**MUTUAL FUND PRICE PREDICTION USING CONVOLUTIONAL NEURAL NETWORKS**

(Pushkaraj Bhor, Adwait Bhosale, Rohan Bhole ,Dhairyashil Bhosale, Aditya Bhosale)

Abstract:

***Investing in funds has the effect of indirectly employing asset management professionals with specialized knowledge and experience, which can result in a diversified investment through the use of a portfolio. In this study, we focus on learning the patterns of prices rather than time points to predict fund prices. We convert time-series data into 2-dimensional images and analyze them using a convolutional neural network. To improve the fund price forecasting performance, we consider the following aspects. A fund should be recommended according to the level of risk aversion. The risk level of the fund is determined by the proportion of risky assets. Therefore, when estimating the fund price, the risk level of the fund needs to be considered. In this study, we use 15 additional variables, such as foreign stock indexes, foreign exchange rates, and stock indices, in addition to the fund price data. The appropriate filter size, which plays an important role in this process, is proposed. In addition, types of networks and architectures are selected as suitable for forecasting the fund price. We also demonstrate that the number of output classes can be adjusted to increase the future return of the fund. Through this methodology with multiple variables, we can achieve a 25% cumulative profit for 2 years. This means that multi-variable models have a higher cumulative return than the single-variable model and thus a higher average of all funds for active investors.***

Keywords : Convolutional neural networks, fund price , multiple variables

**INTRODUCTION :**

Many companies are making an effort to generate revenue by analyzing financial data using machine learning techniques and artificial intelligence to provide customized products and services to customers . These efforts also apply to the economy and the financial industry. In addition to existing models, such as credit rating and default forecasting, trading systems have improved, and the performance of techniques such as stock price forecasting and portfolio selection has improved. In this paper, we propose a customized fund recommendation framework based on a convolutional neural network (CNN) to analyze fund price time series data.

In general, people use investment to increase their capital. There are various ways of investing. Unlike investment professionals working in financial institutions, ordinary people need to learn numerous investment-related techniques to make their own investments and accumulate a wealth of knowledge about the assets in which they are investing. Therefore, many people who do not have sufficient time to study or the ability to build an investment system use funds to invest their money. A fund is a financial investment product that manages funds collected from investors and distributes profits to those investors when profits are generated. However, when investing in funds, people should select the appropriate fund products. First, people should set the appropriate amount of investment. Second, they need to look at the expected return on the fund and the fund type. Third, they should find a fund that fits their investment propensities. In addition, transaction fees and management fees may vary depending on the management company or the sales company. A fund has a base price, i.e., the price that is used to calculate the daily fund returns. This base price is also used for additional setting or fund rebalancing, and it fluctuates daily as the prices of stocks and bonds that constitute the fund change. In general, the base price starts at 1,000, which means that if the base price is 1,100, a 10% return is achieved. In this study, we focus on the base price of the fund and investigate the effect of the domestic and foreign stock price index and the exchange rate on the base price of the fund through the CNN. Furthermore, we design a system that recommends funds using past patterns learned through the CNN. In the case of funds, it takes three months to publicly announce the assets of the fund. Additionally, there exist numerous types of assets, including deposits, bonds, and domestic and foreign stocks. Therefore, substantial effort is needed to analyze the fund base price with only information that individuals can obtain. In addition, funds can be divided into stock, bond, and hybrid types according to the proportion of stocks and classified into domestic and overseas depending on the investment area. A company that sells a fund should identify the investment propensity of the customer and recommend a fund that includes risky assets appropriately. Therefore, to analyze the base price of a fund, it is necessary to consider the investment proportion of risk assets.

When investing, people set the overall investment universe according to the type and characteristics of the asset and monitor the asset price. If a certain asset is considered to be an appropriate time for investing, people will make a buying decision. A portfolio represents the type and proportion of these assets. Investors usually have their own investment techniques to achieve good performance. There will be investment techniques for investors who are familiar with them and can achieve good results. They use not only fundamental analysis to analyze the intrinsic value of the company but also technical analysis, which is based on ‘support’ and ‘resistance’. However, among the various investment assets, the fund does not have a corporate value; thus, it relies mainly on the fund type and technical analysis. Technical analysis uses a 2-dimensional candle chart consisting mainly of time and asset prices. If we can automate the process of using 2-dimensional candle charts as information for investment decisions by using a CNN that is effective at analyzing visual images, this will minimize human effort and provide an appropriate indicator for investments. However, it is necessary to convert the 2-dimensional candle chart into an image that is effective for learning with the CNN. In this study, we examine the possibility of applying the CNN model to analyze fund prices.

