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Feature selection in single and ensemble learning-based bankruptcy prediction models

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Abstract

Feature selection is an important data preprocessing step for the construction of an effective bankruptcy prediction model. The prediction performance can be affected by the employed feature selection and classification techniques. However, there have been very few studies of bankruptcy prediction that identify the best combination of feature selection and classification techniques. In this study, two types of feature selection methods, including filter- and wrapper-based methods, are considered, and two types of classification techniques, including statistical and machine learning techniques, are employed in the development of the prediction methods. In addition, bagging and boosting ensemble classifiers are also constructed for comparison. The experimental results based on three related datasets that contain different numbers of input features show that the genetic algorithm as the wrapper-based feature selection method performs better than the filter-based one by information gain. It is also shown that the lowest prediction error rates for the three datasets are provided by combining the genetic algorithm with the naïve Bayes and support vector machine classifiers without bagging and boosting.

KEYWORDS

bankruptcy prediction, data mining, ensemble classifiers, feature selection, machine learning

1 | INTRODUCTION

Bankruptcy prediction is critical as providing a way for financial institutions to measure the financial distress of public firms, focusing on evaluating the likelihood that a firm may go bankrupt, before it actually happens. In this process, a credit risk assessment mechanism must be employed in order to make correct decisions on whether loan customers belong to a high risk group or are likely to go bankrupt (Huang, Chen, Hsu, Chen, & Wu, 2004; Lin, Hu, & Tsai, 2012).

As a consequence, developing effective bankruptcy prediction models has become an important goal in the accounting, finance, and computing communities. Recent reviews and surveys of the literature, for example, by Balcaen and Ooghe (2006), N. Chen, Ribeiro, and Chen (2016), Crook, Edelman, and Thomas (2007), Kumar and Ravi (2007), Lin et al. (2012), and Verikas, Kalsyte, Bacauskiene, and Gelzinis (2010), have shown that there are many statistical and machine learning techniques that have been developed and applied for bankruptcy prediction. Of the two main types of techniques, machine learning has been most widely used and has been shown to outperform statistical techniques.

To make the prediction models more effective, it is very important to choose those representative factors (or input variables) that can "describe" the status of a firm well, for example, financial ratios. However, as there is no exact answer about which input variables are the best for bankruptcy prediction, different input variables have been used to develop prediction models in different studies (Liang, Lu, Tsai, & Shih, 2016).

In many studies, the approach used to examine the discriminatory power of the collected input variables (or features) has not been systematic making it more difficult to distinguish between cases where there is a danger of bankruptcy or not. To insure improvement, the feature selection process should be performed over the collected dataset. However, according to Lin et al. (2012), who survey 130 related studies, feature selection prior to model construction was considered in only half of them.

The aim of feature selection, as a preprocessing step in data mining, is to filter out unrepresentative features from a given dataset, which allows the constructed model to perform better than the one without feature selection (Chandrashekar & Sahin, 2014; Dash & Liu, 1997; Guyon & Elisseeff, 2003). In general, two types of feature selection methods, the filter- and wrapper-based methods are widely used in many pattern recognition problems (cf. Section 2.1).

Recently, Zelenkov, Fedorova, and Chekrizov (2017) combine a wrapper method based on the genetic algorithm (GA) with different single and ensemble classifiers for the bankruptcy prediction of Russian firms. However, they do not consider filter-based methods. In Liang et al. (2016), three filter and two wrapper feature methods are chosen to combine with several single classifiers for the Chinese and Taiwanese datasets. However, ensemble classifiers are not constructed for further comparisons. Therefore, in bankruptcy prediction, the question as to what kind of prediction technique can produce the greatest performance improvement by which type of feature selection methods remains unanswered.

In other words, according to our literature review (cf. Section 2.2), the feature selection effect on different statistical and machine learning techniques including single and ensemble classifiers has not been fully studied. Therefore, the objective of this study is to examine the performance of various prediction models, with and without feature selection, by using different well-known statistical and machine learning techniques. In particular, two types of feature selection methods, the filter- and wrapper-based methods are used. Moreover, single and ensemble learning techniques, including bagging and boosting methods (Breiman, 1996; Schapire, 1990), are also employed. Consequently, the contributions of this paper are to identify which combination of feature selection and classification technique performs the best for bankruptcy prediction. In addition, the best combination identified in this paper can be used as one representative baseline for future researches.

