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Stock Forecasting using Fuzzy Neural Networks, Technical Indicators, and Foreign Exchange Rates

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ABSTRACT

Using features derived from technical indicators of stocks and foreign exchange rates, this paper presents a forecasting plan for the KOSPI's rise and fall after one day based on the neural network with weighted fuzzy membership functions (NEWFM). To extract the features to be used in NEWFM, select the three technical indicators in the first step: Relative Strength Index (RSI), Commodity Channel Index (CCI), and Current Price Change (CPC). The second phase extracts 13 features derived from the KOSPI data from the three technology indicators selected in the first stage. It also extracts one feature derived from the technical indicators of the KRW/USD exchange rates from the KRW/USD exchange rates. In this way, 14 features will be used as inputs to NEWFM to forecast the KOSPI's rise and fall in a day. NEWFM uses 13 and 14 features to show forecasting performance of 58.86% and 59.38%, respectively. These experiments show that the KRW/USD exchange rates affects the rise and fall of KOSPI stock prices.

Key words : Stock, Foreign Exchange Rate, Technical Indicators, NEWFM, Feature Extraction.

1. INTRODUCTION

Intelligent systems have been proposed for financial forecasting, such as stock forecasts and foreign exchange rate forecasts [1][2]. For intelligent systems, multiple structures of fuzzy neural network are presented along with algorithms for learning, adaptation, and rule extraction[3][4]. Using this fuzzy neural network, various applications for financial forecasting are being made [5]. Nonlinear time series forecasting methods [6], stock transactions using profit-and-loss determination systems [7], and forecasts of turning points [8] are being studied based on historical statistical indicators.

KIM used 12 technical indicators (Technical Indicators) as features for the Support Vector Machine (SVM) to forecast KOSPI rise and fall in one day [9]. Tsaih learned the data derived from technical indicators by using the feature of reasoning neural networks to forecast the S&P 500 index [10]. Using these learned results, several rules were created to form a rule-based system. However, the SVM used by KIM has the disadvantage of not being able to provide interpretable general rules such as fuzzy rules. Tsaih provides generalized rules but has the disadvantage of artificially creating rules based on experience, unlike in automatic creation or extraction of rules, as in fuzzy neural networks.

Using the 14 features derived from the foreign exchange rate and the technical indicators of the stock, this paper forecasted the rise and fall of the KOSPI one day after the neural network with weighted fuzzy membership functions (NEWFM) [11][12] based. The 14 features consist of one feature derived from the foreign exchange rate technical index in addition to the 13 features simplified for a specific segment in the three technical indicators used for forecasting stocks. In addition, using 13 features, excluding one derived from the foreign exchange rate technical index, this paper obtained the forecasting performance of the KOSPI rise and fall after one day and 14 features, including one derived from the foreign exchange rate technical index, respectively. In doing so, we tested how the KRW/USD exchange rates affects the KOSPI's rise and fall in one day.

This paper made it possible to interpret the features by presenting learned weighted fuzzy belonging function for the 14 features used in NEWFM. To verify that these 14 features could be applied to the experimental group, an experimental group of KRW/USD exchange rates was used in the same period as the 1989-1998 experimental group used by the KIM [9]. Using 13 features, excluding one derived from the foreign exchange rate technical index, the forecast performance of the KOSPI's rise and fall in one day was 58.86% [9]. In addition, 14 features, including one feature derived from the foreign exchange rate technical index, were used to indicate the forecasting performance of the KOSPI's rise and fall in one day. One feature derived from the foreign exchange rate technical index showed an improvement of 0.52% in the forecasting performance of the KOSPI's rise and fall in one day. The results of these experiments show that the KRW/USD exchange rates improves the forecasting performance of the KOSPI's rise and fall in one day.

2. PREPROCESSING FOR KOSPI FORECASTING MODEL

In this paper, the KOSPI data and the KRW/USD exchange rates are used as inputs to forecast the KOSPI rise and fall after one day. Extracts 14 newly derived features using the technical indicators used to forecast such inputs. The 14 features extracted like this are used as features of NEWFM for the KOSPI's rise and fall forecasting in one day.

