The Ensemble-based Neural Network Model for Providing an Explainable Warnings about a Market Index

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ABSTRACT

Detecting a market crash and understanding why this decline is occurring are important for successful investment. However, it is challenging to create Artificial Intelligence (AI) models that can predict and explain the stock market, which has high uncertainty. This paper proposes an ensemble-based, artificial neural network model to predict a market crash and to provide signals and rationale for warnings. This method creates multiple decision-makers and uses them to create a warning index that can detect risk phases in advance. Furthermore, the method can provide key variables that have had a significant effect on the warning index. This paper has contributed to obtaining excellent results in the prediction problem of the market index and to creating an explainable AI model that can increase the understanding of warnings and market states.

CCS CONCEPTS

• **Information systems → Expert systems**.

KEYWORDS

early-warning system, explainable A.I., ensemble model, market index

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1 INTRODUCTION

One of the critical tasks of a financial company is to predict a market crash and to prevent damage caused by these risks. Unexpected market movements affect financial companies' investment success or failure. However, it is challenging to predict the risks. Because a market index is both directly and indirectly affected by various factors and has a non-stationarity, the influence of factors can change over time. As a result, to predict rapid drops in the market index, it is necessary to analyze various factors and to model the impact of various factors on the market crash based on data analysis.

Advancements in computer science technology has produced successful results in various areas. Similarly, the number of cases in which computer science technologies such as big data and artificial intelligence have been applied increases in the area of finance. Siebenbrunner et al. [6] empirically showed the answer to a question related to market stability by using a supervised learning model. To predict stock prices, Zeng et al. [9] proposed the application of a deep learning-based model for video prediction instead of traditional statistical models such as the autoregressive integrated moving average (ARIMA). Liu et al.[3] propose an open-source framework that facilitates the use of deep reinforcement learning. Deep reinforcement learning has attracted attention as a powerful tool in quantitative finance despite its steep learning curve.

As in the previously mentioned case, we propose an ensemble-based model that applies computer science concepts. The proposed method can predict a rapid drop in a market index by using ensemble techniques. In addition, by providing the user with information about factors that greatly influenced the model's results, it is possible to explain how the model derived the results.

To achieve this purpose, we have carried out the following tasks. 1) We propose a formula that can be defined for market crashes. 2) The warning index and key variables are derived from the ensemble-based, artificial neural network models. 3) The warning index is evaluated to determine whether it well detects the risk phase and whether it achieves good results for investments using the index. 4) Someone with domain knowledge evaluates whether the key variables derived from the model well represent the state of the market.

This paper makes the following contributions: In general, it is known that making a prediction related to a market index with high uncertainty is difficult. The proposed method can predict a rapid drop in the market index in advance and provide an early warning to users. The proposed model also contributes to creating an explainable AI model by providing not only a warning but also information that influences the model's results.

This paper is organized as follows. Chapter 2 discusses related works. Chapter 3 describes the proposed method, and Chapter 4 evaluates the performance of the proposed model. Finally, Chapter 5 describes the conclusion and future work.

2 RELATED WORK

The early-warning system, which predicts risks in advance and enables preparation for these risks, has been actively researched in not only disaster-related fields but also finance. Vidal et al. [8] proposed a method to quantitatively express the pessimistic/optimistic atmosphere for a market index by using the price information of stocks, which constitutes the market index. The authors created a sentiment index using their proposed method and explained how to use it as a warning indicator. Using a dataset derived from [5], Fricke et al. [1] predicted a financial crisis using a variety of methods, from regression analysis to ANNs, and compared the performance of each model. Tolo et al. [7] explained that using the recurrent neural network structure can improve the performance of financial crisis prediction problems based on time series data.

