Journal of Optimization in Industrial Engineering
Vol.14, Issue 2, Summer & Autumn 2021, 169-186
DOI: 10.22094/JOIE.2020.1877455.1685

Research Article

A Hybrid Model Based on Machine Learning and Genetic Algorithm for Detecting Fraud in Financial Statements

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Received 27 August 2019; Revised 03 August 2020; Accepted 05 August 2020

Abstract

Financial statement fraud has increasingly become a serious problem for businesses, governments, and investors. In fact, this threatens the reliability of capital markets, corporate heads, and even the audit profession. Auditors, in particular, face their apparent inability to detect large-scale fraud, and there are various ways to identify this problem. In order to identify this problem, the majority of the proposed methods are based on existing algorithms and have only attempted to identify human or simple data mining methods that have high overhead and are also costly. The data mining methods presented so far have had high computational overhead or low accuracy. The present study aims to present a model in which an improved ID3 decision tree with a support vector machine is used as a hybrid approach and also to improve the performance and accuracy, genetic algorithm and multilayer perceptron neural networks are applied. A more efficient feature selection is used to reduce computational overhead. The tree proposed in the proposed method has the lowest depth possible and therefore has high velocity and low computational overhead. For this purpose, the financial statements of 151 listed companies in the Tehran Stock Exchange during 2014-2015 are surveyed. 125 financial ratios are extracted using an ANOVA test and 23 fraud-related ratios are selected as model input data. The proposed model is able to predict financial statement fraud with high accuracy of about 80% compared to similar models.

Keyword: Support vector machine, Improved decision tree, Fraud detection, Classification.

1. Introduction

Financial statement fraud is increasingly a serious problem for businesses, governments, and investors. In fact, this threatens the reliability of capital markets, corporate heads, and even the audit profession. Auditors, in particular, face their apparent inability to detect large-scale fraud. In recent years, the US financial markets have been seriously damaged by numerous disclosures of fraudulent practices by some companies. WorldCom, Enron, Adolfia, Global Cracking, and Tico are just a few of the financial statement scandals that have fluctuated the stock market and eroded public confidence (Vakili fard & Ahmadi, 2010).

Financial statement fraud is increasingly a serious problem for businesses, governments, and investors. In fact, this threatens the reliability of capital markets, corporate heads, and even the audit profession. Auditors in particular face their apparent inability to detect large-scale fraud. Hundreds of millions of dollars in monetary judgments are typically made against companies with formal public accounting services.

From the audit perspective, fraud is a very serious issue as it is often associated with trying to conceal, distort, and mislead the users of the audited records and reports. Attempts to misrepresent information can also occur at the management level, as this is widely accepted following the collapse of large corporations.

Data mining is not just limited to social interactions, science, and engineering, but it is also used in medicine, insurance, recommender systems, financial systems, anti-spyware, etc. (Bahrami & Hosseini Shirvani, 2015; Farzai et al., 2015; Ghorbani & Farzai, 2018). Although data mining methods have many applications in different sciences, so far the adoption of these methods by academics and control organizations to detect fraud has not been significant. In the early stages of this research, problem statement and basic concepts in the domain are examined. Based on recent events and observations, information theft, and financial scandals, it can be argued that intra-organizational fraud is likely to occur in any company or entity, whether commercial or non-commercial, and specific to a particular level or category of that set (Andon, Paul, et al., 2015), (Lookman & Selmin Nurcan, 2015).

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2. Literature Review

2.1. Fraud

According to the Auditing Standards Committee (2015), "fraud" is any deliberate or fraudulent act by one or more managers, employees, or third parties to gain an unjust or illegal advantage. Although fraud has a broad legal meaning, what concerns the auditor are fraudulent practices leading to the significant misstatement of financial statements. The purpose of some frauds may not be to distort financial statements. Auditors do not make legal judgments about fraud. The committee argues that fraud involving the involvement of one or more of the unit managers is referred to as "fraud of managers" and fraud that is only perpetrated by the staff of the unit is referred to as "employee fraud". In both cases, there may also be collusion with third parties outside the unit concerned (Iranian Audit Organization, 2015).

Rezai and Riley (2010), in their book, divided fraud into two categories of management fraud and employee fraud, and below provides a further classification of these two types of fraud, as illustrated in Fig 1. Fraud can be divided into several types, the most common of which are the confiscation of assets and financial errors. Confiscation of assets often involves employee fraud, including embezzlement, cash or inventory robbery, and payroll fraud; financial errors are regarded as fraudulent financial statements, which are often the responsibility of management. The US Department of Justice defines corporate fraud in three broad areas: accounting or financial fraud, fraud, and deviant behavior. Accounting fraud involves the distortion of financial information through accounting or misleading investors. The most common accounting schemes include asset sales, side trading, exchange trades, investment costs, quick cash earnings, and deferred expenses (Rezaee & Riley, 2010).

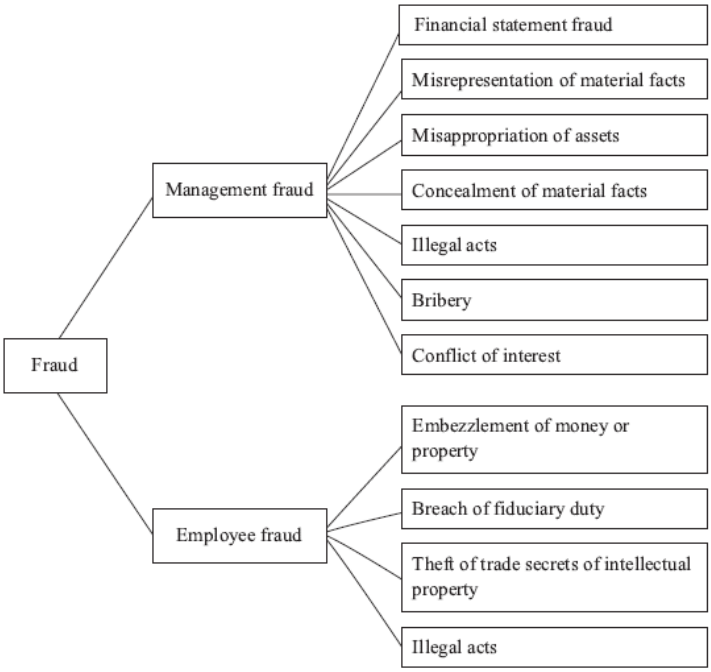

Fig. 1. Fraud Types (Rezaee & Riley, 2010)

2.2. Machine learning

Machine learning is how to write a program that will improve your performance through the learning experience. Learning can change the structure of the program or data. Machine learning is a relatively new field in computer science and it is currently undergoing growth. Machine learning is a very active field of research in computer science (Ziming Yin et. al. 2014). There are various sciences related to machine learning including artificial intelligence, psychology, philosophy, information theory, statistics and probability, control theory, and so on.

A computer program from experience E has learned about task T if its performance improves if measured by criterion P after that experience.

Some reasons for using machine learning to solve problems include:

- Large amounts of data may contain important information humans cannot detect (data mining).
- When designing a system, all of its features may not be known while the machine can learn them while working.
- The environments may change over time. The machine can adapt to them by learning about these changes.
- etc.

Some applications of machine learning include robot control, data mining, speech recognition, text recognition, internet data processing, bioinformatics, computer games, and thousands of other examples. The basics of evaluating machine learning algorithms are classification accuracy, solution accuracy and quality, and performance speed. Machine learning is divided into two general categories of

supervised learning and unsupervised learning (Senthil Kumar et. al. 2013).

2.3. Genetic Algorithm

The scope of the genetic algorithm is vast and using it for optimizing and solving problems has been expanded with the advances of science and technology. Genetic algorithm is one of the evolved computing subsets directly related to artificial intelligence. In fact, the genetic algorithm is one of the subsets of artificial intelligence. The genetic algorithm can be called a general search method that mimics the laws of natural biological evolution. In each generation, better approximations of the final response are obtained through the selection process proportional to the value of the responses and the reproduction of the responses selected by operators mimicking natural genetics. This process makes the new generations more adaptable to the problem conditions (http://hkamal.persiangig.com/document/genetic, 2018). Note that, the genetic algorithm can be utilized in both single-objective (Hosseini Shirvani & Babazadeh Gorji, 2020; Hosseini Shirvani, 2018a; Hosseinzadeh & Hosseini Shirvani, 2015) and multi-objective optimization problems (Farzai et al., 2020; Hosseini Shirvani et al., 2018; Hosseini Shirvani, 2018b). In this paper, the single-objective application of the genetic algorithm is engaged.

