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Full Length Research Paper

Developing a hybrid evaluation process for product acceptability: An empirical study in automobile industry

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Product acceptability has become a very important issue as manufacturers have to decide whether product factors influence consumer decision on the purchase. In recent years, the evaluation of product acceptability has been a topic of continuous and extensive research. Unfortunately, manufacturers and designers often misunderstand what consumers really want. Hence, how to evaluate the acceptability of product is one of the key problems of product development. In this study, we proposed a hybrid evaluation process for acceptability problem in an attempt to evaluate product acceptability with better performance. A real case, car evaluation, was tested to show that the product acceptability problem can be easily evaluated and predicted using the proposed approach. The results show that it can solve the product acceptability problems and could be extended to other industries.

Key words: Acceptability evaluation, product acceptability, product development, consumer decision.

INTRODUCTION

Cars touch the lives of hundreds of millions of people nearly everywhere in the world on a daily basis (Byun, 2001). Aside from buying a house, a car is perhaps the largest purchase that most people make. Buying a car is regarded as a reflection of consumers' needs and a decision marking problem. The choice of any product involves complex human behaviors, influenced by many interrelating factors concerned with the product (Li and Chang, 2010). It also contains the consumer making a choice and external characteristics that include price, brand and capability (Wu et al., 2009). When consumers consider buying a car, there are many factors that could influence their decision on the car purchase, such as the price, the cost of regular maintenance, comfort, and safety (Nath, 2009). Consumers appear to regard the purchase of a new vehicle for private use as a major investment that merits doing at least some homework (Alam, et al., 2010). As the car market becomes rigidly competitive, acceptability of a new car is a critical aspect of evaluation car market.

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In a rapidly changing and competitive market environment today, enterprises have become increasingly interested in customers' need and develop products that satisfy the customer demands because it will increase the enterprise's competitiveness (Liao et al., 2008; Alam, 2009). Constant changes in customer needs lead manufactures to produce new and improved designs. Unfortunately, manufacturers and designers often misunderstand what consumers really want. Ishikwan (1983) stated that the term "quality" refers to the ability of a product to satisfy the consumers' requirements and expectations. The consumer's response must be taken into consideration, not only to evaluate the acceptance of the final product, but also from the beginning of the process and its development (Morganosky and Cude, 2000). Fierce market competition now compels product developers to meet very short development cycle times and to address the demands of highly diverse target markets (Lai et al., 2005). An appropriate method for evaluating a car is useful to both customers and producers. An analytic method not only reduces the dealer's burden, but also may increase sales. In addition, it plays a kind of strategic role, increasing customer services in the competitive market environment. Byun (2001) proposed a methodological extension of the AHP approach for selecting a vehicle purchase model. Lai et al. (2005) presented an approach to assist designers in enhancing the feeling quality of a car product. Alnoukari and Alhussan (2008) employed data mining techniques for predicting future car market demand. Chen et al. (2008) proposed a hybrid procedure that incorporates artificial intelligence methods to classify objectively production performance in real-world problems faced by the automobile parts industry.

Data mining is becoming an increasingly essential tool to transform the data into information since its process discovers interesting information from the hidden data which can either be used for future prediction and intelligently summarizing the details of the data (Hashim et al., 2010). These techniques had great popularity in the research area and in commercialization, and they were flexible enough to perform satisfactorily in a variety of application areas, including manufacturing, marketing, finance, and health care (Alam and Khalifa, 2009). There are many achievements of applying data mining techniques to various problems. Data mining application are characterized by the ability to deal with the explosion of business data and accelerated market changes, these characteristics help providing powerful tools for decision makers, such tools can be used by business users for analyzing huge amount of data for patterns and trends (Tan et al., 2006). Millions of databases have been used in business management, government administration, scientific and engineering data management, and many other applications (Alnoukari and Alhussan, 2008). The explosive growth in data and databases has generated an urgent need for new techniques and tools that can intelligently and automatically transform the processed data into useful information and knowledge. It provides enterprises with a competitive advantage, working asset that delivers new revenue, and to enable them to offer better service and retain their customers (Stolba and Tjoa, 2006). Consequently, data mining has become a research area with increasing importance and it involved determining useful patterns from collected data or determining a model that fits best on the collected data (Tan et al., 2006).

