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A comparison of machine learning techniques with a qualitative response model for auditor's going concern reporting

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Abstract

Audit reports can take the form of a non-going concern (clean) report or Going concern (financial distress) report. If a firm is facing going concern uncertainty problems the auditor has a further choice of issuing two types of audit reports, namely the modified report or the disclaimer report. The issuance of the wrong type of report can have consequences for the auditor. Prior studies have developed models in an attempt to predict the type of audit report that should be issued to clients. However, all these studies, without exception, focused on the decision whether to issue a non-going concern report or a going concern report. The present study extends this area of research by comparing three predictive models that can help facilitate the decision on the type of going concern report that should be issued. Two of the predictive models are on based machine learning techniques (Artificial Neural Networks and Expert Systems) while the third is a qualitative model (Multiple Discriminant Analysis). The validity of the models are tested by comparing their predictive ability of the type of audit report which should be issued to the client. The results of the study indicate that the artificial neural network model has a superior predictive ability in determining the type of going concern audit report that should be issued to the client. © 1999 Elsevier Science Ltd. All rights reserved.

Keywords: Non-going concern; Multiple discriminant analysis; Expert systems

1. Introduction

The auditor's reporting responsibility for firms experiencing going-concern uncertainty problems has been a constant source of debate over the last two decades (Carmichael and Pany, 1992). When a firm experiences difficulties in its ability to remain solvent (defined in the literature as a ''going-concern'' problem) the auditor has to issue a going-concern uncertainty (GCU) report. In the presence of going concern uncertainties, there are two types of audit reports that can be issued, namely the *modified report* and the *disclaimer report*. The structure of the two forms of audit report are different. The modified report states that '*an audit has been conducted and that the financial statements present a true and fair view of the company's state of affairs*'. In addition, an explanatory paragraph cites that uncertainties could threaten the ability of the company to continue as a going concern. The disclaimer report, however, while describing the nature of the going concern uncertainty concludes, by stating that, because of the nature and significance of the uncertainties the auditor is unable to and cannot express an opinion on the financial statements. Thus, while the first report provides an opinion (albeit a modified one) the second report discloses the auditor's inability to provide an opinion. In a recent study the disclaimer report was considered as sending a graver signal of financial distress than did the modified one (Anandarajan and Jaenicke, 1995).

The issuance of the wrong type of report can have serious consequences for the auditor. For example, the issuance of an audit report which is perceived to send a strong and positive signal may result in litigation for the auditors by third parties such as investors and lenders, who may have relied on such a report. The consequences are exacerbated by what is referred to as the *Rosenblum rule* which can hold an auditor liable for negligence to a foreseen class of users [1]. Similarly the issuance of an audit report perceived as sending a negative signal, or one unfavorable to the client, could result in 'auditor switching' (Teoh, 1989) and loss of future business revenues to the audit firm. As either choice of report could have potentially costly consequences to an auditor (either in the form of litigation or lost client revenue)

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[1] A foreseen class of users is defined as forseeable third parties who use audited financial statements and hence rely on the auditor's report in the normal course of business.

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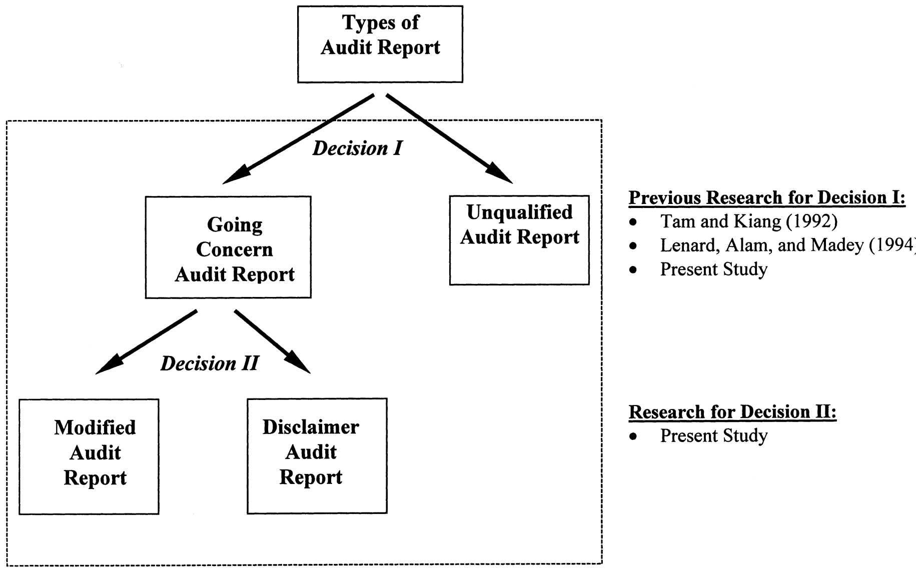

