Bankruptcy Type Prediction Using A Hybrid Artificial Neural Networks Model[*]

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The prediction of bankruptcy has been extensively studied in the accounting and finance field. It can have an important impact on lending decisions and the profitability of financial institutions in terms of risk management. Many researchers have focused on constructing a more robust bankruptcy prediction model. Early studies primarily used statistical techniques such as multiple discriminant analysis (MDA) and logit analysis for bankruptcy prediction. However, many studies have demonstrated that artificial intelligence (AI) approaches, such as artificial neural networks (ANN), decision trees, case-based reasoning (CBR), and support vector machine (SVM), have been outperforming statistical techniques since 1990s for business classification problems because statistical methods have some rigid assumptions in their application. In previous studies on corporate bankruptcy, many researchers have focused on developing a bankruptcy prediction model using financial ratios. However, there are few studies that suggest the specific types of bankruptcy. Previous bankruptcy prediction models have generally been interested in predicting whether or not firms will become bankrupt. Most of the studies on bankruptcy types have focused on reviewing the previous literature or performing a case study. Thus, this study develops a model using data mining techniques for predicting the specific types of bankruptcy as well as the occurrence of bankruptcy in Korean small- and medium-sized construction firms in terms of profitability, stability, and activity index. Thus, firms will be able to prevent it from occurring in advance.

We propose a hybrid approach using two artificial neural networks (ANNs) for the prediction of bankruptcy types. The first is a back-propagation neural network (BPN) model using supervised learning for bankruptcy prediction and the second is a self-organizing map (SOM) model using unsupervised learning to classify bankruptcy data into several types. Based on the constructed model, we predict the bankruptcy of companies by applying the BPN model to a validation set that was not utilized in the development of the model. This allows for identifying the specific types of bankruptcy by using bankruptcy data predicted by the BPN model. We calculated the average of selected input variables through statistical test for each cluster to interpret characteristics of the derived clusters in the SOM model. Each cluster represents bankruptcy type classified through data of bankruptcy firms, and input variables indicate financial ratios in interpreting the meaning of each cluster.

The experimental result shows that each of five bankruptcy types has different characteristics according to financial ratios. Type 1 (severe bankruptcy) has inferior financial statements except for EBITDA (earnings before interest, taxes, depreciation, and amortization) to sales based on the clustering results. Type 2 (lack of stability) has a low quick ratio, low stockholder's equity to total assets, and high total borrowings to total assets. Type 3 (lack of activity) has a slightly low total asset turnover and fixed asset turnover. Type 4 (lack of profitability) has low retained earnings to total assets and EBITDA to sales which represent the indices of profitability. Type 5 (recoverable bankruptcy) includes firms that have a relatively good financial condition as compared to other bankruptcy types even though they are bankrupt. Based on the findings, researchers and practitioners engaged in the credit evaluation field can obtain more useful information about the types of corporate bankruptcy.

In this paper, we utilized the financial ratios of firms to classify bankruptcy types. It is important to select the input variables that correctly predict bankruptcy and meaningfully classify the type of bankruptcy. In a further study, we will include non-financial factors such as size, industry, and age of the firms. Thus, we can obtain realistic clustering results for bankruptcy types by combining qualitative factors and reflecting the domain knowledge of experts.

1. Introduction

Bankruptcy prediction has been extensively studied in the accounting and finance field. It can have an important impact on lending decisions and the profitability of financial institutions in terms of risk management. Many researchers have focused on constructing a more robust bankruptcy prediction model. Early studies primarily used statistical techniques such as multiple discriminant analysis (MDA) (Altman, 1968), regression analysis (Meyer and Pifer, 1970) and logit analysis (Hamer, 1983; Ohlson, 1980) for bankruptcy prediction.

Recently, however, many studies have demonstrated that artificial intelligence (AI) approaches, such as artificial neural networks (ANN), case-based reasoning (CBR), and support vector machine (SVM), have been outperforming statistical techniques such as MDA and logit analysis since 1990s in for business classification problems because statistical methods have some rigid assumptions in their application (Maher and Sen, 1997; Shin and Han, 1999; Shin and Han, 2001; Shin et al., 2005).

Many researchers have reported that ANN is superior to statistical methods in dealing with the problem of complex and nonlinear pattern classification in bankruptcy prediction studies (Atiya, 2001; Boritz and Kennedy, 1995; Fletcher and Goss, 1993; Jo et al., 1997; Leshno and Spector, 1996; Odom and Sharda, 1990; Tam and Kiang, 1992; Wilson and Sharda, 1994; Zhang et al, 1999). In particular, the multilayer perceptron (MLP) network trained by the back-propagation(BP) algorithm is mostly used because of its massive computation and generalization capability.

Although many researchers have focused on developing a bankruptcy prediction model, few studies classify bankruptcy types. Previous bankruptcy prediction models have been generally interested in predicting whether or not firms will become bankrupt. In this study, we propose a model that provides more useful information about the types of corporate bankruptcy to researchers and practitioners engaged in the accounting and finance field. The model predicts the specific types of bankruptcy as well as the occurrence of bankruptcy in terms of profitability, stability, and activity index. Thus, firms will be able to prevent it from occurring in advance.