Over the last few years, the fashionable classification technique, support vector machine (SVM), was successfully applied to a wide range of domains (Li and Jiang, 2004; Schebesch and Stecking, 2005). The support vector machine (SVM) was introduced to deal with the classification problem. In addition, now, ensemble classifiers are an active area of research in machine learning and pattern recognition (Rodriguez et al., 2006). It is a meta-classifier that combines the predictions of single classifiers called base classifiers with the equal weight or weights based on estimated prediction accuracy (Kuncheva, 2004). Therefore, this study planed to employ SVM classifier and ensemble methods for the product acceptability problem.

Product quality for the manufacturer can be viewed as minimizing deviations from specifications of the product's objectively measured attributes. However, consumers view product quality subjectively. They often only recognize through a combination of their experience, especially making judgments based on first impression, or based on the product's price and value, and the extent to which it satisfies their needs. Han et al. (2004) proposed a method to identify some of the design of features of a mobile phone critical to user satisfaction. Hsiao and Huang (2002) presented a neural network based method to examine the relationships between product form parameters and adjective image words. Lai et al. (2005) adopted gray prediction and neural network models to find out the finest design combination of product form elements for matching a given product image represented by a word pair. Poirson et al. (2007) applied genetic algorithms to determine influencing objective variables of brass musical instruments. Akay and Kurt (2009) presented a neuron-fuzzy method to convert affective consumer needs into explicit form features of products. However, there is no published research that used feature ranking, a pre-processing step in the data mining process, to explore and rank the importance of related features in product development.

Effective evaluation process should be developed to help manufacturer predict product acceptability more accurately. Thus, how to develop more accurate evaluation and prediction process has become an important research topic. Therefore, the aim of this study is to provide an evaluation process that can be used for automotive market, as well as many other areas. In this work, we presented a hybrid evaluation process aimed to calculate the degree of importance ratings for features of a product and estimate product acceptability.

The proposed process applied Relief and Information Gain (IG) to rank importance of the product features. The advantage of Relief is simplicity and effectiveness for assessing the importance of features. In addition, the advantage of IG is often used to decide which of the attributes are the most relevant. Therefore, Relief and IG are suitable to select most related factors in the product development process. In addition, it adopted Support Vector Machine - Sequential Minimal Optimization (SVM-SMO) and ensemble classifiers to solve the problem in an attempt to predict results with better performance. The hybrid evaluation process was developed to assist vehicle manufacturers to evaluate importance of product features and to predict product acceptability.

METHODOLOGY

Feature ranking

Features ranking is not to say that we have ignored those methods that evaluate attributes; on the other hand, it is possible to obtain ranked features with respect to their relevance from these methods. Ranking methods are based on statistics, information theory, or on some functions of classifier's outputs (Duch et al., 2003). Ranking of relevant features is an important problem that has been extensively studied and a number of different measures and features ranking methods have been developed (Kononenko and Kukar, 2006). In this study, we used two well-known attribute ranking techniques, which are Relief and Information Gain. The two methods used ranking to measure the importance of features.

Relief

Relief is one of the most successful algorithms for assessing the importance of features due to its simplicity and effectiveness (Kira and Rendell, 1992). Relief assigns a grade of relevance to each feature, and those features valued over a user given threshold are selected. In this work, we rank the importance of the features according to the principle: the larger the weights, the more important the features. The basic algorithm of Relief (Arauzo-Azofra et al*.,* 2004) is described as follows:

Relief (dataset, M….)
For 1 to M:

K_1= Random example from dataset.
Neighbors = Find some of the nearest examples to K_1.
Perform some evaluation between K_1 and K_2.
Return to the evaluation.

