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Machine Learning Models and Financial Distress Prediction of Small and Medium-Sized Firms: *Evidence from Egypt* [1]

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ABSTRACT

This study, using artificial neural networks, support vector machines as tools of machine learning derived from artificial intelligence (AI), multivariate discriminant analysis (MDA) and logistic regression (LR), assesses the role of financial ratios, firms' characteristics, and macroeconomic indicators in predicting financial distress among Egyptian small and medium-sized firms (SMEs). Our empirical findings reveal that combining financial variables with the variables of firms' characteristics (age and industry) increases the accuracy of predicting financial distress among firms of this kind. However, the inclusion of macroeconomic information has no impact on the predictive accuracy of neural networks. Moreover, in a comparison we also assess the predictive accuracy of multilayer perceptrons (MLPs) to support vector machines (SVM), and other traditional statistical techniques. According to the benchmarking results of the MDA, LR, SVM and MLP models, the neural network model (MLPs) outperforms MDA, LR and SVM as regards the predictive accuracy of the out-of-sample set.

Key words: financial distress, artificial intelligence, prediction, small and medium-sized firms.

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1. Introduction

Small and medium-sized firms are the backbone of the economic growth of many national economies, particularly emerging ones such as Egypt where the SMEs constitute an important tool for economic and social development. The growth of this sector was considered an important indicator of the development of the multi-level capital market, since it reflects the horizontal and vertical expansion of this market (Hu, 2011). Moreover, corporate soundness today goes to the top of any policy-makers' agenda; thus, financial distress prediction models and their applications for small and medium-sized firms have attracted the attention of numerous stakeholders, including investors, corporate managers, lending institutions, auditors, suppliers, together with planners, government legislators, shareholders (Zhou, et al., 2015; Wang and Li, 2007). At the same time, inefficient predictions of the credit risk lead to significant losses and crises (Loeffler and Posch, 2011).

Numerous efforts have been made by academic researchers and practitioners over the past few decades to develop financial distress prediction models. For instance, (Beaver, 1966; Altman, 1968) point out the use of financial ratios in predicting bankruptcies. Such financial prediction models have been developed using univariate and multivariate analysis. Following the pioneering study of (Altman, 1968), significant efforts have focused on developing financial distress prediction models to mitigate the negative impact of financial distress (Altman, 1983; Taffler, 1984; Peel, 1990; Morris, 1997; Chava, et al., 2004; Demyanyk and Hassan, 2010; Pustylnick, 2011). However, the ability to use financial ratios as potential predictors has begun to decline due to recent developments in the business environment and the emergence of numerous globally financial distressed firms (Mensah, 1984). The complexity of business practices, as a result of changes to firms' economic and operational environment has negatively affected the ability of traditional statistical methods to predict financial distress. According to (Keasey and Watson, 1991), the limitations of these traditional methods may justify the need to continuously develop of financial distress prediction models. In addition, the financial crisis of

2008 has caused a credit crunch, shrinking liquidity, and higher levels of systematic risks to businesses all over the world (Paolone and Pozzoli, 2017; Dunis, et al., 2016; Modina, 2015). (Ioannidis, et al., 2010) also indicate the adverse effects related to such phenomena, for example, reducing the levels of investment and consumption, increasing the unemployment rate, and an overall economic slowdown caused by hindrances to the channelling of funds between net savers and borrowers.

As a result of the adverse effects of the recent financial crisis, policy-makers in most countries have adopted different types of intervention that might reduce the likelihood of financial distress. These efforts range from the pursuit of a loose monetary policy to the bailing out of insolvent financial institutions (Gutierrez et al., 2010). However, the ability of these interventions to make bankruptcy rare is still an open question. For instance, the introduction of the 1988 Basel Accord, i.e. Basel I, which established capital adequacy requirements, and its amendments in Basel II were not very useful in preventing the occurrence of the recent financial crisis. Furthermore, (Daines, et al., 2010) state that commercially available corporate governance rankings have no useful information for predicting future restatements, security litigation, or firm performance. Accordingly, stakeholders have become increasingly interested in different ways of quantifying credit risk, i.e. the risk of loss arising from the failure of a counter party to make a promised payment associated with a firm's lending activities. The identification and quantification of such credit risk is steadily becoming more important for improving the efficiency, accuracy and consistency of risk management initiatives. Characterising credit risk also brings direct benefits not only to credit approval, but also to credit management, risk based pricing, loan security and loan portfolio management. This points to the need to expand and develop methodologies that can incorporate both qualitative and quantitative information in the analysis of such events.

For these reasons, the attention of numerous researchers has been drawn to investigating artificial intelligence, particularly neural networks models and support vector machines, as alternative methodologies for predicting financial distress (Mselmi, et al., 2017; Peat, 2017; Mansouri, et al., 2016; Ciampi and Gordini, 2013; Hajek and Olej, 2013; Rafiei et al., 2012; Lee and Choi, 2012). For instance, (Tinoco and Wilson 2013) apply the multilayer perceptron (MLP) against logistic regression for forecasting financial distress in a sample of firms listed on the London stock exchange. The results confirm the predictive ability of MLP against logistic regression. (Mselmi, et al., 2017) employ the SVM, MLP-ANN, LR and Partial Least Squares (PLS) to predict the financial distress of French small and medium-sized firms. Their findings show that the SVM model is the best classifier of distressed firms in the short term (t-1). Moreover, the MLP-ANN model outperforms both the LR model and the PLS model over the same period. Over the long term (t-2), the MLP-ANN model shows higher sensitivity than either the LR model or the PLS model, but still underperforms the SVM model.

In the Egyptian context, there has been a noticeable increase in the phenomenon of financial distress and financial failure which leads to negative consequences for individuals and business organizations. According to the Central Bank of Egypt (CBE) and its report of 2013, the non-performing loans in the local market banks rose by the end of March to record 52 billion LE compared to 50.7 billion at the end of December in the previous year, and then increased by 1.3 billion pounds within three months. Moreover, the value of non-performing loans at the end of June 2016 increased by 3.4 billion Egyptian pounds to reach 55.2 billion compared with the total value of loans, 937 billion pounds. This implies that there was a positive trend in the size of non-performing loans. This underlying problem can be attributed to the following factors: (1) the unplanned expansion of credit; (2) the absence of an effective credit scoring system in which the risk of financial distress can be predicted. In addition, several limitations negatively influence the prediction accuracy of the financial distress models. First, the majority of these models commonly depend on financial ratios for capturing the real function between the risk factors and financial distress. However, the exclusive dependence on these financial ratios and ignoring other variables, such as non-financial and economic variables, negatively affects the predictive power of financial default models, particularly for small and medium-sized firms (Charalambakis and Garret, 2015; Qi, et al. 2014; Bihmani, et al., 2013; Keasey and Watson, 1991). Second, Most of the traditional methods used in predicting financial distress are parametric methods, as they require prior assumptions regarding the real function between the independent and dependent variables. These strict assumptions commonly hinder the ability of these models in capturing the real function of the phenomenon under study (Xie, et al., 2011; Jen et al., 2010). Finally, there is scant of literature that have examined the financial distress phenomenon within Egyptian small and medium-sized firms, particularly the role of ANNs and SVM as non-parametric methods for handling the restrictions related to the normality distribution assumption of the financial data set and overcoming the problem of imbalanced data sets.

Accordingly, one of the main objectives of the present study is to build an early warning system to forestall financial distress in Egyptian SMEs. Such a system would meet the various needs of the multiple stakeholders of these SMEs by reducing or avoiding all the costs associated with financial distress. Moreover, the present study try to answer the following questions:

1. whether the inclusion of non-financial and macroeconomic indicators with the firm's financial ratios enhances the explanatory power of the designated financial distress model.
2. whether the inclusion of non-financial indicators with the firm's financial ratios enhances the predictive accuracy of the designated financial distress model.
3. whether the forecasting accuracy of artificial neural networks outperforms the support vector machine and other traditional statistical methods, i.e. logistic regression and multivariate discriminant analysis, in predicting the financial distress of SMEs in Egypt.