We designed a model that integrates BPN and SOM for the prediction of bankruptcy types based on the cases of Korean small- and medium-sized construction firms. The process of a hybrid approach using two ANNs consists of the following steps. In the first step, we develop a back-propagation neural network (BPN) model for bankruptcy prediction and construct a self-organizing map (SOM) model to divide bankruptcy data into several types. In the second step, we predict the bankruptcy of companies by applying the BPN model to a validation set that was not utilized in the development of the model. Then we can identify specific bankruptcy types by using the bankruptcy data predicted by the BPN model.

The remainder of this paper is organized as follows. Section 2 outlines a previous study on bankruptcy prediction and bankruptcy types, including a review of prior studies relevant to the research topic of this paper. Section 3 provides a description of the methodology of ANNs which includes the BPN and SOM. Section 4 describes the model building process, including research data, variables, and experimental designs. Section 5 describes the experimental results and analysis. Finally, Section 6 discusses the conclusions and future research topics.

2. Related Work

2.1 Bankruptcy Prediction

The prediction of bankruptcy has been extensively studied since the late 1960s. In this section, we review previous studies by focusing on traditional statistical techniques and ANN for bankruptcy prediction. Most bankruptcy prediction models commonly use financial ratios for estimations. Beaver (1966) contributed significantly to the prediction of bankruptcy by using a univariate test. Altman's (1968) model, based on MDA, takes the value obtained from the Z score, and shows a high classification rate for predicting bankruptcy one year in advance. MDA has been a popular analytical technique for studies on bankruptcy prediction.

The adoption of logit analysis, on the other hand, essentially avoids all of the problems discussed with respect to MDA. Ohlson (1980) demonstrated that logit analysis is more relevant than MDA for bankruptcy prediction. These statistical methods are known to have some rigid assumptions such as the linearity, normality, and

independence among inputs. Thus, since the 1990s, many studies have demonstrated that data mining techniques, such as ANN, are superior to statistical methods such as MDA and logit analysis.

The first adoption of ANN for bankruptcy prediction was researched by Odom and Sharda (1990). The model selected five input variables which were used in Altman's (1968) study. They compared the performance of an ANN model with that of MDA. The result showed that ANN accurately classified 81.81% in the validation set while MDA obtained only 74.28%.

It was also researched by Tam and Kiang (1992), Leshno and Spector (1996), and Jo et al. (1997) that compare classification accuracy between ANN and discriminant analysis for bankruptcy prediction. Tam and Kiang (1992) compared the performance of an ANN model with that of a linear discriminant analysis (LDA), logit analysis, decision tree, and k-nearest neighbor. They used the bank's bankruptcy data collected for the period from 1985 to 1987. The empirical result showed that a neural network model outperformed other techniques for one year prior to the training data set. Leshno and Spector (1996) evaluated the prediction capability of various ANN models in terms of different data spans, learning techniques, and the number of iterations for bankruptcy prediction. The performance of ANN models was also compared to results of discriminant analysis. They concluded that the performance of ANN models is more accurate than that of the conventional discriminant models. Jo et al. (1997) applied discriminant analysis as statistical method

and CBR and ANN as artificial intelligence method for the prediction of bankruptcy in Korean firms. They empirically represented the effects of the number of independent variables, the selection method of the input variables, and the standardization. The result showed that ANN outperformed the other two methods.

The study on performance comparison of ANN and logit analysis for bankruptcy prediction was performed by Fletcher and Goss (1993), Zhang et al. (1999), and Tseng and Hu (2010). Fletcher and Goss (1993) compared an ANN model with a logit model. Their model used three financial ratios due to the small sample size. They used the 18-fold cross-validation method to evaluate the robustness of the proposed model. The result indicated that the BPN model provided more accurate classifications than the logit model. Zhang et al. (1999) also compared ANN with a logit model in terms of performance, and used the 5-fold cross-validation method to assess the robustness of neural classifiers. They concluded that ANN is clearly superior to logit analysis for bankruptcy prediction and advised ANN researchers to use a large number of sets of random starting seeds and to experiment on hidden nodes. Tseng and Hu (2010) compared four different methods. They employed logit analysis, quadratic interval logit model, BPN, and radial basis function network (RBFN) to predict bankruptcy in England firms. They concluded that RBFN is superior to other methods in terms of classification accuracy.

A few studies have attempted to apply

unsupervised neural networks for bankruptcy prediction. Lee et al. (2005) compared supervised and unsupervised neural networks in terms of classification accuracy for predicting bankruptcy in Korean firms. Discriminant analysis and logit analysis were also employed for benchmarks. The empirical results showed that BPN has a predictive power when an output variable is given. Boyacioglu et al.(2009) compared four different neural network models, support vector machines and three multivariate statistical methods for bankruptcy prediction in Turkish banks. They constructed four neural network models, namely MLP, SOM, competitive learning, and learning vector quantization (LVQ). They concluded that the MLP and LVQ neural networks outperformed the other methods.

