Detection of financial statement fraud and feature selection using data mining techniques

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A B S T R A C T

Recently, high profile cases of financial statement fraud have been dominating the news. This paper uses data mining techniques such as Multilayer Feed Forward Neural Network (MLFF), Support Vector Machines (SVM), Genetic Programming (GP), Group Method of Data Handling (GMDH), Logistic Regression (LR), and Probabilistic Neural Network (PNN) to identify companies that resort to financial statement fraud. Each of these techniques is tested on a dataset involving 202 Chinese companies and compared with and without feature selection. PNN outperformed all the techniques without feature selection, and GP and PNN outperformed others with feature selection and with marginally equal accuracies.

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1. Introduction

Financial fraud is a serious problem worldwide and more so in fast growing countries like China. Traditionally, auditors are responsible for detecting financial statement fraud. With the appearance of an increasing number of companies that resort to these unfair practices, auditors have become overburdened with the task of detection of fraud. Hence, various techniques of data mining are being used to lessen the workload of the auditors. Enron and Worldcom are the two major scandals involving corporate accounting fraud, which arose from the disclosure of misdeeds conducted by trusted executives of large public corporations. Enron Corporation [17] was an American energy company based in Houston, Texas. Before its bankruptcy in late 2001, Enron was one of the world’s leading electricity, natural gas, pulp and paper, and communications companies, with revenues amounting to nearly $101 billion in 2000. Long Distance Discount Services, Inc. (LDDS) began its operations in Hattiesburg, Mississippi in 1983. The company’s name was changed to LDDS WorldCom [18] in 1995, and later it became WorldCom. On July 21, 2002, WorldCom filed for Chapter 11 bankruptcy protection in the largest such filing in US history at that time.

Financial statements are a company’s basic documents to reflect its financial status [3]. A careful reading of the financial statements can indicate whether the company is running smoothly or is in crisis. If the company is in crisis, financial statements can indicate if the most critical thing faced by the company is cash or profit or something else. All the listed companies are required to publish their financial statements every year and every quarter. The stockholders can form a good idea about the companies’ financial future through the financial statements, and can decide whether the companies’ stocks are worth investing. The bank also needs the companies’ financial statements in order to decide whether to grant loans to them. In a nutshell, the financial statements are the mirrors of the companies’ financial status. Financial statements are records of financial flows of a business. Generally, they include balance sheets, income statements, cash flow statements, statements of retained earnings, and some other statements. A detailed description of the items listed in the various financial statements is given below:

- Balance sheet
  A balance sheet is a statement of the book value of an organization at a particular date, usually at the end of the fiscal year. A balance sheet has three parts: assets, liabilities, and shareholders’ equity. The
difference between the assets and the liabilities is known as the ‘net assets’ or the ‘net worth’ of the company.

- **Income statement**

Income statements, also called Profit and Loss Statement for companies indicate how net revenue (money received from the sale of products and services before expenses are subtracted, also known as the ‘top line’) is transformed into net income (the result after all revenues and expenses have been accounted for, also known as the ‘bottom line’). The purpose of the income statement is to show managers and investors whether the company made or lost money during the period under consideration.

- **Cash flow statement**

A cash flow statement is a financial statement that shows incoming and outgoing funds during a particular period. The statement shows how changes in balance sheet and income accounts affect cash and cash equivalents. As an analytical tool the statement of cash flows is useful in determining the short-term viability of a company, particularly its ability to pay bills.

- **Statement of retained earnings**

The statement of retained earnings, also known as ‘statement of owners’ equity’ and ‘statement of net assets’ for non-profit organizations, explains the changes in company’s retained earnings over the reporting period. It breaks down changes affecting the account, such as profits or losses from operations, dividends paid, and any other items charged or credited to retained earnings. Next, we will describe the key characteristics of financial fraud that can be observed through the financial ratios calculated on the basis of the financial statements published by companies.

### 1.1. Financial ratios

Financial ratios are a valuable and easy way to interpret the numbers found in financial statements. They can help to answer critical questions such as whether the business is carrying excess debt or inventory, whether customers are paying according to terms, whether the operating expenses are too high, and whether the company assets are being used properly to generate income.

- **Liquidity**

Liquidity measures a company’s capacity to pay its liabilities in short term. There are two ratios for evaluating liquidity. They are:

1. **Current ratio** = Total current assets / Total current liabilities
2. **Quick ratio** = (Cash + Accounts receivable + Any other quick assets) / Current liabilities

The higher the ratios the stronger is the company’s ability to pay its liabilities as they become due, and the lower is the risk of default.

- **Safety**

Safety indicates a company’s vulnerability to risk of debt. There are three ratios for evaluating liquidity. They are:

1. **Debt to equity** = Total liabilities / Net worth
2. **EBIT/Interest** = Earnings before interest and taxes / Interest charges
3. **Cash flow to current maturity of long-term debt** = (Net profit + Non-cash expenses) / Current portion of long-term debt

- **Profitability**

Profitability ratios measure the company’s ability to generate a return on its resources. There are four ratios to evaluate a company’s profitability. They include:

1. **Gross profit margin** = Gross profit / Total sales
2. **Net profit margin** = Net profit / Total sales
3. **Return on assets** = Net profit before taxes / Total assets
4. **Return on equity** = Net profit before taxes / Net worth

- **Efficiency**

Efficiency evaluates how well the company manages its assets. There are four ratios to evaluate the efficiency of asset management:

1. **Accounts receivable turnover** = Total net sales / Accounts receivable
2. **Accounts payable turnover** = Cost of goods sold / Accounts payable
3. **Inventory turnover** = Cost of goods sold / Inventory
4. **Sales to total assets** = Total sales / Total assets

Financial statement fraud may be perpetrated to increase stock prices or to get loans from banks. It may be done to distribute lesser dividends to shareholders. Another probable reason may be to avoid payment of taxes. Nowadays an increasing number of companies are making use of fraudulent financial statements in order to cover up their true financial status and make selfish gains at the expense of stockholders. The fraud triangle is also known as Cresseys Triangle, or Cresseys Fraud Triangle. The fraud triangle seeks to explain what must be present for fraud to occur. The fraud triangle describes the probability of financial reporting fraud which depends on three factors: incentives/pressures, opportunities, and attitudes/rationalization of financial statement fraud [37,38]. The fraud triangle is depicted in Fig. 1, and it is discussed below.

