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A COMPARATIVE STUDY OF MACHINE LEARNING ALGORITHMS AS AN AUDIT TOOL IN FINANCIAL FAILURE PREDICTION

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Abstract

The main aim of this study is to show usage of machine learning as an audit tool. Within this main aim, the object of this study is to compare the classification performances of machine learning algorithms in financial failure and to determine the best algorithm. Financial failure has been one of the major research topic in accounting and finance. Financial failure is an im-portant task for internal auditors too. As an assurance activity internal auditors should give an assurance about the company continuity Early studies used traditional statistical techniques. With the development of computer science and technology, artificial intelligence and machine learning have been used in order to increase the accuracy. The output that has been used in this study is classification accuracy. Our data set consist of 216 companies' financial data between the period 1983-2012. As a result of the study it was seen that rule based classification algorithms' are more successful than the others. The decision table algorithm from this rule based classification algorithms has reached the highest classification performance with a ratio of 91.8%.

Keywords: Financial failure prediction, Machine learning, Classification, Data mining, Audit tool

JEL Classification: G33, G17, C45

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FİNANSAL BAŞARISIZLIK TAHMİNİNDE DENETİM ARACI OLARAK MAKİNE ÖĞRENİMİ ALGORİTMALARININ KARŞILAŞTIRMALI ÇALIŞMASI

Öz

Bu çalışmanın temel amacı, denetim aracı olarak makine öğrenmesinin kullanımını göstermektir. Bu ana amaç kapsamında, bu çalışmanın amacı, finansal başarısızlıkta makine öğrenmesi algoritmalarının sınıflandırma performanslarını karşılaştırmak ve en iyi algoritmayı belirlemektir. Finansal başarısızlık, muhasebe ve finans alanında en çok çalışılan konulardan biridir. Finansal başarısızlık iç denetçiler için de önemli bir konudur. Çünkü iç denetçiler bir güvence faaliyeti olarak işletmenin sürekliliği hakkında da güvence vermelidirler. İlk çalışmalar geleneksel istatistiksel teknikleri kullanmıştır. Bilgisayar bilimi ve teknolojinin gelişmesiyle birlikte, doğruluğu arttırmak için yapay zeka ve makine öğrenimi kullanılmaktadır. Bu çalışmada sınıflandırma doğruluğu çıktı olarak kullanılmıştır. Veri seti 1983-2012 dönemine ait 216 şirketin finansal verilerinden oluşmaktadır. Çalışma sonucunda kural tabanlı sınıflandırma algoritmalarının diğerlerinden daha başarılı olduğu görülmüştür. Bu kural tabanlı sınıflandırma algoritmalarından karar tablosu algoritması % 91,8 oranı ile en yüksek sınıflandırma performansına ulaşmıştır.

Anahtar Kelimeler: Finansal başarısızlık tahmini, Makine Öğrenmesi, Sınıflandırma, Veri Madenciliği, Denetim aracı

JEL Sınıflandırması: G33, G17, C45

1. Introduction

Internal auditing is an independent, objective assurance and consulting activity designed to add value and improve an organization's operations. It helps an organization accomplish its objectives by bringing a systematic, disciplined approach to evaluate and improve the effectiveness of risk management, control, and governance processes (IIA, 2018). We want to highlight two important points from this definition.

- Risk management: Risk assessment is a component of internal control and risk management is the main focus area of internal audit. Also in accordance with the law no 6102 Turkish Commercial Code 378, a committee has to be established to manage the risk. Internal audit will support upper management about risk management in this manner.
- Adding value: One of the way that internal auditers to add value is to use the technology in audit process. This issue is supported by the below IPPF standards.
  - ❍ 1210 Proficiency
  - ❍ 1220 Due Proffesional Care
  - ❍ 1230 Contiuning Proffessional Developmet
  - ❍ 2320 Analysis and Evalutaion

  Using technology will led internal auditors various opportunities. Time and cost savings, minimizing audit risk, audit all operations etc.

