A study on stock direction prediction based on multiple input source using transformer

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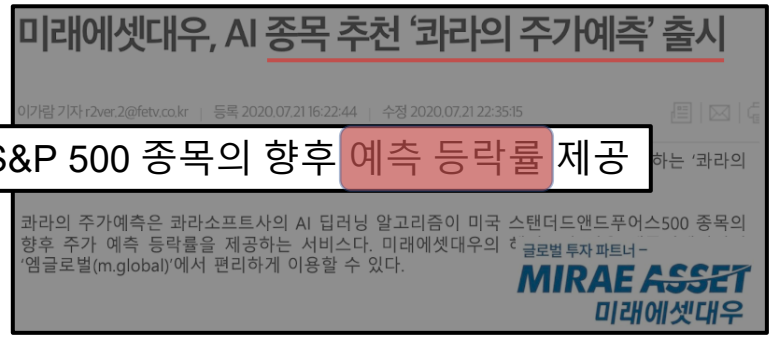
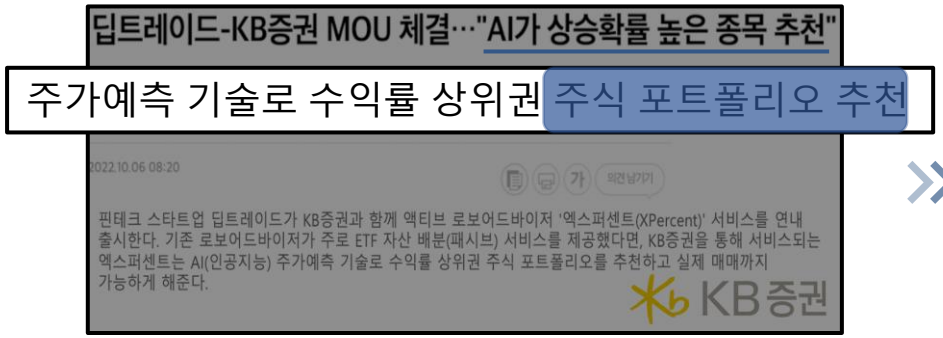
Stock Price Prediction



Stock prospect suggestion



Portfolio recommendation

Core Task

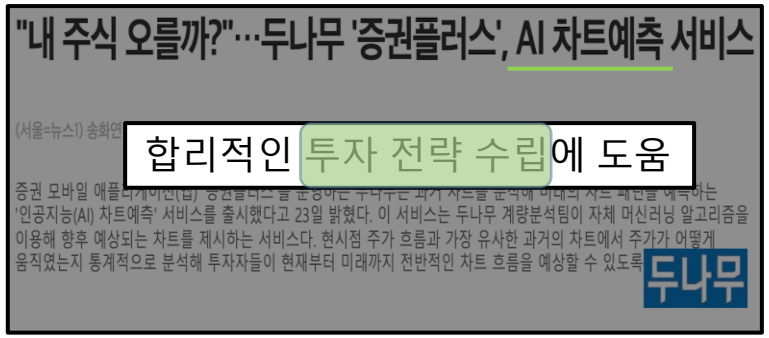
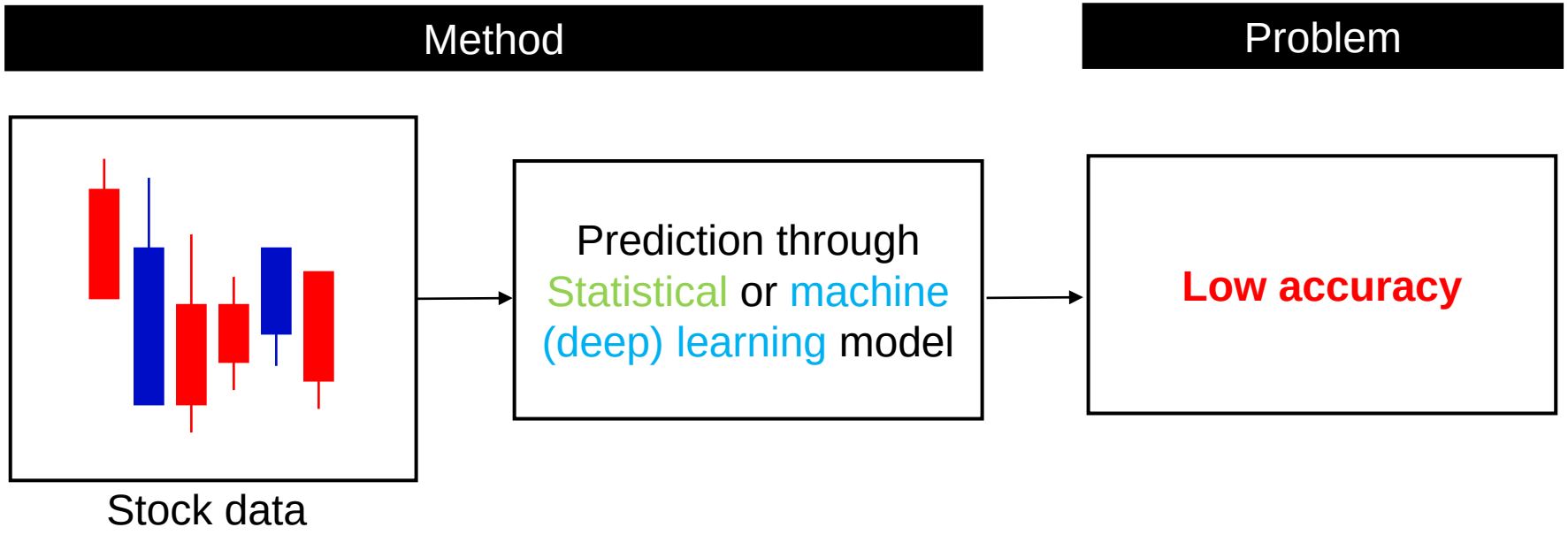


