An Empirical Examination on Forecasting VN30 Short-Term Uptrend Stocks using LSTM along with the Ichimoku Cloud Trading Strategy

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Outline

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01

Introduction

Introduction: Background

- Fundamental analysis and technical analysis are the most prominent methods.

- Nonetheless, they have significant shortcomings.

- Researchers have started to explore more sophisticated approaches

Introduction: Literature Review

- Krauss et al. [1] create a profitable trading strategy by using an ensemble of different models to predict trends.

- Zhang et al. [2] proposed deep and wide area network (DWNN), a new type of neural network that employ a combination of convolutional neural network (CNN) and recurrent neural network (RNN).

Introduction: Literature Review

- Makrehchi et al. [3] use labelled social media text as inputs.
- In Vietnam, researchers have also started to show interest in using deep-learning to predict the local stock market [4-7].
- Lim et al. [8] create an automated trading strategy based on the Ichimoku Cloud for both Japan and the USA stock markets.

Introduction: Motivation

- The Ichimoku Cloud, for the most part, is only used as an automated trading strategy
- Studies in Vietnam are still lacking
- Most studies conducted in this field use accuracy as the main criteria for their proposed models

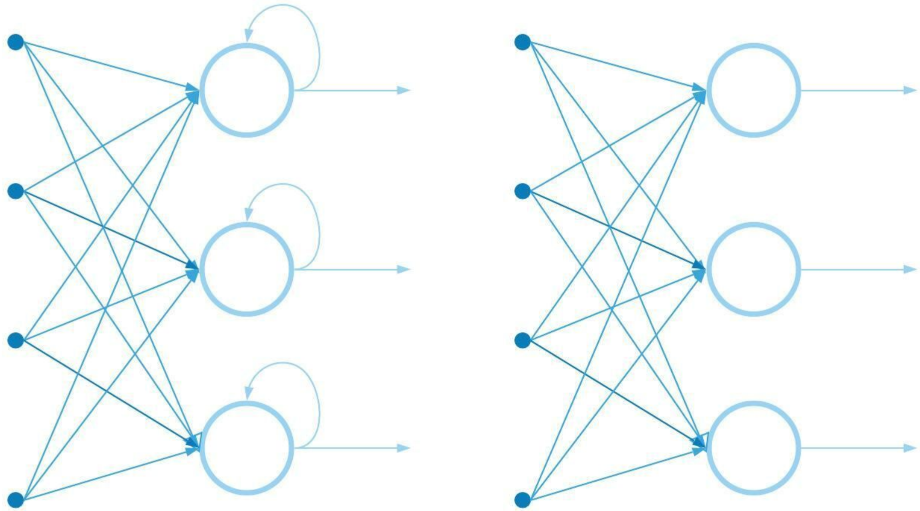
Introduction: Objectives and contribution

- Demonstrate how the Ichimoku Cloud trading strategy can be implemented in an effective deep-neural network
- We propose a combination of a model and a practical, profitable trading strategy specialized for a niche stock market
- Finally, in this paper we follow a traditional scientific framework while evaluating the performance by the standards of the modern financial world

