UNIVERSITY OF
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TO INVESTIGATE THE SUITABILITY OF COMBINING MACHINE LEARNING AND EXPERT KNOWLEDGE TO CREATE A PROFITABLE TRADING ALGORITHM

by

NABEEL-OSMAN MOHAMED OSMAN JUMA

(W1929230)

Supervised by
DR. PHILIP WORRALL

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DECLARATION

I, Nabeel-Osman Mohamed Osman Juma, declare that I am the sole author of this Project; that all references cited have been consulted; that I have conducted all work of which this is a record, and that the finished work lies within the prescribed word limits.

This has not previously been accepted as part of any other degree submission.

Signed : Nabeel-Osman

Date : 7th September 2023

FORM OF CONSENT

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Abstract:

The debate between long term investing and trading has managed to generate significant interest among academics and professionals throughout the years. The study aims to draw a conclusion on that debate. The LSTM is used to classify price movements while the efficacy of various famous trading strategies are put to the test. Additionally, the K-means algorithm is employed to help shortlist cryptocurrencies based on their tail risk while using the largely famous MVO algorithm to optimise a portfolio based on these coins.

Results of the report indicate the presence of pros and cons for both sides. Where the risk is comparatively lower for long term investing, the returns are comparatively lower too. Returns generated through trading surpass those obtained by investing at a cost of higher risk. Findings also suggest that data-driven strategies can yield higher risk adjusted returns when compared to its investment counterparts based on the Sharpe ratio.

The study however also places emphasis on context and the importance of an investor’s risk tolerance. Furthermore, the project opens up new avenues for future research that involves recommendation of a technique based on an investors risk appetite.

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Chapter 1: Introduction

Stock trading is the dynamic and captivating activity at the heart of financial markets that gives individuals and institutions a chance at investing in a company and profit from its growth and success. It involves the purchase and sale of shares of ownership of publicly listed companies.

The concept of stock trading originated in the 13th century in Antwerp as it was the centre of trade. The similarity reflected was a result of merchants purchasing goods in anticipation of an increase in its price to net a profit. However, modern day stock trading wasn't created until 1611 in Amsterdam where the Dutch East India company became the only publicly listed company traded on the exchange for some years (Hwang, 2023).

Inspite of having ancient roots, the digital era has brought about a revolution in the field of stock trading. With the emergence of online platforms, the financial markets that were originally only exclusive to professionals were now open to the humble retail investor. Additionally, the financial markets, initially limited to bonds, stocks and commodities, have now been extended to cryptocurrencies.

The impact of technology isn't only restricted to broadening of the number of assets but to the method in which they have been traded as well. Where initially the markets were considered efficient (Fama, 1970), recent works have been demonstrating methodologies to generate returns in excess (Chong, et al., 2014) of the traditional buy and hold method.

This report focuses on the performance of modern-day trading methodologies with a particular focus on cryptocurrency trading. While exploring the already established markets and some currently emerging markets, we aim to evaluate if technology can be used to navigate the highly complex and volatile cryptocurrency market.

Chapter 2: Background:

2.1 Trading:

The purchase of an asset and selling it off after it has either reached its target (or stop loss), or the maximum duration for which it has to be held is known as trading. Traders are usually split in two major groups, namely retail and institutional traders. This split is usually based on the amount of funds they manage. The retail traders use a small to medium sized capital. Institutional traders encompass banks, funds and groups that have access to a huge capital. The trades initiated by retail and institutional traders are usually carried out on exchanges and dark pools. The general public, through brokers can trade on exchanges. However, it is a little different while trading on the dark pool. They are made available when a large amount of stock needs to be traded. This is also commonly referred to as a block deal. A block deal is conducted on the dark pool so as to avoid the purchase of the huge quantity of stock at an adverse price and to also prevent it from affecting the wider market. Dark pools are usually used by mutual and pension funds which state that the benefits obtained by using these services is ultimately passed on to retail investors who invest in these funds (Chen, 2022).
Traders can further be classified based on their trading styles:

- Swing traders: People who hold an asset for a few days.
- Day traders: Traders who buy/short an asset and hold that position for a maximum duration of that day.
- Scalpers: They hold a position for a small fraction of time. They usually purchase a huge volume of an asset for a small movement in price.
- High Frequency Traders: They are a subtype of scalpers, but they conduct a huge number of trades every minute. While scalpers can perform their trades manually, HFT traders generally use algorithms to perform their functions.

2.2 Introduction to Cryptocurrency:

A cryptocurrency is a form of currency that is digital in nature and utilises cryptography to secure the transfer of assets. It's decentralised nature and peer to peer running methodology enables the elimination of banks as intermediaries. Its secure nature is due to blockchain which is a distributed and immutable ledger. The use of cryptographic addresses helps keep those involved anonymous. However, all transactions are public. The price of any cryptocurrency depends on the advancement of the technology it uses, their acceptance by the masses and the increase in its demand. The 24/7 nature of cryptocurrencies, their global presence and their volatile nature have helped harness interest for them. The 31,735.27% returns that bitcoin has generated since 2010 hasn’t gone unnoticed either (LazyPortfolioEtf, 2023). Bitcoin and other cryptocurrencies have led to an emergence of their own exchanges like Binance, Coinbase, Kraken, etc to name a few.

Understanding cryptocurrencies and the modern twist they extend to financial markets requires an understanding of their price movement and trading behaviour which are often obtained from established market theories. These theories act as a benchmark based on which investors and traders interpret the market trends. An understanding of strategies and concepts like mean reversion or mean variance portfolio optimisation requires some foundational knowledge of the classic market theories.

2.3 Market Theories:

2.3.1 The Market Efficiency Theory:

The market efficiency theory or the Efficient Market Hypothesis (EMH) was first introduced by Eugene Fama in the 1960’s (Fama, 1970) . It refers to the belief that financial markets are efficient in nature and maintains that it is impossible for investors and traders to make abnormal profits from financial markets. The EMH observes that market efficiency exists in 3 forms, namely weak, semi-strong and strong. It holds strong to the belief that ideally, any trader/player, be it institutional or retail would have the same amount of knowledge regarding a particular security at any given time. This would result in a total random outcome. Karl Pearson compares this theory to a drunk who is left in the middle of the field. He would be staggering around in a completely random fashion. However, the chances of him ending up at the position he was left would be the highest compared to any other place (Pearson, 1905).

- The weak form of this theory elaborates that stock prices and trading values, in short, historical data and their resultant patterns would not be useful in predicting future price movements effectively and consistently. This form rebukes technical analysis.
- The semi strong section of this theory further encapsulates publicly available data like news announcements, financial reports, earning reports and other similar relevant information have little to no value to consistently lead to an increase in profits for investors. This form debunks fundamental analysis.
- The strong section of this theory believes that no information, whether public or private can give anyone, whether retail, institutional or insider any additional edge to generate consistent profits.

This theory is closely related to the random walk model.

2.3.2 The Random Walk Model:

The Random Walk model is very similar to the market efficiency theory. It states that the stock market prices cannot be predicted and that they follow a random pattern (Fama, 1965). The randomness of future prices is attributed to a fact that financial markets are continuously getting influenced by external factors like news and their resultant investor sentiments. The three forms of random walk model are:

- Random Walk with a Drift: this means that price follows a linear trend or movement. It means that its drifts upwards or downwards in a linear direction.
- Pure Random Walk: This form of random walk model follows that there is no drift or trend. It states that the expected future price is zero, meaning, it expects price to remain unchanged over a period of time.

- Random Walk with Jumps: This form as the name suggests explains the presence of spikes or jumps in price movements. These movements or 'jumps' are attributed to unexpected news or sudden events that affect the financial markets.

Proponents of the Random Walk model and the Market Efficiency theory believe that trying to beat the market is futile and that investors are better off following the buy and hold strategy, also known as passive investing or diversifying their portfolios. The other side of the coin are people who believe that the market in managed by demand and supply, that history repeats itself and that there is a method to this madness; meaning there are ways to beat the market consistently. They believe that even though the information available to everyone is the same, there still is the fact that everyone processes information differently (hen, et al., 2021). This leads us to the alternate way of looking at the financial markets.

2.3.3 Wyckoff Theory:

Alternatively known as Wyckoff Method, it was a theory first postulated by Richard D. Wyckoff in the early 20th century. Wyckoff has largely been accepted as one of the greatest traders of all time. He has famously claimed in his book The Day Trader's Bible, that the market briefly predicts its own future and those that learn to identify it can have a distinct advantage over the rest. Apart from identifying these patterns, he assigns great importance to a trader's ability to focus his mind and control his emotions (Wyckoff, 2000). He postulated a theory to help achieve this. In his theory, Wyckoff explains that there is an ongoing battle between buyers (demand) and sellers (supply) that drives the price movement. He further elaborates that one can gain insight by looking at the resultant price action and its corresponding volume. This helps in identifying probable positions of major players and smaller players can position themselves accordingly. His theory has multiple principles which emphasise on having a rule-based trading system so as to avoid making trading decisions influenced by emotions. It also additionally supports the theory that market manipulation occurs and provides a guide to help identify entry and/or exit positions of big players (or market makers). The Wyckoff theory forms the premise of the modern-day technical analysis.

The above-mentioned theories offer a keen understanding of market dynamics. However, taking into consideration the limitations posed by theoretical models, traders often look towards technical analysis that provides a more hands-on approach in enabling them to understand historical data on price charts to make informed decisions.

2.4 Technical Analysis:

The most commonly used method for trading stocks by both retail as well as institutional traders, irrespective of their trading style, is known as technical analysis. It is a methodology which encapsulates the analysis of statistics that market activity generates, especially past prices and volume (Rico Nur Ilham, 2022). It follows the statement that 'history repeats itself'. It helps traders identify trends, supply zones, demand zones and thus generate buy and sell signals.

While technical analysis, helps provide an overall view of the market, it is the technical indicators that help in providing a more refined viewpoint.

2.5 Technical Indicators:

Technical analysts employ a range of tools to aid their analysis known as technical indicators. These indicators are insights and visualisations generated by applying mathematical calculations to historical price and volume. Some of the major technical indicators used are RSI, Moving Averages, Bollinger bands, etc.