Chart pattern suggestion

Conventional methods of Stock Price prediction

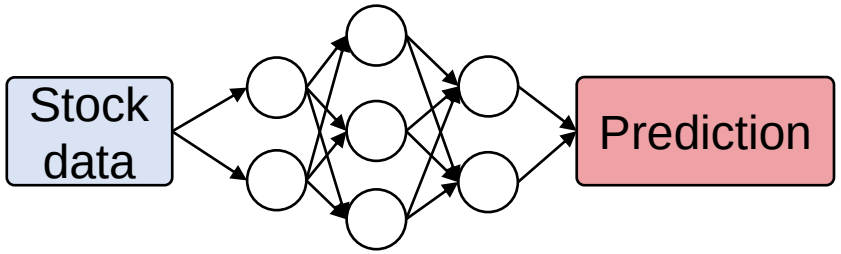
- Use only stock data
- **External situations** or **economic indicators** may not be reflected in stock prices.
- **Low** prediction accuracy



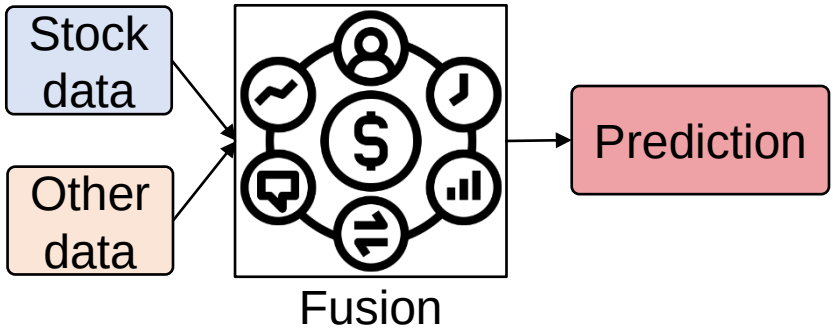
Related work

- Modality description

Using only stock data[1]



Data fusion[2]



Problematic

- Need to find the appropriate fusion method for stock prediction

Motivation

- Letting the model learn external situations or economic indicators

➢ It can be of great help to improve accuracy.

Modality Search

- Modality search affecting stock price data

Adopt effective data fusion method

- Adopting a fusion method to match the searched data

Proposed Method : Modality

Modality description

① Stock price

- Stock price data

② Month & days of the week[4]

- Month & days of the week

③ Macroeconomic indicator[5,6]

- -Data readings reflect the economic circumstances of a particular country, region, or sector.

