Use of Artificial Neural Network (ANN) in Predicting Financial Distress: A Case of Emerging Economy.

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Abstract
The objective of the study is to use Artificial Neural Network (ANN) algorithm to identify the important factors those can accurately predict financial distress (FD) of non-manufacturing firms of Pakistan using a panel data of 271 companies from 2013 to 2016. The results of the study based on Artificial Neural Network established that firm-specific variables (profitability, liquidity and leverage) are very important variable in predicting financial distress. Further the results concluded that sustainable growth rate, going concern (TATA and FCF), earning manipulation and size of the firm play moderately important role in financial distress prediction. On the other hand, macroeconomic indicators (GDP growth and Inflation) contribute least in forecasting financial distress of a firm. This study can assist probable financers, investors and regulators to tell if the firm is viable to an extent that they can invest in it or it might go into FD in the future.

Keywords: *Artificial Neural Network, earning manipulation, financial distress, going concern and sustainable growth.*

1. INTRODUCTION

Financial distress (FD) and bankruptcy are one of the most alarming conditions facing firms regardless of their nature of operation and size (Charitou, Neophytou, & Charalambou, 2004). Financial distress prediction (FDP) has been a burning topic among researcher and practitioners as it helps investors, creditors, regulators and shareholders to identify prior signs of default and bankruptcy since last 60 years. During the global financial crises of 2008, various well-known corporations collapsed or faced severe financial crunch which indicated that the existing FDP models need to be improved. Existing FDP models are based only on observables at the firm level as there is an urgent need to examine the dynamic macro environment, probability of accounting manipulation and sustainable growth to forecast FD (Tinocoa, Nolmes, & Wilson, 2018; Tinocoa & Wilson, 2013).

The financial distress prediction (FDP) is an essential context that so many financial institutions and researchers have pursued to create the appropriate prediction models and theories (Sun, Li, Fujita, Fu, & Ai, 2019). FD had a serious impact on the financial and nonfinancial firms among developed, emerging and developing countries (Newton, 2009). A number of industrial and financial institutions have gone into bankruptcy while many are in trouble because they are prone to losing money as being unable to avoid their risks of developing internal and external financial crisis (Mselmi, Hamza, Lahiani, & Shahbaz 2019).

In addition, as the consequences of global economic crises of 2008, the econometric models which predict FD while incorporating financial conditions in business cycles have gained importance among policymakers, academicians and practitioners (Inekwe, Jin, & Valenzuela, 2018). Therefore, the main goal of FDP is to describe the relationship among financial indicators, macroeconomic variables and firm’s performance (Mselmi, Hamza, Lahiani, & Shahbaz 2019; Altman et al., 2014; Arabsalehi & Mahmoodi, 2012). Some of the main issues of financial distress in different countries are differences in capital paradigms, accounting practices, socio-economic and political reforms (Sun et al., 2019; Mahtani & Garg, 2018).

Therefore, the purpose of current study is to use Artificial Neural Network (ANN) in investigating the importance of firm-level financial indicators (i.e., liquidity, leverage, profitability and size),

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macroeconomic variables (i.e., inflation and GDP growth), Sustainable Growth Rate (SGR), Earning Manipulation (EM) and Going Concern (i.e., free cash flow to total assets and total accruals to total assets) in financial distress prediction.

2. LITERATURE REVIEW

2.1 Predictors of financial distress (FD)

The most used and important information to forecast default or bankruptcy is extracted from the historical data of the companies, including financial statement ratios, information about the previous payment problems of firms, and information about the possible payment difficulties for management from the other firms related to them.

Previous works on FDP and related theoretical studies are abstract. Hence, predictors of FD are recognized on their importance in the earlier works. Adnan and Dar (2006) conducted a meta-analysis on 98 FDPs and contended the significance of accounting ratios, like cash flow, liquidity, profitability ratios, and leverage in forecasting FD. Shumway (2001) included more ratios such as firm size, the standard deviation of historical returns and, volatility to forecast FD and established that these indicators are important predictors. Waqas and Md-Rus (2018) considered these market indicators to augment the effectiveness of FDP model. Conversely, accounting manipulation is widely ignored by the global and local researchers as an important factor which can indicate the FD prior to bankruptcy and failure of the firms