2.4. Multilayer perceptron network

In this type of network, the connection is only from i to i + 1 and there is no reverse. The above network is actually created by the interconnection of three single layer perceptron networks. One layer is called the output layer and the other two layers are called the middle layers. The first layer outputs form the second layer input vector, and so the second layer output vector constructs the third layer inputs, and the third layer outputs form the true Rattan network response (Razavi et al., 2016). In other words, the signal flow process in the network takes place in a predetermined direction (from left to right, layer to layer). Each layer can have a number of different neurons with different conversion functions, meaning that the models of neurons in the layers can be considered differently. During training the MLP network using BP learning algorithm, the calculations are first performed from the network input to the network output and then the calculated error values are propagated to the previous layers (https://chistio.ir ،2019). Functional signals and signals going back (right to left) are the error signals that move along the path (from left to right of the network). Fig 2 illustrates these two releases.

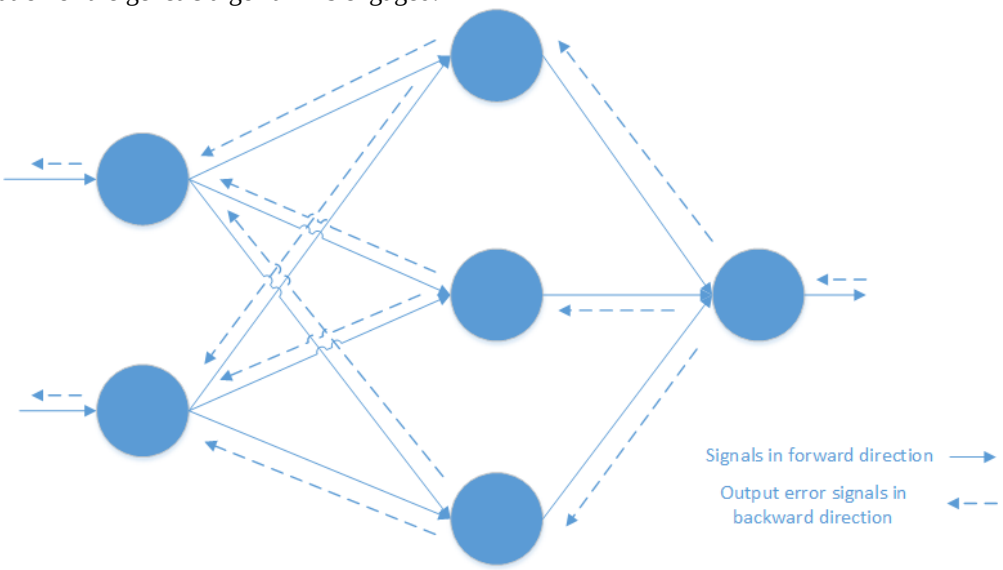

Fig 2. Signal propagation in bp algorithm

2.5. Decision tree

The decision tree structure in machine learning is a predictive model that contributes the observed facts about a phenomenon to inferences about the target value of the phenomenon. The machine learning technique for deriving a decision tree from data is called decision tree learning, which is one of the most common data mining methods (Kantesh Kumar, et. al., 2014).

Each node corresponding to a variable and each arc to a child represent a possible value for that variable. A leaf node, with the values of the variables represented by the path from the tree root to that leaf node, represents the predicted value of the target variable. A tree represents a structural decision tree whose leaves represent clusters and branches represent seasonal combinations of traits that result in these clusters (Ojeme Blessing et. al, 2014). Learning a tree can be done by subdividing a resource set into subsets based on a trait value test. This process is repeated recursively in each subdirectory resulting from the separation. The return operation is complete when the separation is no longer beneficial or one class can be applied to all the samples in the subgroup.

Decision trees are capable of generating human-readable descriptions of relationships within a dataset and can be used for classification and prediction tasks. This

technique has been widely used in a variety of fields such as plant disease diagnosis and customer marketing strategies. (Ojeme Blessing et. al, 2014). This decision structure can also be introduced in the form of mathematical and computational techniques that help describe, classify and generalize a set of data.
Types of Tree Properties Decide on two types of batch and real traits, which are batch traits that accept two or more discrete values (or symbolic traits) while the true traits derive their values from the set of real numbers.

2.5.1. Development of decision trees with decision graphs

Decision graphs are generalizations of decision trees that have decision leaves and nodes. One feature that distinguishes decision graphs from decision trees is that decision graphs can be linked. Transplantation is a condition in which two nodes have a common child, and this condition represents two subunits that have common characteristics, and therefore are considered a set (Dionysios, 2018). In the decision tree, all paths go from the root node to the leaf node with the AND compound. In a decision graph, it is possible to use seasonal combinations or ORs to link two or more paths together.
The way objects are categorized in decision graphs is the same as the one used in decision trees. Each decision tree and decision graph define a category (a partition of object space into separate categories). The set of functions represented by a graph is exactly the same as the set represented by a tree. However, the set of categories included in the definition of a decision function is different. For example, the classification for function (A ∧ B) ∨ (C ∧ D) is different. The graph and the corresponding decision tree of this function are shown in Fig. (3). The decision tree divides the object's space into seven categories, while the graph divides the decision space into two categories (Dreżewski, et. al. 2015).

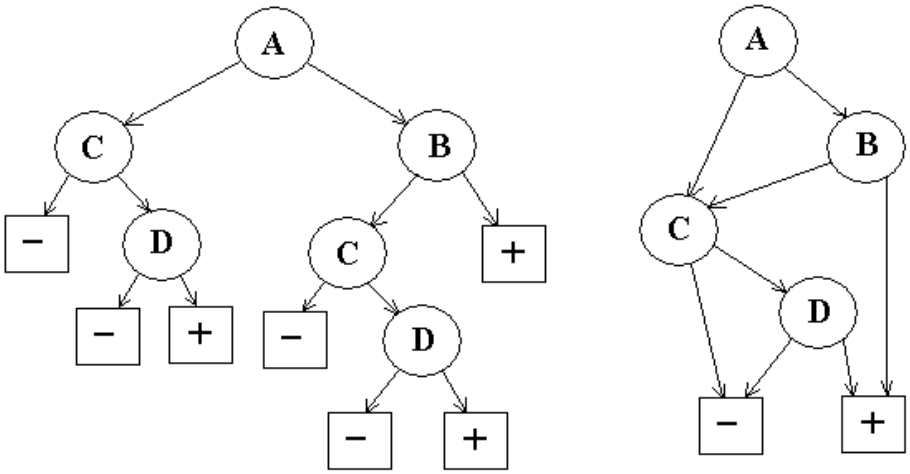

Fig. 3. An example of a decision graph (Dreżewski, et. al. 2015).

2.6. Research background

Sudan Chen (2016), in a study entitled "Detection of Fraudulent Financial Statements Using the hybrid Data Mining Approach", established a valid fraud detection model for the financial statements, both fraudulent and tested non-fake financial statements, of the companies listed on the Taiwan Stock Exchange between 2002 and 2013. In the first step, two decision tree algorithms, including (CART) and (CHAID), are used to select the main variables. The second step involves the combination of CART, CHAID, Bayesian network, support vector machine, and artificial neural network to develop fraud detection models. Based on the results, the detection performance of the CHAID-CART model with the overall accuracy of 87.97% is the most effective model.
Kim et al. (2016), in their research entitled "Detecting fraudulent financial misstatement with fraud intention using multi-class cost-sensitive training", used polynomial logistic regression, support vector machine, and Bayesian networks, as predictive tools to detect and classify misrepresentations based on fraudulent intentions to extend the classifier to three levels. They evaluated the aspects of previous research to detect fraudulent intentions and the implications of false statements. Aspects such as short-term profit ratio and firm performance scale indicate discriminatory potential.
Larry Dashtbeaz et al. (2015), in a study entitled "Data Search and Discovery Process for Financial Statement Fraud," gave an overview of the data mining processes used to detect financial fraud, particularly corporate financial statement fraud. In their research, they stated that the most important methods used to detect financial fraud include logistic regression, neural networks, Bayesian inference networks, and decision trees, which are important solutions to the inherent problems of data identification and classification.
Mohammad Youssef et al. (2015), in a study entitled "Fraudulent financial reporting: an application of fraud models to Malaysian public listed companies" investigated the possibility of fraudulent financial statements in the Malaysian Stock Exchange companies

using fraud triangle model, rhombus fraud model, and pentagonal fraud model. In this study, the fraud risk factors derived from these fraud models provided a new perspective on the discovery of fraud in the financial statements of Malaysian companies. The results also introduced new measurable criteria and new fraud risk factors such as greed and ignorance.