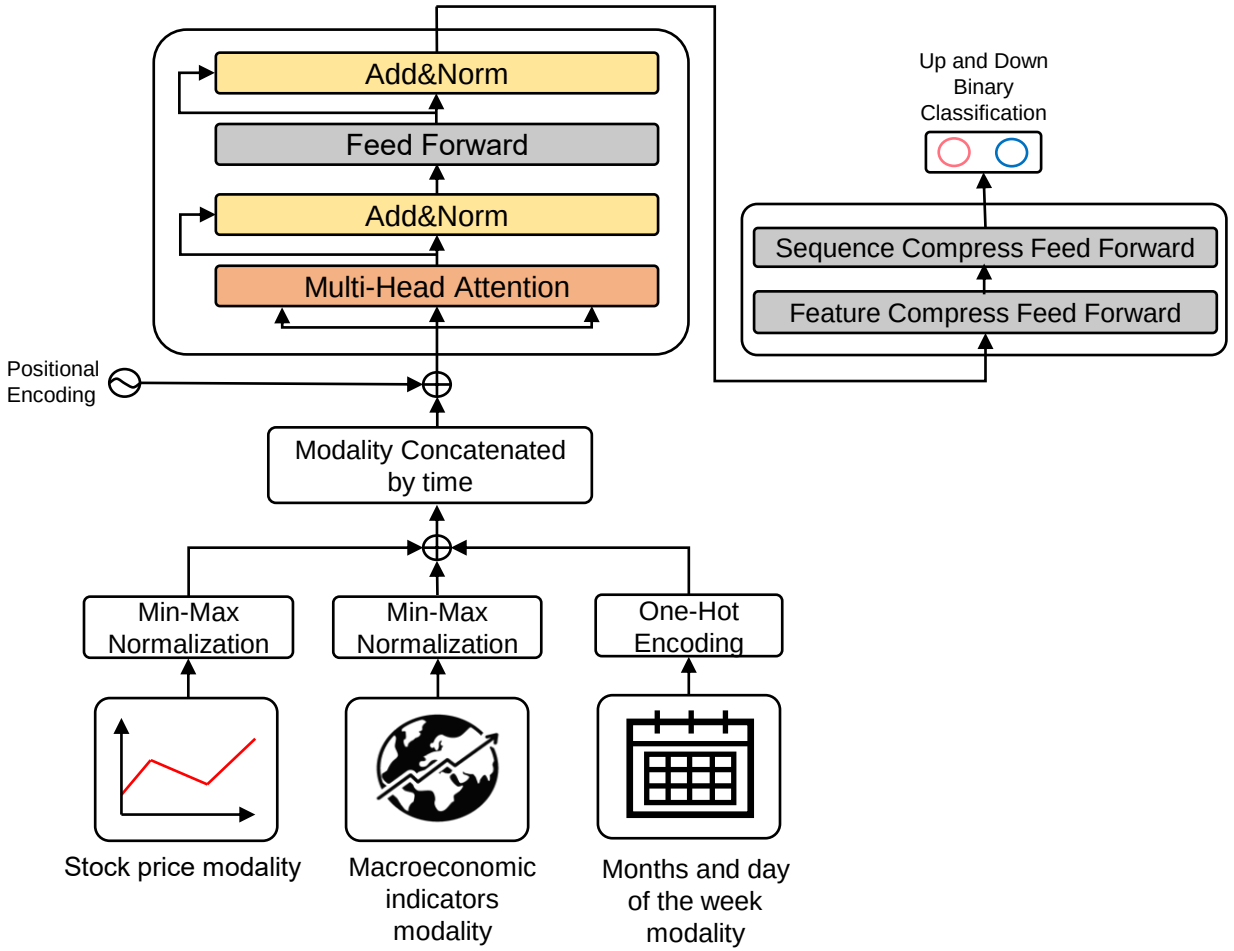
[4] R. J. Rogalski, “New findings regarding day-of-the-week returns over trading and non-trading periods: a note,” The Journal of Finance, vol. 39, no. 5, pp. 1603–1614, 1984.
[5] M. Adam and G. Tweneboah, “Macroeconomic factors and stock market movement: Evidence from ghana,” Available at SSRN 1289842, 2008.
[6] F. Jareño Cebrián and L. Negrut, “Us stock market and macroeconomic factors,” 2016.

Proposed Method: Model structure

- Modality description

Modality	Data Name
Stock price modality	KDD 17 stock pice dataset
	Technical indicator [3]
Month & days of the week modality [4]	Months
	Day of the week
Macroeconomic modality [5,6]	NASDAQ 100
	US 2 year Bond Yield
	US 10 year Bond Yield
	US 30 year Bond Yield
	US Dollar Index
	WTI Oil Price