All of the decisions about the company depends on the continuity. Financial failure is closely associated with risk management and financial failure is the most important risk among the risks. So, prediction of the financial failure is important for all stakeholders. Providing 1% increase in the performance of models that used for prediction of the financial performance can result in a significant decrease in the amount of the losses incurred by all stakeholders, especially creditors and investors. For this reason, it can be said that financial failure has been one of the major research topic in accounting and finance. Financial failure is an important task for internal auditors too. As an assurance activity internal auditors should give an assurance about the company continuity. The explanations show that an early warning system is an important tool for internal auditors to estimate financial failure.

Early studies used univariate techniques to predict the financial failure (Beaver, 1966;1968; Tamari 1968). Altman (1968) was the first researcher who used the multivariate statistic techniques. After this study, there a lot of statistical studies were done such as multiple regression by Mayes and Pifer (1970), logit by Ohlson (1980), probit by Zmijewski (1984). In these studies, correct classification success reach to 95%. But the common matter in these studies is that they ignore the assumptions of the statistical techniques (Yıldız, 2001). Such an aprroach, put a question mark in the generalization of the obtained results,continuity of the performance of models and application of the models to the real world (Eisenbeis,1977; Altman & Eisenbeis, 1978; Booth, 1983; Karels & Prakash 1987; Kim & Kang, 2010). Recently, numerous studies have demonstrated that artificial intelligence can be an alternative method to traditional statistical methods (Odom & Sharda, 1990; Tam & Kiang, 1992; Atiya, 2001; Barniv et al., 1997; Bell, 1997; Pompe & Feelders, 1997; Boritz & Kennedy, 1995; Etherige & Sriram, 1997; Fletcher & Goss, 1993; Wilson & Sharda, 1994; Kotsiantis et al., 2005; Tsai & Wu, 2008; Huang et al. 2004; Shin et al.2005; Min & Lee, 2005; Gestel et al. 2006; McKee & Lensberg, 2002; Shin & Lee, 2002; Kim & Han, 2003; Yu et all., 2014; Barboza et al., 2017; Wang, 2017).

Machine learning studies were done by engineers, mathematician and data scientist generally. We consider that artificial intelligence and machine learning should be used by all professionals from differrent disciplines such as accounting and finance. Thus we used differrent and various machine learning algorithms in this study. The main purpose of this study is to examine machine learning as an early warning system to internal auditors.

When review the literature, we see that certain algorithms used such as Support Vector Machines (SVM), Neural Networks and Genetic Algorithm. Also, these studies compared the machine learning methods with statistical methods. So, differency and variety of the machine learning algorithms can be considered contribution of this study. In this scope, we compared the 16 machine learning algorithms' performances and 216 companies' data to determine which algorithms are more suitable for financial failure prediction. We compared the performance of the algorithms using accuracy measurement. This study is one of the studies done with so much data and used so much algorithm in the literature.

The remainder of this study is organized as follows. Section two is a brief description of the machine learning and machine learning algorithms used in the study. Section three provides a review of the machine learning applications for the financial failure. Section four research data and metholodology. Section five summarizes and analyses empirical results and section six discusses the conclusions and future research issues.

2. Machine Learning

Studies about the artifical intelligence has led the creation of algorithms that will be alternative to the statistical techniques in recent years. The name of these algorithms are Machine Learning and instead of relying on mathematical theory, their aim is to imitate the human intelligence abilities by benefit from computers. Development in central processing unit (CPU) technologies are increasing the interest to these algorithms.

Artificial intelligence and machine learning terms have been used interchangeable. Because, boundaries of these terms are not clear. Artifical intelligence is rather broad and upper term that imitate human intelligence's all abilities. So, there is no any application that meet one to one artificial intelligence term. With the usage of artifical intelligence, we can analyze deeply huge amount of information, in a short time. Machine learning algorithms, present particular ability of human intelligence in a too limited field. As seen in Figure 1, machine learning is a subfield of artifical intelligence.

