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INTERIM REPORT

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ABSTRACT

Ever since the concept of the stock market was introduced, predicting future prices has been a challenging goal. In recent years, there have been several methods and approaches introduced and implemented to achieve such a goal. Technical Analysis is one of these methods raised to predict the future. Cryptocurrency market was no exception to this movement. Exponentially growing market and high profit rate has lured people to seek for newer, better, and faster trading strategies with each of them insisting to be the best one. This project aims to prove the profitability of some well-known TA strategies by implementing past Bitcoin prices and comparing them to strategies based on ML models. To focus on TA, which utilizes purely on price trends and chart patterns, non-numerical data including social media posts or news are excluded from analysis. In terms of TA models moving average and RSI are used. For Machine Learning Model, Long Short Term Memory model, a type of Recurrent Neural Network is used. The project compares profitability of trading strategies based on either TA or ML model to determine the higher profiting one. As the project progresses, it will prove whether these some rules of thumb are truly winning strategies, even compared to the latest machine learning models.

ACKNOWLEDGEMENT

I would like to send my greatest regard to my project supervisor Dr. C L Yip for giving me the chance to challenge this topic as my final year project. Without his help, I would not have been able to consolidate ideas into reasonable topics to tackle. Special thanks to Mable for dramatically increasing my writing skill which had stopped improving since middle school.

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ABBREVIATIONS

API Application Program Interface

BTC Bitcoin

CSV Comma Separated Values

LSTM Long Short-Term Memory

MA Moving Average

ML Machine Learning

MSE Mean Squared Error

RMSE Root Mean Squared Error

RNN Recurrent Neural Network

SVM Support Vector Machine

TA Technical Analysis

WDNN Wide and Deep Neural Network

1. INTRODUCTION

1.1 Background: Proliferation of cryptocurrency and rapid growth market

Cryptocurrency started as a decentralized digital asset [1], meaning it is the currency that has neither a physical entity nor central authorities allowing them to exist outside the controls. When it first started, people focused on the technical aspect of it, how it could be utilized for privacy and freedom from the system. However, the growing attention toward cryptocurrency has highlighted its aspect as a digital asset resulting in a steep rising in prices.

The cryptocurrency market has been growing exponentially in recent years. Back in 2013, the total size of bitcoin, the leading cryptocurrency, market was barely over 1 billion USD. Then, in April 2021, the Bitcoin market capacity reached over 1,000 billion USD. It did decline right after, to around 600 billion USD, but the market recovered quickly, it is valued at 1,100 billion USD [2]. It is an indisputable fact that the cryptocurrency market has been growing at an unbelievable rate. This site is just bitcoin, consisting of about 45% of the whole cryptocurrency market, not including hundreds of other cryptocurrencies on the market. Details of market capacity and BTC dominance over market can be seen in Appendix

A rapidly growing market means industries and individuals are eager to find a way to predict prices. There are countless attempts to make appropriate predictions and these analyses could fall into roughly two categories: technical and fundamental. The major difference between these two categories is utilizing background knowledge to value the asset. Fundamental analysis studies this information related to assets, related market trends, and so on to evaluate the asset value. In the case of cryptocurrency, the fundamental analysis would utilize information such as blockchain-related aspects (hash rate, number of active addresses, transaction value), financial aspects (market capacity and trading volume), or even the background of founding team members. [3]

In contrast, technical analysis (TA), a method which is adopted in this project, focuses primarily on the trend of the asset price. It focuses on changes in price, trading volume and applies statistical and mathematical methods to try to predict the future price. Despite modern impression of the term “technical” this method has a long history linking back to the late 1800s when not everyone could gain access to information related to stocks. As time passed, the number of research and technological developments introduced hundreds of trends and signals to be utilized today. [4]

The indicator used for TA can be roughly divided into 2 categories: leading and lagging. Leading indicators give trade signals when the trend is about to start whereas lagging indicator give signal after the trend is started. Indicators belong to one of 4 types (trend, momentum, volatility, and volume) based on parameter they exhibit.

Trend indicators show the strength and direction of a trend by comparing price to certain baseline. Widely used trend indicator include Moving Averages. Momentum indicators compare current closing price to previous closings to measure the speed of price movement. Relative Strength Index (RSI) is one of them. Volatility indicator, such as Bollinger Band measure rate of price change. Volume indicator, as the name suggests, measure strength of trend based on traded volume. Details regarding the Technical Indicators used for the trading strategies are discussed in chapter 3

1.2 Project goals

The major goal of this project is to predict future price of cryptocurrency using both TA and machine learning model. For TA, the focus is to find the highest profiting technical indicator and verify its statistical significance using testing. For machine learning models, profitability as well as accuracy of prediction will be considered and compared against TA.

