The most important advantage of ANN is learning. A trained ANN can reach satisfactory results with incomplete and faulty inputs. The ANN is more sensitive to changes or faults in a system as compared to traditional computing systems. Any problem in these systems may cause the system to halt or create an important error in results. However, an ANN is not affected as much as a traditional computing system if some of neurons are damaged. ANN can learn and adapt to different environments without requiring the completion of retraining. ANN is a parallel distributed processing: All processing units in ANN run simultaneously, so the ANN is fast and provides a speedy response. However, another key characteristic is that ANN makes no assumption about the used data. Any kind of data could be used as input for ANN. This is the most important advantage of ANN technology. The ANN method also possesses disadvantages whereby a possibility that it may not achieve accurate results: This technology may produce unreasonable and irrelevant results. Sometimes ANN cannot be trained. While other statistical techniques generate understandable and interpretable parameters for problems, compared to ANN weights cannot be

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interpretable. In other words, the model used by ANN remains as a black box. ANN's features have attracted some interest from researchers and researchers have used ANN analysis to predict future returns and classify stocks to portfolios **(Wong, Goh and Quek, 2002; Kryzanowski, Galler and Wright, 2013).** Nevertheless, prior studies are generally limited in nature: **(Quah and Srinivasan ,1999)** applied ANN analysis to Singapore Stock Exchange and **(Albanis and Batchelor ,2007)** applied this analysis to a sub-sample of firms listed in the London Stock Exchange. ANN, been used to investigate the usefulness of publicly available predictors (sources from Bursa Malaysia). The data mining approaches which are ANN, Decision Tree and Linear Regression also has been adapted to a credit risk management investigation by using financial statistic from 24 companies as an input for ANN and to forecast credit risk in the manufacturing sector **(Pacelli, 2011).** The outcome shows that ANN can predict credit risk for these companies. Due to the uncertainty and volatility of the stock prices in the market, it is a challenging mission for the stock market predictor across the world to do the prediction **(Suresh Kumar and Elango, 2012)**. The researcher had adapted ANN to predict future stock prices more accurately and fast. This study used available daily stock data of Tata Consultancy Services Limited (TCS) from the National Stock Exchange beginning from 1 November 2009 to 12 December 2011. They used previous close and open price, high price, low price and closing price as indicators to predict future stock prices of this company.

The passage of the new Federal law regarding class actions lawsuits requires auditors to report FFR when they find it during corporate audits **(Taylor, 2015).** One source for these new analytical procedures is Artificial Intelligence in the form of ANN's has shown promise in auditing, accounting, finance, economics, and other fields **(Fanning et al., 2015).** In this research, ANN has been integrated and traditional statistical techniques **(McLachlan, 2002)** to develop a robust technique for predicting FFR.

Past researchers have attempted to build models that will predict the presence of FFR. Results from a logit regression analysis of 75 fraud and 75 non-fraud firms have indicated that non-fraud firms have boards with significantly higher percentages of outside members than fraud firms **(Beasley, 1996).(Green and Choi, 1997)** developed an ANN fraud classification model. The model used five ratios and three accounts as input. The results showed that ANN has significant capabilities when used as a fraud prediction tool. A financial statement classified as fraudulent alerts the auditor to conduct further investigation. **(Fanning and Cogger ,2015)** used ANN to develop a fraud prediction model. They compared the performance of their model with linear and quadratic discriminant analysis, as well as logistic regression, and claimed that their model is more effective at predicting fraud than standard statistical methods.

Although there are many types of ANN in the literature, **Multilayer Perpetron (MLP)** are frequently used for many problems. MLP consist of input layer, hidden layer(s), and output layer. An example of MLP architecture is shown in **Figure 1.**An MLP ANN consists of neurons that are ordered into layers. The first layer is called the input layer, the last layer is called the output layer, and the layers between are hidden layers. Each neuron in a layer relates to all neurons in the next layer. The connection between the i and j neuron is characterized by the weight coefficient and the neuron by the threshold coefficient. The weight coefficient reflects the degree of importance of the given connection in the ANN. The output layer is the dependent variable; meanwhile, the hidden layer has