02

Theories

Recurrent Neural Network

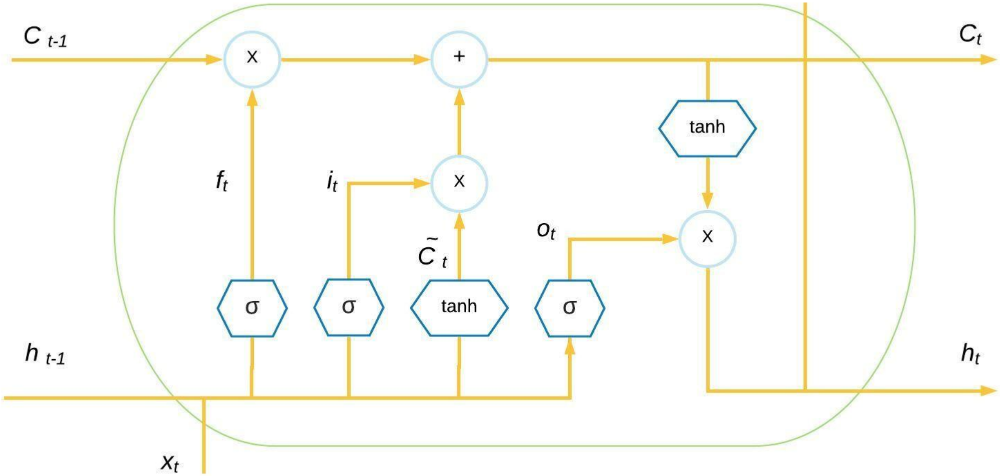


Recurrent Neural Network

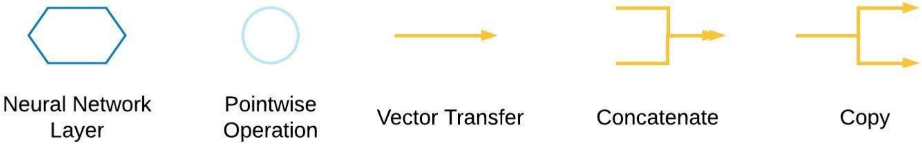
Feed-Forward Neural Network

Weaknesses: Exploding and Vanishing Gradients

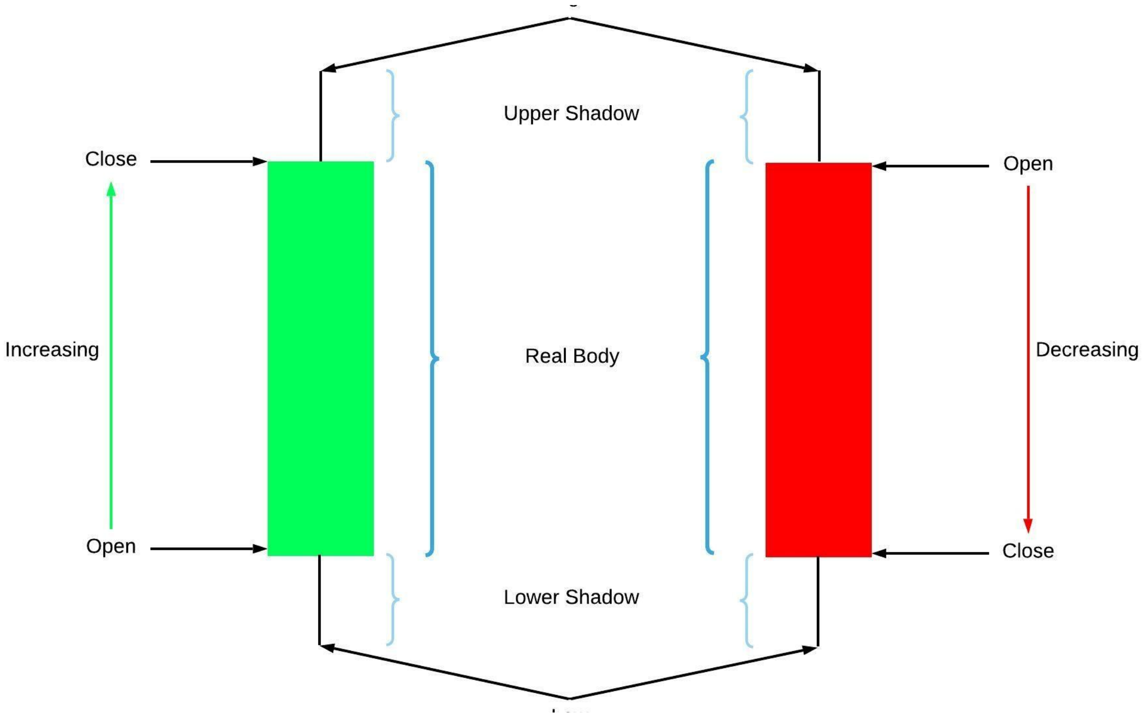
LSTM



f_t, i_t, o_t mean Forget gate, Input gate and Output gate respectively



Ichimoku Cloud: Candlestick



Ichimoku Cloud: Visualization

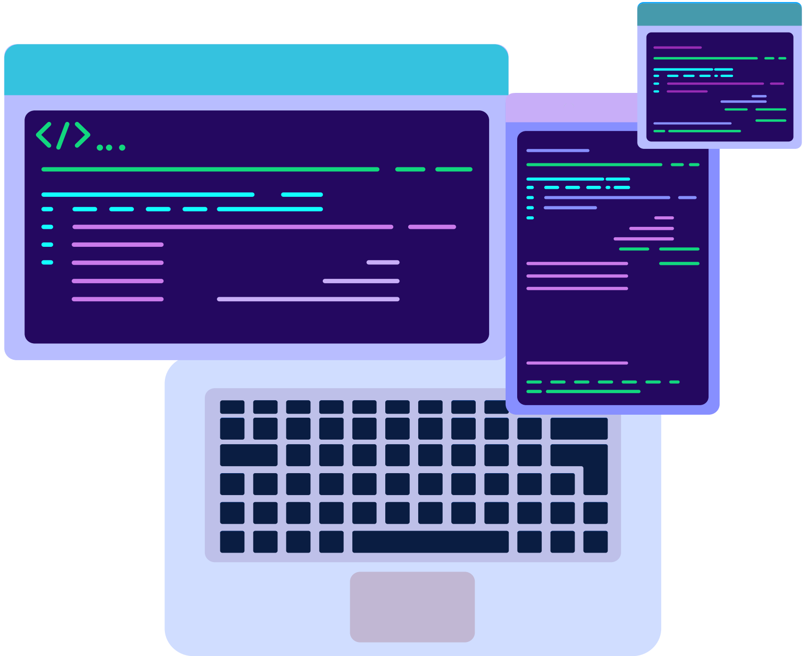
Root Mean Square Propagation (RMSprop)

Resilient backpropagation (Rprop)

- Address the wide difference in gradients’ magnitudes