1.3 Project scope

To concentrate on the topic, the project will mainly deal with Bitcoin, the largest cryptocurrency has been chosen to evaluate. With high market share over 50%, Bitcoin tend to show high correlation against other major cryptocurrencies. The figure below shows correlation heatmap of past six-month daily price of 10 largest market capacity cryptos. Excluding USDC and USDT which are stable coins with prices pegged to US dollar, Bitcoin shows strongest correlation among them. High correlation means the trend in Bitcoin price often influence others. This leads to conclusion that successful prediction of Bitcoin could be utilized for other possible cryptocurrencies. In terms of time scope, past 5 years historical dollar denominated price of Bitcoin is collected daily, hourly and once a minute.

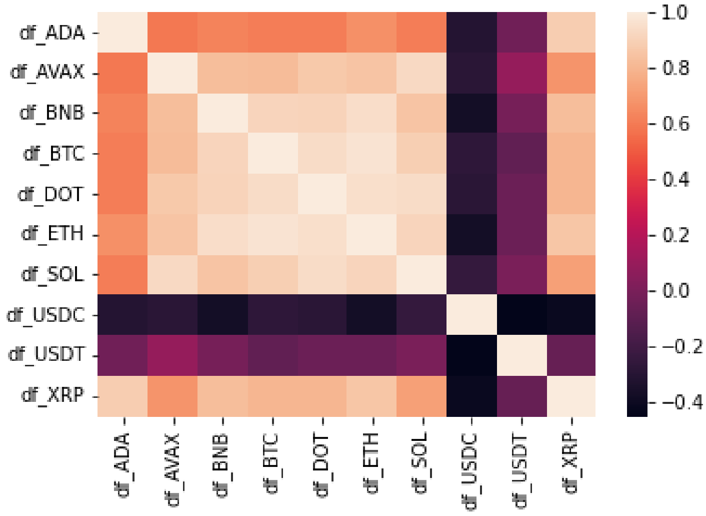


Figure 1 Correlation Table of Major Cryptocurrencies

1.4 Report Outline

The report has 6 parts. Chapter 1 provides some background knowledge about the topic and a brief introduction Chapter 2 explains a general description of the literature researched until now to expand knowledge about the topic. Chapter 3 illustrates the details of methodology to achieve the targeted goal of the project. Chapter 4 discusses about finding and analyze details. Chapter 5 describes limitations faced during the project and possible extension and Chapter 6 act as a conclusion of this report

2. LITERATURE REVIEW

This chapter discusses literature review regarding past researches in forecasting Cryptocurrency market. There have been several research regarding the TA of cryptocurrency, some even made comparisons against ML models. These studies have provided guidance for further steps of this project.

2.1 Previous Research

As mentioned, there have been attempts to utilize TA to predict the price of Cryptocurrency and even statistical analysis of results. This chapter will describe summary of past research categorized into 2 parts: TA and ML

2.1.1 Technical Analysis of Cryptocurrency

Though not as popular as ML approach, there has been attempts to predict future price of BTC by utilizing TA. For example, a study by Shaen Corbet in 2019 found significant support for moving average strategies, especially variable-length moving average rule performs the best.[5] Whereas a study by Klaus Grobys in 2020 states (1, 20) MA strategy worked best compared to other popular MA strategies in market. [6] Detailed explanation regarding TA strategies will be provided in Chapter 3.

As time period for data tested for each research is different, it is reasonable for different TA to perform differently. Furthermore, considering quickly changing cryptocurrency market, those tests may give different result if done today. Depending on the study, the targeted cryptocurrency was inconstant some of which intentionally excluded BTC to minimize impact over other Cryptos.

2.1.2 Machine Learning Implementation on Cryptocurrency

Due to uncertainty and nonlinearity of Bitcoin price, Artificial intelligence models such as machine learning are actively used to predict prices. Support Vector Machine (SVM) showed superiority in 5-day interval price prediction [18]. In terms of whole market trend instead of individual Cryptocurrency price level, Light Gradient Boosting Model (LGBM) showed better prediction compared to SVM or Random Forest (RF)[19]. Another research argued statistical models such as Logistic Regression are better than complicated machine learning models such as RF, SVM at prediction [20].

2.1.3 Comparison against ML

Extended literature review provided studies regarding TA comparison against ML models [7]. According to a study by Dan Anghel covering comparison between ML and TA rules to find superior predictive ability, selected ML rules showed underperformance against simple TA rules especially incorporating trading costs. He specifically mentioned “implementing them (ML rules) in practice is not worth the effort, as cheaper and easier to us TA strategies are sufficient” meaning the effort and difficulty of implementing ML is not worth trying. This result may differ considering prior research based on two year data until Feb 2020, when BTC price was far below current level.

According to past studies, it is controversial whether TA and ML models are useful tools to predict future price. The result varied for types of Cryptocurrency, time range of data collection, different types of technical indicators used or even types of ML models. Therefore, carefully approach toward methodology is crucial to obtain optimal outcome.

3. METHODOLOGY

To ensure continuous workflow of project, the whole process has been divided into phases to ease development.

