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A Meta-Learning Approach to Predicting Financial Statement Fraud

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ABSTRACT: An "ultimate learning algorithm" is one that produces models that closely match the real world's underlying distribution of functions. To try to create such an algorithm, researchers typically employ manual algorithm design with cross-validation. It has been shown that cross-validation is not a viable way to construct an ultimate learning algorithm. For machine learning researchers, "meta-learning" should be more desirable than manual algorithm design with cross-validation. Meta-learning is concerned with gaining knowledge about learning methodologies.

One meta-learning approach involves evaluating the suitability of various algorithms for a learning task in order to select an appropriate algorithm. An alternative approach is to incorporate predictions from base algorithms as features to be evaluated by subsequent algorithms. This paper reports on exploratory research that implemented the latter approach as a three-layer stacked generalization model using neural networks, logistic regression, and classification tree algorithms to predict all categories of financial fraud. The purpose was to see if this form of meta-learning offered significant benefits for financial fraud prediction.

Fifteen possible financial fraud predictors were identified based on a theoretical fraud model from prior research. Only public data for these possible predictors were obtained from U.S. Securities and Exchange Commission filings from the period 1995–2002 for a sample of 50 fraud and 50 non-fraud companies. These data were selected for the year prior to when the fraud was initiated. These variables were used to create a variety of neural network, logistic regression, and classification tree models while using holdout sample and cross-validation techniques.

A 71.4 percent accurate neural network model was then stacked into a logistic regression model, increasing the prediction accuracy to 76.5 percent. The logistic regression model was subsequently stacked into a classification tree model to achieve an 83 percent accuracy rate. These results compared favorably to two prior neural network studies, also employing only public data, which achieved 63 percent accuracy rates. Model results were also analyzed via probability-adjusted overall error rates, relative misclassification costs, and receiver operating characteristics.

The increase in classification accuracy from 71 percent to 83 percent, the decline in estimated overall error rate from 0.0057 to 0.0035, and the decline in relative mis-

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classification costs from 2.79 to 0.58 suggest that benefits were achieved by the meta-learning stacking approach. Further research into the meta-learning stacking approach appears warranted.

Keywords: meta-learning; fraud prediction; model stacking; classification tree algorithm; neural network; logistic regression.

INTRODUCTION

During recent years, financial fraud, as exemplified by the Enron, WorldCom, Parmalat, and Adelphia corporate scandals, has cost investors hundreds of billions of dollars of lost market capitalization, ruined numerous lives, and created a crisis of confidence in corporate governance mechanisms. Since independent audits by the public auditing profession are one of the main elements of the corporate governance structure, the performance of the audit profession has been severely criticized. U.S. auditors have had new auditing standards imposed (such as SAS NO. 99 [AICPA, 2003]) that highlight their responsibility to evaluate fraud risk in audit planning.

Appropriate consideration of the risk of financial fraud is difficult for many auditors. Research indicates that financial fraud annually occurs in only approximately 0.28 (Bishop 2001, 13) of public company audits. One survey indicated that 40 percent of audit partners had never encountered a single material irregularity (defalcations and management fraud) during their entire careers. It also indicated that for those 60 percent of audit partners experiencing a material irregularity, the experience rate was about 1.3 percent of all audit engagements (Loebbecke et al. 1989). This lack of direct experience with financial fraud makes it difficult for auditors to both identify relevant fraud risk factors and weigh them appropriately.

Financial fraud risk has historically been assessed by auditors reviewing a list of potential financial fraud risk indicators, or "red flags." Auditors consider both the quantity and specific configurations of the fraud risk indicators to evaluate financial fraud risk. This approach is problematic, however, since there is no one-to-one mapping of the fraud risk indicators and actual financial fraud. Hackenbrack (1993) found high variability in the importance ratings assigned by auditors to various fraud risk factors. He also found that auditors assigned primarily to smaller-company audits placed less emphasis on fraud risk factors than did auditors assigned primarily to large clients. During the last decade researchers have developed a limited number of quantitative fraud risk estimation models via techniques such as logistic regression and neural networks. The fraud risk estimation models were developed using standard cross-validation techniques. These models have not been widely adopted by the audit profession, due to concerns about their robustness in a real-world setting.

Meta-learning has been developed as a means of designing robust learning systems (Peng et al. 2002). It provides an alternative approach to manual construction for developing learning systems. Meta-learning is concerned with gaining knowledge about learning methodologies. One meta-learning approach involves evaluating the suitability of various algorithms for a learning task in order to select an appropriate algorithm. An alternative approach, utilized in this research, is to incorporate predictions from base algorithms as features to be evaluated by subsequent algorithms. This approach was implemented as a three-layer stacked generalization model that incorporates the financial fraud predictions of neural network, logistic regression, and classification tree algorithms. "Stacked generalization is considered a form of meta-learning because the transformation of the training set conveys information about the predictions of the base-learners (i.e., conveys meta-knowledge)" (Vilalta et al. 2002, 37).

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This research was exploratory, with the primary purpose of determining whether the "stacking" form of meta-learning offered significant benefits for this task when compared with the performance of the individual algorithms.

A theoretical fraud model from prior research was used to identify 15 variables that were possible financial fraud predictors. Data from public U.S. Securities and Exchange Commission filings for these possible predictors were then obtained for a sample of 50 fraud and 50 non-fraud companies from the period 1995–2002. These data were selected for the fiscal year *prior* to when the financial fraud was reported to have been initiated. The variables were then used to create a variety of neural network, logistic regression, and classification tree models while using holdout sample and cross-validation techniques. These models established base prediction level accuracy for the data set.

A 71.4 percent accurate neural network model was stacked into a logistic regression model. This initial stacking increased the classification accuracy to 76.5 percent. The logistic regression model was subsequently stacked into a classification tree model. The classification tree model had an 83 percent accuracy rate. This accuracy rate compared favorably to the 63 percent accuracy rate achieved by neural networks in both the Green and Choi (1997) and Fanning and Cogger (1998) studies. These were the only two identified prior studies that used only public data sources, as did this study. The design of this study was significantly different from both of the prior neural network studies. The Green and Choi (1997) study limited its fraud prediction to revenue cycle frauds, which constitute only approximately 50 percent of financial frauds (Committee of Sponsoring Organizations of the Treadway Commission [COSO] 1999). Fanning and Cogger (1998) were concerned with fraud detection in the initial year of the fraud rather than fraud prediction from years prior to the fraud initiation. Model results were analyzed via actual error rates, probability-adjusted overall error rates, relative misclassification costs, and receiver operating characteristics.