In addition to academic achievements, various services exist for quantifying risk in market indexes. The Fear&Greed Index(https://edition.cnn.com/markets/fear-and-greed) serviced by CNN comprehensively analyzed seven indicators, including stock price strength and stock price breadth, to quantitatively express the fear and optimism inherent in the market. The Chicago Options Exchange Volatility Index, also known as VIX, is an indicator of the volatility of the U.S. stock market. This index is calculated using the weighted prices of put and call options in the index over a 30-day period. When the value of the VIX index increases, people have a greater sense of fear in the market. The Boom&Shock Index, which two Korean companies jointly developed, was recently announced. This index refers to the proportion of investments in U.S. large-cap assets and cash assets and is released in newspapers once a week.

Preemptive detection of risks to market indexes is an important task both academically and industrially.

3 PROPOSED METHOD

3.1 Data

In general, a market crash arises from the divergence between the expectations of market participants and the actual published fundamental value. Therefore, the proposed method utilized the price and spread data that reflect the consensus of market participants and macroeconomic indicators that can represent the actual state of the economy. Commodity prices, bond interest rates and spreads, global market/sector representative indices, CDS, and FX data were selected as consensus data of market participants. In addition, information representing actual macro-environment data was obtained from four countries: the USA, Europe, China, and Korea.

Financial crises are also caused by non-economic factors, such as opinions, political issues, and international events. For example, events such as the announcement of the U.S. Fed's monetary policy, currency war, inflation issue, and central bank stance can also cause stock prices to rapidly drop. We produced a quantified value about these events by analyzing news data from Reuters.

Since the data collection and pre-processing process is outside the scope of the main contribution of this paper, it is not discussed in detail.

3.2 Definition of Risk and Risk Phase

- $MarketIndex_t$ is defined as the value of target market index on day t.
  (e.g., the value of the S&P 500 at time t, if the U.S. is the target market.)
- $Window_{20}(t)$ is set of $MarketIndex_t$ for the past 20 days from time t.
- T is set of t.

step 1:
For i $\in getlength(T) - 20$ **do**

$$IWMDD_{window_{20}(t)} = \frac{Max(Window_{20}(t)) - Min(Window_{20}(t))}{\log(\arg\min(t) - \arg\max(t))}$$

step 2:
Select the $Window_{20}(t)$ with top 15% of the MDD and define it as a risk.
If consecutive dates are defined, they are considered as same risk phase.
step 3:
Create a label with a value of -1 to 1 using the lowest point within 20 business days before the start and 60 business days after the end of the risk phase.

Table 1: Algorithm to define risk and risk phase

The risk and risk phases are defined using the algorithm in Table 1. First, the algorithm calculates the Interval-Weighted Maximum DrawDown (IWMDD) for a specific window size from the historical data of a target index. The IWMDD is a time-weighted method of traditional MDD, in which the difference between the maximum value and minimum value is divided by the logarithm of the interval between the two values. The larger the difference between the minimum value and maximum value during a short interval is, the higher the IWMDD. The MDD over a unit period is employed to make candidates for risk phases because a short-term rebound is sometimes observed when the market index rapidly drops. Second, as indicated in step 2, the date with the more considerable MDD value was defined as the risk phase and labeled with a number. The risk phases of consecutive days were considered the same phase. As a result, 43 risk phases can be defined for the S&P index from 2000 to 2022, with an average MDD over a unit period of 8.22%. We create the label data for training using this risk phase data. Last, as indicated in step 3, labels of [-1, 1] were created using the lowest point within 20 business days before the start of the risk phase and the lowest point within 60 business days after the last day of the risk phase. Using min-max normalization, the algorithm normalized the label between 0 and 1, and when the label was 0, a small negative term was added to define the label of the non-risk phase.

3.3 The proposed Model

The proposed model was created using the ensemble technique. The ensemble technique [4] is an approach that performs complex decision-making by combining simple decision-making models. The ensemble method can be classified into three types. Bagging refers to a technique such as sampling that extracts data; boosting refers to a process of weighting data or model results; and a stacking method creates a new model based on the output from multiple models.

