Chapter 5

CONCLUSION AND FUTURE WORKS

5.1 Introduction

The decision-making process in trading will be affected by the sentimental of human. In order to minimize the issues of human error with the emotional biases, deep reinforcement learning (DRL) models are vital to employ in the decision-making process of the trading strategy. The research is to using the deep reinforcement learning (DRL) for automated trading in stock market. The aims are to compare the different model performance among DQN, PPO and SAC, minimize the emotional biases and improved decision making which is automation in trading system. The study is proposed to achieve the following objective:

a. To obtain the policy that give optimized return.
b. To train agent that will not be influenced by the sentimental with using SRDRL model.
c. Develop a dashboard that visualize the return of the agent that trained on different mechanism.
d. Compare the performance within model and discuss the strength and weakness between different model (DQN, PPO and SAC).

The input data of the research is S&P 500. To enhance the results that obtained from model is accurate and reliable, data preprocessing and data cleaning steps are required to improve the quality of the data. After that EDA will takes place to identify the patterns of the dataset. Features engineering also added (30-day moving average and 100-day moving average) to let the agent familiar in the real-time stock market conditions.

5.2 Achievements

Data preparation was carried out as the initiate step to ensure the input data used for the model development was consistent and formatted. The data of S&P 500 was imported from the Yahoo Finance. The cleaned dataset can be obtained by handles the missing data points and removing the duplicates and outliers that occurred in the dataset. The implementation of the SAC, DQN and PPO for the trading strategy was evaluated the performance based on the key metrics such as F1-score and cumulative return over time. Based on the DRL models which are DQN, SAC and PPO, estimate SAC will outperform than others models (DQN and PPO) due to ability to handle continuous action spaces and high stability in dynamics environments. SAC is expected to be the best performance model for the automated stock trading, followed by PPO and DQN as the least effective. DQN estimate with the poorest performance due to the discrete action space might be unable to fully capture the complexity of the stock trading where continuous action is more preferred. PPO not fully exploit the advantages of continuous action spaces as SAC does.

5.3 Future Works / Recommendations

The dashboard development for the performance analysis to visualize and analyze the performance of different DRL models (DQN, SAC and PPO). The dashboard can including Sharpe ratio, net worth over time and agent comparison. Based on this, the simultaneous visulization in the same graph to show the performance of all DRL models. In the graph will required net worth comparison, Sharpe ratio analysis, volatility and rish analysis.

The policy analysis of 3 models will allow to analyze in details about the performance metrics where return, Sharpe ratio and standard deviation. The behavioral insight also can provide a clear breakdown of each of the DRL models including the action making at certion key time and correlate the action with the changes in net worth.

For the better performance of the models, the diversity of the data should be increased. The data of other indices like the Hang Seng Index of Hong Kong, the Straits Time Index of

Singapore, the Financial Times Stock Exchange 100 Index of the United Kingdom, the Shanghai Composite Index of China, and the volume should be taken into account. This should give more information to the models so that the models can get more clues to make better predictions.

Next, the real-time deployment and backtesting should be required. The model testing in the live trading enviroment with the stock market enhance the insights into their true performance and adaptability. The backtesting frameworks such as QuantConnect or Backtrader to simulate the real-world trading environment, helps assess the refine strategy and risk-adjusted returns. High frequency trading (HFT) to make the model more applicable in the real-world trading.