Moreover, a broad theoretical and empirical literature has been produced since the 1930s on the determinants of prediction for FD (Duan, Sun & Wang, 2012; Ohlson, 1980; Altman, 1968). There have been several studies in different economies and the majority of default studies were concentrated on the firm-specific financial indicators (Fitzpatrick, 1932; Courtis, 1978). In his seminal work, Fitzpatrick (1932) analyzed 13 ratios and highlighted a couple of very important ratios (net worth to debt and net income to net worth) as predictors of FD. In 1937, Chudson showed a significant relationship between FD and firm-specific variables (e.g., leverage and profitability). Several other attempts have been made to use financial variables to recognize distressed and non-distressed firms. Table I, represents the indicators that are considered as the significant ratios at least in one or more studies. The research mainly restricted to firm-level and macroeconomic factors.

In general, previous evidence strongly suggests that the ability to accurately evaluate the probability of FD for a company is significantly heterogeneous. In this regard, Sandin and Porporato (2007) investigated the performance of financial ratio analysis to predict FD in an emerging and developing economies. The outcome of the study established that profitability, leverage and liquidity of the firms were significant indicators of financial trepidation. A summary of empirical evidence of the developed, emerging and developing countries is provided in table II

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Table I Summary of empirical literature

Financial indicators	**Frequency of work**
Net Profit/TA	54
Current ratio	51
WC/TA	45
RE/TA	42
EBIT/TA	35
Revenue/TA	32
Quick ratio	30
Total debts/TA	27
Current assets/TA	26
Net income/Net worth	23
Cash/TA	18
MVE/BVE	16
CF operation/TA	15
CF operation/TL	14
Quick assets/TA	13
Current assets/Total sale	12
EBIT/interest	11
Inventory/Sale	10
Operating income/TA	10
CF operations/revenue	10
Net income/revenue	9
long-term debt/TA	9
net worth/TA	8
total liabilities/net worth	8
cash/current liabilities	8
working capital/revenue	7
net sales/TA	7
log of total assets (size)	6
Net cash flow/debts	6
operating expenses/operating income	6

Source: Authors

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Table II Summary of empirical literature from developed, emerging and developing economies

Author	**Country**	**Methodology/variables**	**Results**
Ameur et al (2008)	US	Logistic regression	Found liquidity and profitability ratios as most important variables in default prediction.
Boritz et al., (2007)	Canada	Z score and O score	Tested models performed accurately
Caeremynck (2003)	Belgium	Relationship between audit report type	Found association between audit opinion and FD
Geng et al., (2015)	China	Neural Network	Found profitability, liquidity and leverage as important predictors of financial distress.
Gordini (2014)	Italy	Genetic Algorithm	Found size of the firm predicts financial distress with high accuracy
Bandyopadhyay (2006)	India	Multiple Discriminant Analysis (MDA)	Developed new z score model for Indian firms
Moradi et al (2013)	Iran	SVM	High accuracy of SVM

Source: Authors

2.2 Financial distress prediction (FDP) models

There are three major categories of financial distress prediction (FDP) studies based on models being used. These three groups are the theoretical models, statistical models and artificial intelligence models. It is obvious that all three categories are comparable in terms of their predictive power and accuracy. Statistical models normally follow classical standard modeling procedures. They could be either multivariate or univariate and they emphasis on symptoms of bankruptcy using accounting information (Aziz and Dar, 2004).

On the other hand, theoretical models concentrate on qualitative causes of FD. Such models build theoretical arguments using multivariate statistical models. Further, artificial intelligence models focus on symptoms of default using financial information of the company. These are multivariate models are based machine learning and computer technology (Aziz and Dar, 2004). Basically, the prediction of FD is dichotomous in that the company is either in default or not. The possibility related to the occurrence of FD can be frequently estimated using statistical and artificial intelligence methods, while managerial bankruptcy is often predicted by performing a univariate or multivariate analysis. In a univariate analysis, the association of separate figures or ratios and concerning FD is evaluated, while in a multivariate analysis, multiple ratios and weights are applied to obtain a prediction function of FD (Kasgari *et al*., 2013).

