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*Original Research*

# Fraudulent Financial Reporting in the Banking Sector of Bangladesh: A Prediction

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**Abstract**

The purpose of this study is to predict the areas in financial statements susceptive to fraud in the banking sector of Bangladesh. Data of 13 years ranging from 2006 to 2018 of 29 listed banks in Bangladesh were examined for the purpose of this study. Financial data suggested by International Standard on Auditing (ISA) 240 as fraud risk indicators were used as the independent variables and banks identified by Centre for Policy Dialogue (CPD) to be engaged in fraud, scam and heists were taken as dependent variable. Multilayer Perceptron Network (MLP), a class of feedforward Artificial Neural Network (ANN) model was used as the analytical tool. It is found that loan disbursement, assets, profit, operating expenses and tax are the areas that can signal the probable fraud in financial statements of the listed banks of Bangladesh. The findings of this study will have policy implications for auditors and the regulators of money market in Bangladesh.

**Keywords:** Fraud, Fraudulent Financial Reporting, Artificial Neural Network (ANN)

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## Introduction

Banking sector has a remarkable contribution to any economy. A transparent, efficient and accountable banking system is necessary for risk absorbent money market and smooth economic growth. With 56 scheduled banks Bangladesh is progressing with the objectives of developing economy, employment and efficient money market. Total bank deposit stood at BDT. 10441.5 million as at of June 2018 (Bangladesh Bank). The country has adopted financial inclusion program, rural banking, microcredit program for the development of the financial sector. Recently the country has also adopted BASEL III for the banking sector of the country. But it is a dismal fact that the country's banking sector is facing some serious challenges due to poor governance, default loan and noncompliance. The sector is already facing scam, heist and fraud cases. Amount of Non-Performing Loan (NPL) is increasing and ROA and ROE of the banks are decreasing (Bangladesh Bank, 2018). Bangladesh ranked 130th among 141 countries with a score of 38.3 on the scale of 100 in the soundness of banking (Global Competitiveness Report, 2019).

Financial statements reflect the performance of an organization. Creditors, investors and other users use these statements to make decision on investing in the organization. Cost of debt, financial distress, ease of lending, financing decision depend upon the accuracy and completeness of these statements. Therefore, many professional, national, international and governing bodies have lined out the guidelines for the importance, requirements and inclusion of crucial information in the financial statements of the organization. On the dark side, illegal advantages can be pursued through fraudulent reporting. False information is incorporated in or at worst omitted from the statements to mislead the users while the statements were supposed to provide with objective, timely and true information. Misappropriation and misleading disclosures are also considered and fraudulent reporting.  FFR is aimed at seizing the assets to defraud the investor (Financial Express, 2019). Bangladesh ranked at 126th position with a score of 43.7 at strength of accountancy and auditing standards (Global Competitiveness Report 2019).

Fraud is the intentional act to obtain illegal advantage committed by those inside or outside of the organization (ISA 240). Theft, bribery, false accounting, corruption, collusion and deception are considered as fraudulent acts (Bangladesh Fraud Audit Manual). Global fraud cases are on the rise and banks are increasing their investment in deterring fraud (KPMG, 2019). Forensic Accounting is in the place to detect, investigate and fraud related issues. It uses theories and principles of accounting with the investigative skill and auditing techniques to sort out white collar crimes and financial disputes. But FD is not an easy task. Painstaking efforts are needed due to the magnitude and types of fraud to unveil them. Detecting, sorting out and explaining the fraud is have always been ambiguous and tedious task. That's why auditors use techniques in their investigation. RFs are therefore very helpful and handy in uncovering and signaling the fraud in the financial reporting. RFs have varying weights that pose conspicuous significance (Gullkvist & Jokipii, 2013). But auditors apply RFs rarely as symptoms of fraud (Yucel, 2013). Financial Ratios can be used as proxies of RF. They are easy to use for measuring and analyzing the financial performance (Delen, Kuzey, & Uyar, 2013) of companies with varying sizes and heterogeneous industries. Data mining is a more rigorous process that provide more accuracy in uncovering the fraudulent areas (Chen, 2016). ANN is the tool that can be reliably used as an alternative of regression analysis for fraud detection purposes.

### *Objective of the Study*

The main objective of this study is the detection of fraudulent reporting in the banking sector of Bangladesh. The specific objectives are:

- To note the role of Forensic Accounting in Fraud Detection and tools used to detect fraudulent areas.
- To find out the areas more prone to fraudulent reporting.

### Scope for further Study

ANN has been used solely for detection purpose. Support Vector Machine (SVM), Decision Tree (DT), Chi-Square Automatic Interaction Detector (CHAID), Classification and Regression Tree (CART), Gini Index, Classification Tree C5.0, Quick Unbiased Efficient Statistical Tree (QUEST) can be used combinedly to get more sophisticated result. Few nonfinancial variables have been used in the analysis. Inclusion of more financial ratios and nonfinancial variables can reveal some unknown areas of fraud.

