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인공신경망과 사례기반추론을 이용한 기업회계이익의 예측효용성 분석 : 제조업과 은행업을 중심으로

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Utilization of Forecasting Accounting Earnings Using Artificial Neural Networks and Case-based Reasoning : Case Study on Manufacturing and Banking Industry

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■ Abstract ■

The financial statements purpose to provide useful information to decision-making process of business managers. The value-relevant information, however, embedded in the financial statement has been often overlooked in Korea. In fact, the financial statements in Korea have been utilized for nothing but account reports to Security Supervision Boards (SSB). The objective of this study is to develop earnings forecasting models through financial statement analysis using artificial intelligence (AI). AI methods are employed in forecasting earnings : artificial neural networks (ANN) for manufacturing industry and case-based reasoning (CBR) for banking industry.

The experimental results using such AI methods are as follows. Using ANN for manufacturing industry records 63.2% of hit ratio for out-of-sample, which outperforms the logistic regression by around 4%. The experiment through CBR for banking industry shows 65.0% of hit ratio that beats the statistical method by 13.2% in holdout sample. Finally, the prediction results for manufacturing industry are validated through monitoring the shift in cumulative returns of portfolios based on the earning prediction. The portfolio with the firms whose earnings are predicted to increase is designated as best portfolio and the portfolio with the earnings-decreasing firms as worst portfolio. The difference between two portfolios is about 3% of cumulative abnormal return on average. Consequently, this result showed that the financial statements in Korea contain the value-relevant information that is not reflected in stock prices.

Keyword : Financial Statement Analysis, Forecasting Accounting Earnings, Artificial Neural Networks, Case-based Reasoning

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1. Introduction

Earnings are the most frequently reported accounting numbers on business newspapers as well as financial statements. The business managers and financial analysts have constantly utilized the information given by those earning numbers for investment decision-making process.

Earnings are generally referred to earnings per share (EPS). EPS itself can represent the capability of a firm in making profit, but usually it is used in connection with a stock price. The stock price divided by EPS is called price-earnings ratio (PER), which shows how the investors cast back profits to the firm value. Therefore, investors often utilize PER to detect the miss-valued firms compared to their profitability.

Beyond the investment decision processes, earnings can be employed in capital budgeting and financial planning for the subsequent year. Based on the forecast earnings, a firm can assign its financial resources properly and establish strategic business plans. In consequence, the correctly estimated earning numbers are able to lead a firm to healthy financial status.

Since a number of critical business activities depart from earnings as seen from the above, the identification of future earnings and cash flows is the task that must precede any procedure in business activity planning. On this background, this study tries to forecast the accounting earnings through financial statement analysis.

The objectives of this paper are as follows. First, it is to validate value-relevance of information contents embedded in Korean financial statements. Second, it is to identify significant predictive descriptors through financial statement analysis in predicting one year-ahead accounting earnings. Despite the crucial role of the earnings in accounting literature, there have been few studies to provide empirical evidence in predicting accounting earnings. Third, different from prior research that mostly used aggregate data set, it is to identify the information contents from financial statements on the industry-specific level. Especially, this study tries to build new earning forecasting models for banking industry that has been so far eluded from the research scope because of unique accounts on financial statements. That is, we construct accounting earning forecasting models using artificial neural networks (ANN) for manufacturing industry and case-based reasoning (CBR) for banking industry. We also compare the predictive ability of these models with that of traditional statistical models such as logistical regression.

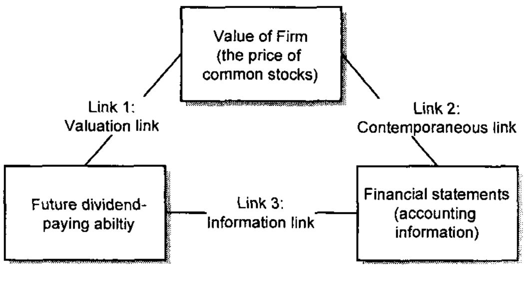
The remainder of this paper is organized as follows. Section 2 shows the relationship between financial statements and value of firm. The third section reviews prior forecasting models for accounting earnings. The fourth section proposes our research models. The fifth section presents the empirical analysis and results for our models. Finally, we summarize the conclusion from our experimental results.

2. Linking between Financial Statements and Value of Firm

If the uncertainty exists and the market is incomplete or imperfect, the stock price becomes incapable of playing its full part in the market. This situation makes an assumption that the financial reports might be able to supply useful information that is not reflected in stock prices to investors to value a firm. The financial accounting moves its focus, in this context, from measurement perspectives to informational perspectives.

Beaver [5] explains the relationship between the financial information and the value of a firm as shown in [Figure 1]. The reason that each firm has its own value and different prices in stock market is due to the different future economic gains expected by investors. He defined future dividend-paying ability as the true attribute to the different values of firms. The future dividends contain liquidation dividends in addition to regular cash dividends.

However, the real future dividend-paying ability is not observable. Here the accounting information emerges to pay a role. Nevertheless, the theoretical background does not guarantee that the financial statements should afford useful information related to the future dividends. It's a matter of empirical question.



[Figure 1] The Link between Financial Statements and Value of a Firm [5]

Assuming that the information link exists and the market is efficient enough, the link between the value of a firm and the financial information is considered contemporaneous. That is, the financial statements have certain value- relevant accounting information. Ball and Brown [2] presented the empirical evidence whether accounting earnings and some of its components capture the information that is contained in stock prices. Thereafter a group of researchers strove to verify the role of accounting information in capital market.

This research, based on the relationships presented from the above, attempts to test whether the information and contemporaneous link really exist in Korean stock market.

3. Prior Forecasting Models for Accounting Earnings

There have been many claims of market efficiency with respect to public available accounting information, but little research into the competing claim of fundamental analysis [20]. A few researchers headed by Ou and Penman, however, have attempted to predict earnings through financial statement analysis. They have intended to construct and validate earnings prediction models using various statistical methodologies. Most prior researches using financial statement analysis put their basis largely on Ou and Penman's framework.