Information Gain (IG)

Information gain measures the importance of features with the respect to the class. IG is a measure based on entropy which is a commonly used in the information theory measure. It is in the foundation of the IG attribute ranking methods. IG looks at each feature in independence and measures the importance of a feature with respect to the class. IG obtained as follows:

$$IG\,(Y;X) = H(Y) - H(Y \mid X) \tag{1}$$

The entropy of Y is given by:

$$H(Y) = -\sum_{y \in Y} p(y) \log_2 (p(y)) \tag{2}$$

The conditional entropy of Y given X is:

$$\mathrm{H}\,(Y \mid X) = -\sum_{x \in X} p\,(y) \sum_{y \in Y} p(y \mid x) \log_2 (p(y \mid x)) \tag{3}$$

Support vector machine - sequential minimal optimization (SVM-SMO)

Support vector machine (SVM) represents a learning technique which follows principles of statistical learning theory (Vapnik, 1995). It is a supervised machine-learning tool with wide application in classification studies. For example, it has been widely used for solving problems in pattern recognition, classification and regression (Lin et al., 2008). A linear machine learns to separate two classes via a linear decision function defined by a weight vector w and a bias *b*, $w^T x + b = 0$. SVM constructs an optimal linear decision function in a high-dimensional feature space non-linearly related to the input space. For such, given a dataset with n examples (x_i, y_i), where each x_i is an input instance and $y_i \in$ {+1, -1} for the case of two possible classes "positive and negative". The objective of the classifier is to define a boundary between the examples with positive class and those with negative class. The boundary is a hyperplane such that all the examples satisfy;

$$f(x) = sign\,(w \cdot x + b) \tag{4}$$

The problem of finding the best boundary is better formulated not with one but with three parallel hyperplanes such that;

$$\begin{aligned} &H : y = w \cdot x + b = 0 \\ &H_1 : y = w \cdot x + b = 1 \\ &H_2 : y = w \cdot x + b = -1 \end{aligned} \tag{5}$$

The distance between H_1 and H_2 is called a margin and has a magnitude of $\frac{2}{\|w\|}$. The classifier with the largest margin will show the best generalization for data points that were not in the example set. Thus, the problem of finding the best hyperplane is transformed into a linearly constrained optimization problem, namely, to maximize the margin between H_1 and H_2, subject to the constraint;

$$y_i (x_i \cdot w + b) - 1 \geq 0 \quad \forall i = 1, ..., n \tag{6}$$

Thus, SVMs are trained to solve the following optimization problem (Cristianini and Taylor, 2000):

Minimize $\frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i$

Subject to $y_i (w \cdot x_i + b) \geq 1 - \xi_i$ and $\xi_i \geq 0$ for $i = 1, ..., n,$ (7)

Where, C is a regularization parameter that imposes a trade-off between training error, and the variables, ξ_i are slack variables which are needed in order to allow misclassifications in the set of inequalities (due to overlapping distributions).

The restrictions are imposed to ensure that no training pattern should be within the margins. However, they are relaxed by the slack variables to avoid noisy data. The first part of the objective function tries to maximize the margin between both classes in the feature space, whereas the second part minimizes the misclassification error.

The classifier represented in Equation (7) is still restricted by the fact that it performs only a linear separation of the data. This can be overcome by mapping the input examples to a high-dimensional space, where they can be efficiently separated by a linear SVM. This mapping is performed with the use of Kernel functions, which allow access to spaces of high dimensions without knowing the mapping function explicitly, which usually is very complex. The Kernel functions compute dot products between any pair of patterns in this new space. Thus, the only modification necessary to deal with non-linearity is to substitute any dot product among patterns by the Kernel product. Kernel functions are used to implicitly map data to new feature spaces. Kernel functions are of from;

$$K(x_i, x_j) \in R \tag{8}$$

There are different kernel functions used in SVM. The selection of the appropriate kernel function is very important, since the kernel defines the feature space in which the training set examples will be

Table 1. The attributes description of the car evaluation dataset.