This study contributes to the financial fraud research stream by exploring the use of a three-layer stacked generalization meta-learning model that combines outputs of neural network, logistic regression, and classification tree models for predicting financial statement fraud. The increase in classification accuracy from 71 percent to 83 percent, the decline in estimated overall error rate from 0.0057 to 0.0035, and the decline in relative misclassification costs from 2.79 to 0.58 suggest that benefits were achieved by the meta-learning stacking approach. Further research into the meta-learning stacking approach appears warranted.

PRIOR LITERATURE ON QUANTITATIVE FRAUD PREDICTION MODELS

Early fraud research focused on identifying individual "red flags" (fraud risk indicators) that were present in financial statement frauds. Albrecht et al. (1980) identified 95 red flags from a review of literature and known fraud cases. A subsequent study of these red flags by Albrecht and Romney (1986) found 31 of 87 red flags to be significant predictors of fraud. The red flags identified in these studies formed the basis for current auditing professional standards and subsequent research into financial fraud prediction.

The Albrecht fraud risk indicator research led practicing auditors to use a red flag checklist approach in audit planning to identify audits where fraud risk is higher. This approach involves an auditor reviewing a lengthy checklist of possible red flags and checking off the ones that are present in the audit. Judgment is then used to decide how to respond to the presence or absence of one or more of the individual fraud risk indicators.

The red flag checklist approach to financial fraud auditing has persisted despite a 1989 field experiment by Pincus (1989), who found that subjects without a red flag checklist were able to outperform subjects with a red flag checklist in predicting fraud from reviewing a comprehensive

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audit case. Her subjects were 137 auditors at a large CPA firm. About one-half of the subjects used a red flag checklist; about one-half did not, but rather relied solely on their past experience and knowledge. The audit cases presented to the subjects varied between a fraud and a non-fraud situation. One possible explanation for the experimental result is that due to the large number of potential red flag cues on a red flag checklist, the red flag checklist subjects focused more on irrelevant red flag cues, thereby focusing less on relevant red flag cues—a "dilution" effect. The unaided subjects, on the other hand, focused only on the more relevant cues suggested to them by their past experience and knowledge.

Loebbecke and Willingham (1988) developed, through examination of numerous SEC Accounting and Auditing Enforcement Releases for the presence of various red flags, a model proposing that fraud occurs when the following three factors occur: conditions, motivation, and attitude. This apparently was the first theoretical financial fraud model in the U.S. audit literature.

The Loebbecke and Willingham (1988) three-factor financial fraud model was subsequently tested by Loebbecke et al. (1989) in a study that employed 77 material financial reporting fraud cases from a single international auditing firm. They partially validated the model by finding that at least one of the three model components was present in 88 percent of the fraud cases. They used a fraud-only sample, and validation on non-fraud cases was not undertaken.

The three-factor financial fraud model in Loebbecke and Willingham (1988) was further validated via a study by Bell et al. (1993), who used a cascaded logit model to show that red flags (fraud risk indicators) have significant predictive ability. They used the same sample of 77 fraud cases used in Loebbecke et al. (1989), but also added 305 non-fraud cases. Thus, in contrast to Loebbecke et al. (1989), Bell et al. (1993) used both fraud and non-fraud cases and a validation sample. The first stage utilized the red flag cues to reach assessments of the three components of the Loebbecke et al. (1989) study (conditions, motivation, attitude), and the second stage used these three assessments to arrive at an overall assessment of management fraud risk. Their holdout sample accuracy was 85.7 percent.

The Bell et al. (1993) study was followed by one from Fanning et al. (1995), who applied logistic regression and two neural network models to the same data set as Bell et al. (1993). The neural network models were developed via back-propagation neural networks, a type of knowledge induction technique. They developed a neural network that was 90 percent accurate on a validation sample. The network, however, used a total of 47 input variables reflecting various red flag questions.

Hansen et al. (1996) used a logistic version of the Generalized Qualitative Response Model to predict fraud using the same data as Bell et al. (1993). They achieved an 89.3% accuracy rate on holdout samples developed using a 19-fold classification method.

Bell and Carcello (2000) analyzed a number of logistic regression derived quantitative fraud risk models. Their research was based on the same 77 fraud engagements and 305 non-fraud engagements that had been used in Bell et al. (1993). These data were from a single auditing firm and were primarily from the 1980s, but some dated back to the late 1960s. Their data consisted of fraud cases where financial fraud had been discovered by the auditors. Logistic regression produces an output that can be interpreted as the probability of fraud. The "best" model employed seven variables and was 75 percent accurate on a 202-company holdout sample using a fraud cutoff probability of 50 percent. Thus, the conclusion from this line of research, employing the same data set, was that reasonably accurate, quantitative financial fraud prediction models using a subset of red flags were possible. The limitation, however, is that the whole line of research was based on a single sample from a single auditing firm that dated back to the 1960s. It was not clear whether these results would hold up with other data sets from more recent time periods.

Since prior research had shown logistic regression based financial fraud prediction models to be reasonably effective, Eining et al. (1997) did a laboratory experiment to examine how auditors

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might fare with such a model. They used auditors from one Big 6 firm to examine the effectiveness of three types of decision aids in helping auditors assess the risk of management fraud. They looked at red flag checklists, a logistic regression model, and an expert system. Their subjects who received the logistic regression model output "discriminated among the cases significantly better than those with no assessment (checklist and unaided control group)" (Eining et al. 1997, 2). Subjects who used the expert system outperformed the logistic regression subjects even though "the only difference between the expert system and the logit model was the inclusion of constructive dialogue in the expert system" (Eining et al. 1997, 2). In other words, the expert system provided them the same data as the logistic regression model but "talked the subjects through the decision process," thereby increasing their reliance on the logistic regression model outputs.

Green and Choi (1997) followed the neural network approach of Fanning et al. (1995). Green and Choi (1997) published a quantitative fraud risk model employing endogenous financial data. They limited their fraud prediction to revenue cycle frauds only, a restriction that means their model applied to only approximately 50 percent of all public company financial statement frauds per the COSO (1999) report. Their fraud sample consisted of 86 public company financial statements from the period 1982–1990 that were subsequently found to contain fraud. The fraud sample was matched to 86 non-fraud public companies on the basis of year, size, and industry. They developed three neural network models using a variety of trend and ratio variables, which were judgmentally selected. Their best neural network model had an overall accuracy rate of 63 percent and employed eight financial variables. They noted that "An inherent weakness of NNs [neural networks] is that the internal structure makes it difficult to trace the process by which output is reached. This is why NNs lack explanatory capabilities" (Green and Choi 1997, 25). A complex neural network has been described as somewhat equivalent to a "black box," where you can see inputs and outputs but not the operations in the box itself.