The earliest studies on FDP had employed statistical models in this regards, univariate studies, focused on distinct accounting ratios and an evaluation pertaining to the ratios of successful and unsuccessful companies, which had a significant effect on the advancement of forthcoming models. In 1930, a study by Bureau of Business Research (BBR) found eight ratios of accounting that could be regarded as good indicators of a corporation, namely total assets with working capital, fixed assets to net worth, reserves to surplus to total assets, total and fixed assets, total assets to net worth, sales and total assets, the current ratio, total assets to cash (Bellovary et al., 2007).

2.2.1 Statistical models

Various statistical models had employed in studies of financial distress prediction (FDP). In this regard, multivariate statistical methods have used in various researches (Ganesalingam and Kuldeep, 2001). This traditional method of deducing the ratios of financial models has been brought in use since the 1930s. In a study by Fitzpatrick (1932), being the first researcher who used this technique for paired samples of failed and non-failed companies in the U.S. Beaver (1966) provided a very comprehensive insight of financial ratios discriminatory power to detect financial distress and financial distress

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companies. The main characteristics of this technique are that univariate analysis highlights the single indications of the firms' forthcoming FD with the classification of one ratio provided at one time. There are some criticisms about this method. According to Dimitras *et al.* (1996), this technique criticized that due to the correlation present within the associated difficulty and ratios when attaining strong signals for distinct variables that provide conflicting forecasts for a firm. Furthermore, the certainty of any firm's financial status is itself a complex issue which cannot be examined using any single ratio and can have another disadvantage. There are other factors as well which can define the status of a company's financial standing and therefore, any kind of single financial ratio does not suffice to carry the overall information related to it (Edmister, 1972). Consequently, the univariate analysis replaced by multivariate techniques.

The multivariate discriminant analysis (MDA) is a statistical technique that finds a linear combination of variables which can best discriminate (mutually exclusive and collectively exhaustive) distressed and non-distress firms (Altman, 1968). Altman (1968) employed MDA to classify businesses into financially distressed and non-distressed groupings based on their individual characteristics. Subsequently, MDA has applied in various studies (Gilbert *et al*., 1990; Hillegeist et al.,, 2004). Multivariate discriminant analysis requires three restrictive assumptions. Firstly, the independent variables included in the model, are normally distributed. The classification of this is complex for the data acquired in the model estimation especially when the dispersal of that data is done from the structure of multivariate normality (Richardson and Davidson, 1984). In fact, it appears that the first assumption of multivariate normality is frequently violated (Deakin, 1976), which might result in a significant bias (Lin, 2009). Although some transformation procedures like square root and logarithm of certain variables along with outlier elimination could be justified as being helpful, which can reduce problem effects, most of the times this assumption is violated (e.g., dummy variables in the model). Secondly, the variance and covariance matrices model or matrices of group dispersion can be equal transversely for the successful and unsuccessful firms.

Lastly, the most studies evaluate models merely in terms of their overall predictive accuracy assuming equal costs for both misclassifications of failed and non-failed firms. In addition, with multicolinearity between its independent variables might start a crucial issue when these procedures are used hierarchically (Hair, et al., 1998). Furthermore, it argued that when certain data that was used for model estimation of MDA classification then it served to be more sensitive for the departing data from multivariate normality (Richardson and Davidson, 1984). In addition, Black and Scholes (1973) introduced a simple method of corporate bonds and stock's valuation which derived from a company's assets. Hence, this method by Merton (1974) employed as a structural model for FDP, whereby the company's parity was viewed as a possibility on the overall assets on its residual value pertaining to the company is due to the equity holders following the settlement of all its obligations.

Further, Zeta model (Altman, Haldeman & Narayanan, 1977) was a second-generation model that aimed to be more effective and improved than the previous one when it came to the classification of bankrupt companies up to five years before distress. The features of the ZETA model have not completely revealed since the model is a proprietary effort. Altman et al., (1977) suggested that ZETA model should be used to predict the loss five years prior to its occurrence while having the validity of 70% and 90% for five and one year respectively prior unsuccessful ventures. This model can be useful for bigger firms as they will have more losses to cover.