Fig. 1. Focus of present study.

some guidance in this area may be of interest to practicing auditors.

As indicated in Fig. 1, many researchers such as Tam and Kiang (1990); Lenard et al. (1994), among others, have developed neural network models to help auditors make the decision on whether to issue the client-firm a going concern or non-going concern audit report (Decision I in Fig. 1). None of these studies, however, have considered that there are, in fact, different degrees of financial distress and that auditors do have a choice between two types of going concern reports they can issue (referred to as Decision II in Fig. 1). Either choice could prove to be critical, and have consequences for the auditor.

The objective of this study is therefore to facilitate the decision making process of auditors in relation to the choice of report to be issued in the presence of going concern uncertainties. In particular this study compares the predictive ability of two machine learning techniques (Artificial Neural Networks, and Expert Systems) and Multiple Discriminant Analysis. This article,

1. examines the viability of using machine learning techniques to assist auditors to predict the type of GCU report to be issued; and
2. compares the predictive accuracy of the two machine learning techniques and the multiple Discriminant model.

2. Literature review

Auditing researchers have developed a variety of models to help identify which type of audit report to issue for going concern reporting. By using such models auditors can plan their audit to increase testing and to satisfy themselves that their report is justifiable. Previous studies in the field can be classified into two major categories. The first group of studies focus on *qualitative techniques* such as Multivariate Discriminate Analysis (Mutchler, 1985; Kida, 1980; Levitan and Knoblet, 1985) and Logit (Menon and Schwartz, 1987; Bell and Tabor, 1991; Chen and Church, 1992) to predict going-concern uncertainty. The second group of studies utilized *machine learning techniques* such as artificial neural networks to develop the going concern predictive model (Tam and Kiang, 1992; Hansen et al., 1992; Lenard et al., 1994). Results from these studies indicate that the predictive ability of the neural network models have been equal or better than the qualitative models (Lenard et al., 1994).

These studies do not, however, identify the type of GCU report which should be issued by the auditor, namely, whether it should be a modified or a disclaimer report. This is a vital aspect because the Auditing Standards Board (ASB) does not provide auditors with any guidance on when to issue a modified or a disclaimer report. As there are no guidelines available to auditors in this area, it is left to the auditors to use their judgment in making the choice (LaSalle and Anandarajan, 1996). The current study extends this line of research, by developing models based on machine learning (Artificial Neural Networks, and Expert systems) and statistics (Multiple Discriminant Analysis), to identify the type of GCU report which should be issued.

2.1. Machine learning techniques

Machine learning refers to computer techniques that generate reliable output from input characteristics representing a domain of interest. Two of the most commonly used forms of machine learning are Artificial Neural