In this section, the various prediction models for accounting earnings are reviewed. In addition to the prediction models through financial statement analysis like Ou and Penman's, time-series and other prediction models from the previous research are examined.

3.1 Time Series Forecasting Models

Beaver [4] initiated the time series forecasting for accounting earnings on a full scale. He analyzed the time series of EPS divided by total assets per share that is Return on Asset (ROA), for fifty-seven firms through 1948 to 1968. His conclusion stated that the time series of ROA follows a mean-reverting process. Lookabill [17] supported Beaver's assertion afterwards.

However, Jensen [16] criticized Beaver's findings, maintaining that the time series of EPS would not contain the serial correlation even if ROA would. Jensen also stated that EPS itself should be a meaningful research topic, not such ratios as are made out of EPS divided by some accounting values. Thus, the subsequent research including Ball and Watt [3] began to concentrate on the time series characteristics of EPS. The end results by Ball and Watt indicated that the time series of EPS has a little negative autocorrelation and follows a sub-martingale in overall, which was verified by Brooks and Buchmaster [6] later. However, the above models did not take into account the firm-specific perspective. The model for firm A could not be suitable for firm B.

On the other hand, Watt and Leftwich [24] developed a firm-specific model. They came to two conclusions. First, the model follows a random walk or random walk model with a trend. Second, the firm-specific time series seems to possess structural change by different estimation period. Afterwards, Albrecht *et al.* [1] provided empirical evidence for the claims of Watt and Leftwich.

3.2 Prediction Models by Financial Analysts

Financial analysts get reputation by directing their customers to distinguished investment decisions. Especially, the estimated accounting earnings that are believed to hold certain connection with stock prices are supplied as one of the important investment information (for instance, Value Line Investments Service Co.). The financial analysts not only utilize the time series data, but probe into more diverse and updated data including interview records with top managers and macroeconomic index. As a result, it is postulated that the estimation of accounting earnings by financial analysts be more accurate than the estimated values from the time series models.

Brown and Rozeff [8] first tested the prediction error of accounting earnings by financial analysts. They reached a conclusion that the yearly and quarterly predictions of accounting earnings by Value Line have less prediction errors than the time series models. However, their research was criticized for a small sample size (fifty firms) and a short sampling period.

Fried and Givoly [12] extracted 173 firms for eleven years from S&P Earning Forecaster for their study. They suggested that the prediction by financial analysts is superior both in prediction errors and degree of the correlation with stock returns.

3.3 Prediction Models by Business Managers

By the intuition, business managers seem to be superior in predicting accounting earnings to financial analysts due to more opportunities to access inside information. The research on this subject, however, appeared in controversy.

Lorek *et al.* [18] concluded that the prediction by business managers is not so good as that of the time-series models. On the other hand, Jaggi [15] declared that business managers perform better in earnings prediction than financial analysts. Imhoff and Pare [14] brought to an end that there are no significant difference in prediction ability between business managers and financial analysts, and that the performance of time series models is inferior to business mangers.

Patell [21] found a significant correlation between accounting earnings prediction by managers and stock price movements. He observed the variation in the mean of stock returns adopting Ball and Brown's approach. Furthermore, he took Beaver's methodology to examine the shift of the variance of abnormal returns. The results indicated that stock prices are revised to rise and the variance of abnormal returns tends to increase in the week of public announcement of predicted earnings from managers.

3.4 Prediction Models through Financial Statement Analysis

Rosenberg and Marthe [22] and Oh and Penman [20] developed two representative models using financial statement analysis. Both researches are regarded to be similar in that they employ the financial statement analysis and adhere to fundamental analysis. Yet, two researches took distinct approaches. While Ou and Penman endeavored to find accounting descriptors that are correlated with future payoffs, Rosenberg and Marthe [22] attempted to discover the financial statement measures that are related to risk and which thus predict expected stock returns.

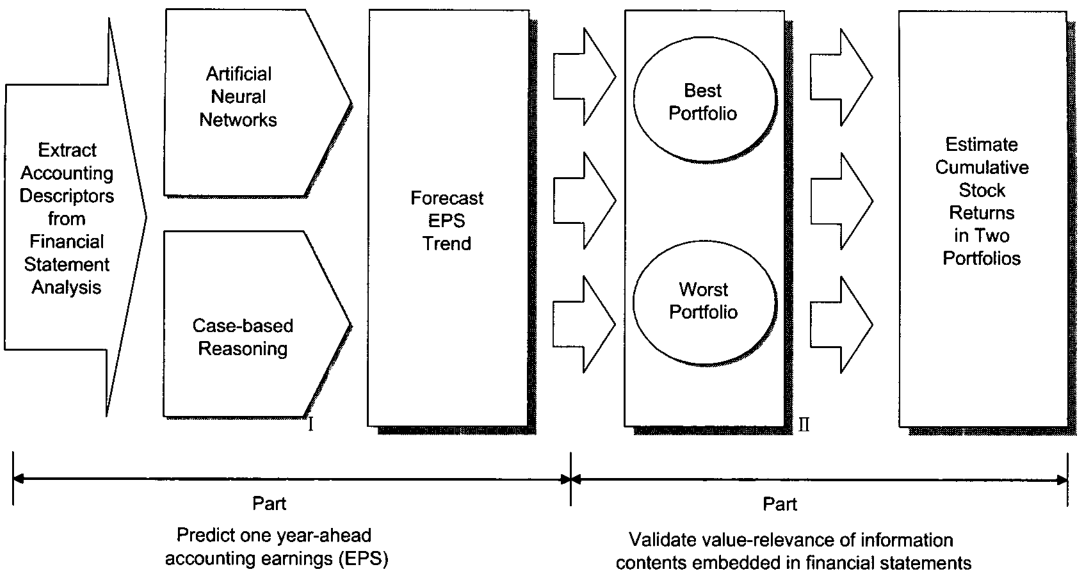
Holthausen and Larcker [13] also studied on the predictive ability and information contents of accounting variables. They found fifteen variables significant for the period of 1978 to 1988.