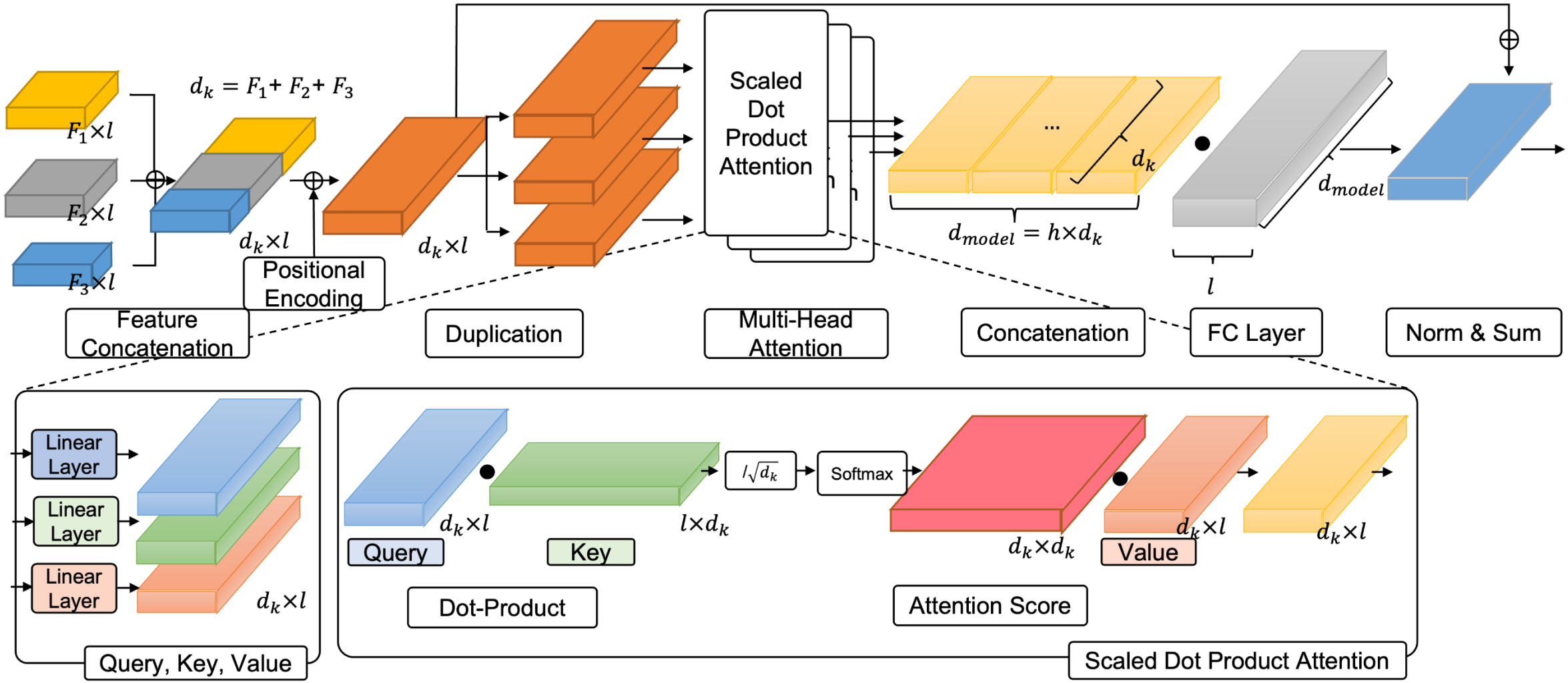
- Model overview



[1] Y. Kara, M. A. Boyacioglu, and Ö. K. Baykan, “Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the istanbul stock exchange,” Expert systems with Applications, vol. 38, no. 5, pp. 5311–531