- Requires large batch size
- Slow when randomness in stochastic gradients descent is big

Rprop to RMSprop

- Adopting the use of the sign of gradient from Rprop along with the efficiency of mini-batches update and averaging over mini-batches



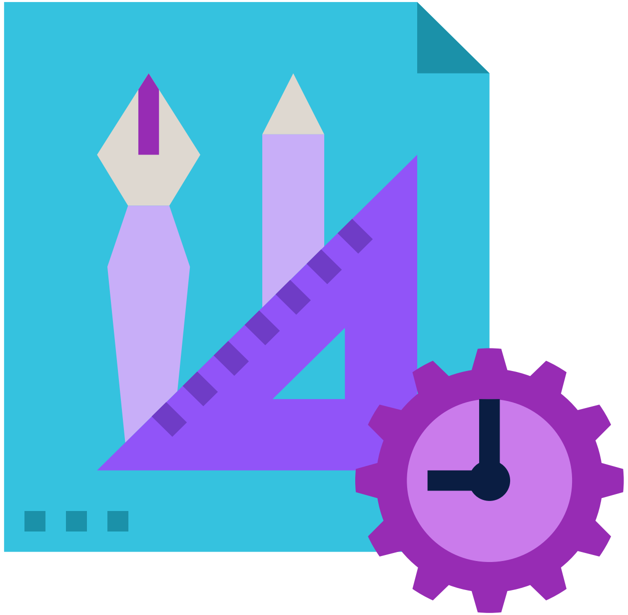
Categorical cross-entropy and Robust Scaler

Categorical cross-entropy

Loss function for multi-class classification tasks with discrete values

Robust Scaler

Standardization is biased to outlier values. Robust data scaling addresses this.