A study by Fanning and Cogger (1998) employed neural networks on a sample of 204 fraud/non-fraud cases. They used 20 predictive variables, which were developed based on a review of the prior literature. Their sample was drawn primarily from SEC Accounting and Auditing Enforcement Releases (AAERs). However, they matched fraud and non-fraud companies for "the first fraud year (Fanning and Cogger 1998, 31). This means that they were not predicting fraud but rather trying to detect it once it had occurred. Their neural network based model was 63 percent accurate on a holdout sample. Their accuracy result is virtually identical to the Green and Choi (1997) neural network; this is not surprising, since both studies samples were mostly taken from the same AAERs.

Feroz et al. (2000) report on research that tested the ability of both logistic regression and neural networks to predict the targets of SEC investigations. They analyzed 209 firms mentioned in SEC Accounting and Auditing Enforcement Releases and could find sufficient data for only 42 of these firms. Firms may be investigated by the SEC for reasons other than financial fraud, so this study is similar to but not strictly a fraud study. They used a control sample of 90 additional firms with the same size and SIC codes as the firms that were the subject of SEC investigations, to make up a total sample of 132 firms. They considered only seven publicly available red flags, one of which was prior auditor turnover and one of which was financial distress as measured by a bankruptcy prediction model. Their logistic regression model had an average accuracy of 70 percent and their artificial neural network had an average accuracy of 81 percent when they varied target percentages in the training and testing groups between 10 percent and 50 percent. This compares with an accuracy level of 52 percent for the logistic regression model and 72 percent for the artificial neural network when the training and testing proportions were each 50 percent. All accuracy percentages were adjusted for the prior probability of occurrence.

A very recent study, Chen et al. (2009), reported on the use of logistic regression and neural networks to predict fraud litigation from 1993–2002 in Taiwan. They used a sample of 74 firms

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that had been sued and a matched sample from the same time periods and industries comprising 148 non-sued firms. All firms were publicly traded firms, and the sued firms faced lawsuits based on allegations of fraud. This research employed a questionnaire to gather information from internal auditors about 27 internal control related risk factors for the subject companies. These 27 variables were then evaluated via logistic regression and neural networks. An interesting aspect to this study was that the researchers had 30 CPA subjects from Big 4 audit firms with an average of 11 years' experience read the testing data set to see if they could assess the presence or absence of fraud litigation. The CPAs correctly classified 60 percent of the cases presented to them. A logistic regression model was able to correctly classify 72.8 percent of the testing cases, while a neural network model was able to correctly classify 80.6 percent of the testing cases. These percentages were not adjusted for the prior probability of fraud.

Table 1, Financial Fraud Prediction Models, summarizes nine significant studies from the previous research stream on financial fraud models. It shows that the primary techniques for building financial fraud models have been logistic regression and neural networks. It also shows that accuracy levels for the various different samples have generally ranged from 60 percent to 80 percent on holdout samples. However, it should be noted that only two of the nine studies summarized in Table 1 utilized only publicly available data, as does the current research. These studies, by Green and Choi (1997) and Fanning and Cogger (1998), both achieved 63 percent prediction accuracy.

The two techniques with the highest level of learning in prior fraud prediction research were logistic regression and neural networks. As noted by Peterson and Martinez (2005, 1), "Sometimes a combination of two or more algorithms may be able to perform much better than any of the algorithms individually." The combination of algorithms can be a form of "meta-learning."

META-LEARNING

This research is an exploratory study employing a meta-learning approach. Meta-learning attempts to distill "meta-knowledge" from a knowledge base. Meta-knowledge may be defined as global knowledge or global models. This contrasts with context-specific knowledge, which only applies to a particular problem or a particular method of knowledge extraction. One problem with individual learning algorithms, which was noted by Giraud-Carrier and Provost (2005), is that each contains a bias; therefore, the models derived from them are somewhat context-specific, depending on modeling techniques, a set of assumptions, and judgments made in applying them.

A "meta-model" is a model that attempts to solve the problem of combining different classifier or predictor outcomes into an integrated model. The practical side is that it may improve over the individual models developed from specific knowledge extraction methods or specific machine learning algorithms.

The meta-learning methodology employed in this study is called "stacking" or "stacked generalization." Basically, it is the combining of predictions from models developed by different learning algorithms. The output of the different models forms the "meta-data." This meta-data is then combined to form a new prediction.

This study builds on prior research by using outputs from logistic regression, neural networks, and decision tree derived models to build a meta-model. This approach is illustrated in Figure 1, Meta-Model Approach in This Study.

The value of the meta-model approach is evaluated via a comparison of actual error rates, probability-adjusted overall error rates, relative misclassification costs, and receiver operating characteristics for the meta-model versus the underlying models.

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TABLE 1

Financial Fraud Prediction Models

Year	Author(s)	Model Type	Number of Variables	Number of Cases	Model Accuracy on Holdout Sample
1989	Loebbecke, Eining, and Willingham	General Model	3	77 Fraud	88% of Fraud Cases Had At Least 1 of 3 Variables
1993	Bell, Szykowny, and Willingham	Cascaded Logistic Regression	47-First Stage 3-Second Stage	77 Fraud/305 Non-Fraud	85.7%
1995	Fanning, Cogger, and Srivastava	Logistic Regression and Neural Networks	47	77 Fraud/305 Non-Fraud	87% Logistic Regression and 90% Neural Networks With Varying Validation Samples
1996	Hansen, McDonald, Messir, and Bell	Generalized Qualitative-Response Model [EGB2]	47	77 Fraud/305 Non-Fraud	89.3%
1997	Green and Choi	Neural Network	8	86 Fraud/86 Non-Fraud	63%
1998	Fanning and Cogger	Neural Network	20	102 Fraud/102 Non-Fraud	63%
2000	Bell and Carcello	Logistic Regression	7	77 Fraud/305 Non-Fraud	75%
2000	Feroz, Kwon, Pastena, and Park	Logistic Regression and Neural Network	7	42 Fraud/90 Non-Fraud	52% Logistic Regression and 72% Neural Network
2006	Chen, Huang, and Lin	CPAs Unaided Judgment, Logistic Regression and Neural Networks	27	74 Fraud/148 Non-Fraud [Taiwan Data]	60% CPAs, 73% Logistic Regression, and 81% Neural Network