The rest of this study is organized as follows. Section 2 reviews the literature on predicting financial distress in terms of the predictors and classification techniques. Section 3 discusses the methodology. Section

4 reports and discusses the results; and section 5 presents some conclusions and discusses their implications.

2. Literature Review and Hypotheses Development

The vast literature on financial distress prediction models assesses firms' likelihood of financial distress, in a given time horizon, by focusing on the selection of predictors and classification techniques. This strand of the literature proposes several groups of predictors and classification techniques for this purpose (Beaver, 1966; Altman, 1968, Ohlson, 1980; Rafiei, et al., 2012; Mansouri et al., 2016; Peat, 2017; Mselmi, et al., 2017).

Since the early work of (Beaver, 1966;Altman, 1968) a set of financial and economic ratios have been used to predict corporate bankruptcy. (Ohlson, 1980) also develops a model for bankruptcy prediction based on seven financial ratios and two dichotomous indicators. As noted by (Ohlson, 1980), (Altman, 1968; Beaver, 1966) the financial ratios of distressed companies deteriorate two or three years before default occurs, whereas the financial ratios of non-distressed companies are stable during the same period.This may explain the declining ability of models to classify distressed companies, especially when the forecast period is greater than two years. (Keasey and Watson, 1991) also point out that improved understanding of the underlying stochastic characteristics of firms would reduce forecasting errors.

The empirical evidence of bankruptcy prediction shows that the Altman model outperforms the Kida model as an early warning tool for corporate bankruptcy prediction, with a 93.8% average predictive accuracy over the five years before a firm is liquidated (Al Khatib and Al Bzour, 2011). Both multivariate discriminant analysis (MDA) and logistic regression have been commonly and frequently applied to assess the likelihood of a certain corporate to fall into bankruptcy. According to (Aziz and Dar, 2006) their empirical findings confirm the reliability of the MDA and logit models in achieving high predictive accuracy regarding business failure. Moreover, (Keener, 2013) examines the use of logistic regression to predict the likelihood of bankruptcy for companies representing the US retail industry. The results indicate that firms with a lower cash to current liabilities ratio, lower cash flow margins, and higher debt to equity ratio increase their probability of becoming insolvent. (Treewichayapong, et al., 2011) conclude that the binary logistic regression model is superior to the Cox proportional Hazards model in reducing type I error and increasing prediction accuracy. (Noga and Schnader, 2013) investigate the association between book-tax differences (BTDs) and bankruptcy, using a hazard model. The results reveal that abnormal changes in book-tax differences (BTDs) can be used as an ex-ante approach to identify firms which have an increased likelihood of going bankrupt in the coming five-year period. (Benjamin and Jozef, 2013) investigate the impact of loan default and/or audit opinion as variables on the predictive ability of Hazard bankruptcy prediction. They infer that the inclusion of those variables improves the predictive accuracy regarding financially distressed samples with Hazard model characteristics. (Keasey and Watson, 1991) demonstrate that macroeconomic conditions highly affect the accuracy of financial distress prediction models. (Ciampi and Gordini, 2013) also confirm that industry type is a critical determinant in predicting corporate financial distress. (Qi, et al., 2014) confirm the significant positive impact of firm age on the predictive accuracy of the designated model in the field of financial distress prediction. (Altman, et al.m 2010), (Rikkers and Thibeault, 2011; Altman, et al., 2016) acknowledge the usefulness of including non-financial information with financial information to improve the accuracy of the financial distress prediction model. Moreover, the results of (Hu, 2011;Wolter and Rosch, 2014) show that the GDP indicator is one of the significant predictors for the financial distress of small and medium-sized firms, where the macroeconomic variables have incremental information from which predict the corporate financial distress.

Another strand of the literature is mainly concerned with the forecasting techniques of financial distress. A significant number of empirical researchers are increasingly applying artificial neural networks (ANNs) as one of the most important alternatives in bankruptcy prediction. Many of their studies support the superior ability of ANNs against MDA and other statistical methods, for the following reasons. First, the ANNs can capture the complex relationships between the variables used for prediction. Second, ANNs overcome the problems of non-normality distribution and the existence of nonlinear relationships which negatively affect the accuracy of the traditional statistical methods (Odam and Sharda, 1990). According to (Bell, 1997), ANNs outperform the ability of the logit model to detect marginally distressed banks. (Yang, et al., 1999) confirm the superiority of backpropagation neural networks to other statistical method. (McNelis, 2005) investigates the use of neural networks, the discriminant analysis, logit model, probit model, and Weibull method to examine credit card risk for German credit cards. The results show that the scores of the neural networks and logit models are identical. At the same time, neural networks greatly outperform discriminant analysis, probit, and Weibull specifications in terms of out-of-sample accuracy. (Kim, 2011) states that ANNs and the support vector machine (SVM) are widely applicable models for predicting the bankruptcy of Korean hotels. However, ANNs are more accurate in predicting bankruptcy than SVM, due to the lower relative error costs. (Mehrazin, et al., 2013) build three neural networks of radial basis function based on the variables of (Altman's model, 1983), (Zmijewski's, model, 1984) and combinatory models. The results show that the accuracy of the model trained with Altman model's variables surpasses that of the other two models in predicting bankruptcy. (Lee and Choi, 2012) assess the predictive accuracy of the Back-Propagation Neural Network (BPNN) model against the MDA model, using the same variables of Altman's Z-Score model to predict Korean delisted firms. Their empirical findings show that the BPNN models outperform the MDA models and achieve lower type I error. (Ciampi and Gordini, 2013) use the BPNN, LR and MDA to construct a model for predicting financial distress among small firms in Italy; the results show that the BPNN model is superior to both LR and MDA. However, the predictive accuracy of the logit model is closer to that of the BPNN Model since the logit model achieves less of a type I error than the MDA model does. In addition, (Peat and Jones, 2012) show that the BPNN also achieves higher predictive accuracy than does logistic regression. Moreover, (Ligang, et al., 2014) use the support vector machine (SVM) as a powerful classification method for predicting bankruptcy. The results confirm the SVM as a good alternative for the purpose.

Accordingly, this study sets out to assess the contribution of financial, non-financial and macroeconomic variables in predicting the financial distress of SMEs in the Egyptian context, and to examine whether the MLP-BPNN improves the predictive accuracy of the designated model compared with the SVM and multivariate analysis models, i.e. LR and MDA. This leads to the formulation of the following hypotheses:

H_1: The inclusion of non-financial information, macroeconomic indicators and firms’ financial ratios in SMEs’ financial distress prediction models significantly increases the explanatory power of the financial distress models. This main hypothesis is further divided into four sub-hypotheses as follows:

$H_{1.1}$: The inclusion of firms’ financial ratios in SMEs’ financial distress prediction models significantly increases the explanatory power of the financial distress models.

$H_{1.2}$: The inclusion of non-financial information and firms’ financial ratios in SMEs’ financial distress prediction models significantly increases the explanatory power of the financial distress models.

$H_{1.3}$: The inclusion of macroeconomic indicators and firms’ financial ratios in SMEs’ financial distress prediction models significantly increases the explanatory power of the financial distress models.

$H_{1.4}$: The inclusion of non-financial information, macroeconomic indicators and firms’ financial ratios in SMEs’ financial distress prediction models significantly increases the explanatory power of the financial distress models.

H_2: The inclusion of non-financial information and firms’ financial ratios in the SMEs' financial distress prediction models significantly increases the accuracy of these models.

$H_{2.1}$: The inclusion of firms’ financial ratios in SMEs’ financial distress prediction models significantly increases the accuracy of these models.

$H_{2.2}$: The inclusion of non-financial information and firms’ financial ratios in SMEs’ financial distress prediction models significantly increases the accuracy of these models.