When financial stability or profitability is threatened by economic, industry, or entity operating conditions, or excessive pressure exists for management to meet debt requirements, or personal net worth is materially threatened, the management will face the incentives or pressures to resort to fraudulent practice. Pressure can come in the form of peer pressure, living a lavish lifestyle, a drug addiction, and many other aspects that can influence someone to seek gains via financial fraud. When there are significant accounting estimates that are difficult to verify, or there is oversight over financial reporting, or high turnover or ineffective accounting internal audit, there are opportunities for fraud. For instance, a cashier can steal money out of the cash register because it is there. If the cashier is required to drop all cash into an underground safe for which he does not know the combination, opportunity will not exist. When inappropriate or inefficient communication and support of the entity’s values is evident, or a history of violation of laws is known, or management has a practice of making overly aggressive or unrealistic forecasts, then there are risks of fraudulent reporting due to attitudes/rationalization. Rationalization is a grey area in the fraud triangle. Opportunities and incentives exist or they don’t. Rationalization depends on the individuals and the circumstances they are facing [19,37]. Understanding the fraud triangle is essential to evaluating financial fraud. When someone is able to grasp the basic concept of the fraud triangle, they are able to better understand financial frauds, how they occur, why they occur, and what to do to stop them.

### 1.2. Variables related to financial statement fraud

Based on expert’s knowledge, intuition, and previous research, it is important to identify some key financial items that are relevant for detection of financial statement fraud. These are listed below:

- **Z-score**: The Z-score is developed by Altman [2]. It is a formula for measurement of the financial health of a company and works as a tool to predict bankruptcy. It is used to detect financial statement fraud.

![Fig. 1. Components of the fraud triangle.](image-url)
financial fraud as well. The formula for Z-score for public companies is given by:

\[
Z\text{-score} = \frac{\text{Working capital}}{\text{Total assets}} \times 1.2 + \frac{\text{Retained earnings}}{\text{Total assets}} \times 1.4 + \frac{\text{Earnings before income tax}}{\text{Total assets}} \times 3.3 + \frac{\text{Market value of equity}}{\text{Book value of total}} + \frac{\text{Liabilities}}{\text{Sales}} + \frac{\text{Total assets}}{\text{Current liabilities}}
\]

- A high debt structure increases the likelihood of financial fraud as it shifts the risk from equity owner to the debt owner. So, the financial ratios related to debt structure such as (i) Total debt/Total assets and (ii) Debt/Equity need to be carefully considered when searching for indications of fraud.
- An abnormal value reported as a measure of continuous growth such as sales to growth ratio is also a factor that may be indicative of fraudulent financial practice.
- Many items of the financial statements such as Accounts receivable, Inventories, Gross margin etc. can be estimated to some degree using subjective methods and different accounting methods can often lead to different values even for the same company.
- According to previous research, many other financial ratios can be considered for fraud detection, such as Net profit/Total assets, Working capital/Total assets, Net profit/Sales, Current assets/Current liabilities and so on.
- The tenure of CEO and CFO: According to the auditors’ experience and previous research, the high turnover of CEO and CFO may indicate the existence of financial fraud in the company.
- Some qualitative variables such as previous auditor’s qualifications can be considered to determine the likelihood of fraudulent bookkeeping.

Data mining has been applied in many aspects of financial analysis. Few areas where data mining techniques have already been used include: bankruptcy prediction, credit card approval, loan decision, money-laundering detection, stock analysis, etc. However, research related to the use of data mining for detection of financial statement fraud is limited. The main objective of this research is to predict the occurrence of financial information fraud in companies as accurately as possible using intelligent techniques. Financial accounting fraud can be detected by a human expert by using his/her experiential/judgemental knowledge, provided he/she has sufficient expertise. However, in this case, human bias cannot be eliminated and the judgments tend to be subjective. Hence, we resort to data-driven approaches, which solely rely on the past data of fraudulent and healthy companies and their financial ratios. When data mining techniques (most of them barring a few statistical ones are artificial intelligence based) are employed to solve these problems, they work in an objective way by sifting through the records of fraudulent and healthy companies. In the process, they discover knowledge which can be used to predict whether a company at hand will perpetrate financial accounting fraud in future. Data mining techniques have another advantage in that they can handle a large number of records and financial ratios efficiently. According to Kikos et al. [23], artificial intelligence methods have the theoretical advantage that they do not impose arbitrary assumptions on the input variables. An auxiliary aim of this research is to select the most important financial items that can explain the financial statement fraud. The results obtained using this research will be useful for auditors engaged in the prediction of financial statement fraud. In fact, emerging companies can carefully monitor those financial statements for getting long-term advantages in the competitive market. Further, it will be useful for investors who plan to invest in such companies.

The rest of the paper is organized as follows. Section 2 reviews the research done in the area of financial statement fraud detection. Section 3 provides an overview of the data mining techniques that are used in this paper. Section 4 describes the feature selection phase of data mining. Section 5 presents the results and discusses the implications of these results. Finally, Section 6 concludes the paper.