2.5.1 Moving Averages:

Moving averages are a fundamental tool that help in technical analysis. They are used to smooth out price movements. Moving averages are usually calculated using the closing prices of each time period. They are used to identify trends. A moving average calculated over a shorter time period sticks to the price compared to that calculated over a longer period of time. The two major types of moving averages are simple moving average and exponential moving average. The simple moving average uses the normal moving average calculation. However, the exponential moving average assigns more weight to recent prices in the time period. They are generally used in the same fashion. The golden cross and the death cross calculated on the daily timeframe are famous trend reversal indicators used by technical analysts.

Calculation: n = number of period

$$MA_n = \frac{\sum_{i=1}^{n} D_i}{n}$$

2.5.2 Relative Strength Index:

The RSI is one of the most frequently used oscillators. Its values range from 0 to 100. Its calculation includes averages of positive and negative price changes. This shows how fast the price has moved in either direction. The RSI indicator is usually calculated over a 14-day period. A value above 70 is generally classified as overbought. Price in this zone is expected to slow down its upwards trajectory and a retrace is expected. Conversely, RSI below 30 is known as to be in the oversold zone. It is important to note that the overbought/oversold zone and even the 14-day period values can be changed according to requirements.

Calculation:

n_{up} = Average of n-day up close

n_{down} = Average of n-day down close

$$\mathrm{RSI} = 100 - \left[\frac{100}{1 + \frac{n_{up}}{n_{down}}} \right]$$

2.5.3 Bollinger Bands:

Another famously used oscillator is the Bollinger bands. In its default setting, the Bollinger bands has 3 bands. The middle band is a 20-period simple moving average. The upper and lower bands are 2 standard deviations of the moving average towards each side. The Bollinger band is usually utilised in mean reverting strategies.

2.6 Mean Reversion Trading:

While these technical indicators provide some form of insights into market patterns, using them in trading strategies help capitalise on these insights. One such strategy that utilises indicators like Bollinger bands and RSI is mean reversion trading.

Mean reversion trading is based on the theory that the price peaks and valleys are temporary. It is the ability of an asset to revert to its mean value. In terms of cryptocurrency trading, the theory suggests that it has to be shorted when the price increases as compared to its mean value. Similarly, we go long on the coin when it falls below its mean. It assumes that any asset is fundamentally stable. While using an oscillator like Bollinger bands for this strategy, the price can be shorted when it goes above its upper band. Similarly, the asset can be bought when it goes below its lower band. However, it is important to note that this class of strategies do not work too well in trending markets.

2.7 Momentum Trading:

The opposite of the mean reversion trading style is the momentum trading style. This type of trading capitalises on existing trends. Moving averages are the preferred choice of indicators for this type of trading.

Momentum trading is basically the buying or selling of an asset based on the assumed strength of its trend. Moving averages help identify short term and long term trends. Their general principle is when price is above a certain moving average, the asset is classified to be in an uptrend. If it is below a certain moving average, it is classified to be in a downtrend. However, this strategy may not work so well in volatile conditions.

2.8 Contrarian Trading:

Trading in the financial markets is a zero-sum game. This means that there is always a seller to a buyer in a trade. Additionally, for every person wanting to go long, there is someone who expects the market to go lower. This gives rise to a contrarian viewpoint. Traders following the contrarian style of trading strongly support strategies based around mean-reversion, buy the dip, and sell the rally techniques. Research has been conducted on testing the effectiveness and validity of the contrarian trading style. It has been shown to work better with high frequency trading which aims to profit from price imbalances and arbitrage. It has been seen to work better than the usual buy and hold investment technique. However, mean reversion-based contrarian trading strategies haven't been very successful on longer time frames (Balvers, et al., 2002).

2.9 Machine Learning in Cryptocurrency:

Unlike the traditional form of trading like mean reversion or momentum or the contrarian method of trade, the evolution of technologies has led to the use of machine learning algorithms for price prediction. Additionally, the vast amount of market data generated by cryptocurrencies helps in making their trading a good used case to utilise advanced machine learning algorithms like deep learning and neural networks to find patterns and make predictions. To develop strategies and forecast pricing, a huge number of machine learning algorithms have been used. Some of the very common algorithms like k-means and LSTM would be explained below.

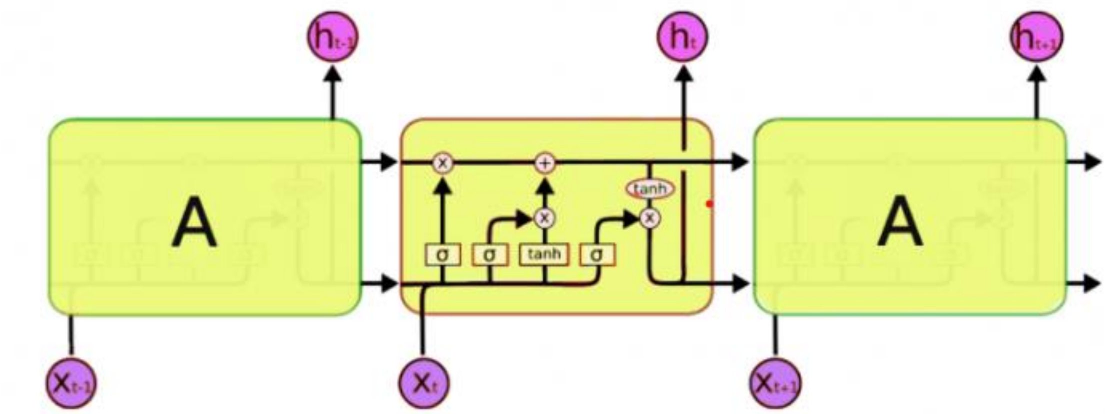
2.9.1 K-means Clustering:

K-means is an important unsupervised machine learning algorithm. It is used to form clusters by dividing the datapoints where it tries to minimise the distance between each datapoint within the cluster. Additionally, it aims to maximise the distance between two data points from separate clusters (Klaas, 2019).

The process is started by first calculating the number of clusters needed or by random selection. There are various methods of obtaining this number. One very widely used method is known as the elbow method. It involves the calculation of the sum squared distances known as inertia between the data points and the number of clusters. As the number of clusters increases, there is a decrease in the inertia as each datapoint can now find a centroid closer to it. However, after a certain number of clusters, the fall in inertia reduces greatly thereby giving it an "elbow" point. This point is usually considered to be the optimal number of clusters 'k'. Then we initialise a fixed number (k) of centroids Following the initialising of the centroids, each data point is assigned to the centroid closest to it, thereby making it the member of that cluster. New centroids are then calculated by taking the mean of all the datapoints. The datapoints are then again reassigned to the centroids closes to them to form new clusters. These two steps keep on repeating till there is no significant change in the clusters. This is when the clusters that have been formed are finalised.

2.9.2 Long Short Term Model:

A type of RNN architecture, the LSTM has revolutionised the field of sequence modelling and analysis. The traditional RNNs had issues with capturing long term dependencies due to the vanishing gradient problem. LSTMs contain a feedback loop that help in 'remembering' the previous data and thus help it capture long term dependencies. This helps it become very important for predicting sequential time series data like stock prices, and other text and speech data.



The LSTM has 3 parts. The first part, also known as the forget gate decides on the importance of the information sent. In addition to the current input, it takes in the previous cell state to calculate and output a forget factor for each input. Basically, if any information is deemed irrelevant, it is forgotten. The second part, also known as the input gate, regulates new information flow into memory. It does this by first deciding which values need updating and then by calculating new candidate values that would later be added to the memory cell. This is how it learns new information from the data provided as input.

The third part known as the output gate collects all the updated information and passes it onto the next timestamp. Meaning, it decides what information needs to be given as output and which consequently would be contributing to the current hidden state. The role of this gate is of vital importance to influence the decisions of the model. This entire cycle is known as a single timestamp.

Inspite of having various advantages, LSTM can have some disadvantages that need to be taken into consideration. They are computational complex and can sometimes be referred to having a black box nature. That is, it is difficult to sometimes provide an explanation about their predictions. Longer sequences sometimes suffer because of their inability to solve the vanishing gradient problem for sequences that are longer. Additionally, the LSTM memory cells have a limited capacity to retain long-term information for such longer sequences. Their complex structure can sometimes introduce gradient noise. They, sometimes overfit causing them to capture noise and outliers in the training data.

While the success obtained by using machine learning models hasn't gone unnoticed, they aren't the only option to obtain success in the financial markets. One of the famous methodologies of creating diverse portfolios is known as the mean variance optimisation or MVO.

2.10 Mean Variance Portfolio Optimisation:

The Mean Variance Optimisation is a revolutionary portfolio management system developed by Harry Markowitz in 1952. It is used for quantifying the risk and the expected returns for the purpose of investment. He did this by introducing the concept of portfolio diversification.

The main components of the MVO are:

- Expected return: Calculated as the average of past returns.
- Risk: The measure of how much an assets returns could fluctuate.
- Covariance: The measure to see how similarly two assets move.

It starts by first calculating the expected returns, risk and covariance. Then by using various mathematical techniques, it aims to find fixed weights to maximise the returns for a level of risk or to minimise the risk for a level of returns.

Having acquired some foundational understanding, the literature review section can now shed light on how these techniques have been utilised for cryptocurrency trading and trading in general.

Chapter 3: Literature Review:

It is important to note that the buy and hold strategy is the most commonly used comparative baseline by many of the studies in the upcoming parts. It involves the holding a security for an extended period of time regardless of market fluctuations. It is based on the belief that irrespective or short-term market fluctuations, the security's price will always go upwards. It is a trade-off between lower transaction costs because of fewer trades and the exposure the investor has to market risks. It can also lead to having a lock in period for the investor's investment. It has been seen to improve rewards while also reducing the investment risk a great deal (Ng & Muhammad, 2014).

3.1 Use of Technical Indicators in the Market:

There is a lot of controversy over whether technical indicators can be used to outperform the buy and hold strategy. Neftci believes that traders using technical analysis for day-to-day forecasting are doing so without any formal reference. He concludes that buy and sell signals generated by technical analysis and their well-defined rules are useless at prediction (Neftci, 1991). Tanaka-Yamawaki and Tokuoka in their work conclude that indicators related to the moving averages like SMA and EMA perform satisfactorily. However, they disregard RSI and MACD as technical indicators useful for price movement forecasting (Tanaka-Yamawaki & Tokuoka, 2007).