The rest of this paper is organized as follows. Section 2 overviews feature selection and reviews related work where feature selection is performed. The research methodology is described in Section 3. Section 4 presents the experimental results, and some conclusions are offered in Section 5.

2 | LITERATURE REVIEW

2.1 | Feature selection

Before constructing a bankruptcy prediction model, a training dataset should be collected. A training dataset usually contains a number of data samples, each one of which is composed of several related features, including financial ratios and corporate governance indicators, and their associated class labels, such as either bankruptcy or nonbankruptcy (Liang et al., 2016).

Feature selection is a process where a subset of representative features is selected from the training dataset for use in model construction. There are several advantages to be obtained by performing feature selection. For example, the feature dimensionality is reduced in the feature space, which could enhance generalization because the overfitting problem is reduced. In addition, the computational cost of training a prediction model is also reduced (Chandrashekar & Sahin, 2014; Guyon & Elisseeff, 2003).

A variety of feature selection methods have been proposed, which can be categorized into filter, wrapper, and embedded methods. According to recent surveys by Lin et al. (2012) and Sun, Li, Huang, and He (2014), most related studies considering feature selection are based on filter- and wrapper-based methods.

Generally speaking, filter-based methods perform two operations, ranking and subset selection. First, each individual feature is ranked based on certain criteria. The feature evaluation step can be either univariate or multivariate. Next, the features with the highest rankings are chosen for the later model construction process. In general, statistical methods, such as principal component analysis, information gain, and stepwise regression, are used.

In contrast, in the wrapper-based methods, the quality of the selected features is evaluated by utilizing a specific predefined classifier. This method is composed of two basic steps, which are searching a subset of features and evaluating the selected subset of features based on the performance of the classifier. These two steps are executed repeatedly until the desired quality is reached. Some examples of recent representative wrapper-based methods are genetic algorithms and particle swarm optimization.

2.2 | Work related to bankruptcy prediction by feature selection

Table 1 lists recent works related to bankruptcy prediction where feature selection is performed for model construction. In particular, the prediction models constructed and feature selection methods used are presented.

We can find some limitations in the recent related works listed in Table 1. First, in most studies, feature selection is performed with filter-based methods. In addition, very few employ both filter- and wrapper-based methods for the later model construction process. Second, few studies constructed the prediction models by both statistical and machine learning techniques.

Specifically, only Zelenkov et al. (2017) combined the GA as feature selection with single and ensemble classifiers, whereas Yu et al. (2014) focused on the linear discriminant analysis as a filter-based feature selection method and ensemble learning technique. In Liang et al. (2016), two types of feature selection methods are considered, but they only compared several single classifiers.

TABLE 1 Comparison of related works

Work	Feature selection: Filter	Feature selection: Wrapper	Prediction models: Statistical techniques	Prediction models: Machine learning
Chou, Hsieh, and Qiu (2017)		GA		Fuzzy clustering
Zelenkov et al. (2017)		GA	LR ensembles	DT/KNN/SVM/NB ensembles
Liang et al. (2016)	SDA/SLR/*t* test	GA/RFE		SVM/KNN/DT/BPNN/NB
Danenas and Garsva (2015)	CorFS		LR	SVM/RBFNN
Kim, Kang, and Kim (2015)	VIF			SVM ensembles
Gordini (2014)	VIF		LR	SVM/GA
Li, Li, Wu, and Sun (2014)	MDA	GA		SVM
Xu, Xiao, Dang, Yang, and Yang (2014)	PCA/RS		LR	SVM/BPNN
Yu, Miche, Severin, and Lendasse (2014)	LDA		LDA ensembles	SVM ensembles
M.-Y. Chen (2013)	PCA			ANFIS
Chuang (2013)	RS		LR	CBR
Hajek and Michalak (2013)	CorFS/ConFS	GA	NB/LDA	BPNN/RBFNN/SVM/RF
Saberi, Mirtalaie, and Hussain (2013)		MC		BPNN