The proposed method utilizes ensemble techniques of bagging, boosting, and stacking. Fig.1 shows the entire process of the proposed method. In the data collection step, we collect the data described in the previous section 3.1 and construct a value pool. In the learning stage, similar to the concept of bagging, each model is trained by sampling n features from the value pool. Similar to

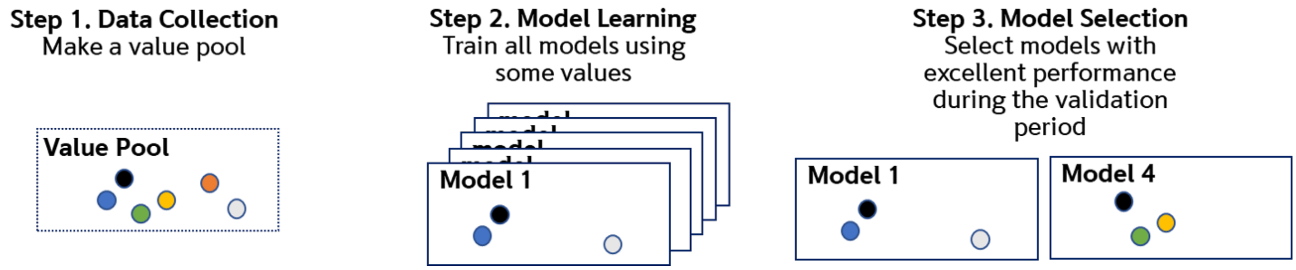

Figure 1: Entire process of the proposed method: data collection, model learning, and model selection. The final result is derived based on the selected model.

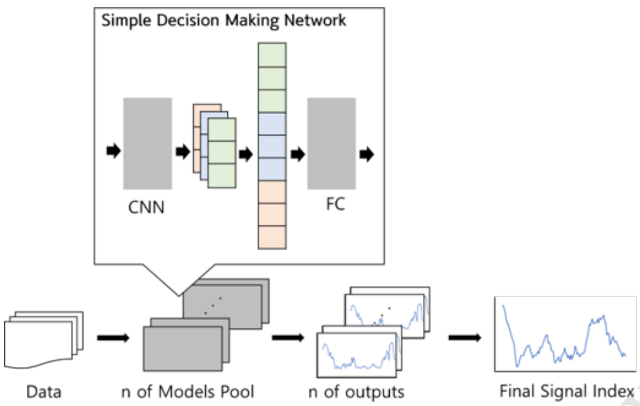

Figure 2: The structure of proposed model

the concept of stacking, models with excellent performance in a specific period are selected, and the final results are derived using these models. If a value is used more than another value, similar to the concept of boosting, it can be considered that this value has a greater influence on the result.

Fig. 2 shows the structure of each model. One model consists of a convolution neural network (CNN) and a fully connected neural network (FC), and the model of input data is a two-dimensional matrix whose size is (n, m). n denotes the number of variables selected by the model, and m means the past period of one data used for training. The CNN layer uses a kernel of size (n, d), and when the input data passes through the CNN layer, the data are compressed into a one-dimensional vector space. By concatenating the results of the CNN, it passes through the FC layer to derive the final output. The final output has a value of [-1, 1], and when the value is 1, it means a risk phase. However, when a final output is serviced, it is multiplied by -1 because 1 has a positive feeling and -1 has a negative sense.

Five individual models composed of a CNN and FC are combined to make one decision-maker. Due to the high uncertainty of the market index's prediction problem, each decision-maker may converge on different results depending on the initial value. To alleviate this problem, the proposed method uses the deep ensemble method [2], in which slight noise is added to the result of the loss function when it has few errors, and in the opposite case, in which considerable noise is added. In the interval where the prediction is relatively good, the results of the five models are similar, and in the opposite case, they show different results. The average of five models' output is used to determine the final decision of a decision-maker. If the four models make a decision near to 1, a value near 1 is used for the decision. As a result, it is possible to create a distribution of results for an uncertain prediction problem, which can be utilized to alleviate uncertainty.