3.1 Project Framework

Python will work as primary programming language. It is chosen for its rich library regarding data processing and transformation. To addon, simplicity of Python will reduce time consumption of whole coding process. Data related libraries such as **Pandas** and **Numpy** is expected to be utilized for large numbers. useful for experimentation while working on the data with the machine learning models. **Anaconda** will work as Machine learning platform to use **Jupyter**, useful tool regarding machine learning. **Backtesting.py** has been used to form backtesting environment alongside with **TA-Lib** to import some of intended TA indicators. **Sklearn** library is main library used to perform data pre-processing, train-test spliiting, normalization and algorithm fitting. **Keras** was also utilized to ease the process of building deep learning model.

3.2 Data Collection

To perform technical analysis, historic data of Bitcoin price is mandatory. As mentioned, in this study, 5-year dollar-denominated BTC price data will be utilized collected from cryptodatadownload.com which provides past historic prices of major exchange platforms. Specifically, prices data of BTC by every minute, hour, and day will be used. The collected data consist of opening, high, low, and closing prices alongside trading volume and time. After collection, the data will be cleaned to make sure there is no missing entries.

3.3 TA Implementation

To achieve the original goal of predicting future prices several technical indicators will be analyzed. Some of the indicators which will be analyzed are listed below. Possible indicators may be introduced as the project progresses

3.3.1 Moving Average(MA)

Moving average, a widely used trend indicator, utilize a series of averages over different periods. Not just limited to the Simple Moving Average (SMA) which is unweighted average for intended time period, there are variations including Weighted MA, Exponential MA, and so on. Following figure shows mathematical formula to calculate SMA and WMA with n latest day, for last k entries, p for price, m for target day Even within the same type of MA, changing the time slot can result in different analyses. Moving average is believed to be suitable for Cryptocurrency as unlike stock market where trade

$$SMA_k = \frac{1}{k} \sum_{i=n-k+1}^{n} p_i = \frac{p_{n-k+1} + p_{n-k+2} + \ldots + p_n}{k}$$

Figure 2: Formula for Simple Moving Average

Major limitation of Moving Average includes relatively slow response to sudden price change, especially when using longer time period. Furthermore, as lagging indication, MA might be useful to tell the trend but only signals after trend has started

3.3.2 Relative Strength Index (RSI)

As previously mentioned, RSI is a momentum indicator used to measure the recent price change magnitude evaluating overbought or oversold condition. RSI value ranges from 0 to 100 where above 70 is considered overvalued, under 30 is considered undervalued condition. RSI is calculated via following steps

1. price difference compared to previous day is called Up if positive and Down if negative.
2. Find average of each Up and Down and name as Average Up (AU) and Average Down (AD).
3. Relative Strength (RS) = AU/AD
4. RSI = RS / (1+RS)

Limitations of RSI include it is not useful for stable asset which price stays in certain boundaries. Plus, RSI may lead to misleading signal or remain at overbought or oversold for a long time when market features a strong trend.

3.3.3 Bollinger Band

Bollinger Band is one of volatility indicator which shows set of trendlines positively and negatively plotted certain multiplier times standard deviation away from center simple moving average. The multiplier may be altered depending on user preference. Limitation of Bollinger band include as lagging indicator, not suitable for price prediction. The bands are reactive to price change but does not ensure about future trend.

3.4 Performance Evaluation (TA)

After analysing the specific technical indicators, they are tested using historical data to measure the return. The return is calculated by taking a record of total asset price which will be continuously updated through trading strategies that will be utilizing the technical indicators mentioned above. Not just limited to the returns, statistical analysis will be used to evaluate the efficiency of predicting the future prices. Statistical analysis would include hypothesis testing of strategy against simple buy and hold strategy to test whether TA shows significant profit. Regarding the back testing process, Python work as main language with Backtesting.py provides environment. Some of TA indicators are implemented from TA-Lib..

3.5 Machine Learning Implementation

After completing testing of TA trading rules and best performing trading strategy found, ML models are implemented and utilized for forecasting Bitcoin prices. As performance of machine learning model is highly dependent on input data characteristic as well as type of model, ML implementation required further research. After successful implementation of ML model and measuring profitability, comparison against TA will be performed. The following section will discuss about information about ML model and details regarding procedure.