The development of integrated models using ANN and other techniques such as fuzzy and genetic algorithms (GA) is conducted to develop more powerful techniques by adopting the advantages of each technique. Kim and Han (2001) suggested fuzzy neural network models for bankruptcy prediction. The proposed model used fuzzy membership function for data preprocessing. The results showed that the performance of fuzzy neural networks is more accurate than that of the conventional neural networks. Hong and Shin (2003) adopted GA to select optimal or near optimal input variables for bankruptcy prediction. The results demonstrated that the performance of the proposed GA-based input selection method outperformed those of models using statistical methods such as univariate test and stepwise

method. Kim (2004) proposed an instance selection approach using GA. GA is used to find the optimal connection weights between layers and instances. The results showed that the proposed method was promising in enhancing classification accuracy.

Recently, Lee and Choi (2013) proposed a bankruptcy prediction model for Korean firms in different industries. They selected different groups of independent variables to develop a bankruptcy prediction model for construction, retail, and manufacturing industry. They compared the prediction accuracy of an ANN model with that of the MDA using not only an entire sample, but also an industry sample. The results showed that the performance using the industry sample is more accurate than that of the entire sample. The performance of ANN outperformed that of MDA.

2.2 Classification of Bankruptcy Types

While many researchers have focused on developing a bankruptcy prediction model, few studies have classified the bankruptcy types by using data mining techniques. Most of the studies have focused on reviewing the previous literature or performing a case study. Argenti (1976) investigated bankruptcy as a process by conducting a literature review and expert interviews. Three bankruptcy types were suggested by considering financial and nonfinancial factors: start-up firm, young firm, and mature firm.

The first type of bankruptcy refers to start-up firms with inadequate management in

terms of skills or personality. It mainly occurs in small firms, and most firms of this type become bankrupt. The second type is applied to young firms, and most firms of this type also become bankrupt after a much steeper growth and decline. These firms enter bankruptcy when the operational and financial management is not properly considered during the growth stage. Firms in the last type become bankrupt because they do not respond appropriately to environmental changes.

Moulton et al. (1996) suggested four distinctive bankruptcy types based on firm and industry growth patterns. The first type of failing firm is a result of the deterioration of the market. Firms of this type have decreasing sales in declining industries. The second type is caused by the inadequacy of the market. Firms of this type have decreasing sales in a growing industry. Their debt grows substantially over the five years before bankruptcy, and their assets decline. The decline in return on assets in the final year is the largest. The third type is involved in the fight for market share. These firms have increasing sales in declining industries. However, their assets and debts grow much more rapidly than their sales. The last type is related to the loss of control. Firms of this type have increasing sales in growing industries. Sales, assets, and debt growth are higher than in any other group, and the speed of decline is fast. Although this type is called loss of control, many bankruptcy cases are the result of unfortunate and specific events.

Ooghe and De Prijcker (2008) studied the relationship among the characteristics of a firm, the causes of bankruptcy, and the financial effects to acquire insight into the bankruptcy type. They performed a literature review and case study and suggested four types of bankruptcy processes in terms of the firm's maturity and management characteristics: unsuccessful start-up firm, ambitious growth firm, dazzled growth firm, and apathetic established firm.

The first type of bankruptcy firm is the start-up firm. These firms become bankrupt because their management is seriously deficient in the management skills and experience needed in the related industry. Thus, they do not have the ability to solve the financial problems facing them. The second type is the ambitious growth firm, which is caused by risk-seeking managers. These firms lack the necessary financial means to implement the most cost-effective recovery plan. A number of these firms become bankrupt because they cannot appropriately respond to environmental factors. The third type is dazzled growth firms, which tend to overlook the firm's operational structure. This leads to a severe increase in expenses and deterioration in profitability. The firms enter bankruptcy after steep growth and decline. The last type is the apathetic established firm. Although these firms have the ability to manage a profitable organization, there is a lack of commitment and motivation. They do not notice that their sales are gradually declining because of an attitude of indifference toward their firm. These firms cannot survive because stakeholders become mistrustful and all financial means are exhausted.

3. Methodology

ANNs consist of a densely interconnected set of information-processing units, called neurons. This has been extensively accepted in numerous studies dealing with complex and nonlinear patterns. ANNs can be categorized into two learning types, supervised or unsupervised. Supervised learning has a training set which consists of inputs and corresponding desired outputs. The BPN has been the most widely used model in the supervised learning type. Unlike supervised learning, unsupervised learning consists only of inputs for learning. The SOM is a popular neural network technique. The network is only provided with a set of inputs and no desired output is given.

3.1 Back-Propagation Neural Network (BPN)

The back-propagation neural (BPN) network
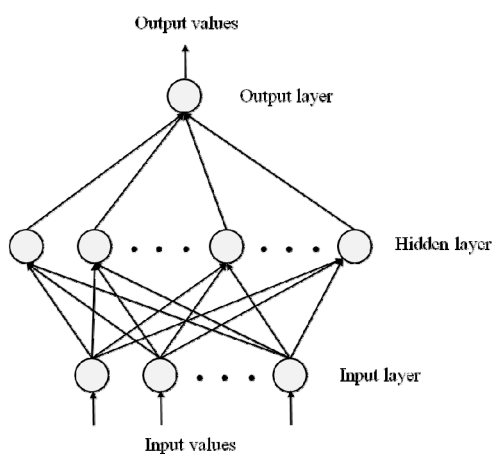
⟨Figure 1⟩ The architecture of MLP
(Rumelhart et al., 1985)

(Hecht-Nielsen, 1989) is one of the most widely used neural network techniques. It generally consists of several layers of processing elements called neurons: an input layer, an output layer, and one or more hidden layers, referred to as an MLP. The input layer represents the external information that is fed into the network. The output layer (also called the output map) produces the final solution of the model. In the network, there are one or more hidden layers which recognize the complex and non-linear patterns.