H_3: Artificial neural networks, particularly multilayer perception, significantly outperform the forecasting accuracy of the support vector machine, logistic regression, and multivariate discriminant analysis.

3. Forecasting Methods

3. 1 Multivariate Discriminant Analysis (MDA)

MDA is a statistical technique used to divide an observation set into one of more than two priori groups (Kim, 2013). MDA is based on the linear combination of independent variables to determine which variable can be used as a predictor. In the case of bankruptcy prediction, the discriminant function can be defined as follows (Altman, et al., 1994):

$$Z = \sum_{i=1}^{n} W_i X_i \qquad (1)$$

where Z is the discriminant score. W_i represents the discriminant weight which reflects the relative importance for each independent variable and X_i denotes the independent variables.

Based on these functions, each firm was classified as bankrupt or non-bankrupt by comparing its single composite discriminant score with an ordinary cut-off value (k=0). The firm was considered distressed (bankrupt) when Z<k, whereas Z≥k denoted a healthy (non-bankrupt) firm.

To build an MDA model, the independent variables can be selected either by applying stepwise discriminant analysis or the data mining approach (Back, et al., 1996, and Shirata, 1998).

3. 2 Binary Logistic Regression Model (LR)

The logistic regression model is based on the cumulative logistic probability function. (Ohlson, 1980) employs binary logistic regression for the bankruptcy prediction which can be defined as follows:

$$\text{Prob}\,(y_i = 1) = \frac{1}{(1 + e^{-z_i})} \qquad (1)$$

$$Z_i = \beta_0 + \sum_{j=1}^{n} \beta_i X_{i,j} + \varepsilon \qquad (2)$$

where Y_i represents the dependent variable. Its value was one if the firm was bankrupt and zero otherwise. β_i denoted the regression coefficients of the independent variables; $X_{i,j}$ represented our independent variables and ε was the error term. According to (Treewichayapong, et al., 2011), a firm is to be classified as bankrupt when the computed probability exceeds 0.5 (i.e. 0.5 is the default cut-off point).

The logistic model appeared to produce lower type I errors than MDA did (Collins and Green, 1982). However, the superiority of either to the other is neither definitive nor clear (Kim, 2011).

3. 3 Artificial Neural Networks (ANNs)

Artificial neural networks (ANN), as a non-parametric data-driven approach, have been proposed as an alternative technique for bankruptcy prediction. (Zhang, et al., 1998) summarize all the applications of neural networks. As illustrated by (Shahwan, 2006) several distinguishing features support the adoption of ANN as a generalized non-linear forecasting model. First, ANNs require few prior assumptions about the structure of the problem under study. Second, ANNs are a valuable tool for complex phenomena, especially for capturing the non-linear characteristics observed in a financial data set. In this context, neural networks implement function *f* for mapping a set of given input values $x_{i,t} = \left(x_{0,t}, x_{1,t}, \ldots, x_{I,T}\right)$ into some output values, where $y_{k,t} = f\left(x_{i,t}\right)$ (Shahwan, 2006). (For further details regarding the use of ANNs in bankruptcy prediction, see Altman and Narayanan, 1997).

Different types of neural network can be used in bankruptcy prediction. One of the most widely used models for this work is multilayer perceptions (MLPs). According to (Gençay and Stengos, 1997) feedforward neural networks with sufficient hidden units can approximate any type of a class function very accurately. Accordingly, an MLP with a "log sigmoid activation function" in both a hidden and an output layer can be defined as follows (McNelis, 2005) and El-Sanhoty et al. (2006):

$$n_{j,i} = w_{j,0} + \sum_{k=1}^{k^*} w_{j,k} X_{k,i} \tag{3}$$

Where $n_{j,i}$ is a weighted sum from the input layer. $W_{j,0}$ is constant, $W_{j,k}$ is the weight of the connection between neuron (j) at the input level and neuron (k) at the hidden layer, and X_i represents the numbers of input variables used as predictors in bankruptcy prediction.

$N_{k,i}$ is the output from the logistic function at the hidden layer. Accordingly, the output of the neural network at the output layer (Y_k) can be defined as follows:

$$N_{k,i} = \frac{1}{1 + e^{-n_{j,i}}} \tag{4}$$

$$Y_k = \frac{1}{1 + e^{-n_k}} \tag{5}$$

where n_k as the net-weighted input received by neuron K at the output layer can be defined as:

$$n_k = \sum W_{k,j} N_{k,i} \tag{6}$$

MLP is trained using the generalized delta rule (momentum learning). According to (Delurgio, 1998) the momentum learning algorithm updates the weights of ANNs as follows:

$$\Delta W_{ij}(\text{new}) = \alpha \delta_{ij} O_j + \beta \Delta w_{ij}(\text{old}) \tag{7}$$

where α is the learning coefficient. The value of this coefficient should be assigned within the following range $0 < \alpha \leq 1$. δ_{ij} is the derivative of the sum of squared error with respect to the weight, O_j is the output value at node j, β is the momentum coefficient, which varies between 0 and 1. $\Delta w_{ij}(old)$ denotes the previous changes in w_{ij}.

3. 4 Support Vector Machine (SVM)

The support vector machine (SVM) allows a machine learning technique based on statistical learning theory to be used. Recently, the use of SVM in bankruptcy prediction has gained considerable attention among academic researchers and practitioners, due to its high accuracy (Ligang, et al., 2014; Mselmi, et al., 2017). According to (Vapink, 1995), SVM searches the maximum margin hyper-plane that satisfies the request of classification, and then makes the margin of separation by using a certain algorithm beside the optimal hyper-plan, while preserving the accuracy of its classification. Accordingly, the SVM classifier function can be defined as follows:

$$y(x) = \mathrm{sgn}\left(\sum_{i=0}^{n} y_i \, \alpha_i k_{(x_i, x_j)} + b\right) \qquad (8)$$

where $y(x)$ indicates the class to which point x_i belongs. It will be equal (+1) for a distressed firm and (-1) for a non-distressed firm. (α_i) denotes the Lagrange multipliers kernel function $k_{(x_i,x_j)}$ which transforms the distress prediction input data into the maximum dimensional feature space. Here the distress prediction problems are separable and increase the capacity of the learning machines.

4. Data Collection and the Measurement of Variables

4. 1 Data Collection

Our initial population consisted of 96 firms representing the small and mediumsized firms listed on the Nile Exchange (NILEX) as a market for mid and small capped enterprises, and the Egyptian exchange over the period from January 2013 to December 2016. NILEX plays a pivotal role in providing the required funding for SMEs. These firms were identified according to the definition proposed by the Egyptian Financial Regulatory Authority of small and medium-sized firms. A firm is classified as a small and medium-sized firm when its issued and paid capital ranges somewhere between LE 1 million and LE 100 million when submitting their listing application for the first time, and the issued capital does not exceed LE 200 million later (Financial Regulatory Authority Report, 2019).

16 firms related to the financial institutions sector (e.g., banks, insurance companies, and brokerage firms) were excluded from our initial sample because they had more heterogeneous characteristics than the rest of our initial sample. Moreover, 14 other listed firms were excluded because their annual reports were not available. Following (Jantaej 2006; Altman, et al., 2016 and Agostini, 2018) the following criteria were adopted in determining the incidence of financial distress: (1) the firm had experienced financial losses for two consecutive years; (2) the firm had not paid dividends for two consecutive years; and (3) the market value of the firm was less than its book value over the same period. Thus, based on the above criteria, our final data set illustrated in Table (1), panel A consisted of 66 firms. This final set was classified into 29 distressed firms which met the distress conditions over the period 2015-2016 and 37 non-distressed firms. Moreover, Table 1, panel B shows the decomposition of the final sample firms, where our data set was divided into five according to sector: Health care, Services, Retailers, Construction, and Manufacturing.