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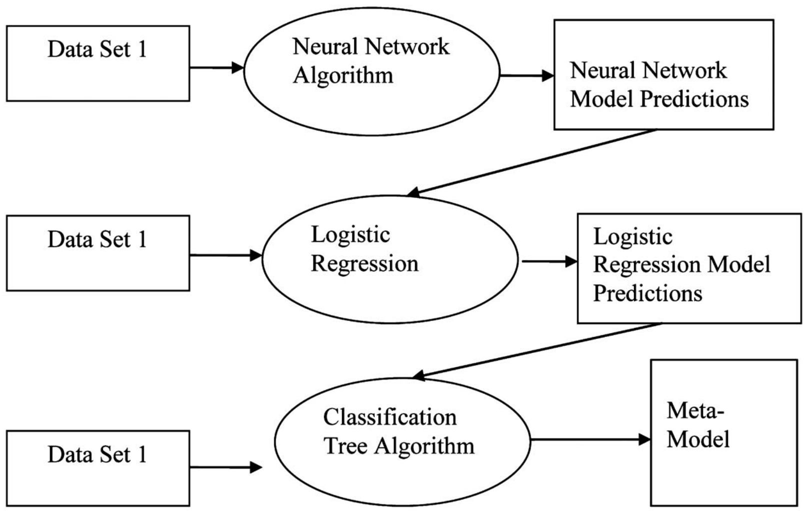
FIGURE 1
Meta-Model Approach in This Study



IDENTIFICATION OF FRAUD VARIABLES

Gillett and Uddin (2005) reported on a financial fraud study that employed structural equation modeling on survey data received from 139 CFOs. The data were generated by having the CFOs respond to questions about five different financial fraud scenarios. Gillett and Uddin (2005) developed a final model that had nine interrelated factors that influenced the CFOs' intentions to commit financial fraud.

One problem with implementing the Gillett and Uddin (2005) theoretical fraud model in audit practice is that auditors are not able to directly assess the nine factors in the model. Another problem is that their model only included factors that influenced *intentions* to commit financial fraud. The fraud standards in SAS NO. 99 described the following three elements of fraud that were derived from the Loebbecke and Willingham (1988) model:

- incentive/pressure;
- attitude/rationalization; and
- opportunity.

Fraud *intentions* encompass both incentive/pressure and attitude/rationalization, but not opportunity. Thus, the Gillett and Uddin (2005) model fails to include the SAS NO. 99 factor of "opportunity."

To overcome the previous limitation, I created an expanded version of the Gillett and Uddin (2005) model, labeled the Hypothesized Financial Fraud Model, that included the third fraud element: "opportunity." Fraud intentions are influenced by the Gillett and Uddin (2005) "rationalization," "subjective norm," and "motivation" factors. These three factors fit the SAS No. 99 "attitude/rationalization" and "incentive/pressure" fraud elements. The "opportunity" factor, which corresponds to the SAS No. 99 "opportunity" fraud element, has been added to the Gillett and Uddin (2005) model.

In order to make predictions with the Hypothesized Financial Fraud Model, it is necessary to

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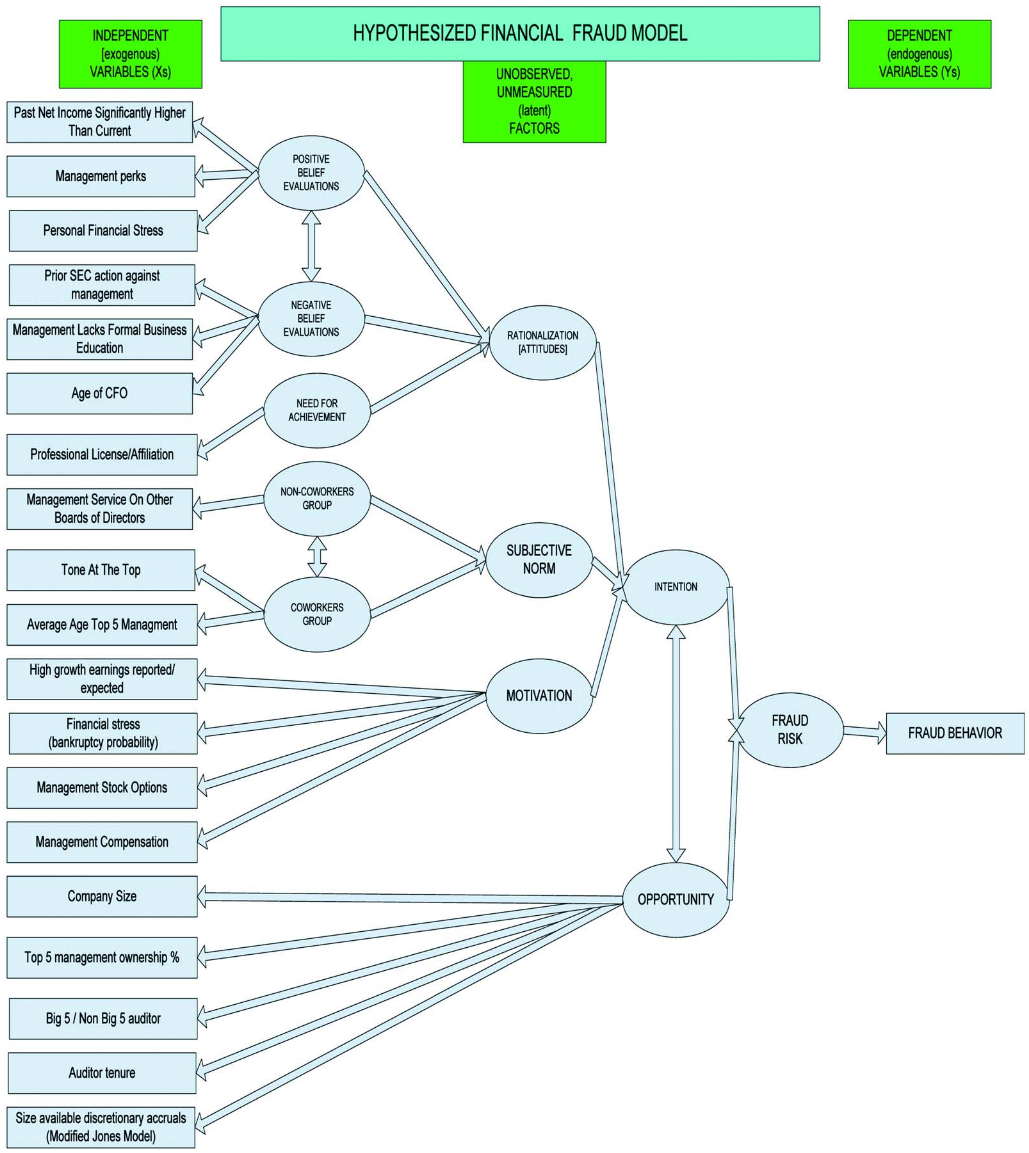
develop data for variables that are surrogates for the elements in the model. Prior research was reviewed to identify 19 potential independent variables that were thought to capture aspects of the theoretical model. These 19 potential independent variables were then linked to the theoretical factor to which they are thought to correspond in Figure 2, Hypothesized Financial Fraud Model with Possible Independent Variables.