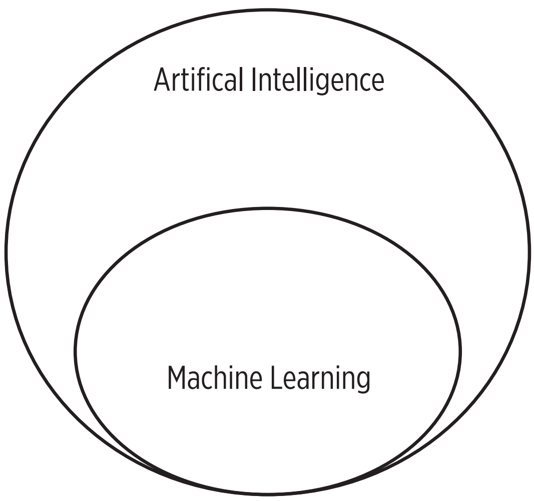

Figure 1. Machine Learning and Artificial Intelligence

Due to statistical techniques are developed for studying with few data, they are incapable to solve a large amount of data and complicated relations. Increasing performance and showing developments in time by using new data are the most significant features that distinguish machine learning algorithms from the traditional computer algorithms. It was seen that very successful practices have been developed by using these algorithms in the literature. With the development of social media, a large amount of data about the human behaviours have been collected. Machine learning methods are used in analyzing these types of data.

Machine Learning algorithms can be divided into subgroups according to intented use such as classification, clustering, pattern recognition and correlation analysis.To predict the financial failure, classification algorithms are used in this study.

2.1. Classification Algorithms Used in the Study

Hundreds of machine learning classification algorithms are available. A few of them have been selected and used in this study. But we highlight that this is one the studies that used so many machine learning algorithms in the literature.

Machine learning algorithms that we compared in our study was summarized in Table 1.

Table 1: Algorithms Used in Study

	Classifier Algorithm	Function
Rules Based	ZeroR	Predicts the majority class (if nominal) or the average value (if numeric)
	OneR	1R classifier
	JRip	Ripper algorithm for fast, effective rule induction
	Decision Table	Builds a simple decision table majority classifier
	PART	Obtains rules from partial decision trees built using j4.8
Function Based	Simple Logistic	Builds linera logistic regression models with built-in attribute selection
Neural Networks	Multilayer Perceptron	Backpropagation neural network
Lazy Algorithms	Knn	K nearest neighbors classifier
Bayes	Naive Bayes	Standard probabilistic Naive Bayes Classifier
	Bayes Net	Learns Bayesian nets
Trees	J48	C4.5 decision tree learner
	Random Forest	Constructs random forests
	Decision Stump	Builds one-level decision trees
	Hoeffding Tree	Used to decide the number of instances to be run in order to achieve a certain level of confidence
	LMT (Logistic Model Trees)	Builds logistic model trees
	Random Tree	Constructs a tree that considers a given number of random features at each node

Explaning algorithms in detail is beyond the scope of study. So, in the next section literature about the machine learning usage in financial failure is handled.

3. Prior Research on Prediction Financial Failure Using Machine Learning

We review the prior studies on prediction financial failure using machine learning. We summarize these studies in Table 2.

Table 2: Prior Research on Prediction Financial Failure Using Machine Learning

Reference	Applied Algorithm	Benchmark Algorithm
Ahn & Kim (2009)	Hybrid Case Based Reasoning and Genetic Algorithm	
Kotsiantis et al. (2005)	Naive Bayes, Local DS, RIPPER, Decision Tree (C4.5), SVM (Sequential Minimal Optimization), Neural Network (RBF)	
Pompe & Feelders (1997)	Classification Trees, Neural Networks	Linear Discriminant Analysis
Atiya (2001)	Neural Network	
Tsai & Wu (2008)	Neural Network	
Odom & Sharda (1990)	Neural Network	Multiple Discriminant Analysis
Boritz & Kennedy (1995)	Neural Network	Discriminant Analysis, Logit, Probit
Etherige & Sriram (1997)	Neural Network	Multivarite Discriminant Analysis, Logit
Barniv et al. (1997)	Neural Network	Multiple Discriminant Analysis, Logit
Wilson & Sharda (1994)	Neural Network	Discriminant Analysis
Fletcher & Goss (1993)	Neural Network	Logit
Bell (1997)	Neural Network	Logit
Zhang et al. (1997)	Neural Network	Logit
Tam & Kiang (1992)	Neural Network	Linear Classifier, Logistic regression, Knn, ID3
Huang et al. (2004)	Support Vector Machine	Neural Network
Min & Lee (2005)	Support Vector Machine	Multiple Discriminant Analysis, Logit, Neural Network
Shin et al. (2005)	Support Vector Machine (SVM)	Backpropagation Neural Networks (BPN)