2. Literature review

There has been a limited use of data mining techniques for detection of financial statement fraud. The data mining techniques used include decision trees, neural networks (NN), Bayesian belief networks, case based reasoning, fuzzy rule-based reasoning, hybrid methods, logistic regression, and text mining. Extant research in this direction is reviewed in the following paragraphs.

According to Kirkos et al. [23], some estimates stated that fraud cost US business more than $400 billion annually. Spathis et al. [42] compared multi-criteria decision aids with statistical techniques such as logit and discriminant analysis in detecting fraudulent financial statements. A novel financial kernel for the detection of management fraud is developed using support vector machines on financial data by Cecchini et al. [9]. Huang et al. [20] developed an innovative fraud detection mechanism on the basis of Zipf’s Law. The purpose of this technique is to assist auditors in reviewing the overwhelming volumes of datasets and identifying any potential fraud records. Kirkos et al. [23] used the ID3 decision tree and Bayesian belief network to detect financial statement fraud successfully.

Sohi and Venkataram [41] used back-propagation NN for the prediction of financial statement fraud. There are other researchers who used different NN algorithms to detect financial reporting fraud. Cerullo and Cerullo [10] explained the nature of fraud and financial statement fraud along with the characteristics of NN and their applications. They illustrated how NN packages could be utilized by various firms to predict the occurrence of fraud. Calderon and Cheh [8] examined the efficacy of NN as a potential enabler of business risk based auditing. They employed different methods using NN as a tool for research in the auditing and risk assessment domain. Further, they identified several opportunities for future research that include methodological issues related to NN modeling as well as specific issues related to the application of NN for business risk assessment. Koskivaara [25] investigated the impact of various preprocessing models on the forecast capability of NN when auditing financial accounts. Further, Koskivaara [26] proposed NN based support systems as a possible tool for use in auditing. He demonstrated that the main application areas of NN were detection of material errors, and management fraud. Busta and Weinberg [7] used NN to distinguish between ‘normal’ and ‘manipulated’ financial data. They examined the digit distribution of the numbers in the underlying financial information. The data analysis is based on Benford’s law, which demonstrated that the digits of naturally occurring numbers are distributed on a predictable and specific pattern. They tested six NN designs to determine the most effective model. In each design, the inputs to the NN were the different subsets of the 34 variables. The results showed that NN were able to correctly classify 70.8% of the data on an average.

Feroz et al. [15] observed that the relative success of the NN models was due to their ability to ‘learn’ what were important. The perpetrators of financial reporting frauds had incentives to appear prosperous as evidenced by high profitability. In contrast to conventional statistical models replete with assumptions, the NN used adaptive learning processes to determine what were important in predicting targets. Thus, the NN approach was less likely to be affected by accounting manipulations. The NN approach was well suited to predicting the possible fraudsters because the NN ‘learnt’ the characteristics of reporting violators despite managers’ intent to obfuscate misrepresentations. Brooks [6] also applied various NN models to detect financial statement fraud with great success. Fanning and Cogger [13] used NN (AutoNet) for detecting management fraud. The study offered an in-depth examination of important publicly available predictors of fraudulent financial statements. The study
reinforced the efficiency of AutoNet in providing empirical evidence regarding the merits of suggested red flags for fraudulent financial statements. Ramamoorti et al. [37] provided an overview of the multi-layer perceptron architecture and compared it with a Delphi study. They found that internal auditors could benefit from using NN for assessing risk. Zhang et al. [46] conducted a review of the published papers that reported the use of NN in forecasting during the time period 1988–98.

Aamodt and Plaza [1] and Kotsiantis et al. [27] used case based reasoning to identify the fraudulent companies. Further, Deshmukh and Talluru [12] demonstrated the construction of a rule-based fuzzy reasoning system to assess the risk of management fraud and proposed an early warning system by finding out 15 rules related to the probability of management fraud. Pacheco et al. [34] developed a hybrid intelligent system consisting of NN and a fuzzy expert system to diagnose financial problems. Further, Magnusson et al. [30] used text mining and demonstrated that the language of quarterly reports provided an indication of the change in the company’s financial status. A rule-based system that consisted of too many if–then statements made it difficult for marketing researchers to understand key drivers of consumer behavior [22]. Variable selection was used in order to choose a subset of the original predictive variables by eliminating variables that were either redundant or possessed little predictive information.

3. Methodology

The dataset used in this research was obtained from 202 companies that were listed in various Chinese stock exchanges, of which 101 were fraudulent and 101 were non-fraudulent companies. The data also contained 35 financial items for each of these companies. Table 1 lists these financial items. Of these, 28 were financial ratios reflecting liquidity, safety, profitability, and efficiency of companies. We performed log transformation on the entire dataset to reduce its dimension. Then we normalized each of the independent variables of the original dataset during the data preprocessing stage. Furthermore, ten-fold cross-validation is performed to improve the reliability of the result. Then, we analyzed the dataset using six data mining techniques including MLFF, SVM, GP, GMDH, LR, and PNN. The block diagram in Fig. 2 depicts the data flow. We chose the six techniques because MLFF, GMDH and PNN fall under the NN category, SVM comes from statistical learning theory, GP is an evolutionary technique, and logistic regression is a traditional statistical technique for classification. Thus, these methods had varied background and different theories to support them. In this way, we ensured that the problem at hand is analyzed by disparate models, that had varying degree of difficulty in implementation and also exhibited varying degree of performance on different data mining problems. In other words, the problem is studied and analyzed comprehensively from all perspectives.