In addition to other statistical tools, Logit analysis is used by various studies to predict FD. Ohlson (1980) found that logit technique can be used in the prediction of FD first time. Ohlson (1980) used the nine accounting indicators to predict the likelihood of corporate FD. He estimated a prediction error rate of approximately 15%, which was relatively greater than the roughly 5% that was frequently reported in earlier studies. Ohlson (1980) believed it would not be possible to explain the difference by various estimation measures or even bringing variations when choosing different predictors, having potential exceptions of non-accounting data, such as data on market prices, which he failed to use as predictors. Kim and Gu (2009), used the estimations of logistic regression models to predict FD among hospitals. In the final model, out of 13 potential indicators, one indicator was retained. It was the

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operating cash flow to total liabilities ratio. The developed model could predict 84% and 91% of cases related to bankruptcy accurately, 91% during one year and 84% for two years.

Zmijewski (1984) employed probit analysis; it was a static approach to predict FD among various U.S firms. Probit analysis is a transformation of the linear probability model. The number of studies that used logit analysis more than probit analysis as it needs a lot of computational effort as compared to logit analysis due to its non-linear estimation (Zmijewski, 1984). Logit analysis and Probit analysis can be preferred for predicting FD especially when classification along with the likelihood of failure occurrence is required (Zmijewski, 1984). Both of these techniques give an idea of occurrence using the dichotomous as the dependent variable with coefficient used as an independent variable.

In addition, Beaver and McNichols (2005) employed a hazard model and discovered significant failures through three of the accounting ratios possessing descriptive influence, namely EBITDA with total liabilities, return on assets and total liabilities with total assets. Campbell, Hilscher and Szilagyi (2008) used a hazard model and explored that Merton's Model of probability hardly contributed to any prognostic power.

2.2.2 Theoretical Models

Trade-off, cash management and balance sheet decomposition are a few well know theoretical models which are tested in various studies of FDP. The core objective of the business is to maintain capital structure in a way to optimize shareholder wealth (Tinocoa et al., 2018). Therefore, balance sheet decomposition approach identifies the variation in various accounts and ratios of balance sheet to forecast financial well-being of the firm. However, the direction of change in capital structure is one of the limitations of such models Therefore, the theoretical model should differentiate whether the changes in capital structure is due to growth or financial anxiety. On this ground, Kim and Gu (2009) established that decomposition approach may not effectively predict financial trepidation. Moreover, cash management theory states that the most business emphasis on short-term cash management techniques. However, cash management theories, to a great extent, explain business failure (Aziz and Dar, 2004). Furthermore, the theoretical models are used comparatively in a small number of studies and are not as popular as statistical and artificial intelligence models (Tinocoa et al., 2018).

2.2.3 Artificial Intelligence Models

Artificial intelligence models include different techniques, such as rough sets, neural networks (NN), recursive partitioning and support vector machines (SVM) are widely tested on cross-sectional data to accurately predict financial distress (Martens et al., 2011). Many efforts have been made for developing a model that is able to predict FD. Two vital issues in FDP are bankruptcy prediction and credit scoring, whereby many analytical and statistical with machine learning ways are being used in order to plan FDP models. The aim of machine learning and data mining techniques in FDP are to come up with an effective model that can provide more accurate predictions. The latest techniques of data mining are of neural networks (NN), decision trees, genetic algorithms (GA), fuzzy logic, and also SVM.

Single classifier methods based on artificial intelligence for FDP include neural networks (NNs), evolution algorithms (EAs), rough sets (RSs), case-based reasoning (CBR), and SVM etc. These are employed for default prediction due to the productive research results attained by means of computer and artificial intelligence technology, and unlike statistical methods, they are not bound by rigid assumptions. Yang et al., (2011) developed a model which was a combination of partial least squares (PLS), which has feature selection with SVM to provide data integration, and this model proved to possess superior predictive ability with regard to FDP.

Recently, a new field of intelligent data analysis known as data mining has been established and developed, and it has begun to emerge and expand rapidly in the background of ample data and scarce information. Approaches like data mining involve recognition of patterns with their classification as a consequence of non-parametric and the nonlinear adaptive-learning based characteristics used for neural networks (NNs). The artificial neural network (ANN) model is comprised of interconnected processing units, known also as neurons or nodes in specific (Denton *et al.*, 1990). Within the basic ANN model,

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these neurons are pattered in layers. There ought to be three layers, one as the input layer, second or more as hidden layer/layers, and lastly the output layer. The performances of the NN models with regards to the prediction of corporate default have been frequently checked with Logit and MDA models, the results of the majority of the researches have proven that the NN models are better predictors than the statistical models, probably due to the strong mapping ability of the NN models according to the structure of the network (Wu et al., 2006). Many researchers conducted studies that were based on various hybrid methods of devised with two or three algorithms, with neural networks (NNs) being the most popular and following it are SVMs or case-based reasoning (CBR) with other methods.