## Theoretical Framework

### *Fraud*

Fraud is the deceitful act committed deliberately. Individuals engage in fraud to deceive other individual, organization, customer or government. Fund swindles, asset misappropriation, corruption and bribery are the most common types of fraud. Fraudsters engage in fraudulent reporting, providing misleading information, misclassification of transaction, incorporating incomplete and sham disclosure, siphoning off money and stealing corporate coffers to devise fraud. Factors leading fraudulent behavior are combined in a framework known as Fraud Triangle.


Figure 1: Fraud Triangle
Source: Cressey (1953)

Pressure can either be personal or organizational. Individual commits fraud because of personal debt. Continuation of luxurious lifestyle may also lead to fraud. Impractical revenue target, implausible goal may induce the employee to fraudulent behavior.

Opportunity is the most noteworthy reason behind deceitful act. Improper ICS, poor security for corporate coffers, unguarded assets, easily concealable assets are more prone to theft and misappropriation. Again, employee can abuse their position and power to achieve illegal and undue advantages that is detrimental to the organization and other people. Unobtrusive organizational role, ambiguous accounting policies, discretion level at policy making may also result in fraudulent action.

Rationalization is the stage where the fraudster tries to justify his crimes. Fraudster rationalizes it by doing it for business purpose or he/she has a power position in the organization. Previous scam or fraud cases are also held as reason for prospective fraud. Fraudster rationalizes his/her crime because other might have done them in the past.

KPMG (2010) conducted a survey on "Profile of Fraudster" based on fraudulent cases in South Africa, India, Europe and Middle East. According to that survey, most of the fraudsters are graduate men. Senior managers are mostly engaged in deceitful acts than the working level employees and the loss caused by the managers are 12 times more than that of caused by the employee. It also emphasized that perpetrators have long term employment with the organization, and they are usually from operation and finance department of the organization. Updated version of the report says that the perpetrator is employed for at least 6 years and are known as esteemed kudos within the organization. 60 percent of the fraud is induced by personal gain and 27 is by rationalization.

### *Artificial Neural Network (ANN)*

ANN has identical layout of human brain with multiple neurons to process information. It imitates the processing system of human nerves. It takes in and combines numerous inputs and process them to reach to a logical conclusion. It takes in data and train themselves to recognize the patterns in the data and then predict the outputs for a new set of similar data. It can process complex pattern of events or business transactions. ANN is an artificial intelligence that reach to logical conclusion while using the rapid calculation ability of the computer.

### *Multilayer Perceptron Network (MLP)*

MLP is one type of ANN. It is made of layers of neurons. These neurons are the central processing components of the system. The processing and output units are connected by lines known as nodes. The fundamental structure is made of an input layer, a processing layer that is hidden known as Black Box and an output layer. The layers are interconnected through the nodes. The connections among the nodes are more important than the tasks they perform. Data from input layer is flowed to the hidden layer along with adjustable weights assigned to them. The weight indicates the degree of importance and influence among the nodes. The weights are set to random values at first and are adjusted directly from training data using a plausible error function to generate better output through iteration. The inputs are multiplied to the corresponding weight and their sum is sent as input to the neurons in the hidden layer. These neurons are linked with a numerical value called the bias. Bias of each neuron is added to the input sum. This combined value is transmitted through a threshold function called the Activation Function. This function determines whether a specific neuron will be passed on later or not. An activated neuron transmits data to the neurons of the next layer over the nodes. In this manner, the data is propagated through the network and is called Forward Propagation. Neurons with the maximum value is transmitted to the output layer to provide the final results.

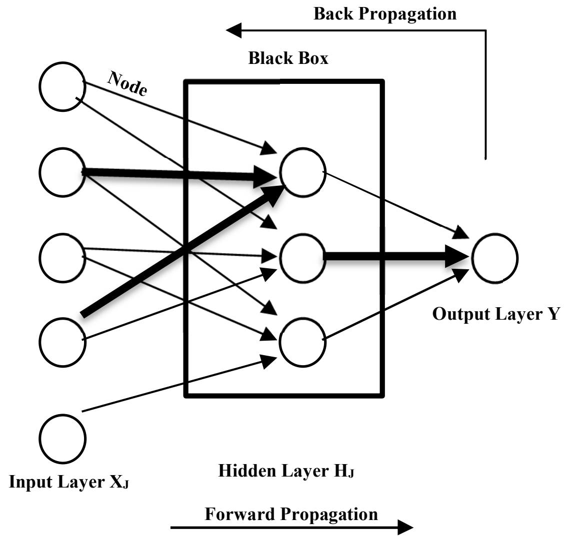


Figure 1: Construction of Artificial Neural Network

During the training process along with the input, the network also has the output fed to it. So, the predicted output is compared against the actual output to realize the error in the prediction. The magnitude of the error indicates how wrong the prediction is. The information is then transferred backward through the network. This is called Back Propagation. The error is corrected through back propagation process. Based on this information the weights are adjusted. This cycle of forward and back propagation is iteratively performed with multiple inputs. This process continues until our weights are assigned such that the network can predict the pattern correctly. The error rate defines the accuracy of the model. The number of iterations must not be neither too small so the model cannot capture the process or too large so data may overfit resulting in poor prediction. At an optimal level of iteration, the model grasps the data and process them to reach to a logical conclusion. During the processing, the model can adapt its structure to the flow of information. ANN is trained to understand the patterns and detect the possible anomaly with high accuracy.