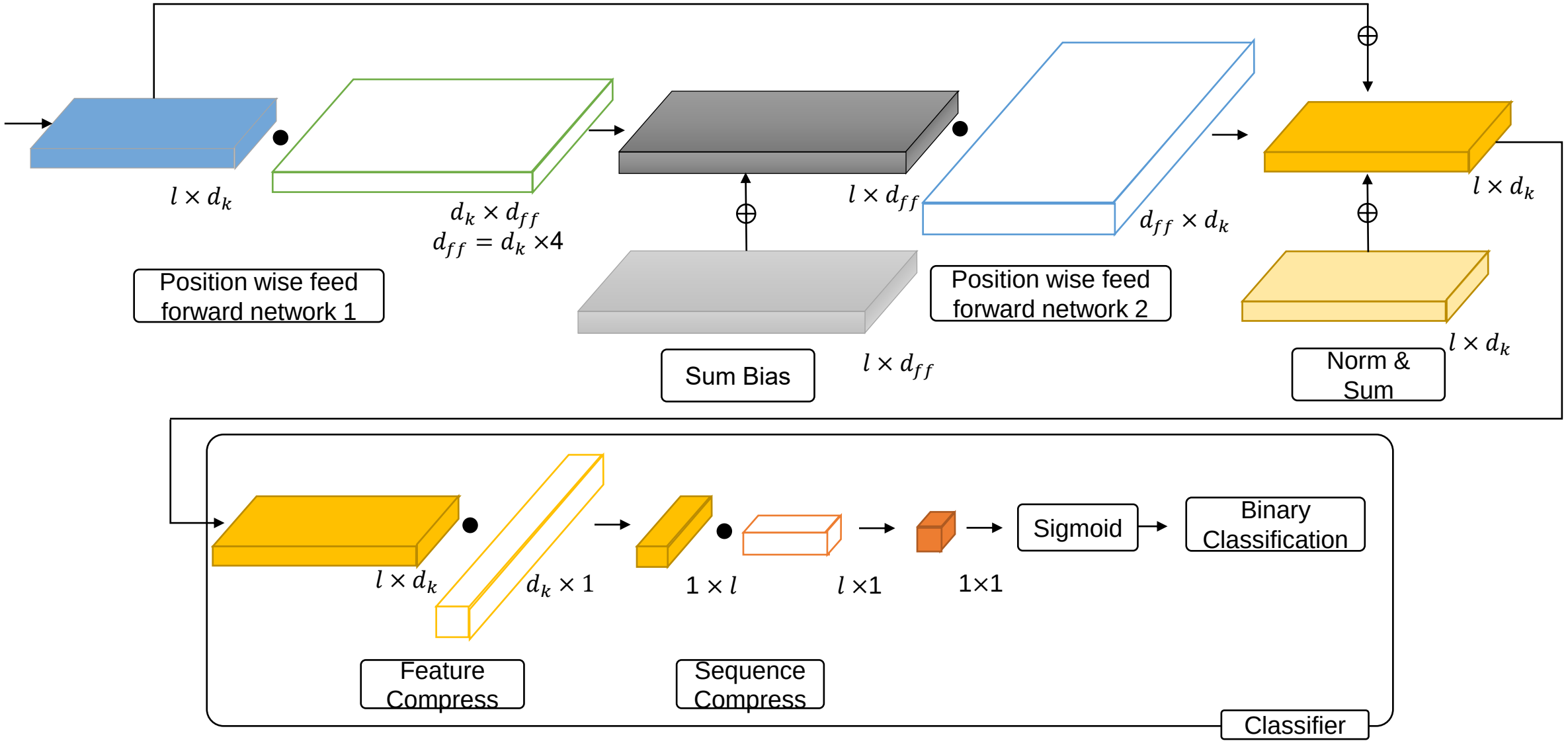
Proposed Method

Transformer Encoder in propoded Mehtod



Proposed Method

Transformer Encoder in propoded Mehtod



Experimental Setting

Data description

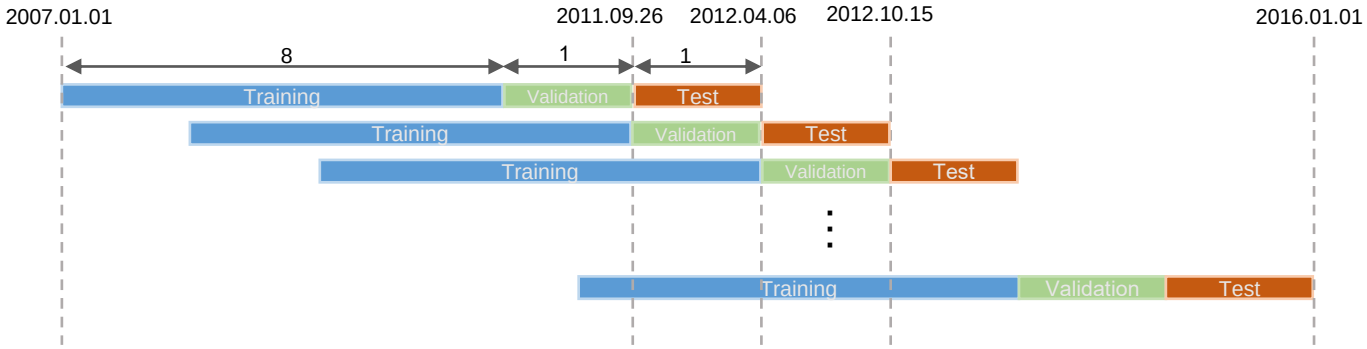
Modality	Source	Data name
Stock price modality	KDD17 (6)	Open
		High
		Low
		Close
		Volume
		Adjusted Close
	Technical Indicator (12)	Updown
		Change
		10-day Moving Everage
		Weighted 10-day Moving Average
		Momentum
		Stochastic K%
		Stochastic D%
		RSI (Relative Strength Index)
		MACD (Moving Everage Convergence Divergence)
		Larry William's R%
		A_D (Accumulation /Distribution) Oscillator
		CCI (Commodity Channel Index)

Modality	Source	Data name
Months & day of the week modality	Date(17)	Months
		Day of the week
Macroeconomic indicator modality	Macroeconomic Indicator (6)	NASDAQ100
		US 2year Bond Yield
		US 10year Bond Yield
		US 30year Bond Yield
		US Dollar Index
		WTI Oil Price

- The number of entire time step is 2518.
- The number of stock in kdd dataset is 50.

Experimental Setting

Time series blocked cross-validation[7]