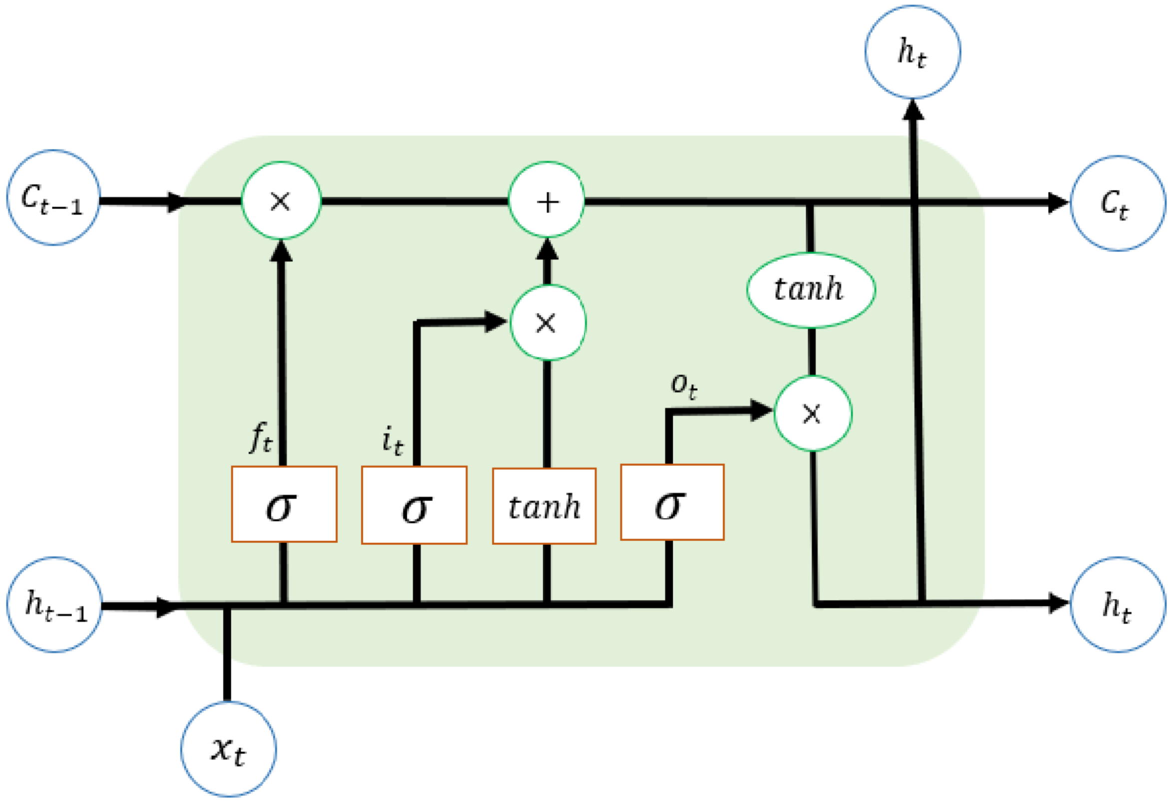
3.5.1 Background of Machine Learning

Deep learning is type of machine learning method based on artificial neural networks implemented by mimicking the structure of human brain neurons. Examples of Deep Learning model includes deep neural networks, multilayer perceptron, convolutional neural network and so on.

As overfitting issue of artificial intelligence were solved, deep neural network evolved multiple hidden layers between input layers and output layers. This multilayer perceptron showed suitable for predicting price level in Taiwanese Stock market [8]. Deep neural network using candle chart and TA as input values showed 8 % higher accuracy compared to other artificial neural network models in Indian stock market [9]. As further application algorithm of deep neural network led to convolutional neural network. Which normally used to analyse visual data outperformed simple buy and hold strategy in US stock market by taking 15 technical indicators converted into visual images to predict future trend [10].

3.5.2 LSTM Model

Unlike common neural network models that do not consider the temporal order of data, Recurrent Neural Network (RNN) can internally remember input variables by introducing the sequence concept. Through this, past learning results can be used for current learning, so it is a deep learning model suitable for processing time series data that appear sequentially such as voice and stock price. However, the longer the parallax of the data, the more the problem of vanishing gradients occurs in which past data are not properly learned at the present point [11]. In the case of stock price analysis with a prolonged lag in the data, this long-term dependence problem can reduce the efficiency of stock price forecasting. Long Short-Term Memory model (LSTM) is an RNN model that evolved to solve these long-term memory problems, and its use is expanding in the analysis of time-series data such as stock prices as introduced in 1997[12].



$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_{i)} \quad (1)$$

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_{f)} \quad (2)$$

$$c_t = f_{tc_{t-1}} + i_t Tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_{c)} \quad (3)$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_{o)} \quad (4)$$

$$h_t = o_t Tanh(c_t) \quad (5)$$

Figure 3: LSTM Architecture and formula

In Figure 3, the LSTM layer consists of hidden state h_t and cell state C_t. The hidden state value at time t refers to the output state, which is the output value. The biggest feature of the LSTM model is that cell state was added to the basic RNN model. The cell state plays a role in determining how much existing information is to be delivered to the next step through the gate. Through this process, long-term memory problems can be solved by allowing information from a long time ago to be reflected in current information. This strength of LSTM is highly useful in predicting prices such as stock prices and cryptocurrencies that show long-term memory properties.

