COMP7705 Project

Detailed Project Proposal

Project Title: Trend and Pattern Recognition of Stock Price Charts by CNN-based Model in Asia Equity Markets

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Aim

The financial markets are known for their inherent complexity and volatility, making accurate prediction of stock prices a challenging task. Nonetheless, numerous researchers and investors are willing to accept the challenge as solving this puzzle would provide significant benefits. By successfully predicting stock prices, investors can make more informed choices, optimizing their investment strategies and maximizing their financial outcomes. This ability to anticipate market movements and identify undervalued or overvalued stocks empowers investors to capitalize on favorable opportunities and mitigate potential risks. It is indicating that an accurate stock price prediction would serve as a valuable tool for enhancing financial performance and achieving better investment outcomes.

In real life, it is believed that certain patterns and trends exist in stock price movements, and financial institutions would make decisions based on observation on the charts of different market indexes. While deep learning technologies have advanced in recent years, the performance of different machine learning models has been enhanced remarkably. One of the famous deep learning models, convolutional neural networks (CNN), is widely used as image classifier or object detection model as CNN excel at extracting visual information and features from raw image data. Based on this characteristic, this model would be suitable for analyzing stock market index charts. By training a CNN model using historical stock market data, the model can potentially learn to recognize and capture patterns indicative of stock price movements.

This proposal aims to explore and investigate the feasibility and practicality of stock price prediction using CNN model. By training models using pre-processed financial data from different stock markets, a CNN price detection model would be finalized. It is believed that it would effectively analyze historical stock market data and provide accurate forecasts of future price movements.

Brief Literature Review

In modern financial markets, fundamental and technical analysis have long been the major strategies used by investors, whether they are retail individuals or professional practitioners, to seek profit opportunities. Although the efficient market hypothesis [1] posits that the current asset prices should reflect all the available information and the predictability of the prices in the future based on the past information is limited, there were empirical studies that suggested pattern seeking behavior (as done in technical analysis) is still prevalent among investors. A research based on a brokerage firms' proprietary dataset in Germany showed that the stock trading volume of the private investors was around 30% higher on a day when a salient trading signal could be observed. [2] Behavioral finance is one of the most well-known explanations in supporting trend and pattern discovery strategies. As it is stated that not all investors are fully rational and risk averse in reality, there could be mispricing and hence investment opportunities by analyzing the past information. [3]

Regardless of the effectiveness of the technical analysis, financial charts, such as the OHLC and volume charts, are very easily accessible to the general public and are often treated as a handy analytical tool to visualize the market movement for investors. Meanwhile, with the great advancement of the computational power of computers in the past 15 to 20 years, machine learning and deep learning paves another way for researchers to analyze the financial markets. Not only are these ML/AL techniques able to capture hidden non-linearity of the information, but they also enable hybrid use of many types and sources of data to train a model via features engineering. [4] A literature survey recently published in 2024 [5] has found that LSTM or RNN-based models are the most widely used model among researchers for predicting stock price movement. This is probably due to the fact that these models have their unique strengths in processing sequential data, to which a majority of financial data belong.

In recent years, there has been increasing numbers of papers published that try to bridge the gap between the traditional chart analysis and the rapid-evolving deep learning models. While some of them were adopting CNN-based model to process the chart images such as the candlestick charts, MACD lines, RSI charts, etc. [6][7], some proposed alternative representation of market data by conducting features engineering and used a preprocessed input tensors to train a CNN model. Examples include Gramian Angular Field (GAF), Markov Transition Field (MTF) [8] or by aggregating feature vectors across the time axis to form a 2D tensor as the CNN input. [9] There also existed models combining CNN and LSTM models which are capable to fit both chart images and numeric time series data to train a prediction model. [9]

Among all the previous research findings, the proposed project will take an in-depth research paper from University of Chicago & AQR Capital [10] as the fundamental reference, where the team will extend the work in multiple aspects as discussed in 'Proposed Methodology' section below and try to evaluate the effectiveness of the model in constructing an overperforming portfolio in Asia markets. From the original paper, the researchers focused on studying the US stock markets. They collected data of the daily stock prices for all firms listed on NYSE, AMEX and NASDAQ. The OHLC charts, moving average lines and volume bars were constructed with 5-day, 20-day and 60-day intervals. Each of the interval have a fixed spatial resolution for its charts and each pixel can either be black or white only. With the trained model, they constructed several decile portfolio for different combinations of lookback and holding periods. Interestingly, it is found that the CNN model proposed by the researchers seem to perform better than the traditional technical analysis by comparing the Sharpe ratio of the portfolios. The paper also shared extensive discussion on the correlation of the CNN models and other common technical indicators, and also the model robustness. These leave our project team a great potential to further explore such topic.