2.1 Experimental Data

In this paper, we experimented with the KOSPI experimental group from 1989 to 1998 used by KIM to evaluate the forecasting performance of KOSPI rise and fall in one day [9]. In addition, to test how the KRW/USD exchange rates affects the KOSPI's rise and fall in one day, the KOSPI experiment group was tested using the KRW/USD exchange rate for the same period. The KIM used 2,347 training sets for training in the entire 2,928 experimental groups, and 581 verification sets for holdout sets. In this paper, if the next day's KOSPI rose from today's KOSPI, it was marked as 2, and if the next day's KOSPI fell from today's KOSPI, it was marked as 1.

2.2 Feature Extraction

Tsaih generated derived data from technical indicators using the features of technical indicators and share price fluctuations [10]. The KIM used 12 technical indicators to forecast the KOSPI's rise and fall in one day [9]. In this paper, the three technical indicators in Table 1 were used to forecast the rise and fall of the KOSPI one day later. Table 2 describes 13 features derived from the three technical indicators in Table 1 and one feature derived from one technology indicator using the KRW/USD exchange rate. As such, 14 features were used in this paper to forecast the rise and fall of the KOSPI one day later. These 14 features consist of features that are simplified for specific segments, as illustrated in Table 2 by the three technical indicators used to forecast shares.

Figure 1: Graph of CCI

Figure 1 illustrates how the derived data described in Table 2 were generated. Generally, the technical indicators used in forecasting stocks have features of each purchase and sale. As shown in Figure 1, the Commodity Channel Index (CCI) refers to short-term sales when it changes from -100 up to -100 down. This means selling stocks, which can be seen as a fall in stock prices. Also, when changing from -100 down to -100 up means a purchase. This means buying stocks as a rise in stock prices. Relative strength index (RSI) has the same features as CCI at values of 30 and 70.

Current Price Change (CPC) is a recently made technical indicator that does not yet have a reference value for purchase and sale. Therefore, in this paper, feature was generated by dividing the range from 0.2 and 0.8. In addition, the meaning in Table 2 refers to the closing price of today's shares minus the average value of the stock prices over the past five days. If the difference is positive, it is 2 for tomorrow's stock price to rise, and 1 for negative tomorrow's stock price to fall.

3. NEURAL NETWORK WITH WEIGHTED FUZZY MEMBERSHIP FUNCTION (NEWFM)

NEWFM is a kind of fuzzy neural networks using the bounded sum of weighted fuzzy membership functions (BSWFMs). Figure 2 explains the structure of the NEWFM that is composed of three layers (input, hyperbox, and the class layer). An hth input can be used as $I_h=\{A_h=(a_1, a_2, \dots, a_n), class\}$, where *class* is classification node and A_h is n features of an input. The fourteen numbers of derived features in Table 2 were used as inputs in Figure 2.

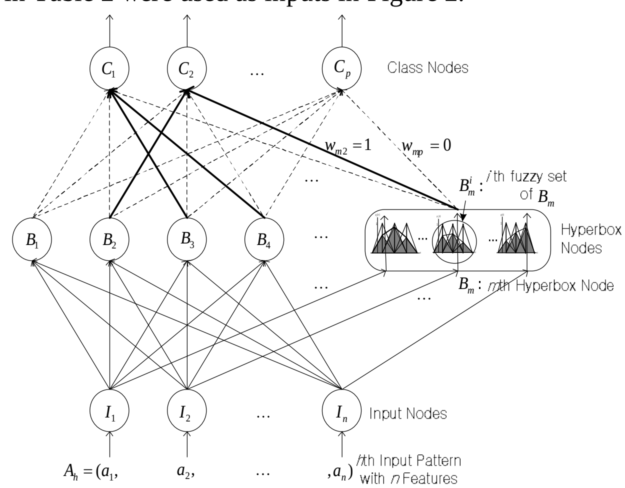

Figure 2: Structure of NEWFM

The Adjust(B_l) operation adjusted the weights and the center of membership functions in Figure 3. W_1, W_2, and W_3 are moved up or down, v_1 and v_2 are moved up to a_i, and v_3 stays in the same position. After finishing Adjust(B_l), each of all fuzzy sets in hyperbox node B_l in Figure 2 contains three *weighted fuzzy membership functions* (*WFMs*). The WFM means grey membership functions in Figure 4. The *bounded sum* of WFMs (BSWFM) in the ith fuzzy set of $B_l^i(x)$ denoted as $\mu_b^i(x)$ defined by:

$$\mu_b^i(x) = \sum_{j=1}^{3} B_l^i(\mu_j(x)). \tag{1}$$

The BSWFM means bold line in Figure 4. The two BSWFMs graphically show the difference between the rise and fall of KOSPI for each feature.