In their research entitled "Detection of Financial Statement Fraud Using Data Mining Technique and Performance Analysis", Tangod and Kulkarni (2015) investigated and concluded the application of two data mining methods called "Key Classification" and "MLFF" algorithm. That the information contained in the financial statements contains fraudulent indicators. In addition, a relatively small number of financial ratios largely determine the classification results. They also concluded that the neural network had a higher accuracy than both other models.

In a study entitled "The Role of Auditors in the Prevention, Detection and Reporting of Fraud: The Case of the United Arab Emirates (UAE)", Halbouni (2015) identified the processes that internal and external auditors follow to detect fraud during an audit. The sample included 53 auditors in the UAE. The results showed that the responsibility for identifying fraudulent incidents with internal auditors is somewhat stricter than that of internal auditors. Overall, the results of this study indicated that it is the responsibility of internal auditors to detect and report fraudand that external auditors should also increase their search for fraud detection and disclosure.

3. Methodology

There is no specific theoretical framework for identifying and classifying entities into fraudulent or healthy companies in financial reporting. According to the Iranian auditing standards Nos. 240 and 450, the criteria for making a misstatement can be set based on the characteristics of the financial statements audited by the auditors or the auditing organization. Therefore, according to previous research such as Daghmeh Qi Firouzjaie (2014), Etemadi and Zalaghi (2009), Haghighi and Boroujeri (2009), and Maham et al. (2012), to classify sample companies as fraudulent and healthy, the following criteria must be met for at least three years (2014-2015) in the financial statements of the fraudulent companies and those companies with the following three conditions are classified as fraudulent companies.

1. Unacceptable audit opinion
2. Tax differences with tax area according to Income tax statement, tax file and paragraph of audit report
3. Existence of significant adjustments and restated financial statements.

The reasons for choosing these criteria are that in the first criterion - the existence of significant fraud, it can give rise to an unacceptable commentary and the second criterion in tax disputes is largely due to the misinterpretation of tax laws and the incorrect application of the relevant clauses in certain tax laws. And maintaining liquidity and other potential violations. For the third criterion, the misstatement and manipulation of items, especially profit and loss items in the preceding years, may give rise to the re-submission of financial statements and be a reason for the likelihood of fraud in the financial statements.

Thus, by the above criteria, first, a list of listed companies in the Tehran Stock Exchange that committed financial statements fraud between 2014 and 2016 is prepared and the number of fraudulent companies is determined based on the availability of corporate information. Then, the number of healthy companies in the same period is determined and samples are randomly selected using a simple random sampling method.

It is not possible to match the companies of the two groups in terms of industry because there is no industry or similar industry that sufficiently has both fraudulent and healthy companies. Thus, sampling will use all the companies listed on the Tehran Stock Exchange, although the goodness of industries is that the generalizability of the model increases. Companies are matched only for the financial year.

The independent variables in this study are financial ratios. By studying and researching the required financial ratios, 125 financial ratios were selected. But in order to avoid high correlations between some ratios and failure to provide similar information, ratios with high correlations were identified and eliminated by T-test. This combination of correlation analysis and T-test resulted in the final selection of 54 independent variables that provide meaningful and non-overlapping information.

Then, these variables are extracted from the financial statements of fraudulent and healthy firms in the studied years, selected by the linear regression model of variables that have significant correlation with fraudulent financial statements, and used as the input variables of machine learning models and genetic algorithm.

Table 1 reports the mean, standard deviation, and ANOVA test for the proportions of fraudulent and non-fraudulent companies. Univariate tests refer to several variables that may be useful in detecting fraudulent companies. Out of the 54 variables tested, 23 variables significant at 1 to 5% significance level are summarized in Table 1 and the other variables were not significant.

Table 1
Mean, standard deviation and ANOVA test for the proportions of fraudulent and non-fraudulent companies

No.	Variables	fraudulent		non-fraudulent		ANOVA test	
		Mean	Standard deviation	Mean	Standard deviation	F. test	Prob
X3	Liabilities/total assets	0.85833	0.44489	0.65925	0.3841	2.56392	0.0424
X5	Current ratio	1.21892	0.61016	1.38891	1.63254	28.4676	0.000
X6	Quick ratio	0.60161	0.98004	0.33792	0.46287	17.5058	0.000
X17	Log (CGS)	6.04435	0.73651	5.97154	0.57365	3.72523	0.0114
X18	Net profit/total assets	0.0649	0.15732	-0.04232	0.21988	3.562	0.0005
X20	Net profit/ cost of goods sold	0.01673	0.38055	-0.27322	0.79488	4.73992	0.0018
X21	cost of goods sold/total assets	0.9863	0.77065	0.74075	0.47496	4.04693	0.0458
X24	Operating Profit/sale	-0.09499	0.5091	0.08085	0.2547	9.08334	0.003
X25	Earnings before interest and taxes/sale	-0.2684	0.79852	0.03012	0.38876	10.8867	0.0012
X27	Gross profit/total assets	0.07984	0.13457	0.15411	0.13015	10.8077	0.0012
X28	Earnings before interest and taxes/total assets	-0.03922	0.22325	0.07747	0.17022	13.4629	0.0003
X32	Earnings before interest and taxes/current liabilities	0.08746	0.48497	0.25052	0.46879	4.01394	0.0466
X33	(Current assets - Inventory)/ current liabilities	0.71192	1.16493	0.39511	0.47679	6.68665	0.0105
X34	Inventory/ current liabilities	0.67699	0.61788	0.82381	0.55213	4.0639	0.0244
X35	Cash/ total liabilities	0.08976	0.20681	0.08966	0.20554	3.71495	0.0188
X38	Current liabilities / total assets	0.73133	0.42745	0.57907	0.32242	6.33887	0.0127
X39	Capital / total assets	0.14167	0.44489	0.34075	0.3841	8.36056	0.0043
X42	Inventory/ sale	0.85829	0.91738	0.57365	0.52389	6.49386	0.0117
X43	Accounts Receivable/ sale	0.68403	0.64249	0.43578	0.63394	5.10144	0.0251
X44	Sale / fixed assets	3.94599	3.66542	5.44689	6.05732	5.78711	0.0021
X47	cost of goods sold/sale	0.89015	0.18465	0.82466	0.1531	5.49606	0.0202
X48	Operating costs/sale	0.08085	0.34518	0.01235	0.04305	4.98701	0.0268
X53	Inventory/ current assets	0.54712	0.27773	0.69299	0.39575	5.24274	0.0232

The significant differences in mean values between fraudulent and non-fraudulent companies and the high statistical significance ($p < 0.000$) indicate that these ratios are related to fraudulent financial statements. The proposed model has several steps as follows:

1. data pre-processing;
2. data transfer;
3. Selecting effective features using genetic algorithms and neural networks;
4. Training and calculation of the weights of decision tree algorithms and support vector machine;
5. Making a Decision Tree;
6. Transform the decision tree and optimize it;
7. Making a support vector machine.

The general flowchart of the research method can be seen in Fig. 4.