In a study by Ravisankar & Ravi (2010), several hybrids were built using a similar concept. During the first phase, these hybrids were made up of NNs being multilayered feed forward, then RS, probabilistic NNs and genetic programming (GP). The GP-GP fusion hybrid demonstrated the most efficient with having an increased significance of 10%. During the second phase, overall characteristics were initially chosen using the Group Method of Data Handling (GMDH), f-statistic, t-statistic, which is a fairly unfamiliar NN. In this most of the classifiers have been qualified by the counter propagation NN, GMDH and with a theory of fuzzy adaptive resonance map. With the consequence of having t-statistic-GMDH and GMDH-GMDH based hybrids performed better than the others.

ANN is a computer program that imitates the human learning process and brain function (Balcaen and Ooghe, 2006). This technique was applied to FDP in the early 1990s, and since then application of this model has continuously increased and currently, some of the major commercial loan and FDP products are based on NN models (Balcaen and Ooghe, 2006). The main advantage of NN models is their flexibility to the data characteristics. These models deal with distinct non-linear parameters/ functions and complex patterns. They are also free from the assumptions that apply to some of the statistical techniques such as MDA. To construct different classification schemes, researchers used Discriminant analysis, which is a statistical technique that assigns unclassified observed data to its relevant group. Eisenbeis et al., (1972) depicted that neural networks are more accurate to predict firm default in comparison with MDA. The majority of the ANNs models, in FDP, are based on hidden layer perception network structure (Figure 1).

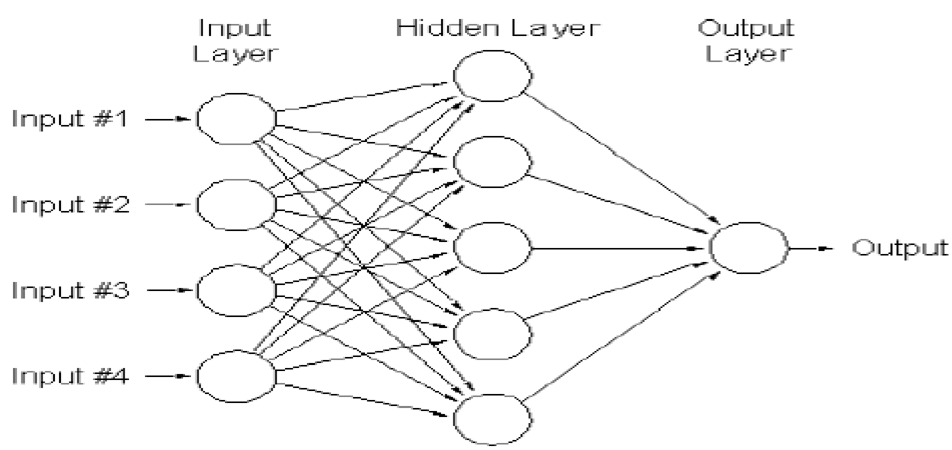

Figure 1 Structure of ANN

ANN is a mathematical archetype based on neurological models. ANNs are similar, dynamic systems of extremely organized interrelating parts. They comprise of numerous neurons that get spread and arrange themselves in layers. In general, for modeling functions in terms of indefinite mathematical terms, neural networks can be applied. This technique is a computer-based program, which copies the human learning procedure and the brain function. In this regard, the network is formed by neurons which are called processes elements or nodes. These nodes are connected to each other and organized in layers.

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Interconnections, which link the neurons, have specific associated weights. These determine the influence of incoming input on the activation level on the neuron (Mucherino et al., 2009).