Using the algorithm described in section 3.2, the risk and non-risk phases are classified in the market index information. In the risk phase, it was labeled as a positive number, and in the opposite case, it was marked as a negative number. The proposed method is trained using this label data and the loss function, as shown in Equation 1. The more likely the model and label have the same sign, the more optimized the weights of the neural network layers. To implement the deep ensemble method, the process of training is performed twice. Equation 1 is applied in the first training as a loss function, and in the second training, the loss value obtained from the first training is subtracted from the second loss value as noise.

$$\underset{w}{\text{maximize}} \quad \{\hat{y} \times y\} \tag{1}$$

The proposed method creates a large number of decision-makers and selects a decision-maker with good performance in a specific period. If the proposed method is operated as a service, there are predicted and actual values for each operation date. By the dot product of the predicted value and actual label, the operating score of each model can be calculated. The proposed method utilizes statistics on the operation score of each decision-maker to select an excellent decision-maker to be used for calculating the warning index and deriving key variables.

Two statistical values are extracted based on the scenario operated for the same period with the start date changed by one day. The first statistical value is the ranking measured by the operating score, and the second statistical value is the standard deviation of the ranking. For example, assume that the decision-maker performance over 240 business days from time t is compared. The dot product of each decision-maker's predicted and actual values for 210 business days from t-240 to t-30 is employed to compute one operating score. In the above case, 30 operating scores can be obtained per decision-maker, and average and deviation information can be calculated.

$$\text{Performance of Decision-Maker}_{test} = \frac{R_{test}(DM) - Q_1(R_{test}(DM))}{\sigma(R(DM))} \quad (2)$$

Using Equation 2, we can select a decision-maker to be used for deriving the final result. In Equation 2, $R_{test}(DM)$ means the decision-maker's average ranking in the test period. $Q_1(R_{test}(DM))$ means the operating score of the decision-maker whose operating score is in the top 25%, and $\sigma(R(DM))$ is the standard deviation of the decision-maker in the test period. As a result, while having a better operating score for 30 days, maintaining a high ranking than other decision-makers is preferentially selected.

The selected decision-makers derive the final output, referred to as the warning index and key variables. The warning index is the average of the results of the selected decision-makers. The closer this index is to -1, the more likely the current state of the market index is in a risk phase. Because more than half of the selected decision-makers have changed the decision that the current time is in the warning phase, the proposed method notifies users of early warning when the warning index changes from positive to negative. The key variables entail the list of variables used by the selected models. If the selected models use a specific variable in common, it can be considered a critical variable that can explain the market state or the warnings.

4 EXPERIMENTS

In this chapter, quantitative and qualitative evaluations were performed to evaluate the proposed method. The experiment was conducted nine times, considering 120 business days (Monday-Friday, public holidays were not considered) as a test set from April 2018 to May 2022. We experimented with walk forward validation using an expanding window. For example, the data before April 05, 2018, can be defined as training data and the data from April 06, 2018, to September 20, 2018, can be defined as the test set. In the second experiment, data up to September 20, 2018, are selected as training data, and data until March 07, 2019, are selected as test data.

4.1 Quantitative evaluation

We tested how well the proposed model detects risk phases and whether the proposed warning index is useful when it is applied to investment. We describe only a part of the evaluation in this chapter, and all results of the quantitative evaluation are provided in the appendix.

Fig. 3 shows the results of the proposed model and the quantitative evaluation method using it. The blue line represents the U.S. market index, S&P500, and the green line represents the risk phase of the proposed model. The red bar indicates the warning index. In the figure, there were two warning alarms in 120 business days. The first warning alarm was provided in the non-risk phase (area with the blue box at the top), and the second warning alarm was provided in the risk phase (area with the red box at the top). If the warning was provided in the risk phase, it was judged to be a true positive, and if the sign was not provided, it was considered a false positive. Using this method, precision, recall, and accuracy were calculated.