3.1. Pre-processing data

Initially, the dataset is collected and the data are prepared and preprocessed. Different methods are used in data preparation and preprocessing. First, some properties have unique values. These attributes cannot create useful knowledge in the dataset. Therefore, this feature set must be deleted from the data. For example, we can mention the name and surname. Some transactions may also have large amounts of missing data. These transactions should also be removed from the dataset. On the other hand, some attribute values may have noise and missing values, so they should also be corrected in the dataset. The next step is to use the anomaly detection tool. Data outside the dataset is identified and deleted. In order to work on the data as input, some properties must be extracted from them. Typically, some pre-processing operations are performed on the data before selecting and extracting features.

3.2. Data Transfer

In this section, the data is in the right domain. That is, the data must be transferred to the suffering specified in the system, and the data outside the suffering is problematic data and must be deleted. The data should be in the right range, meaning that, for example, if there is an age field, someone aged 55 to 70 should be considered very old in the system, which will be automatically completed from the dataset.

3.3. Selecting effective features using genetic algorithms and neural networks

Genetic algorithms, with their considerable capability to derive meaning from complex data, can be used to extract patterns and identify methods that are very complex and difficult for humans and other computer techniques to be aware of. The genetic algorithm, as one of the data mining tools, can be used for classification. Here, we try to use the perceptron neural network algorithm, optimized by a genetic algorithm, to identify more effective features, and thus identify more effective financial ratios for the corporate fraud. In fact, the strategy presented by Ledsa et al. (2008) is used here.

Determining the network structure is one of the influential steps in how to train the network, although the number of high neurons in the network increases its complexity and the network may be over-fitted, affecting the predictability of the network. Therefore, for each training algorithm, the number of neurons increased from one to four. The data are thermalized in the range of 1 to 2 and the tansig transition function is used. The two most commonly used optimization algorithms based on

biological transformations are Genetic Algorithm. In the genetic algorithm, population includes possible responses in the form of an array of chromosomes. Grid weights are optimized by a genetic algorithm. So, each population is randomly assigned as a grid weight. The MSE function is introduced as a cost function, and the population chromosomes are then arranged to achieve the lowest cost function. A certain number of better members are transferred to the next generation at the lowest cost. At this stage, three genetic algorithm operators (selection, intersection, and transformation) are activated to generate the next generation population. This cycle continued until the desired solution was achieved to obtain the desired network weights.

Finally, in this section, 23 financial ratios are examined and, if possible, their number is reduced, thereby reducing computational overhead as well as noise, if possible. This process is illustrated in Fig 6. For ease of operation, each ratio uses Att and a specified number is shown in Fig. 5.

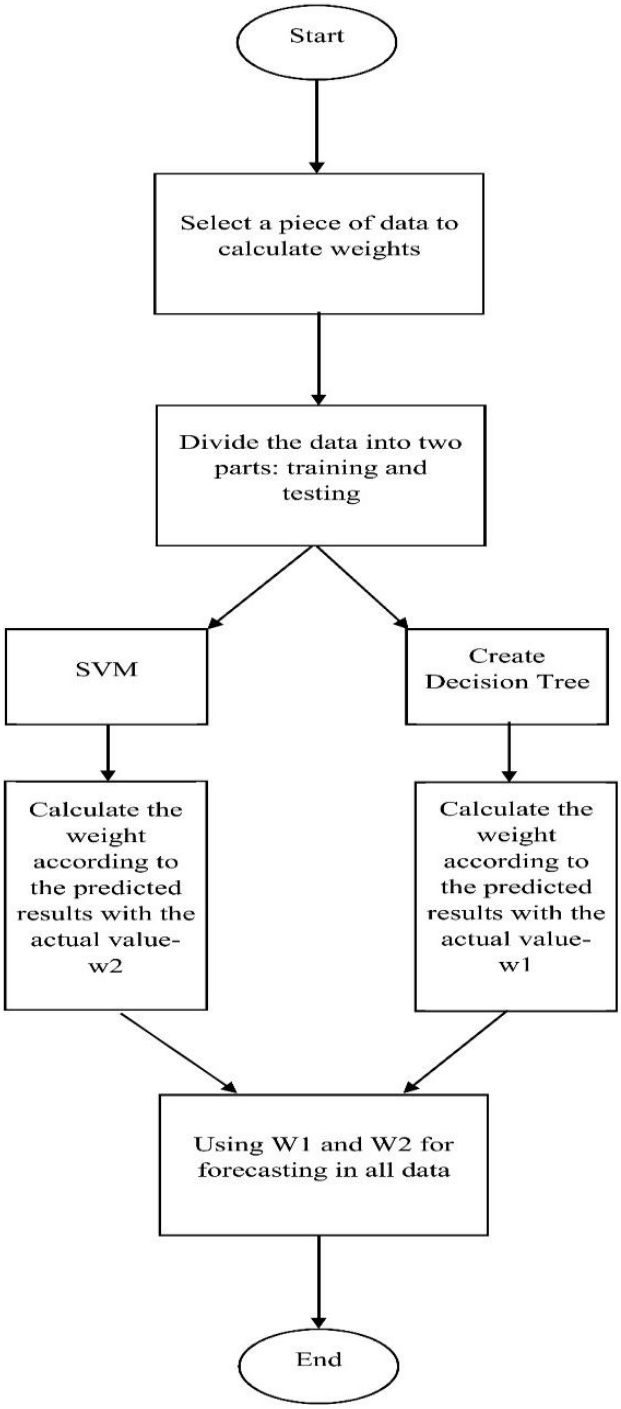

Fig. 4. Proposed research model

Att1	:	Liabilities/total assets
Att2	:	Current ratio
Att3	:	Quick ratio
Att4	:	Log (CGS)
Att5	:	Net profit/total assets
Att6	:	Net profit/ cost of goods sold
Att7	:	cost of goods sold/total assets
Att8	:	Operating Profit/sale
Att9	:	Earnings before interest and taxes/sale
Att10	:	Gross profit/total assets
Att11	:	Earnings before interest and taxes/total assets
Att12	:	Earnings before interest and taxes/current
Att13	:	(Current assets - Inventory)/ current liabilities
Att14	:	Inventory/ current liabilities
Att15	:	Cash/ total liabilities
Att16	:	Current liabilities / total assets
Att17	:	Capital / total assets
Att18	:	Inventory/ sale
Att19	:	Accounts Receivable/ sale
Att20	:	Sale / fixed assets
Att21	:	cost of goods sold/sale
Att22	:	Operating costs/sale
Att23	:	Inventory/ current assets

Fig. 5. List and title of the ratios used

In the proposed method, first, the feature selection task is performed and the more effective features are selected. The input dataset can be seen in Fig. 6, which is the effect of the features sorted.

Att1 : 0
Att16 : 0
Att15 : 0
Att14 : 0
Att13 : 0
Att23 : 0
Att19 : 0
Att20 : 0
Att18 : 0
Att21 : 0
Att7 : 0
Att22 : 0
Att4 : 0
Att3 : 0
Att2 : 0
Att17 : 0
Att9 : 0.0905061414027294
Att6 : 0.0949449035096511
Att12 : 0.100474368655747
Att11 : 0.104421869607332
Att5 : 0.105127953476521
Att8 : 0.114018997382377
Att10 : 0.120272737712267

Fig. 6. The influence of the characteristics of the financial ratios used (in order)

Considering the above table, we can conclude that the financial ratios of zero coefficient have no effect on the output, while the financial ratios such as pre-interest income and sales tax, net interest income, pre-interest income and tax liability, current earnings before interest and taxes on total assets, net profit on total assets, operating profit on sale and gross profit on total assets have the greatest impact on whether or not the company is fraudulent. Here, we can eliminate ineffective financial ratios so that the algorithm is able to perform data mining more quickly. Moreover, in this section, we can see which ratios have the greatest impact on whether or not they are fraudulent, and what drives them. It's about giving the company a cheat. That is, the influential parameters can be identified here and more attention is paid to identifying the fraudulent companies and making important decisions.

3.4. Training and calculation of weights of decision tree algorithms and support vector machines

At the beginning of the work, a percentage of the dataset is used for training and weight calculation. In this section, we intend to use a hybrid algorithm using two decision tree algorithms and a support vector machine. each of the two algorithms has a share of the final answer, increasing the accuracy of the system. An illustration of this step can be seen in Fig. 7.