It is observed that some of the independent variables turned out to be much more important for the prediction purpose whereas some contributed negatively towards the classification accuracies of different classifiers. So, a simple statistical technique using the t-statistic is used to accomplish feature selection on the dataset by identifying the most significant financial items that could detect the presence of financial statement fraud. This is described in Section 4. The features having high t-statistic values were more significant than others. For feature selection, first we extracted the top 18 features (more than half of the total 35 financial items) from the original dataset. Then the dataset with the reduced feature set (only 18 financial items) was fed as input to the above mentioned classifiers, which resulted in new combinations such as t-statistic-MLFF, t-statistic-SVM, t-statistic-GP, t-statistic-GMDH, t-statistic-LR, and t-statistic-PNN. In order to conduct further analysis, we then extracted the top 10 features and the same process was repeated, i.e., the dataset with the reduced feature set (only 10 financial items) was fed to all of the above classifiers. A brief description of the different data mining techniques used in this research is provided below.

3.1. Support vector machines (SVM)

SVM introduced by Vapnik [44] use a linear model to implement nonlinear class boundaries by mapping input vectors nonlinearly into a high-dimensional feature space. In the new space, an optimal separating hyperplane is constructed. The training examples that are closest to the maximum margin hyperplane are called support vectors. All other training examples are irrelevant for defining the binary class boundaries. SVM are simple enough to be analyzed mathematically. In this sense, SVM may serve as a promising alternative combining the strengths of conventional statistical methods that are more theory-driven and easy to analyze, and machine learning methods that are more data-driven, distribution-free and robust. Recently, SVM have been used in financial applications such as credit rating, time series prediction, and insurance claim frauds detection. These studies reported that the performance of SVM is comparable to and even better than other classifiers such as MLFF, case based reasoning, discriminant analysis, and logistic regression.
3.2. Genetic programming (GP)

GP [28] is an extension of genetic algorithms (GA). It is a search methodology belonging to the family of evolutionary computation. GP randomly generates an initial population of solutions. Then, the initial population is manipulated using various genetic operators to produce new populations. These operators include reproduction, crossover, mutation, dropping condition, etc. The whole process of evolving from one population to the next population is called a generation. A high-level description of the GP algorithm can be divided into a number of sequential steps [14]:

- Create a random population of programs, or rules, using the symbolic expressions provided as the initial population.
- Evaluate each program or rule by assigning a fitness value according to a predefined fitness function that can measure the capability of the rule or program to solve the problem.
- Use the reproduction operator to copy existing programs into the new generation.
- Generate the new population with crossover, mutation, or other operators from a randomly chosen set of parents.
- Repeat the second to the fourth steps for the new population until a predefined termination criterion is satisfied, or a fixed number of generations is completed.

The solution to the problem is the genetic program with the best fitness within all generations.

In GP, the crossover operation is achieved by reproduction of two parent trees. Two crossover points are then randomly selected in the two offspring trees. Exchanging sub-trees, which are selected according to the crossover point in the parent trees, generates the final offspring trees. The offspring trees are usually different from their parents in size and shape. Then, mutation operation is also considered in GP. A single parental tree is first reproduced. Then a mutation point is randomly selected from the reproduction, which can be either a leaf node or a sub-tree. Finally, the leaf node or the sub-tree is replaced by a new leaf node or a randomly generated sub-tree. Fitness functions ensure that the evolution goes toward optimization by calculating the fitness value for each individual in the population. The fitness value evaluates the performance of each individual in the population.

GP is guided by the fitness function to search for the most efficient computer program that can solve a given problem. A simple measure of fitness [14] is adopted for the binary classification problem and is given as follows:

\[
\text{Fitness} = \frac{\text{No. of samples classified correctly}}{\text{No. of samples used for training during evaluation}}
\]

The major considerations in applying GP to pattern classification are:

- GP based techniques are free of the distribution of the data, and no a priori knowledge is needed about the statistical distribution of the data.
- GP can directly operate on the data in its original form.
- GP can detect the underlying but unknown relationship that exists among data items and express it as a mathematical expression.
- GP can discover the most important discriminating features of a class during the training phase.

3.3. Multi-layer feedforward neural network (MLFF)

MLFF is one of the most common NN structures, as they are simple and effective, and have found home in a wide assortment of machine learning applications. MLFF starts as a network of nodes arranged in three layers—the input, hidden, and output layers. The input and output layers serve as nodes to buffer input and output for the model, respectively, and the hidden layer serves to provide a means for input relations to be represented in the output. Before any data is passed to the network, the weights for the nodes are random, which has the effect of making the network much like a newborn’s brain—developed but without knowledge. MLFF are feed-forward NN trained with the standard back-propagation algorithm. They are supervised networks so they require a desired response to be trained. They learn how to transform input data into a desired response. So they are widely used for pattern classification and prediction. A multi-layer perceptron is made up of several layers of neurons. Each layer is fully connected to the next one. With one or two hidden layers, they can approximate virtually any input–output map. They have been shown to yield accurate predictions in difficult problems [39].