Within the network, each neuron is connected by a numerical weight associated with it. The BPN learns through an iterative process with the adjustments of these weights. <Figure 1> shows an example of the three-layer MLP used for binary classification problems. The neuron calculates the weighted sum of the input values as shown in (1).

$$X = \sum_{i=1}^{n} x_i w_i \tag{1}$$

where X is the net weighted input to the neuron, x_i is the value of input, w_i is the connection weight of input i, and n is the number of neuron inputs. The weighted sum is transformed by an appropriate transfer function into the neuron's activation value. There are four typical transfer functions: step function, sign function, sigmoid function, and linear function. The transfer function generally used in the BPN is the sigmoid function of the S-shaped form. The sigmoid function transforms the input value in the range of

$+ \infty$ to $- \infty$ into a reasonable value in the range between 0 and 1. Neurons with this function are used in BPN (Negnevitsky, 2004). The transfer function is shown in (2).

$$Y = 1/(1 + e^{-x})$$ (2)

The purpose of training in BPN is to adjust iteratively the weights among the neurons in a direction that minimizes the error. The error is computed by comparing the difference between each predicted output and the corresponding desired output by using error measurements such as mean squared errors (MSE). The error is then propagated backward. MSE can be defined as shown in (3).

$$MSE = \sum (y_d - y)^2 / p$$ (3)

where y_d is the desired output, y is actual output values, and p is the number of training patterns. If the error is positive, y is adjusted in direction of increasing the value, whereas, if the error is negative, y tends to be decreased. The classification or prediction task is performed using the following algorithm for weight updating as shown in (4).

$$w(p+1) = w_i(p) + \alpha \times x_i(p) \times e(p)$$ (4)

where is the learning rate. The training process of neural networks is repeated by the specified p until convergence.

3.2 Self-Organizing Map (SOM)

The self-organizing map (SOM) developed by Kohonen (1982) is a model for exploring and visualizing patterns in high-dimensional datasets. The SOM is a feed-forward ANN. It is different from supervised learning by the fact that the SOM only uses input values and no desired output is given. As shown in <Figure 2>, the SOM has two layers which are the input and output layers. The input layer has as many neurons as it has variables, and its function is to reflect the information. The output layer represents two-dimensional arrangement neurons. Each neuron in the input layer is fully interconnected with each neuron in the output layer. Each neuron i has an associated d-dimensional weight vector, $w_i = [w_{i1}, w_{i2}, \cdots, w_{id}]$, in the output layer. This vector is referred to as the reference vectors that will be used to interpret the final clusters.
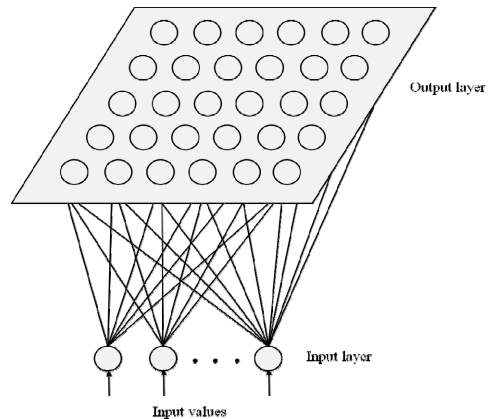
〈Figure 2〉 The architecture of SOM

The dimension d is the same as the input

vector dimension. The SOM is trained iteratively until all input vectors are processed. In each training step, a sample vector x is chosen randomly from the input data set. Distances between x and each weight vector w_i are computed using the Euclidian distance which is widely used with the SOM. The unit in which the connection weights have a higher similarity with x is called the Best-Matching Unit (BMU), denoted by c (Chang and Liao, 2006; Moreno et al., 2006).

$$\|x - w_c\| = \min\{\|x - w_i\|\} \qquad (5)$$

After finding the BMU, the connection weights of the SOM are adjusted. The BMU and its topological neighborhood are moved closer to the input vector (Alhoniemi et al., 1999). The SOM update rule for the weight vector of neuron i is shown in (6).

$$w(t+1) = w_i(t) + \alpha(t) \times h_{ci}(t)[x(t) - w_i(t)] \quad (6)$$

where t is time, $\alpha(t)$ is the learning rate that is a decreasing function of time, and $h_{ci}(t)$ is the neighborhood kernel around c.

$$h_{ci} = \exp(\|r_c - r_i\| / 2\sigma^2(t)) \qquad (7)$$

r_c and r_i are positions of neurons c and i on the SOM grid. Both $\alpha(t)$ and $\sigma(t)$ decrease monotonically with time.

SOM has been extensively used in various application fields, for example, classification (Corridoni et al, 1996; Deschenes and Noonan, 1995; Li et al., 2011; Moreno et al., 2006; Silver and Shmoish, 2008), clustering (Mangiameli et al., 1996; Murtagh, 1995; Martín-del-Brío and Serrano-Cinca, 1993), and forecasting (Van Der Voort et al., 1996). The SOM has the advantage of identifying clusters in a dataset without the restrictive assumptions of the linearity or normality of more traditional statistical techniques (Moreno et al., 2006; Mostafa, 2009).