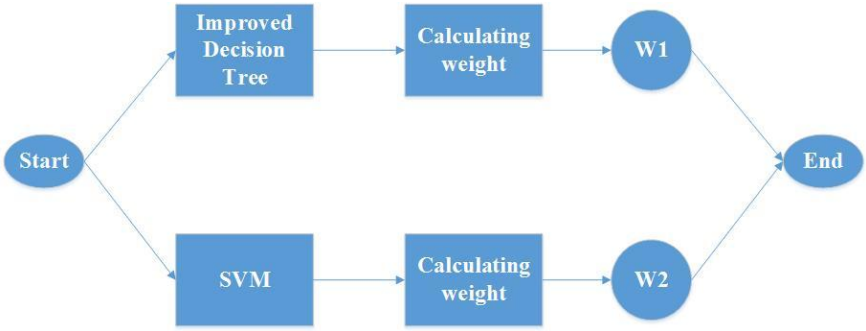

Fig. 7. Architecture used in weight calculation

As can be seen in Fig. 7, the proposed algorithm first calculates the weight using a dataset, so that each algorithm is trained using 70% of the existing dataset and training with the remaining 30% is tested using the score given by the number of correct answers, or weighted, until the weight of the next step is used to calculate the weight for the output of each algorithm. The architecture can also be seen after calculating the weight divided by the number of correct answers to the total number of barley The water is conjectured, and the effect of each algorithm on the final output can be better understood. In this method, after calculating weights, for each record, a prediction is made by the support vector machine and by the optimal decision tree that the predicted value must be multiplied by the weight of the algorithm and the final output of the prediction algorithm is equal. By summing the results of each algorithm, multiply the weight of that algorithm so that the final result is obtained and the classification is correct.

3.5. Making a decision tree

This part of the decision tree is used. The decision tree is a tree from which each branch is chosen. That is, one can choose from the branches that are connected to that node to move from the root node to the lower node. At the end, each end node or so-called node leaves a decision leaf. Each branch up to the leaf has a scenario that makes a decision. In this study, the proposed model based on the improved ID3 decision tree is used which results in its high speed of operation. The ID3 tree is a decision tree that has learning and was first introduced by Ross Quinlan. The idea of the ID3 algorithm is to build a top-down decision tree in which the node is selected by a greedy search through a set of attributes. Here, we used a special template to be able to find the most useful attribute for the classification. To make a useful classification for the learning set, the number of questions has to be reduced or the depth of the decision tree can be said to be reduced. Therefore, this part requires a function to be able to perform the most balanced division, in which the tree depth is greatly reduced and the nodes are balanced in the tree.

Consider a table containing attributes and a class of attributes. This table is called homogeneous if it contains only one class. If a table has multiple classes, then it is called heterogeneous. There are many functions such as entropy, gini index, and classification error to measure homogeneity. Entropy is used here.

$$\text{Entropy} = \sum_{j} - \mathrm{p}_j \log_2 p_j \tag{1}$$

The entropy of a table is zero because its probability is equal to one (tents have one class). The entropy reaches its maximum when all classes in the table have an equal probability. Entropy can be considered as a criterion for measuring irregularity. The more regular the set is, the less varied it is, the less entropy it is, and the less irregular it is, and vice versa. Of course here, since we did an elementary classification in the previous step, the chaos is also low, which in turn speeds up our proposed approach because it will reduce the depth of the decision tree and whatever the deeper the tree, the faster the decision is made.

In this section, we used entropy to obtain the irregularity for each attribute. We used formula (1) to select an attribute in the decision tree that is higher in rank and in some way more important than the other attributes. According to this formula, we calculate the entropy of all attributes in set S and subtract the value of attribute A from the set. Set A is the set of all attributes selected by the father so far in a particular path.

$$G(\mathrm{S}, \mathrm{A}) = Entropy\,(S) - \sum_{v \in Values\,(A)} Entropy\,(\mathrm{v}) \tag{2}$$

For better understanding of formula (2), we can see Fig 6.

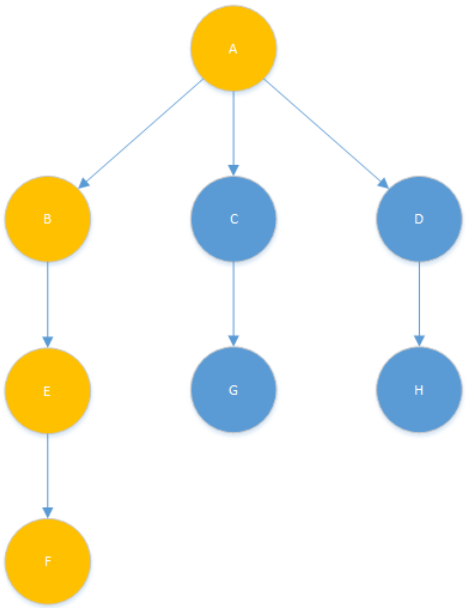

Fig. 8. An example of selecting attributes

As can be seen in Fig 8, we need to the entropy of all of the attributes from the entropy of the selected attributes to reduce the path here (that is, G (S, F) = E (S) - (E (A) + E (B) + E (E) + E (F)). It should be noted, however, that we need to calculate the attributes A used so far in the set A plus the attribute we want to assign. After this, from this set of residuals we calculated the formula for each (2), choosing the attribute with the highest G. In this case, if two attributes had equal G and the probability of this occurrence is not low, then we should add two or any number of attributes that have the highest value G and are equal to the corresponding node. If, for example, in a node, two attributes had equal G, then we added the two nodes to the corresponding node of each of the two children and each of these attributes were considered as a child of this node and then followed the algorithmic procedure for each of these nodes. For example, in Fig. 6 we can see that the value of G is equal to the attributes B, C and D, so all these attributes are at the same level.

This allows us to find the attributes with the most entropy because these attributes have the greatest impact on our final decision. This process of moving forward in the decision tree continues until there is no trait left in any other path. In this case, the decision tree is completely built and finished.

3.6. Improving the decision tree

In order to extract conditions from this tree, as if… then…. where associative rules can be helped, we have transformed the tree into a graph that in many cases, it becomes a tree, and even if it looks like a graph, it will still be a tree for us. The tree is considered so something can be said between the graph and the tree.

In this section, we merge the nodes at each level and add their children to this merge node. This can be seen in Fig 9 to better understand it.

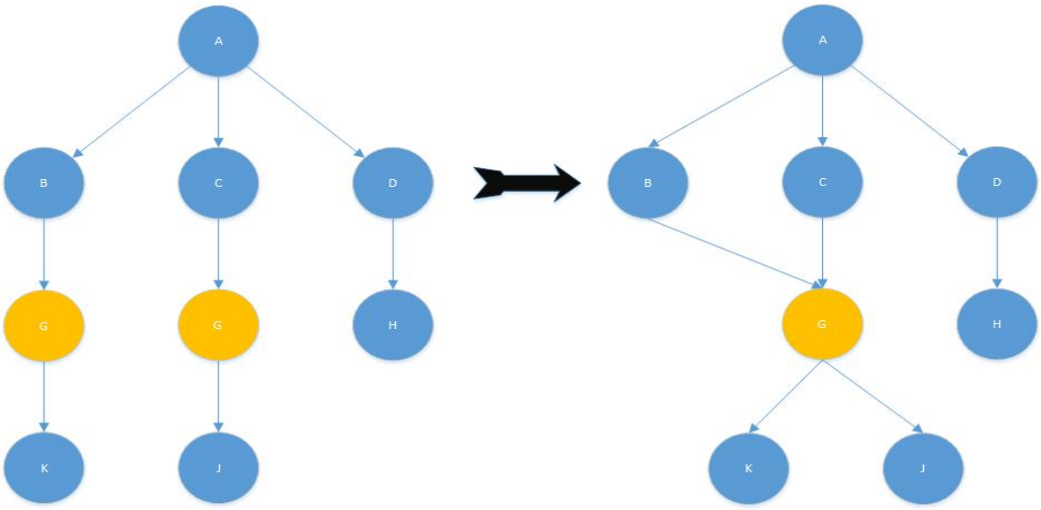

Fig. 9. An example of a decision tree transformation

As can be seen in Fig. 9, nodes B and C had a common child G, with the two nodes G at the same level. In this case, the two nodes become one and their offsprings are added to the new node. Conditions may arise, as in Fig. 10, where the two nodes G are merged, but the situation is that the first node G has a child C and the second node G has a child B and each of these nodes for the opposite G node. It has been visited in the past. This is not a problem either, and it can only be said that when writing a bet, it can be assumed that having the terms B and C, along with its logical And, crosses the path G, that is, A and (B OR C). AND G.