The cell state, the core of LSTM, is the top horizontally drawn line of Fig. 1, which can be maintained through the entire chain of the circulatory neural network like a conveyor belt, can optionally convey to the cell state at what point data should be discarded or maintained by adding input gate, output gate, and forget gate to the circulatory neural network. The first step of LSTM is a forget gate step of determining how long the cell state at the time of t-1 is maintained by the sigmoid layer as shown in Equation 2. The input gate determines how much input information will be received by Equation 2, and the output gate determines the value of the output data by Equation 3. The cell state at the time of t-1 is multiplied by the value output from the forget gate to forget a certain part of the cell state value as shown in Equation 4, and the result of processing the input information and the output value of t-1 is multiplied by the output value of the input gate to determine a new cell state. The power of the cell state is determined by multiplying the new cell state made through Equation 5 by the output value of the output gate. Through this process, better learning can be performed on time series data with a longer sequence than RNN[13-15].

Since the price prediction of Bitcoin analysed in this study is time-series data in which the sequence of data plays an important role, we intend to analyse it using a cyclic neural network model rather than a deep neural network model or convolutional neural network model. It has been revealed that cryptocurrency prices including Bitcoin have long memory characteristics [16,17]. Therefore, we intend to predict the price of Bitcoin and analyse the profitability of the bitcoin investment strategy using the LSTM model that reflects the long memory characteristics well among the circulating neural network models.

3.5.3 Data Preparation and Model Design

Same data used for TA have been used for ML model. However, data have been normalized and split into train and test. For 5-year period data, LSTM model have been compared against simple RNN model. For optimizing algorithm, Adam optimizer was used, and activation function used was hyperbolic tangent.

3.5.4 Model Analysis

The following figure 4 represent graph of predicted price level computed via RNN model and LSTP model. It is clear LSTP shows more accurate prediction compared to RNN. To prove this by number 5 factors are calculated, Mean Absolute Error (MAE), Mean Percentage Error(MPE), Mean Absolute Percentage Error (MAPE), Mean Square Error(MSE) and RMSE(Root Mean Square Error). These five are commonly used indicators to check performance of ML model. Smaller error means higher accuracy and it is clear from table 1 that LSTP shows superior accuracy compared to RNN.

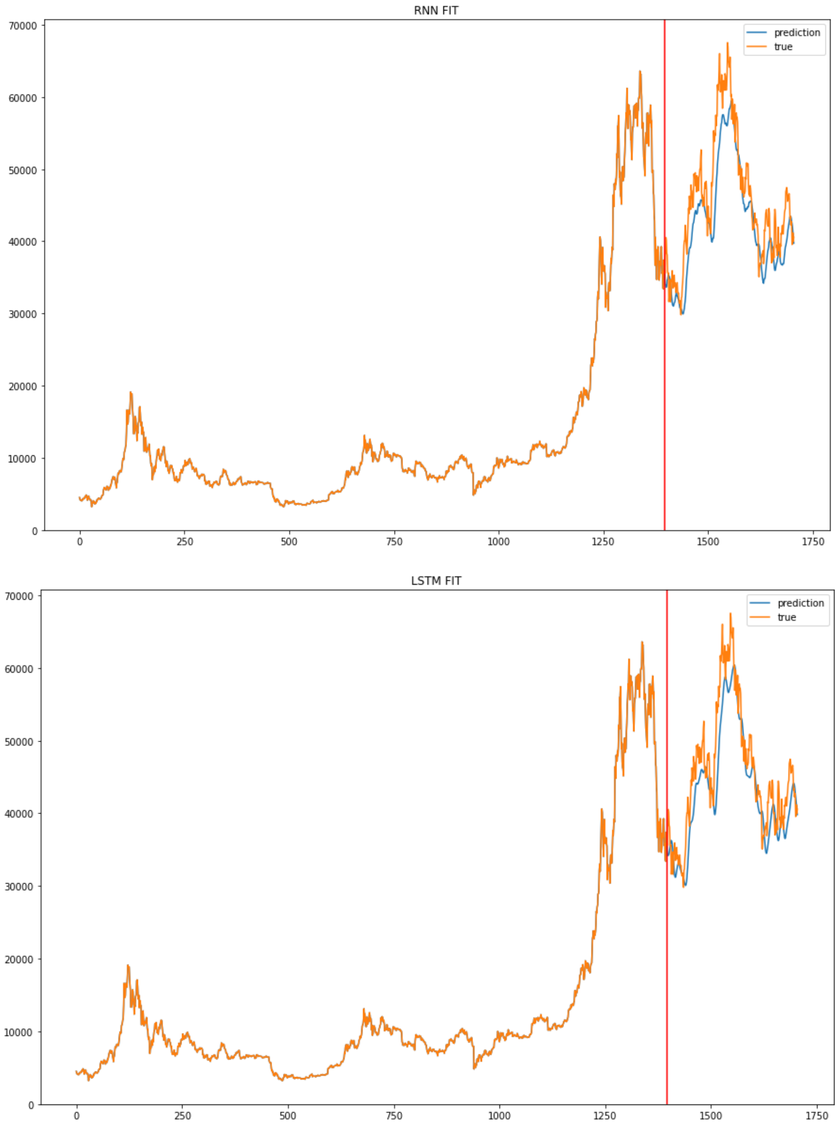


Figure 4: ML model Prediction (RNN and LSTM)