**Literature Review**

Related Works

A. FUND PRICE ANALYSIS

In recent years, human life span has increased, and it is not sufficient to live only by the salary of an individual; thus, people are making an effort to increase their wealth through investment. However, the general public may not be as knowledgeable about investment methods, and knowledge of each investment asset is inadequate; thus, it may be effective to use a fund product managed by an expert. A fund product is composed of a portfolio of financial instruments and risk management by an expert called a fund manager. However, because there are many types of funds, people need to choose a fund that suits them best. Therefore, companies that sell funds, such as banks and securities firms, attempt to sell the right fund products to their customers. In general, many studies relating to stock price prediction using pattern recognition methods or deep learning have been conducted; however, there have been few studies related to funds, although some researchers have studied mutual funds.

B. MACHINE LEARNING - CONVOLUTIONAL NEURAL NETWORKS

There have been many studies that applied machine learning techniques to predict financial time series. Support Vector Machine (SVM) has been widely used to predict financial markets. These studies have also developed SVM to classify short-term price movements into high-frequency data and analyze financial textual data. In recent years, there have been studies that utilized traditional neural networks to predict financial markets before deep learning was utilized. In addition, some studies have suggested that nonlinear neural networks are useful in predicting markets using textual data. Recently, artificial intelligence has become a hot topic, and there have been explosive increases in the use of deep learning as well as machine learning. In particular, research using CNNs, which are effective for image analysis, is being conducted , and this study applies CNNs to forecast fund prices by applying chart analysis. The rapid growth of CNNs started with AlexNet from ILSVRC 2012. AlexNet has made a significant contribution to the development of CNNs and deep learning in that it has made computing calculations possible by using GPUs for existing CNNs . Through AlexNet from ILSVRC 2012, VGGNet , GoogLeNet from ILSVRC 2014, ResNet from ILSVRC 2015, networks have become deeper, and the performance has improved.

**METHODOLOGY**

A. DATASETS AND OUTPUT CLASSES

Funds are divided into five types based on the amount of risky assets and are recommended to investors according to their risk aversion: 1) risk averse, 2) less risk averse, 3) risk neutral, 4) active, and 5) risk loving. Korean funds also invest in overseas stocks, including stocks in North America, South America, Southeast Asia and Europe. Thus, foreign stock indexes and foreign exchange rates can affect the fund base price. The data used in the experiment are fund price data, 9 foreign stock indexes, 4 foreign exchange rates, and 2 stock indexes. The financial data list that we used is presented in Table 1. The duration of the price data for funds varied. We used the price data for 60 working days to construct a heat map and estimate the future fund price, PF, after 60 trading days. Specifically, we used a moving window of 120 trading days and repeated moving the window for 10 days to generate a heat map and labels based on PF. Fund price data were divided into three groups and used as training, validation, and testing sets. We tested two cases of output classes: 2 classes and 4 classes. We obtained a mean, µ, and standard deviation, σ, for each of the risk classes of the funds and used them for labeling. We classified the output class based on the future fund price returns, PF. For 2 classes, we used 1) (−∞, µ) and 2) [µ,∞) as labels. All the experiments were conducted on 4 classes except for the class comparison experiments. Among the risk aversion levels mentioned above, most of the experiments used data of the funds for active investors with the largest amount of data.

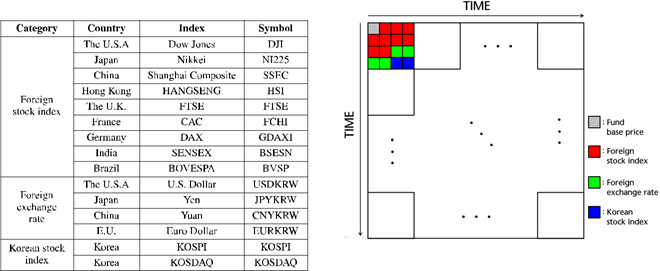


TABLE 1. The list of financial data used for the heat map. FIGURE 1. Heat map design with multiple variables.

B. DATA VISUALIZATION METHOD

Previous studies using CNNs to analyze time-series data used a Gramian angular field (GAF) to convert the data to 2-dimensions images. Chen et al. (2016) also applied the Gramian matrix to calculate nonlinear data using the GAF concept. In this study, we use the concept of the GAF to convert financial time-series data and fund base prices into 2-dimensional images.

Specifically, a total of 16 GAF matrices were obtained. In this study, we attempted to determine whether the performance in predicting the fund price is improved by learning from not only fund price data but also other variables that affect the fund price. Therefore, we tested not only a single-variable case for learning the GAF matrix of the fund price as a heat map but also a multi-variable case for learning all 16 variables as heat maps. When using 16 variables, we used the arrangement in Fig. 1 when drawing the heat map. A sample of this heat map is shown in Fig. 2. The single variable case uses only the fund price. Therefore, only gray is used to draw its heat map. In the case of multiple variables, the fund price, foreign stock price indexes, foreign exchange rates, and stock indexes are represented by gray, red, green, and blue, respectively.