3.4. Group method of data handling (GMDH)

GMDH was introduced by Ivakhnenko [21] in 1966 as an inductive learning algorithm for modeling complex systems. It is a self-organizing approach that tests increasingly complicated models and evaluates them using some external criterion on separate parts of the data sample. GMDH is partly inspired by research in perceptrons and learning filters. GMDH has influenced the development of several techniques for synthesizing (or ‘self-organizing’) networks of polynomial nodes. GMDH attempts a hierarchic solution by trying out many simple models, retaining the best of these models, and building on them iteratively to obtain a composition (or feed-forward network) of functions as the model. The building blocks of GMDH, or polynomial nodes, usually have the quadratic form:

\[
z = w_0 + w_1x_1 + w_2x_2 + w_3x_1^2 + w_4x_2^2 + w_5x_1x_2
\]

where \(x_1\) and \(x_2\) are inputs, \(w_i\) is the coefficient (or weight) vector \(w\), and \(z\) is the node output. The coefficients are determined by solving the linear regression equation with \(z = y\), where \(y\) represents the response vector. The GMDH develops on a data set. The data set including independent variables \(\{x_1, x_2, ..., x_n\}\) and one dependent variable \(y\) is split into a training and testing set. During the process of learning a forward multilayer NN is developed by observing the following steps:

- In the input layer of the network \(n\) units with an elementary transfer function \(y = x_i\) are constructed. These are used to provide values of independent variables from the learning set to the successive layers of the network.
- When constructing a hidden layer an initial population of units is generated. Each unit corresponds to the Ivakhnenko polynomial form:

\[
y = a + bx_1 + cx_2 + dx_1^2 + ex_2^2 + fx_1x_2
\]

where \(y\) is an output variable; \(x_1, x_2\) are two input variables; and \(a, b, ..., f\) are parameters.

- Parameters of all units in the layer are estimated using the learning set.
- The mean square error between the dependent variable \(y\) and the response of each unit is computed for the testing set.
- Units are sorted in terms of the mean square error and just a few units with minimal error survive. The rest of the units are deleted. This step guarantees that only units with a good ability for approximation are chosen.
- Next the hidden layers are constructed so that the mean square error of the best unit decreases.
- Output of the network is considered as the response of the best unit in the layer with the minimal error.
Table 2
Top 18 items selected from financial statements of companies by t-statistic based feature selection.

<table>
<thead>
<tr>
<th>No.</th>
<th>Financial items</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Net profit</td>
</tr>
<tr>
<td>2</td>
<td>Gross profit</td>
</tr>
<tr>
<td>3</td>
<td>Primary business income</td>
</tr>
<tr>
<td>4</td>
<td>Primary business income/Total assets</td>
</tr>
<tr>
<td>5</td>
<td>Gross profit/Total assets</td>
</tr>
<tr>
<td>6</td>
<td>Net profit/Total assets</td>
</tr>
<tr>
<td>7</td>
<td>Inventory/Total assets</td>
</tr>
<tr>
<td>8</td>
<td>Inventory/Current liabilities</td>
</tr>
<tr>
<td>9</td>
<td>Net profit/Primary business income</td>
</tr>
<tr>
<td>10</td>
<td>Primary business income/Primary business income of last year</td>
</tr>
<tr>
<td>11</td>
<td>Primary business income/Last year's primary business income</td>
</tr>
<tr>
<td>12</td>
<td>Fixed assets/Total assets</td>
</tr>
<tr>
<td>13</td>
<td>Current assets/Current liabilities</td>
</tr>
<tr>
<td>14</td>
<td>Capital and reserves/Total debt</td>
</tr>
<tr>
<td>15</td>
<td>Long term debt/Total capital and reserves</td>
</tr>
<tr>
<td>16</td>
<td>Cash and deposits</td>
</tr>
<tr>
<td>17</td>
<td>Inventory/Primary business income</td>
</tr>
</tbody>
</table>

The GMDH network learns in an inductive manner and builds a function (called a polynomial model), that results in the minimum error between the predicted value and expected output. The majority of GMDH networks use regression analysis for solving the problem. The first step is to decide the type of polynomial that the regression will find. The initial layer is simply the input layer. The first layer is created by computing regressions of the input variables and then choosing the best ones. The second layer is created by computing regressions of the values in the first layer along with the input variables. This means that the algorithm essentially builds polynomials of polynomials. Again, only the best are chosen by the algorithm. These are called survivors. This process continues until a pre-specified selection criterion is met.

3.5. Logistic regression (LR)

According to Panik [35], when dealing with logistic regression, the response variable is taken to be dichotomous or binary (it takes on only two possible values), i.e., $y_i = 0$ or 1 for all $i = 1, ..., n$. For instance, we can have a situation in which the outcome of some process of observation is either a success (we record a 1) or failure (we record a 0), or we observe the presence (1) or absence (0) of some characteristic or phenomenon. In addition, dichotomous variables are useful for making predictions, e.g., we may ask the following: Will an individual make a purchase of a particular item in the near future?

Here $y_i = \begin{cases} 1 & \text{yes;} \\ 0 & \text{No.} \end{cases}$

According to Williams et al. [45], LR is a commonly used approach for performing binary classification. It learns a set of parameters, $\{w_0, w\}$, that maximizes the likelihood of the class labels for a given set of training data. Let $x_i \in \mathbb{R}^d$ denote a (column) vector of $d$ features representing the $i$th data point, and $y_i \in \{0, 1\}$ denote its corresponding class label (e.g., clutter or mine). For a labeled (training) data point, $y_i$ is known; for an unlabeled (testing) data point, $y_i$ is unknown. Under the LR model, the probability of label $y_i = 1$ given $x_i$ is given by Eq. (1):

$$P(y_i = 1 | x_i) = \frac{\exp\left(w_0 + w^T x_i\right)}{1 + \exp\left(w_0 + w^T x_i\right)} \quad (1)$$

where $w_0 \in \mathbb{R}$ and $w \in \mathbb{R}^d$ are the LR intercept and coefficients respectively. For a set of $N$ independent labeled data points, $(x_i, y_i)_{i=1}^N$, the log-likelihood of the class labels can be written as Eq. (2):

$$l(w_0, w) = \sum_{i=1}^N \left[ (1-y_i) \log(1-P(y_i)) + y_i \log P(y_i) \right] \quad (2)$$

To maximize the log-likelihood in Eq. (2), a standard optimization approach can be employed, since the gradient (and Hessian) of Eq. (2) with respect to $\{w_0, w\}$ can be readily calculated. Once the LR parameters $\{w_0, w\}$ have been learned, the probability that an unlabeled testing data point $x_i$ belongs to each class can be obtained using Eq. (1).