Note. ANFIS: adaptive-network-based fuzzy inference system; BPNN: back propagation neural network; CBR: case-based reasoning; CFS: correlation-based feature selection; ConFS: consistency-based feature selection; DT: decision tree; GA: genetic algorithm; KNN: k-nearest neighbor; LDA: linear discriminant analysis; LR: logistic regression; MC: Monte Carlo; MDA: multivariate discriminant analysis; NB: naïve Bayes; PCA: principal component analysis; RBFNN: radial basis function neural network; RF: random forest; RFE: recursive feature elimination; RS: rough set; SDA: stepwise discriminant analysis; SLR: stepwise logistic regression; SVM: support vector machine; VIF: variance inflation factor.

This leads to an important question: What kind of feature selection method combined with which kind of prediction model offers the best performance in terms of bankruptcy prediction? To answer this question, in this paper, all of the possible combinations are compared. That is, for the feature selection step, both filter- and wrapper-based methods will be employed. In addition, for model construction, single and ensemble classifiers by both statistical and machine learning techniques will be developed.

3 | RESEARCH METHODOLOGY

3.1 | Datasets

Three related datasets are used in the experiments, which are the Australian credit,[1] German credit,[2] and Taiwan bankruptcy (Liang et al., 2016) datasets. Particularly, the Australian and German credit datasets are the top two most widely used datasets in the literatures of bankruptcy prediction (Lin et al., 2012). The dataset information is listed in Table 2. Because these datasets contain different numbers of features and different ratios of the good and bad cases, using these datasets allows us to reach reliable conclusions.

3.2 | Feature selection

In the literature of feature selection, comparisons of various well-known feature selection methods have been studied, such as Forman (2003) and Kudo and Sklansky (2000). According these studies, we choose one well-known and representative filter- and wrapper-based feature selection method of each type for our experiments, which are the information gain and GA methods, respectively.

To implement these two feature selection methods, the Weka data mining software[3] is used, and their related parameters are based on the default values provided in this software.

3.3 | Prediction model construction

For the prediction models, two statistical and four machine learning techniques are used, which are logistic regression and naïve Bayes (NB) as the statistical models and back propagation neural network, C4.5 decision tree, support vector machine, and k-nearest neighbor as the machine learning-based models.

[1]https://archive.ics.uci.edu/ml/datasets/Statlog+(Australian+Credit+Approval)

[2]https://archive.ics.uci.edu/ml/datasets/Statlog+(German+Credit+Data)

[3]http://www.cs.waikato.ac.nz/ml/weka/

TABLE 2 Dataset information

Dataset	No. of features	No. of good/bad cases
Australian credit	14	307/382
German credit	24	700/300
Taiwanese bankruptcy	95	220/220

The ensemble learning-based models are constructed based on the bagging and boosting combination methods. That is, bagging- and boosting-based models are constructed by each of the statistical and machine learning techniques, respectively. Similar to feature selection, these prediction models are constructed with the Weka software, and related parameters are based on the default values.

3.4 | The evaluation metric

To evaluate the performance of the prediction models, the Type I error is measured. In general, the average prediction accuracy and Types I/II errors are examined for bankruptcy prediction models (Lin et al., 2012). However, because bankruptcy prediction belongs to the class imbalance type of problem where the number of bankrupt cases is much smaller than that of nonbankruptcy cases, it is meaningless to examine the average prediction accuracy (Galar, Fernandez, Barrenechea, Bustince, & Herrera, 2012).

The Types I and II errors are useful to obtain an understanding of the performance of prediction models where the Type I error means the number of bankrupt cases that the model incorrectly classifies into the nonbankrupt class and the Type II error measures the model that incorrectly classifies nonbankrupt cases into the bankrupt class. Of these, Type I error is more critical for financial institutions, because if they make wrong decisions regarding which loan customers who will go bankrupt, bad debts will increase. Therefore, the prediction model that can provide the lowest Type I error rate can be regarded as the best model.

