An Empirical Examination on forecasting VN30 short-term uptrend stocks using LSTM along with the Ichimoku Cloud trading strategy

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Abstract. Stock market forecasting is a highly difficult time-series problem due to its extreme volatility and dynamic. In recent years, on account of the rapid progression of deep learning, researchers have developed highly accurate, state-of-the-art time-series deep learning models. During the process, LSTM emerged as a deep-learning architecture well-suited for financial time-series prediction and achieved remarkable success. This paper proposes a LSTM model that predicts the probability of outperforming the market of all of VN30-index constituents using historical price changes along with the Ichimoku Cloud trading strategy. We buy three stocks with the best probability to sell it ten days later then reinvest the money on the next day using the exact strategy. The yearly return of the above trading strategy is used as the empirical results. The study was conducted in a time period of 9 years - from index's establishment in 2012 to the end of 2020. On average, our trading strategy nets a yearly profit of approximately 9.42%

Keywords: VN-index, Stock Market, Short-term uptrend forecasting, Ichimoku Cloud.

1 Introduction

Precise prediction of the stock market is able to generate an enormous amount of profit. As a result, this topic piqued a great deal of interest from both financial and scientific researchers. At first, traditional statistical approaches such as Moving Averages and Relative Strength Index were struggling to correctly capture the nonstationary, nonlinear and high-noise stock market because of their linear nature. Nowadays, researchers have started to explore more sophisticated approaches that might be more compatible with the chaotic stock market, namely machine and deep-learning architectures and they have found promising results.

There are many different applications of various models and architectures in order to predict the stock market. One of the most common approach is using historical prices as inputs then generate either the actual price or price trends (up or down) as outputs. Huynh et al. [1] achieves nearly 60% and over 65% accuracy for the price trends of S&P 500 index and individual stock respectively. Moreover, Krauss et al.

[2] created a profitable trading strategy by combining deep neural networks, gradient-boosted trees and random forests with an average daily return of 0.45 percent prior to transaction costs. Ghosh et al. [3] later employed Krauss et al. [2]'s framework with improvisation in terms of features and they were able to reach an average daily return of 0.64% using LSTM networks. On the other hand, some researchers tried to tackle this topic on an unorthodox angle such as Makrehchi et al. [4]. They used labelled social media text as inputs and trading strategies based on their model was able to outperform S&P 500 index by 20%. In addition, Oncharoen et al. [5] introduced a risk and reward function in their loss function and the result model was more effective than traditional trading strategies.

In this study, we propose a LSTM network that use historical price changes in percentages and the Ichimoku Cloud strategy to forecast the probability of outperforming the market of all stocks listed in VN30 index. Next, we select the top three stocks with the highest probability as stocks in a short-term uptrend and employ the following short-term trading strategy: we buy the shares of selected short-term uptrend stocks then sell it immediately ten days later. After getting the money from the closure of our position, we reinvest the money right away with the same trading strategy. The yearly return of this trading strategy is used as the empirical results and evaluated with several baselines.

Our paper's contribution lies in three aspects. First, given the concurrent literature of predicting the stock market, the Ichimoku Cloud is not a well-known technical indicator. There are a scarce number of attempts made to explore the power of the Ichimoku Cloud, such as [6]. Nonetheless, they were not able to create a consistently profitable model. Secondly, in the current state of deep-learning application in Vietnam Stock Exchange, researchers mostly focus on creating models that predicting the future prices without practical use. Meanwhile, we propose a combination of a model and a practical, profitable trading strategy specialized for the local stock market. Finally, in this paper we follow a traditional scientific framework while evaluating the performance by the standards of the modern financial world. Hence, our study may prove to be valuable to both scientific researchers and financial experts.

The remainder of this paper is organized as follows. In section 2 we explain the software and hardware used, how we determine the baselines and why we chose VN30 index as the data sample. Section 3 covers our methodology. Section 4 indicates our empirical results. Lastly, we discuss the result and shed some light on what may come in our future works.

2 Data sample, baselines and technology

We specifically chose VN30 index constituents as the targets of our study because we want to avoid stocks with potential price manipulation. In order to be qualified for VN30, a stock must pass strict requirements in terms of liquidity, market cap, free float ratio and reputation. Therefore, stocks listed in VN30 are more likely to reflect the true demand and supply of the market.