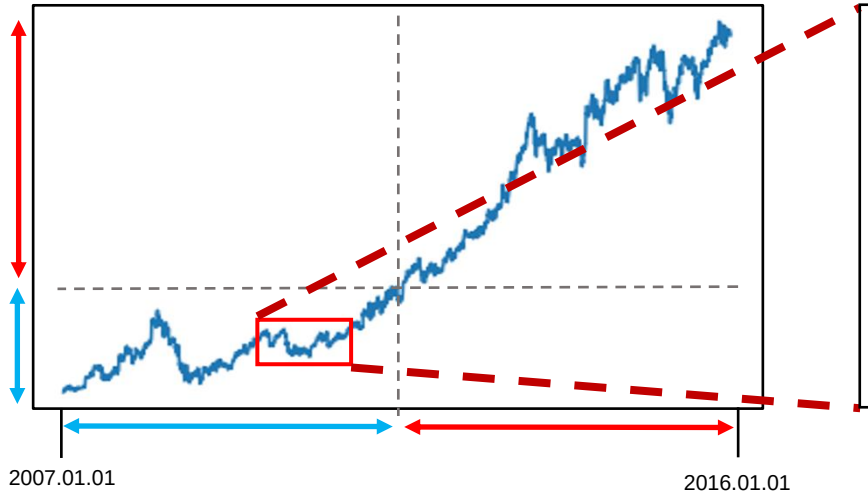


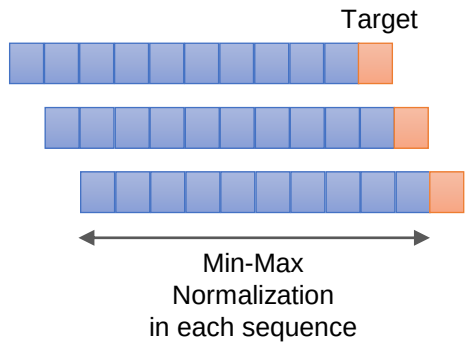
- Normal random split in time series data

➢ The looking forward prediction occurs.

Time step min-max normalization

Scale difference in same period





- Normalization for the entire sequence

➢ Unstable learning.

Experimental Setting

Comparison algorithm

- CNN-BiLSTM-AM[8]: Hybrid deep learning model
- AdvLSTM[9]: Adversarial Training
- DTML[10]: learning correlation between stocks # Transformer

Performance Measure

$$Accuracy(\%) = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

- TP: True Positive
- TN: True Negative
- FP: False Positive
- FN: False Negative

Experimental Result

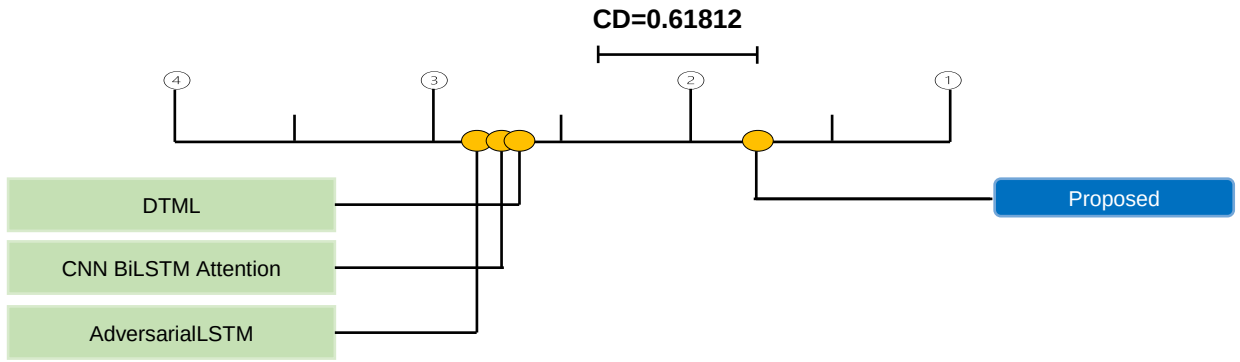
Ranking comparison

	Proposed Method	CNN-Attention BiLSTM [8]	Adversarial LSTM [9]	DTML [10]
Average ranking	**1.72**	2.72	2.78	2.68

Friedman test (Multiple comparisons) [11]

Evaluation measure	Friedman statistic	Critical values (α = 0.05)
Accuracy	24.084	2.557

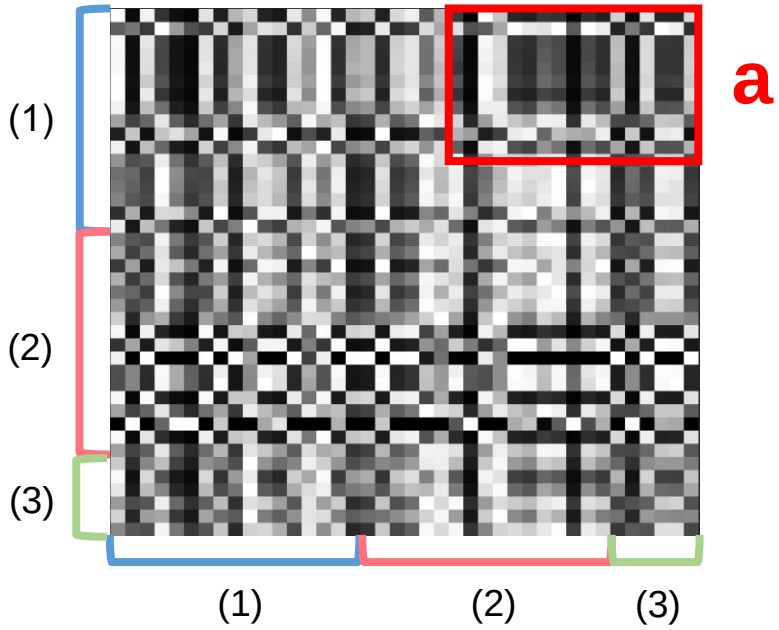
Bonferroni-Dunn test (Post-hoc test) [11]