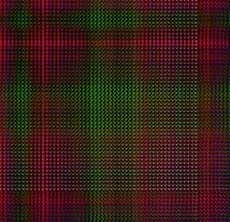


FIGURE 2. A sample of heat map with multiple variables.

C. CONVOLUTIONAL NEURAL NETWORKS

A CNN basically learns weights and biases through an input image from ConvNet, obtains non-linear characteristics through activation functions such as the ReLU function, and ultimately extracts the important features of images by leaving strong signals through spatial pooling. This CNN is learned through feed-forward and back-propagation, and the ultimate goal of the CNN is to reduce the loss of the difference between the output and the ground truth with the gradient. This study follows the workflow shown in Fig. 3 and Fig. 4. The filter of the CNN shares the same weight and bias during window sliding, which means that the window is a weight filter of the CNN and that the sliding is the movement of the filter.



FIGURE 3. The process of the convolutional neural network.

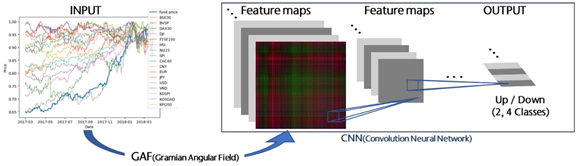
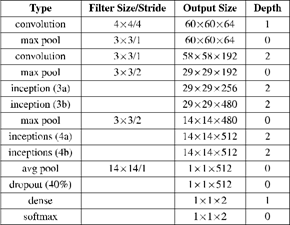


FIGURE 4. Overall framework for training a convolutional neural network.

When analyzing time-series data, RNN and LSTM are the most commonly used models. However, this study uses a CNN to predict the fund base price. This is done so that we can use a weight filter that leaves only meaningful and strong signals, which are characteristics of the CNN. Finally, only significant variables among a total of 16 variables are used. However, because the CNN cannot extract features possessing characteristics of sequential data, such as time-series data, we convert the time-series data into a 2-dimensional matrix using the GAF matrix in subsection III-B such that the x-axis and y-axis possess the characteristics of sequential data. Previously, Chen et al. (2016) used only a single variable for stock price prediction; in contrast, we used 16 variables as the 4 × 4 sequential data form. Therefore, we set the first ConvNet filter size as 4 × 4 with a stride of 4. The filter of the CNN consists of weights that will be calculated when training a model. The stride controls the filter moving through the input data. After shifting one unit at a time, we can obtain a calculated output as a feature of the input data. We use the 4 × 4 filter to allow 16 variables to be weighted and biased according to their correlation. The reason for the window sliding with a stride of 4 is that the first ConvNet layer forms a feature map in which only 16 variables are considered, and the second ConvNet Layer forms a feature map in which the characteristics of a sequence are considered. In addition, the stride of the pooling layer followed by the first ConvNet is set to be from 2 to 1 so that the output size can be 60 × 60 × 64 to match the reduced size. We considered AlexNet, VGGNet 16, GoogLeNet, and ResNet 50 for the CNN network. As mentioned above, the first ConvNet filter of all DNNs is set to 4 × 4 with a stride of 4. Of course, there are networks, such as ResNet 101, Inception v3 [26] and Inception-ResNet, which achieve better performance; however, the images that we use as input are simple images, and thus, a deeper or better CNN was not necessary. Therefore, we attempted to find the network with the most appropriate depth, and we also compared the 5b inception network with two auxiliary classifiers: the 4b inception network with one auxiliary classifier and the 3a inception network without an auxiliary classifier in GoogLeNet. The experiments conducted in this study were based on the 4b inception model. The position of the auxiliary classifier was placed after the 4a inception output. The structure of the network is shown in Table 2.

TABLE 2 . Network structure of the CNN.



**CONCLUSION**

Many people are interested in investing in stocks and funds and are putting substantial effort into predicting their performance. Because data such as common stock prices are time-series data, mathematical models, such as autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroskedasticity (GARCH), and open-source software libraries, such as XGBoost, may be used. In the case of deep learning, sequence-type data are learned and predicted using models such as recurrent neural networks (RNNs), long short-term memory (LSTM), and gated recurrent unit (GRU). Unlike other time-series analysis methodologies, we use a weight and bias filter to leave only significant and strong signals, which are characteristics of CNNs. Through this process, only significant variables among all 16 variables are used (Korean Funds, 9 foreign stock indexes, 4 foreign exchange rates, and 2 Korean stock indexes). We consider the risk level of the fund, the filter size of the convolutional network, the types of networks, the architecture, the number of variables, and the number of classes to predict the fund price. The Gramian angular field (GAF) algorithm is used to convert time-series data into 2-dimensional images with 16 variables, and the filter size of the first convolutional network is set to 4 × 4 with a stride of 4. When analyzing fund prices, it is necessary to consider the risk level of the fund. Using all 16 variables achieves better accuracy than using only the fund price. Comparing many types of networks, including AlexNet, VGGNet 16, GoogLeNet, and ResNet, the GoogLeNet 4b inceptions model and the proposed model achieve the best accuracy. The model using 4 output classes achieves a better cumulative return than the model using 2 output classes, even though the accuracy of the model using 2 output classes is slightly better than the other model.