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Procedures

Procedure: Data sample, baselines and technology

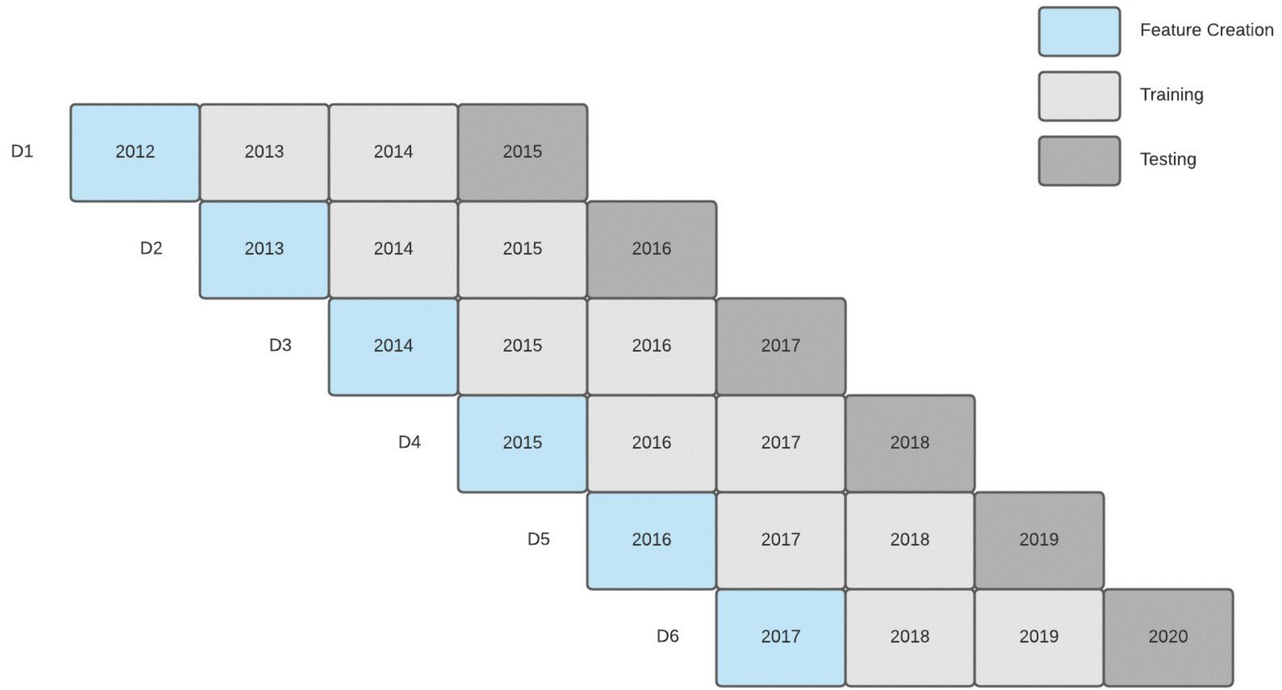
Data sample: VN30-index constituents
Baseline:The Experiment is carried on Google Colab, with the assistance of the following libraries:

- Market indexes, safe investments
- Same model but without the Ichimoku Cloud

The Experiment is carried on Google Colab, with the assistance of the following libraries:

- Pandas
- Numpy
- Tensorflow
- Warnings

Methodology: Dataset Division



Methodology: Features and target variable

Features: 240 timesteps and 5 accompanying features with each timestep:

- Current Closing Price / 10th Last Day Closing Price – 1
- Conversion line / Base line
- Conversion line / Closing price
- Leading Span A / Leading Span B
- Leading Span A / Closing Price