The entire data set needs to be divided into three sub data set known as training set, control set and test set. Each of the sub data set should be allocated with one third of the entire data set. Training set should contain the smallest and test set should contain the largest data set. The control set is the mechanism for the effectiveness feedback of the model.

Zupan (2014) emphasized that ANN works in the finest manner when there is non-linear dependence between the input and output. It can also be applied for linear relationship, but the outcome can be worse than the results of applying simple statistical tools and techniques. Since we are not always sure about the type of relationship among the variables, statistical techniques are recommended to transcribe the data.

## Literature Review

### *Fraud and Forensic Accounting*

Fraud is deceit with the purpose of transpiring personal motive that is considered illegal and it is done intentionally (Anyanwu,1993). Enterprises use tactics and conspiracy that are often a ruse and intended to cheat (Karwai, 2002). Uncovering fraud and deceitful act is a difficult task. That is why in controlling fraud international, local and professional authorities have a major role to play (Vanasco, 1998). The world is facing more fraud incidents and with the implementation of SOX Act 2002, organizations are adopting mechanisms and initiating new methods to combat fraudulent acts (KPMG, 2003). But detecting the fraudulent acts is not a piece of cake. Convoluted fraud affects fraud investigations (Ozili, 2020). Degree of risk is considered a significant factor for constructing a framework for FD (Öztürk & Usul, 2020). Complexity of task and gender status affect the chances of FD. Women showcases more acuity in resolving complicated audit decisions (Chung & Monroe, 2001). Auditors' familiarity with and chances of success in FD in past cases are influencing variables in FD (Moyes & Hasan, 1996). FA can help here to unveil the fraudulent and deceitful act.

FA collects, processes and presents information in a manner that is classified as viable for resolving financial crime (Stanbury & Paley-Menzies, 2010). While satisfying the rules and regulations of the court, FA uses probing and analytical competencies for settling economic crimes (Hopwood, Leiner, & Young, 2008).

It deals with gathering and interpreting financial disputes comprehensively and make an abstract and presentation of the fact concisely (Howard & Sheetz, 2006) while using the theories, ideas and assumptions of the discipline of accounting to solve business related controversies (Okunbor & Obaretin, 2010).

### *Reasons behind Fraud and its Consequences*

Management often has discretionary power in organizational decision making. Even they can use this power for accounting transaction for their own economic benefits. They exert undue influence on accrual transaction with the intention of personal gain. Thus, accrual-based accounting has got a noteworthy role to play in divulging FFR (Song, Lee, & Cho, 2013). Erratic bank owners misuse their power to get illegal and undue advantages. Applying fraudulent techniques and loopholes of accounting, they siphon off larger amount of public money which are never reverted to the bank (Ilter, 2012). Organization with poor governance system are more prone to financial fraud. This may comprise of insufficient board meetings, independent director; less than required member in the committee and poor ICS. Companies are accused of FFR that have lower number of external members (Beasley et al., 2000). Lokanan (2014) emphasized that falling tend in profit provide stimulus to the managers for FFR and asset misappropriation. FFR and FFS are backed by pressure that is considered as undue and incentive that disadvantages other stakeholder to achieve implausible economic growth and rigorous financial targets (AICPA, 2002). Complicated financial situation like excessive leverage and all-equity financing motive the management for FFR (SAS 99).

Share price is affected with the announcement of publicly available information. But penalty for FFR is statistically irrelevant to the stock price. This is because the owners consider that it has nothing to do with long term success of the company. Again, the fraud declaration by the authority has no content in the given information and the mulct is already reflected in the stock price (Eryigit, 2019).

### *Indicator of Fraud and their Proxy*

RFs are not always a success tool in FD. Rather they are circumstances involved in the occurrence of fraud (Elliot & Willingham, 1980). Asset misrepresentation serves a viable measure for unveiling fraud than manipulation of liability does (Wei, Chen, & Wirth, 2017). Although Ozcelik (2020) argued that asset and liquidity along with committee for audit and ICS have nothing to do with the fraudulent acts.

Luxurious lifestyle, lucrative bonus plan, changes in lifestyle of the mangers are remarkable variables that signal FFR. Insufficient and ineffective ICS can be considered along to detect and measure the likelihood of FFR (Kaplan & Reckers, 1995). RFs serve as regressor variable to develop a regression equation that can detect fraud. Influencing risk factors may include complexity in auditing business transactions, inefficient and ineffective ICS, rigorous management practices in achieving financial goals (Bell & Carcello, 2000). Uretsky (1980) concluded that Revising previous RFs and spotting out new ones will require to construct comprehensive questionnaires from perspective that is completely different and probative.