There are 2 categories in our list of baselines. The first one being the market indexes (VN30 and VN-index) and some common, safe investments such as gold, saving accounts (we used the saving interest rate of Agribank, one of the biggest banks in Vietnam) and government treasury bond. We wanted to see how our trading strategy fare against the actual market and common, proven investments. We collected gold historical performance from Kitco, Vietnam market indexes from FireAnt. Agribank saving interest rates from the bank' and government treasury bond's historical rates from Investing.com. The second category consists of similar works. Phan Duy Hung and Tran Quang Thinh propose a fairly complex Multi-Layer Perception (MLP)-Based Non-Linear Autoregressive with Exogenous Inputs (NARX) cryptocurrencies price forecasting model with remarkable success [7]. The last baseline of this study is taken from Xiong et al. [8]'s work. They implemented a heavily elaborate trading strategy in their DDPG algorithm (an improved version of Deterministic Policy Gradient) and recorded a impressive profit

of Deterministic Policy Gradient

We first created a timeline all stocks listed in VN30 index since its establishment in 2012 to the end of 2020 by collecting news from CafeF. We then collected the dividend-adjusted open and closing prices of stocks from the timeline from Cophieu68.

The experiments were carried out in Google Colab. We implemented our source codes with the assistance of the following libraries: Pandas, Numpy, Tensorflow, and Warnings

3 Methodology

This study follows the general procedure from Krauss et al. [2]. There are 4 major phases. In the first phase, we split our data samples to study periods then we divided our study periods into a training and test set. In the second phase, we selected the input and output necessary for our model. The third step is establishing the setup for our model. Ultimately, we applied our trading strategy based on the predictions.

3.1 Creating training and testing sets

Firstly, we divided our original 9-year (2012-2020) period into "study periods" according to Krauss et al. [2] did. The total length of a study period is four years and each study is furtherly divided into training and test set. Since our LSTM model has a time sequence of approximately 1 year (240 days), the first year in a study period was only used to generate features. The remaining three years are split into a 2-year training set and a 1-year testing set. The following figure illustrates how we split our dataset.

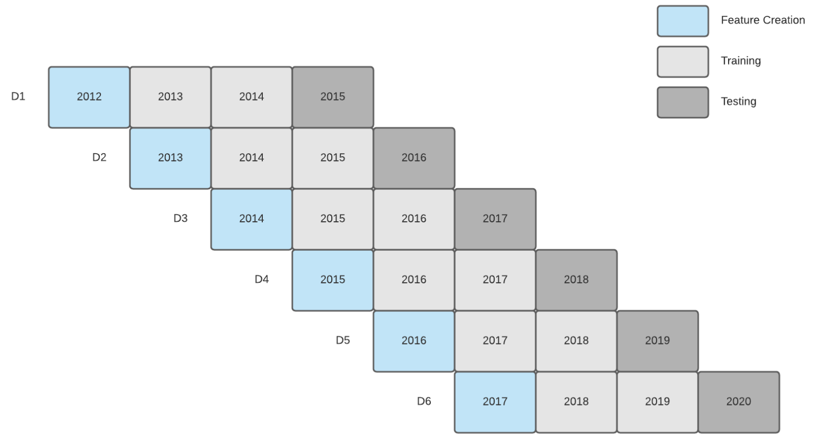

Fig. 1. Dataset division

3.2 Features and target variable selection

Features selection

Firstly, we introduce the calculations used in the Ichimoku Cloud trading strategy in order to avoid confusion in our further explanation

- Conversion line

$$(9\text{-}PH + 9\text{-}PL) / 2 \tag{1}$$

- Base line

$$(26\text{-}PH + 26\text{-}PL) / 2 \tag{2}$$

- Leading Span A

$$(Conversion\ line + Base\ line) / 2 \tag{3}$$

- Leading Span B

$$(52\text{-}PH + 52\text{-}PL) / 2 \tag{4}$$

where n-PH stands for the highest closing price in the most recent n days and n-PL is the lowest closing price in the most recent n days.

Our input consists of 240 timesteps and there are 5 features accompanied with each timesteps:

- Returns in terms of 10th last closing price:

$$\textit{Current Closing Price / 10th Last Day Closing Price} - 1 \quad (5)$$

- Four ratios derived from the Ichimoku Cloud trading strategy:

$$\textit{Conversion line / Base line} \quad (6)$$

$$\textit{Conversion line / Closing price} \quad (7)$$

$$\textit{Leading Span A / Leading Span B} \quad (8)$$

$$\textit{Leading Span A / Closing Price} \quad (9)$$

We chose to use (6), (7), (8), (9) as input features instead of (1), (2), (3), (4) because buying and selling signals in the Ichimoku trading strategy focuses on the relationship between the closing price, the lines and spans rather than the actual numbers. Finally, we used Robust Scaler to standardize our features.