FIGURE 2
Hypothesized Financial Fraud Model with Possible Independent Variables



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The next step in this research was to seek data for the 19 potential variables from public data sources.

SAMPLE SELECTION

A review of public data sources indicated that low-cost, readily available public financial data were present for only some of the 19 potential theoretical independent variables. Accordingly, seven of the 19 variables were dropped from consideration in this study.

Different quantitative measures were created for the 12 variables from the literature review that remained. Some of the literature review variables had more than one quantitative measure; thus this study ended up with 15 potential variables for which empirical quantitative measures were subsequently obtained from publicly available data.

Similar to the Feroz et al. (2002) study, an analysis of SEC Enforcement Releases was made, starting with the year 2002. Companies were selected if the enforcement release alleged fraudulent financial reporting. Once a company name was determined, SEC filings were examined to see if data for the 15 variables in this study could be located. If the company could not be located, then the company was discarded and another company was selected. It was necessary to go back to 1998 in order to locate 50 companies that had allegations of financial fraud. Due to a lack of SEC Enforcement Releases in the target time period, a slight deviation from the previous procedure was necessary toward the end of the data collection in order to locate a total of 50 financial fraud companies. This change resulted in five companies being selected on the basis of financial fraud allegations in the financial press, rather than SEC Enforcement Releases. Once a company was selected, financial statements for the fiscal period *prior to when the fraud was publicly reported to have been initiated* were located. This necessitated going back as far as 1995 to locate data for a few companies. Since data prior to the reported initiation of fraud were used, this is a fraud prediction study rather than a fraud identification study.

A matched-pair design was used since the goal was a two-class discrimination. Fifty non-fraud companies were matched to the 50 fraud companies based on (1) SIC numbers, (2) a market value equal to or larger than the fraud company, and (3) a positive change in net income percentage that was less than 25 percent. The combination of three matching criteria meant that not all three criteria were exact matches. For example, the fraud companies had higher average total assets but a lower average net income. The market value criterion for matching was included in an effort to make market pressures similar for the two samples. It also ensured that companies would be of approximately the same total size.

The positive change in net income percentage criterion was also included to try to make market pressures or expectations similar for the two samples. Many fraud cases result when management faces market pressure to "make the numbers" and goes beyond GAAP to do so. A financial stress variable was included among the variables as it was believed that this variable would act to signal companies that committed fraud due to a negative net income trend.

The financial data were obtained from the October 31, 2005, Compustat database using Standard & Poor's *Research Insight* software (S&P 2005). The nonfinancial data—such as age of CFO, age of top five officers, value of stock options for top five officers, other compensation for top five officers, and top five officer ownership percentages—were obtained from a manual review of SEC filings.

The final result of this process was that a sample of 50 fraud and 50 non-fraud public companies was used to obtain data for 15 variables. These 15 variables were then evaluated via standard statistical tests for both their individual significance/ability to predict fraud.

Table 2, SIC Frequency for Companies Included in Sample, shows that the two 50-company samples contained similar proportions of companies in the various SIC categories.

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TABLE 2

SIC Frequency for Companies in Sample

Two-Digit SIC Code	Fraud Companies	Non-Fraud Companies
10–19	0	2
20–29	6	7
30–39	9	7
40–49	7	6
50–59	8	7
60–69	1	1
70–79	18	18
80–89	1	2
90–99	0	0
Total	50	50

Table 3, Initial Data Year Frequency, shows the time periods from which the data were drawn. You will note that the bulk of the sample is prior to 2002 and therefore would be prior to the implementation of the Sarbanes-Oxley Act.

INDIVIDUAL VARIABLE SIGNIFICANCE

As shown in Table 4, Company Size Data for Initial Data Year, the companies in the fraud and non-fraud portions of the sample were approximately equal when company size is measured on total revenue, with both halves of the overall sample averaging $6.6 billion in total revenue. However, when company size is measured based on total assets the fraud companies were approximately double in size, at $20 billion versus $10 billion. This indicates that the market value selection criterion was only partially successful in matching companies based on size.

The average net income for the 50 fraud companies was $1.6 million, versus $356 million for the fifty non-fraud companies. This difference was created by a small portion of the overall sample. The following cross-tabulation of decile net incomes by fraud and non-fraud status reveals

TABLE 3

Initial Data Year Frequency

Initial Data Year	Fraud Companies	Non-Fraud Companies
1995	1	1
1996	1	1
1997	0	0
1998	7	7
1999	12	12
2000	15	14
2001	12	13
2002	2	2
Total	50	50

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TABLE 4

Company Size Data for Initial Data Year

Item Description		Fraud Companies	Non-Fraud Companies
Revenue	Highest	40,656,000,000	165,639,000,000
	Average	6,553,195,000	6,582,795,000
	Minimum	11,727,000	493,000
	Standard Deviation	10,784,000	24,246,240,000
Net Income	Highest	5,636,000,000	6,295,000,000
	Average	1,613,225	355,917,581
	Minimum	−7,751,000,000	−240,000,000
	Standard Deviation	2,049,275,040	1,100,295,110
Total Assets	Highest	306,577,000,000	255,018,000,000
	Average	19,590,000,000	10,119,980,000
	Minimum	14,064,000	15,301,000
	Standard Deviation	53,904,750,000	38,142,540,000

that, when converted to deciles based on the 100 company sample, the net income variable for the sample halves is reasonably matched. Further, a t-test for means and an F test for variances both reveal no significant difference in the deciled net income data.

Decile	Non-Fraud #	Fraud #	Total
10%	3	6	9
20%	3	6	9
30%	4	5	9
40%	5	4	9
50%	10	9	19
60%	4	5	9
70%	8	1	9
80%	7	2	9
90%	4	5	9
100%	2	7	9
Total	50	50	100

Table 5, Variable Definitions, lists the 15 variables employed in this study and their related definitions. The variables represent implementations for the independent variables in the Hypothesized Fraud Model listed in Figure 2 for which I could obtain data. I attempted to obtain at least one variable affecting each of the unobservable latent factors in the Fraud Model.