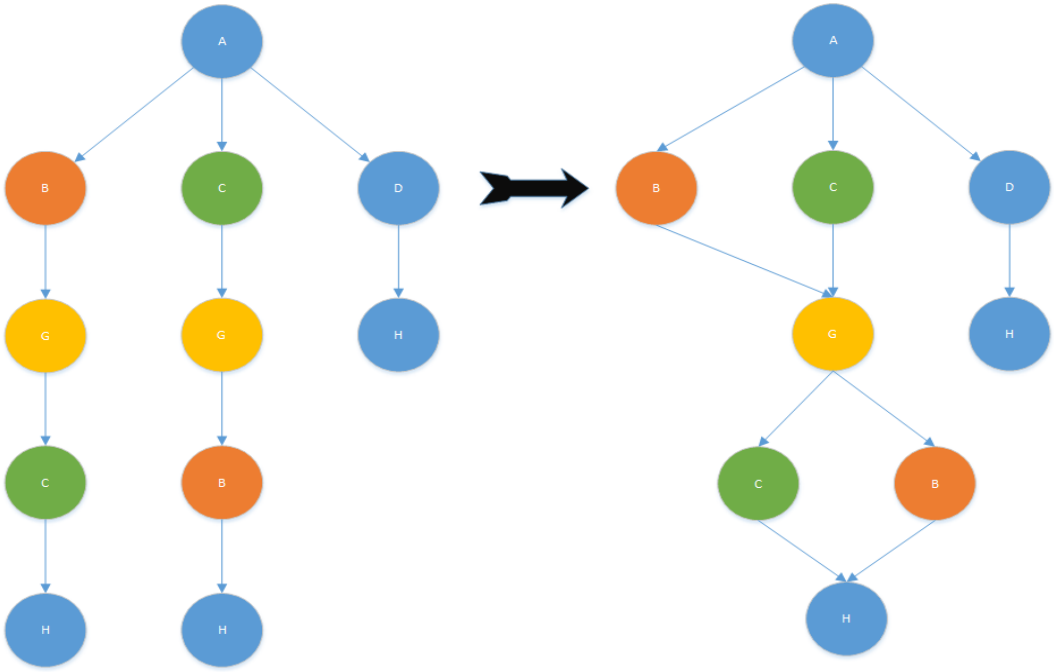

Fig. 10. An example of a particular mode of conversion

Here, we find that each of these attributes in each data can have a different value, for example in Fig. **11, G can have either true or false values for this part of our data. We choose that value whose** frequency is greater in the corresponding attribute in the whole dataset. That is, for example, which of the value of true or false is greater among the G-type attributes, then we choose it. If the value of the two values is equal, then in the decision, we specify or for these two values, for example G = true or G = false.

To extract decisions from the decision graph made here, start from the root node and make a decision towards each leaf we go to.

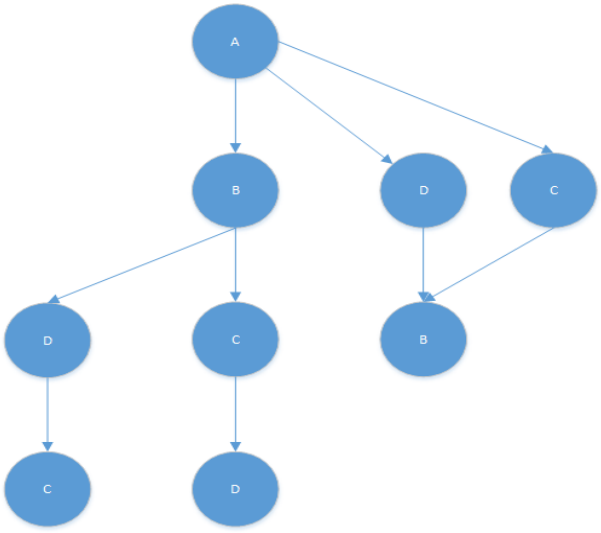

Fig. 11. An example of a decision graph of the proposed method

3.7. Support Vector Machine in the Proposed Model

In this step, the normalization process is first performed and then the results of the normalization are extracted, part of this data is used as training data and the vector machine model is created and then the weight test data of this algorithm is created. It is computed until we can then calculate how effective this part of the algorithm is.

4. Results and Evaluation of the Proposed Model

In this section, the proposed method described in the previous section is examined and the proposed method is compared with the known algorithms called ID3, SVM algorithm, and Bayesian network. As mentioned in the previous section, the proposed solution is based on ID3, which has more advantages than the ID3 method, and in this section, the performance improvement of the proposed method is observed. The proposed approach is evaluated using a three-year dataset of companies, indicating whether or not the company is fraudulent.

The data is first formatted in an appropriate format for analysis, or pre-processed, i.e., the ARFF file is created, which is a standard structure suitable for analysis. It is implemented in Visual Studio 2017 with C # programming language and using libraries like za and zedgraph while working.

The system used here is Windows 10, has 6GB of RAM and Corei7. In this study, the proposed algorithm is compared with ID3, SVM, and Bayesian algorithms. The ID3 and SVM algorithms are the basic algorithms of the proposed method which is derived from the combination of these two methods. It is also compared with one of the famous algorithms called the Bayesian network which can be followed by the results. Observe the buildup for these algorithms.

```
--------Naive Baysian----------
confusionMatrix:
[0,0] = 18 [0,1]=11
[1,0] = 27 [1,1]=124
Correct Prediction Percent = 78.8888888888889%
InCorrect  Prediction Percent = 21.1111111111111%
MeanAbsoluteError(MAE) = 0.215093567412967
MeanSquaredError(MSE) = 0.450450314025597
RelativeAbsoluteError(REA) = 57.1003786873271
Correct Prediction Number = 142
InCorrect Prediction Number = 38
TP: 124
FP: 11
FN: 27
TN: 18
```

Fig. 12. The output of the Bayesian algorithm

```
--------MyAlgorithm----------
confusionMatrix:
[0,0] = 18 [0,1]=9
[1,0] = 27 [1,1]=126
Correct Prediction Percent = 80%
InCorrect  Prediction Percent = 20%
MeanAbsoluteError(MAE) = 0.251683833684513
MeanSquaredError(MSE) = 0.390570453145535
RelativeAbsoluteError(REA) = 66.813909805457
Correct Prediction Number = 144
InCorrect Prediction Number = 36
TP: 126
FP: 9
FN: 27
TN: 18
```

Fig. 13. The output of the proposed algorithm

--------ID3----------
confusionMatrix:
[0,0] = 7 [0,1]=7
[1,0] = 38 [1,1]=128
Correct Prediction Percent = 75%
InCorrect Prediction Percent = 25%
MeanAbsoluteError(MAE) = 0.343346480854847
MeanSquaredError(MSE) = 0.430065588743028
RelativeAbsoluteError(REA) = 91.147375133409
Correct Prediction Number = 135
InCorrect Prediction Number = 45
TP: 128
FP: 7
FN: 38
TN: 7

Fig. 14. The output of the ID3 algorithm

--------SVM----------
confusionMatrix:
[0,0] = 2 [0,1]=4
[1,0] = 43 [1,1]=131
Correct Prediction Percent = 73.8888888888889%
InCorrect Prediction Percent = 26.1111111111111%
MeanAbsoluteError(MAE) = 0.261111111111111
MeanSquaredError(MSE) = 0.510990323891863
RelativeAbsoluteError(REA) = 69.3165467625899
Correct Prediction Number = 133
InCorrect Prediction Number = 47
TP: 131
FP: 4
FN: 43
TN: 2

Fig. 15. The output of the SVM algorithm

According to the obtained results, it can be clearly seen that the proposed algorithm with 80% accuracy and 20% error has the highest accuracy and the least error. Table 2 compares the proposed algorithm with other algorithms. It is quite clear that the proposed algorithm performs much better than other algorithms, and also the ID3 algorithms themselves and the support vector machine, which is the basic algorithm of the proposed method.