Target variable selection

First, we define the cross-sectional median at time t+10 trading return. Perc = [0.5, 0.5] is used for cumulative summing to get thresholds. Then, we use pandas.qcut(Quantile-based discretization function) with the 3 parameters:

- x.rank: rank of all percentage change after 10 day
- perc: thresholds for creating label range
- labels=False: Return label 0 and 1

for splitting data into 2 discrete bins. The result is a column with values of 1 or 0, represent class 1 and class 0, which is classified if corresponding stock return after 10 days is bigger than the cross-sectional median value of all stocks at time t or not. Using these labels as the target variable, our model predicts the probability for each stock in VN30 to outperform the cross-sectional median return in period t+10

3.3 Model specification

Long Short-Term Memory (LSTM) is “a specific recurrent neural network (RNN) architecture that was designed to model temporal sequences and their long-range dependencies more accurately than conventional RNNs” [9] and it was first brought up by Sepp Hochreiter and Jurgen Schmidhuber in 1997 [10]. Our model has 25 LSTM cells followed by a dropout player of 0.1 and then a dense layer with 2 output nodes and softmax activation function

- Loss function: categorical cross-entropy
- Optimizer: RMSProp
- Batch size: 64 with epochs=200
- Early stopping: patience of 8 epochs, monitoring the validation loss
- Validation split: 0.2

3.4 Trading strategy

Our model predicts the probability for each stock in VN30 to outperform the median return after ten days. Then, we bought the shares of three stocks that have the highest chance then sell it ten days later. We then reinvested the recouped money in the following day using the same scheme. In this trading strategy, we spent an approximately same amount of money on each stock with the original principle being 100 000 000 VND. Every purchase was deducted by 0.1% to compensate for brokerage fee and the sale money was deducted by 0.2% (Both brokerage fee and tax account for 0.1% each)

4 Results and discussion

TABLE I. COMPARISONS WITH THE ANNUAL PERFORMANCES OF STOCK MARKET INDEXES AND SAFE INVESTMENTS

	This paper's strategy	VN30	VN-Index	Vietnam 1-year saving	Gold	Vietnam 10-year Treasury Bond
2015	+11.86%	-1.01%	+6.12%	+6.2%	-11.59%	+6.43%
2016	-3.25%	+5.48%	+14.82%	+6.5%	+8.63%	+7.03%
2017	+23.96%	+55.29%	+48.03%	+6.5%	+12.57%	+6.01%
2018	-11.5%	-2.36%	-9.32%	+6.3%	-1.15%	+4.09%
2019	+6.69%	+2.82%	+7.67%	+6.8%	+18.83%	+4.88%
2020	+28.74%	+21.81%	+14.87%	+4.9%	+24.43%	+3.15%
Average	+9.42%	+12.01%	+13.7%	+6.2%	+8.62%	+5.31%

On the one hand, it can be inferred from table 1 that our trading scheme's performance was very competitive with the performance of the local stock market indexes. Overall, VN30 and VN-index's yearly average growth slightly outperformed our methodology's. Nonetheless, we observed that the difference in average yearly performance is greatly exaggerated. In 2017, while our strategy was able to net a notable profit of 28.74%, VN30 and VN-index were able to yield more than twice as much, as they recorded growths of 55.29% and 48.03% respectively. Furthermore, market indexes are not subjected to brokerage fees and tax like our strategy. In terms of consistency, our strategy outperformed the market growths in 3 years (2015, 2019 and 2020) out of 5 years.

	Annual gains		**Average gains per trade**	
	With Ichimoku	Without Ichimoku	With Ichimoku	Withou Ichimoku
2015	+6.43%	-25.06%		-0.74%
2016	+7.03%	-9.25%		+0.12%
2017	+6.01%	+6.42%-		+0.73%
2018	+4.09%	-35.02%		-1.2%
2019	+4.88%	-7.38%		+0.14%
2020	+3.15%	-16.1%		+0.18%
Average per Trade	+9.42%		+5.31%	

On the other hand, on average, our trading strategy outperformed all other safer and more common investments, namely gold, 10-year treasury bond and a 1-year saving account during the 9-year study timeframe.

TABLE II. COMPARISONS WITH THE ANNUAL EARNINGS OF SIMILAR WORKS

	This paper's strategy	Cryptocurrency trading strategy [7]	DDPG [8]
Earnings	+9.42%	+11-15%	+25.87%

As table 2 indicates, while we were able to achieve a fairly impressive amount of profit, our trading strategy has yet to stand out among the literary landscape of financial prediction.

5 Conclusion and future works

Applying deep-learning in Vietnam stock market is a virtually unexplored domain since the 15-year-old market is still at infantile stage compare to 100-year-old giants such as Dow Jones. In order to contribute to this topic, this paper proposes a LSTM model that predict the probability of a VN30 stock outperforming the market and an accompanied trading strategy. We also aim to showcase the Ichimoku Cloud as a viable technical indicator that can be implemented as features in deep-learning models. Besides, our study follows the general procedures of a scientific research while using modern financial standards as critics for empirical analysis. Thus, experts from both academic and financial worlds may find this research valuable.

There are several prospects in our future works. Firstly, the trading strategy employed in this paper is somewhat pristine. In the future, we may consult with professional financial advisors to construct more sophisticated trading principles in our scheme. Lastly, the architecture used in this LSTM model is fairly basic. Attention mechanism, as indicated in the work of Qiu et al. [11], can improve the performance of LSTM and we may look to incorporate this in the next framework.

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