Accordingly, the final data set employed in this study was 66 firms which can be further classified into 29 distressed firms (44% of the total sample) and 37 non-distressed firms (56% of the total sample). To investigate the hypotheses of the study, the total sample was also divided into an estimation sample, known "the training set" (65% of the total sample), which was used for building the model and estimating its coefficients, and a test sample (35% of the total sample) for testing the models of the study and measuring their performance. Two maturities of the forecasting time were considered in the distress prediction, namely, one and two years before the distress event itself.

Table 1: Sample Size and Industry Representation

Panel A: Description of the final data set			**No. of firms**		**Percentage (%)**	
Initial population of small and medium-sized firms			96		100	
(-) Financial firms			(16)		(16.7)	
(-) companies with unavailable financial reports or firms that did not meet the requirements of sample selection			(14)		(14.6)	
Final data set			66		68.7	
Panel B: decomposition of the final sample firm	No. of Firms	% of Sample	Distressed Firms		Non-distressed Firms	
			No. of Firms	Percentage %	No. of Firms	Percentage %
1. Healthcare (H)	12	0.182	5	0.076	7	0.106
2. Services (S)	7	0.106	4	0.061	3	0.045
3.Construction and Real State (C)	14	0.212	6	0.091	8	0.121
4. Retailers (R)	4	0.060	2	0.030	2	0.030
5. Manufacturing (M)	29	0.439	12	0.182	17	0.257
Total Firms	66	100%	29	44%	37	56%

4. 2 Selection of Study Variables

The predictive variables used in this study were classified into three groups; i.e. financial, non-financial, and macroeconomic variables. Regarding the financial variables, these ratios were chosen on the basis of previous studies related to financial distress prediction, and also on their ability to describe the key aspects of the firm's financial and operational performance; i.e. profitability, short-term solvency (liquidity), and long-term solvency. Regarding the non-financial variables, known as the "firms' characteristics", numerous studies (e.g., Keasey and Watson, 1991; Bhimani et al., 2013; Ciampi and Gordini, 2013) confirm that incorporating non-financial with financial information significantly improves the predictive accuracy of financial distress models, particularly in the SMEs. Thus, in the present study, the industry type and firm age were chosen as items of non-financial information. The definition and measurement of the above mentioned variables are illustrated in Table 2.

Table 3 summarizes the results of the T-test and the Mann-Whitney U test used for assessing the equality of the mean and variance of the financial and non-financial variables found in financially distressed and non-distressed firms. The findings of the T-test support the significant difference in the mean for the most financial ratios used for distressed and non-distressed firms at the 1 percent level of significance. However, this difference in the mean of firm size is not significant at an alpha level of 10 percent. The findings of the Mann-Whitney U test supported the existence of statistically significant differences between the variance of most of the financial ratios used for distressed and non-distressed firms at the 1 percent level. However, there were no statistical differences in the variance of firm size and firm age for the distressed and non-distressed firms at the 10 percent significance level.

Table 2: Definition and Measurement of Variables

Variables	Definition and Measurement
NCFTL	It is a type of coverage ratio, measured by the company's net cash flow from operations to total liabilities.
WCTA	It is an indicator of the firm's liquidity (short-term solvency), measured by the working capital to total assets.
ROE	It is the return on equity as an indicator of the firm's profitability, measured by net income to total equity.
ROA	It is the return on assets as an indicator of the firm's profitability, measured by net income to total assets.
GPM	It refers to gross profit margin as an indicator of the firm's financial health, measured by gross profits to total revenues.
EBITSA	It is measured by earnings before interests and taxes to total sales. This ratio can be used as a profitability or performance indicator.
NIOINV	It is measured as the net income divided by the firm's invested capital.
NCFCL	It is measured by a firm's net cash flow from operations to current liabilities.

Firm size	It is measured by taking a natural logarithm of the firm's total assets.
Firm age	It refers to the number of years since the firm has been listed on the Egyptian Exchange.
Industry type	It is expressed as a dummy variable for each industry in the data set.
GDP	It refers to gross domestic product of a country "Egypt" as a macroeconomic indicator.

Table 3: Tests of significant difference between the mean and variance of the distressed vs. the non-distressed firms.

Variables	T – test		Mann – Whitney U test	
	(t) value	Sig. level	Z- value	Sig. level
NCFTL	3.146	0.003	-4.244	0.000
Acid ratio	2.284	0.028	-2.991	0.003
WCTA	3.343	0.001	-3.359	0.001
RoE	4.271	0.000	-5.019	0.000
RoA	5.182	0.000	-4.845	0.000
GPM	3.068	0.004	-2.913	0.004
EBITSA	3.649	0.001	-4.398	0.000
NIoINV.	4.656	0.000	-5.023	0.000
NCFCL	3.803	0.000	-3.353	0.001
ln(Firm.size)	0.067	0.947	-0.548	0.584
Firm Age	1.785	0.081	-1.630	0.100

In the context of the macroeconomic indicators, the GDP was chosen to reflect the stability and condition of the macroeconomic environment. Following (Hu, 2011) (Alifiah, 2013) (Bhimani, et al., 2013; Tinoco and Wilson, 2013) the incorporation of macroeconomic indicators with other traditional indicators led to improved predictive accuracy from the financial distress prediction models.

To test for the existence of a multicollinearity problem among the independent variables, Table 4 reports the results of using a Pearson correlation and variance inflation factor (VIF). Following (Caramanis and Spathis; 2006 and Shumway 2001), a severe multicollinearity problem exists when the VIF values exceed 5. (Anderson, et al., 1990) also point out that a correlation coefficient exceeding 0.7 can be another indicator of multicollinearity. Thus, of 8 financial variables, two, i.e., return on equity (RoE) and return on assets (RoA), were excluded due to their seriously strong correlation with most of the other financial ratios. The remaining financial ratios were the Liquidity Ratios, i.e. Working Capital to total assets, and the Acid ratio; the Profitability Ratios, i.e. Return on invested Capital, Gross profit margin, and operating profit margin; and cash flow ratios, i.e. the net cash flow to total liabilities, and net cash flow to current liabilities.

Table 4: Matrix of Correlation and Variance Inflation Factor

	Ncftl	**Acid Ratio**	**Wcta**	**ROE**	**ROA**	**GPM**	**Ebitsa**	**NI/INV**	**Ncfcl**
Panel A: Correlation matrix									
NCFTL	1								
Acid Ratio	0.327** (0.004)	1							
WCTA	0.337** (0.003)	0.685** (0.000)	1						
RoE	0.483** (0.000)	0.155 (0.106)	0.310** (0.006)	1					
RoA	0.582** (0.000)	0.267* (0.015)	0.365** (0.002)	0.850** (0.000)	1				
GPM	0.496** (0.000)	0.277* (0.012)	0.183 (0.070)	0.424** (0.000)	0.452** (0.000)	1			
EBITSA	0.529** (0.000)	0.253* (0.021)	0.265* (0.016)	0.500** (0.000)	0.597** (0.000)	0.670** (0.000)	1		
NI/INV	0.497** (0.000)	0.196 (0.057)	0.325** (0.004)	0.958** (0.000)	0.889** (0.000)	0.407** (0.000)	0.539** (0.000)	1	
NCFCL	0.807** (0.000)	0.208* (0.047)	0.114 (0.182)	0.400** (0.000)	0.444** (0.000)	0.457** (0.000)	0.468** (0.000)	0.410** (0.000)	1
Panel B: Multicollinearity diagnostic statistics									
Tolerance	0.495	0.370	0.254	0.049	0.113	0.281	0.414	0.070	0.597
VIF	2.018	2.704	3.933	20.477	8.869	3.553	2.415	14.399	1.674

** Significant at 0. 01 (two-tailed), *significant at 0. 05 (two-tailed)

Following (Orth, 2013 and Sun and Li, 2010), both backward and forward selection methods were adopted to reduce the number of financial ratios used in the designated prediction model. Table 5 presents the selection results of both methods. It is clear that both selection methods were consistent in determining three financial ratios, namely, net cash flow to total liabilities, working capital to total assets, and return on invested capital. These three ratios managed to find a significant difference between the distressed and non-distressed firms in the study sample. However, the backward selection method also identified the operating profits margin as another suitable predictor of financial distress. Thus, the four ratios listed in Table 5 were used in the designated model for predicting financial distress.