Characteristic	Attribute	Attribute description	Nominal values
Price	Buying	Buying price	very-high, high, median, low
	Maint	Price of the maintenance	very-high, high, median, low
Tech	Doors	Number of doors	2, 3, 4, 5more
	Persons	Capacity in terms of persons to carry	2, 4, more
	Boot	The size of luggage boot	small, median, big
	Safety	Estimated safety of the car	median, high

classified. Using of different kernel functions in SVM will lead to different performance results.

Sequential Minimal Optimization (SMO) algorithm proposed by Platt (1998) is a method used to quickly train SVM. SMO only uses two Lagrange multipliers at each training step. It was found that SMO had better performance than other SVM training methods in terms of many aspects, such as better scaling with training sample size. In this study, we used the SMO implementation of a SVM in the WEKA. Parameters setting can improve classification accuracy. This work adopted commonly used types of Kernel functions, Polynomial and radial basis functions (RBF), illustrated in Equation (9) Equation (10).

$$K(x_i, x_j) = \exp(-\sigma\|x_i - x_j\|^2) \tag{9}$$

$$K(x_i, x_j) = (x_i, x_j)^d \tag{10}$$

Ensemble techniques

Ensemble is a machine learning technique. The concept of combining classifiers is proposed as a new direction for the improvement of the performance of individual classifiers. Ensemble methods in machine learning aim to achieve higher classification accuracy and efficiency. Ensembles built in this manner often exhibit significant performance improvements over a single predictor in many regression and classification problems (Melville and Monney, 2005). Many methods for constructing ensembles have been developed (Dietterich, 1997), while Bagging, Boosting and Adaboost are most popular ensemble learning algorithms (Oza and Russell, 2001). In this work, we employed the ensemble constructing techniques. All of the techniques combine SVM-SMO classifier to form different ensemble classifiers.

Bagging

Bagging (Breiman,1996), which is also known as bootstrap aggregating, is a meta-algorithm to improve classification and regression models in terms of stability and classification accuracy. Bagging can be used with any type of model. It improves generalization error by reducing the variance of the base classifiers. In general a combined classifier gives better results than single classifiers, because of combining the advantages of the single classifiers in the final solution. Therefore, bagging might be helpful to build a better classifier model.

AdaBoost and MultiBoosting

AdaBoost is a well known effective technique for increasing the accuracy of learning algorithms (Freund and Schapire, 1997). The training and validation sets are switched, and a second pass is performed. Re-weighting and re-sampling are two methods implemented in AdaBoost. We describe a widely used method called AdaBoostM1 that is designed specifically for classification. MutiBoosting is an extension to the highly successful AdaBoost technique for forming decision committees and can be viewed as combining AdaBoost with wagging. It is able to harness both AdaBoost's high bias and variance reduction with wagging's superior variance reduction (Webb, 2000).

THE RESEARCH DESIGN AND EXPERIMENTAL RESULTS

Database overview

In this work, a real-world car evaluation database was taken from the UCI repository of machine learning database (Bohanec and Zupan, 1997). The database is illustrated in Table 1. It contains 1728 instances and classified into four classes, there is no missing value in the dataset. The car evaluation database contains six attributes examples with a car:

1. Buying,
2. Main.
3. Doors.
4. Persons.
5. Lug_boot.
6. Safety.

The architecture of hybrid evaluation process

A hybrid evaluation process was developed by this study to solve the real-world problems of the product acceptability for car manufacturing. The framework of the proposed hybrid evaluation process is shown in Figure 1. As shown in Figure 1, the process for each phase is introduced as follows:

i) Process 1 collection and input raw dataset: It includes the collection of raw data, selecting the data and focusing on the features influence the car evaluation.
ii) Process 2 preprocessing the dataset: This step includes three parts. Firstly, the data are transferred to forms “nominal to numeric” for calculating. Secondly, there are four classes (unacceptable, acceptable, good,