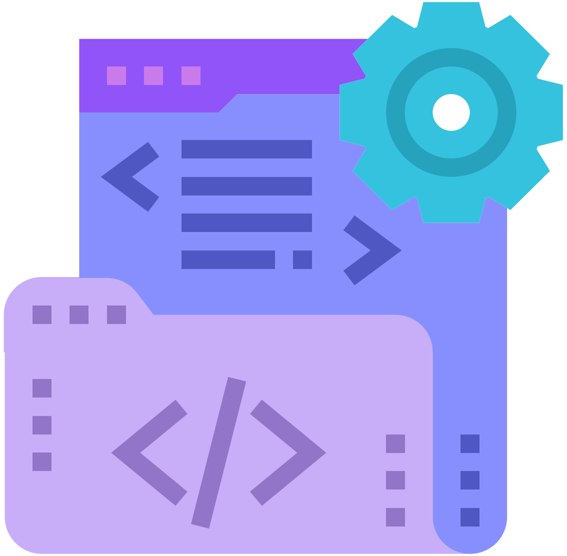
Target variable

Define the cross-sectional median at time t+10. Split the dataset into 2 categories:

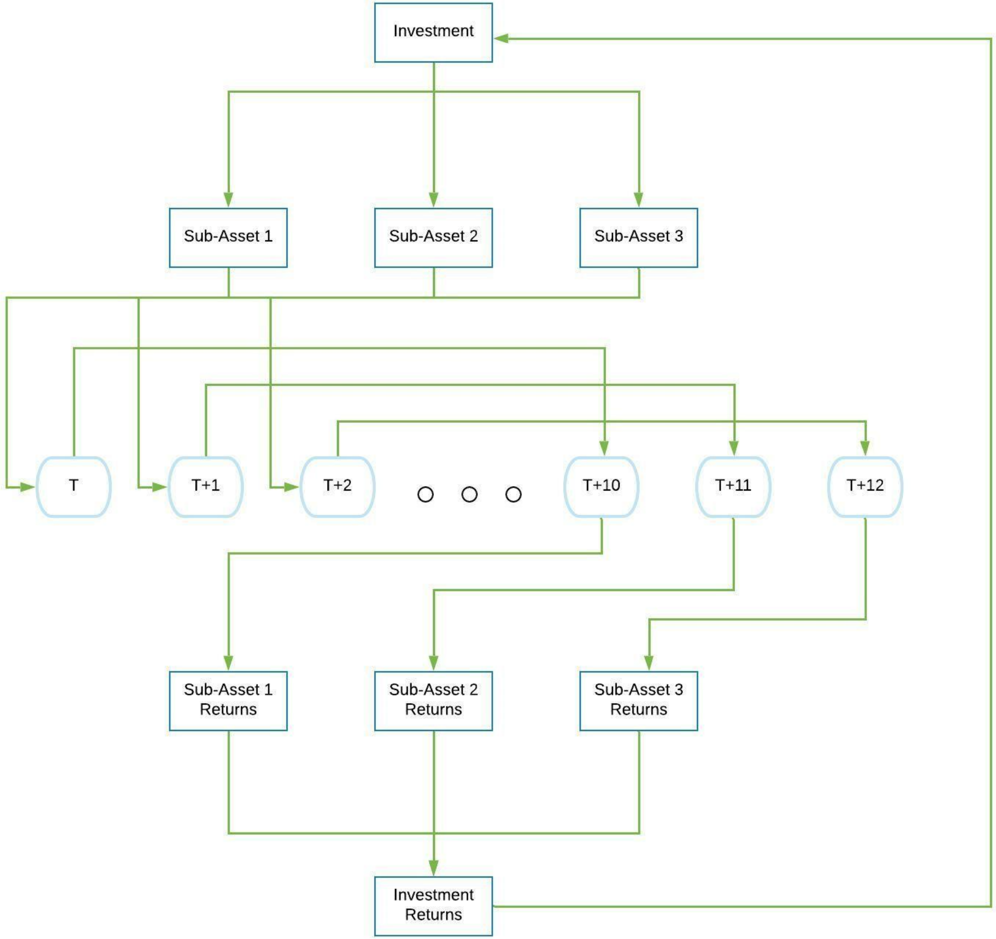
- Class 1 (if the corresponding stock return after 10 days is bigger than the cross-sectional median value of all stocks at time t)
- Class 0 (if the corresponding stock return after 10 days is smaller than the cross-sectional median value of all stocks at time t)