4 | EXPERIMENTAL RESULTS

4.1 | Single classifiers

Figures 1–3 show the Type I error rates of the six prediction models with and without feature selection over the Australian, German, and Taiwanese datasets, respectively. As we can see, most classifiers with feature selection perform better than the ones without feature selection. In particular, GA + NB (4.97%), GA + SVM (8.58%), and GA + SVM (0%) perform the best for the Australian, German, and Taiwanese datasets, respectively.

Specifically, the lowest error rates are obtained by GA after performing the wrapper-based feature selection method allowing for the best single classifiers, that is, NB and SVM. This finding is similar to those of Hua, Tembe, and Dougherty (2009) who found that the wrapper-based methods are more likely to perform better than the filter-based methods.

4.2 | Ensemble classifiers

As an alternative to single classifiers, the bagging and boosting methods are used to construct ensemble classifiers. Due to limitations of space, Figures 4–6 show the Type I error rates obtained with ensemble classifiers for the top three classification techniques with and without feature selection over the Australian, German, and Taiwanese datasets, respectively.

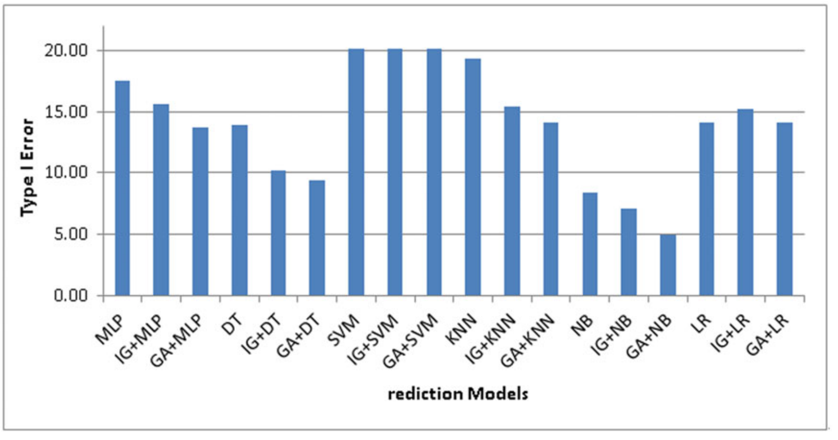

FIGURE 1 Type I errors for the six prediction models with and without feature selection over the Australian dataset. DT: decision tree; GA: genetic algorithm; IG: information gain; KNN: k-nearest neighbor; LR: logistic regression; NB: naïve Bayes; SVM: support vector machine

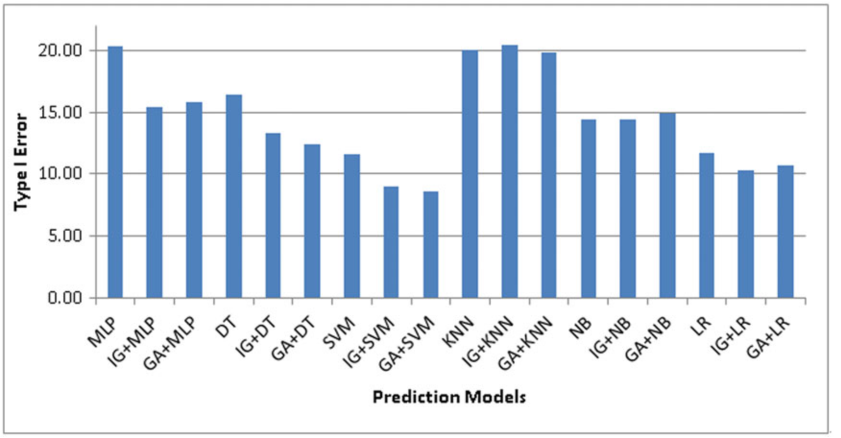

FIGURE 2 Type I errors for the six prediction models with and without feature selection over the German dataset. DT: decision tree; GA: genetic algorithm; IG: information gain; KNN: k-nearest neighbor; LR: logistic regression; NB: naïve Bayes; SVM: support vector machine