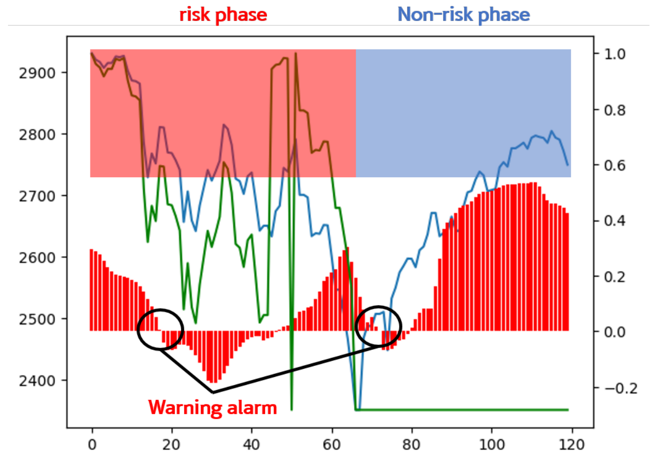

Figure 3: Graph of the warning index, risk phases, and the U.S. market index

Target market index	S&P500
Test period	2018.04 ~ 2022.05
Precision	0.625
Recall	0.833
Accuracy	0.667

Table 2: Quantitative performance of the proposed method in the U.S. Market index

Table 2 shows the back-test results of the proposed model. There is no comparison target due to the difficulty in selecting a comparison target, but it has high precision, recall, and accuracy.

There are 12 phases during the 4-year test period, of which 6 are risk phases. The total number of phases is not large, so whether one more correct answer is obtained has a significant impact on performance. Therefore, we conducted a virtual investment experiment using the warning index as an additional quantitative evaluation. A relatively simple investment strategy—investing in the index when the warning index is positive and holding cash when the warning index is negative—was applied. The case of investing money in the market index was compared with the case of investing money using the warning index.

	100 % SPY	Using warning index
Annualized Yield	12.07%	**15.00%**
Annualized Volatility	20.94%	**13.09%**
2018.04 ~ 2018.12	-5.16%	**-0.99%**
2019.01 ~ 2019.12	**26.10%**	22.80%
2020.01 ~ 2020.12	20.66%	**24.89%**
2021.01 ~ 2021.12	**24.80%**	20.32%
2022.01 ~ 2022.05	-14.68%	**-2.74%**

Table 3: Annualized yield and volatility of two investment strategies

Table 3 shows the comparison results of the two investment strategies. The results refer to the annualized rate of return and volatility over the entire experiment period and show the annualized rate of return for each year. During that period, investing in the U.S. index can yield a return of approximately 12%. However, according to the warning index, a return as high as 15% is possible. In terms of volatility, lower volatility is achieved when an investment is made according to the warning index. The warning index detects the market crash phase when the market index rapidly drops and provides a negative warning index. As shown in the above table, a loss was incurred when investing in SPY ETF at 100% weight in 2018 and 2022. However, the strategy according to the warning index reduces this loss.

4.2 Qualitative Evaluation

Name of Value	Up/Down
China Retail Sales YoY	Down
United States Disposable Personal Income	Up
U.S. Michigan Consumer Sentiment (Expectations)	Down
China Industrial profit YoY	Down
Budget Issue	event
U.S. ISM Manufacturing New Orders Index	Down
U.S. Michigan Consumer Sentiment (Conditions)	Down
Baltic Dry Index (BADI)	Down
USDBRL spot	Up
USDINR spot	Up

Table 4: Top 10 key variables in December 06, 2021

Table 4 shows a list of key variables on the day of the warning, December 06, 2021, and the trend of variables was observed from 3 months before the warning day. We selected relatively recent warning points to explain why decision-makers derived such results. A list of key variables for all warnings is provided in the appendix. On December 6, 2021, the warning index became negative and an early warning was provided to the user. In January 2022, the index briefly became positive, but a re-warning occurred on January 4, 2022, when the index switched signs again.