Table 5: The selected ratios based on backward and forward selection methods

Method / Ratios	Forward Selection		Backward Selection	
	(t) value	**Sig. level**	**(t) value**	**Sig. level**
NCFTL	-2.747	0.008	-2.375	0.021
WCTA	-2.090	0.041	-2.544	0.014
EBITSA	--	--	-2.371	0.021
NIoINV.	-3.376	0.001	-2.207	0.031

Table 6 also presents the correlation matrix and variance inflation factor of the variables used in the study model, which consisted of four ratios representing firms' financial information, two variables, i.e. firm age and industry type, representing firms' non-financial characteristics, and finally the GNP as an indicator of macroeconomic information. It may be noted from Table 6 that the value of VIF for all variables does not exceed (2), indicating that there are no problems of multicollinearity between the independent variables used in this study.

In untabulated results regarding the use of interest rates and inflation rates as additional macroeconomic information in the present study, these two variables were excluded because of a close correlation between the two variables based on the Pearson correlation coefficient where its value exceeded 0.90.

4. 3 Measuring the Variables

In our data set, four logistic regression models – based on the data available at (t-1) and (t-2) before the financial distress event – were used to examine whether the inclusion of non-financial and macroeconomic indicators with the firm's financial ratios enhanced the predictive accuracy of the designated model. These models for predicting financial distress, as defined by Equations (10-17) were used to test H_1 & H_2 and H_3.

Model 1 revealed the impact of financial ratios on the predictive accuracy of the financial distress model based on data at (t-1) and (t-2), respectively and can be defined in Equations 10 & 11 as follows:

$$\mathrm{DF_{it}} = \beta_0 + \beta_1(\mathrm{NCFTL})_{\mathrm{it}-1} + \beta_2(\mathrm{WCTA})_{\mathrm{it}-1} + \beta_3(\mathrm{EBITSA}_{\mathrm{it}-1}) + \beta_4(\mathrm{NIoINV}_{\mathrm{it}-1}) + \varepsilon_\mathrm{i} \quad (9)$$

$$\mathrm{DF_{it}} = \beta_0 + \beta_1(\mathrm{NCFTL})_{\mathrm{it}-2} + \beta_2(\mathrm{WCTA})_{\mathrm{it}-2} + \beta_3(\mathrm{EBITSA}_{\mathrm{it}-2}) + \beta_4(\mathrm{NIoINV}_{\mathrm{it}-2}) + \varepsilon_\mathrm{i} \quad (10)$$

where DF_{it} = 1 if it belonged to the distressed firm group, 0 otherwise. All the variables were as described above. β_0 was constant, β_i represented the regression coefficients of the predictors, all the predictors were as previously defined and ε_i was the error term.

Table 6: Correlation matrix and multicollinearity diagnostic statistics

Variables	Financial ratios				Firm characteristics		Macroeconomic Information
	Ncftl	**Wcta**	**Ebitsa**	**Nioinv.**	**Age**	**Industry**	**GNP**
Panel A: correlation matrix							
NCFTL	1						
WCTA	0.112 (0.185)	1					
EBITSA	0.163 (0.095)	0.357** (0.002)	1				
NIoINV.	0.217* (0.041)	0.009 (0.472)	0.403** (0.000)	1			
Firm Age	-0.039 (0.376)	0.087 (0.245)	-0.093 (0.230)	0.203 (0.051)	1		
Industry	-0.016 (0.870)	0.093 (0.334)	0.054 (0.579)	-0.036 (0.707)	0.211 (0.028)	1	
GDP	-0.097 (0.315)	-0.047 (0.630)	-0.020 (0.839)	-0.025 (0.799)	-0.002 (0.980)	0.018 (0.851)	1
Panel B: multicollinearity diagnostic statistics							
TOL	0.911	0.726	0.721	0.504	0.827	0.686	0.981
VIF	1.097	1.337	1.387	1.983	1.209	1.457	1.019

** Significant at 0. 01 (two-tailed), *significant at 0. 05 (two-tailed)

Model 2 revealed the effect of incorporating non-financial information with the financial ratios on the predictive accuracy of the financial distress model. Based on data at (t-1) and (t-2), model 2 was computed by Equations 12 & 13 as follows:

$$\mathrm{DF_{it}} = \beta_0 + \beta_1(\mathrm{NCFTL})_{\mathrm{it}-1} + \beta_2(\mathrm{WCTA})_{\mathrm{it}-1} + \beta_3(\mathrm{EBITSA_{it-1}}) + \beta_4(\mathrm{NIoINV_{it-1}}) + \beta_5(\mathrm{Firm\ Age_{it-1}}) + \beta_6(\mathrm{Industry\ Type_{it}}) + \varepsilon_\mathrm{i} \qquad (11)$$

$$\mathrm{DF_{it}} = \beta_0 + \beta_1(\mathrm{NCFTL})_{\mathrm{it}-2} + \beta_2(\mathrm{WCTA})_{\mathrm{it}-2} + \beta_3(\mathrm{EBITSA_{it-2}}) + \beta_4(\mathrm{NIoINV_{it-2}}) + +\beta_5(\mathrm{Firm\ Age_{it-2}}) + \beta_6(\mathrm{Industry\ Type_{it}}) + \varepsilon_\mathrm{i} \qquad (12)$$

Model 3 examined the effect of incorporating macroeconomic indicators with the financial ratios on the predictive accuracy of the financial distress model. Based on data at (t-1) and (t-2), model 3 was computed by Equations 14 & 15 as follows:

$$\mathrm{DF_{it}} = \beta_0 + \beta_1(\mathrm{NCFTL})_{\mathrm{it}-1} + \beta_2(\mathrm{WCTA})_{\mathrm{it}-1} + \beta_3(\mathrm{EBITSA_{it-1}}) + \beta_4(\mathrm{NIoINV_{it-1}}) + \beta_5(\mathrm{GDP_{it-1}}) + \varepsilon_\mathrm{i} \qquad (13)$$

$$\mathrm{DF_{it}} = \beta_0 + \beta_1(\mathrm{NCFTL})_{\mathrm{it}-2} + \beta_2(\mathrm{WCTA})_{\mathrm{it}-2} + \beta_3(\mathrm{EBITSA_{it-2}}) + \beta_4(\mathrm{NIoINV_{it-2}}) + \beta_5(\mathrm{GDP_{it-2}}) + \varepsilon_\mathrm{i} \qquad (14)$$

Finally, model 4 examined the effect of incorporating both firm's non-financial characteristics and the macroeconomic indicators with the firm's financial ratios on the predictive accuracy of the financial distress model. Accordingly, based on data at (t-1) and (t-2), model 4 was mathematically defined by Equations 16 & 17 as follows:

$$\mathrm{DF_{it}} = \beta_0 + \beta_1(\mathrm{NCFTL})_{\mathrm{it}-1} + \beta_2(\mathrm{WCTA})_{\mathrm{it}-1} + \beta_3(\mathrm{EBITSA_{it-1}}) + \beta_4(\mathrm{NIoINV_{it-1}}) + \beta_5(\mathrm{Firm\ Age_{it-1}}) + \beta_6(\mathrm{Industry\ Type_{it}}) + \beta_7(\mathrm{GDP_{it-1}}) + \varepsilon_\mathrm{i} \qquad (15)$$

$$\mathrm{DF_{it}} = \beta_0 + \beta_1(\mathrm{NCFTL})_{\mathrm{it}-2} + \beta_2(\mathrm{WCTA})_{\mathrm{it}-2} + \beta_3(\mathrm{EBITSA_{it-2}}) + \beta_4(\mathrm{NIoINV_{it-2}}) + +\beta_5(\mathrm{Firm\ Age_{it-2}}) + \beta_6(\mathrm{Industry\ Type_{it}}) + \beta_7(\mathrm{GDP_{it-2}}) + \varepsilon_\mathrm{i} \qquad (16)$$

In order to test the ability of neural networks and the support vector machine against such traditional statistical methods as multivariate discriminant analysis and logistic regression for forecasting financial distress, the out-of-sample technique was adopted to assess the forecasting performance of the proposed models. Following (Shahwan, 2006) (McNelis, 2005; Tsay, 2002) the contingency matrix was adopted to identify the number of observations that had been correctly and incorrectly classified. According to (Shahwan, 2006) the overall percentage of accurate predictions can be computed as follows:

$$\text{Overall accuracy \%} = \frac{(\mathrm{T}_{11} + \mathrm{T}_{22})}{\mathrm{T}} \qquad (16)$$

where T is the total number of observations in our data set. T_{11} and T_{22} are the total number of observations correctly classified either as bankrupt or non-bankrupt.