Table 6, Significance of Individual Variables, lists the descriptive statistics for the 15 variables for the fraud/non-fraud subsamples. It also shows the Pearson correlation of each variable with fraud/non-fraud status and the fact that only two of the variables were individually significant at a 0.05 two-tailed level of significance.

NEURAL NETWORK MODELS

The first model development approach used in this study was to develop a variety of neural networks via a standard feedforward back-propagation approach. The sigmoid transfer function was utilized. All neural networks were specified with one hidden layer with three nodes. Analysis was performed using the commercial neural network package *XLMiner* (Resampling Stats, http://

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TABLE 5
Variable Definitions

Variable Number	Variable	Variable Definition
1	Change Net Income	Average of net incomes for three prior years divided by current period net income expressed as decile rank based on total sample (1 = lowest decile, 10 = highest)
2	Age CFO	Age of chief financial officer (either financial VP or controller)
3	Age Top 5 Officers	Average age of top five members of management (inclusion in top five based on highest compensation)
4	Sales Growth	Slope of sales revenue line for last four years
5	ML Bankruptcy Probability	Probability of bankruptcy per McKee-Lensberg bankruptcy model (McKee and Lensberg, 2002)
6	Mgmt Stock Options	Total value of stock options outstanding for top five members of management expressed as decile rank based on total sample (1 = lowest decile, 10 = highest)
7	Mgmt Compensation	Compensation (excluding stock options but including bonuses) for top five members of management expressed as decile rank based on total sample (1 = lowest decile, 10 = highest)
8	Company Size	Base 10 log of total assets
9	Top 5 Mgmt Ownership	Percentage of company stock owned by top five members of management
10	Big 4 Auditor	1 = Big 4 audit firm, 0 = other audit firm
11	Auditor Tenure	Number of years that current year auditor has audited company
12	Change In Total Accruals	Total accruals for current year minus total accruals for prior year
13	Earnings Quality	Correlation coefficient of operating cash flow to net income for three year period
14	Size Total Accruals	Total accruals divided by total assets from prior period (Total accruals = change in current assets minus change in current liabilities minus change in cash plus change in short-term debt minus depreciation/amortization expense)
15	Change In Auditor	0 = no change in auditor from prior year, 1 = change in auditor from prior year

www.resample.com/xlminer/capabilities.shtml). Only variables with an individual significance of 0.11 or lower based on Pearson correlation with fraud status were included in this analysis. Eight neural networks were developed altogether, with sample sizes ranging from 91 to 100, depending on which variables were used. Their accuracy varied from 64 percent to 69 percent. The best result achieved of 69 percent accuracy was achieved with the variables V4, V7, and V14. The purpose of this work was to identify the best predictive variable combinations and the base accuracy levels for this approach.

At this point, the sample was split in half, with 50 fraud and non-fraud companies as the development sample and 50 fraud and non-fraud companies as the holdout sample. Prior research indicated that financial stress was related to financial fraud risk. Accordingly, V5-ML Bankruptcy Probability was judgmentally selected as an input along with V8-Company Size and V11-Auditor Tenure. Models based on these variables were 68 percent and 71 percent accurate when developed on half the sample and tested on the holdout half. Table 7, Neural Network Model, shows the accuracy results and the node weightings for the neural network model for which the predictions were used as inputs in the meta-model.

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TABLE 6

Significance of Individual Variables

Variable	Non-Fraud Companies Mean	Non-Fraud Companies Std. Dev.	Fraud Companies Mean	Fraud Companies Std. Dev.	Total Sample Variable Pearson Correlation With Fraud Status	Total Sample Two-Tailed Significance
V1-Change Net Income	−97.47	959.71	−358.29	1415.38	−.11	.31
V2-Age CFO	47.2	7.37	45.56	7.10	−.11	.26
V3-Age Top 5 Officers	50.03	4.90	48.44	6.21	−.14	.16
V4-Sales Growth	.81	1.21	1.72	3.73	.17	.10
V5-ML Bankruptcy Probability	.29	.30	.36	.29	.12	.24
V6-Mgmt. Stock Options	87,162,314	421,421,732	116,622,805	284,280,547	.04	.70
V7-Mgmt. Compensation	2,897,782	2,640,526	5,341,795	8,269,177	.20	.05**
V8-Company Size	8.79	.99	9.21	1.07	.20	.05**
V9-Top 5 Mgmt. Ownership	12.01	13.72	8.31	12.87	−.14	.17
V10-Big 4 Auditor	.90	.30	.94	.24	.07	.47
V11-Auditor Tenure	3.14	1.82	2.56	1.79	−.16	.11
V12-Change In Total Accruals	−.04	.80	−4.16	27.69	−.10	.33
V13-Earnings Quality	.88	.38	.74	.59	−.14	.18
V14-Size Total Accruals	.09	.78	−.11	.32	−.17	.11
V15-Change In Auditor	.10	.30	.20	.40	.14	.19

** Significant at .05 or lower level.

Variables 1, 6, and 7 are reported at the actual values and not their deciled values in this table.

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TABLE 7
Neural Network Model

Neural Network Model Accuracy

		Model Predictions		
		Fraud	**Non-Fraud**	**Percentage Correct**
Actual	Fraud	22	24	47.8%
	Non-Fraud	2	43	95.6%
Overall		24	67	71.4%

Neural Network Inter-Layer Connection Weights

	Input Layer			
Hidden Layer #1	**ML Bankruptcy Probability**	**Company Size**	**Auditor Tenure**	**Bias Node**
Node #1	2.05	−2.05	−0.58	−1.85
Node #2	3.46	−0.05	−1.15	1.33
Node #3	0.62	4.12	−2.91	−2.59

	Hidden Layer #1			
Output Layer	**Node #1**	**Node #2**	**Node #3**	**Bias Node**
1 [Fraud]	−1.58	1.84	1.59	−1.73
0 [Non-Fraud]	1.54	−1.80	−1.61	1.72

LOGISTIC REGRESSION BASED MODELS

The second data analysis approach used in this research was logistic regression. The standard statistical package SPSS version 13.0 for Windows was used for this analysis. A total of ten different binary logistic regression models were developed. Their accuracy levels on 50 percent random validation samples ranged from 61 percent to 70 percent. All ten models were statistically significant. The purpose for developing these models was to evaluate the accuracy rates for this technique.