Examining the market situation from December 2021 to January 2022 shows intensifying inflation and an overheating job market. The manufacturing index has peaked, the Federal Open Market Committee (FOMC) has been quite hawkish, and the US Fed's rate hike has been confirmed. Due to COVID-19, which has hit the global economy hard, China has again implemented intensive lockdown measures.

Among the key variables, China Retail Sales YoY, China Industrial profit YoY, and Baltic Dry Index (BADI) showed a declining trend. These variables are strongly correlated with the Chinese economy, and it is considered that the warning index judged the decline of the Chinese economy as a major factor. In addition, the decision-makers selected the U.S. ISM Manufacturing New Orders Index as a key variable, which is considered to have paid attention to the continued decline of the manufacturing index. The University of Michigan's current and expected sentiment index is declining, and the United States Disposable Personal Income rose, which means that inflation and real incomes have decreased. These factors were selected as the main rationale for judgment. The event variable referred to as the Budget issue was selected as the key variable, which indicates that the issue of Congressional friction related to the increase in US fiscal debt was judged as the main reason for the early warning.

In this way, the user can qualitatively interpret the market situation and gain insight before the market crash by the key variables.

5 CONCLUSION AND FUTURE WORK

Predicting a market crash and responding to risk situations is essential to achieving successful investment results. This paper proposes an artificial neural network model based on ensemble concepts for predicting a rapid drop in the market index and for providing early warnings.

The proposed method generates many decision-makers and selects a good decision-maker among them. The method it can provide an early warning to the user according to the movement of the warning index. In addition, the method can provide the key variables that can explain the warning, contributing to the creation of an explainable AI model. The proposed method was evaluated using the U.S. market index. The results showed excellent performance in quantitative evaluation and that it could explain the market state at the time using key variables.

As a future study, we decided to use the proposed model to create a service that can provide users with more frequent insights. Because the proposed model provides an alarm once or twice a year, it may not be helpful to users most of the time. Our future research aims to find a way to increase user retention by closely analyzing key variables and the strength of the warning index.

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A APPENDIX

Fig. 4 shows the overall result of the proposed model. The test period consists of 6 risk phases and 6 non-risk phases. In the figure, the black circle represents the point at which the warning index is switched from positive to negative and an early warning is provided to the user. In the back-test results, a total of 10 early warnings were