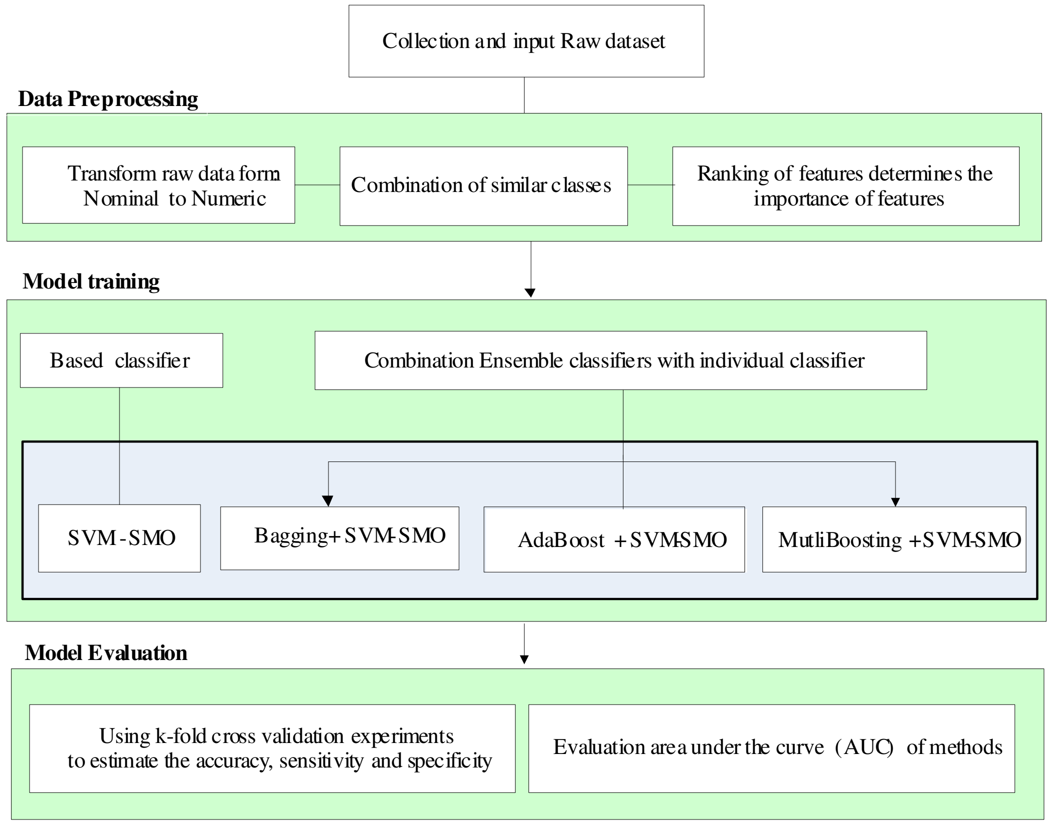

Figure 1. The framework of the proposed hybrid evaluation process.

and very-good) in car evaluation dataset. In this study, we combined the similar classes (acceptable, good and very-good) into one class. The four classes were combined to form two classes (unacceptable, acceptable). Thirdly, we employed two feature ranking methods (Relief and IG) to rank features of the car evaluation dataset.

iii) Process 3 Model training: The experiment adopted single classifier (SVM-SMO) and ensemble classifiers (Bagging, AdaBoost and MutliBoosting) to compute the accuracy, sensitivity, specificity and area under the curve (AUC), respectively. The accuracy, sensitivity and specificity performance measures as followed:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (11)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (12)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (13)$$

In addition, the area under the curve (AUC) is the evaluation criteria for the classifier. It can take values between 0.0 and 1.0 with practical lower bound value 0.5 (chance diagonal). The AUC can be interpreted as the probability of the classifier to correctly classify positive example and negative cases.

iv) Process 4 Model evaluation: The step adopted 10-fold cross validation to evaluate accuracy, sensitivity, specificity, and AUC of those results, and list the comparisons of the calculated results.