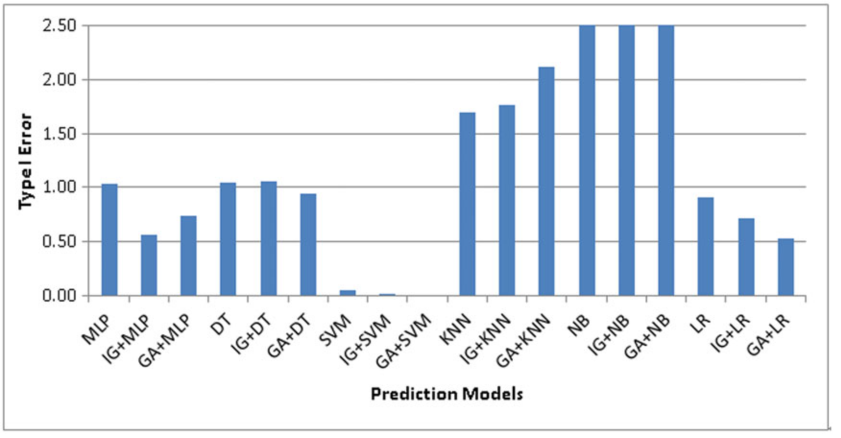

FIGURE 3 Type I errors for the six prediction models with and without feature selection over the Taiwanese dataset. DT: decision tree; GA: genetic algorithm; IG: information gain; KNN: k-nearest neighbor; LR: logistic regression; NB: naïve Bayes; SVM: support vector machine

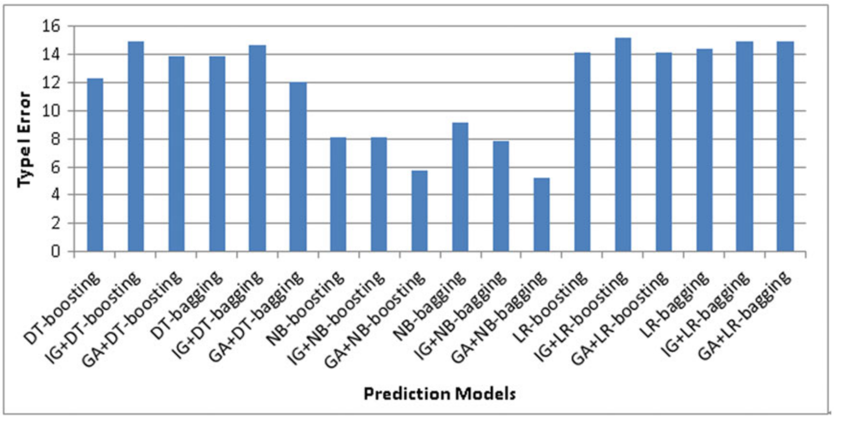

FIGURE 4 Type I errors for the top three ensemble classifiers with and without feature selection over the Australian dataset. DT: decision tree; GA: genetic algorithm; IG: information gain; LR: logistic regression; NB: naïve Bayes

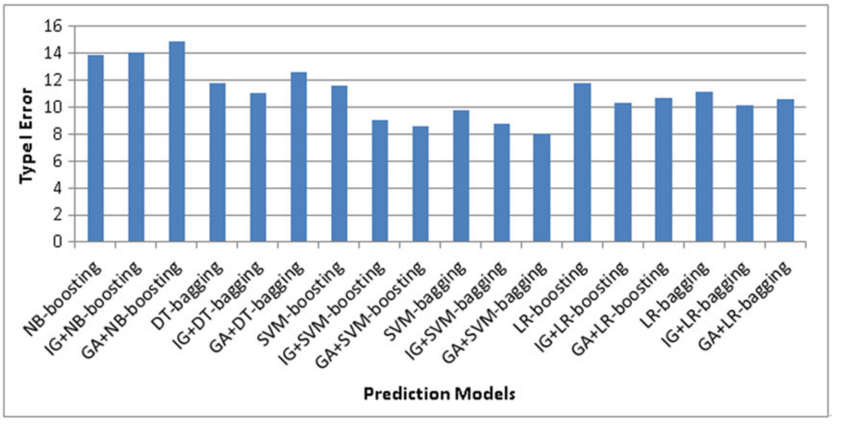

FIGURE 5 Type I errors for the top three ensemble classifiers with and without feature selection over the German dataset. DT: decision tree; GA: genetic algorithm; IG: information gain; LR: logistic regression; NB: naïve Bayes; SVM: support vector machine