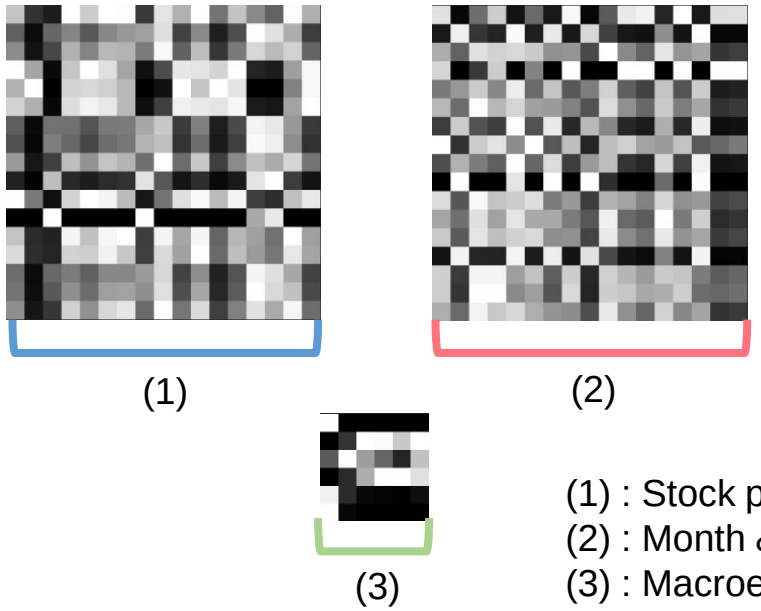
Analysis: between early fusion method and late fusion method

Comparison of the attention map

- Early fusion attention map



- Late fusion attention map



- Part '**a**' is highly activated
- Each modality in late fusion learns the relation between features apart from each other

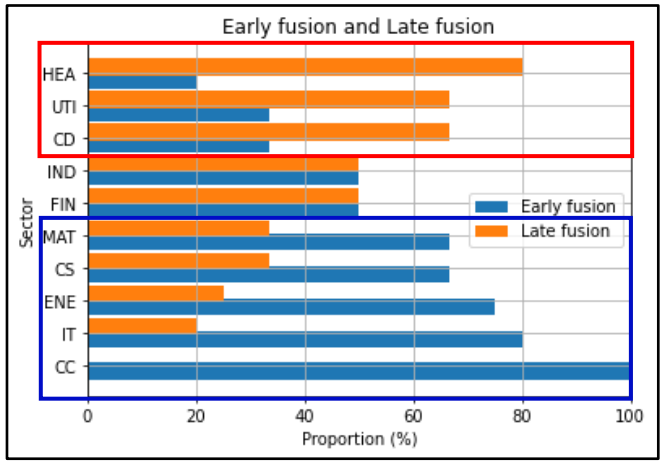
Analysis: between early fusion method and late fusion method

- Numerical Analysis

	The Number of data with high accuracy
Early fusion method	30
Late fusion method	20

- Sector Analysis

Abbreviated sector	Description
IT	Information Technology
CD	Consumer Defensive
FIN	Financial
MAT	Materials
CS	Communication Services
ENE	Energy
UTI	Utility
IND	Industrial
HEA	Healthcare
CC	Consumer Cyclical



- Number of sectors with high classification accuracy in late fusion
  - ➢ 3
- Number of sectors with high classification accuracy in early fusion
  - ➢ 5

Conclusion & Contribution

Conclusion

- A strategy considering multiple information is proposed to enhance the classification accuracy of the stock direction prediction
- Transformers are modified to simultaneously consider information that reflects external context considerations.
- The proposed method outperforms the existing model that uses the stock price data only.
- An in-depth analysis is conducted on the experimental results of early and late fusion.

Contribution

- In Domestic Competition

  - B-cell epitope (linear peptide) prediction competition, **AI Graduate School Challenge**, 2022, **3rd Prize**

- In Domestic Conferences

  - A Study on Prediction of Neural Network Stock Direction Using Technical Indicators, **IEIE**, 2022, **1st author**

Reference

[1] W. Lu, J. Li, J. Wang, and L. Qin, “A cnn-bilstm-am method for stock price prediction,” Neural Computing and Applications, vol. 33, no. 10, pp. 4741–4753, 2021.

[2] I. K. Nti, A. F. Adekoya, and B. A. Weyori, “A novel multi-source information-fusion predictive framework based on deep neural networks for accuracy enhancement in stock market prediction,” Journal of Big Data, vol. 8, no. 1, pp. 1–28, 2021.