Ranked features

How to determine the importance of features is an important problem. In this work, we adopted two feature ranking methods to rank features of the car evaluation dataset. Table 2 shows the features that were ranked from the car evaluation dataset using Relief, IG. As shown in Table 2, each feature is ranked average weights respectively with two feature ranking methods and the rank number in the last column represents the degree of importance. The result demonstrates that is, safety is the most important feature and a door is the indifference feature.

Performance

The comparison of experiments is based on 10-fold cross validation. K-fold cross validation experiments is one of

Table 2. The attributes obtained by feature ranking methods.

Used methods	Average weights					
	Buying	Maint	Doors	Persons	Boot	Safety
Relief	0.045 $\pm$ 0.003	0.034 $\pm$ 0.003	0.012 $\pm$ 0.002	0.204 $\pm$ 0.002	0.017 $\pm$ 0.002	0.236 $\pm$ 0.004
IG	0.033 $\pm$ 0.002	0.028 $\pm$ 0.004	0.002 $\pm$ 0.002	0.219 $\pm$ 0.002	0.012 $\pm$ 0.001	0.229 $\pm$ 0.003
Ranking	3	4	6	2	5	1

common method to compare classification algorithms and estimate the accuracy of the algorithms. In this work, we showed experiments by using the car evaluation dataset and compared the results of single classifier (SVM-SMO) and ensemble classifiers using different kernels. The experimental results are listed by accuracy, sensitivity and specificity as shown in Table 3. Table 3 shows accuracy, sensitivity and specificity results of single classifier (SVM-SMO) and ensemble classifiers using different kernel. In Polynomial kernel, the results showed that single classifier (SVM-SMO) and ensemble classifiers are much the same. In RBF kernel, the accuracy of AdaBoostM1 ensemble classifier had the best performance (accuracy: 0.961) among all these approaches. The results showed that ensemble classifiers are better than single classifier (SVM-SMO).

AUC is an evaluation criterion for the classifier. It can be statistically interpreted as the probability of the classifier to correctly classify acceptable cases and unacceptable cases. In this study, each classification model, statistical results were based on 30 runs of the 10-fold cross validation. Table 4 shows the average of AUC ($\overline{\mathrm{AUC}}$), the corresponding standard error (S.E. derived from 30 AUC values), and 95% confidence interval (CI) using different kernel with single classifier (SVM-SMO) and ensemble classifiers. As can be seen in Table 4, the best results were obtained using RBF kernel. In addition, the results demonstrated that the $\overline{\mathrm{AUC}}$ of ensemble classifiers are better than those of single classifier (SVM-SMO).

DISCUSSIONS AND CONCLUSION

Product acceptability is usually defined in terms of perceived performance of a product or service in relation to the expected performance afterward to purchase or use. In the highly competitive environment, product acceptability of consumers has become an important consideration in the product design process. Therefore, how to evaluate the acceptability of product is one of key problems of product development (Ayo, 2010). Effective evaluation process should be developed to help manufacturer evaluate product acceptability more accurately (Howie, 2008; Lee and Cheng, 2008). In this study, the aim is to provide a hybrid evaluation process for product acceptability evaluation that can be employed for manufacturing, as well as many other areas.

Feature ranking should be developed to help manufacturer determine the importance of product features. Therefore, a meaningful evaluation process is necessary of product acceptability. This work employed two feature ranking methods (Relief and IG) to evaluate importance of car evaluation features. Byun (2001) indicated that most people purchase for a new car rank safety high among their purchase considerations. The result of this work demonstrates that safety is the most important feature and it supports the finding of Byun. Consumers are most likely to select a safety related factor and a safety related feature as their highest priorities in the new vehicle process (Lee and Cheng, 2010). Therefore, the finding of work could be used to assist manufacturers in setting priority factors with regard to the design and promotion of vehicle. In addition, a further research may aim to investigate the key parameters associated with ranking “vehicle safety” as the most critical consideration in car purchase.