Most recently, Charitou and Charalambous [10] applied ANN to predict the directional change of one-year-ahead earnings. They used a large sample of 10,509 observations including 4,898 manufacturing firms from Compustat database for the period of 1982 to 1991. Moreover, they examined both industry-specific and aggregate data and found that the predictive ability of accounting variables on industry-specific level, focusing mainly on manufacturing industry, is at least as high as that on aggregate level.

4. Research Model

The main purpose of this study is to predict accounting earnings through financial statement analysis. The earning is practically defined in diverse form like earnings before interest and taxes (EBIT), operating income, gross income and so on. However, it is customary that an earnings after tax expense, that is net income, is designated as accounting earnings. Moreover, net income is employed in calculation of the various profitability ratios such as PER. So EPS is used as an earnings variable in this study.

This paper suggests a research process to predict one year-ahead accounting earnings through financial statement analysis as follows. First, the comprehensive accounting descriptors for the earnings model are basically extracted from financial statement analysis. Second, the large sets of those descriptors were trimmed to parsimonious sets through statistical model-based preprocessing. Third, with these independent variables selected, the simulation using ANN and CBR is performed. The simulation results are the directions of one year-ahead EPS change. Finally, the firms are selected to build



[Figure 2] The Structure of Research Model

the best and worst portfolios based on the predicted earnings changes. The cumulative returns (CR) of the portfolios are monitored for nine months in the post-announcement of financial statements and compared with that of the index portfolio that is the weighted average of the cumulative stock returns of all the firms used in simulation. [Figure 2] shows the structure of our research model.

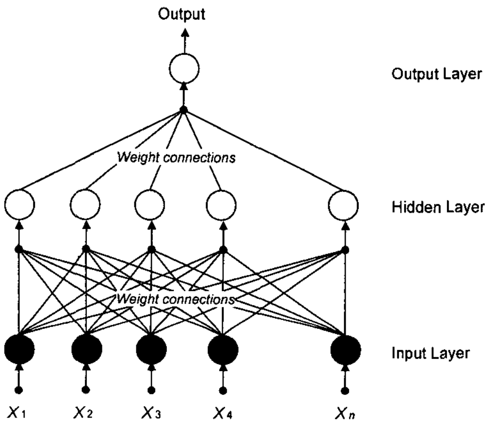
4.1 Artificial Neural Networks (ANN)

The multi-layer perceptron (MLP) is a supervised neural network, by which is meant that the data used for training and testing the network is available paired with the desired response of network, known as the target, or possibly targets for more than one output neuron. Knowledge of the desired response provides a starting point for iteratively modifying the network, by comparing the observed response with the targets and using the error to derive the network's free parameters in a direction that will minimize the error for repeated presentations of the training input data.

The training input data is assembles in the form of vector or patterns, a collection of discrete values (also elements or variables). For each element in all input vector a corresponding input node is provided in the network-input layer. Since the network is being trained by examples, the more example input vectors available, covering the whole range of possible input data behavior, the more accurate will be the resulting network performance. Statisticians would describe the training set as the in-sample set and test set as the out-of sample set.

[Figure 3] shows the MLP neural network in a very compact design example. The network comprises three layers of cell, with interconnections between all combinations of cell layers (adjacent cell in the same layer are not linked). Such a complete-forward-path interconnectivity is known as a multi-connectivity MLP. Network designs with only adjacent later connectivity are also commonly used.

The first layer is in the input representation, shown as black circles, these nodes take on the value of the input data. One case, or pattern, of input node data values is known as an input vector, and the training set comprises many such vectors.



[Figure 3] MLP Neural Networks

The interconnecting lines indicate that the output value by a cell is passed along that line to the next neuron's input stream. When all the input layer data has filtered through the last layer, known as the output layer, one forward pass, or cycle, has been performed. The interconnecting lines are shown with the weight values ; weights are adjustable parameters. They are simulated by multiplying the data value by the weight value. These weights are crucial aspects of the net. Initially assigned random values from a pre-set range, centered around zero, the weights are incrementally adjusted during the training phase so as to achieve the desired output result for given input data. Typical weight initializations are in the rage [-1, 1] or less.

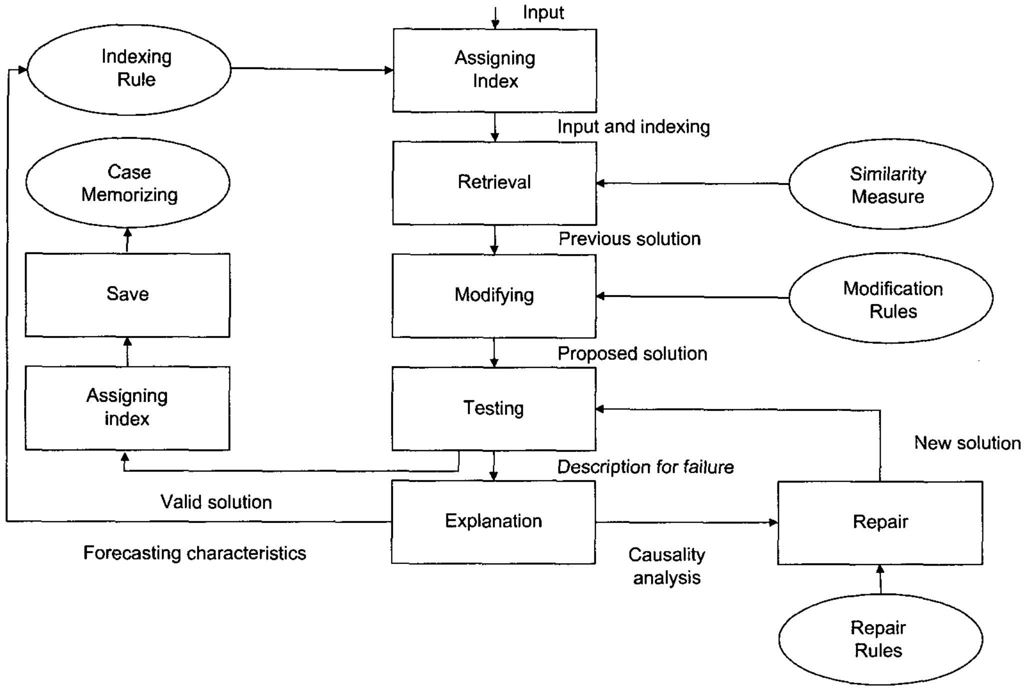
The second layer and all subsequent layers contain processing node, known as artificial neuron, and shown as shaded circles in [Figure 3]. Any layers between the input and output layer are called hidden layers. In general, network designs may contain typically one or two hidden layers with many neurons per layer.