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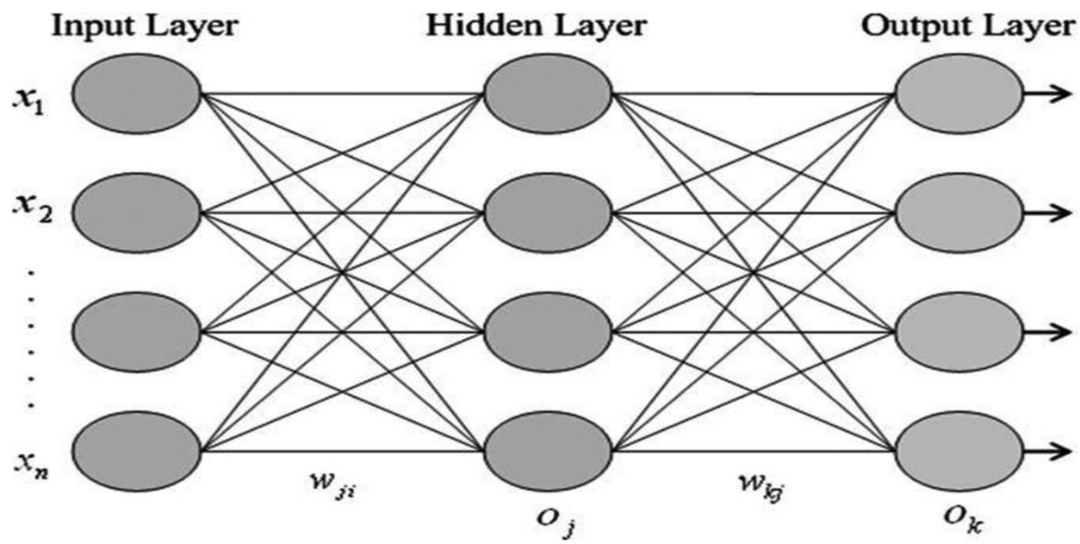
no strings attached to the external environment. The functions are only to receive signals from the input layer and transmit the signals to the output layer**. (Küçükkocaoglu et al., 1997).**



Source: Chen and Du (2009)

Figure 1 : ANN Model

III. RESEARCH METHODOLOGY

The study focuses on public listed companies in Malaysia which with FFR and FD is noted. The financial data is an open data available on the firm's or regulators websites. This ANN study was conducted by used financial ratios from the firm's financial statements such as the working capital, total assets, total liability, inventories, cost of sales, sales and net income. Based on Bursa Malaysia, the sample data taken is based on PN17 companies means the companies which currently facing FD and companies committed financial fraud. This research employs seven proxy variables from 240 observations for quantitative analysis. Information for these proxy variables is in the form of financial and non-financial data. This research defines financial data as information in the form of quantifiable variables, which mainly provide numerical values. In financial reports, financial data provides indicators of PLCs' financial performance such as performance, profitability, liquidity and leverage. Additionally, all numerical values in most of the accounts in financial reports (i.e. Statement of Financial Position and Income Statement) are considered as financial data within the context of this research. In contrast, non-financial data provides non-numerical values, which mostly contain explanation in sentence form (i.e. 'Accounting Policies and Explanatory Notes'). Financial and non-financial data are collected from the financial reports enclosed in Malaysian PLCs' annual reports.

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Table 1: List of Indicators Used (Self-authored)

Variables	Fraud Triangle	Fraud Risk Indicator	Indicator	Ratio	Descriptions
X1	Opportunity	Ineffective monitoring	Performance	Current ratio	Current Asset / Current Liabilities
X2	Opportunity	Ineffective monitoring	Liquidity	Quick ratio	Current Asset - (Inventory/ Current Liabilities)
X3	Rationalization	Unrealistic Profit Trend	Profitability	Profit margin	Net income / Sales
X4	Rationalization	Unrealistic Profit Trend	Profitability	Return on Assets	Net Income / Total Assets
X5	Rationalization	Unrealistic Profit Trend	Profitability	Return On Equity	Net Income / Owner's Equity
X6	Pressure	Threat of Bankruptcy	Leverage	Debt Equity	Debt / Equity
X7	Pressure	Threat of Bankruptcy	Leverage	Debt Ratio	Debt / Total Assets

IV. FINDINGS AND DISCUSSION

SPSSv25 'Multilayer Perceptron Network' procedure has been used to perform this analysis. In this case, 164 companies has been reserved (68.3%) of the sample to the training, 76 companies (31.7%) for testing and 641 companies were excluded for various reasons.

Table 2: Case Processing Summary

		N	Percnt
Sample	**Training**	164	68.3%
	Testing	76	31.7%
Valid		240	100.0%
Excluded		641	
Total		881	

Training	**Cross Entropy Error**	82.562
	Percent Incorrect Predictions	20.1%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error
	Training Time	0:00:00.05
Testing	**Cross Entropy Error**	37.341
	Percent Incorrect Predictions	19.7%
Dependent Variable: Status		
a. Error computations are based on the testing sample.		

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Table 2 gives information about the results of training, testing and applying the final network to the holdout sample. The holdout sample is used to validate the results. From Table 2, the percentage of incorrect predictions is approximately equal across the training, testing and holdout sample. This results in more confident about future cases that would be scored by the network. The estimation algorithm stopped since the error didn't decrease after one step. As the output layer uses the SoftMax activation function (input called logit), the cross entropy error is displayed. This is the error function that the network tries to minimize during training.