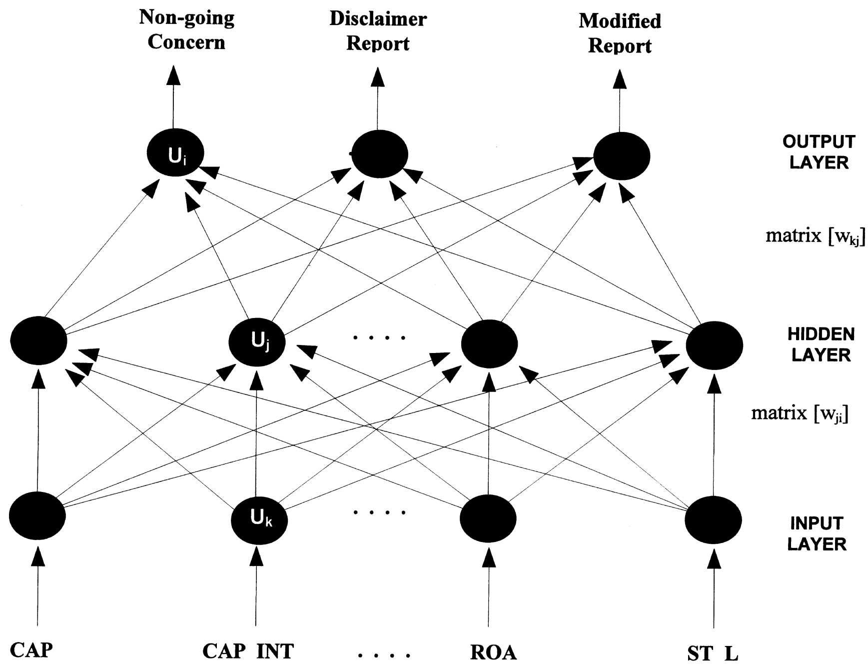

Fig. 2. Structure of the (MLP) artificial neural network.

Networks and Expert Systems. These two techniques are briefly discussed later.

2.1.1. Artificial neural network model development

An Artificial Neural Network (ANN) is a parallel, dynamic system of highly interconnected interacting parts that is based on neurobiological models. It is characterized by a large number of very simple neuron-like computing elements with weighted connections between the elements, where the weights encode the knowledge of the network. In essence, ANNs are a statistical information processing mechanism composed of many processing units or nodes that perform simultaneous computations and communicate using adaptable interconnections called weights. ANN models are very much applicable to the auditing process. This is because,

- the networks can simulate an auditor's utilization of perceived relationships for both quantitative and qualitative cues that provide important intermediate steps towards reaching the auditor's final judgment.
- ANNs are more robust than regression models to missing data and noise because it is effectively a non-parametric learning algorithm and can make use of many more variables than can regression models.
- ANNs generate a complex nonlinear equation that relates many permutations of cue sets used by auditors in arriving at their final judgment.

The Multilayer Perceptron (MLP) is one of the most widely implemented ANN topologies. It is an extension of Rosenblatts perceptron, a device that was invented in the 1950s for optical character recognition. MLPs typically have a three-layer, feedforward, hierarchical structure. As shown in Fig. 2, the input layer of the MLP contains the input neurons (X_i), which initiate primary inputs or activation to the network. These cells have no incoming or entering directed arcs and the input to each neuron is computed as follows:

$$\text{input}_i = \sum_{\text{all } j \text{ neurons connected to } i} w_{ji}\text{output}_j. \quad (1)$$

The output layer of the MLP which contains the neurons (Y_k), presents the outputs of the network as a whole. The output of a neuron is computed according to a transfer function. The selection of the transfer function depends on the nature of the input data and the objective of the network (Fausett, 1994). This study uses the *sigmoid transfer function*, as it is the most suitable if the goal of the neural network is to classify an object from the others (Klimasauskas, 1991). The sigmoid function is mathematically symbolized as follows:

$$\text{output}_i = \frac{1}{1 + e^{\text{gain, input}_i}}. \quad (2)$$

Finally, the hidden layer consists of the intermediate cells or 'hidden units' (Z_j) which receive inputs from preceding cells, and pass on outputs to subsequent cell layers. During the feedforward learning process, each input unit (X_i) receives an input signal and sends the signal to each of the hidden units $Z_1, \ldots, Z_n$. The hidden units then compute their activation and send their signal z_j to the output units. Each output unit computes its activation y_k to form the response of the network for the given input pattern.

The ANN used in this study was developed on NeuroDimensions 3.0, a Windows-based software which utilizes the

Table 1
Independent variables used in the study

Ratio	Variable	Definition
1	Short term liquidity (STL)	Current assets, Current liabilities
2	Liquidity (LQD)	Cash flow from operations, Total liabilities
3	Cash position (CFL_TL)	Cash, Sales (net)-Operating income before depreciation
4	Capital (CAP)	Long term debt, Total assets
5	Financial leverage (FIN_LEV)	Debt in current liabilities, + Long term debt, Preferred stock + common equity
6	Return on investment (ROI)	Profit before interest and tax, Total assets
7	Sales growth (S_Grow)	Sales growth over a five year period
8	Prior year's loss (CP)	Dummy variable (0 = loss in prior year) (1 = no loss in prior year)
9	Cumulative effect of operating losses (ROA)	Retained earnings, Total assets
10	Capital intensiveness (CAP_INTN)	Preferred stock + common equity, Sales
11	Inventory intensiveness (INV_INTN)	Inventory, Sales
12	Receivable intensiveness (REC_INTN)	Receivables (net), Sales
13	Client size (SIZE)	Natural log of total assets
14	Auditor change (A_CHG)	Dummy variable (0 = if $<$ 3 years association) (1 = if $>$ 3 years association)