4. Model Development

4.1 Data and Variables

The sample data consists of 106 financial ratios derived from a financial statement and the corresponding Korean small and medium-sized construction firms. The number of total samples available includes 5,000 firms (2,500 bankrupt cases and 2,500 non-bankrupt cases) from 2002 to 2007. We randomly select 2,500 non-bankrupt firms from among all solvent firms. The data set is split into three subsets: a training set, test set, and validation set of 60%, 20%, and 20% of all data, respectively. The training set is used for model construction and the test set is used to find stopping conditions for learning. The validation data is used to test the validity of the model.

We conduct two stages of the input variable selection process. In the first stage, we select variables using statistical test such as independent-samples t-test and MDA stepwise method. This

method selects variables that satisfy the univariate test, and then significant variables by using the MDA stepwise method to reduce the dimensionality. In the second stage, we select eight input variables by conducting both reviewing that the selected variables in the first stage is evenly distributed among the various index group such as profitability, stability, and activity and removing variables that overlap the meaning. The selected variables for this study are shown in <Table 1>.

〈Table 1〉 Definition of Variables

Indices	Variables	Definition
Profitability	X1	Retained earnings to total assets
	X2	EBITDA to sales
Stability	X3	Quick ratio
	X4	Stockholder's equity to total assets
	X5	Financial expenses to sales
	X6	Total borrowings to total assets
Activity	X7	Total asset turnover
	X8	Fixed asset turnover

4.2 Experimental Designs

In this study, we design a model using two ANNs for the prediction of bankruptcy types. In the first step, we develop a BPN model for bankruptcy prediction, and we construct the SOM model which divides bankruptcy data into several types. In the second step, we predict the bankruptcy of firms by applying the BPN model to a validation set that is not utilized in the development of the model. This allows for

identifying the specific types of bankruptcy by using bankruptcy data predicted by the BPN model. Financial ratios used in this study are standardized using the mean and standard deviation to improve the learning ability of the BPN and SOM, and easily interpret the characteristics of resulting clusters.

4.2.1 Bankruptcy Prediction with BPN

To build a bankruptcy prediction model, we should define the network architecture and learning parameters. That is, we first need to find the optimal network and then decide which learning algorithm to use. Finally, the weights of the network are initialized and updated from a set of training examples. Since there are no certain principles for the design of the model, the optimal network architecture is generally determined by experiments.

We select the MLP network trained by the BP algorithm. The sigmoid transfer function is used in the hidden and output nodes. The number of hidden nodes is determined by experiments. The number of input nodes is the same as the number of input variables. One output node is used for a binary classification. Bankruptcy is defined in terms of outputs, and the range of outputs is [0, 1]. The learning rate is set to 0.3 and momentum is set to 0.5.

4.2.2 Bankruptcy Type Classification with the SOM

Financial ratios are used as input variables

to create a map classifying the bankruptcy types. The self-organizing network with eight nodes in the input layer is used. Selection of the size of the two-dimensional output map is usually chosen by experimentation since there is no definite rule. Therefore, we experiment by setting different widths and lengths in a grid, and then determine the best SOM clustering configuration.

The SOM training is divided into two stages. The first stage finds the large patterns in the data as a rough estimation stage. The second stage adjusts the map to model refined features of the data as a tuning stage. Setting learning parameters, neighborhood, initial learning rate, and cycles, is required for each stage. The starting size of the neighborhood is set to find the number of near units that gets updated by the winning unit during training (IBM, 2012). In the first stage, the number of the neighborhood is set to 5 and the initial learning rate is set to 0.5. In the next stage, the number of neighborhoods is set to 3 and the initial learning rate is set to 0.2. The neighborhood size starts at 5 neighborhood and decreases to 4 during the first stage, and neighborhood size starts at 3 and decreases to 1. The learning rate starts at 0.5 during the first stage and decreases to starts at 0.5 and decreases 0. Thus, the number of neighborhood and the learning rate in the first stage should be larger than the number of neighborhood and the learning rate in the second stage. The learning rate is linearly declined during training over time as a weighting factor. The number of cycles continues for the assigned number of transiting data for each stage of training. The number of cycles is assigned to 80 in the first stage, and 200 in the second stage.

5. Results and Analysis

We developed a model integrating two ANNs for the prediction of bankruptcy type. The first was a BPN model for bankruptcy prediction and the second was a SOM model to divide bankruptcy data into several types. A BPN model with 16 hidden nodes showed the best classification accuracy. In conclusion, a bankruptcy prediction model by BPN correctly classified 78.06% for the training set and 77.30% for the test set. Then, we constructed a SOM model that identifies bankruptcy types by using an actual bankruptcy data set. A 5 x 3 square grid was considered for SOM learning. The results showed that five clusters were classified by using eight financial ratios according to the result of SOM clustering. <Table 2> shows the frequency and ratio of each cluster.