Moreover, the area under the curve (AUC), Gini rank coefficient, F-measure, and Kolmogorov-Smirnov test could be used as forecasting accuracy criteria for the proposed models.

Table 7 presents the descriptive statistics of the independent variables for the financially distressed and non-financial distressed firms where the values of the mean, median, standard deviation, minimum and maximum, as well as the number of observations for each group of the sample are summarized. In the context of the financially distressed firms, Table 7, Panel A shows the financial variables (net cash flow to total liabilities, working capital to total assets, operating profit margin and return on invested capital), in addition to the non-financial variable; (firm characteristics) represented in the age of each firm and industry type. The findings reveal a higher standard deviation of the financial ratios – NCFTL, WCTA and EBITSA – for the distressed firms than for the non-distressed firms; (1,166> 0.934), (0.327> 0.203) and (0.291> 0.164), respectively. It was also noticed for the financially distressed firms that the median value for the ratios of NCFTL and EBITSA exceeded the mean value, indicating negatively skewed distribution, whereas the mean value of the same financial ratios exceeded the median value for the non-distressed firms, indicating positively skewed distribution, as expected.

Table 7: Descriptive Statistics of the distressed vs. Non-distressed Firms

Variables	Financial Ratios				Firm Characteristic					
	NCFTL	WCTA	EBITSA	NIINV	Age	Industry Type C	H	M	R	S
Panel (A): Financially Distressed firms										
Mean	-0.36204	0.09007	-0.28930	0.01509	14.28	0.172	0.138	0.517	0.069	0.103
Median	-0.01400	0.07600	0.02200	0.01000	10	0	0	0	0	0
Standard deviation	1.16623	0.32748	0.29083	0.10087	9.464	0.384	0.351	0.508	0.269	0.313
Minimum	-5.28700	-0.99900	-1.03000	-0.36700	4	0	0	0	0	0
Maximum	0.92900	0.75200	0.75200	0.32400	38	1	1	1	1	1
Panel (B): Non-financially distressed firms										
Mean	0.45102	0.30979	0.17858	0.12465	16.81	0.270	0.216	0.405	0.054	0.108
Median	0.12400	0.30000	0.11500	0.11150	16	0	0	0	0	0
Standard deviation	0.93388	0.20352	0.16365	0.08995	11.04	0.450	0.417	0.497	0.229	0.315
Minimum	-0.36500	-0.02800	0.00400	0.00600	4	0	0	0	0	0
Maximum	4.21400	0.82900	0.74800	0.38700	40	1	1	1	1	1
Panel (C) : The entire data set										
Mean	0.09377	0.21325	0.08919	0.07651	15.70	0.227	0.182	0.454	0.060	0.106
Median	0.05570	0.24100	0.08980	0.04740	12.50	0	0	0	0	0
Standard deviation	1.11090	0.28497	0.24793	0.10893	10.38	0.422	0.388	0.502	0.240	0.310
Minimum	-5.28700	-0.99900	-0.10300	-0.36700	4	0	0	0	0	0
Maximum	4.21700	0.82900	0.74800	0.38700	40	1	1	1	1	1

Note: C, H, M, R, and S refer to construction and real estate, healthcare, manufacturing, Retailers, and services sectors, respectively.

Out of five industry type, it can be observed that the mean and standard deviation values of the four industry types, i.e. Construction and real estate, Healthcare, Retailers, and Services in both distressed firms and non-distressed firms are convergent. However, the manufacturing firms have the highest mean and standard deviation in the selected data set. Table 7, Panel B also indicates that the mean values of WCTA and NIINV for distressed firms was significantly lower than their mean values for non-distressed firms; (0.090< 0.309) and (0.015< 0.125), respectively. This indicates that non-distressed firms have greater flexibility in their asset structure and higher liquidity levels than financially distressed firms, as well as a higher return on invested capital.

5. RESULTS AND ANALYSES

5. 1 Empirical Results of Testing Hypothesis (H_1)

Table 8 reports the findings of the logistic regression models (1&2&3&4) as defined by Equations (10-17) for predicting the distressed vs. non-distressed firms. The main purpose of these proposed models was to investigate whether the incorporation of non-financial information and macroeconomic indicators with the financial ratios was useful in enhancing the explanatory power of the proposed models and their predictive accuracy in distinguishing financially distressed from non-distressed firms. Accordingly, an out-of-sample technique was adopted where 65% and 35% of our data set were adopted as a training set and a test set, respectively.

Table 8 shows that the ratio of return on invested capital (NI/INV) in Model 1 had the highest power to discriminate between the distressed and non-distressed firms over the two prediction periods t - 1 and t - 2, because it had a negative and strongly significant (p-value<0.05) impact on the likelihood of financial distress. In addition, it had the highest Wald statistic value of the four financial ratios used in model 1 over the two prediction periods. The second most important ratio in discriminating between the two groups of firms over the two periods was the ratio of net working capital to total assets, because it retained the same level of significance over the prediction periods (p-value< 0.05). It was also noticed that model 1 retained the same explanatory power over the two periods t - 1 and t – 2, since Cox and Snell's R-squared for the period t - 1 was (0.498) and (0.490) for the period was t -2. It could also be observed that the Hosmer and Lame goodness-of-fit test showed an increase of the chi-square resulting from the test for period t - 1 than that for the value of the chi-square for period t - 2 and a lower level of significance (p-value) resulting from the HL test for period t – 1; (p–value < 0.10) than that for period t – 2; (p-value> 0.10). This indicates that model 1 was better fitted for the sample data and could explain a higher proportion of the financial distress phenomenon. As expected, a negative relationship was found between the four financial ratios and the likelihood of financial distress. Accordingly, $H_{1.1}$ is confirmed.

Model 2 in Table 8 indicated that the firms' financial ratios, firm age, and industry type (retailers) were statistically significant at 5% when estimated at period t – 1. However, the firms' age variable was statistically significant at 10% in period t- 2. It was clear that the four financial ratios became statistically significant when the firms' characteristics were incorporated as variables in the prediction model. At the same time, both the return on invested capital and working capital to total assets were still strong predictors. It was seen, too that the explanatory power of model 2 had increased since Cox and Snell's R-squared had become (0.597) over period t – 1, and (0.550) in prediction period t- 2 than that in model 1. In addition, the result of HL test for model 2 showed a decreasing chi-square: (8.1< 14.3), (5.71< 9.87) and increase of the p-value: (0.424> 0.078), (0.679> 0.274) over the two periods t- 1, and t- 2, than that for model 1 in the same periods. This suggested that model 2 was an adequate model. Accordingly, it can be inferred that a model fitted with firm characteristics as variables is more appropriate than one without these characteristics for predicting financially non-distressed and distressed firms. Thus, the results support $H_{1.2}$.