Backpropagation algorithm to train the network weights. The algorithm utilizes each auditor's cue selection (namely the input variables which in this case comprise the financial ratios) and the auditor's judgment response (the issuance of an audit report) to find a function that relates the selected cue sets (financial ratios and other cues) to the judgment responses. The Backpropagation algorithm is described in detail in Appendix A.

2.1.2. Expert systems development

An Expert System (ES) is a computer based information system which embodies the knowledge of experts, as well as manipulates the expertise to solve problems (Rauch-Hindin, 1988). These systems have the ability to encode and manipulate an auditor's heuristics through their inference paradigms, to make expert diagnosis (Zahedi, 1994). An ES has four major components, namely, knowledge base, inference engine, user-interface, and the explanatory sub system. For a more detailed description of these components, refer to Turban (1990).

The transfer of knowledge into an ES's knowledge base can be accomplished through either programming or auto-learning. Programmed systems require the explicit input of decision rules to build the knowledge base, while auto-learning systems program themselves through the exposure to cases or examples. Researchers such as Goodman (1990); Riesbeck (1988); Turban (1990); among others have highlighted the fact that the auto-learning approach is more efficient as experts find it easier to illustrate their decision making process by resort to examples or cases, rather than by exhaustively detailing every decision rule employed. Owing to the complexity of an auditor's decision-making process prior to issuing an audit report, the auto-learning approach is used in this study.

The ES predictive model was developed using the 1st Class ES development tool. This software incorporates rule induction as the method of knowledge representation within the ES. Rule induction is defined as '*a process of going from specific observations about the objects and initial hypothesis to an inductive assertion that accounts for the observation*'' (Messier and Hansen, 1989). Typically these observations are entered into the ES through past examples of an auditor's decision making process; while rule induction extracts the underlying logic from these examples (Shaw, 1987).

The inductive process in this study was carried out using the ID3 algorithm. The algorithm takes objects of a known class which are described in terms of attributes, to iteratively generate rules, which can correctly classify all given instances. In other words, the algorithm uses the financial ratios to generate rules, which can be used to identify the type of audit report that should be issued to the client. ID3's ability to rapidly converge on an accurate rule, as well as, its insensitivity to parameters such as attribute values make it suitable to map the auditor's decision making process (Quinlan, 1984). The ID3 algorithm which is shown below, is explained briefly in Appendix B.

$$E(c) = -\sum_{i=10}^{n} p(C_i)\log_2 p(C_i). \quad (3)$$

2.2. Multiple discriminant model development

The two most popular statistical models used for prediction in auditing are Multiple Discriminant Analysis (MDA) and logistic regression. Neither technique is clearly superior to the other nor does either provide substantially better results. Hence this study uses MDA as a comparative prediction technique because of its repeated use in auditing (Kida, 1980; Mutchler, 1985; Levitan and Knoblet, 1985).

MDA is a statistical technique, which is used to classify objects into distinct groups on the basis of an object's characteristics. In simple terms, a linear discriminant function is developed which computes a score for an object. This function is the weighted linear combination of an object's observed values on the discriminating characteristics. The weights represent the relative importance and impact of the various characteristics. On the basis of this discriminant function, an object is then classified.