	RNN	LSTP
MAE	3.78e+03	3.34e+03
MPE	6.82%	5.51%
MAPE	8.03%	7.14%
MSE	2.26e+07	1.79e+07
RMSE	4.76e+03	4.23e+03

Table 1: ML model Performance Comparison

4. RESULT AND ANALSYS

4.1 Simple Moving Average Crossover

Moving Average Crossover is one of the simplest and widely used trading strategy based on two moving averages. When shorter period moving average crosses either above or below longer period moving average, or crossover in other word, indicates a trading signal. When shorter period MA exceeds longer period MA it is a buy signal and opposite case as a sell signal. The strategy performs differently depending on what to set as short and long periods. It is crucial to find highest performing strategy by changing the parameters. Therefore, I had performed SMA crossover with short period ranging from 5 to 100 at interval of 5 and long period ranging from 20 to 200 at interval of 5 for daily Bitcoin price data for past 5 years. As the heatmap in appendix B suggests, (10, 40) and (15, 35) showed highest performances. However, I figured the interval is too large and period greater than 50 seems insignificant, ran another test ranging up to 50 with interval of 1. The following heatmap shows profitability level for each short and long periods.

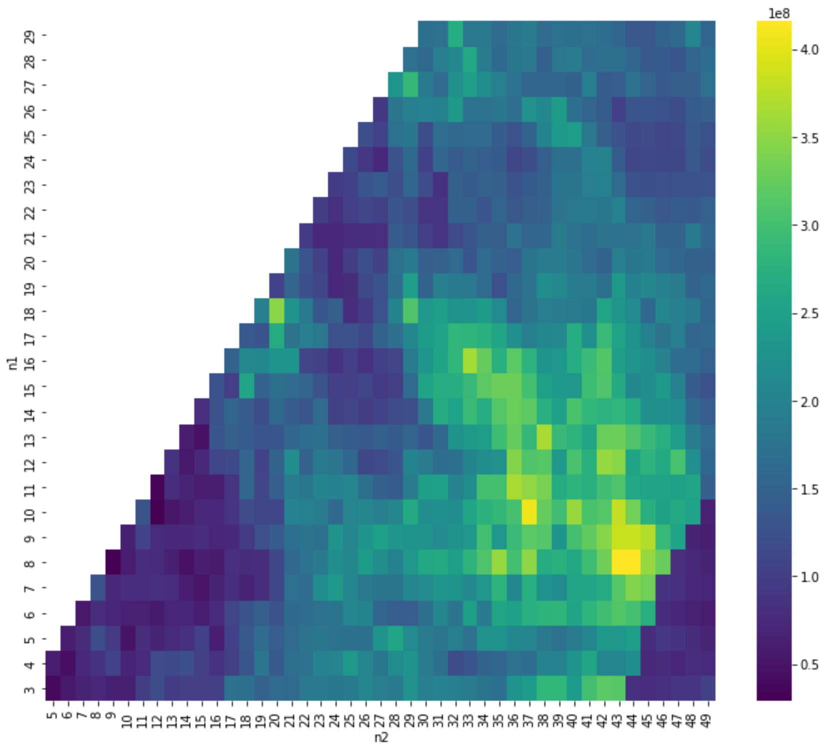


Figure 5 SMA crossover return heatmap for 1 day interval

Highest profiting periods is (8, 44) which earned 4,157% where simple buy and hold would return 745%. It is notable that for strategy based on such simple indicator, profit return is well above the buy and hold.

To see if different time period would influence the result, the similar process has been applied to past price data for recent 1 year and 3 years data. As expected, (8,44) crossover was no longer highest profiting one. Instead, (29,31) for 1 year and (29,32) for 3 years showed highest profit with each -13% and 240% returns. It appeared crossover between relatively short and long period such as (8,44) was effective when price was continuously rising yet insufficient for drastic price drop occurred in recent years. The new crossovers do not earn as much as 5 year crossovers but surpassed buy and hold return meaning each of them are successful strategies. Plus, comparably row return is understandable as the price of Bitcoin was dramatically low in 2017.

4.2 RSI

RSI is also very popular indicator widely used. Typical criteria of 30 and 70 was used which means lower than RSI of 30 is considered as sign to buy and 70 as sell. Just like SMA, RSI did outperform simple buy and hold for recent 5-year period. However, by modifying time slot to 1- and 3-year, RSI did not seem to be sufficient compared to SMA. Especially for 1 year time, where SMA still made profit of 61%, RSI made negative profit of -15% which is understandable considering price of Bitcoin was highly volatile for recent year. Modification of period for RSI may have improved the result but did not make significant change in profit.