Omar, Johari, & Smith (2017) suggested that Financial ratios serve as the detector of financial fraud and hence can unearth FFR. Due to the simplicity and resiliency of their nature, FRs are used to detect FFR as the proxies of RFs (Agyei-Mensah, 2015). FRs are popular for the prediction purpose of financial distress and the business risk of failure (Maricica & Georgeta, 2012) and for FD (Kanapickienė & Grundienė, 2015). FRs are applied among peer organizations and in case of performance measure among industries on an average basis (Kieso, Weygandt, & Warfield, 2012). Different tools and techniques have been applied to spot out the fraud in the financial statements prepared by the companies (Ravisankar et al., 2011). ANN is subjective to judgement and prone to error. The accuracy rate of the model may vary, and the structure of the model is not impeccable. But it is more accurate than using regression analysis to detect the fraud. Oumar & Augustin (2019) applied ANN for the detection of fraud in credit card cases. Zhou & Kapoor (2011), Zakaryazad & Duman (2015), Hansen et al., (1992), Chen et al., (2006) used ANN to detect fraud in the financial statements.

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## Methodology

This study attempts to find out the areas of fraud in the financial statements prepared by the banks listed on Dhaka Stock Exchange (DSE). We took the data of 29 banks out of 30 listed on DSE. 13 years of data (2006 to 2018) were collected for the analytical purposes. The financial and nonfinancial data were collected from the published annual report of the banks. The data are of the solo basis of the banks not the consolidated results. The dependent variable is the differentiation between the fraudulent and nonfraudulent banks. Fraudulent banks are assigned with value 1 and 0 is assigned to nonfraudulent bank. Report published in 2018 by Center for Policy Dialog (CPD) is used to identify the fraudulent banks. FRs presented in Table 1 are used as the independent variables. The three categories of ratios were based on the guidelines of ISA 240.

Table 1: Independent Variables for the Study

| Variables | Definition |
|---|---|
| **Financial** | |
| **Pressure:** | |
| DTE | Debt-to-Equity Ratio (Total Liabilities ÷ Total Equity) |
| DEBTR | Debt Ratio (Total Liabilities ÷ Total Assets) [8][9][10][22][29][48][49] |
| **Opportunity:** | |
| LTA | Logarithm of Total Assets [8][9][29][52] |
| NOITA | Net Operating Income to Total Assets |
| **Rationalization:** | |
| NETINTTA | Net Interest Income to Total Assets |
| NITA | Net Income to Total Assets [41][49] |
| **Others:** | |
| APE | Assets per Employee |
| CLASSLOAN | Percentage of Classified Loan |
| DIRFEE | Directors' Fee |
| EPS | Earnings Per Share (EPS) |
| LOANDEP | Loan to Deposit Ratio |
| MDFEE | Managing Director's Fee |
| PBTNETINT | Profit before Tax to Net Interest Income |
| PRVLN | Provision for Loans |
| ROA | Return on Asset [8][48][49][52] |
| ROE | Return on Equity |
| Tax | Tax amount due |
| TOE | Total Operating Expenses |
| **Nonfinancial** | |
| AUDIND | Number of Independent Director in the Audit Committee |
| AUDMET | Number of Audit Committee Meeting |
| IND | Number of Independent Director in the Board Committee |

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Multilayer Perceptron function in IBM Statistics SPSS 26 was used for the analysis. 21 (71.1%) banks were taken for training sample, 6 (20.2%) for testing sample and 2 (8.8%) banks were reserved as holdout sample for control purposes. The processing summary is presented in Table 2 and Descriptive Statistics is presented in Table 3.

Table 2: Case Processing Summary

| | | N | Percent |
|---|---|---|---|
| Sample | Training | 268 | 71.1% |
| | Testing | 76 | 20.2% |
| | Holdout | 33 | 8.8% |
| Valid | | 377 | 100.0% |
| Excluded | | 0 | |
| Total | | 377 | |

Table 3: Descriptive Statistics

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| APE | 377 | 6.78 | 699.30 | 68.0714 | 48.01008 |
| AUDIND | 377 | .00 | 3.00 | 1.2016 | .90018 |
| AUDMET | 377 | .00 | 50.00 | 8.9602 | 6.33766 |
| CLASSLOAN | 377 | .00 | .82 | .0687 | .12730 |
| DEBTR | 377 | .85 | 1.96 | .9405 | .12018 |
| DIRFEE | 377 | .00 | 12.78 | 3.3272 | 2.63902 |
| DTE | 377 | -13.17 | 123.53 | 12.0756 | 7.42987 |
| EPS | 377 | -8.30 | 311.49 | 17.2982 | 40.33708 |
| IND | 377 | .00 | 8.00 | 1.5146 | 1.30890 |
| LOANDEP | 377 | .04 | 7.57 | .8757 | .36741 |
| LTA | 377 | 4.06 | 6.18 | 5.0570 | .37711 |
| MDFEE | 377 | .85 | 23.02 | 9.7728 | 3.96516 |
| NETINTTA | 377 | -.06 | .06 | .0241 | .01066 |
| NITA | 377 | -.23 | .10 | .0111 | .01837 |
| NOITA | 377 | -.06 | .11 | .0286 | .01472 |
| PBTNETINT | 377 | -7.09 | 201.00 | 1.4650 | 10.33663 |
| PRVLN | 377 | -315.00 | 6527.00 | 1037.2944 | 1086.45589 |
| ROA | 377 | -.23 | .24 | .0128 | .02651 |
| ROE | 377 | -.12 | .54 | .1584 | .08463 |
| Tax | 377 | -188.00 | 7626.00 | 1360.5623 | 1111.56481 |
| TOE | 377 | 227.00 | 19357.00 | 3467.4589 | 2872.75068 |
| Valid N (listwise) | 377 | | | | |