3.6. Probabilistic neural network (PNN)

PNN is a feed-forward NN involving a one pass training algorithm used for classification and mapping of data. PNN was introduced by Specht [43] in 1990. It is a pattern classification network based on the classical Bayes classifier, which is statistically an optimal classifier that seeks to minimize the risk of misclassification. Any pattern classifier places each observed data vector $x = [x_1, x_2, x_3, \ldots x_n]^T$ in one of the predefined classes $c_i, i = 1, 2, \ldots, m$ where $m$ is the number of possible classes. The effectiveness of any classifier is limited by the number of data elements that the vector $x$ can have and the number of possible classes $m$. The classical Bayes pattern classifier [40] implements the Bayes conditional probability rule that the probability $P(C|x)$ of $x$ being in class $c_i$ is given by:

$$P(c_i | x) = \frac{P(x|c_i)P(c_i)}{\sum_{j=1}^m P(x|c_j)P(c_j)} \quad (3)$$

where $P(x|c_i)\equiv$ the conditioned probability density function of $x$ given set $c_i$, $P(c_i)$ is the probability of drawing data from class $c_i$. Vector $x$ is said to belong to a particular class $c_i$, if $P(c_i|x) > P(c_j|x), \forall j = 1, 2, \ldots, m$ and $j \neq i$. This input $x$ is fed into each of the patterns in the pattern layer. The summation layer computes the probability $P(c|x)$ that the given input $x$ is included in each of the classes $c_i$ that is represented by the patterns in the pattern layer. The output layer selects the class for which the highest probability is obtained in the summation layer. The input is then made to belong to this class. The effectiveness of the network in classifying input vectors depends on the value of the smoothing parameter.

4. Feature selection

Feature selection is critical to data mining and knowledge based authentication. The problem of feature selection has been well studied in areas where datasets with a large number of features are available, including machine learning, pattern recognition, and statistics. Piramuthu [36] observed that about 80% of the resources in a majority of data mining applications are spent on cleaning and preprocessing the data, and developed a new feature selection method based on Hausdorff distance for analyzing web traffic data. Feature selection is of paramount importance for any learning algorithm which when poorly done (i.e., a poor set of features is selected) may lead to problems related to incomplete information, noisy or irrelevant features, not the best set/mix of features, among others [45]. Mladenic and Grobelnik [31] reviewed various feature selection methods in the context of web mining. Chen and Liginlal [11] developed a maximum entropy based feature selection technique for knowledge based authentication.

In this study, we employed a feature selection phase by using the simple t-statistic technique. t-statistic is one of the efficient feature
selection techniques. The features are ranked according to the formula shown below [16,29]. In fact, Liu et al. [29] were the first to propose t-statistic for the purpose of feature selection in the field of bioinformatics.

\[
t-\text{statistic} = \frac{|\mu_1 - \mu_2|}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}
\]  

where \(\mu_1\) and \(\mu_2\) represent the means of the samples of fraudulent companies and non-fraudulent companies for a given feature respectively, \(\sigma_1\) and \(\sigma_2\) represent the standard deviation of the samples of fraudulent companies and non-fraudulent companies for a given feature respectively. \(n_1\) and \(n_2\) represent the number of samples of fraudulent companies and non-fraudulent companies for a given feature. The t-statistic values are computed for each feature and the top 18 features with the highest t-statistic values are considered in the second case. A high t-statistic value indicates that the feature can highly discriminate between the samples of fraudulent and non-fraudulent companies.

The top 18 financial features that are selected by the t-statistic based feature selection are shown in Table 2. The feature subset formed with the top 18 features is fed as input to MLFF/SVM/GP/GMDH/LR/PNN for classification purpose in the first case. Similarly, the feature subset formed with the top 10 features is fed as input to MLFF/SVM/GP/GMDH/LR/PNN for classification purpose in the second case. The block diagram for all these combinations is shown in Fig. 3. Ten-fold cross-validation is used to ensure better validity of the experiments. It should be noted that the t-statistic is employed for feature selection are shown in Table 2.

### 5. Results and discussion

The dataset analyzed in this paper comprised 35 financial items for 202 companies, of which 101 were fraudulent and 101 were non-fraudulent. Since the financial items had a wide range, we first performed natural logarithmic transformation, and then normalization during the data preprocessing phase. We employed the GP as implemented in the tool Discipulus (available at www.rmltech.com and downloaded on 20th August, 2008). For MLFF, GMDH, and PNN, we employed Neuroshell 2.0 [33] and for SVM and LR, we used KNIME 2.0.0 [24].

The sensitivity is the measure of the proportion of the number of fraudulent companies predicted correctly as fraudulent by a particular model to the total number of actual fraudulent companies. The specificity is the measure of the proportion of the number of non-fraudulent companies predicted as non-fraudulent by a model to the total number of actual non-fraudulent companies. In all cases, we presented the average accuracies, sensitivities, specificities, and area under the Receiver Operating Characteristic curve (AUC) for the test data, averaged over 10-folds. We ranked the classifiers based on AUC.