In the future, we plan to find a suitable algorithm for transforming time series of various variables into one image. In addition, we expect to be able to develop algorithms for merging existing variables with discrete variables such as the net profit of companies.

REFERENCES

[1] R. Y. M. Li, S. Fong, and K. W. S. Chong, ‘‘Forecasting the reits and stock indices: Group method of data handling neural network approach,’’ Pacific Rim Property Res. J., vol. 23, no. 2, pp. 123–160, 2017.

[2] X. Yang, S. Mao, H. Gao, Y. Duan, and Q. Zou, ‘‘Novel financial capital flow forecast framework using time series theory and deep learning: A case study analysis of Yu’e Bao transaction data,’’ IEEE Access, vol. 7, pp. 70662–70672, 2019.

[3] K. Lu, Y. Lyu, X. Li, and Y. Zhang, ‘‘A new method for evaluating information system growth of SMES based on improved bp neural network,’’ Inf. Syst. E-Bus. Manage., pp. 1–14, 2019.

[4] K. Kohara, T. Ishikawa, Y. Fukuhara, and Y. Nakamura, ‘‘Stock price prediction using prior knowledge and neural networks,’’ Intell. Syst. Accounting, Finance Manage., vol. 6, no. 1, pp. 11–22, 1997.

[5] B. Ko, J. W. Song, and W. Chang, ‘‘Crash forecasting in the Korean stock market based on the log-periodic structure and pattern recognition,’’ Phys. A, Stat. Mech. Appl., vol. 492, pp. 308–323, 2018.

[6] E. C. Chang and W. G. Lewellen, ‘‘Market timing and mutual fund investment performance,’’ J. Bus., pp. 57–72, 1984.

[7] W. G. Droms and D. A. Walker, ‘‘Mutual fund investment performance,’’ Quart. Rev. Econ. Finance, vol. 36, no. 3, pp. 347–363, 1996.

[8] J. Patel, S. Shah, P. Thakkar, and K. Kotecha, ‘‘Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques,’’ Expert Syst. Appl., vol. 42, no. 1, pp. 259–268, 2015.

[9] K.-J. Kim, ‘‘Financial time series forecasting using support vector machines,’’ Neurocomputing, vol. 55, nos. 1–2, pp. 307–319, 2003.

[10] L.-J. Cao and F. E. H. Tay, ‘‘Support vector machine with adaptive parameters in financial time series forecasting,’’ IEEE Trans. Neural Netw., vol. 14, no. 6, pp. 1506–1518, Nov. 2003.

[14] N. Chapados and Y. Bengio, ‘‘Cost functions and model combination for VAR-based asset allocation using neural networks,’’ IEEE Trans. Neural Netw., vol. 12, no. 4, pp. 890–906, Jul. 2001.

[15] R. Sitte and J. Sitte, ‘‘Analysis of the predictive ability of time delay neural networks applied to the S&P 500 time series,’’ IEEE Trans. Syst., Man, Cybern. C, Appl. Rev., vol. 30, no. 4, pp. 568–572, Nov. 2000.

[16] T. Geva and J. Zahavi, ‘‘Empirical evaluation of an automated intraday stock recommendation system incorporating both market data and textual news,’’ Decis. Support Syst., vol. 57, pp. 212–223, 2014.

[17] X. Ding, Y. Zhang, T. Liu, and J. Duan, ‘‘Deep learning for event-driven stock prediction,’’ in Proc. IJCAI, 2015, pp. 2327–2333.

[18] M. Längkvist, L. Karlsson, and A. Loutfi, ‘‘A review of unsupervised feature learning and deep learning for time-series modeling,’’ Pattern Recognit. Lett., vol. 42, pp. 11–24, 2014.

[19] J.-F. Chen, W.-L. Chen, C.-P. Huang, S.-H. Huang, and A.-P. Chen, ‘‘Financial time-series data analysis using deep convolutional neural networks,’’ in Proc. 7th Int. Conf. Cloud Comput. Big Data (CCBD), Nov. 2016, pp. 87–92.