4.2 Case-Based Reasoning (CBR)

Over the last few years a reasoning paradigm and computational problem-solving methods have increasingly attracted more and more attention. Among those methods, CBR is a technology that allows finding analogies between a current working situation and past experiences that are reference cases. CBR makes direct use of past experiences to solve a new problem by recognizing its similarity with specific known problem and by applying its solution to find a solution for the current situation. CBR has the following characteristics.

First, CBR does not require an explicit domain model and so elicitation becomes a task of gathering case histories. Second, the implementation is reduced to identifying significant features that describe a case, and easier task than creating explicit model. Third, by applying database techniques, large volumes of information can be managed. Finally, CBR systems can learn by acquiring new knowledge as cases making maintenance easier.

[Figure 4] shows the process of CBR that can be represented by a schematic cycle [23]. A new problem is matched against the cases in the case base and one or more similar cases are retrieved. A solution suggested by the matching cases is then reused and tested for success. Unless the



[Figure 4] The General Process of Case-based Reasoning [23]

retrieved case is a close match the solution will probably have to be revised producing a new case that can be retrieved.

Several successful CBR systems have been developed in a variety of fields and CBR applications are beginning to emerge in accounting research and practices as well [7].

5. Empirical Analysis and Results

5.1 Case Selection

The annual financial statements are obtained from the database of National Institute of Credit Evaluation (NICE) in Korea. The comprehensive sample sets are formed from all manufacturing and banking firms listed on Korean Stock Exchange. In the preliminary study, the manufacturing industry was clustered into five sub-industry groups, considering the sub-industry's size in view of number of firms, sales amount and market share among the sub-industry groups. Only those belonging to the following five sub-industry groups in the manufacturing industry are left : food and beverages, textiles and garments, electricity and electronics facility, chemical, and machinery industries.

642 listed firms are first observed for the period of 1987 to 1996. A set of 616 manufacturing firms is selected. On the other hand, only 26 banks are observed. Out of 616 manufacturing firms, only those that comply with the following selection criteria are selected.

First, the firms that are under legal management during the sample selection period are eliminated from the sample because of the continuity of data sets. Second, those firms whose

〈Table 1〉 The Number of Manufacturing Companies Selected in Each Step

Total number of firms selected from National Institute of Credit Evaluation :	616 firms
After selecting only those firms whose public offering is initiated before January 1, 1987 :	262 firms
After selecting only those firms that are not under legal management during sample selection period :	223 firms
After the firms whose total assets are less than 50 billion won or the number of employees is less than 100 are excluded :	198 firms
After selecting only those firms whose fiscal year ends on December :	139 firms
After common missing values are excluded :	102 firms

〈Table 2〉 The Number of Banks Selected in Each Step

Total number of firms selected from National Institute of Credit Evaluation :	26 firms
After selecting only those firms whose public offering is initiated before January 1, 1987 :	18 firms
After excluding those firms that change the types of business :	16 firms
After selecting only those firms that are not under legal management during sample selection period :	18 firms
After common missing values are excluded :	15 firms

total assets are less than 50 billion won or the number of employees is less than 100 are excluded to consider the possible size effect. Finally, the fiscal year of firms selected must end on December 31 so that the monitoring periods of the post-announcement portfolios become the same for all firms in the sample.

Given all the criteria, 139 manufacturing firms and 16 banks remain in the sample. However, any of the firms containing missing values on the accounts of financial statements must be excluded to ensure data integrity. After excluding the firms with the missing values accounts for any one year from 1987 to 1996, 102 manufacturing firms and 15 banks are finally chosen for the empirical analysis. In <Table 1> and <Table 2>, the number of the firms selected on each criterion is provided.

The monthly stock return information is obtained from the Korean Investors Service (KIS) for the period of January 1987 to June 1997. The firms with fiscal year-end on December 31 usually publicize the financial statements on March 31 in the subsequent year so that the CR of the portfolios with selected firms are observed for 9 months after publication of financial statements.

There are more comments on the selection criteria. The case selection process attempts to lessen the size effect by eliminating manufacturing firms on both extremes in the size criteria. Since the elimination of large-sized manufacturing firms whose total assets are more than 1,000 billion won or the number of employees is more than 10,000 reduces the total sample size to less than 70 firms, the higher size limits are not applied for manufacturing industry. On the other side, both higher and lower size criteria are dropped for the banking industry. <Table 3> shows the descriptive statistics on the samples

〈Table 3〉 Descriptive Statistics on the Samples

Industry	Employee & assets	Mean	Median	Min	Max	SD
Food & Beverages	No. of employee	3,058	2,570	553	6,463	1,842
	Total assets*	566,972	377,679	136,819	1,768,269	514,773
Textiles and Garments	No. of employee	2,345	1,659	443	9,609	1,873
	Total assets	681,505	360,809	79.696	2,196,050	612,249
Chemical	No. of employee	1,706	964	272	13,191	2,615
	Total assets	767,154	193,510	50,486	9,739,476	2,026,214
Machinery	No. of employee	9,151	2,012	332	47,174	14,063
	Total assets	2,344,726	465,761	51,243	8,928,856	3,239,440
Electricity Facility	No. of employee	9,196	3,765	180	59,086	14,858
	Total assets	2,134,175	963,229	63,534	15,838,458	3,813,936
Banking	No. of employee	3,988	2,698	803	9,253	3,259
	Total assets	14,417,521	7,356,420	1,330,046	37,409,399	13,674,829

Note) * Unit : Million won.

by each industry.