## Findings and Analyses

Table 4 gives the summary results of training and testing and the holdout sample. Holdout sample provides verification to the model. The error rate in Training is 5.6%. After the Training, the network finds the error and corrected them through Back Propagation. The error rate of Testing is 14.5%. Considering all the error it can be said that the model is good and hence can be used for prediction. These Incorrect Predictions signifies the goodness of the model. Cross Entropy Error represents the error that the model tries to correct during Training and Testing.

Table 4: Model Summary

| | | |
|---|---|---|
| Training | Cross Entropy Error | 47.417 |
| | Percent Incorrect Predictions | 5.6% |
| | Stopping Rule Used | 1 consecutive step(s) with no decrease in error[a] |
| | Training Time | 0:00:00.19 |
| Testing | Cross Entropy Error | 25.505 |
| | Percent Incorrect Predictions | 14.5% |
| Holdout | Percent Incorrect Predictions | 15.2% |
| Dependent Variable: Fraud | | |
| a. Error computations are based on the testing sample. | | |

Table 5 represents how well the network has classified the items. Each sample has a predicted response of 1 if its pseudo-probability is greater than 1. 190 out of 194 cases that were not involved in fraud have classified properly for training purposes and the classification accuracy is 97.9%.

Table 5: Model Classification

| Sample | Observed | Predicted | | |
|---|---|---|---|---|
| | | .00 | 1.00 | Percent Correct |
| Training | .00 | 190 | 4 | 97.9% |
| | 1.00 | 11 | 63 | 85.1% |
| | Overall Percent | 75.0% | 25.0% | 94.4% |
| Testing | .00 | 52 | 3 | 94.5% |
| | 1.00 | 8 | 13 | 61.9% |
| | Overall Percent | 78.9% | 21.1% | 85.5% |
| Holdout | .00 | 23 | 1 | 95.8% |
| | 1.00 | 4 | 5 | 55.6% |
| | Overall Percent | 81.8% | 18.2% | 84.8% |
| Dependent Variable: Fraud | | | | |

ROC (Receiver Operating Characteristic) curve shows the specificity and sensitivity of all cutoffs in the model for diagnostic test. This represents how well the model fits the input with the output. The more the line tends towards the upper left corner (2nd quadrant) of the curve the better. Table 5 represents the numerical explanation of the ROC curve. The value of 0.965 for fraud case represents the probability of a random case to be selected as Fraud. The lines of the curves tend towards the upper left corner and probability of AUC is 0.965, thus it can be concluded that the model is very good.

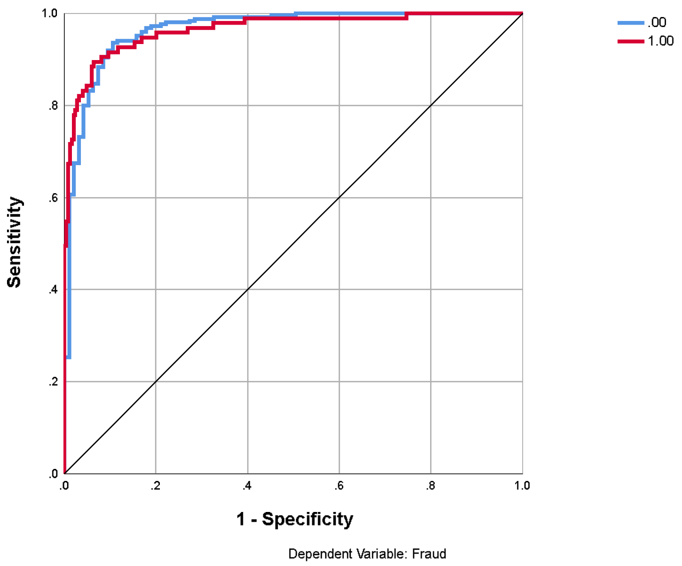


Figure 2: ROC Curve

Table 6: Area Under the Curve (AUC)

| | | Area |
|---|---|---|
| Fraud | .00 | .965 |
| | 1.00 | .965 |

Importance indicates the measure of changes in the model's predicted value for the different values of the independent variable. More importance value signifies the strength of the independent variable in prediction. Normalized importance is the importance value of each independent variable divided by the largest importance value.