However, present day research has led to a newfound belief in technical analysis. Where the older research lent support to the buy and hold strategy over the use of technical indicators to generate trading opportunities, newer research finds returns from technical analysis to be higher than those generated by the buy and hold methods (Kwon & Kish, 2010). Osler does research on using support and resistance as entry points for intraday trading. The zones weren't consistent, and their power of prediction were found to vary over the chosen stocks. However, he does come to the conclusion that, even though inconsistent in some assets, he found an increase in price reaction at those zones (Osler, 2000). Also, it has been documented that when price crosses such a level, the speed of the price movement increases, thus lending support to the existence and importance of such levels. This was done by using statistical tests based on bootstrapping to compare the bounce frequencies of price at these zones (which were calculated on the daily time frame) to the bounce frequencies at arbitrary zones. Although, there was variation seen in the strength of these zones for different scripts, it still proves that these zones have the ability to interrupt or reverse trends (Osler, 2003). Another research that utilises technical indicators like RSI, moving averages, MACD and Bollinger bands for trading cryptocurrency has shown an increase in returns generated by trading Bitcoin. Here, moving average crossovers and RSI were found to be useful in generating profitable returns (Jain, et al., 2022).

3.2 Moving Averages for Trading:

Gunasekarage and Power find that the previous assumptions of moving average based trading returns being equal to that achieved by the buy and hold strategy are incorrect. Infact, they find that these returns are in excess when dealing with the emerging south Asian markets. They too come to the conclusion that the market is inefficient (Gunasekarage & Power, 2001). Further research done on the comparison of results produced by using simple moving average (SMA) and exponential moving averages (EMA) have revealed that the SMA has yielded better results. However, it has been seen that moving averages of a certain period may be best suited a particular asset. Meaning that it may not be one period fits all (Vinicius Amorim Sobreiro, 2016).

3.3 RSI for Trading:

Gill Cohen and Elinor Cabiri research on the use of oscillators like RSI and MACD. Their aim was to see how consistently these technical indicators could outperform the market's buy and hold strategy. They find that these oscillators outperform the market during bear markets only, while they underperform during the bull cycle (Gil Cohen, 2015). However, Chong et al. in their research paper find that the RSI indicator using a simple technique explained previously and calculated over a 14 period resulted in an increase in returns compared to the buy and hold returns of the Dow Jones Industrial average. It proved to be robust inspite of having a 1% transactional fee added to each trade. They go as far as concluding that the markets are inefficient and that certain assets can be traded profitably using certain rules (Terence Tai-Leung Chong, 2014).

3.4 Bollinger Bands for Trading:

John Bollinger, the creator of Bollinger bands, explains them to be lines that are plotted in and around a structure of price while forming an envelope. He explains that the action of price next to the bands are of primary interest. Furthermore, it doesn't give specific buy or sell signals but rather how far away the price has moved relative to its mean (Bollinger, 2001).

Jääskeläinen in his paper compares the results obtained by using Bollinger bands as a form of mean reversion trading and moving averages as a form of momentum trading. It was seen that bitcoin, when traded using Bollinger bands generated returns in excess of those generated by the buy and hold strategy and the momentum trading strategy, showing the importance of Bolinger Bands in trading (Jääskeläinen, 2022). One of the major problems of the buy and hold strategy or any form of investment strategy is their performance during a market crash; like the covid market crash. Additional research has been conducted to see the performance of technical indicators during the COVID-19 crash and has resulted in excess returns being generated by Bollinger bands and trading range breakout strategies. These results have held true even after deducting transactional costs. Furthermore, this research was carried out over a variety of assets like S&P 500, Bitcoin, Oil, Gold and Vix markets (Camillo Lento, 2022).

3.5 Mean Reversion Trading:

Mean reverting behaviour has been observed in the forex markets. However, recent research shows that bitcoin too displays mean reverting tendencies in smaller time frames. Additionally, the research found that it had a stronger negative reverting tendency instead of positive reverting tendencies. This means that when the price of bitcoin fell, the return to the mean was faster and of a greater magnitude compared to when the price spiked upwards (Shaen Corbet, 2010). It is important to note that the usual method of this strategy is utilised in pair trading wherein two coins (or assets) that have a high positive correlation are taken. When they diverge from each other, the coin that deviates to the upper side is shorted while the one that deviates to the lower side is bought. Profits are booked when they revert to their mean position. The research done by Fil and Kristoufek shows that bitcoin displays mean reversion behaviour in the 5 minutes time frame but not as effectively in the daily timeframe. The difference goes to such an extent that when used on the 5 minutes timeframe, the strategy yields a 11.8% positive return monthly. However, when performed on the daily timeframe, it yields negative returns of 0.07% over the same duration (Fil & Kristoufek, 2020). Another feature of mean reversion in cryptocurrencies is that the further the price distends away from its mean, the more severe is its reversion. Volume also has an impact on bitcoin’s volatility. This is important as higher volatility means larger swings and hence consequently more reverting to mean trades (Nicola, 2021). Mean reversion strategies usually employ the help of oscillator based technical indicators to find ‘reversing zones’.

3.6 Momentum Trading:

Shen et al. show how momentum-based trading when undertaken for the crypto market can yield positive returns. They believe it is because of the increased volatility and volume. However, they find a link between momentum and liquidity. Meaning the momentum in Bitcoin is because of an added influx of volume and not late informed trading. This points to the direction that certain time periods might be comparatively more profitable to trade in using momentum trading strategies (Dehua Shen, 2021). However, no single parameter can be applied to all cryptocurrencies. Chu et al. have found that momentum trading worked well on the top 6 cryptocurrencies. Momentum trading has also been seen to outperform mean reversion-based strategy even in high frequency setting (Jeffrey Chu, 2020). Cohen in his research finds that the RSI when used to trade cryptocurrencies as a momentum indicator generates results that outperform those achieved by the buy and hold strategy. However, he does emphasise that the strategy worked well for medium level timeframe like 60 or 120 minutes compared to the smaller timeframes of 5 and 15minutes (Cohen, 2023). It is also important to note that though momentum trading provides an edge during a rally, it still falls prey to false breakouts, trend reversals and sudden news related market shocks. Moving averages are generally known as momentum indicators. However, oscillators can occasionally be used for this purpose as well.

3.7 Contrarian Trading:

Caporale and Plastun originally start their research based on momentum trading. However, while analysis BTC and ETH, they realise BTC gave a positive abnormal return, while ETH gave a negative abnormal return. This pointed towards a contrarian approach that may be useful while trading ETH. Momentum trading was also seen to generate abnormal returns. However, considering that the dataset was from 2015-2019, a timing famous for the crypo-boom, the returns achieved by momentum trading cannot be used as benchmarks for future returns (Guglielmo Maria Caporale, 2020). Representative heuristic is when people overreact to new information compared to old information. This leads to an overreaction in price movement. These extreme overreactions and their consequent price reversals can be exploited to make profitable trades following the contrarian principle (Oliver Borgards, 2021). Contrarian trading has seen to be very profitable and relevant in volatile assets like hard metals, energy stocks and cryptocurrencies. De Bondt and Thaler tested the contrarian theory on a larger scale. This is where they had created a famous strategy. They started by building two portfolios: a winner portfolio and a loser portfolio. They showcased profits by shorting the winner portfolio and buying the losing portfolio. The result of their research shows that the losing portfolio outperformed the winner portfolio and peaked within 2-3 years. They outperformed the market by almost 20%. Additionally, most of the gains were seen during the month of January, thus explaining the January effect which means that the losers experienced reversals during January. The effect however lasted for multiple months (WERNER F. M. De BONDT, 1985).

3.8 Machine Learning for Trading Cryptocurrencies:

One major method of utilising machine learning algorithms is using technical indicators as inputs for predicting prices. Awotunde et al. used an LSTM model using technical indicators as inputs for price forecasting and saw an increase in accuracy (Joseph Bamidele Awotunde, 2021). Similarly, Akyildirim et al. use technical indicators as inputs to their support vector machine model and obtain an accuracy of 55-65% for predicting their returns (Erdinc Akyildirim, 2021). Alahamari and Ali use the ARIMA model to forecast bitcoin pricing by using just the normal close price (Alahmari, 2019). Betancourt and Chen utilise reinforcement method to learn optimal actions and self-attention networks to identify networks and links between continuous data elements (Carlos Betancourt, 2021).

Overall, the above part shows that machine learning algorithms can be utilised to provide a trader an edge when it comes to trading. It can also help influence investment decisions and predicting changes in public sentiment to an asset.

3.9 K-means Clustering:

Being an unsupervised machine learning clustering algorithm, K-means generates clusters based on the premise that inter cluster distance should be maximised while intra cluster distance should be minimized. This means all the datapoints within a particular cluster should be as close as possible. Similarly, the distance between two different clusters should be as large as possible (Klaas, 2019).

Conducting research of a 12-year dataset of the Malaysian stock market, Aslam et al. in their paper use Fama French three factor model as an input to the k-means clustering algorithm. Stocks are classified based on their exposure to 'market, size and value' risk. In the result, they identify that K-means clustering did infact yield improved positive returns compared to the market benchmark (Bilal Aslam1, 2022). Nanda et al. also perform a similar research in the Indian stock market using the K-means clustering algorithm. They use volatility and moving averages as inputs on K-means, SOM and Fuzzy C-means clustering. They compare the result obtained and conclude that K-means provides clusters that are the most compact in nature. This helps in portfolio diversification as the inter cluster distance is the highest (S.R. Nanda, 2010). Henkam et al. in their research utilise the k-means clustering algorithm as a combination with GARCH C-vine copula model to yield a model which anoints stablecoins as good portfolio diversifiers. They achieve this by first using K-means to obtain clusters from 100 different cryptocurrencies based on their price movement. Of this, 8 different cryptocurrencies with different risk to return characteristics are chosen. The resultant diversified portfolio has stablecoins to provide downside protection while also giving CVaR levels of around 70%. This means that they can provide safe haven to cryptocurrency investors in a time of market turmoil (Herve M. Tenkam, 2022). Hamzh Al Rubaie uses K-means to perform price movement prediction. He starts by calculating various technical indicators like RSI, MACD, Bollinger Bands and Ichimoku Cloud as the choice of technical indicator. He preprocesses the technical indicator values and uses them as input for the k-means clustering algorithm. The resultant clusters are separated into groups having similar technical indicator characteristics. He postulates that the clusters represent different market conditions like oversold/overbought or uptrend/downtrend. The strategy when back-tested shows an accuracy of 90-93% for predicting short term trend (Rubaie, 2019). Chiang et al. use K-means clustering to cluster stocks from the S&P 500 together based on their volatility. They classified the stock clusters into high, medium and low volatility. LSTM is then used to forecast the market volatility for each day. Based on the expected volatility, the weight of the clusters is adapted. That is, in high volatility conditions, the algorithm increases the weightage to stocks in the low volatility clusters. Similarly, in lower volatility conditions, the algorithm increases the weightage to stocks in the high volatility clusters. The adaptive clustering algorithm showed an increase in return compared to the buy and hold strategy on the S&P 500 (David Enke, 2016).