5.2 Data Preprocessing

Neural networks learn from data. Certain amounts of quality data are needed to accomplish a satisfactory level of learning in a specific application domain. The performance of neural networks depends heavily on the quality of data. However, business data usually include various kinds of noise, which may lead to performance degradation. So the data for learning should be generally preprocessed.

The preprocessing methods are various : log transformation, differentiation, simple linear scaling, moving average, and the combination of two of any methods. The selection of preprocessing methods mostly depends on the characteristics of the data used. The preprocessing increases the quality of data in most cases, but it is done only to the extent that the information power in the original data is preserved. This study hardly uses data preprocessing because the most variables used takes a differential form or ratio. However, the log transformation for a few variables is performed to normalize the data that are severely skewed in one direction.

5.3 Variable Selection

5.3.1 Manufacturing Industry

In this paper, an EPS is used as an earnings variable. Most previous researches also adopt EPS as an earnings variable [9, 10, 13, 19, 20].

Ou and Penman [20] chose, as the earnings variable in year t + 1, the change in primary EPS before extraordinary items. In their research, the drift term was applied to take out the firm-specific trend. The drift term was estimated as the average EPS change over the four years prior to year t + 1 as shown in Equation (1).

$$\Delta eps = eps_{it+1} - eps_{it} - drift_{it+1} \quad (1)$$

As a dependent variable, this paper selects the EPS change for the year of 1990 to 1995. The data of EPS before 1990 are not available because the Korean Accounting Principles were modified in 1990 that the announcement of EPS on financial statements became an obligation. Also, the drift term is not considered under the short sampling period in this study.

For selecting independent variables, the accounting descriptors used in the prior studies are reviewed as candidates in this study. The candidates of independent variables are shown in <Table 4>.

To obtain the effective independent variables, this study uses stepwise selection by logistic regression. In general, stepwise selection is performed through forward Insertion and backward dropping.

All variables of which coefficient estimates in this multivariate estimation are not significant at the 0.10 level are dropped, leaving four variables. The selected four variables consist of percentage change in sales/inventory(x10), return on assets(x18), percentage change in total assets(x21), and net profit ratio(x34). Statistics of those 4 variables from logistic regression is shown in <Table 5>.

In addition to the independent variables in the above, this paper constructs another set of independent variables through the process of cross validation method. Theoretically, the independent variables extracted from the same data set must be consistent though the structure of data is changed. However, the data from a real business world does not follow a rule. So the different independent variables are observed for each group divided by the cross validation

〈Table 4〉 The Candidate Accounting Descriptors for Manufacturing Industry

Variable	Variable Name	Variable	Variable Name
X1	Current ratio	X21	% Change in total assets
X2	% Change in current ratio	X22	Debt to equity
X3	Sales to cash	X23	% Change in debt to equity
X4	Quick ratio	X24	% Change in retained earnings
X5	% Change in quick ratio	X25	Return on equity (ROE)
X6	% Change in inventory turnover	X26	% Change in ROE
X7	Sales/inventory	X27	Sales/total assets
X8	% Change in investment/total assets	x28	% Change in sales/assets
X9	Sales/inventory	X29	% Change in sales
X10	% Change in sales/inventory	X30	Gross profit ratio
X11	% Change in investment	X31	% Change in gross profit ratio
X12	Investments	X32	% Change in depreciation
X13	Depreciation/plant assets	X33	Operating income/sales
x14	% Change in depreciation/plant assets	X34	Net profit ratio
X15	Sales/plant assets	X35	% Change in net income
X16	% Change in sales/plant assets	X36	Cash dividends
X17	% Change in capital expense/total assets	X37	Cash dividends/cash
X18	Net return on total assets (ROA)	X38	Dividends/net income
X19	% Change in net ROA	X39	% Change in net income
X20	% Change in ordinary ROA		

<Table 5> Statistics of Selected Independent Variables by Logistic Regression for Manufacturing Industry

Variable	Coefficient	S.E.	Wald statistic	p-value
x10	0.0152	0.0054	7.9896	0.0047***
x18	21.3033	9.3107	5.2351	0.0221**
x21	-0.0158	0.0072	4.7549	0.0292**
x34	-37.566	11.4509	10.7624	0.0010***
Constant	0.6306	0.1977	10.1779	0.0014***

Note) *** significant at 1%, ** significant at 5%.

method. <Table 6> shows the independent variables for ten groups.

<Table 6> The Independent Variables Selected by Logistic Regression for Each Group by Cross Validation for Manufacturing Industry

Data Set	Variable Name
LR 1	X10, X34
LR 2	X10, X13, X27, X34
LR 3	X2, X6, X21, X30, X34
LR 4	X9, X21, X30
LR 5	X10, X18, X21, X25, X31, X34
LR 6	X10, X21, X34
LR 7	X6, X21, X30, X34
LR 8	X1, X9, X21, X30, X31, X34
LR 9	X2, X7, X10, X15, X30, X34
LR 10	X6, X21, X34

As observed in <Table 6>, the variables appearing the most frequently and more than 3 times are the following five variables : 1) percentage change in inventory turnover(x6), 2) percentage change in sales/inventory(x10), 3) percentage change in total assets(x21), 4) gross profit ratio(x30), and 5) Net profit ratio(x34).

5.3.2 Banking Industry

The dependent variable for the banking industry as well as the manufacturing industry is the EPS change for the year of 1990 to 1995. For selecting independent variables, this paper pooled the comprehensive candidate variables based on valuation theory for banks by Copeland *et al.* [11] . Considering the different viewpoint towards the earnings-generating process, the candidate independent variables are extracted from the earnings components of free cash flows to shareholders in the equity approach for valuation. <Table 7> shows the variables analyzed for the banking industry.