Table 7: Independent Variable Importance

| | Importance | Normalized Importance |
|---|---|---|
| DTE | .059 | 65.6% |
| DEBTR | .051 | 57.4% |
| LTA | .086 | 95.8% |
| NOITA | .043 | 47.8% |
| NETINTTA | .040 | 45.4% |
| NITA | .046 | 51.4% |

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| | Importance | Normalized Importance |
|---|---|---|
| APE | .075 | 84.3% |
| CLASSLOAN | .035 | 38.7% |
| DIRFEE | .033 | 36.5% |
| EPS | .035 | 39.3% |
| LOANDEP | .089 | 100.0% |
| MDFEE | .032 | 36.0% |
| PBTNETINT | .039 | 43.4% |
| PRVLN | .024 | 27.4% |
| ROA | .061 | 68.6% |
| ROE | .042 | 47.0% |
| Tax | .048 | 53.4% |
| TOE | .071 | 79.4% |
| AUDIND | .021 | 23.1% |
| AUDMET | .032 | 35.3% |
| IND | .039 | 44.2% |

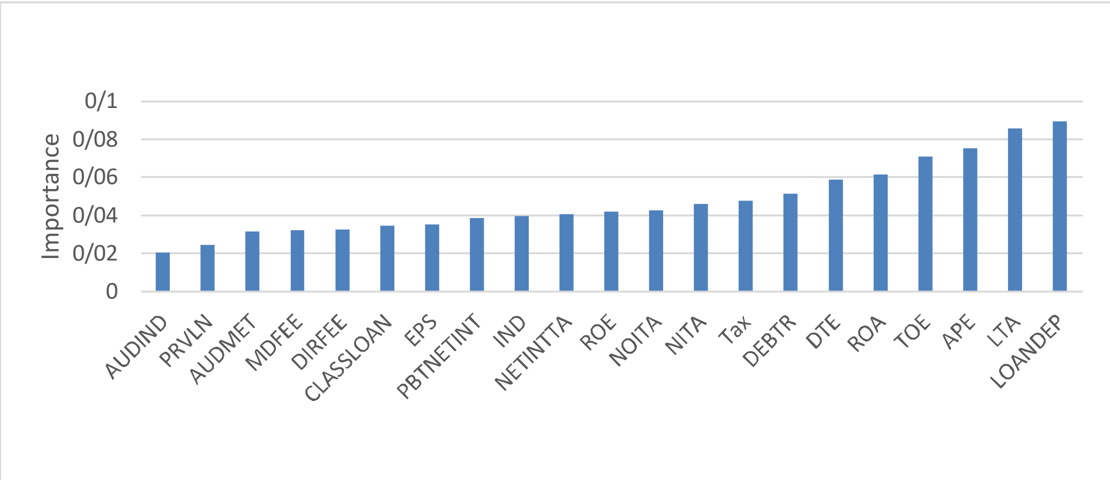


Figure 3: Normalized Importance of Independent Variables

From the Table 7 and Figure 3, it is found that Loan to Deposit Ratio (LOANDEP), Logarithm of Total Assets (LTA), Assets per Employee (APE), Total Operating Expenses (TOE), Return on Asset (ROA), Debt-to-Equity Ratio (DTE), Debt Ratio (DEBTR), Tax, Net Income to Total Assets (NITA) are the most important variables that can detect the fraud in the financial statements of the listed banks. Based on ISA 240 it can be conclude that most of the fraud are backed by pressure and rationalization. Assets are most susceptible to fraud. Operating expenses are also the area that needs inspection. Loans provides by the banks is the most sensitive indicator of fraud. Thus, in order to predict and detect the fraud in the financial statements prepared by the listed banks of Bangladesh theses mentioned variables should be closely examined by the auditors.

## Conclusion

The number of bank failure is increasing in Bangladesh. The industry is going through a crisis with serious challenges jeopardizing the sector. Efficiency, profitability and robustness of the banks are at low ebb. Banks are running out of money due to fraud, scam, heist and other malpractices. Investors are losing confidence in investing in the banks. Deteriorating conditions may lead to failure of this sector leaving the economy and economic growth vulnerable to collapse. Fraudsters fudge the financial statements to defraud the bank. This paper is designed to find the areas that can detect FFR and FFS. Many techniques have been applied to find the fraud in financial statements. ANN is most popular technique used to predict the fraudulent areas in financial statements. Multilayer Perceptron Network (MLP) which is one type of ANN can consider the nonlinearity among the data to detect any anomaly. It is more reliable and sophisticated than conventional regression analysis. FRs and nonfinancial data were used as proxies of RFs to detect the areas susceptible to fraud. Fraud was motived by the factors of the Fraud Triangle. Assets, debt and expenses of the banks should be scrutinized closely to detect and deter any fraudulent case. The authority needs to investigate these areas closely while inspecting the documents of the banks. Inclusion of more line items of the financial statements and nonfinancial data can give a clearer view of the fraud. Application of multivariate statistical method like Discriminant Analysis or Principal Components Analysis (PCA) can detect the relationship among the data that ANN could not capture. Again, CART, CHAID and other models can be used combinedly with ANN to get more refined results.