Gestel et al. (2006)	Least Squares Support Vector Machine (LS-SVM)	
McKee & Lensberg (2001)	Genetic Programming	
Kim & Han (2003)	Genetic Algorithm	
Barboza et al. (2017)	SVM, Boosting, Bagging, Random Forest	Artificial Neural Network, Logit, Discriminant Analysis
Wang (2017)	SVM, Neural Network, Autoencoder	Logit, Genetic algorithm, Inductive learning

As seen in the literature review, artificial intelligence methods have been used in financial failure since 1990s, include neural network, SVM, decision tree, genetic algorithm, extreme learning machine.

Ahn & Kim (2009) offerred a hybrid model in bankruptcy prediction. Case based reasoning and genetic algorithm were used in their studies. The study results showed that prediction accuracy of conventional case based reasoning may be improved significantly by using genetic algorithm.

Kotsiantis et all. (2005) compared machine learning algorithms. They applied Naive Bayes, Local Decision Stump, RIPPER, Decision Tree (C4.5) , Seguental Minimal Optimization and Neural Network (RBF algorithm). It was found that learning algorithms can predict bankruptcy with satisfying accuracy.

Pompe & Feelders (1997), made a comparison between the performance of linear disriminant analysis, classification trees and neural networks in bankruptcy prediction. They used 576 firms' annual reports. As a result of the study they cannot concluded that one learning algorithm clearly outperformed the other algorithms.

Atiya (2001) applied neural networks to predict the bankruptcy. Researcher used 716 solvent firms and 195 defaulted firms. The model reached 85.50% correct classification rate. Tsai & Wu (2008), investigated the performance of a single classifier as the baseline classifier to compare with multiple classifiers and diversified multiple classifiers by using neural networks based on three datasets.

Odom & Sharda (1990) applied neural network to predict bankruptcy. They used five input variables and 129 firms' data. They compared the result obtained from neural network to MDA. As a result, neural network correctly classified %81.81 while MDA achieved 74.28%.

Boritz & Kennedy (1995), examined the effectiveness of different neural networks in predicting bankruptcy. The neural networks were compared against traditional bankruptcy prediction techniques such as discriminant analysis, logit, and probit. The results showed that the level of Type I and Type II errors varies greatly across techniques. The Optimal Estimation Theory neural network has the lowest level of Type I error and the highest level of Type II error while the traditional statistical techniques have the reverse.

Etherige & Sriram (1997), used two artificial neural networks (ANNs), categorical learning/instar ANNs and probabilistic (PNN). The results indicated that traditional MDA and logit perform best with the lowest overall error rates. However, when the relative error costs are considered, the ANNs perform better than traditional logit or MDA. Also, as the time period moves farther away from the eventual failure date, ANNs perform more accurately and with lower relative error costs than logit or MDA.

Barniv et al. (1997), used artificial neural networks (ANNs), multi-state ordered logit and nonparametric multiple discriminant analysis (NPDA) for predicting the three-state outcome of bankruptcy filing. The study compared the classification accuracy of these procedures. They used a sample of 237 publicly traded firms which had complete data. For the entire sample and estimation samples, ANNs provide significantly better three-state classification than logit and NPDA.

Wilson & Sharda (1994), investigated the performance of a single classifier as the baseline classifier to compare with multiple classifiers and diversified multiple classifiers by using neural networks based on three datasets. By comparing with the single classifier as the benchmark in terms of average prediction accuracy, the multiple classifiers only perform better in one of the three datasets.

Fletcher & Goss (1993) compared performances of neural network with logit regression model in bankruptcy. They used 3 input variables and 36 companies's data. The study showed that neural network classified more accurate. Bell (1997), compared predictive abilities of neural network and logit. The study indicated that, at least for the bank failure prediction problem, neither the logit model nor the neural network model dominates the other in terms of predictive ability across the entire frontier of all possible model cutoffs. Zhang et al. (1997), presented a general framework for understanding the role of artificial neural networks (ANNs) in bankruptcy prediction. The method of cross-validation is used to examine the between-sample variation of neural networks for bankruptcy prediction. Based on a matched sample of 220 firms, findings of the study indicated that neural networks are significantly better than logistic regression models in prediction as well as classification rate estimation. In addition, neural networks are robust to sampling variations in overall classification performance. Tam & Kiang (1992) compared neural networks classification performance with linear discriminant model, logit regression, Knn and ID3. They used 118 companies' data. As a result neural network outperforms to other methods.