4.3 LSTP

As the performance of ML models are measured using MAE, MSE, RMSE, the performance of ML model in terms of profit level is necessary to compare against TA back testing results. To calculate profitability of ML model, profit is calculated by implementing new trading strategy based on price difference between actual and predicted price level. When t+1 closing price predicted by ML model is higher than current closing price by more than 5%, it considered as buy signal and sell signal when predicted price level is below current price level.

4.4 Comparison between TA and ML

	SMA	RSI	B&H	LSTM
Cumulative Return	-13.6%	-25.4%	-32.6%	-23.2%
Volatility	35.6	30.7	39.7	10.7
Maximum Draw Down	-37.0%	-34.3%	-40.4%	-25.3%
Exposure Time	44.4	32.3	100	68.7

Table 2: Result table

The table shows back testing result done for recent 365 days with commission rate of 0.1%. Unlike long term back testing data done for 3-year or 5-year, recent drop in Bitcoin price indicates simple buy and hold strategy for recent year would return -32.6%. SMA strategy, which showed significantly higher profit level in long term is not as successful yet manage to show higher return than B&H. In same period, LSTM showed higher than B&H provide reason to apply ML model in cryptocurrency market. LSTM showed superior in aspects of volatility and Maximum Draw Down compared to other indicators. However, LSTM showed highest exposure time meaning there are greater chance of exposure to sudden market risks.

5. Limitations

5.1 Challenges

It is inevitable to face challenges as project progress as the aim of project is to verify the effectiveness of TA strategies and further utilize to predict future price of BTC. This section highlights some challenges introduced during the project and further extension if applicable.

5.1.1 Limitations of TA

As explained, TA considers only trade related information. Recent drastic changes in BTC price are often related to fundamental aspects of cryptocurrency which TA is unable to consider. Taking fundamental aspect of cryptocurrency into account requires Natural Language Processing of News and Social Network Services which is beyond scope of this project. The question would be will TA be able to promptly respond to unexpected price change occurred by external issues.

Apart from the natural limitation of TA, there are also limitation regarding each of the indicators. As previously mentioned in chapter 1, indicators have categories (lagging and leading) and types (trend, momentum, volatility, and volume) related parameter resulting different pros and cons. Building strategy based on single indicator could maximize its advantage yet also lead to maximizing its weakness. To solve this issue, combining multiple indicators to set trading rule is in process. Combining indicators to build ne strategy was rejected during the research due to exponentially growing combination resulting excessive load of back testing required.

5.1.2 Limitation of ML model

This research used only LSTM model under assumption of Cryptocurrency being sequential data. However, single model is not sufficient to prove usefulness of ML in price prediction of BTC. In this research, LSTM showed better performance compared to simple buy and hold with sufficient predictivity yet did not match return of SMA based strategy. Due to limited time and skill, more comprehensive research regarding variety model was constrained.

Furthermore, as discussed in result section, LSTM showed relatively lower cumulative return and higher exposure time compared to SMA which can be explained as trading strategy based on LSTM was overly active buy and selling without proper profit would rather lead to decrease in final return due to commission rate. For future project combining successful TA based strategy with price level predicted via ML model could be utilized to maximize advantage of both models.

5.2 Possible extensions

Considering the project was conducted only on Bitcoin and single ML model, the research can further be extended by implementing variety of Cryptocurrencies. The project has intentionally excluded non-numerical data such as news or social media, but numerous studies have shown that there is statically significant correlation between price of cryptocurrency against such non-numeric data. Adding such data through NLP could lead to higher accuracy in prediction.

6. CONCLUSION

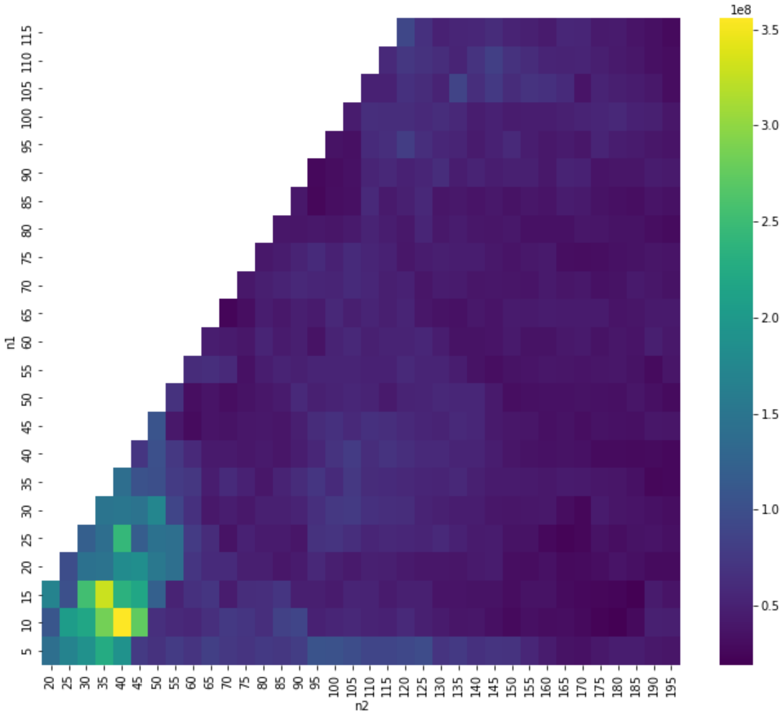
This project focuses on proving the effectiveness of TA on cryptocurrency and comparing it against ML models. such trading strategies will be tested against historical time series data of dollar denominated Bitcoin price. Related papers have been searched to enhance understanding of topics and choose methodologies for testing.