Table 2
Accuracy of predictions (%) and error of predictions (%)

	Percentage of correct predictions	**Percentage of incorrect predictions**
Proposed Ago.	80%	20%
Baysian Ago.	78.88%	21.11%
ID3 Ago.	75%	25%
SVM Ago.	73.88%	26.11%

Given the precision obtained, it is quite evident that the proposed method performs much better than the other methods, while the Bayesian algorithm performs better than the ID3 and SVM algorithms. The ID3 algorithm also performs better than the SVM algorithm. It can be clearly seen here that the proposed hybrid method can achieve higher accuracy than the Bayesian network by integrating ID3 and SVM methods, each of which has a lower accuracy than the Bayesian network. The proposal uses the improved ID3 and the improvement process outlined earlier. This tree has the lowest possible height and thereby the lowest overhead.

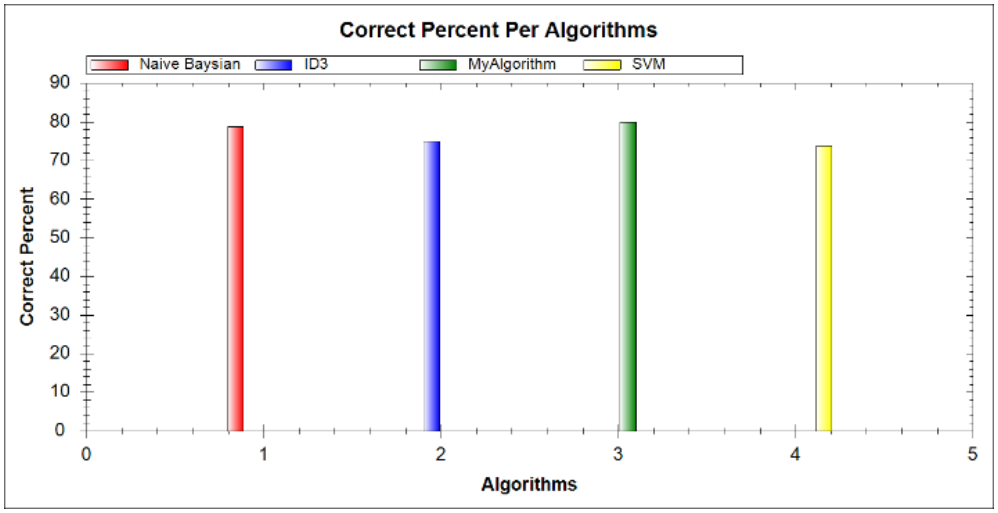

Fig. 16. Proportion of correct prediction among test data for the proposed algorithm and other algorithms investigated

As can be seen from this graph, our proposed method has more accurate prediction accuracy than other Bayesian algorithms, SVM, and ID3 algorithms. This is because in our prediction method, we considered only those test data with the greatest impact on the output and therefore did not use the data not affecting the output, thus greatly reducing the time of analysis. We reduced it while other algorithms are less accurate because of using all the parameters because some parameters may have distances which may have no effect on the output but because in other algorithms we build the model for pre The nose of these parameters have been used to create noise and reduce noise The proposed algorithm also employs a hybrid approach that can be seen to perform well and perform much better than other methods and perform better than the methods based on them.

In the graph presented in Fig. 17, we can see the percentage of incorrect forecasts. According to this graph, it can be understood that the proposed method has lower values than the other methods because it was said earlier with the correct prediction percentage, so the proposed method is less accurate, so the proposed method works better than the other methods has done.

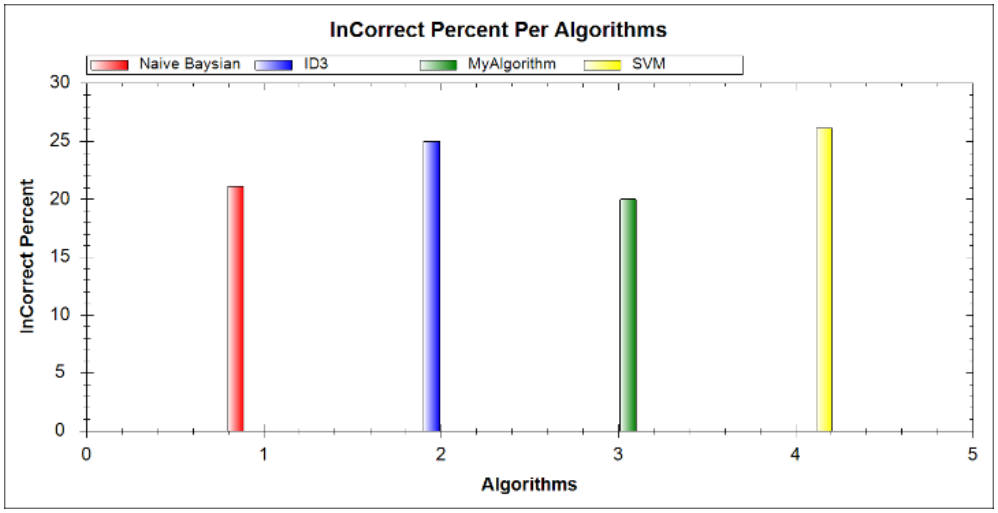

Fig. 17. Incorrect prediction percentage among test data for the proposed algorithm and other algorithms investigated

According to the diagram in Fig. 17, it can be concluded that the studied algorithms have nearly the same prediction error, but the proposed algorithm has a lower one because the higher the accuracy rate, the lower will be the false rate. And this shows the proper performance of the proposed method. It can be seen that the mean error rate (MSE) in the proposed method is lower than all other methods and the ID3 algorithm is lower than the SVM algorithm, while the Bayesian algorithm has a lower error rate than the SVM algorithm. This error rate not only checks for the incorrectness but also calculates the distance of the predicted answer from the actual answer. In this case, the proposed algorithm behaves much better than the other algorithms. If we look at this graph we can see this because the ID3 algorithm has a worse prediction than the Bayesian algorithm. Since the distance was not considered, the ID3 was worse than the Bayesian network. However, as seen in Fig. 18, the ID3 algorithm has a lower MSE than the Bayesian algorithm, meaning that it has a lower error rate. In general, MSE is very important in data mining and is highly credible.

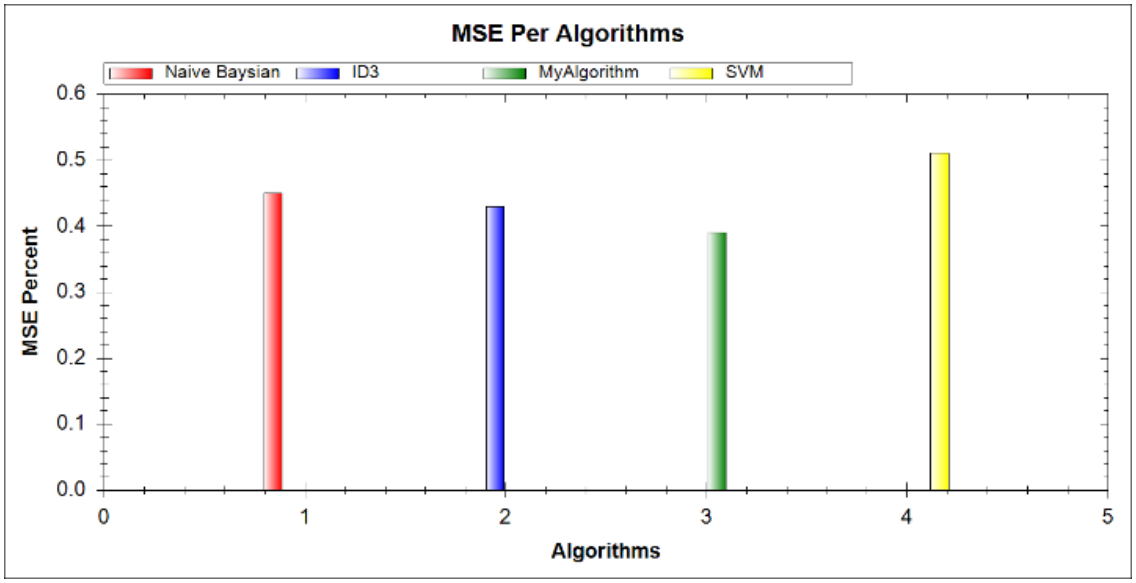

Fig. 18. The MSE benchmark among the proposed algorithm and other similar algorithms investigated

Following is the Confusion Matrix for the proposed method and other methods investigated in this study.