3.10 Use of LSTM in Cryptocurrency Market:

There has been significant interest in Long Short-Term Memory models in relation to predicting stock prices. There are a huge number of studies showcasing the effectiveness of various LSTM models for predicting market trends and for aiding trading decisions (Wu, et al., 2018) (Chao Zhong, 2023). Unlike the traditional feedforward, having feedback connections enables LSTM based models to learn sequential or temporal dependencies in time series data and thus making them suitable for stock price prediction (Felix Gers, 2000). Considering the complex and non-linear nature of the stock market, research has been done to utilise historic data, technical indicators and the implementation of risk management strategies to help in making profitable trading decisions. Having a robust risk management strategy can sometimes offset the low accuracy rate obtained by machine learning algorithms (Silva, et al., 2020). There's research showing LSTM performing better than other models like ARIMA models (Ebru Seyma Karakoyum, 2018) and support vector regression (SVR) (Bathla, 2020).

LSTM have been used in a variety of ways for stock predicting:

- Predicting stock movements: The most common use of LSTM is to predict stock prices. These predictions can be useful in guiding stock trading decisions (David M. Q. Nelson, 2017).
- Algorithmic Trading Strategies: The prediction power of LSTM can be used to generate buy and sell signals so that an automated trading algorithm can capitalise of price movements (Christopher Krauss, 2017).
- Sentiment Analysis: LSTM as a part of Listening to Chaotic Whispers (LTCW) can be used to analyse public sentiment or news regarding a certain asset and thus influence buy or sell decisions in trading (Ziniu Hu, 2018).
- High frequency trading: Yao et al. have concluded in their paper that the result obtained by LSTM prediction outperformed those achieved by random prediction (Siyu Yao & Peng, 2018).
- While considering a volatile asset like cryptocurrency, it is important to understand what kind of data and features are being used as an input. Tran et al. in their research saw that fewer features helped in creating an LSTM model that had the best MSE and Mean Percentage Error while predicting bitcoin prices. Additionally, it was seen that past historic data that went too far back acted as noise. The optimum data utilised for this purpose was found to be of 1 month (Phoebe Tran, 2022).

3.11 Mean Variance Portfolio Optimisation:

Mean Variance Optimisation or MVO, discovered by Markowitz in 1952 has widely been used to create diverse portfolios for financial markets. It has been accepted as providing the base for portfolio allocation methods. It provides a framework to create a trade-off between risk and reward while optimising the diversification benefits it provides (Jang Ho Kim, 2021). Ever since its inception, there have been various modifications in the mean variance optimisation methodology to help improve its efficiency. Introduction of various machine learning algorithms have been seen to boost its efficiency. Using XGBoost to help select some stocks before using the MVO to apply weights to them, has seen to improve returns in some stock markets (Wei Chen, 2021). The MVO and its weight assigning characteristics was initially rightly expected to face issues with markets that have low liquidity. Researchers tried to have a look at this hypothesis by trying it out on the Columbian stock exchange. From this result, they found that the MVO fared satisfactorily in the Columbian market. However, trying to reduce the risk below a certain level led to a massive reduction in the corresponding rewards. The researchers conclude that the MVO can give only satisfactory results where there in a reduced number of security or assets available. They suggest diversifying the markets to increase the number of assets available for investing (Fernando García, 2015).

Chapter 4: Problem Statement:

The literature papers reviewed above show us that various approaches like LSTM, MVO, technical indicators and trading strategies like mean reversion and momentum trading have been applied to various types of financial markets, including cryptocurrencies. However, there is still an evident gap in applying these techniques in a composite layered format while placing emphasis on the risk reward ratio and the corresponding costs incurred with the ultimate aim to enhance profits in the cryptocurrency markets. Moreover, exploring the performance of various trading strategies remains unexplored.

Aims and Objectives:

The aim of this project is to evaluate whether a profitable rules-based trading algorithm can be created for the cryptocurrency market using Binance.

Objectives:

- To evaluate the design and implementation of a profitable investment or trading strategy while minimising risks.
- To investigate the impact of the change in volatility due to change in time frames on the success ratio of the strategy.
- To assess the efficacy of various technical indicators on price movements.
- To check the feasibility of a contrarian approach to trading
- To analyse the impact of a machine learning algorithm on the outcome of the strategy.

Chapter 5: Data and Pre-processing:

5.1 Data Source Justification:

Selection of platform: There are multiple platforms available for trading cryptocurrencies. However, Binance as a platform and as an exchange trumps the other platform for various reasons. Firstly, the trading fees is among the lowest. Additionally, there are no fees for historic data collection using their API. Their API is very well documented. Binance has hundreds of coins listed on their platform. This provides more trading/investment opportunities. Binance also boasts of a global user base and is therefore less stringent than its counterparts. Coinbase on the other hand, which is a strong competitor to Binance, is focussed on having a largely US centric clientele. It has an additional requirement of having an SSN. Thus, with its proven track record and the features listed above, Binance helps instil confidence in its API users.

5.2 Data Description and Preparation:

For the ease of understanding, this topic would be divided into 2 parts - the investment section and the trading section.

The datasets for the investment part as well as the trading part are both timeseries in nature.

5.2.1 Investment:

5.2.1.1 Data Structure:

For the investment section of this project, the dataset utilised had the daily closing prices for a period of 1 year. There were 3 different datasets, each for different date ranges. The first column for each of these datasets had the date followed by 350+ columns containing cryptocurrency names on the top row followed by their respective close prices in subsequent rows.

	A	B	C	D	E	F	G	H
1	Date	BTCUSDT	ETHUSDT	BNBUSDT	NEOUSDT	LTCUSDT	QTUMUSD	ADAUSDT
2	10-08-2022	23954.05	1853.57	328.8	11.69	61.59	4.194	0.5374
3	11-08-2022	23934.39	1880.19	323.6	11.72	61.84	4.207	0.5303
4	12-08-2022	24403.68	1958.28	327.9	12.03	62.88	4.289	0.5402
5	13-08-2022	24441.38	1983.55	324.3	12	63.8	4.287	0.5593
6	14-08-2022	24305.24	1935.31	317.6	11.5	63.14	4.166	0.5695
7	15-08-2022	24094.82	1899.06	319.5	11.28	60.67	4.097	0.5499
8	16-08-2022	23854.74	1876.67	316.1	11.16	61.33	4.013	0.557

Figure 1 Investment Dataset

Figure 1 contains a snippet of one of the investment datasets.

5.2.1.2 Selection Criteria:

All these cryptocurrencies are traded against tether or USDT to generalise their value.

5.2.1.3 Data Preprocessing:

Some of these datasets are missing values for some days for some cryptocurrencies. This is because the overall cryptocurrency market is very volatile in nature. As cryptocurrencies are unregulated, they keep getting listed and delisted without prior notice. Thus, certain cryptocurrencies exist in certain datasets and are missing in others. To deal with datasets with some cryptocurrencies that aren't mainstream and thus missing some values, we directly drop columns having null values. This helps in removing any cryptocurrencies that don't exist for the entirety of that dataset.

5.2.1.4 Data Limitations:

- Choosing cryptocurrencies traded against only USDT leads to other cryptocurrency pairs being ignored during this project. Meaning, for example, bitcoin might not have performed well against the USDT during a given period. However, it might have performed well against another cryptocurrency like Ethereum. Meaning BTCETH would have been a better investment recommendation compared to BTCUSDT in this scenario.
- There is a limited amount of data available through the Binance API during one code request. Due to this reason, there was a need to collect data for 3 consecutive years in 3 different annual intervals. However, these datasets cannot be combined to create one 3-year dataset as there are multiple cryptocurrencies missing in atleast one of the datasets that have a full year's worth of data in atleast another dataset.
- Additionally, the deletion of a partial cryptocurrency data can introduce survivors bias in the recommendation. Since each dataset is divided into train and test dataset, there is a chance that a cryptocurrency might exist throughout the train dataset and might have been delisted in the test part of dataset. Thus, the threat of a cryptocurrency that gets delisted in the train dataset getting recommended is removed and may give unfair success bias to the strategy.

5.2.2 Trading:

5.2.2.1 Data Structure:

For the trading part, the dataset used are classified into 3 parts depending on the time intervals of the data it contains. The three time periods used are 5mins, 15mins and 1hour. Each dataset has been collected for a period of 5 years. Apart from the usual Open Time, Open, High, Low, Close and Volume, the data obtained also contains 'Quote Asset Volume', 'Number of Trades', 'Taker Buy Base Asset Volume' and 'Taker Buy Quote Asset Volume'. It is shown in Fig(b). The Quote Asset Volume refers to the total volume of the 'Quote asset' that is traded. Quote asset is the second asset of the pair. E.g. It is USDT in a BTC/USDT pair. 'Number of trades' specify the number of trades within that given time period. 'Taker Buy Base Asset Volume' is the amount of base asset (or BTC in the above example) purchased at market price. This shows buying momentum. Similarly, the 'Taken Buy Quote Asset Volume' is the amount of quote asset purchased at market price. This shows a selling momentum.

However, it is important to note that only the columns Open time, Open, High, Low and Close columns are used in this paper.

Open Time	Open	High	Low	Close	Volume	Quote Ass	Number of	Taker Buy	Taker Buy
01-07-2020 0.00	9138.08	9138.16	9080.1	9122	1737.642	15831395	17535	752.8015	6859354
01-07-2020 1.00	9121.99	9131.73	9101	9125	792.5112	7226390	10046	363.7297	3316753
01-07-2020 2.00	9125	9146.67	9112.87	9135.11	1075.679	9827406	12986	562.6958	5140847
01-07-2020 3.00	9135.1	9141.66	9113.11	9138.59	672.2818	6137850	9955	315.3282	2879170
01-07-2020 4.00	9138.55	9162.85	9138.17	9147.3	1116.286	10215681	12751	643.4008	5888155

Figure 2 Trading Dataset

Figure 2 contains a snippet of one of the hourly trading datasets.

5.2.2.2 Selection Criteria:

BTCUSDT is the cryptocurrency of choice for the trading part.