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## Appendix

<table>
<tr><th colspan="4">Appendix A: Network Information</th></tr>
<tr><td rowspan="23">Input Layer</td><td rowspan="21">Covariates</td><td>1</td><td>DTE</td></tr>
<tr><td>2</td><td>DEBTR</td></tr>
<tr><td>3</td><td>LTA</td></tr>
<tr><td>4</td><td>NOITA</td></tr>
<tr><td>5</td><td>NETINTTA</td></tr>
<tr><td>6</td><td>NITA</td></tr>
<tr><td>7</td><td>APE</td></tr>
<tr><td>8</td><td>CLASSLOAN</td></tr>
<tr><td>9</td><td>DIRFEE</td></tr>
<tr><td>10</td><td>EPS</td></tr>
<tr><td>11</td><td>LOANDEP</td></tr>
<tr><td>12</td><td>MDFEE</td></tr>
<tr><td>13</td><td>PBTNETINT</td></tr>
<tr><td>14</td><td>PRVLN</td></tr>
<tr><td>15</td><td>ROA</td></tr>
<tr><td>16</td><td>ROE</td></tr>
<tr><td>17</td><td>Tax</td></tr>
<tr><td>18</td><td>TOE</td></tr>
<tr><td>19</td><td>AUDIND</td></tr>
<tr><td>20</td><td>AUDMET</td></tr>
<tr><td>21</td><td>IND</td></tr>
<tr><td colspan="2">Number of Units[a]</td><td>21</td></tr>
<tr><td colspan="2">Rescaling Method for Covariates</td><td>Standardized</td></tr>
<tr><td rowspan="3">Hidden Layer(s)</td><td colspan="2">Number of Hidden Layers</td><td>1</td></tr>
<tr><td colspan="2">Number of Units in Hidden Layer 1[a]</td><td>8</td></tr>
<tr><td colspan="2">Activation Function</td><td>Hyperbolic tangent</td></tr>
<tr><td rowspan="4">Output Layer</td><td>Dependent Variables</td><td>1</td><td>Fraud</td></tr>
<tr><td colspan="2">Number of Units</td><td>2</td></tr>
<tr><td colspan="2">Activation Function</td><td>Softmax</td></tr>
<tr><td colspan="2">Error Function</td><td>Cross-entropy</td></tr>
<tr><td colspan="4">a. Excluding the bias unit</td></tr>
</table>

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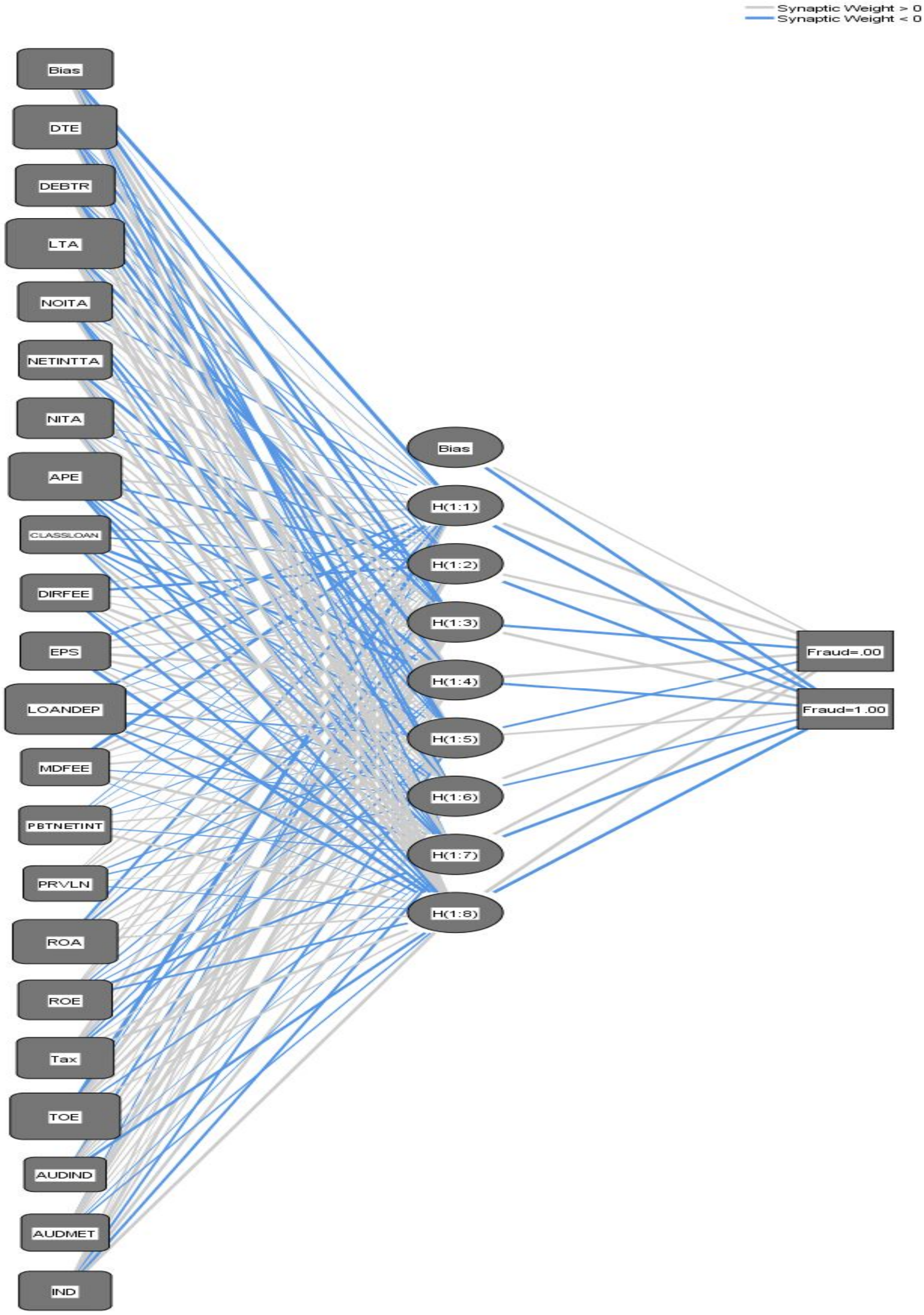
# Appendix B: Structure of the Model




Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Softmax

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## Appendix C: Parameter Estimates

| Predictor | | Predicted | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Hidden Layer 1 | | | | | | | | Output Layer | |
| | | H(1:1) | H(1:2) | H(1:3) | H(1:4) | H(1:5) | H(1:6) | H(1:7) | H(1:8) | [Fraud=.00] | [Fraud=1.00] |
| Input Layer | (Bias) | -1.276 | .009 | -.959 | .695 | .965 | -.442 | -.274 | 1.493 | | |
| | DTE | -.029 | -.254 | -.479 | .566 | -.440 | -.542 | .416 | .152 | | |
| | DEBTR | .418 | -.276 | -.043 | -.975 | -.487 | .599 | .456 | .537 | | |
| | LTA | -.066 | .102 | -.839 | .392 | -.175 | .332 | .817 | 1.201 | | |
| | NOITA | -.336 | .153 | .695 | .032 | -.311 | -.636 | -.254 | .785 | | |
| | NETINTTA | -.041 | .507 | .041 | -.871 | .269 | .629 | -.252 | 2.162 | | |
| | NITA | -.052 | -.523 | -.003 | .611 | .326 | .284 | -.370 | 1.594 | | |
| | APE | .713 | -.727 | .179 | -.673 | -.123 | -.288 | -.592 | -.676 | | |
| | CLASSLN | .809 | -.415 | .139 | -1.216 | -.459 | -.327 | .740 | -.436 | | |
| | DIRFEE | .414 | -1.236 | .249 | .299 | 1.464 | .363 | -.026 | -.838 | | |
| | EPS | -.683 | .619 | .442 | 2.117 | 1.058 | -.102 | .519 | -2.012 | | |
| | LOANDEP | -.665 | -.061 | .349 | .004 | -.446 | -.218 | -.540 | -.711 | | |
| | MDFEE | -1.411 | .670 | .591 | .087 | .640 | -.193 | 1.916 | -.042 | | |
| | PBTNETIT | -.090 | -.010 | .100 | -.154 | -.027 | .440 | -.175 | .835 | | |
| | PRVLN | .043 | .220 | .145 | .430 | -.301 | -.293 | .099 | -.145 | | |
| | ROA | -.523 | .111 | -.406 | .446 | .274 | .304 | .100 | .505 | | |
| | ROE | .107 | .479 | .105 | -.180 | -.072 | -.139 | -.794 | -.586 | | |
| | Tax | .615 | .010 | 1.044 | -.174 | -.416 | .119 | .457 | .962 | | |
| | TOE | -1.898 | -.111 | 2.018 | .169 | 1.105 | .162 | -.322 | .338 | | |
| | AUDIND | .091 | -.430 | .449 | .102 | .304 | .154 | -.017 | -.709 | | |
| | AUDMET | -.146 | 1.168 | .919 | .118 | .201 | .051 | -.078 | -.232 | | |
| | IND | .384 | .029 | 1.209 | .322 | -.434 | .704 | -.525 | .858 | | |
| Hidden Layer 1 | (Bias) | | | | | | | | | .366 | -1.150 |
| | H(1:1) | | | | | | | | | 1.310 | -1.765 |
| | H(1:2) | | | | | | | | | .871 | -1.233 |
| | H(1:3) | | | | | | | | | -1.032 | 1.476 |
| | H(1:4) | | | | | | | | | 1.707 | -.960 |
| | H(1:5) | | | | | | | | | -.560 | .603 |
| | H(1:6) | | | | | | | | | .972 | -.495 |
| | H(1:7) | | | | | | | | | 1.035 | -1.296 |
| | H(1:8) | | | | | | | | | 1.446 | -1.462 |



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