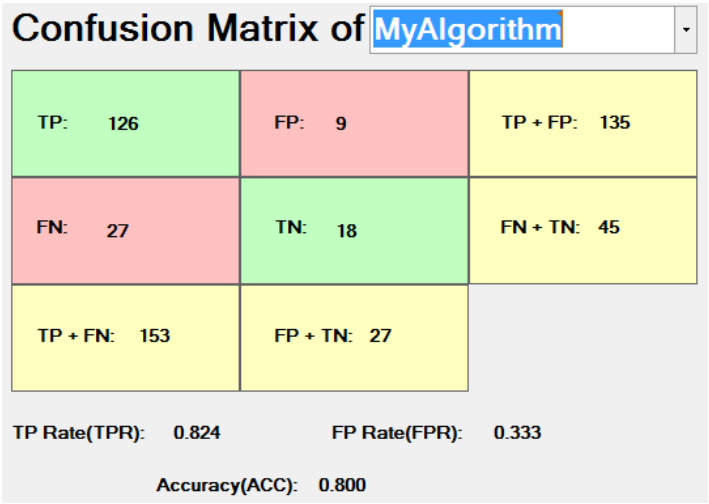

Fig. 19. Confusion matrix for the Suggested method

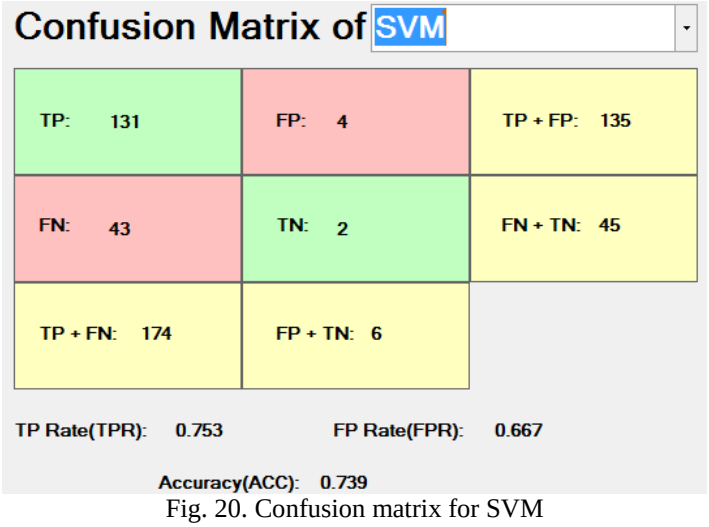

Fig. 20. Confusion matrix for SVM

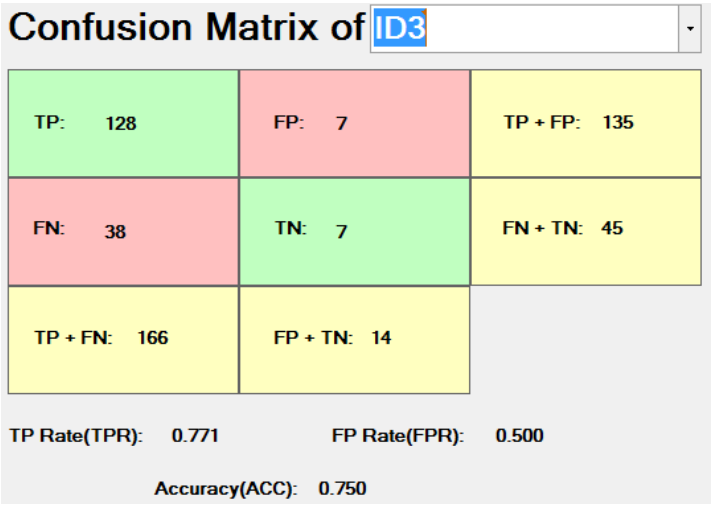

Fig 21. Confusion matrix for ID3

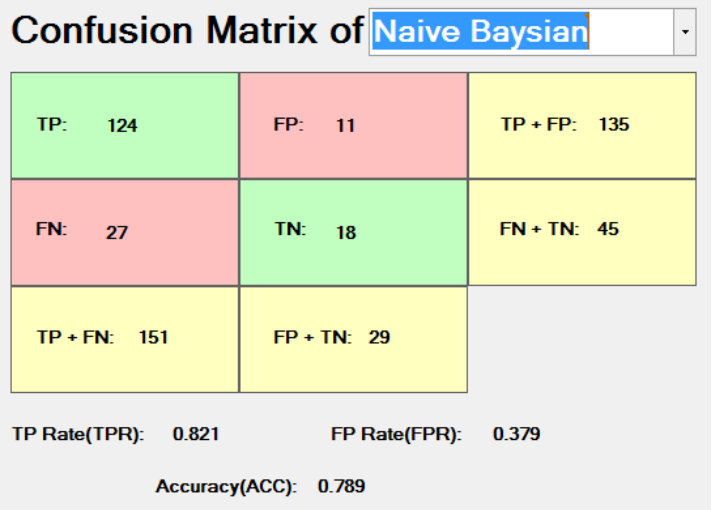

Fig. 22. Confusion matrix for baysian

Here, it can be seen that the proposed method is more accurate because it contains more TP and TN values and also less FP and FN than the other algorithms investigated here. Because the higher the algorithm, the higher the TP and TN, which means that the test data set is more or less false, and the FP and FN represent the opposite, which are false predictions.

5. Discussion and Conclusion

Knowledge is nowadays a valuable and strategic resource as well as an asset for evaluation and forecasting, and providing these solutions in the discovery of fraudulent companies increases the accuracy as well as decreases the effective and permanent workforce for fraud detection and detection. That is to say, a solution such as the one proposed can be fully investigated by fraudulent companies, and this does not require a human workforce, but rather the system itself can intelligently detect and provide information. In this study, a strategy was presented to evaluate and predict corporate financial fraud forecasts, and it was found that the method presented here performed well and showed a relatively high improvement over its basic algorithms, ID3 and SVM. Proposed 6.66 percent improvement over ID3 algorithm and 8.27 percent improvement over SVM. Further work with the Bayesian network algorithm was also investigated and it was found that the proposed method performs much better than the Bayesian algorithm and has higher accuracy and lower error rates. The Bayesian algorithm performs much better than the SVM and ID3 algorithms, but it is observed that if the MSE error rate is investigated, the ID3 has a lower error rate than the Bayesian, because the MSE is only dependent on TP, TN, FP and FN. The data used in this study included 60 companies over a period of 3 years, which means that the data analyzed here had 180 records. Here, the data was initially processed and transitions were performed on the data until the data became the input data required by the proposed algorithm. The results show a complete improvement of the proposed method. Therefore, according to the results of the model presented with 80% accuracy and 20% error, it has the highest accuracy and the lowest error rate. So, it can be used to predict fraud or as a representative of fraud in various surveys.

6. Suggestions for Future Research

- In the proposed method, entropy is used, but other methods can be used or merged with other methods. For example, if we combine this with a value-based method like Gain, it is likely to perform better because entropy also has disadvantages, but its speed is high, and here we were looking for a method that The speed is high, but the accuracy of the proposed method can be greatly enhanced by integrating this method or alternative methods.
- The proposed method can also be used with the improvement in C4.5 algorithm, i.e. the proposed method can be implemented on C4.5 with the same improvement as on ID3 in this study, so that its performance cannot be increased but it cannot be Cut said that its performance is improving, but it should be tested to verify the performance.

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