5.2.2.3 Data Preprocessing:

It is a clean dataset without any null values. However, it doesn't contain indicators like RSI, moving averages and Bollinger Bands. They had to be calculated for their respective methodologies.

5.2.2.4 Data Limitations:

One major concern for the performance of the trading algorithm is the assumption that the orders get filled at the required price. However, that is not realistic even when trading BTCUSDT. Inspite of BTCUSDT being the largest traded cryptocurrency pair, it has its high and low volume phases. Even though price has been seen to reach a particular level, it doesn't mean that the entire order may have been fulfilled there. This gives rise to slippages. Slippages aren't taken into account in this paper.

Chapter 6: Methodology:

6.1 Software and Libraries:

The software utilised for this report is anaconda for python programming. The libraries utilised in the various codes here are Pandas, Matplotlib, NumPy, Keras, Sklearn, SciPy, Mpl_toolkits for the code. Additionally, the Binance library is needed to access the API to download data.

6.2 Evaluation Matrix:

BTCUSDT is selected as the buy and hold choice to judge the performance of any investment or trading strategy for multiple reasons. Some of them are listed below:

- Being the first cryptocurrency, it provides a benchmark performance which is considered to be the gold standard to compare your strategies' returns against.
- It is considered to have a comparatively lower risk as it has the cryptocurrency investor's trust.
- It is very liquid, meaning chances of filling orders are the highest at a given price.
- Considering that it has a very high trading volume, it has a high amount of historical data which is available for analysis and backtesting.

6.3 Investment Strategy: K-means + Mean Variance Optimisation Strategy:

Objective: The main aim of this part of the project was to construct a cryptocurrency portfolio that places emphasis on minimising tail risk and maximising the return to risk reward. To achieve this, the strategy sees the integration of the k-means clustering algorithm along with mean variance portfolio optimisation method.

Dataset: This study will utilise the different annual datasets having daily close prices. This is to generalise the performance and robustness of the strategy. Following the preprocessing steps, the datasets are divided into two parts – the train and test data each having 6 months each. The test data will be helpful in visualising the performance of the recommended portfolio.

K-means Clustering:

The k-means clustering is used to segregate the cryptocurrencies based on three metrics:

- Mean returns
- Volatility
- Average Lowest 5% returns (or tail risk)

```
# Calculating the Lowest_5% returns
average_values = {}
for column in returns.columns:
    column_sorted = returns[column].sort_values()
    threshold_index = int(len(column_sorted) * 0.05)
    threshold_value = column_sorted.iloc[threshold_index]
    lowest_5_percent = column_sorted[column_sorted <= threshold_value]
    average_values[column] = lowest_5_percent.mean()

features['Lowest_5%'] = features.index.map(average_values)
```

Figure 3 Calculating the Tail risk

The mean of the returns will help finding out the expected returns. The volatility is the standard deviation of the returns and explains how far the price could deviate from its mean returns. The Average lowest 5% returns is used to identify the tail risk. This basically means how low the asset has previously been. It is also known as the tail risk. The tail risk calculation is shown in Figure 3. The higher the average lowest 5% returns value is, the lower is the drawdown on a particular asset.

The elbow method is used to determine the optimal number of clusters for all three datasets.

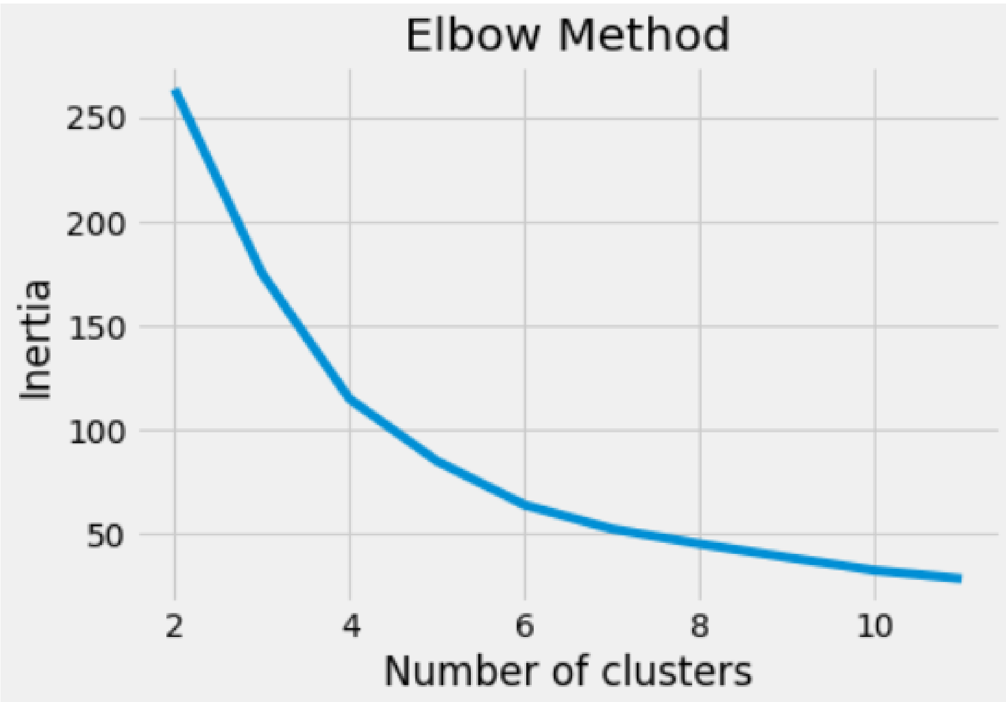


Figure 4 The Elbow Method

Figure 4 is an example of the results for one of the datasets when it’s metrics are passed through the elbow method code. Based on this, the optimum number of clusters is chosen to be 4 for this dataset. The input parameters are then scaled to generalise their value and to make sure that none of the parametric values get undue advantage. They are then plotted using matplotlib library.

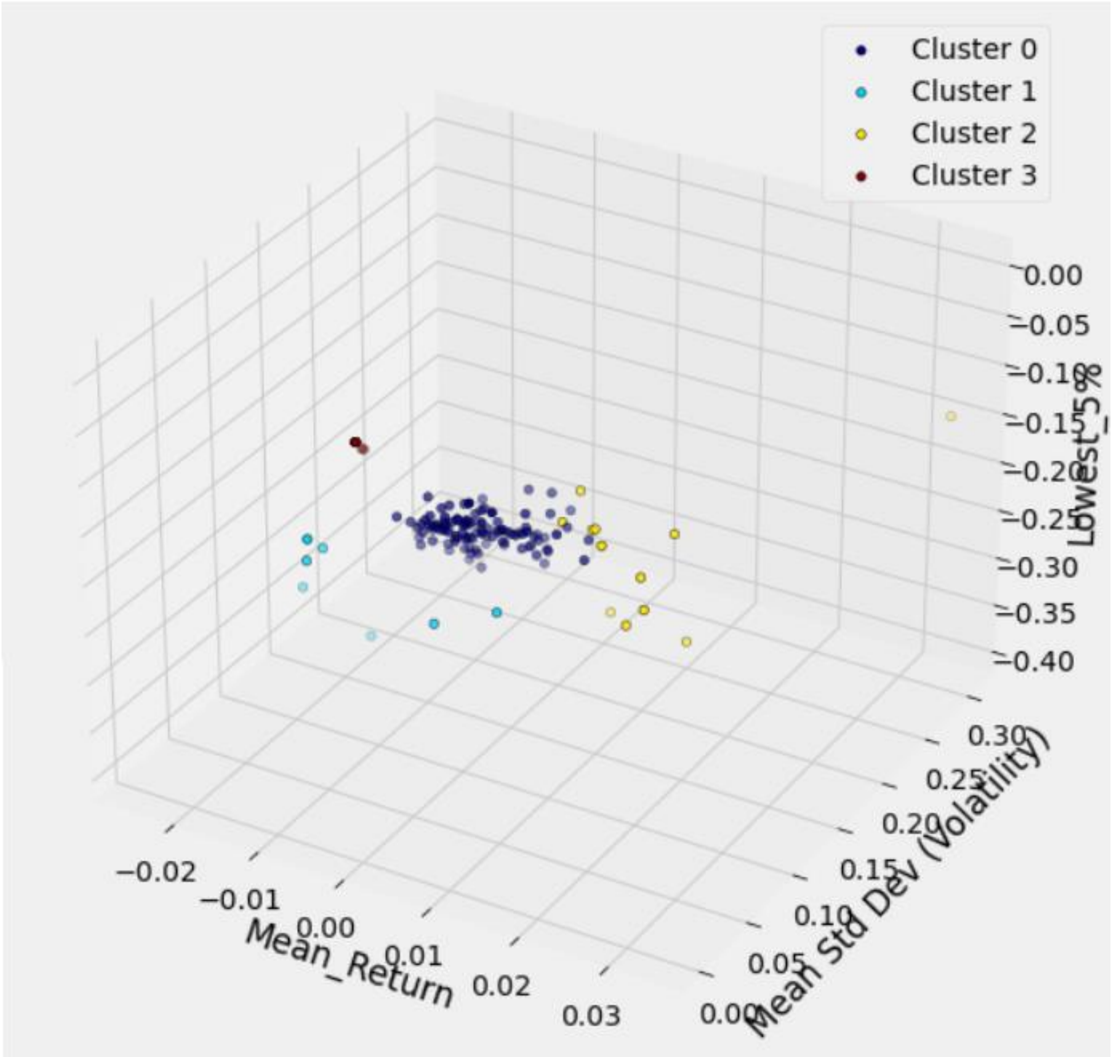


Figure 5 Plotting the clusters in 3D

Figure 5 Shows the datapoints divided into different clusters and plotted on the 3D-graph.

```
In [39]: optimal_cluster = cluster_stats.loc[
             (cluster_stats['Lowest_5%'].idxmax()), 'Cluster']
```

Figure 6 Cluster Selection

The cluster with the highest average lowest 5% returns is chosen as the optimal cluster as shown in Figure 6. The members of this cluster are then passed through the mean variance optimisation algorithm.

Mean Variance Optimisation:

The main objective of using MVO is to maximise the risk adjusted returns based on historic performance. It does this by finding best portfolio weights that will help in maximising the Sharpe ratio obtained.