Huang et al. (2004), applied SVM machine learning algorithm. They used backpropagation neural network (BNN) as a benchmark and obtained prediction accuracy around 80% for both BNN and SVM methods. Min & Lee (2005) applied SVM to the bankruptcy prediction. Also they compare the obtained results from SVM to multiple discriminant analysis (MDA), logistic regression analysis (Logit), and three-layer fully connected back-propagation neural networks (BPNs). The study results showed that SVM outperforms to the other methods. Shin et al. (2005), compared the classification performances of SVM and BPN in bankruptcy prediction. They used 2320 medium size manufacturing firms. According to the study results, SVM outperforms to BPN.

Gestel et al. (2006), applied Least Squares Support Vector Machine (LS-SVM) classifiers, also known as kernel Fisher discriminant analysis in order to automatically infer and analyze the creditworthiness of potential corporate clients. They used 422 firms' data. The suggested nonlinear kernel based classifiers yield better performances than linear discriminant analysis and logistic regression.

McKee & Lensberg (2001), investigated a hybrid approach to bankruptcy prediction, using a genetic programming algorithm to construct a bankruptcy prediction model with variables from a rough sets model. They used data from 291 US public companies for the period 1991 to 1997. The study findings indicated that genetic programming coupled with rough sets theory can be an efficient and effective hybrid modeling approach both for developing a robust bankruptcy prediction model and for offering additional theoretical insights. Kim & Han (2003), proposed a genetic algorithm-based data mining method for discovering bankruptcy decision rules from experts' qualitative decisions. The results of the experiment showed that the genetic algorithm generates the rules which have the higher accuracy and larger coverage than inductive learning methods and neural networks.

Barboza et al. (2017), compared the performances of the machine learning algortihms with neural network and statistical techniques. SVM, boosting, bagging and random forest were used as a machine learning algorithms. Their study result showed that bagging, boosting and random forest outperform to others.

Wang (2017) used SVM, neural network with dropout and autoencoder machine learning algorithms in bankruptcy prediction. Researcher aslo compared the performances of these algorithms with logit, genetic algorithm and inductive learning. As a result of the study SVM, neural network with dropout and autoencoder accuracies outperforms to other models.

SVM and neural network are the most used algorithms in the financial failure prediction literature. Also, limited number of machine learning algorithms were used. So, variety of machine learning algorithms can be considered contribution of the study. We used several machine learning studies that have not been used before to predict the financial failure and we compared the performances of them.

All machine learning algorithms have their strengths and weaknesses. Searching for best financial failure prediction models are in still progress. Our aim is not to discuss the strengths and weaknesses of these methods. We just try to show the usage of machine learning in accounting and finance.

4. Data and Method

The dataset obtained from Istanbul Stock Exchange, consisted of a total 216 firms, 108 of which were financial failure and 108 non financial failure firms in the period 1983 until 2012[3].

In the selection of financial failure companies, general accepted criterias in the literature were used. These criterias are:

- Bankruptcy,
- Loosing half of the capital,
- Loosing %10 percentage of the assets,
- Make a loss three years in row,
- Have difficulty in solvency,
- Stop the manufacturing,
- Liabilities more than assets

Companies that are included in the scope of one or more of these criterias were determined as financial failure and companies that are not included in the scope of these criterias are determined not financial failure. In the selection of non financial failure companies, we paid attention that financial failure criteria have not been comply with financial failure criterias in the past. Due to, difficulties in finding financial failure company; data, sector, size and type was not considered in the selection process. Even if it is a negative situation because it is increasing the difficulty of the problem, it turns into positive in our study with regard to generalize the results that obtained from study.