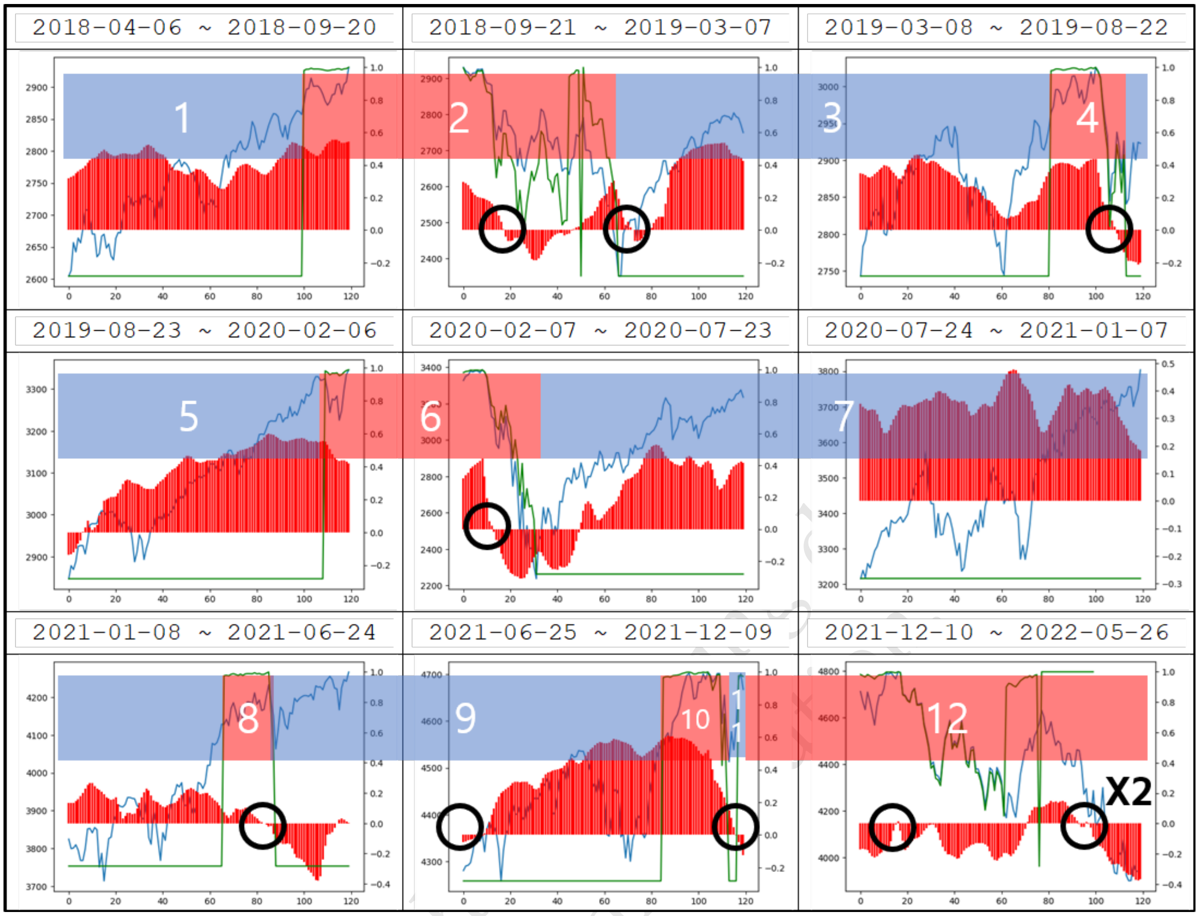

Figure 4: Graph of the warning index in the entire data

provided, of which 7 times were alerts during the risk phase defined in this paper. The proposed method has a high recall because the risk phase defined in this paper is well identified.

Table 5 shows a list of key variables for all warnings in the test period. In October 2018, the trade conflict between the United States and China rekindled, and the United States arbitrarily accelerated monetary tightening to solve overheating of employment and inflation. In addition, the dollar strengthened, which caused disputes regarding exchange rates between various countries. There were two warnings in October 2018 and January 2019. The former warning was issued before the decline, but the latter warning failed because it was issued after the decline appeared. However, analyzing the key variables of this period, the decision-makers paid attention to event variables for trade wars as important variables in judging the period. The proposed method selected key variables, such as variables for the manufacturing slowdown, US inflation and austerity, and exchange rate information, to explain the relevant timing.

Examining the market conditions in August 2019, the FOMC started cutting interest rates as an insurance policy and started Not-QE. The trade conflict between the US and China has intensified, including the designation of a currency manipulator and the imposition of additional tariffs, and U.S. employment slowed as global exports fell. The proposed method selects the Chinese consumer sentiment index, Korean export price index, drop in PP price, and currency war as key variables. The model paid attention to the trade conflict between the US and China and the slowdown in the global manufacturing economy. As a result, it is considered that the model judged global imbalances and provided warnings while choosing variables that indicate a booming US consumer economy and falling real interest rates. As a result, the proposed model judged and warned of global imbalances by selecting variables that represent the booming US consumption economy and falling real interest rates in addition to previously described scenarios.