Statistical Measures: The daily returns and its mean are carried on from the K-means part. We then calculate the covariance matrix. The mean of the returns helps in determining the expected returns of an asset. The expected returns of assets when weighted by their individual portfolio weights help in providing us with the expected returns of the portfolio. The covariance matrix on the other hand helps in managing the risk of the portfolio by diversifying it. It does this by first creating a covariance matrix that calculates the similarity of movement between two cryptocurrencies. The more the cryptocurrencies differ from each other, the more they help in creating a diverse portfolio. In other words, it's not just the risk of an individual asset that helps determine the risk of a portfolio but their movement in relation to each other. This is calculated by covariance.

Objective Function – Sharpe Ratio:

The Sharpe ratio is used here to help obtain the risk adjusted returns. It is the ratio of the difference between 'expected return of the portfolio' and the 'risk-free return' to the 'standard deviation of the portfolio'. The annual risk-free rate here is taken to be 0.148. The annual risk-free rate considered for the MVO algorithm is the highest returns the investor can obtain without any risk. The investment returns obtained from treasury bonds can generally be considered as a measure of risk-free returns. However, it is a little complicated for cryptocurrencies. This is because any general example of obtainable yield taken into consideration might prove to be too small and negligible compared to the rewards generated by cryptocurrencies. Thus, for the purpose of this report, the risk-free rate is considered to be the annual returns of 14.8% on a stablecoin offered by Binance (Binance-Team, 2020).

```
In [46]: # Optimal asset weights
         optimal_weights = pd.Series(filtered_solution.x, index=filtered_optimal_weights.index)
```

```
In [47]: # Calculate the portfolio returns for the test period
         test_returns = test_data[filtered_optimal_weights.index].pct_change().dropna()
         portfolio_test_returns = (filtered_optimal_weights * test_returns).sum(axis=1)

         # Get the initial price of BTCUSDT
         initial_btc_price = test_data['BTCUSDT'].iloc[0]

         # Align the first return to be zero
         portfolio_test_returns.iloc[0] = 0
         btc_test_returns = test_data['BTCUSDT'].pct_change().dropna()
         btc_test_returns.iloc[0] = 0

         # Calculate the scaled returns
         scaled_portfolio_returns = (1 + portfolio_test_returns).cumprod() * initial_btc_price
         scaled_btc_returns = (1 + btc_test_returns).cumprod() * initial_btc_price
```

Figure 7 Performance Calculation

```python
In [48]: # Function to calculate drawdowns
def calculate_drawdowns(return_series):
    # Calculate the running maximum
    running_max = return_series.cummax()
    # Ensure the value never drops below the initial capital
    running_max[running_max < return_series.iloc[0]] = return_series.iloc[0]
    # Calculate the percentage drawdown
    drawdown = (return_series / running_max) - 1
    return drawdown

# Calculating drawdowns for portfolio and BTCUSDT
portfolio_drawdown = calculate_drawdowns(scaled_portfolio_returns)
btcusdt_drawdown = calculate_drawdowns(scaled_btc_returns)

# Calculating max drawdowns in percentages for portfolio and BTCUSDT
max_drawdown_portfolio = portfolio_drawdown.min() * 100
max_drawdown_btcusdt = btcusdt_drawdown.min() * 100

# Calculate the Sharpe ratio for both series
# Assuming daily risk-free rate same as before
portfolio_sharpe_ratio = (portfolio_test_returns.mean() - daily_rf_rate) / portfolio_test_returns.std()
btcusdt_sharpe_ratio = (btc_test_returns.mean() - daily_rf_rate) / btc_test_returns.std()
```

Figure 8 Maximum Drawdown

The MVO algorithm provides weights for different cryptocurrencies in the clusters based on its Sharpe ratio. We apply a threshold to the weights to obtain a smaller number of cryptocurrencies as we would like to avoid investment in a large number of cryptocurrencies. The coins obtained after application of threshold are then passed through the MVO for a second round to reallocate weights to them. This then results in the optimal portfolio with its optimal weights. The weight is the percentage of the capital to be allotted to a particular cryptocurrency. The calculation to show the performance of the optimised portfolio in comparison to BTCUSDT is shown in Figure 7. The calculation of the drawdown of both the portfolio and BTCUSDT is given in Figure 8.

6.4 Trading:

Objective: The main objective of this part is to see what trading styles can be used to obtain profits in trading cryptocurrencies over various timeframes. We also aim to see what kind of impact the very popular machine learning algorithm LSTM has on a trading style.

Datasets: The datasets used are of 3 different timeframes, namely, 5mins for the scalping trader, 15mins for intraday trader and hourly for the swing type trader. All datasets are for a period of 5 years.

6.4.1 Mean Reversion Trading Style:

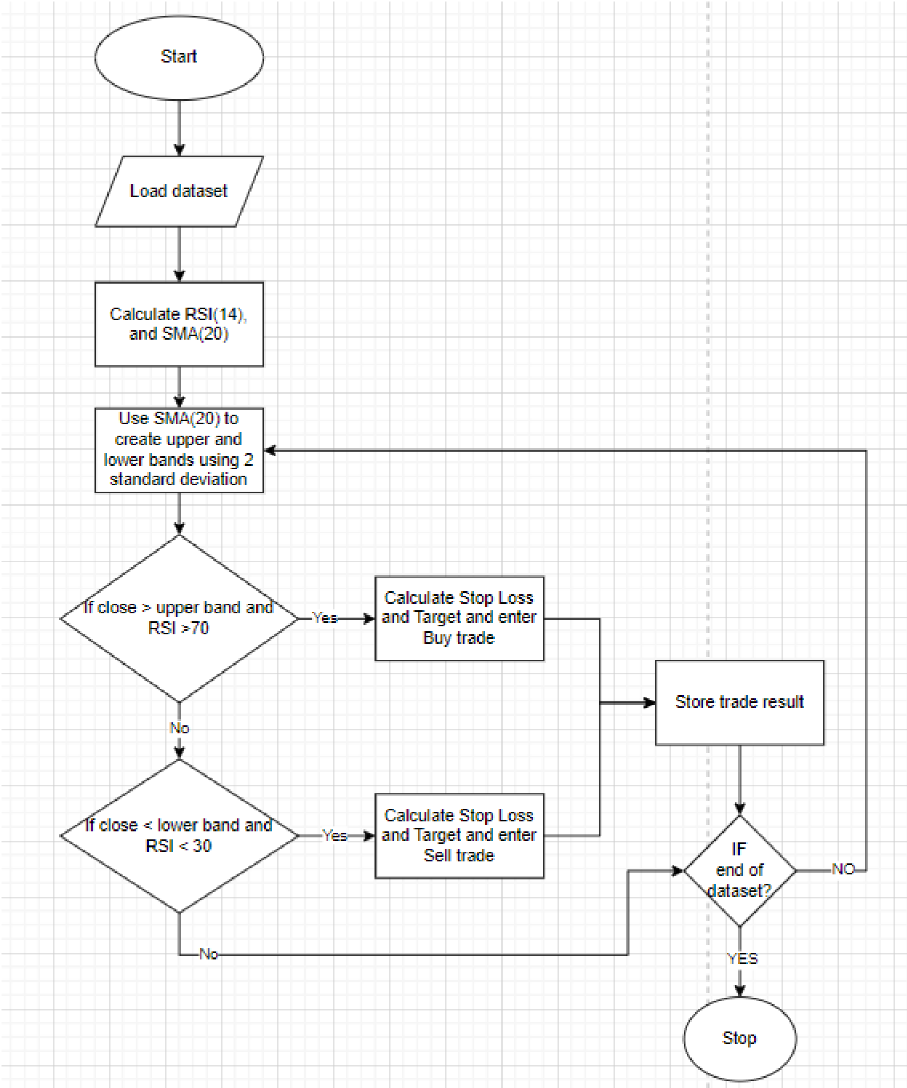


Figure 9 Mean Reversion Flowchart

The Figure 9 shows a flowchart of the mean reversion strategy that has been employed.

```
if position == 0:
    if close < lower_band and rsi < 30 and prev_rsi >= 30:
        entry_price = close
        position = 1
        stop_loss = entry_price * 0.95  #5% stop loss
        target = entry_price + (entry_price-stop_loss)
        num_trades += 1
    elif close > upper_band and rsi > 70 and prev_rsi <= 70:
        entry_price = close
        position = -1
        stop_loss = entry_price * 1.05  #5% stop loss
        target = entry_price - (stop_loss-entry_price)
        num_trades += 1
```

Figure 10 Implementation Of Mean Reversion

```python
def calculate_drawdowns(return_series):
    running_max = return_series.cummax()
    running_max[running_max < return_series.iloc[0]] = return_series.iloc[0]
    drawdown = (return_series / running_max) - 1
    return drawdown

def calculate_max_drawdown(drawdown_series):
    return drawdown_series.min() * 100  # returns max drawdown in percentage
```

Figure 11 Calculation of Drawdowns and Max Drawdowns

Strategy: A very commonly used strategy that utilises two technical oscillators like Bollinger Bands and RSI. The strategy involves the short selling of BTCUSDT when price closes above the upper Bollinger band and its corresponding RSI value is above 70. Similarly, when the price closes below the lower Bollinger band and the value of RSI is below 30, we go long on the asset. This strategy has been implemented in Figure 10. The stop loss and target are fixed at 5% of the entry price. The trade results are then stored in a dataframe. Figure 11 shows the calculation of drawdowns of both the strategy and BTCUSDT. The max drawdown has been calculated as well.