After logistic regression is performed with each candidate variable, only three accounting descriptors are observed at F-value > 2.725 : Percentage change in call loan(x4), Percentage change in total equity(x29), Percentage change in non-operating income(x37) (See <Table 8>). These variables are used as input variables for logistic regression for the banking industry.

However, to ensure more independent variables for CBR simulation, then the univariate analysis is performed. Through Independent-Samples T-test, the following six variables whose p-values are less than 0.05 are added. <Table 9> shows the results of univariate analysis for selecting the independent variables.

The variable x4, Percentage change in call

〈Table 7〉 The Candidate Accounting Descriptors for Banking Industry

Variable	Variable name	Variable	Variable name
X1	Loans to total assets	X22	% Change in provisions
X2	% Change in loans to total assets	X23	Debt to equity
X3	% Change in loans	X24	% Change in debt to equity
X4	% Change in call loans	X25	% Change in total liability
X5	% Change in cash	X26	% Change in retained earnings
X6	% Change in deposits	X27	ROE
X7	% Change in foreign exchange (FX) deposits	X28	% Change in ROE
X8	% Change in marketable securities	X29	% Change in total equity
X9	% Change in other liability	X30	% Change in domestic interest income
X10	% Change in net tangible Fixed Assets	X31	% Change in foreign interest income
X11	% Change in acceptances outstanding	X32	Net interest revenue to net income
X12	Interest revenue to total assets	X33	% Change in fee income
X13	% Change in interest revenue to total assets	X34	% Change in foreign interest expense
X14	ROA	X35	% Change in non-interest expense
X15	% Change in ROA	X36	% Change in provisions for credit losses
X16	% Change in total assets	X37	% Change in non-operating income
X17	% Change in deposits	X38	% Change in taxes
X18	% Change in FX deposits	X39	% Change in net income
X19	% Change in long-term borrowings	X40	Dividend to net income
X20	% Change in call money	X41	% Change in dividend to net income
X21	% Change in other liability		

loan, appears in both the results of multivariate and univariate analysis. With eight variables altogether, two sets of independent variables are constructed in this study. The first independent variable set consists of all eight variables together(x3, x4, x11, x17, x24, x27, x29, x37) and the second variable set consists of six variables(x3, x11, x24, x27, x29, x37), which remain after excluding x4 and x17 that have the highest p-values within the group.

5.4 Model Performance

The experiments of earnings forecasting are performed using artificial intelligence (AI) methods : ANN for the manufacturing industry and CBR for the banking industry. Both experiments are benchmarked with the results of logistic regression as a statistical method.

With two independent variable sets, the predictive ability of accounting descriptors for the manufacturing industry is tested. As for the network parameters, the default values are adopted in simulation, which leaves learning rate to 0.1 and momentum to 0.1. In addition to determining the parameters, the search for the number of hidden nodes is carried out for different three nodes, 3, 5, 10 for one data set, and only the networks with the hidden node producing the best result in the training sample is

〈Table 8〉 The F-values for Each Candidate Independent Variable Using Logistic Regression for Banking Industry

Variable	F-value	p-value	Variable	F-value	p-value
X1	0.6076	0.4357	X22	1.2217	0.269
X2	1.907	0.1673	X23	0.8878	0.3461
X3	1.899	0.1682	X24	0.9331	0.3341
X4	**4.0827**	**0.0433****	X25	0.0021	0.9634
X5	0.3105	0.5773	X26	0.7529	0.3856
X6	1.3352	0.2479	X27	0.6518	0.4195
X7	0.2766	0.5989	X28	0.1898	0.6631
X8	0.0225	0.8808	**X29**	**3.0831**	**0.0791***
X9	0.0125	0.9111	X30	0.8478	0.3572
X10	0.7508	0.3862	X31	1.1634	0.2808
X11	0.1172	0.7321	X32	0.3789	0.5382
X12	0.3041	0.5814	X33	0.0041	0.9487
X13	0.9142	0.339	X34	0.0071	0.9326
X14	0.0019	0.9654	X35	1.8197	0.1774
X15	0.4074	0.5233	X36	0.3217	0.5706
X16	0.5022	0.4785	**X37**	**4.1419**	**0.0418****
X17	1.5052	0.2199	X38	0.7902	0.3740
X18	0.7875	0.3749	X39	0.1893	0.6635
X19	0.1048	0.7461	X40	0.182	0.6696
X20	0.048	0.8265	X41	0.3838	0.5356
X21	2.1146	0.1459			

Note) ** significant at 5%, * significant at 10%.

〈Table 9〉 The Significant Independent Variables from Univariate Analysis (Independent-Samples T-test) for Banking Industry

Variable	Class Type	No. of Classes	Mean	SD	SE of Mean	p-value
X3	EPS Increase	29	0.155	0.110	0.020	0.005***
	EPS Decrease	23	0.121	0.059	0.012	
X4	EPS Increase	23	1.183	3.643	0.760	0.048**
	EPS Decrease	29	0.347	1.320	0.245	
X11	EPS Increase	29	0.508	0.899	0.167	0.025**
	EPS Decrease	23	0.568	0.752	0.157	
X17	EPS Increase	29	0.060	0.115	0.021	0.044**
	EPS Decrease	23	0.093	0.072	0.015	
X24	EPS Increase	29	0.058	0.122	0.023	0.009***
	EPS Decrease	23	0.085	0.072	0.015	
X27	EPS Increase	29	-1.234	3.228	0.599	0.016**
	EPS Decrease	23	-2.730	4.581	0.955	

Note) *** significant at 1%, ** significant at 5%.

tested for the input variables set.

The number of cases in the banking industry is too small to run the simulation using ANN that needs a certain number of cases to teach the networks. So CBR as an alternative way is selected for the banking industry.

The two input data sets, one with all the variables selected from univariate or multivariate analysis and the other with all except x4 and x11 are used for modeling CBR.

In the CBR experiment, the most common way to influence the case retrieval is adjusting the weights of the slots. The relative slot's weights represent an important knowledge about the application domain. The initial weights are the same, 1, to all the input variables used, and the experiments with several different weights are attempted.

