CHAPTER V : CONCLUSION

5.1 Overview of the Study

This study is aimed to evaluate the performance of three traditional ML and three deep learning models in predicting stock movements by assessing the evaluation indicators. The traditional ML models selected are Logistic Regression (LR), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGB). Three Deep Learning models selected are Deep Belief Network (DBN), Multilayer Perception (MLP), and Stacked Auto-Encoder (SAE) to foresee the direction of the stock prices.

This study has a total of 2,000 trading days of data taken before date February 1st, 2018 of each stock data from thirty largest companies in Bursa Malaysia. There are twenty popular technical indicators used as features generated in this study. When applying Walk-Forward Analysis (WFA) method, there are 250 trading days of train set and 5 trading days of test set which produces 350 training session. Thus, there are 1,750 trading signal as the output for each stock and each ML model.

The trading signals is then evaluated based on directional and performance evaluation indicators. Six directional evaluation indicators are Accuracy Rate (AR), Precision Rate (PR), Recall Rate (RR), F1 Score, Area Under the Graph (AUC) and Mean Square Error (MSE) whereas four performance evaluation indicators are Winning Rate (WR), Annualized Return Rate (ARR), Annualized Sharpe Ratio (ASR) & Maximum Markdown (MDD). For performance evaluation indicators, there is two additional strategy included for comparison to ML models, which is ‘Buy-and-Hold’ strategy and KLCI index. Lastly, a statistical test is performed in order to analyse significant difference between the evaluation indicators between the trading strategies.

5.2 Contribution of the Study

From the perspective of Malaysian stock trading strategy, it can be determined that:

- Deep learning models have better performance in terms of predicting stock price movement than traditional ML models in all directional evaluation indicators. The values obtained from AR, PR, F1 are the highest from deep learning and the MSE has the lowest value.
- All the performance evaluation indicators for traditional ML models are more efficient in terms of profitability and risk assessment than deep learning algorithms. WR, ARR, and ASR of all ML models have better performance than those of benchmark index and B&H strategy. However, MDD of all ML models are significantly more than the benchmark index but some have significantly similar value as B&H strategy.
- Some traditional ML models have similar performance to some of the deep learning models. Consequently, it can be ascertained that deep learning models might sometimes not be the most compatible or the best in trading strategy. Therefore, it is suggested to apply both traditional ML and deep learning models so that it could complement each other as it proves that ML can help in decision-making of stock price prediction.

5.3 Practical Implications from the Study

The contribution of this study can impact the judgement for the investors or analysts in investment decision making. This is because they are people who are aiming to either maintain or boost their profit value by investing in the listed company's stock with higher expected income. The study can also be significant for the stock trading prediction developer companies because they provide services for investors in price prediction through website, software, or applications. With this information, the investors, analysts, and the service developers are able to choose which ML models to be implemented as their trading strategy so that they can generate the best stock investment judgments based on their objectives. Moreover, this study is beneficial for researchers as the findings can contribute to extension of ideas and data analysis on predicting stock prices and stock trading strategy. This then can also help improve the application of ML in quantitative trading and time series prediction.

5.4 Limitation of the Study and Suggestions for Future Research

There are some limitations in this paper. This will provide opportunities for future recommendation. For suggestions, it is best to include more features into the algorithms as it gives better comparison between ML algorithms. For example, other assets including exchange rates or commodity prices, or add more known technical analysis indicators to the study but with advantage and disadvantages taken into account. Other than that, increase the number stock data because it helps increase the performance of ML algorithm as the discussed in paper. Lastly, instead of comparing three traditional ML and three deep learning models, it is recommended to do more so that the finding would be more consistent.