〈Table 2〉 Size of Resulting Clusters for Model Construction Set

Clusters	Frequency	%
1	555	27.75%
2	290	14.50%
3	290	14.50%
4	328	16.40%
5	537	26.85%
Total	2000	100.0%

We calculated the average of selected input variables through input variable selection process

〈Table 3〉 Average of Each Cluster for Input Variables in the Model Construction Set

Variables	Average					
	Type 1	Type 2	Type 3	Type 4	Type 5	Total
X1	-0.645	-0.740	-0.267	-0.474	0.084	-0.380
X2	0.114	-0.333	-0.067	-0.556	-0.265	-0.189
X3	-0.487	-0.631	-0.292	-0.568	-0.096	-0.388
X4	-0.869	-1.269	-0.072	-0.814	0.491	-0.437
X5	1.722	0.257	0.447	-0.469	-0.475	0.376
X6	1.256	0.985	0.432	0.039	-0.439	0.442
X7	-0.834	0.077	-0.456	0.631	0.160	-0.140
X8	-0.608	0.192	-0.347	0.712	0.170	-0.029

for each cluster to interpret characteristics of the derived clusters. <Table 3> shows the averages of each cluster for all input variables.

Each cluster represents bankruptcy type classified through data of bankruptcy firms, and input variables indicate financial ratios in interpreting the meaning of each cluster. The financial ratios of type 1 have inferior financial statements except for EBITDA (earnings before interest, taxes, depreciation, and amortization) to sales based on the clustering results. First, this type has a high financial expense to sales and total borrowings to total assets. This means that firms do not have stable assets that operate in the long term. These firms lack the necessary assets to perform the most cost-effective recovery plan. Second, they have low retained earnings to total assets that measure the firm's ability to accumulate earnings using its assets and low stockholder's equity to total assets. Finally, this type has low total asset turnover and fixed asset turnover. These ratios represent the indices of activity, and indicate how well the business is using its total assets or

fixed assets to generate sales. A low ratio indicates that the firm is not doing an efficient job in generating sales with relatively small total assets or fixed assets. Thus, it is impossible for the firms included in this cluster to recover as normal companies due to loss of debt capacity and the highest level of credit risk.

Type 2 has a low quick ratio, low stockholder's equity to total assets, and high total borrowings to total assets. First, a low quick ratio indicates that the firm does not have the ability to use its assets to quickly retire its current liabilities. Second, low stockholder's equity to total assets indicates that the financial structure of the firm is not good. Finally, as mentioned above, high total borrowings to total assets means that the firms do not have secure assets that operate in the long term. Thus, it is almost impossible for firms in this cluster to recover as normal companies.

Type 3 has a slightly low total asset turnover and fixed asset turnover. These ratios indicate how well the business is using its total assets or fixed assets to generate sales. As

〈Table 4〉 Characteristics of Bankruptcy Types

Bankruptcy types	Description
Type 1: Severe bankruptcy	Inferior financial statements as compared to other clusters Low retained earnings to total assets and stockholder's equity to total assets High financial expenses to sales and total borrowings to total assets Low total asset turnover and fixed asset turn over
Type 2: Lack of stability	Relatively low indices of stability as compared to other indices High total borrowings to total assets Low stockholder's equity to total assets and low quick ratio
Type 3: Lack of activity	Relatively low indices of activity as compared to other indices Low total asset turnover and fixed asset turnover
Type 4: Lack of profitability	Relatively low indices of profitability as compared to other indices Low retained earnings to total assets and EBITDA to sales
Type 5: Recoverable bankruptcy	Relatively good financial statements as compared to other clusters High retained earnings to total assets which represents profitability. High quick ratio and stockholder's equity to total assets Low financial expenses to sales and total borrowings to total assets

mentioned in type 1, low indices of activity indicate that the firm is not doing an efficient job in generating sales with relatively small total assets or fixed assets.

Type 4 has low retained earnings to total assets and EBITDA to sales which represent the indices of profitability. First, retained earnings to total assets measure the firm's ability to accumulate earnings using its assets. This ratio represents the profitability that reflects the firm's age. A start-up or young firm would have low retained earnings to total assets [1]. Second, EBITDA to sales measure the firm's profitability by comparing its sales. However, this type has advantages in terms of the stable financial structure and activity even though they are bankrupt firms.

Type 5 includes firms that have a relatively good financial condition as compared to other bankruptcy types even though they are bankrupt.

This type has good financial statements for all financial ratios except for the EBITDA to sales for bankrupt firms. Firms in this type have high retained earnings to total assets. In particular, stockholder's equity to total assets is relatively high and financial expenses to sales and total borrowings to total assets are relatively low compared to other clusters. However, the financial condition could get worse according to changes in the economic environment even though the financial structure is in relatively good condition. The characteristics of each bankruptcy type are summarized in <Table 4>.

After developing the BPN and SOM models, we applied the models to a validation set to test their validity. We then predicted the bankruptcy of firms for the validation set, and classified specific bankruptcy types based on the bankruptcy prediction data from the BPN and SOM models.

A bankruptcy prediction model based on the BPN correctly classified 76.30% for the validation set. A total of 513 firms were classified as bankrupt, and 487 firms were classified as solvent. The bankruptcy data of 513 firms was used to classify specific bankruptcy types. Thus, we can first predict bankruptcy firms, and then notice a certain bankruptcy type when given new data in the real world. <Table 5> shows the frequency and ratio of each cluster for the validation set.