First, the results of the 10-fold cross-validation method for the standalone techniques viz. MLFF, SVM, GP, GMDH, LR, and PNN without feature selection are presented in Table 3. From Table 3 we observe that PNN with 98.09% accuracy and 98.09% sensitivity outperformed all other classifiers (as indicated by bold faced numerals in the Table 3). GP yielded the next best result with 94.14% accuracy and 95.09% sensitivity. We also observe that PNN is the best classifier among all others in terms of AUC as well. The best results obtained by Bose and Wang [5], who employed canonical discriminant analysis (CDA), classification and regression tree (C&RT) and exhaustive pruning NN on the same dataset are also presented in Table 3 for ease of comparison. From Table 3 we can observe that the results obtained in this study are always superior to the results obtained by them for all cases, except SVM and LR.

As the next step, we used t-statistic for feature selection and extracted the most important features. First, we considered the top 18 features for constructing the reduced feature subset. Later, this feature subset is fed to all the above classifiers for the purpose of classification. The average results of all the classifiers over all folds with 18 features are presented in Table 4. From Table 4 we observe that GP outperformed other classifiers with 92.68% accuracy and 90.55% sensitivity, whereas PNN came close behind with 95.64% accuracy and 91.27% sensitivity (as indicated by bold faced numerals in Table 4). Furthermore, results based on AUC indicated that GP yielded highest accuracy followed by PNN, which yielded marginally less accuracy. This makes us infer that the selected feature subsets

### Table 3
Average results of dataset with all features using 10-fold cross-validation.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLFF</td>
<td>78.36</td>
<td>80.21</td>
<td>76.35</td>
<td>7827.90</td>
</tr>
<tr>
<td>SVM</td>
<td>70.41</td>
<td>55.43</td>
<td>84.13</td>
<td>6978.00</td>
</tr>
<tr>
<td>GP</td>
<td>94.14</td>
<td>95.09</td>
<td>93.05</td>
<td>9407.10</td>
</tr>
<tr>
<td>GMDH</td>
<td>93.00</td>
<td>91.46</td>
<td>95.18</td>
<td>9331.85</td>
</tr>
<tr>
<td>LR</td>
<td>66.86</td>
<td>63.32</td>
<td>70.66</td>
<td>6699.10</td>
</tr>
<tr>
<td>PNN</td>
<td>98.09</td>
<td>98.09</td>
<td>98.09</td>
<td>9809.00</td>
</tr>
<tr>
<td>CDA [5]</td>
<td>71.37</td>
<td>61.96</td>
<td>80.77</td>
<td>7136.5</td>
</tr>
<tr>
<td>C&amp;RT [5]</td>
<td>72.38</td>
<td>72.40</td>
<td>72.36</td>
<td>7238</td>
</tr>
<tr>
<td>Exhaustive pruning NN [5]</td>
<td>77.14</td>
<td>80.83</td>
<td>73.45</td>
<td>7714</td>
</tr>
</tbody>
</table>

### Table 4
Average results of dataset with reduced features (top 18 features selected by t-statistic) and using 10-fold cross-validation.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLFF</td>
<td>78.77</td>
<td>76.98</td>
<td>81.28</td>
<td>7912.80</td>
</tr>
<tr>
<td>SVM</td>
<td>73.41</td>
<td>72.07</td>
<td>75.04</td>
<td>7355.55</td>
</tr>
<tr>
<td>GP</td>
<td>92.68</td>
<td>90.55</td>
<td>95.27</td>
<td>9290.95</td>
</tr>
<tr>
<td>GMDH</td>
<td>90.68</td>
<td>93.46</td>
<td>88.34</td>
<td>9089.95</td>
</tr>
<tr>
<td>LR</td>
<td>70.36</td>
<td>62.91</td>
<td>78.88</td>
<td>7089.50</td>
</tr>
<tr>
<td>PNN</td>
<td>95.64</td>
<td>91.27</td>
<td>94.16</td>
<td>9271.75</td>
</tr>
</tbody>
</table>
have a high discriminatory power and the ‘left-over’ features have very little to contribute to the success of financial fraud detection. Furthermore, in order to conduct an exhaustive study over this dataset, in the second set of experiment we considered only the top 10 features (based on the values of the t-statistics) for constructing the reduced feature subset. The top 10 features can be seen in the first ten rows of Table 2. We repeated the experiments as in the first case. The average results for all the classifiers over all folds with 10 features are presented in Table 5. From Table 5 we observe that PNN outperformed other classifiers with 90.77% accuracy and 87.53% sensitivity (as indicated by bold faced numerals in Table 5), whereas GP came second with 89.27% accuracy and 85.64% sensitivity. Moreover, results based on the AUC indicated that PNN yielded the highest accuracy followed by GP, which yielded only marginally less accuracy.

In order to find out whether the difference in average AUCs is statistically significant or not, we conducted a t-test between the top performer and the remaining classifiers (i) without feature selection, (ii) with feature selection including top 18 features, and (iii) with feature selection including top 10 features. In case of the dataset without feature selection, the t-statistic values between the average AUCs obtained by PNN and that of other classifiers are presented in Table 6. From Table 6 we observe that t-statistic values are more than the critical value of the test statistic, which is 1.73 at the 10% level of significance. Thus, we infer that PNN significantly outperformed other classifiers without feature selection. In case of the dataset with feature selection and considering only the top 18 features, the t-statistic values between the average AUCs obtained by GP and that of other classifiers are presented in Table 7. From this table we can observe that PNN significantly outperformed all classifiers except GMDH and PNN. Considering only the top 10 features, the t-statistic values between the average AUCs obtained by PNN and that of other classifiers are presented in Table 8. From this table we can observe that the GP significantly outperformed all classifiers except GMDH and PNN. From these results we can say that the GP significantly outperformed all classifiers except GMDH and PNN.