Table 1: Initial features and their formulas

Feature name	**Formula**
RSI (Relative Strength Index)	$100 - \frac{100}{1 + (\sum_{i=0}^{n-1} Up_{t-i} / n)/(\sum_{i=0}^{n-1} Dw_{t-i} / n)}$
CCI (Commodity Channel Index)	$\frac{M_t - SM_t}{0.015 \times D_t}$
CPC (Current Price Change)	$\frac{1}{1 + e^{-(\frac{C_t - MA_{t-1,t-i}}{MA_{t-1,t-i}} \times 100)}}$

C_t is the closing price at time *t*, L_t is the low price at time *t*, LL_t is the lowest low price in the past *t* days, H_t is the high price at time *t*, HH_t is the highest high price for the past *t* days, MA_t is the moving average of *t* days, M_t is $(H_t + L_t + C_t)/3$, SM_t is $\sum_{i=1}^{n} M_{t-i+1} / n$, D_t is $\sum_{i=1}^{n} \left| M_{t-i+1} - SM_t \right| / n$, Up_t is an upward price change, and Dw_t is a downward price change.

Table 2: The definition of fourteen numbers of derived variables

Variables		**Description**
KOSPI	RSI1	Assigns 2 when RSI rises from 70 down to 70 up; 1 otherwise.
	RSI2	Assigns 1 when RSI falls from 70 up to 70 down; 2 otherwise.
	RSI3	Assigns 2 when RSI rises from 30 down to 30 up; 1 otherwise.
	RSI4	Assigns 1 when RSI rises from 30 up to 30 down; 2 otherwise.
	CCI1	Assigns 2 when CCI rises from 100 down to 100 up; 1 otherwise.
	CCI2	Assigns 1 when CCI falls from 100 up to 100 down; 2 otherwise.
	CCI3	Assigns 2 when CCI rises from -100 down to -100 up; 1 otherwise.
	CCI4	Assigns 1 when CCI rises from -100 up to -100 down; 2 otherwise.
	CPC1	Assigns 2 when CPC rises from 0.8 down to 0.8 up; 1 otherwise.
	CPC2	Assigns 1 when CPC falls from 0.8 up to 0.8 down; 2 otherwise.
	CPC3	Assigns 2 when CPC rises from 0.2 down to 0.2 up; 1 otherwise.
	CPC4	Assigns 1 when CPC rises from 0.2 up to 0.2 down; 2 otherwise.
	CPC5	Assigns 2 when $C_t - MA_{t-1,t-5}$ is greater than 0; 1 otherwise.
USD/KRW	CPC6	Assigns 2 when $C_t - MA_{t-1,t-5}$ is greater than 0; 1 otherwise.

Table 3: Experimental data used for forecasting KOSPI

Training instances for SVM	**Holdout instances for SVM**	**Total instances**
2347	581	2928

Table 4: Comparisons of performance results for Kim with NEWFM

	NEWFM with KRW/USD exchange rates	**NEWFM without KRW/USD exchange rates**	**SVM[9]**
Performance (%)	59.38	58.86	57.83