<Table 5> Size of Resulting Clusters for the Validation Set

Clusters	Frequency	%
1	78	15.21%
2	100	19.49%
3	72	13.84%
4	97	18.91%
5	167	32.55%
Total	513	100.0%

We also computed averages to show the descriptive difference among the five bankruptcy types according to each financial ratio for the validation set that is not used for the model construction. <Table 6> shows the average of each type for eight variables.
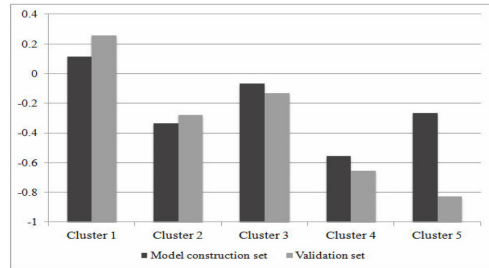
<Figure 3> shows the difference in the mean between a model construction set and a validation set. By applying a validation set to the bankruptcy type classification model constructed by the SOM, we found the average financial ratios for each type similar to those of the model construction set except for retained earnings to sales and EBITDA to sales.

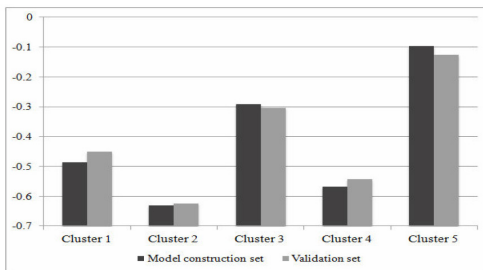<Table 6> Average of each cluster for input variables in the validation set

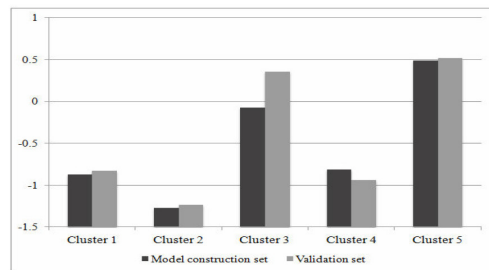| Variables	Average					
	Type 1	Type 2	Type 3	Type 4	Type 5	Total
X1	-0.483	-0.684	-0.255	-0.562	-0.285	-0.475
X2	0.257	-0.277	-0.131	-0.656	-0.829	-0.241
X3	-0.450	-0.624	-0.305	-0.542	-0.126	-0.432
X4	-0.830	-1.233	0.355	-0.936	0.515	-0.602
X5	1.167	0.393	0.563	-0.510	-0.201	0.565
X6	1.202	0.865	0.418	0.117	-0.271	0.594
X7	-0.829	0.038	-0.457	0.595	-0.011	-0.212
X8	-0.585	0.111	-0.298	0.573	0.318	-0.052

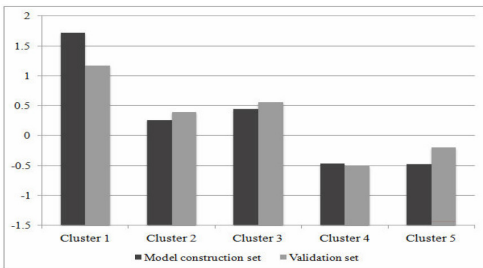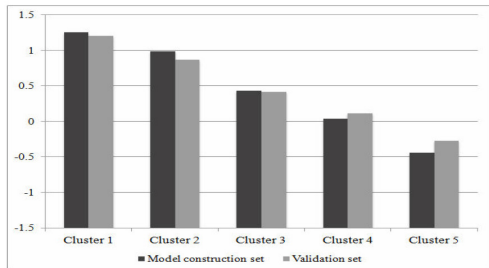(a) Retained earnings to total assets

(b) EBITDA to sales
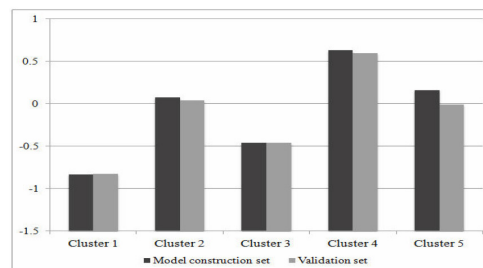
(c) Quick ratio

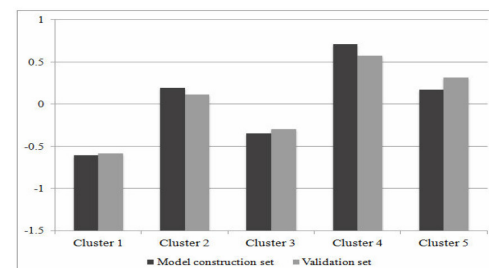(d) Stockholder's equity to total assets

(e) Financial expenses to sales

(f) Total borrowings to total assets

(g) Total asset turnover

(h) Fixed asset turnover

⟨Figure 3⟩ The Difference in the Mean Between A Model Construction Set and A Validation Set

6. Conclusions

The prediction of bankruptcy has been extensively studied in the accounting and finance field. However, there have been few studies that classify the specific bankruptcy type by using data mining techniques. We proposed a hybrid approach using two ANNs to predict bankruptcy types. As well as predicting the bankruptcy of firms in advance, the proposed model can predict the specific types of bankruptcy.