Methodology: Model specification

- 2 layers of 25 LSTM cells each that precede a dropout layer of 0.1 and a dense layer with 2 output nodes.
- Loss function: categorical cross-entropy
- Optimization: RMSprop
- Batch size: 64 with epochs=200
- Early stop: patience of 10 epochs, monitoring the validation loss
- Train- validation ratio: 0.2



Methodology: Trading strategy



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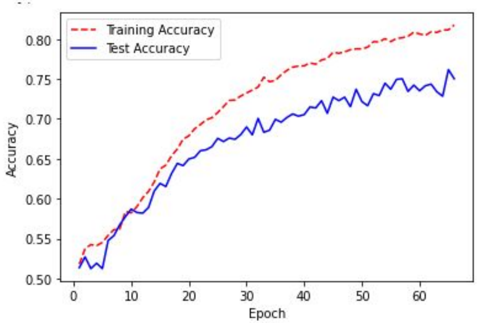
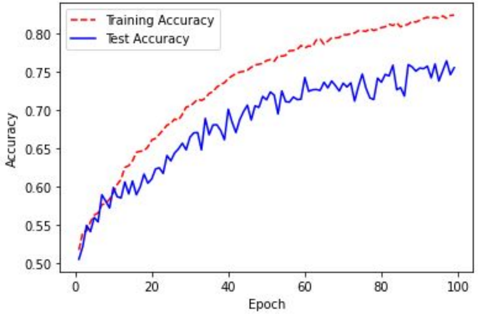
Results

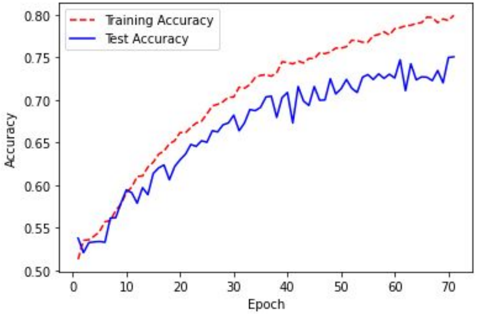
Experimental Results: Training Performance