CLASSIFICATION TREE MODELS

Quinlan's (1986) classification tree induction technique was used to initially analyze the 15 variables. This technique breaks data sets down into classification trees with various nodes leading to a final node (leaf) containing a classification result. These trees can be expressed as a set of If-Then rules.

RuleQuest Research's *See5 Release 2.03* (RuleQuest, http://www.rulequest.com) commercial software was used on the data. *See5* uses entropy measure based induction learning to create classifiers which can be expressed as either classification trees or sets of if-then rules. The classifiers are created by evaluating the information gain at each potential node of the classification tree (Ludwig and Piovoso 2005, 154). A more detailed description and examples of how this approach works are available in McKee (1995).

The purpose of this analysis was to evaluate accuracy rates for this technique. Two models were developed. One utilized V-2, V-6, and V-9 in a seven-rule model and achieved a 60 percent

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accuracy level with tenfold cross-validation. The second model used V5, V8, V9, and V11 in a three-rule model and achieved 69 percent accuracy with tenfold cross-validation.

The nature and direction for the variables in the individual rules in both 100-company sample *See5* models appear to be consistent with fraud theory. Thus, this classification tree analysis demonstrates that it is possible to predict fraudulent financial reporting with a relatively small set of variables.

META-MODEL

The next stage of this research was to construct a meta-model that predicted fraud based on the predictions from the underlying individual models. There are a wide variety of approaches, some very complex, that could be used to combine predictions into a meta-model. The model "stacking" approach used in this study was to include the binary prediction, fraud or non-fraud, from the first fraud model as an input variable in the second fraud model and then repeat this by including the binary prediction, fraud or non-fraud, from the second fraud model as an input variable in the third fraud model. The following order was judgmentally selected for the model sequencing:

Neural Network Prediction→Logistic Regression Prediction→Classification Tree Prediction.

The previously discussed 71.4 percent accurate neural network model using variables V5-ML Bankruptcy Probability, V8-Company Size, and V11-Auditor Tenure was used as the first fraud model. The binary fraud predictions from the neural network model and the 15 variables were then entered as the 16 input variables for the logistic regression model.

As displayed in Table 8, Accuracy of 16-Variable Logistic Regression Model Used in Meta-Model**,** the logistic regression model was 76.5 percent accurate. The three statistically significant (.10 or less) variables in the logistic model were the Neural Network Model Prediction, V12-Change in Total Accruals, and V14-Size of Total Accruals. The Logistic Regression model binary fraud predictions and the 15 variables were then used as 16 variable inputs to develop a classification tree model.

The resulting classification tree model was 82.7 percent accurate. The variables used in this model were Logistic Regression Probability, V14-Size of Total Accruals, V8-Company Size, and V5-ML Bankruptcy Probability. This model utilized only 81 companies of the 100 companies since 19 of the companies were missing data on one or more of the required variables.

The final model can be expressed as the following set of If-Then rules:

IF Logistic Regression Probability is ≤ 0.64; and
IF V14-Size of Total Accruals is 1 ≤ 0.0875; and
IF V8-Company Size is ≤ 8.43, THEN classify as non-fraud.

TABLE 8

Accuracy of 16 Variable Logistic Regression Model Used In Meta-Model

		Model Predictions		
		Fraud	**Non-Fraud**	**Percentage Correct**
Actual	Fraud	29	12	70.7%
	Non-Fraud	7	33	82.5%
Overall		36	45	76.5%

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IF V8-Company Size is $>$ 8.43 and V5-MLBankruptcy Probability is $\leq$ 0.22,
THEN classify as non-fraud.
ELSE classify as fraud.

The error results for the 81 companies using the final model are given in the following matrix:

		Actual Fraud Status		Totals	Accuracy
		Fraud	Non-Fraud		
Predicted Fraud Status	Fraud	38	3	41	92.7%
	Non-Fraud	11	29	40	72.5%
Totals		49	32	81	82.7%

Note that only three of the 41 fraud companies were misclassified, for a 92.7 percent accuracy rate for this category. On the other hand, 11 of the 40 non-fraud companies were misclassified, for a 72.5 percent accuracy rate in this category.

A listing of the significant variables used in the three models, other than the prediction from the preceding model, is given in the following matrix:

	Neural Network	Logistic Regression	Classification Tree
V5	x		x
V8	x		x
V11	x		
V12		x	
V14		x	x

OVERALL ERROR RATES, PRIOR PROBABILITIES, AND MISCLASSIFICATION COSTS

Overall error rates declined as models were stacked to form the meta-learning model. The accuracy rate of 71.4 percent for the neural network model improved to 76.5 percent when the outputs from this model were stacked into the logistic regression model. The final classification tree model accuracy, which incorporated the logistic regression predictions, was 82.7 percent. Thus, the stacking approach to meta-learning offers improvement in prediction accuracy for this sample.

As noted earlier in this paper, the probability of financial statement fraud for a public company is roughly 0.01, while the probability of not having a financial statement fraud is 0.99. Given that the fraud/non-fraud rates are quite different from equal probabilities, it is important to adjust overall model accuracy for the prior probability of an outcome state. One way this can be done is by calculating an *estimated overall error rate* (EOER) in the following manner:

$$EOER = [Type\ I\ Error \times Probability\ of\ Failure] + [Type\ II\ Error \times Probability\ of\ Failure]$$

(Etheridge et al. 2000, 541).

As displayed in Table 9, Estimated Error Rates for Various Fraud Models, the prior formula was used to calculate the EOER for the fraud models that were part of the meta-learning model. The table shows the EOER decreasing from 0.0057 to 0.0035 as the models are stacked to form the final model.

The EOER adjusts for prior probabilities but not misclassification costs. There is no best way to assess misclassification costs, since their importance depends on who is impacted. Auditors generally consider Type II fraud misclassifications (incorrectly predicting a firm that has fraud as non-fraud) as more expensive than Type I fraud misclassifications (incorrectly predicting a firm that does not have fraud as fraudulent). The reason for this is that the Type I misclassification is

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TABLE 9

Estimated Error Rates For Various Fraud Models

Model Description	Type I Error Rate	Type II Error Rate	Estimated Overall Error Rate (EOER)
Neural Network	.0444	.5217	.0057
Logistic Regression	.1750	.2927	.0047
Classification Tree	.2750	.0732	.0035

EOER = [Type I Error × Probability of Fraud] + [Type II Error × Probability of Fraud]. Probabilities were estimated at .01 fraud and .99 non-fraud for U.S. public companies based on Bishop (2001, 13) fraud rate of .0028 for discovered U.S. public company frauds being judgmentally increased for non-discovered frauds.
(Etheridge et al. 2000, 543–544)

typically resolved through the application of additional audit procedures. There are several techniques that permit misclassification costs to be incorporated into the model development. When this is not done, researchers can use relative cost ratios to study misclassification costs. The estimated relative cost (RC) of using a fraud model is computed as:

$$RC = (Probability\ of\ Type\ I\ Error \times Relative\ Cost\ of\ Type\ I\ Error) + (Probability\ of\ Type\ II\ Error \times Relative\ Cost\ of\ Type\ II\ Error)$$

(Etheridge et al. 2000, 543–544).