2.3. Hypothesis development

This study examines the predictive accuracy of the two

Table 2
Univariate analysis of research variables

Variable	Going concern Mean	Standard deviation	Non going concern Mean	Standard deviation	*t-value*
CAP	0.081	0.249	0.001	0.005	1.820[a]
CAP_INT	−0.007	0.008	0.045	0.137	−1.740[a]
CP	−0.040	0.107	−0.002	0.007	−2.040[a]
FIN_LEV	8.110	40.667	0.258	0.920	1.110
INV_INT	0.032	0.078	0.006	0.006	2.370[b]
LQD	−0.245	0.928	0.136	0.555	−1.980[a]
REC_INT	−0.863	0.070	0.547	1.500	−2.220[b]
ROA	−0.125	0.120	−0.005	0.029	−5.560[b]
ST_L	0.008	0.029	0.819	1.730	−2.470[b]

[a] Significant at 0.1 level.
[b] Significant at 0.05 level.

machine learning techniques in determining which type of audit report should be issued. The predictive accuracy of the machine learning techniques is compared to the results of a qualitative technique, namely multiple discriminate analysis. Thus, the null hypothesis to be tested is stated as follows:

> Ho: There is no significant difference between the predictive accuracy of the machine learning techniques and that of the qualitative model in determining the type of audit report that should be issued to a firm.

3. Research methodology

3.1. Sample selection

The auditing literature has used many variables to examine the financial health of a firm. According to Mutchler (1985) many of these variables represent ''information cues'' that auditors use to determine whether a firm is in financial distress. In particular the Statement of Accounting Standard (SAS) No. 59 The Auditor's Consideration of an Entity's Ability to Continue as a Going Concern notes that negative cashflows, working captial deficiencies and operating losses are indicative of financial distress that should result in a qualified report. The ratios used in this study, shown in Table 1, were selected after reviewing the finance and accounting literature dealing with bankruptcy and failure prediction models, and capture the aforementioned characteristics of financial distress.

According to the guidelines given in paragraph 5 of SAS No. 56, a firm's financial information should be evaluated relative to industry measures or norms. Based on these guidelines, the information used in this was converted to industry standardized measures, thus indicating the relative standing of the firm within the specific industry distribution. The transformation for conversion into industry-standardized form is given by:

$$\mathrm{ST}(X_{i,t}) = [X_{i,t} - X_{\mathrm{I},t-1}]/\mathrm{SD}(X_{i,t-1}), \tag{4}$$

where, $X_{i,t}$ = Firms's ratio X_i for year t, (t = 1991) $X_{\mathrm{I},t-1}$ = Industry mean ratio X_{I}, for year $t-1$ ($t-1$ = 1990)[2] $\mathrm{SD}(X_{i,t-1})$ = Standard deviation of ratio X across firms in industry I for year $t-1$.

The experimental sample for the study was drawn from the 1992 Disclosure database. This database contains the financial statements of all firms on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX). The following criteria were used in the sample selection:

1. The financial statements must relate to the period after SAS Nos. 58 and 59 came into effect.
2. The firms must have been issued either a modified report or disclaimer between the years 1990–1991.
3. The reasons for the issuance of the above mentioned reports must relate to going concern uncertainties.

The 1990 ratios of 125 firms were used to calculate the industry mean ratio, as given in Eq. (3). For the 1991 period there were 45 which received disclaimer and modified audit reports. An additional 45 firms which received non-going concern audit reports over the same period were included in the sample. This was performed because it was necessary to match the experimental firms with control firms (Chen and Church, 1992; Lenard et al., 1994). Of the population sample of 90 firms, 61 were chosen at random, to be used for the analysis.

3.2. Procedure for designing the predictive models

A five-step procedure is proposed for using the machine learning techniques. This is as follows:

Step 1 Presents a description of the firms in terms of financial ratios as inputs into the system.
Step 2 For each firm the audit report which was issued by the auditor, was entered as outputs of the system.

[2] The prior year's industry distribution is used because in actuality the distribution of the industry ratios of the end of the year being audited is not available.

Table 3
Prediction accuracy of ANN vs MDA for non-going concern and going concern audit reports

	ANN (%)	ES (%)	MDA (%)	Ho: μANN−μMDA (*t-value*)	Ho: μES−μMDA (*t-value*)
Training sample	100.0	87.0	95.0	—	—
Hold-out sample					
Overall reports:	85.8	69.1	74.1	5.71[b]	1.39
Non-going concern report	90.0	75.0	81.0	6.01[b]	1.50
Going-concern report:					
Modified report	80.0	66.0	72.1	4.01[b]	1.00
Disclaimer report	83.2	60.3	74.4	1.63[a]	0.88

[a] Significant at 0.1 level.
[b] Significant at 0.01 level.

Step 3 Create the neural network topology/inductive rules from the given training sample.