The sample data was derived from a financial statement and corresponding Korean non-audited construction firms. In this study, the BPN was used to construct a model to predict bankruptcy, and the SOM was employed to divide bankruptcy into several types. By adopting the constructed model of BPN and SOM, we can predict the types of bankruptcy for new data in the real world. The empirical results show that each of the five bankruptcy types has different characteristics according to the eight financial ratios. Based on the findings, researchers and practitioners engaged in a related field can obtain more useful information about the types of bankruptcy of firms.

This study has some limitations. First, we should define relevant parameters such as the size of the two-dimensional output map, neighborhood, learning rate, and cycles by setting different condition through trial and error because the SOM clustering results are greatly affected by the values of the parameters because of the complexity of the operation process. Therefore, this approach to derive the meaningful experiment result from the SOM clustering is time-consuming and costly in analyzing the best clusters according to bankruptcy type.

Second, we considered the financial ratios of firms to categorize bankruptcy types. It is important to select the input variables that correctly predict bankruptcy and meaningfully divide the type of bankruptcy. In a further study, we will also need to include non-financial factors such as size, industry, and age of the firms. Thus, we can obtain realistic and effective clustering results by incorporating qualitative factors and reflecting the domain knowledge of experts.

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국문요약

하이브리드 인공신경망 모형을 이용한 부도 유형 예측

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부도 예측은 회계와 재무 분야에서 꾸준히 연구되고 있는 분야이다. 초기에는 주로 다중판별분석 (multiple discriminant analysis)와 로짓 분석(logit analysis)과 같은 통계적 방법을 이용하였으나, 1990년대 이후에는 경영 분야의 분류 문제를 위해 많은 연구자들이 인공신경망(back-propagation neural network), 사계기반추론(case-based reasoning), 서포트 벡터 머신(support vector machine) 등과 같은 인공지능을 통한 접근법을 이용하여 통계적 방법보다 분류 성과 측면에서 우수함을 입증해왔다. 기존의 기업의 부도에 관한 연구에서 많은 연구자들이 재무비율을 이용하여 부도 예측 모형을 구축하는 것에 초점을 맞추어왔다. 부도예측에 관한 연구가 꾸준히 진행되고 있는 반면, 부도의 세부적인 유형을 예측하여 제시하는 것에 대한 연구는 미흡한 실정이었다. 따라서 본 연구에서는 수익성, 안정성, 활동성 지표를 중심으로 국내 비외감 건설업 기업들의 부도 여부뿐만 아니라 부도의 세부적인 유형까지 예측가능한 모형을 개발하고자 한다. 본 연구에서는 부도 유형을 예측하기 위해 두 개의 인공신경망 모형을 결합한 하이브리드 접근법을 제안하였다. 첫 번째 인공신경망 모형은 부도예측을 위한 역전파 인공신경망을 이용한 모형이며, 두 번째 인공신경망 모형은 부도 데이터를 몇 개의 유형으로 분류하는 자기조직화지도(self-organizing map)을 이용한 모형이다. 실험 결과를 통해 정의된 5개의 부도 유형인 심각한 부도(severe bankruptcy), 안정성 부족(lack of stability), 활동성 부족(lack of activity), 수익성 부족 (lack of profitability), 회생 가능한 부도(recoverable bankruptcy)는 재무 비율에 따라 유형별로 상이한 특성을 갖는 것을 확인할 수 있었다. 본 연구 결과를 통해 신용 평가 분야의 연구자와 실무자들이 기업의 부도의 유형에 대한 유용한 정보를 얻을 것으로 기대한다.

주제어 : 부도 예측, 부도 유형 분류, 인공신경망, 역전파 인공신경망, 자기조직화지도

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저 자 소 개

조 남 옥

이화여자대학교에서 빅데이터 분석 기법을 경영분야에 적용하는 연구로 경영학 박사 학위를 취득하였고, 현재 이화여자대학교 경영대학 박사후 연구원으로 재직 중이다. 주요 연구분야는 지능형 의사결정지원시스템, 데이터 마이닝, 텍스트 마이닝, 빅데이터 분석 및 응용 등이다.

김 현 정

이화여자대학교 통계학사, 경영학 석/박사 학위를 취득하고, 한국산업은행 리스크관리본부와 딜로이트컨설팅에 재직했으며, 현재 이화여자대학교 경영대학 연구교수로 재직 중이다. 주요 연구분야는 지능형 의사결정지원시스템, 데이터 마이닝과 인공지능 응용, 빅데이터 분석 및 비즈니스 인텔리젼스 등이다.

신 경 식

현재 이화여자대학교 경영대학 경영학부 교수로 재직 중이다. 연세대학교 경영학과를 졸업하고 미국 George Washington University에서 MBA, 한국과학기술원(KAIST)에서 인공지능, 지식기반 시스템 등 지능형 기법을 경영분야에 적용하는 연구로 경영공학 Ph.D.를 취득하였다. 주요 연구분야는 데이터 마이닝과 비즈니스 인텔리젼스, 빅데이터 분석/비즈니스 애널리틱스, 인공지능 응용과 지식공학 등이다.