[3] Y. Kara, M. A. Boyacioglu, and Ö. K. Baykan, “Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the istanbul stock exchange,” Expert systems with Applications, vol. 38, no. 5, pp. 5311–531

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[6] F. Jareño Cebrián and L. Negrut, “Us stock market and macroeconomic factors,” 2016.

[7] W. Bao, J. Yue, and Y. Rao, “A deep learning framework for financial time series using stacked autoencoders and long-short term memory,” PloS one, vol. 12, no. 7, p. e0180944, 2017.

[8] W. Lu, J. Li, J. Wang, and L. Qin, “A cnn-bilstm-am method for stock price prediction,” Neural Computing and Applications, vol. 33, no. 10, pp. 4741–4753, 2021.

[9] F. Feng, H. Chen, X. He, J. Ding, M. Sun, and T.-S. Chua, “Enhancing stock movement prediction with adversarial training,” arXiv preprint arXiv:1810.09936, 2018.

Reference

[10] J. Yoo, Y. Soun, Y.-c. Park, and U. Kang, “Accurate multivariate stock movement prediction via data-axis transformer with multi-level contexts,” in Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining, pp. 2037–2045, 2021.

[11] B. Trawi´nski, M. Sm ̨etek, Z. Telec, and T. Lasota, “Nonparametric statistical analysis for multiple comparison of machine learning regression algorithms,” International Journal of Applied Mathematics and Computer Science, vol. 22, no. 4, pp. 867–881, 2012.

Thank you

Appendix
Detailness of the entire modality

Modality	Source	Data Name	
Stock price modality	KDD17	Open	The price at which the financial security opens in the market when trading begins.
		High	Intraday highest trading price.
		Low	Intraday lowest trading price.
		Close	The price at which the financial security closes in the market when trading ends.
		Volume	The number of shares transacted every day.
		Adjusted Close	A stock's closing price to reflect that stock's value after accounting for any corporate actions.
	Technical Indicator	Updown	$C_t - C_{t-1}$
		Change	$\frac{C_t - C_{t-1}}{C_{t-1}}$
		10-day Moving Everage	$\frac{C_t + C_{t-1} + \cdots + C_{t-10}}{10}$
		Weighted 10-day Moving Average	$\frac{(n) \times C_t + (n-1) \times C_{t-1} + \cdots + C_{t-10}}{(n + (n-1) + \cdots + 1)}$
		Momentum	$C_t - C_{t-n}$
		Stochastic K%	$\frac{C_t - LL_{t-n}}{HH_{t-n} - LL_n} \times 100$
		Stochastic D%	$\frac{\sum_{i=0}^{n-1} K_{t-i}\%}{n}$
		RSI (Relative Strength Index)	$\frac{\sum_{i=0}^{n-1} K_{t-i}\%}{n}$
		MACD (Moving Everage Convergence Divergence)	$MACD(n)_{t-1} + \frac{2}{n} + 1 \times (DIFF_t - MACD(N)_{t-1})$
		Larry William's R%	$\frac{H_n - C_t}{H_n - L_n} \times 100$
		A_D (Accumulation /Distribution) Oscillator	$\frac{H_t - C_{t-1}}{H_t - L_t}$
		CCI (Commodity Channel Index)	$\frac{M_t - SM_t}{0.015 D_t}$

Modality	Source	Data Name	
Months & day of the week modality	Date	Months	Encoded months data using One-Hot Encoding.
		Day of the week	Encoded day of the week data using One-Hot Encoding.
Macroeconomic indicator modality	Macroeconomic indicator	NASDAQ100	A stock market index made up of 102 equity securities issued by 101 of the largest non-financial companies listed on the Nasdaq stock exchange.
		US 2year Bond Yield	The yield received for investing in a US government issued treasury security that has a maturity of 2 years.
		US 10year Bond Yield	The yield received for investing in a US government issued treasury security that has a maturity of 10 years.
		US 30year Bond Yield	The yield received for investing in a US government issued treasury security that has a maturity of 30 years.
		US Dollar Index	An index of the value of the United States dollar relative to a basket of foreign currencies, often referred to as a basket of U.S. trade partners' currencies.
		WTI Oil Price	A specific grade of crude oil and one of the main three benchmarks in oil pricing, along with Brent and Dubai Crude.

C_t: the adjacent close price, L_t: the low price,
H_t: the high price at time t,
$DIFF : EMA(12)_t - EMA(26)_t$,
EMA: exponential moving average,
$EMA(k)_t : EMA(k)_{t-1} + \alpha \times (C_t - EMA(k)_{t-1})$,
α smoothing factor: 2/1+k,
k: time period of k day exponential moving average LL_t
HH_t: lowest low and highest high in the last t days,
$M_t : H_t + L_t + C_t/3$,
$SM_t : (\sum_{i=1}^{n} M_{t-i+1})/n$,
$D_t : (\sum_{i=1}^{n} |M_{t-i+1} - SM_t|)/n$,
UP_t: the upward price change,
Dw_t: the downward price change at time t