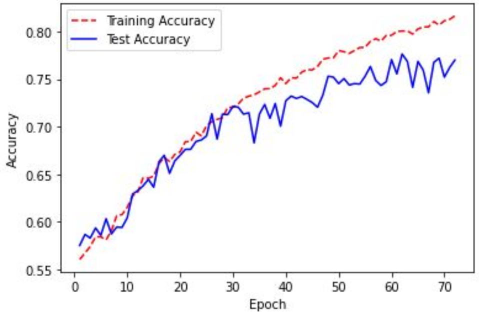
2015



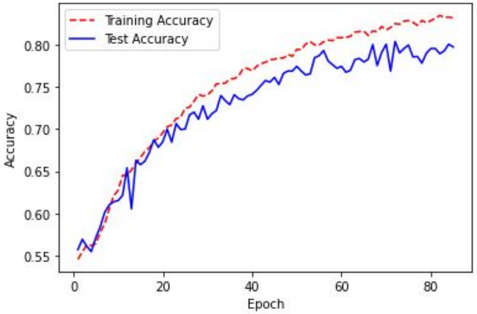
2016



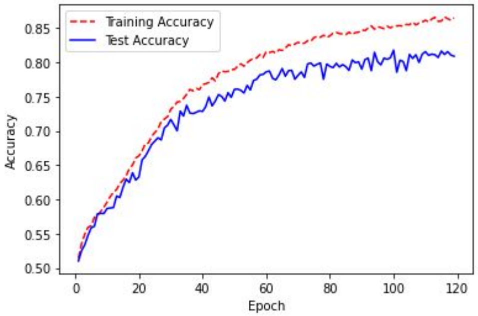
2017



2018



2019



2020

Experimental Results: Financial Performance

	With Ichimoku				Without Ichimoku			
Year	Sub-investment 1	Sub-investment 2	Sub-investment 3	Average	Sub-investment 1	Sub-investment 1	Sub-investment 1	Average
2015	+33.21%	+16.35%)	+46.0%	+31.849%	-22.59%	-30.24%	-10.89%	-21.239%
2016	+17.24%	+6.89%	+22.12%	+15.418%	-19.96%	-18.3%	+3.14	- 11.708%
2017	+21.41%	+27.46%	+16.74%	+21.87%	+24.85%	+58.4%	+62.07%	+ 48.436%
2018	-23.56%	-22.86%	+4.78%	-13.878%	-19.42%	-27.83%	-12.9%	-20.049%
2019	+10.56%	+22.31%	+4.11%	+12.328%	+8.65%	+5.82%	-0.88%)	+4.529%
2020	+25.12%	+14.32%	+14.97%	+18.134%	-2.72%	-25.34%	-23.44%	-17.168%

Experimental Results: Financial Performance

	This paper's strategy	VN30-Index	VN-Index	Vietnam 1-year saving	Gold	Vietnam 10-year Treasury Bond
2015	+31.849%	-1.01%	+6.12%	+6.2%	-11.59%	+6.43%
2016	+15.418%	+5.48%	+14.82%	+6.5%	+8.63%	+7.03%
2017	+21.87%	+55.29%	+48.03%	+6.5%	+12.57%	+6.01%
2018	-13.878%	-2.36%	-9.32%	+6.3%	-1.15%	+4.09%
2019	+12.328%	+2.82%	+7.67%	+6.8%	+18.83%	+4.88%
2020	+18.134%	+21.81%	+14.87%	+4.9%	+24.43%	+3.15%
Average	+14.287%	+12.01%	+13.7%	+6.2%	+8.62%	+5.31%

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Conclusion

Reference

1. Krauss, C., Do, X. and Huck, N., 2017. Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500. European Journal of Operational Research, 259(2), pp. 689-702.
2. Zhang, R., Yuan, Z. and Shao, X., 2018. A New Combined CNN-RNN Model for Sector Stock Price Analysis. In: 2018 IEEE 42nd Annual Computer Software and Applications Conference (COMPSAC). IEEE, pp.546-551.
3. Makrehchi, M., Shah, S. and Liao, W., 2013. Stock Prediction Using Event-Based Sentiment Analysis. In: 2013 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT). pp. 337-342.
4. Tra, N., Tien, H., Dat, N. and Vu, N., 2019. VN-INDEX TREND PREDICTION USING LONG-SHORT TERM MEMORY NEURAL NETWORKS. Journal of Science and Technology: Issue on Information and Communications Technology, 17(12.2), p .61.
5. Do, Q. and Trang, T., 2020. Forecasting Vietnamese stock index: A comparison of hierarchical ANFIS and LSTM. Decision Science Letters, 9, pp. 193-206.
6. Lien Minh, D., Sadeghi-Niaraki, A., Huy, H., Min, K. and Moon, H., 2018. Deep Learning Approach for Short-Term Stock Trends Prediction Based on Two-Stream Gated Recurrent Unit Network. IEEE Access, 6, pp. 55392-55404.
7. Ngoc Hai, P., Manh Tien, N., Trung Hieu, H., Quoc Chung, P., Thanh Son, N., Ngoc Ha, P. and Tung Son, N., 2020. An Empirical Research on the Effectiveness of Different LSTM Architectures on Vietnamese Stock Market. 2020 International Conference on Control, Robotics and Intelligent System, pp. 144–149.
8. Lim, K.J.S., Yanyali, S. and Savidge, J., 2015. Do Ichimoku Cloud Charts Work and Do They Work Better in Japan?. International Federation of Technical Analysts Journal, 2016 Edition, Forthcoming.