Step 4 Test the machine learning techniques with new examples (hold-out sample). This is where the predictive accuracy of the machine learning techniques is measured.

Step 5 Validated solution is added to the system for use in future problem solving.

To assess the predictive accuracy of the machine learning techniques and that of the qualitative models the sample was split into two distinct groups namely, a training group[3] (37 firms) and a holdout or testing group (24 firms). Once the models were trained, the holdout sample was used to test their predictive accuracy.

This 'train-and-test' procedure was performed for five iterations, with a new, randomly-selected sample of 37 training data sets and 24 testing data sets used each time for the machine learning and the discrimination models. The data sets for the five iterations were created from the original sample using jackknifing. The jackknife technique is a useful statistical procedure which produces unbiased estimates for the probability of misclassification (Chen and Church, 1992). The predictive accuracy rate of the three models were calculated as the sum of the outcomes from the five iterations of the holdout samples.

4. Data analysis and results

Univariate analysis was performed to determine whether the samples of going concern firms and non-going concern firms were from different populations. As can be observed from the *t-values* in Table 2, all variables except for financial leverage (FIN_LEV) were significantly different for both groups at the 10% level. This indicated that the two sets of groups represented different populations.

A good measure of the accuracy of the three models is in their performance in predicting the type of audit report that firms should receive in the holdout group. Analysis proceeded by calculating the overall accuracy of each of the predictive models. Table 3 presents the results of utilizing the three techniques to evaluate the 24 holdout samples, in terms of the average percentage of correct classifications. ANN had the highest accuracy (85.8%) in predicting the correct audit report to be issued, while the ES, MDA models had an accuracy rate of 69.1, and 74.1%, respectively.

The models predictive ability was compared for Decision I, i.e. should the auditor issue a GCU or a non-GCU report for the firm being audited. As can be observed in Table 3, the firms with non-going concern problems were correctly classified with an accuracy rate of 90% for ANNs, 75% for ES, and 81% for MDA. Pairwised *t*-tests were conducted to assess the significance of the differences of the models. The ANN model significantly outperformed the MDA at the 0.01 level, thus supporting the findings of Lenard et al. (1994). However, the MDA model performed significantly better than the ES model.

Decision II was tested next, i.e. if a firm was to receive a GCU report, which form was it to take, modified or disclaimer? Yet again, the ANN model outperformed MDA model with a predictive accuracy rate of 80.0% for the modified, and 83.2% for the disclaimer, compared to MDAs 72.1 and 74.4%, respectively. The ES model's predictive accuracy, however, was inferior to that of MDA at 66 and 60.3%, respectively. Hence, the hypothesis proposed in this study was only partially supported, in that only one of the machine learning techniques namely ANN, was significantly

Table 4
Prediction accuracy of ANN vs ES for non-going concern and going concern audit reports

	ANN (%)	ES (%)	H_o: μ_{ANN}-μ_{ES} (*t*-value)
Training Sample	100.0	87.0	—
Hold-out sample			
Overall reports:	85.8	69.1	4.47[b]
Non-going concern report	90.0	75.0	3.67[a]
Going-concern report:			
Modified Report	80.0	66.1	2.13[a]
Disclaimer Report	83.2	60.3	2.06[a]

[a] Significant at 0.1 level.
[b] Significant at 0.01 level.

[3] A training group is used to train the machine for the ANN and rule based models, while for MDA it is used to create the discriminant function.

different in its predictive accuracy from the qualitative model. A comparison of the two machine learning techniques, as shown in Table 4, indicated that the ANN models performed better that the ES in both audit Decisions I and II.

The ES model's inferior performance could perhaps be explained in terms of the noise contained in the real world data used in this study. Unlike ANNs, the ES has a very low tolerance to noise. This is because in inductive learning, explicit rules are formed for a given class, and a single wrong example could easily lead to a misleading rule, thereby lowering the prediction rate. Moreover, ESs unlike ANNs ignore the interaction effect each variable has on each other (Fisher and McKusick, 1989), resulting in the loss of considerable amount of valuable information, and thereby resulting in the inferior predictive accuracy of the final outcome.