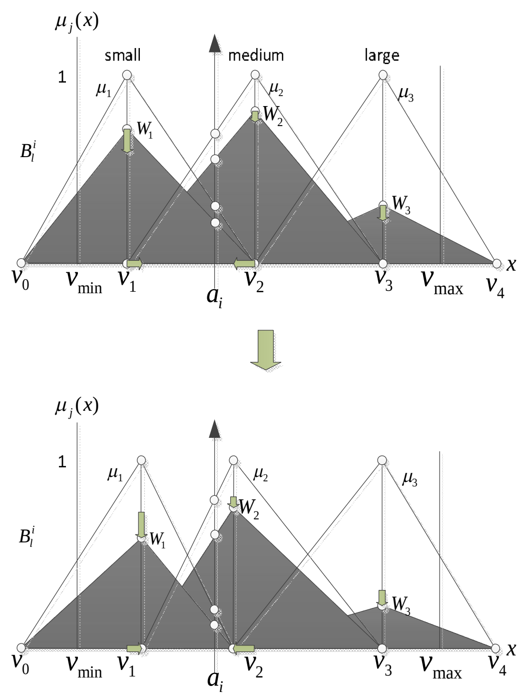

Figure 3: Example of before and after *Adjust*(B_l) operation

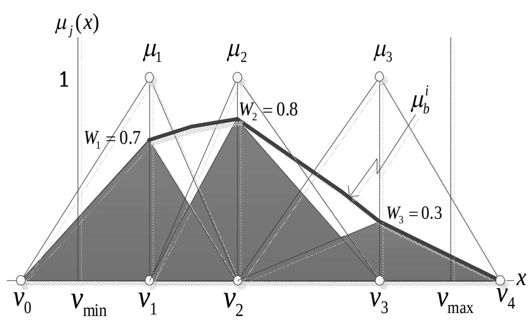

Figure 4: Example of the 3 BSWFMs

4. EXPERIMENTAL RESULTS

This paper was experimented with KOSPI data from 1989 to 1998 used by KIM to evaluate the forecasting performance of KOSPI rise and fall in one day [9]. KIM used Support Vector Machine (SVM) to evaluate forecasting performance about 20% of the total data.

Table 4 shows a comparison of the forecasting performance of SVMs and NEWFMs used by KIM. The forecasting performance of NEWFM in Table 4 utilizes 14 features derived from the technical indicators presented in Table 2. The experiment in this paper compared the forecasting performance using the 14 features, including one feature derived from the technical index of the KRW/USD exchange rate among the 14 features, and 13 features not included. Table 3 shows the total 2,928 experimental groups used by KIM. It shows that 2347 experimental groups were used for training (train), and 581 experimental groups were used for testing.

As explained in Table 4, the results of these forecasting performance indicated an improvement of 0.52% in the forecasting performance of the KOSPI's rise and fall in one day's time, with one feature derived from the foreign exchange rate technical index. The results of these experiments show that the KRW/USD exchange rate improves the forecasting performance of the KOSPI's rise and fall in one day.

Table 2 compares the 12 features used in the experiment in [9] with those used in NEWFM. In this paper, the classification performance is obtained by using the BSWFM produced by NEWFM, and by this classification performance, the low-importance features were eliminated and minimized with five features. These five feature were used to forecast the rise and fall of the KOSPI in one day.

Table 3 shows the NEWFM classification performance comparison for GANN and GAIS. In Table 1, when tested with data for each year used in Training instance for GANN, NEWFM shows better performance than GANN for all years and means. GAIS averaged 65.47% of the total data, using only the selected data, while NEWFM showed 67.62% improvement.

5. CONCLUSION

Using features derived from technical indicators of stocks and foreign exchange rates, this paper presents a forecasting plan for the KOSPI's rise and fall after one day based on the NEWFM. The 14 features consist of one feature derived from the foreign exchange rate technical index in addition to 13 features simplified by a specific segment in the three technical indicators used for forecasting stocks. By presenting learned weighted fuzzy functions for these 14 features, it is possible to interpret the features. To verify that these 14 features could be applied to the experimental group, a experimental group of KRW/USD exchange rates was used in the same period as the 1989-1998 experimental group used by the KIM [9]. Using 13 features, excluding one derived from the foreign exchange rate technical index, the forecast performance of the KOSPI's rise and fall in one day was 58.86% and 14 features, including one derived from the foreign exchange rate technical index, were used to indicate the forecasting performance of the KOSPI's rise and fall in one day. One feature derived from the foreign exchange rate technical index showed an improvement of 0.52% in the forecasting performance of the KOSPI's rise and fall in one day. The results of these experiments show that the KRW/USD exchange rate improves the forecasting performance of the KOSPI's rise and fall in one day.

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