Effective prediction methods should be developed to help manufacturer predict product acceptability more accurately. More and more researchers are seeking better strategies through the help of prediction models. In the pervious work, several methods have been developed in order to successfully handle these tasks of predict product acceptability (Pettijohn et al., 2002; Jaakkola et al., 2007; Rejeb et al., 2008). However, there is no published paper that applied data mining techniques to solve product acceptability problem. Recently, special types of predictive models, ensemble methods, have been well studied in the data mining community. Generally, ensemble method can be built using different base classifiers that are more accurate than a single classifier. It also improves the performance of predictions. In this work, SVM-SMO and ensemble classifiers were adopted to build models in an attempt to predict accuracy with better performance. In addition, kernel setting can improve the SVM-SMO classification accuracy. Polynomial and RBF kernel functions were adopted to gain a better performance. As shown in Tables 3 to 4, the accuracy results ranges from 0.865 to 0.961 and the $\overline{\mathrm{AUC}}$ are between 0.829 and 0.994. Hence, it was revealed that the product acceptability problem can be efficiently solved by the proposed hybrid evaluation process. The best result was obtained by using RBF kernel. In this

Table 3. The accuracy, sensitivity and specificity results of SVM-SMO and ensemble classifiers using different kernel.

Kernel	Polynomial kernel				RBF kernel			
	Single classifier	Ensemble classifiers			Single classifier	Ensemble classifiers		
Classifiers	SVM-SMO	Bagging SVM-SMO	AdaBoostM1 SVM-SMO	MultiBoosting SVMO-SMO	SVM-SMO	Bagging SVM-SMO	AdaBoostM1 SVM-SMO	MultiBoosting SVM-SMO
Accuracy	0.865 (0.002)	0.865 (0.002)	0.865 (0.002)	0.865 (0.002)	0.956 (0.001)	0.958 (0.003)	0.961 (0.002)	0.960 (0.002)
Sensitivity	0.869 (0.041)	0.867 (0.042)	0.869 (0.041)	0.869 (0.041)	0.963 (0.024)	0.960 (0.027)	0.965 (0.023)	0.964 (0.024)
Specificity	0818 (0.041)	0.820 (0.042)	0.820 (0.041)	0.818 (0.041)	0.929 (0.026)	0.931 (0.025)	0.937 (0.024)	0.935 (0.023)

Note: The numbers in parentheses are the standard errors.

Table 4. Comparison of the $\overline{\text{AUC}}$ results of SVM-SMO and ensemble classifiers using different kernel.

Kernel	polynomial kernel		RBF kernel	
Classifiers	Estimated $\overline{\text{AUC}}$	95% Confidence Intervals	Estimated $\overline{\text{AUC}}$	95% Confidence Intervals
SVM-SMO	0.829 (0.002)	0.828-0.829	0.953 (0.005)	0.952-0.955
B+SVM-SMO	0.850 (0.003)	0.849-0.850	0.973 (0.002)	0.972-0.974
A+SVM-SMO	0.839 (0.006)	0.836-0.841	0.993 (0.003)	0.992-0.994
M+SVM-SMO	0.840 (0.006)	0.838-0.842	0.994 (0.001)	0.993-0.994

Note1: The numbers in parentheses are the standard errors. Note2: B: Bagging, A: AdaBoostM1. M: MultiBoosting.

study, the performances of using RBF kernel are better than those of using polynomial. Therefore, choosing different kernels really affects the results and the RBF kernel is a better choice for the problem. Furthermore, the results of this work demonstrated that ensemble classifiers are generally more accurate than single classifier (SVM-SMO). In this study, the process not only assists manufacturer in evaluating the importance of product features but also predicts product acceptability. Therefore, the proposed process in implementation can be extended to other areas to improve the product acceptability problems. Such as the health care industry, services industry and financial industry, can consider product acceptability assessing using this approach. In addition, other attributes of influencing the importance of a product that consumers really need, can be used for feature ranking to objectively rank the importance of attributes.

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