The classification table (Table 3) below shows the practical results of using the network. For each case, the predicted response is 1 if that cases predicted pseudo-probability is greater than 0.5. For each sample, the cells on the diagonal of the cross-classification of cases are correct predictions and the cells off the diagonal of the cross-classification of cases are incorrect predictions. Of the cases used to create the model, 5 of the 33 cases who previously had committed fraud are classified correctly. 1 of the 131 fraudulent cases that had financially distressed are classified correctly. Overall, **79.9%** of the training cases are classified correctly in Table 3, corresponding to the **20.1%** incorrect prediction, shown in Table 2.

Table 3: Classification Table

Sample	Observed	Predicted		
		Fin Distress	**Fraudulent**	**Percent Correct**
Training	**Fin Distress**	131	1	100.0%
	Fraudulent	33	5	0.0%
	Overall Percent	100.0%	0.0%	79.9%
Testing	**Fin Distress**	61	0	100.0%
	Fraudulent	15	0	0.0%
	Overall Percent	100.0%	0.0%	80.3%
Dependent Variable: Status				

V. PREDICTED BY OBSERVED- CHART

For categorical dependent variables, the predicted-by-observed chart, presented displays clustered box plots of predicted pseudo-probabilities for the combined training and testing samples. The x axis corresponds to the observed response categories, and the legend corresponds to predicted categories. The left most box plot shows, for cases that have observed category 0, the predicted pseudo probability of category 0. The portion of the box plot above the 0.5 mark on the y axis represents correct predictions. The portion below the 0.5 mark represents incorrect predictions. The network is very good at predicting cases with the 0 category using the 0.5 cut-off, so only a portion of the lower whisker and some outlying cases are misclassified. The next box plot to the right shows, for cases that have observed category 0, the predicted pseudo-probability of category. Since there are only two categories in the target variable, the first two box plots are symmetrical about the horizontal line at 0.5. The third box plot shows, for cases that have observed category 1, the predicted pseudo-probability of category 0

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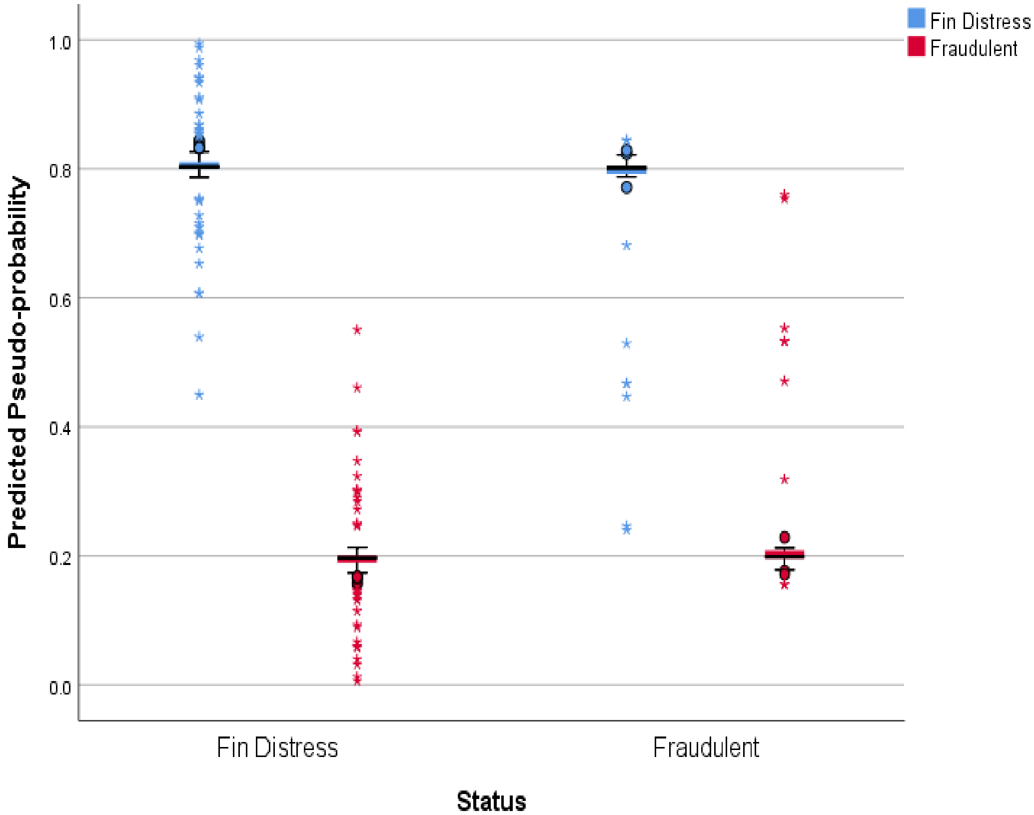