Table 8: Logistic regression results for financial distress

Variables	Model 1		Model 2		Model 3		Model 4	
	t – 1	t – 2	t – 1	t – 2	t – 1	t – 2	t – 1	t - 2
NOCTL	-0.689 (1.610)	-0.815 (2.525)	-0.858* (2.800)	-0.937* (2.798)	-0.677 (1.565)	-0.806 (2.526)	-0.838 (2.623)	-0.925* (2.761)
WCTA	-3.084** (8.472)	-2.321** (4.279)	-3.905** (9.930)	-2.249** (4.937)	-3.095** (8.486)	-2.390** (4.437)	-3.958** (9.947)	-2.798** (6.385)
EBITSA	-2.125 (1.464)	-3.345* (2.701)	-3.783* (2.701)	-4.147* (2.811)	-2.141 (1.494)	-3.403* (2.881)	-3.815* (2.769)	-4.225* (2.837)
NIINV.	-10.538** (8.983)	-8.439** (6.602)	-13.242** (11.829)	-7.780** (5.075)	-10.540** (9.029)	-8.394** (6.577)	-13.286** (11.913)	-7.826** (5.051)
Age			0.077** (6.709)	0.048* (2.914)			0.077** (6.064)	0.048* (2.894)
Industry								
Medical			-0.164	1.034			-0.211	1.010

			(0.030)	(1.181)			(0.048)	(1.113)
Retailer			-3.449** (3.799)	-0.234 (0.023)			-3.275** (3.835)	-0.257 (0.031)
Services			-0.046 (0.003)	-0.137 (0.023)			-0.080 (0.008)	-0.162 (0.032)
Construction			1.685 (2.495)	2.026** (4.026)			1.696 (2.506)	2.013** (3.965)
Manufacturing			0.319 (0.164)	0.262 (0.120)			0.322 (0.167)	0.259 (0.116)
GDP					-15.191 (0.046)	-30.428 (0.186)	-26.117 (0.109)	-18.787 (0.063)
Constant	1.457** (12.421)	1.217** (8.880)	2.418 (0.585)	-1.859 (0.396)	1.851 (0.975)	2.008 (1.137)	3.193 (0.653)	-1.292 (0.121)
Cox & Snell's R^2	0.498	0.490	0.597	0.550	0.498	0.491	0.598	0.551
Hosmer-Lameshow (HL test)	14.389 (0.078)	9.876 (0.274)	8.100 (0.424)	5.717 (0.679)	12.047 (0.147)	15.032 (0.059)	13.175 (0.106)	14.558 (0.068)

Note: (t – 1) and (t – 2) represent the times when data were derived, respectively, one year and two years before the financial distress event. The absolute value of the Wald-statistics is reported in parentheses. *denotes significant at 10%, and **denotes significant at 5%.

Model 3 in Table 8 incorporated the four financial ratios with the macroeconomic indicator (GDP). The results show a negative correlation between the GDP and the likelihood of financial distress, as expected, although this was not significant in either t-1 or t-2. In addition, no significant improvement in the predictive ability of the model was found. The Cox and Snell's R-squared equalled the predictive accuracy of the model using only the financial ratios. At the same time, the goodness of fit based on the HL test indicated a reduced ability of the designated model to fit our data set. Accordingly, we inferred that adding the GDP as an indicator of macroeconomic information to the firms' financial ratios reduced the predictive ability of the designated model to fit our data set. Accordingly, $H_{1.3}$ is not supported.

Finally, model 4 in Table 8 shows that adding the macroeconomic indicator to both the financial ratios and the firms' characteristic variables had no significant impact on the explanatory power of the model. According to Cox and Snell's R-squared, the results of model 4 almost equaled the results of model 2. In addition, the model was less representative of the study sample data based on the HL test. Accordingly, $H_{1.4}$ is not supported.

Overall, the results of model 2 indicated that the incorporation of non-financial information with a firm’s financial information support the explanatory power of the designated financial distress model. Thus, H_I is partially supported.

5. 2 Empirical Results of Testing Hypothesis (H_2 & H_3)

Table 9 summarizes the forecasting accuracy of the proposed bankruptcy prediction models; i.e. MDA, LR, the support vector machine and MLP-BPNN under different predictors (Model 1 and Model 2) as measured by the contingency matrix.

As indicated in Table 9, based on the out-of-sample technique, the predictive accuracy of model 1 based on the contingency matrix criterion is less accurate compared to model 2 particularly at time *t-1*. Thus, $H_{2.1}$ is not supported. Moreover, the Multilayer Perceptron (MLP) as a certain kind of Neural Network achieved the highest accuracy level of all the models in classifying the distressed and the non-distressed firms based on the data sets available at *t-1* and *t-2*. Moreover, the use of non-financial and financial variables in model 2 enhanced the forecasting ability of MLP, reducing type II error to 0%. At the same time, the forecasting accuracy of MLP outperformed the other forecasting techniques; its forecasting accuracy reached 91.3% in both *t-1* and *t-2*. The MDA technique was found to be the least accurate prediction method based on data available at *t-1* and *t-2,* due to the increase in type I error compared to other methods. However, the predictive accuracy of multivariate discriminant analysis is comparable to the performance of logistic regression based on the data available at *t-2*.

Moreover, the use of financial ratios with the MDA achieved the highest type II error of all the models. These findings are in line with the findings of (Ciampi and Gordini, 2013; Lee and Choi, 2012). Overall, our findings based on the overall accuracy percentage of the contingency matrix concept of model 2 at t-1 supported the superiority of MLP (91.3%) to those of MDA (82.6%), LR (87%), and SVM (87%). The results of model 2 confirm that the incorporation of non-financial information with a firm's financial information, particularly at time t-1, also support the predictive accuracy of the designated financial distress models. Thus, $H_{2.2}$ is fully supported.

Table 9: Out-of-Sample Forecasting Accuracy of MLP, LR, SVM and MDA

Statistical Methods	Observed State		Model 1				Model 2			
			Predicted state (type I and Type II errors) (%)		Correctly (incorrectly) classified firms %		Predicted state (type I and Type II errors) (%)		Correctly (incorrectly) classified firms %	
			1	0			1	0		
Panel A: (t – 1)										
MDA	Distressed firms	1	70	(30)	78.3	(21.7)	70	(30)	82.6	(17.4)
	Non-distressed firms	0	(15)	85			(8)	92		
LR	Distressed firms	1	80	(20)	82.6	(17.4)	80	(20)	87	(13)
	Non-distressed firms	0	(15)	85			(8)	92		
SVM	Distressed firms	1	80	(20)	87	(13)	80	(20)	87	(13)
	Non-distressed firms	0	(8)	92			(8)	92		
MLP	Distressed firms	1	90	(10)	87	13	100	(0)	91.3	(8.7)
	Non-distressed firms	0	(15)	85			(15)	85		
Panel B: (t – 2)										
MDA	Distressed firms	1	60	(40)	73.9	(26.1)	80	(20)	73.9	(26.1)
	Non-distressed firms	0	(15)	85			(31)	69		
LR	Distressed firms	1	80	(20)	73.9	(26.1)	80	(20)	73.9	(26.1)
	Non-distressed firms	0	(31)	69			(31)	69		
SVM	Distressed firms	1	90	(10)	78.3	(21.7)	80	(20)	82.6	(17.4)
	Non-distressed firms	0	(31)	69			(15)	85		

MLP	Distressed firms	1	80	(20)	91.3	(8.7)	90	(10)	91.3	(8.7)
	Non-distressed firms	0	(0)	100			(8)	92		

Notes: MLP refers to the Multilayer Perceptron as a certain type of artificial neural network, LR is Logistic Regression, SVM refers to the Support Vector Machine and MDA is Multivariate Discriminant Analysis. Bold letters indicate the highest forecasting accuracy.