The dataset is arbitrarily split into two subsets; about 66% of the data set were used for developing the model, remaining 34% of the data set were used for testing the model. So training set includes 143 company, test set includes 73 company. 38 company is financial failure and 35 company is not financial failure in the test set. To compare the the performance of models equally the same training and test data sets were used in all models.

3. We updated the data that used in Yildiz's (2001) research.

Table 3:Dataset

	Training	Test	TOTAL
Financial Failure	70	38	108
Not Financial Failure	73	35	108
TOTAL	**143**	**73**	**216**

The selected variables for this research are shown in Table 4.

Table 4:Variables and Definitions

Variable	Definition
X1	Current Assets/Short Term Liabilities
X2	(Current Assets-Inventories)/Short Term Liabilities
X3	Cash and equivalents/ Short Term Liabilities
X4	Net Working Capital/Assets
X5	Inventories/Assets
X6	Short Term Trade Receivables/Assets
X7	((Inventories+ Short Term Trade Receivables)-Short Term Liabilities)/Continuous Capital
X8	(Short Term Liabilities-Cash and equivalents)/Inventories
X9	(Current Assets-Short Term Liabilities)/Sales Revenues
X10	(Net Profit/Sales Revenues)*(Sales Revenues/Assets)*(Assets/Shareholders' Equity)
X11	Liabilities/Assets
X12	Liabilities/Equities
X13	Long Term Liabilities /Assets
X14	Operating Profit/Financial Expenses
X15	Short Term Liabilities /Sources
X16	Short Term Liabilities/Liabilities
X17	Short Term Liabilities / Long Term Liabilities
X18	Non-current Assets/ Shareholders' Equity
X19	Non-current Assets/(Shareholders' Equity+Long Term Liabilities)
X20	Tangible Non-Current Assets (Net)/ Shareholders' Equity
X21	Tangible Non-Current Assets /Assets

X22	Current Assets/Assets
X23	Non-Current Assets / Current Assets
X24	Short Term Liabilities / Shareholders' Equity
X25	Assets/ Shareholders' Equity
X26	Sales Revenues/Assets
X27	Sales Revenues /Tangible Non-Current Assets (Net)
X28	Cost of Sales/Inventories
X29	Sales Revenues /Short Term Trade Liabilities
X30	Sales Revenues /Cash and equivalents
X31	Sales Revenues /Non-Current Assets
X32	Sales Revenues /Shareholders' Equity
X33	Sales Revenues /Current Assets
X34	Operating Profit/ Sales Revenues
X35	Net Profit/ Sales Revenues
X36	Gross Profit/Assets
X37	Operating Profit/Assets
X38	Net Profit/Assets
X39	Gross Profit/ Sales Revenues
X40	Sales Revenues / Continuous Capital
X41	Net Profit/ Continuous Capital
X42	Financial Expenses / Sales Revenues

Firstly, a model was developed by using the training data set for all algorithms and then correct classification performance of test data was measured.