Table 10, Relative Misclassification Costs of Meta-Learning Models, uses the previous formula to calculate the RC at cost ratios varying from 1:1 to 50:1 for the three components of the meta-learning model. This table shows a continued improvement in misclassification costs as the models are stacked.

Figure 3, Computed ROC Curves for Meta-Learning Model and Components, shows the performance of the three meta-learning model components in terms of receiver operating curve factors of sensitivity and specificity. The stacked classification tree model equals or exceeds the two models that provided its inputs in terms of sensitivity but is inferior to the logistic regression model in specificity. In other words, compared with the two other models, the stacked classification tree model is more accurate in predicting fraud, but it is less accurate than the logistic regression model in predicting non-fraud.

LIMITATIONS

One limitation of this research is that the sample was not a random selection. Taking a totally random sample of public companies and then analyzing the selected companies for fraud or non-fraud status would be extremely cost prohibitive, given that the yearly financial fraud rate for public companies is estimated to be significantly less than 1 percent. Although generalizing from a nonrandom sample is always problematic, I believe the sample selection method was appropriate given the cost of an alternative selection methodology.

Several aspects of this research were highly subjective. For example, the order of the models entering the meta-model and the selection of the models themselves were judgmentally determined. A different researcher may have made different judgments.

Another potential problem is that it is possible that companies classified as non-fraud may in

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TABLE 10

Relative Misclassification Costs of Meta-Learning Models

Model	Cost Ratio For Type II versus Type I Errors	Estimated Relative Cost for Given Cost Ratio	Sum of Relative Costs for All Cost Ratios
Neural Network	1:1	0.2831	
	10:1	0.4783	
	20:1	0.4990	
	30:1	0.5063	
	40:1	0.5101	
	50:1	0.5124	
			2.7893
Logistic Regression	1:1	0.2338	
	10:1	0.2820	
	20:1	0.2871	
	30:1	0.2889	
	40:1	0.2898	
	50:1	0.2904	
			1.6720
Classification Tree	1:1	0.1741	
	10:1	0.0915	
	20:1	0.0828	
	30:1	0.0797	
	40:1	0.0781	
	50:1	0.0771	
			.5833

Relative Cost (RC) = (Probability of Type I Error × Relative Cost of Type I Error) + (Probability of Type II Error × Relative Cost of Type II Error)
(Etheridge et al. 2000, 543–544)

fact have had undiscovered frauds. The financial press was reviewed for subsequent years to try to minimize this possibility, although this cannot assure that none of the companies actually experienced a financial fraud.

CONCLUSIONS

Prior research on quantitative financial fraud prediction models employed primarily logistic regression and neural networks for model construction. This study makes a significant contribution to the fraud research literature by (1) using more recent sample data than prior studies did, (2) using a classification tree algorithm for predicting financial fraud, and (3) exploring the use of meta-learning for financial fraud prediction. The meta-learning approach in this study involved stacking the results of a neural network and logistic regression models into a classification tree model.

Two prior studies utilizing neural networks and publicly available data achieved a 63 percent financial fraud prediction accuracy on holdout samples. The neural network model that formed the initial layer in this study's stacked model was significantly higher, with 71 percent accuracy on a holdout sample. Furthermore, the stacked model had an 83 percent overall accuracy and was 93 percent accurate in predicting just the financial fraud cases. This is pretty significant given that the data used for the predictions were taken from the financial statements at least a year prior to the

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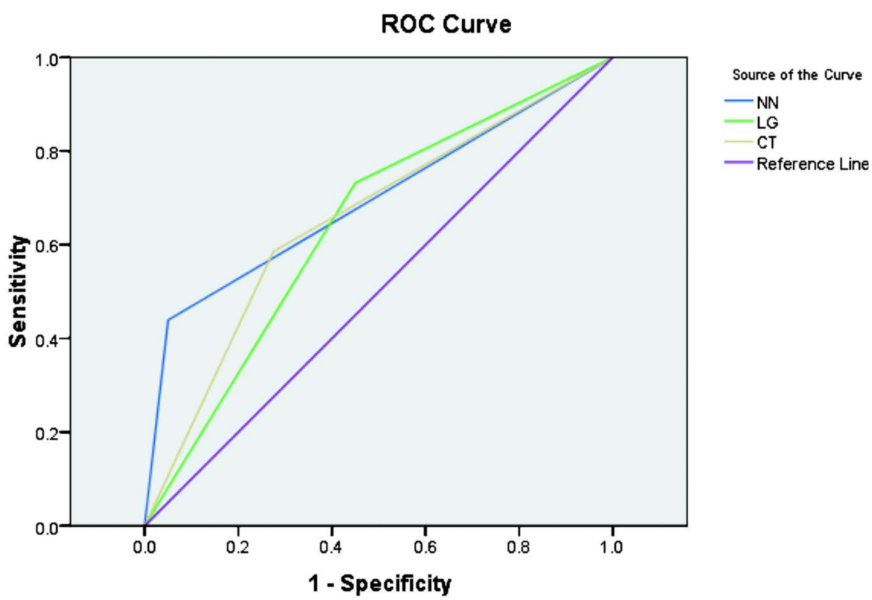
FIGURE 3
Computed ROC Curves for Meta-Learning Model and Components



ROC curve computed on 81 cases with no missing data using SPSS Version 16, with nonparametric assumption and 95% confidence level.

NN=Neural network
LG=Logistic regression
CT=Classification tree

year in which the frauds were initiated. The longer window makes the prediction more difficult than simply trying to classify companies using data from the year in which the fraud was discovered.

The primary purpose of this research was to determine if the stacking form of meta-learning offered significant benefits for the task of financial fraud prediction for public companies. The stacking approach resulted in an increase in classification accuracy from 71 percent to 83 percent, a decline in the estimated overall error rate from 0.0057 to 0.0035, and a decline in relative misclassification costs from 2.79 to 0.58. These three improvements all suggest that benefits were achieved by the meta-learning stacking approach. Further research into the meta-learning stacking approach appears warranted.

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