Both TA and ML models showed higher cumulative return compared to B&H proving its effectiveness. However, comparison between TA and ML showed that ML model was not sufficient to reach performance of simple TA based trading strategy. It seems the well known rule of thumb outplayed latest technology for Bitcoin.

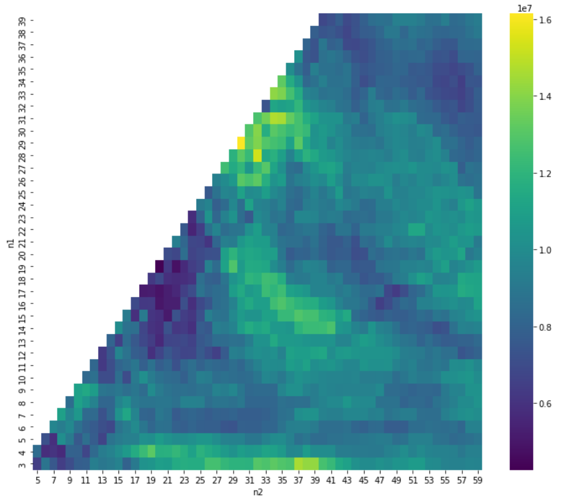
The project succeeded in a way by successfully comparing TA and ML model in Bitcoin price prediction but could have been improved by extending the limited aspects discussed in previous sections such as variety of Cryptocurrency and lack of comprehensive modeling. Based on current project, the ultimate goal is to comprehend both TA and ML model to build highest profiting strategy which could be utilized for personal use.

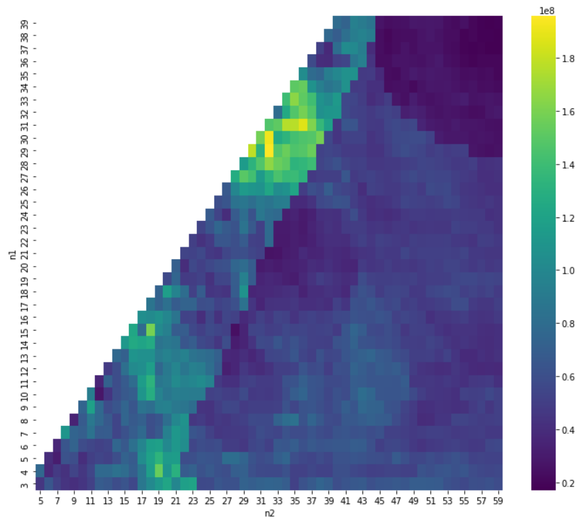
APPENDICES


Zoom 1d 7d 1m 3m 1y YTD ALL
Jan 1, 2017 → Oct 27, 2
Percentage of Total Market Cap
60%
40%
20%
0%
Jan '17
Jul '17
Jan '18
Jul '18
Jan '19
Jul '19
Jan '20
Jul '20
Jan '21
Jul '21
2018
2019
2020
2021
Bitcoin
Ethereum
Binance Coin
Cardano
Tether
Solana
XRP
Polkadot
Dogecoin
USD Coin
Others
coinmarketcap.com



Appendix B Profitability Heatmap for Rough Interval SMA crossover





Appendix C Profitability Heatmap for SMA crossover recent 1 year (left) 3 year (right)

Table 3 Project Timeline

Date	Goals
September 15, 2021	● Literature review ● Finalize topic
October 15, 2021	● Research for further literature review ● Complete data collection
October 30, 2021	● Pre-process data ● Investigate possible candidates for back testing
November 15, 2021	● Exploratory data analysis
November 30, 2021	● initiate building testing algorithms
December 30, 2021	● Test algorithms ● Evaluate results and improve on algorithm
January 23, 2022	● Interim presentation **(Deliverable 2)** ● Work on detailed interim report **(Deliverable 2)**
February 15, 2022	● Analyse and evaluate performance of models ● Start improving on top models
March 15, 2022	● Finalize codes ● Analyse findings
April 18, 2022	● Final report **(Deliverable 3)** ● Final presentation **(Deliverable 3)**
May 4th, 2022	● Prepare project poster

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