In February 2020, some areas of China were closed due to COVID-19. The trade war between the US and China, which had a major impact on markets in the previous period, has shown signs of easing. FOMC announced another tightening action, and the insurance rate cut ended. The model focused on Korean export prices, Philadelphia Fed manufacturing index, USDCNH strength, and US wholesale sales were compared with those of the previous month, and LDPE prices were selected as variables for representing the alleviation of the trade war. On the other hand, indicators related to China's economic recovery, such as iron prices and China's financial loans

Warning Day	Key Variable									
2018-10-17	USDMXN spot	USDKRW swap point (12m)	**(evt) Liquidity Issue**	electricity prices	USDZAR swap point (12m)	SKEW Index	China Consumer Expectation Index	U.S. 5 Year Treasury	U.S. ISM Manufacturing New Orders Index	VVIX/VIX ratio
2019-01-02	Gold price	Korea Real Estate Purchase Price Index	USDMXN spot	**(evt) Trade Conflict**	USDZAR swap point (12m)	**(evt) Currency War**	Korea Interest Rate Spread index (10y-3y)	USDKRW spot	LME index	MSCI ACWI Health care
2019-08-08	Gold price	PP price	MSCI ACWI IT index	US Consumer Confidence Index	U.S. Personal Income MoM	China Consumer Expectation Index	South Korea FOB Exports YoY	South Korea Export Price Index YoY	U.S. MBA 30-Year Mortgage Rate spread U.S. 10 Year Treasury	**(evt) Currency War**
2020-02-26	South Korea Export Price Index YoY	Steel price	China Financial Loans YoY	Korea Real Estate Purchase Price Index	Gold price	LDPE price	United States Philadelphia Fed Manufacturing Index	US Wholesale Sales MoM	expert's forecast 6m (from news)	USDCNH spot
2021-05-05	Sugar Prices	Greece 10 Year Treasury	South Korea Leading Economic Index	VIX index	Italy CDS 5y	Korea Real Estate Purchase Price Index (Apartment)	United States ISM Purchasing Managers Index	US Consumer Confidence Index	US ATLANTA Fed Rate of Wage Growth for Low-Skilled Persons	US Wholesale Inventories MoM
2021-06-25	China Retail Sales YoY	South Korea Export Price Index YoY	VIX index	MSCI ACWI Industrials	**(evt) Financial Regulation Reforms**	US ATLANTA Fed Rate of Wage Growth for High-Skilled Persons	U.S. Michigan Consumer Sentiment (Conditions)	**(evt) Inflation Issue**	**(evt) Currency War**	Italy CDS 5y
2021-12-06	China Retail Sales YoY	United States Disposable Personal Income	U.S. Michigan Consumer Sentiment (Expectations)	China Industrial profit YoY	**(evt) Budget Issue**	U.S. ISM Manufacturing New Orders Index	U.S. Michigan Consumer Sentiment (Conditions)	Baltic Dry Index (BADI)	USDBRL spot	USDINR spot
2022-01-04	**(evt) Financial Regulation Reforms**	U.S. Michigan Consumer Sentiment (Conditions)	U.S. Michigan Consumer Sentiment (Expectations)	China Industrial profit YoY	China Consumer Sentiment Index	U.S. ISM Manufacturing Exports Index	United States Disposable Personal Income	United States Average Hourly Earnings	USDBRL spot	China Retail Sales YoY
2022-04-20	USDBRL spot	United States Average Hourly Earnings	US Building Permits MoM	US BEI 10y	China Consumer Sentiment Index	China FDI YoY	DXY/OITP ratio	MSCI ACWI Communication Sys.	U.S. Michigan Consumer Sentiment (Conditions)	expert's forecast 6m (from news)
2022-04-26	USDBRL spot	United States Average Hourly Earnings	China Consumer Sentiment Index	US Building Permits MoM	DXY/OITP ratio	**(evt) Financial Regulation Reforms**	MSCI ACWI Communication Sys.	MOVE index	US BEI 10y	U.S. Michigan Consumer Sentiment (Conditions)

Table 5: List of key variables for all warnings: (evt) means event variables derived from news

from the previous year exhibited a downward trend. The model was paying attention to several inflation-related indicators in a situation where China's domestic economy did not recover.

In July 2021, there was an atmosphere of concern about inflation in the market, and employment indicators were below expectations. The FOMC mentioned tapering. The decision-makers focused on inflation-related indicators, where wages and product prices rose due to the large-scale fiscal policy implemented in response to the coronavirus.