5. Discussion and conclusions

In today's litigious environment, issuance of the wrong type of audit report could have serious consequences for the auditor. Researchers have developed various types of predictive models to minimize the consequential risks to which auditors are exposed. However, all these previous studies, without exception, have focused exclusively on whether an auditor should issue a non-going concern or a going concern report. This study therefore takes the auditor's decision-making process a step further. Once the decision is to issue a GCU report, the auditor has to choose between issuing a disclaimer report and a modified audit report.

In this study, two machine learning based techniques were developed to facilitate the decision on which form of audit report should be issued. The models developed were based on actual decisions of auditors. The predictive ability of the models were then tested by comparing their predictive ability with that of a MDA model using real-world examples. The results indicate that the ANN model has a higher predictive accuracy than both the MDA and ES models.

The use of the ANN model can prove to be a persuasive analytical tool when an auditor discusses problems with clients and recommends changes in the financial statements. In our opinion the ANN will serve a dual purpose: it can be used at the end of an audit to determine which opinion is most appropriate for a financially distressed firm. This is most relevant in today's environment where auditors are being sued for issuing the wrong type of report. (It is estimated that the Big-Six audit firms have already incurred millions of dollars in terms of damage expenses). The ANN predictive model can also be used at the beginning of an audit to make an initial risk assessment of the client, especially when an auditor is handling a new client facing financial stress. By making an initial risk assessment of the financial position of the firm using the ANN model, the auditor can determine the necessary audit procedures to perform. In addition the model can be used as a training device for junior auditors.

Although the predictive models have several advantages and uses, they also have their limitations. The number of variables which can be input into the models are limited. It should also be emphasized that the model cannot, and should not entirely replace professional judgment, should be used to provide auditors with objective information to determine the type of report to be issued. It must be noted that many important qualitative variables such as management ability and future plans (that could potentially mitigate the stress faced by a firm) are not formally incorporated into the models.

Appendix A. Explanation of the backpropagation learning algorithm

The mathematical basis for the BP algorithm is the optimization technique steepest gradient method. The steps of the BP algorithm is given below:

Step 1 Initialize weights to connections [$\mathbf{w}_{jk}$] and [$\mathbf{v}_{ij}$] with random weights.Feedforward

Step 2 Input X_i ($i = 1,\ldots n$) receives an input signal and passed the signal to the hidden units Z_j.

Step 3 Each of the hidden units Z_j ($j = 1,\ldots,n$) sums the weighted input signals net input to $Z_j = \theta_j + \sum_{i=1}^{n} x_i v_{ij}$ and applies the activation function to compute the output signal.

Step 4 Each of the output unit Y_k ($k = 1,\ldots,n$) sums the weighted input signals net input to $Y_k = \theta_k + \sum_{j=1}^{n} z_j w_{jk}$ and applies the activation function to compute the output signal.Backpropagation of error

Step 5 Each of the output units compares its computed activation with a target to determine association error $e_k = y_k - t_k$. Based on e_k,, ($_j$ which is the portion of error correction weight adjustment for $\mathbf{w}_{jk}$ that is due to an error at output unit Y_k is calculated as follows:

$$\partial_k = e_k \theta_k + \sum_{j=1}^{n} z_j w_{jk},$$

and sent to all neurons in the previous layers. (Similarly ($_j$ is calculated and compared for each hidden unit in Z_j. After all the (factors have been determined the weights for all layers are updated simultaneously.

Step 6 When the training converges and the system error decreases below an acceptable threshold, the ANN is considered to be trained and then applied over the testing data set.

Appendix B. Rule induction ID3 algorithm

The rule induction ID3 algorithm is given below:

Step 1 Choose an attribute X with values $x_1,\dots,x_n$.
Step 2 Categorize the data set according to attribute X. Each of the set of examples C will have a value x_i for X.
Step 3 C is sorted out into subsets $c_1,\dots,c_n$ where, c_1 contains those examples in C with values x_1 of X and so forth.
Step 4 The probability of being in class C_i is $P(C_i)$. The attribute X compute measures of uncertainty of classification,

$$E(c) = -\sum_{i=1}^{n} p(C_i)\log_2 p(C_i).$$

Step 5 Choose the attribute which produces the lowest uncertainty of classification.
Step 6 Continue steps 1–5 for the selection node at the next level of the decision tree.
Step 7 Stop when all $E(C)$ values becomes 0.

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