When we take a close look at the top 10 and top 18 features shown in Table 2, we observe that most of these features are associated with the firm’s ability to generate profit or income. Among the top 10 features, eight features are associated with the profitability of the firm. A closer looks reveals that among the top 10 features, four are associated with primary business income, and five are associated with either gross or net profit earned by the firm. This indicated that a fraudulent firm usually tried to inflate the profit or the income figures in order to create an impressive financial statement. Any unusual income or profit figures should be a reason for suspicion and further investigation by an auditor.

When the present dataset of 35 dimensions (financial items) is visualized using the tool Neucom [32] in the principal component analysis, we noticed three predominant clusters and nine outliers. This provided a possible reason for the spectacular performance of PNN because PNN is tolerant to outliers [4]. While comparing the dataset with and without feature selection, it is noticed that even after reducing the number of features to almost one third of the original number, the change in accuracies is at most 5% in all the cases except PNN, where the accuracies are reduced by 8%. From this we can infer that the t-statistic is a simple and efficient feature selection technique for picking up very significant features that ensured better accuracies. Based on our experiments, we conclude that PNN without feature selection outperformed methods such as MLFF, SVM, GP, GMDH, and LR. After feature selection, GP performed well compared to all other techniques, and PNN yielded marginally less accuracies when top 18 features are selected. Similarly, PNN outperformed all other techniques when top 10 features are selected. Also, we concluded that our results are much superior to an earlier study on the same dataset.

It should be noted that while all the techniques have equal cost, the technique that is preferred and recommended is totally dictated by the dataset at hand. Since accuracy is a major concern for financial analysts, we should select that technique which yields less misclassifications and consumes less time. This is because the performance of all of these techniques depends on the dataset on which they are used. Having said that, everything else (i.e., accuracies, sensitivity, specificity, etc.) being equal, we should select that technique which is less cumbersome, easy to understand, and easy to implement.

### Table 5

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLFF</td>
<td>75.32</td>
<td>67.24</td>
<td>80.02</td>
<td>7501.65</td>
</tr>
<tr>
<td>SVM</td>
<td>72.36</td>
<td>73.60</td>
<td>60.56</td>
<td>7164.35</td>
</tr>
<tr>
<td>GP</td>
<td>89.27</td>
<td>85.64</td>
<td>93.16</td>
<td>893.995</td>
</tr>
<tr>
<td>GMDH</td>
<td>88.14</td>
<td>87.44</td>
<td>89.25</td>
<td>8834.40</td>
</tr>
<tr>
<td>LR</td>
<td>70.86</td>
<td>65.23</td>
<td>76.46</td>
<td>7084.45</td>
</tr>
<tr>
<td>PNN</td>
<td>90.77</td>
<td>87.53</td>
<td>94.07</td>
<td>9079.85</td>
</tr>
</tbody>
</table>

### Table 6

<table>
<thead>
<tr>
<th>Classifier compared</th>
<th>t-statistic at 10% level of significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLFF</td>
<td>7.84</td>
</tr>
<tr>
<td>SVM</td>
<td>15.66</td>
</tr>
<tr>
<td>GP</td>
<td>2.11</td>
</tr>
<tr>
<td>GMDH</td>
<td>2.49</td>
</tr>
<tr>
<td>LR</td>
<td>11.58</td>
</tr>
</tbody>
</table>

### Table 7

<table>
<thead>
<tr>
<th>Classifier compared</th>
<th>t-statistic at 10% level of significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLFF</td>
<td>5.13*</td>
</tr>
<tr>
<td>SVM</td>
<td>5.28*</td>
</tr>
<tr>
<td>GMDH</td>
<td>0.69</td>
</tr>
<tr>
<td>LR</td>
<td>6.40*</td>
</tr>
<tr>
<td>PNN</td>
<td>0.08</td>
</tr>
</tbody>
</table>

The * indicates that the result is statistically significant.

### Table 8

<table>
<thead>
<tr>
<th>Classifier compared</th>
<th>t-statistic at 10% level of significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLFF</td>
<td>5.36*</td>
</tr>
<tr>
<td>SVM</td>
<td>5.69*</td>
</tr>
<tr>
<td>GMDH</td>
<td>0.83</td>
</tr>
<tr>
<td>LR</td>
<td>6.35*</td>
</tr>
</tbody>
</table>

The * indicates that the result is statistically significant.
6. Conclusion and future research directions

This paper presents the application of intelligent techniques to predict financial statement fraud in companies. The dataset consisting of 202 Chinese companies is analyzed using the stand-alone techniques like MLFF, SVM, GMDH, GP, LR, and PNN. Then, t-statistic is used for feature subset selection and top 18 features are selected in the first case and top 10 features are selected in the second case. With the reduced feature subset the classifiers MLFF, SVM, GMDH, GP, LR, and PNN are invoked again. Results based on AUC indicated that the PNN was the top performer followed by GP which yielded marginally less accuracies in most of the cases. Also, the results obtained in this study are better than those obtained in an earlier study on the same dataset. Ten-fold cross-validation is performed throughout the study. Prediction of financial fraud is extremely important as it can save huge amounts of money from being embezzled. Our study is an important step in that direction that highlights the use of data mining for solving this serious problem.

With regards to the future research directions, we can extend this work by extracting 'if-then' rules from different classifiers. These rules can be helpful for easy understanding of the prediction process for the end user because they make the knowledge learnt by these techniques transparent. This type of knowledge elicitation can help in providing early warning. In addition to the data mining techniques used in this research, hybrid data mining techniques that combine two or more classifiers can be used on the same dataset. Also, text mining algorithms for sentiment analysis of the textual description of the financial statements can be used together with data mining algorithms for assessing the financial items in the financial statements to provide better prediction of financial statement fraud.

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References


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