Figure 2: Predicted by Observed Chart

VI. THE ROC CURVE

The ROC curve, presented in Figure 3, gives a visual display of the sensitivity and specificity for all possible cut offs in a single plot. The chart displays two curves, one for the category FD and one for the category Fraudulent. This chart is based on the combined training and testing samples. The area under the curve is a numerical summary of the ROC curve, and the values in the table represent, for each category, the probability that the predicted pseudo-probability of being in that category is higher for a randomly chosen case in that category than for a randomly chosen case not in that category. For example, for randomly selected FFR cases and FD companies, there is a 0.491 probability that the model-predicted pseudo-probability of default is equal with FD cases. While the area under the curve is a useful one-statistic summary of the accuracy of the network, we need to be able to choose a specific criterion by which Fraud cases are classified. The predicted-by-observed chart provides a visual start on this process.

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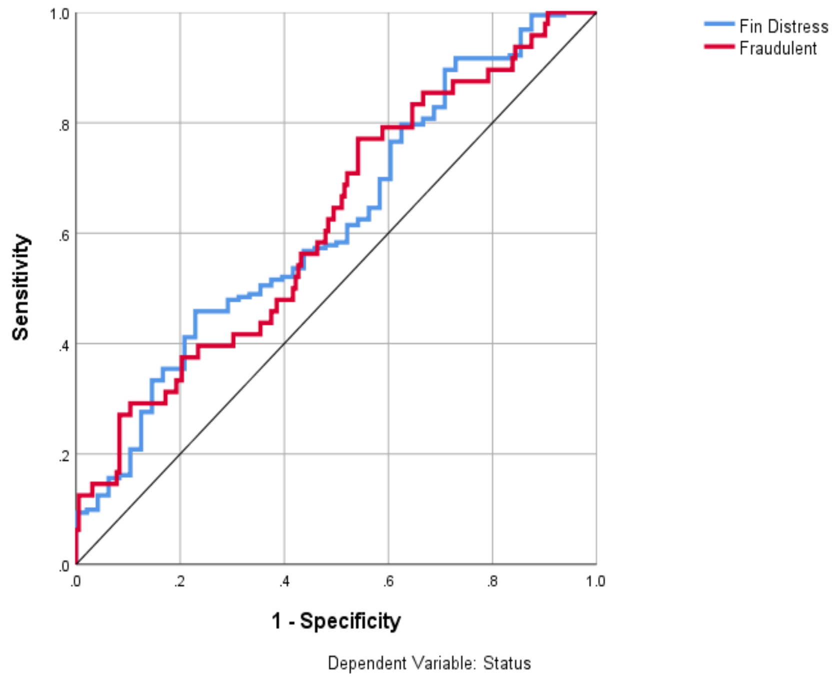

Figure 3: ROC Curve

This study uses seven financial ratios adapted from the study by **(Spathis,2002)** as the independent variable (inputs) for predicting FFR using ANN. By using trial and error, this study focuses on six factors, namely, transfer function, training function, learning function, hidden neural network, Epoch(EN) and Treshold (TH), that are usually being used to improve the performance of ANN to develop the prediction model (Basheer, 2000) The main factors are related with the means squared error (mse) to arrive at the optimized model. Lower mse indicates that lower error would be made by the model in predicting FFR, and this would present the optimal model that could be used to predict FFR. This model was generated from neural network system using IBM SPSS statistical software. The neural network model above is derived from the proposed factors in Table VI. Logsid function represents the transfer function, and trainml represents the training function. Meanwhile, the optimal hidden neural network, EN and TH are selected at 2, 1 consecutive test with no hidden layer and no decrease in error and whereby TH 0.82, respectively. The lowest (mse) of 0.0113 shows the possible accuracy of classification for FFR in large market capitalization.

According to the research done by (**Omar, 2014; Salama, 2014; Salem Lofti)** their true prediction is only at 85.13% per cent, while the false prediction is 13.82 per cent , By comparing the model created by the study and this model, it shows that this model is far more reliable based on the R = 0.9487. Besides, the number of variables used for the study is also similar to this study in which seven variables are used. The difference is only on the selection of ratios used.

VII. CONCLUSION

Meanwhile, the study by indicates that ANN can predict FFR in a faster and easy manner. This is because ANN is derived from a mathematical intelligence system. The network needs to be trained to identify the pattern of

FFR before it could validate the rest of the data. Based on the analysis, it only requires few minutes for the network to validate the rest of the data. **(Omar, 2014)** So, in terms of time, ANN is far more efficient compared to other techniques because it requires less time to analyse and produce the results. Perhaps, if other researchers were to use larger data, the time taken would probably be more but would still be at acceptable level.

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