In the research models of ANN and CBR, the entire data are divided into two data sets to generalize the results. The first data set is for constructing a model (training and validation data), and the second set is to test the constructed model (holdout data). However, if the number of cases is not enough, it is hard to divide the data set. As for this research, especially, the number of cases in the banking industry is only 52, so it is not persuadable that the prediction model is generalized. Therefore the research needs to obtain enough number of the cases to ensure a generalized model.

For this reason, we adopt cross validation method that Weiss and Kulikowski [25] employed to get reliable error. The cross validation method divides the entire data into several groups without overlapping. One of the data groups is left for the validation of a model and the other groups are used in the model construction. This process is repeated until every single group is employed for validation. In this study, the entire data for the banking industry are divided into 10 groups.

5.4.1 Manufacturing Industry

<Table 10> to <Table 12> show the hit ratio results of the experiments for the manufacturing

〈Table 10〉 The Performances of Logistic Regression for Manufacturing Industry

(Unit : Hit ratio, %)

Models	Training Sample			Holdout Sample		
	EPS Decrease	EPS Increase	Overall	EPS Decrease	EPS Increase	Overall
LR1	58.8	58.0	58.4	69.4	57.1	63.4
LR2	64.7	63.1	63.9	63.9	58.3	61.1
LR3	65.4	67.4	66.3	54.6	68.4	62.0
LR4	61.5	67.1	64.4	48.8	46.7	47.9
LR5	63.4	64.0	63.7	47.2	60.0	53.5
LR6	49.0	72.8	61.4	40.9	81.5	56.3
LR7	59.1	66.9	63.0	52 5	71.0	60.6
LR8	65.2	65.5	65.4	58.8	54.1	56.3
LR9	64.1	64.6	64.4	72.7	57.9	64.8
LR10	55.9	66.9	61.4	64.9	70.6	67.6
Average	60.7	65.6	62.7	57.4	62.6	59.4

〈Table 11〉 The Performances of ANNs with frequently Used Variables for Manufacturing Industry

(Unit : Hit ratio, %)

NN(5-3-1)*	Training Sample			Holdout Sample		
	EPS Decrease	EPS Increase	Overall	EPS Decrease	EPS Increase	Overall
NN1	59.9	66.1	63.0	63.6	63.2	63.4
NN2	58.2	68.3	63.3	61.2	73.9	67.6
NN3	65.2	64.9	65.0	62.2	55.9	59.0
NN4	69.2	56.6	62.9	50.0	60.8	55.4
NN5	63.2	60.1	61.7	58.1	57.5	57.8
NN6	66.5	65.4	60.0	43.2	67.6	55.4
NN7	62.9	64.0	63.4	55.3	69.7	62.5
NN8	63.8	65.6	64.7	64.7	59.5	62.1
NN9	62.3	67.4	64.9	62.2	55.9	59.0
NN10	60.1	63.0	61.5	58.0	76.2	67.1
Average	63.1	64.1	63.0	57.8	64.0	60.9

Note) * 5 Input nodes, 3 hidden nodes, and 1 output node.

〈Table 12〉 The Performances of ANNs with Variables from Stepwise Selection for Manufacturing Industry

(Unit : Hit ratio,%)

NN(4-3-1)*	Training Sample			Holdout Sample		
	EPS Decrease	EPS Increase	Overall	EPS Decrease	EPS Increase	Overall
NN1	61.0	66.7	63.8	69.2	62.2	65.7
NN2	57.7	69.1	63.4	58.8	71.4	65.1
NN3	58.8	60.5	64.6	63.3	53.7	58.5
NN4	71.0	62.6	66.8	58.4	62.5	60.4
NN5	68.4	59.5	63.9	64.3	60.5	62.4
NN6	63.4	59.3	61.4	48.6	64.1	56.4
NN7	64.1	62.7	63.4	52.8	65.7	59.2
NN8	65.0	62.1	63.6	81.3	56.4	68.8
NN9	60.7	66.7	63.7	69.4	62.9	66.2
NN10	58.9	50.0	59.4	66.7	71.4	69.0
Average	63.9	62.9	63.4	63.3	63.1	63.2

Note) * 4 Input nodes, 3 hidden nodes, and 1 output node.

industry. In the experiments, the cross validation method is used to increase the validity of the model, so in total the earnings forecasts result in 10 hit ratios. <Table 10> shows the forecasting result of logistic regression model as our benchmark model and <Table 11> and <Table 12> present the hit ratios by ANN with each input variable set as our proposed models.

The hit ratio of logistic regression is 62.7% in the training sample and 59.4% in the holdout sample. Total hit ratio is 61.0%, which is the corresponding result equivalent to that from Ou and Penman's [20], 62% over 1973~1977 and 60% over 1978~1983. Both in training and holdout sample, the percentage of EPS increase predicted correctly outperforms that of EPS decrease predicted correctly.

In comparison with ANN performances between two different input variable sets, the variable set from stepwise selection (See <Table 12>) has a superior result to the other set (See <Table 11>). For the holdout sample, the variable set from stepwise selection exceeds the other by 2.3% around. Compared with Charitou and Charalambous [10], the result from this study is slightly higher than their hit ratio, 62.9% in holdout sample. However, this comparison doesn't consider the different data sets and sampling periods.

5.4.2 Banking Industry

<Table 13> shows the hit ratios of logistic regression for the banking industry. These results using logistic regression as a benchmark model are compared with those using CBR as our proposed model.