Based on ANNs, the output value is made by neurons due to processing their inputs then these values will be sent to the next layer. There are three main values including first, independent variables, which are called inputs, second dependent variables, which are known as training values and third output values, which are estimated by the model. Under FD, organizations' monetary characteristics serve as independent variables like firm-specific variables where the dependents variable is defined as; a distressed or non-distressed firm. There are many kinds of neural networks having multilayers, through them information flow and which follow the estimation's method. The multilayer perception network is one of the most commonly used. The layers are connected by weights, which are similar to coefficients between the neurons in the layer. A layered network consists of at least an input and an output layer. There may exist more than one layer as well, between any input and the output layer. Different kinds of ANNs have a different number of layers.

An ANN model is also comprised of interconnected processing units, known as nodes (Denton et al., 1990). In a conventional ANN model, neurons get arranged in a minimum three layers that are one input layer, with one or more layer(s) (hidden), and also one output layer. In this, the performances of the NN models with regard to the prediction of corporate default have been frequently associated with the Logit and MDA models, with results of the majority of the researches have proven that the NN models are better predictors than the statistical models, probably due to the strong mapping ability of the NN models according to the structure of the network (Wu et al., 2006).

3. METHODOLOGY

The purpose of the research is explanatory in nature and a quantitative research designed is employed. Further, the study attempts to examine the impact of earning manipulation, sustainability growth rate, going concern and firm-level determinants along with macroeconomic variables to predict FD with reference to 271 non-financial companies of Pakistan during post-recession years of 2013-2016. Initially, the data gathered 306 companies from various sectors as classified by the State Bank of Pakistan (SBP). Due to data insufficiency and missing observations, 35 companies were dropped in the process of initial screening. Artificial Neural Network (ANN) hyperbolic tangent function is selected to calculate weight sum of values of the hidden layer to connect it with outer layer. The resulting values of the output layer are calculated using the Softmax activation function using SPSS 21. The selection and justification of statistical analysis for the study have been comprehensively discussed in the literature.

In this study, FD is measured using Altman (1968) z score model. Based on this model, a quantitative z score less than 1.81 suggests that the firm has a high probability of experiencing FD while a z-score greater than 2.67 suggests that the firm has a low risk of FD and the score between 1.81 and 2.67 categorize firm as neither 'distressed' nor 'non-distressed' (Altman et al., 2017). Further, table III shows the measurement of input variables.

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Table III Measurement of input variables

Variable		Measurement
Profitability		Net income/ total revenue
Liquidity		Current ratio
Leverage		Debt ratio
Sustainability growth rate		ROE*(1-Payout ratio)
Going Concern	Total Accrual to Total Assets (TATA)	(ΔWC_t - $\Delta Cash_t$ - ΔChange in income tax $payable_t$ – Dep and $Amort_t$)/ $Sales_t$
	Free Cash Flow (FCF)	Operating cash flow to total assets
Earning Manipulation [Beneish (1997) M Score]		M Score = -4.84 + .92DSRI +.528GMI+ .40AQI+ .89SGI+ 0.11DEPI -.17SGAI+ 4.67ACCRUALS - .32LEVI
TATA		(ΔWC_t - $\Delta Cash_t$ - Δincome tax $payable_t$ – Dep and $Amort_t$)/ $Sales_t$
Firm size		Log of total assets
Inflation		Annual Inflation Rate
GDP growth		$(GDP_t – GDP_{t-1})$ / GDP_{t-1}

4. RESULTS

This section represents ANN results. Table IV is a summary of case processing which shows that total 1084 cases are analyzed. Out of these 1084 cases, 762 cases were allocated to the training sample and rest 322 to the testing sample. The table shows 69.2% cases were allocated to the training sample and 30.8% cases were allocated to the holdout sample.

Table IV Summary of case processing

	Training sample	Testing sample	Total
N	750	334	1084
Percentage	69.20%	30.80%	100%

Further model fit statistics show that the model is a good fit as percent of incorrect prediction in the training sample was 4% and percent of incorrect prediction in the holdout sample was only 3.9 percent.

Further, classification table V shows the percent of correct and wrong prediction of three categories across training and the holdout sample. The table depicts that in the training sample model correctly predicted 651 not distressed cases which makes 99.4% of total number of cases in the training sample. However, not distressed cases were wrongly predicted as 2 cases of grey and 2 cases of distressed cases. Additionally, the table exhibits that out of 84 cases of distressed category, 80 cases are correctly predicted making it 95.2% correct predictions. While only 4.85 per cent cases were wrongly forecasted as grey and not distressed firms combined.