6.3.2 Momentum Trading Style:

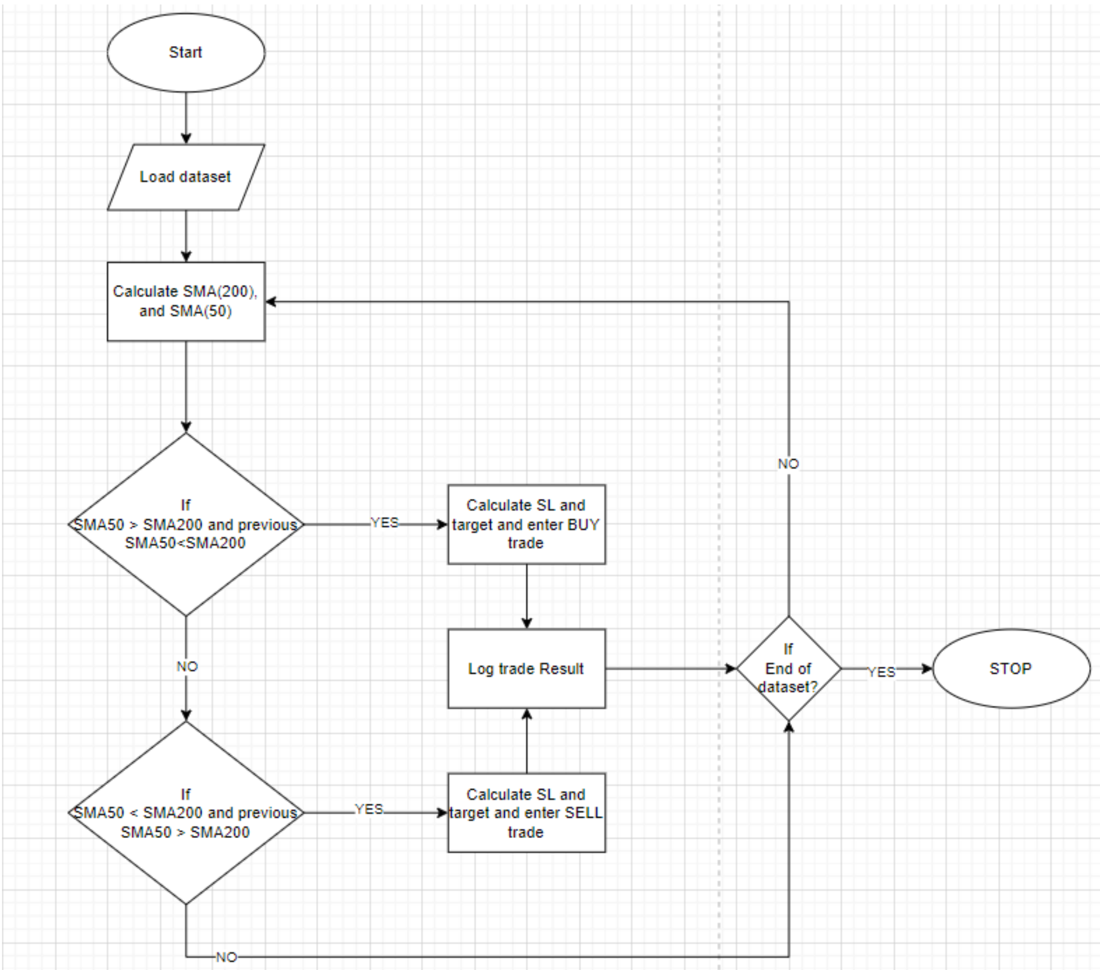


Figure 12 Momentum Trading Flowchart

Figure 12 above shows a flowchart depicting a very commonly used momentum type of trading strategy. It starts by the calculation of two simple moving averages of 50 period and 200 period respectively. When the current value of 50 SMA is above the current value of the 200 SMA and the previous value of the 50 SMA is below the previous value of the 200 SMA, it signifies a buy signal. This is done to signify a crossover and to avoid getting into trades based solely on the 50 SMA being above the 200 SMA. This is also known as golden cross. Alternatively, when the current value of 50 SMA is below the current value of the 200 SMA and the previous value of the 50 SMA is above the previous value of the 200 SMA, we enter a short selling trade. This is famously known as the death cross.

```
if position == 0:
    if short_ma > long_ma and prev_short_ma <= prev_long_ma:
        risk_per_trade = 0.03 * capital
        entry_price = close
        position = 1
        stop_loss = entry_price * 0.95
        target = entry_price + (entry_price-stop_loss)
        num_trades += 1

    elif short_ma < long_ma and prev_short_ma >= prev_long_ma:
        risk_per_trade = 0.03 * capital
        entry_price = close
        position = -1
        stop_loss = entry_price * 1.05
        target = entry_price - (stop_loss-entry_price)
        num_trades += 1
```

Figure 13 Implementation of Momentum Trading Strategy

Figure 13 shows the implementation of the strategy in code. The trades and their corresponding results are finally logged in a dataframe. The drawdowns and max drawdowns are calculated and plotted to showcase the risk of the trading system compared to the buy and hold of BTCUSDT similar to Figure 11.

6.4.3 Contrarian Trading Style:

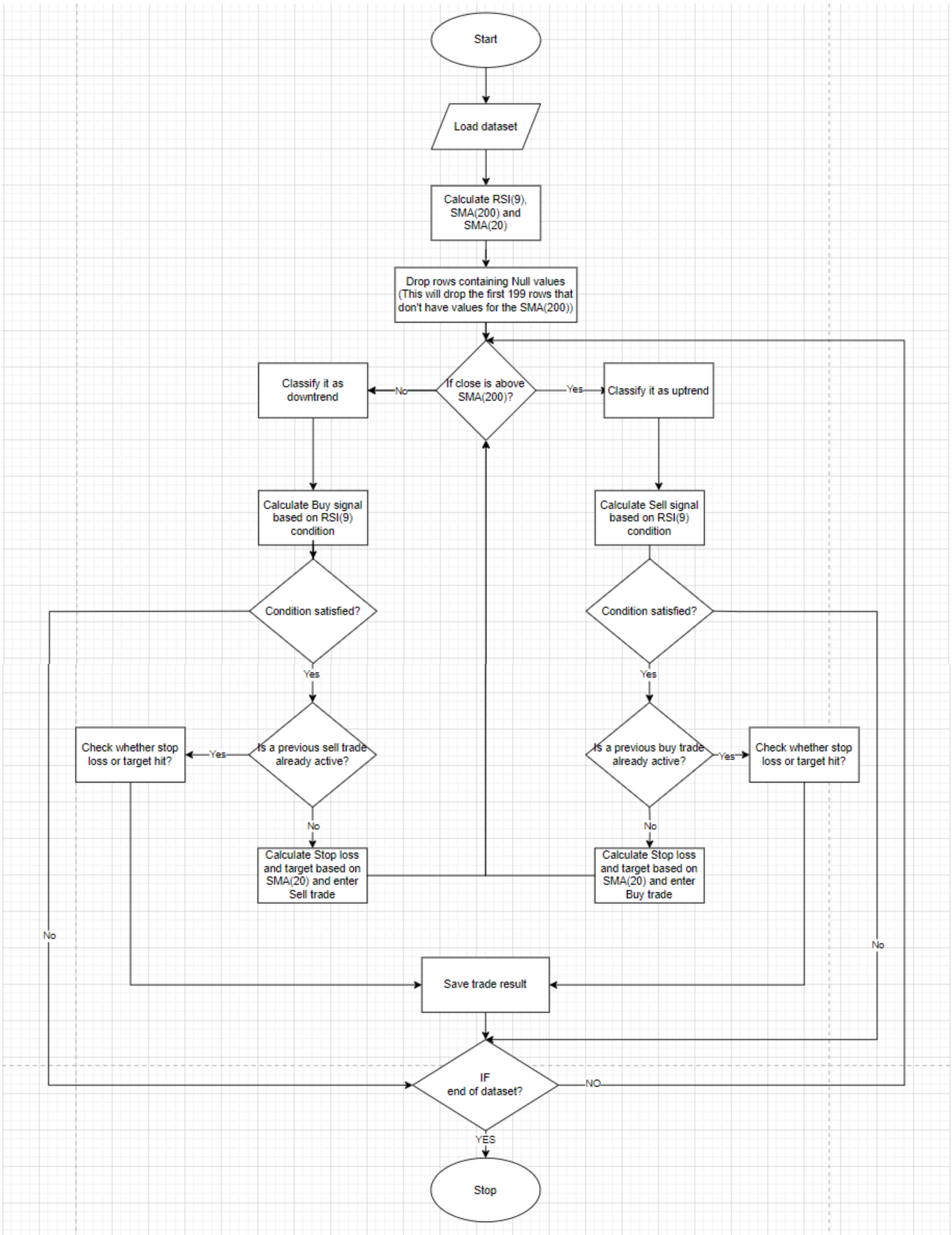


Figure 14 Contrarian Strategy Flowchart

Figure 14 depicts the contrarian trading strategy. This strategy incorporates the use of 200 SMA, RSI and Bollinger bands. However, the parameters for calculating the RSI are a bit different. Firstly, the RSI is calculated over 9 periods. This is done to increase its sensitivity to price changes. To counter noise being classified as signals, the overbought zone and oversold zone are changed to 80 and 20 respectively. This makes it difficult for the price to trigger a trade. It counteracts the reduction of RSI period. The upper band and lower band for the Bollinger band are changed to 1.5 times the standard deviation above and below the 20 SMA respectively. This helps in calculating stoplosses based on the modified Bollinger Band.

Optimisation of code: The initial code from the previous methodology used to calculate indicators by calling their respective functions while accessing a particular row. This methodology took too long to run datasets for this strategy. To optimise this and to increase the speed of backtest, a novel flag system was developed incorporated in the code. This system as shown in Figure 15, calculates the values for the indicators and important levels before starting the iteration of the dataset.

```
#Calculate RSI, SMAs, Signals, Stop Loss, and Targets
dataset["RSI"] = calculate_rsi(dataset)
dataset["200_SMA"] = calculate_sma(dataset)
dataset["20SMA-SL"] = calculate_sma_SL(dataset)

#Drop the first 200 rows as there will be Null values for 200_SMA
dataset = dataset.dropna()

#Flag for uptrend and downtrend
dataset["Uptrend"] = dataset["Close"] > dataset["200_SMA"]
dataset["Downtrend"] = dataset["Close"] < dataset["200_SMA"]

#Calculating Buy_Signal and Sell_Signal
dataset["Sell_Signal"]=np.where((dataset["Uptrend"] == True)&(dataset["RSI"]>20)&(dataset["RSI"].shift(1)<20), True, False)
dataset["Buy_Signal"] = np.where((dataset["Downtrend"] == True) & (dataset["RSI"]<80)&(dataset["RSI"].shift(1)>80), True, False)

#Calculating the buy stop loss levels
std_dev = dataset["Close"].rolling(window=20).std()
dataset["buy_Stop_Loss"] = dataset["20SMA-SL"] - (1.5 * std_dev)

#Calculating Buy Target
dataset["Buy_Target"] = dataset["Close"] + 1*(dataset["Close"] - dataset["buy_Stop_Loss"])

#Calculating the sell stop loss levels
dataset["sell_Stop_Loss"] = dataset["20SMA-SL"] + (1.5 * std_dev)

#Calculating Sell Target
dataset["Sell_Target"] = dataset["Close"] - 1*(dataset["sell_Stop_Loss"] - dataset["Close"])
```

Figure 15 Implementation of Contrarian Strategy

The implementation of this code has helped in obtaining the same results but at a faster rate.