The average hit ratio of logistic regression for banking industry is 68.3% in the training sample and 51.8% in the holdout sample. As shown in <Table 13>, however, the results in the holdout sample are fluctuated with a large variation. On the other hand, the hit ratios of CBR in the holdout sample are relatively stable. The hit ratios of CBR in the holdout sample are shown in <Table 14>. The hit ratio of CBR with all variables (i.e., the first independent variable set) is 57.5% and it is improved by almost 8% when x4 and x17 excluded. It means that x4 and x17 may act to generate redundant relations in retrieving similarity. Compared with <Table 13>, CBR results in both input variable sets show better performance than logistic regression (See

〈Table 13〉 The Hit Ratios from Logistic Regression for Banking Industry

(Unit : Hit ratio, %)

	Training Sample			Holdout Sample		
	EPS Decrease	EPS Increase	Overall	EPS Decrease	EPS Increase	Overall
LR1	65.2	72.2	68.3	50.0	80.0	63.6
LR2	68.2	79.0	73.2	57.1	50.0	54.6
LR3	80.0	62.5	73.2	25.0	42.9	36.4
LR4	84.6	26.7	63.4	100.0	50.0	63.6
LR5	60.9	66.7	63.4	66.7	80.0	72.7
LR6	67.2	79.0	73.2	42.9	50.0	45.5
LR7	80.8	40.0	65.9	100.0	25.0	45.5
LR8	66.7	64.7	65.9	40.0	50.0	45.5
LR9	80.8	46.7	68.3	33.3	25.0	27.3
LR10	73.9	61.1	68.3	50.0	80.0	63.6
Average	72.8	59.8	68.3	56.5	53.3	51.8

<Table 14>).

〈Table 14〉 The Hit Ratios in Holdout Sample from CBR for Banking Industry

(Unit : %)

Data Sets	First input variable Set*		Second input variable Set**	
	Exact	False	Exact	False
CBR1	58.3	41.7	58.3	41.7
CBR2	66.7	33.3	66.7	33.3
CBR3	50.0	50.0	66.7	33.3
CBR4	66.7	33.3	58.3	41.7
CBR5	75.0	25.0	75.0	25.0
CBR6	50.0	50.0	58.3	41.7
CBR7	58.3	41.7	91.7	8.3
CBR8	50.0	50.0	58.3	41.7
CBR9	50.0	50.0	50.0	50.0
CBR10	50.0	50.0	66.7	33.3
Average	57.5	42.5	65.0	35.0

Note) 1. * x3, x4, x11, x17, x24, x27, x29, x37.
2. ** x3, x11, x24, x27, x29, x37.

The final stage of the experiments is validation by constructing portfolios with the selected firms based on the earnings prediction and applying to real stock market. The portfolios are constructed only with the manufacturing firms. As of the banking industry, the number of banks is such small that the portfolios are not diversified enough to minimize the systematic risk.

The portfolios for the manufacturing industry are built on the prediction of EPS change for 1996. Those manufacturing firms with EPS in 1996 to be predicted to increase are incorporated into a best performance portfolio. Similarly, a worst portfolio is comprised of those firms with EPS in 1996 to be predicted to decrease. Since this study uses the cross validation methods, to generate ten different data groups, the validation is also done for each ten data group independently. The difference in the CR between the best and worst portfolios is fluctuated from 0.46% to 10.66%, with the mean of 3.31%. The average CR of those ten groups for nine months after announcement of financial statements is presented in <Table 15>. The CR is calculated through the following Equation (2).

$$CR_m = \sum_{j=1}^{m} \sum_{i=1}^{N} \frac{1}{N} R_{ij} \qquad (2)$$

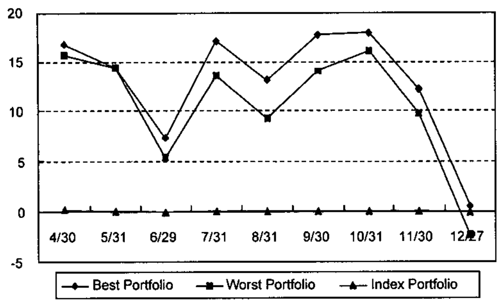
Where R_{ij} = the ratio of return for stock i in month j

In total, 82 manufacturing firms are selected for the construction of portfolios. The number of the firms used for the best portfolio varies from 25 to 58, and for the worst portfolio 24 to 57 firms are included.

As shown in <Table 15> and [Figure 5], the CR after the eight month holding period for the best portfolio is 0.52%, about 0.55% higher than that for the index portfolio, while the CR for the worst portfolio is recorded about 2.33% lower than that for the index portfolio. When stocks are

〈Table 15〉 The Cumulative Returns (CR) for Each Portfolio

Date (yy-mm-dd)	Cumulative Returns (%)		
	Best Portfolio	Worst Portfolio	Index Portfolio
96-04-30	16.71	15.71	0.154
96-05-31	14.41	14.39	0.095
96-06-29	7.41	5.36	0.002
96-07-31	17.09	13.69	0.041
96-08-31	13.20	9.31	0.041
96-09-30	17.74	14.04	0.074
96-10-31	17.97	16.08	0.066
96-11-30	12.19	9.77	0.039
96-12-27	0.52	-2.36	-0.034



[Figure 5] The Movement of the Cumulative Returns (CR) for Each Portfolio

assigned to long and short sides of zero-investment hedge positions on the basis of this prediction, the difference in the CR between two sides of the position is about 2.9% for the 9-month post-announcement period. Consequently, these results show that the financial statements in Korea contain the value-relevant information that is not reflected in stock prices.

6. Conclusion

This study investigated the earnings forecasting models for the manufacturing industry and the banking industry. From our experimental results, this paper reached the following conclusions.

First, the value relevant information that is not reflected in stock prices lies in the financial statements in Korea. Second, as of the banking industry, this study proved that the earnings forecasting model can be constructed through financial statement analysis especially based on equity approach of valuation. Finally, AI methods such as ANN and CBR proved themselves to be as useful tools for earnings forecasting as they do for other financial and accounting domains.

This study has the following limitations. First, the portfolio trading was tested only for one period. It should be validated whether that the earnings prediction models are capable of obtaining consistent cumulative abnormal returns. Second, since the number of cases for the banking industry is so small, the learning ability of CBR is doubtful. Thus the experiments with more cases must be done in the future research. Third, when portfolios are constructed, the risk characteristics are ignored, which may be able to change the experiment results drastically. The component representing risk should be considered and incorporated in the future study.

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