Furthermore, out of total 23 grey cases in the training sample, 10 grey cases were wrongly predicted as not distressed cases, 8 were correctly predicted while 5 cases were categorized as distressed

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case. The overall predictive strength of this category in the training sample is 34%. The training sample overall correct per cent of prediction is 97%.

Similarly, the table 4.3 shows the results of the testing sample for all three categories of FD. It shows that, in hold out sample, there were 268 cases in non-distressed category and 99.3% were predicted correctly. Moving forward, the table also depicts that out of 12 grey cases 4, 4, and 4 cases were categorized as not distressed, grey and distressed respectively which makes 33.3% correct forecast in this category. Moreover, out of 42 cases of distressed category, 39 cases were correctly anticipated and it makes 96% correct predictions. Overall testing sample prediction power remained 96%.

Table V Classification

Sample	Observed	Predicted			
		Non-distressed	Grey	Distressed	Percent Correct
Training	Non-distressed	651	2	2	99.4%
	Grey	10	8	5	34.8%
	Distressed	1	3	80	95.2%
	Overall Percent	86.9%	1.7%	11.4%	97.0%
Testing	Non-distressed	266	2	0	99.3%
	Grey	4	4	4	33.3%
	Distressed	1	2	39	92.9%
	Overall Percent	84.2%	2.5%	13.4%	96.0%

Dependent Variable: Financial Distress (Distressed Firm; Grey Firm and Not Distressed Firm)

Table VI shows the importance of the independent variable in predicting the dependent variable (FD). The table shows that firm profitability, liquidity and leverage are three every important and significant predictor of FD with normalized importance score of 100% and 92.4% and 75.5% respectively. Moreover, Firm Size (22.6%), Free Cash Flow (43.8%), TATA (21.9%), Sustainability Growth Rate (48.8%), and Earning Manipulation (MSCORE = 24.7%) are a moderately important variable to forecast FD. While macroeconomic variable like inflation (INFL = 2.2%) and GDP growth (GDP = 2.45%) are least important variables in this model.

Table VI Independent Variable Importance

Factors	Importance	Normalized Importance
M SCORE	.057	24.7%
Sustainability Growth Rate	.112	48.8%
Liquidity	.213	92.4%
Free Cash Flow	.101	43.8%
TATA	.050	21.9%
Leverage	.173	75.2%
Profitability	.230	100.0%
Firm Size	.052	22.6%
GDP growth	.006	2.4%
Inflation	.005	2.2%

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5. CONCLUSION

The results of the study based on Artificial Neural Network established that firm-specific variables (profitability, liquidity and leverage) are very important variable in predicting financial distress. Further the results concluded that sustainable growth rate, going concern (TATA, and FCF), earning manipulation (Beneish M score) and size of the firm play moderately important role in financial distress prediction. On the other hand, macroeconomic indicators (GDP growth and Inflation) contribute least in forecasting financial distress of a firm.

This study has yielded various worthy contributions for the existing literature as well as future researches based on exploring more about corporate FD in Pakistan. Mainly, threefold: (1) methodology, (2) policy implications, (3) theoretical development. Under theoretical development, the gap between the required knowledge regarding the apprehension of the implications of earning manipulation and sustainable growth on FD has been discussed. Furthermore, previous literature has more attribute of FD related to the developed countries where rules and regulations are strict and the economy is also somewhat stabilized, and so this study fills the gap for empirical evidence in regards to developing counties.

This study will assist policymakers to predict the company's solvency status and other requirements using going concern, as the findings of this study will help regulators to pay attention towards financial failures when using public funds (Khoja et al., 2019). The results of this study also give an operative guide to the regulators for monitoring performance and also evading financial failure related issues. This study can assist probable financers to tell if the firm is viable to an extent that they can invest in it or it might go into FD in the future as they will have to initially purchase shares to plan on any profit from the company (Alifiah, 2014). The findings will also help in assessing the firm's insolvency risks.

In conclusion, the current study focused on the financial ratios after being analyzed from the firm's financial statements, however, the archives and previous data can reflect on the firm's financial viability by using its quantitative accounting history in terms of pension obligation, lawsuits and lease-related payments and so on. These areas mostly show an outflow of finances, thus showing the level of debt of the company if these are not paid off on time.

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