In addition, following (Chen, 2011; Tinoco and Wilson, 2013; Altman, et al., 2016) numerous performance measures, i.e. the area under the curve (AUC), Gini rank coefficient, F-measure, and the Kolmogorov-Smirnov test were also adopted to assess the ability of the proposed methods to discriminate between the financially distressed and non-distressed firms. Table 9 summarizes the performance measures for the proposed methods estimated at *t-1* and *t-2,* using the out-of-sample set. Table 10 Panel A, based on the four chosen criteria at time *t-1*, indicates that the MLP achieved the highest score for forecasting accuracy for both model 1 (based only on a firm's financial ratios) and model 2 (based on the firm's financial and non-financial information). The AUCs of MLP for model 1 and model 2 (0.969; 0.981) outperformed other forecasting methods; i.e. MDA models (0.88; 0.90), Logit models (0.89; 0.92), and SVM models (0.93; 0.93). For the Gini rank coefficients, the MLP models, MDA, Logit models and SVM models showed an acceptable standard of performance. However, the MLP models were superior to all the other models. The findings of the Kolmogorov-Smirnov (K-S) test indicate that the MLP in both model 1 and model 2 found strong significant differences between the cumulative probability distribution of the distressed and non-distressed firms. The MLP models' z-values (2.140 for model 1 and 2.195 for model 2) were higher than the z-value of others; i.e. the MDA models (1.463; 1.957) and logit models (2.012; 2.140), and the SVM (2.140; 2.0140) in models 1 and 2, respectively. This improvement in model 2 also suggests that the inclusion of firms' characteristics as variables in the firm's financial ratios supports the predictive accuracy of the proposed methods.

Table 10: Performance Measures of the Models

	Multivariate Discriminant analysis (MDA)		Logistic Regression (LR)		Support vector Machine (SVM)		Multilayer Perceptron (MLP)	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Panel A: (t – 1)								
F-Measure	73.8%	77.9%	80%	84.3%	84.3%	84.3%	85.8%	90.9%
AUC	0.88	0.90	0.89	0.92	0.93	0.93	0.969	0.981
Gini rank	0.76	0.80	0.78	0.84	0.86	0.86	0.938	0.962
Kolmogorov-Smirnov test	1.463 (0.03)	1.957 (0.001)	2.012 (0.001)	2.140 (0.000)	2.140 (0.00)	2.140 (0.00)	2.140 (0.000)	2.195 (0.000)
Panel B: (t – 2)								
F-Measure	66.7%	72.9%	72.9%	72.9%	78.3%	80%	89%	85.8%
AUC	0.87	0.78	0.81	0.80	0.88	0.85	0.948	0.957
Gini rank	0.74	0.56	0.62	0.60	0.76	0.77	0.896	0.914
Kolmogorov-Smirnov test	1.463 (0.028)	1.170 (0.129)	1.463 (0.028)	1.464 (0.010)	1.719 (0.005)	2.016 (0.00)	2.195 (0.000)	2.195 (0.000)

Notes: Bold lettering indicates the highest forecasting accuracy and the values between parentheses are the significance level of the Kolmogorov-Smirnov test.

Similarly, the findings in Table 10 panel B at time t-2 also document how the discriminatory power of the MLP models outperforms the other methods deployed, according to the four measures of the models' performance. For instance, the AUC of MLP (0.948; 0.957) outperform the AUCs of MDA (0.87; 0.78), LR (0.81, 0.80), and SVM (0.88, 0.85). It was also observed that the AUCs of both the MDA and logit models showed a remarkably reduction in period *t - 2*, whereas the AUCs of the MLP models were still impressive. Accordingly, H_3 is fully supported, showing that the forecasting accuracy of the MLP outperforms that of the support vector machine, LR and MDA, in predicting financial distress among Egyptian SMEs.

6. Conclusions and Implications

In this study, numerous financial, non-financial and macroeconomic indicators were adopted to develop a reliable financial distress prediction model for small and medium-sized Egyptian firms. The intermediate purpose was to investigate the impact of these indicators on the explanatory power and predictive accuracy of the designated financial distress prediction model. A sample of distressed and non-distressed firms was adopted for this purpose. Artificial neural networks, i.e. MLPs and SVM, and other traditional statistical techniques, i.e. logistic regression and multivariate discriminant analysis, were also adopted to build a suitable financial distress prediction model. The findings with logistic regression showed that the designated model for predicting financial distress was more competent when the firm's financial and non-financial information were involved in the model. Such integration between non-financial information, i.e. firm age and industry type, with the firm's financial ratios – i.e. net cash flow to total liabilities, working capital to total assets, return on invested capital, and operating profit margin - supports the explanatory power of the financial distress predictive model. According to Cox and Snell's R-squared, based on the data available at times t-1 and t-2, the explanatory power of the designated models were 0.597 and 0.550, respectively. However, extending the model by using microeconomic indicators had no significant impact on the predictive accuracy of the designated model. These findings demonstrate the possibility of using publicly available information to predict the financial distress among SMEs in the Egyptian context.

Moreover, based on the accuracy of the out-of-sample forecasting, the overall accuracy percentage of the contingency matrix supported the superiority of MLPs (91.3%) to MDA (82.6%), LR (87%) and SVM (87%). These findings shed light on the ability to use MLPs as a non-parametric data-driven approach and thereby achieve the lowest type I error of all traditional statistical methods, i.e. MDA and LR, in predicting the financial distress of small and medium sized firms. The results also indicate that MLPs are better than the support vector machine at predicting these events. In addition, based on four performance measurements, i.e. the F-measure, AUC, Gini coefficient, and Kolmogorov Smirnov test, support the superiority of MLPs to other proposed methods.

Obtaining an accurate forecast mainly depends on the predictors included in the model; thus, future studies should investigate the forecasting accuracy of the proposed models by including additional information such as market-based data. Moreover, the inclusion of variables related to a firm's governance mechanisms, i.e. the number of board meetings, number of board directors, and ownership structure, could be a fruitful extension of the present study. It may be worthwhile to investigate how well other techniques used in predicting financial distress such as data envelopment analysis perform I relation to the above methods and the characteristics of small and medium-sized firms. In addition, using a hybrid combination of artificial neural networks and traditional statistical methods for forecasting financial distress could be another extension of the present study. Moreover, the small size of the selected sample is one of the limitations of the current study. Thus, increasing the sample size is required by futures studies to test and generalize the current results.

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ملخص البحث باللغة العربية

تهدف هذه الدراسة إلى تقييم مساهمة المؤشرات المالية وخصائص الشركات، ومؤشرات الاقتصاد الكلي في التنبؤ بالتعثر المالي للشركات المصرية المساهمة الصغيرة والمتوسطة، ومن ناحية أخرى، تهدف الدراسة إلي مقارنة نماذج التنبؤ بإستخدام الشبكات العصبية الاصطناعية، ومتجهات الدعم التمييزي كنماذج للتعلم الآلي المستمدة من الذكاء الإصطناعي، مع النماذج التقليدية مثل التحليل التمييزي متعدد المتغيرات والانحدار اللوجستي لتحديد التحسن في أداء نموذج التنبؤ بالتعثر المالي، بالنسبة لمساهمة المتغيرات غير المالية والاقتصادية. وقد توصلت نتائج الدراسة إلي أن إستخدام كل من المتغيرات المالية ومتغيرات خصائص الشركات (العمر ونوع الصناعة) يزيد من دقة التنبؤ بالتعثر المالي بين الشركات من هذا النوع. و في ذات الوقت، فإن إدراج المعلومات ذات الصلة بالاقتصاد الكلي ليس لها أي تأثير على الدقة التنبؤية للشبكات العصبية. علاوة على ذلك، ووفقًا لنتائج استخدام عينة الاختبار ومقاييس الأداء تؤكد النتائج التي توصلت إليها الدراسة تفوق نموذج الشبكات العصبية المتعددة الطبقات من حيث دقة التنبؤ على باقي الأساليب الأخري المستخدمة.

الكلمات المفتاحية: التعثر المالي، الذكاء الاصطناعي، التنبؤ، الشركات الصغيرة والمتوسطة.

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