Reference/Citation

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[3] P. V. Azzopardi, Behavioural Technical Analysis: An Introduction to Behavioural Finance and Its Role in Technical Analysis. Great Britain: Harriman House, 2010.

[4] I. K. Nti, A. F. Adekoya, and B. A. Weyori, “A systematic review of fundamental and technical analysis of stock market predictions,” Artificial Intelligence Review, vol. 53, no. 4, pp. 3007–3057, Aug. 2019. doi:10.1007/s10462-019-09754-z

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[6] Kusuma, Rosdyana Mangir Irawan et al. “Using Deep Learning Neural Networks and Candlestick Chart Representation to Predict Stock Market.” ArXiv abs/1903.12258 (2019): n. pag.

[7] O. Sezer and A. Ozbayoglu, “Financial trading model with stock bar chart image time series with deep convolutional Neural Networks,” *Intelligent Automation and Soft Computing*, 2018. doi:10.31209/2018.100000065

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[9] J. M.-T. Wu, Z. Li, N. Herencsar, B. Vo, and J. C.-W. Lin, “A graph-based CNN-LSTM stock price prediction algorithm with leading indicators,” *Multimedia Systems*, vol. 29, no. 3, pp. 1751–1770, Feb. 2021. doi:10.1007/s00530-021-00758-w

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Proposed Methodology

In light of the limitations of the paper, our team is proposing to explore 5 major domains:

1) Stock sector and market capitalisation segmentation
The paper trained the model agnostic to the stock characteristics - such as sector / industries and market capitalisation. While our team acknowledges that segmenting the data set will reduce the size of the training dataset, we believe it is worthwhile comparing the outcomes when being trained on stocks of different sectors or market capitalization. A stock with higher retail participation would see stronger technical trading patterns than one concentrated with large institutional investors who look at fundamental factors more than technical indications. Examples of stock indices for small mid cap stocks include: TSEMOTHERS for Japan; KOSDAQ for Korea; Chi-next, CSI1000 and CSI2000 for China; NIFTY mid / and small cap 100 Index for India etc. Our team would also like to investigate if the performance would vary amongst industries where the stock is in.

2) Different time intervals
The paper selected 5-day, 20-day and 60-day interval charts as inputs. Our team would like to explore if performance would improve when we change the lookback period, such as replacing the 60-day charts with 1-year instead, which is a more common time horizon in the industry.

3) Higher resolution (higher frequency data)
The paper used daily OHLC and volume charts as inputs. We would like to explore how performance would change if we use higher frequency data to train the model - such as 15-minutes OHLC and volume charts. With this higher frequency data, we could also formulate a portfolio with a shorter investment horizon (such as intraday).

4) Portfolio construction and multi class classification
One major limitation of the methodology in the paper that our team identified is that the trading decision was based on a binary classification (up or down). This methodology omits the magnitude of the up / down move. Our team proposes to perform a 4-class classification instead: tentatively: up by above 5%, up by 0-5%, down over 0-5%, down over 5%, and construct the portfolio by buying stocks with the highest probability weighted return and shorting the lowest.

Milestones

Tasks		Estimated completion time	Estimated number of learning hours
1	Literature Review	2024-03-22	15
2	Raw market data collection	2024-04-08	30
3	Data pre-processing & feature engineering	2024-04-30	45
4	Deep learning models training & testing; Portfolio performance evaluation	2024-05-31	75
5	Hyperparameter tuning	2024-06-18	60
6	Result analysis & interpretation	2024-06-30	30
7	Report Writing	2024-07-13	30
8	Presentation deliverables (e.g. PPT, dashboard development)	2024-07-13	15
			Total: 300

Deliverables

Items ***(All development work will be presented in Python Jupyter Notebook)***	
1	Raw market datasets
2	Pre-processed datasets & image data (charts)
3	Deep neural network models (CNN-based) built from different market data (by geographical region / markets segmentation) and the resulting portfolio
4	Stock price prediction ensemble model
5	Interim & final report for in-depth analysis / discussion / evaluation
6	Presentation of the outcome (Web dashboard / PPT)