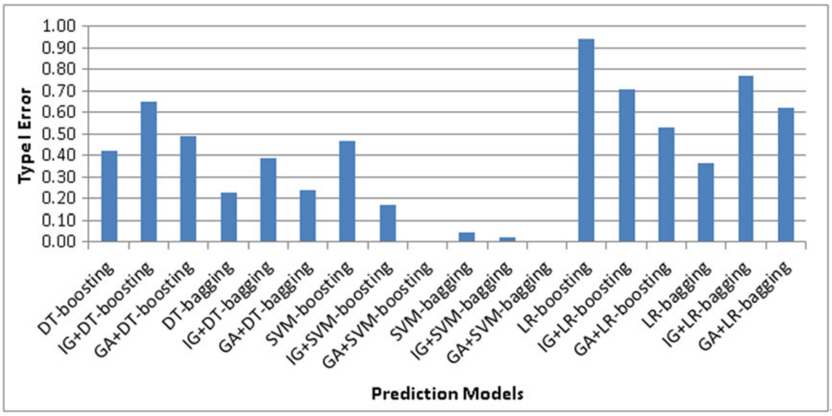

FIGURE 6 Type I errors for the top three ensemble classifiers with and without feature selection over the Taiwanese dataset. DT: decision tree; GA: genetic algorithm; IG: information gain; LR: logistic regression; SVM: support vector machine

TABLE 3 Comparison between the best single and ensemble classifiers

Classifiers	Type I errors
Australian dataset	
GA + NB	4.97%
GA + NB-bagging	5.24%
German dataset	
GA + SVM	8.58%
GA + SVM-bagging	8.01%
Taiwanese dataset	
GA + SVM	0%
GA + SVM-bagging/boosting	0%

Note. GA: genetic algorithm; NB: naïve Bayes; SVM: support vector machine.

From these results, we can observe that the best performances for the Australian, German, and Taiwanese datasets are obtained by GA + NB-bagging, GA + SVM-bagging, GA + SVM-bagging, and GA + SVM-boosting, respectively. These results are the same as the ones for single classifiers showing that the wrapper-based feature selection method by GA make for the best ensemble classifiers, that is, NB-bagging, SVM-bagging, and SVM-boosting, providing the lowest error rates.

A comparison of the best single and ensemble classifiers over the three datasets shown in Table 3 is helpful in order to understand whether ensemble classifiers can outperform the single ones. We find that ensemble classifiers do not necessarily perform better than single best classifiers. That is, the performance differences between single and ensemble classifiers are not significant based on the Wilcoxon signed-rank test (Demsar, 2006). The optimal model for bankruptcy prediction is produced by combining a well-performing feature selection method with a suitable single classifier. This is because constructing classifier ensembles requires larger memory and computational time than constructing a single classifier.

5 | CONCLUSION

Constructing an effective bankruptcy prediction model is very critical for financial institutions to make correct loan decisions. Because there are no generally agreed financial ratios and related factors with which to train the model, feature selection is an important technique to examine the discriminatory power of the collected features, that is, input variables or attributes, used to distinguish between bankrupt and nonbankrupt cases.

In this paper, we study the effect of performing filter- and wrapper-based feature selection on single and ensemble learning-based prediction models. We found that executing a feature selection step to filter out some unrepresentative input features leads to better performance in most classifiers than the ones without feature selection. In particular, the GA as a wrapper-based feature selection method outperforms the information gain algorithm, which is a filter-based feature selection method.

On the other hand, the combination of GA and NB and support vector machine classifiers perform the best over the Australian, German, and Taiwanese datasets, which can be regarded as the baseline for future research studies.

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