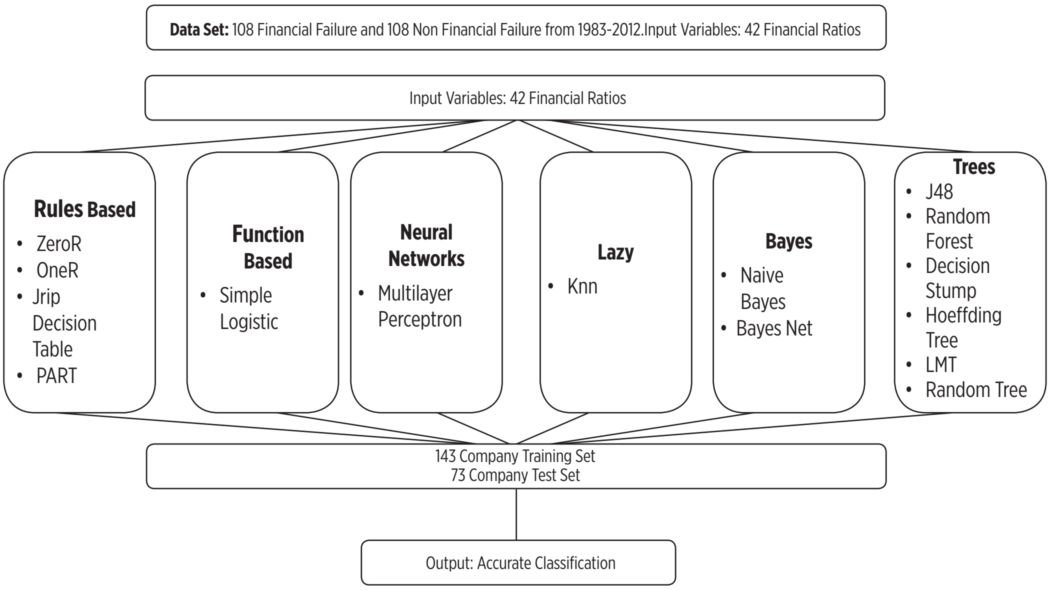

Figure 2: Methodology of the Study

Finally, models were tested by Marascuillo Procedure (Berenson et al., 2013:575-577) to find meaningful differences between these algorithms' correct classification performances.

5. Empirical Results

After developing each model, correct classification performance of the test data set was measured. Models and correct classification performances are seen in the Table 5. It was seen that rule based machine learning algorithms show more successful classification performances. Decision Table is the most successful machine learning algorithm by the rate 91.78%.

Table 5: Correct Classification Rates of Each Model

Model no	Family	Algorithm	Correct %
1	bayes	Naive.Bayes	69.86
2	bayes	Bayes.Net	87.67
3	function	mlp	86.3
4	function	Simple.Logistic	80.82
5	lazy	knn	76.71
6	rules	ZeroR	47.94
7	rules	Jrip	89.04
8	rules	Decision.Tables	91.78
9	rules	OneR	86.3
10	Rules	PART	80.82
11	trees	j48	86.3
12	trees	Random.Forest	87.67
13	trees	Decision.Stump	89.04
14	trees	Hoeffding.Tree	68.49
15	trees	LMT	86.3
16	trees	Random.Tree	82.19

We did not prefer chi-square to test inequality of the performance. Because chi-square test do not show which proportions are significantly different from others. So, differences of the machine learning algorithms' performances were tested by Marascuillo Procedure. The results are seen in the Table 6.

Table 6: Marascuillo Procedure Results

Model No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
2	*															
3	*															
4	*															
5		*														
6	*	*	*	*	*											
7	*				*	*										
8	*			*	*	*										
9	*					*										
10	*					*		*								
11	*					*										
12	*				*	*										
13	*				*	*										
14		*	*	*		*	*	*	*	*	*	*	*			
15	*					*								*		
16	*					*		*						*		

(*) p < 0.05 h0= equality of proportations rejected.

As seen in the Table 6 model 8 (correct classification success is 91.78%) is statistical different from the models 10, 14 and 16, but is not statististical different from other models. This is not a negative situation because all of the models' performances high and close to each other.

6. Conclusion

Risk management is a vital function for companies in today's business environment. As a component of the internal audit, risk assesment is one of the core audit tasks of internal auditors. So, as a part of the risk management, financial failure is handled in this study. Assurance provided by internal audit regarding to financial failure will be important for all stakeholders.

Usage recent technological developments in audit activities could help internal auditors in decision making. Recent developments in computer science like machine learning provide many advantages to all users. It is evaluted that using machine learning as an audit tool will promote efficieny and effectiveness of internal audit. In the light of these explanations the main aim of this study is to show the usage of machine learning in financial failure prediction.

This study compared and concluded the progress of machine learning algorithms regarding financial failure prediction and checked to see the performance of various algorithms in the context of financial failure prediction.

It was seen that machine learning algorithms are achieve the same success when compared with statistical techniques. 16 machine learning algorithms were developed by using training set consist of 143 unit company. Testing the correct classification performance of these algorithms on test data set consist of 73 company. Our experimantation results demonstrate that Decision Table algorithm has the highest level of accuracies than others. Generally it can be said that, rule based machine learning algorithms show more successful classification performance.

Further research should include another quantitative and qualitative data in the analyis. Due to financial ratios limitations, using other information such as market share, human resource management, corporate governance issues, etc. will be increased the model performance. Also, machine learning is an audit task for internal auditors. Compliance of the algorithms used in audit process should also be audited by internal auditors.

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