Strategy: The close of the price, when above the 200 SMA is classified as an uptrend. Similarly, when the price closes below the 200 SMA, it is classified as a downtrend. However, a sell signal is generated when the current value of the RSI is above 20 and the previous value of the RSI is below 20 while the simple moving average signals ‘Uptrend’. The upper band of the Bollinger band is considered to be the stop loss for the trade. The target is calibrated to be equal to the Stoploss points. Similarly, when the current value of RSI is below 80 and the previous value of RSI is above 80 while the SMA signals ‘Downptrend’, we go long on the asset. The stoploss of this trade would be the lower band of the Bollinger band. The target like before would be the equal to the stoploss points. Calculation of the trading system’s performance in comparison to the buy and hold strategy for BTCUSDT in addition to their drawdowns are calculated and displayed similar to Fig 11. The trades and their results are then finally logged in a dataframe.

```
#Calculate the profit for each trade
trade_info_df["Profit"] = np.where(trade_info_df["Trade Result"] == "Stop Loss Hit", -0.031, 0.029)
```

Figure 16 Profit Calculation including 0.1% cost

To improve the robustness of the results, a 0.1% trading cost has been levied in each trade. This is because that is the actual trading fee charged by Binance per trade. Additionally, each trade has been worked in such a way that it risks 3% of the capital. That means the quantity of the asset (BTCUSDT here) will be calculated in such a way that its cost is equal to 3% of the total capital. The levying of 0.1% fee is shown in Figure 16.

6.4.4 The Contrarian Strategy with LSTM:

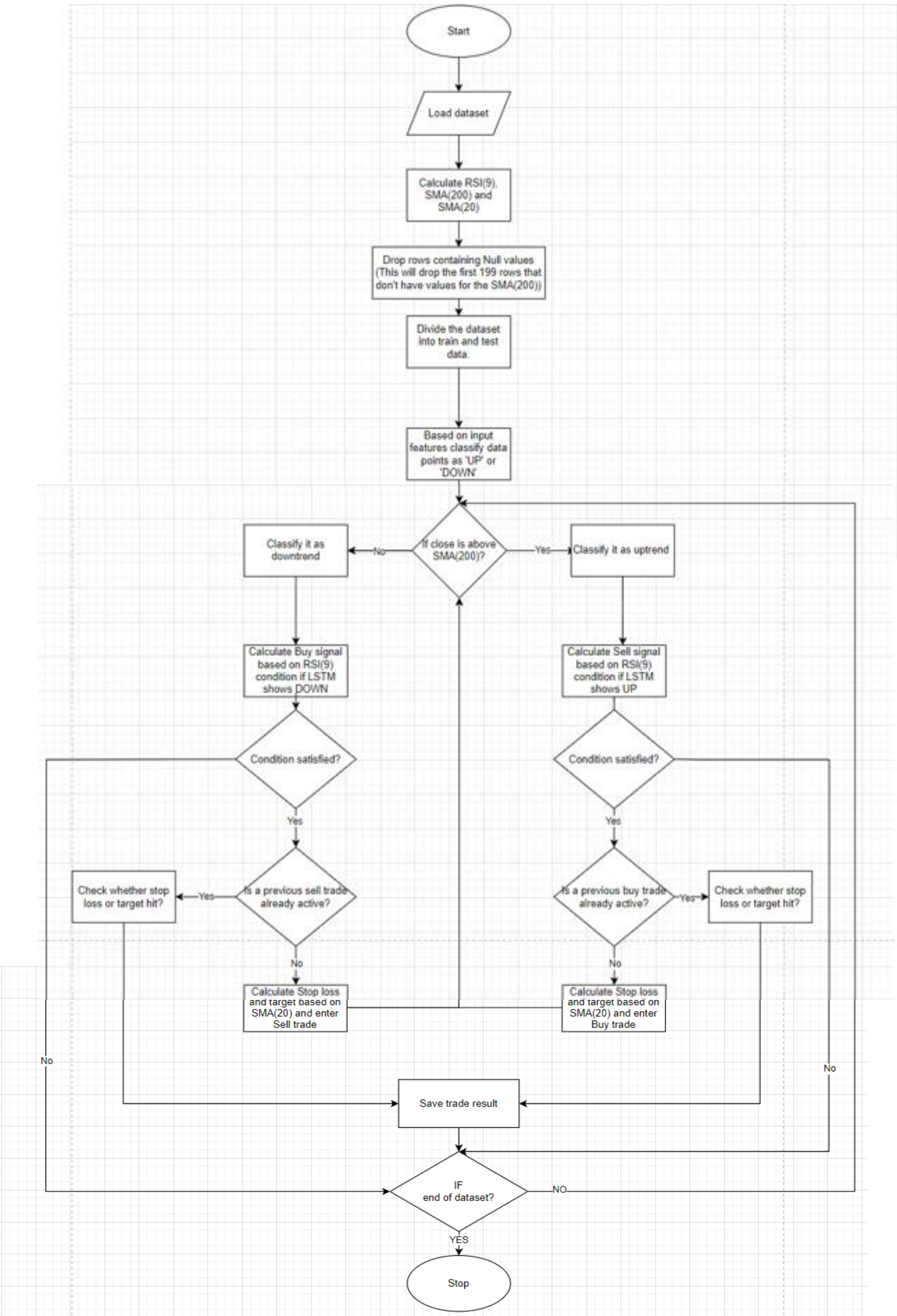


Figure 17 LSTM + Contrarian Strategy Flowchart

Figure 17 depicts a flow chart for the machine learning algorithm LSTM used as a classifier as an additional movement classifier flag for the contrarian trading strategy described above.

The LSTM model:

```
# Define the functions calculating RSI and SMAs
def calculate_rsi(data, period=9):
    # Calculate the price differences (deltas)
    deltas = data['Close'].diff()

    # Calculate the gains and losses- Inputs value as '0' where condition is False
    gains = deltas.where(deltas > 0, 0)
    losses = -deltas.where(deltas < 0, 0)

    # Calculate the average gains and losses over the RSI period
    avg_gain = gains.rolling(window=period, min_periods=1).mean()
    avg_loss = losses.rolling(window=period, min_periods=1).mean()

    # Calculate the Relative Strength (RS) and the Relative Strength Index (RSI)
    rs = avg_gain / avg_loss
    rsi = 100.0 - (100.0 / (1.0 + rs))

    return rsi
```

Figure 18 Calculation of RSI

The LSTM model has been optimised using feature engineering. The values for RSI (as shown in Fig 18), 200 SMA and the close price are calculated and used as input. MinMiaxScaler is used to scale the feature between 0 and 1. The dataset is divided in two parts. 80% of the data is used as the train part of the data and the remaining 20% is used as the test part of the data. The batchsize is maintained at 32. However, changes in the number of epochs doesn't seem to improve the performance of the LSTM model. This could possibly be because the model hasn't been able to find anything useful in the input parameters. The buy and sell signals have the same parameters as that of the contrarian parameters with an addition of the LSTM UP and DOWN flag as shown in Figure 19.

```
predicted_directions = np.where(predicted_close_prices > np.roll(predicted_close_prices, -1).reshape(-1, 1), 1, 0).flatten()
```

Figure 19 LSTM as a Classifier

These have been applied utilising the contrarian approach too. A prediction of the price going up is needed in the sell signal parameter, while the converse is needed for the buy signal. It is important to note that the strategy doesn't permit more than 1 buy or sell trade to exist at one time. This helps in reducing multiple trade entries due to price fluctuations resulting due to noise. The performance of the portfolio compared to the buy and hold of BTCUSDT, and their respective drawdowns are calculated in the same manner as shown in Figure 11. Trading fees and 3% capital per trade cap are applied as shown in Figure 16.

Chapter 7: Results:

After the detailed explanation of the diverse methodologies of trading and investing in the cryptocurrency markets, it is now important to look to the result section to examine the results obtained by them.

7.1 Investment Strategy: K-means + Mean Variance Optimisation Strategy:

7.1.1 Dataset 1: 2020-2021

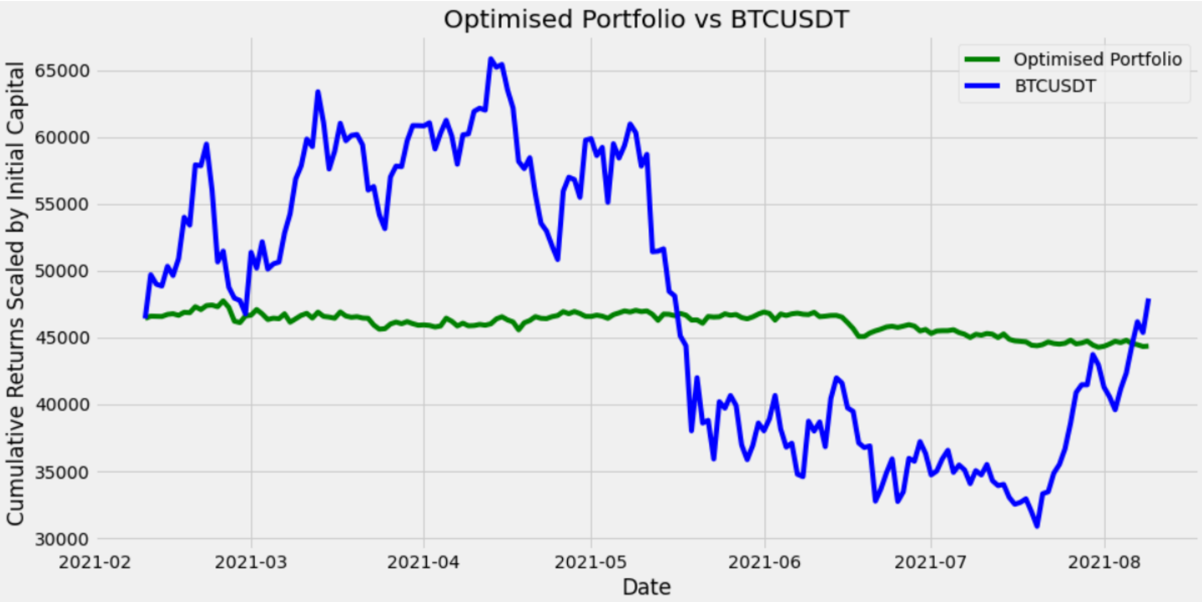


Figure 20 Portfolio Performance Chart Dataset 1

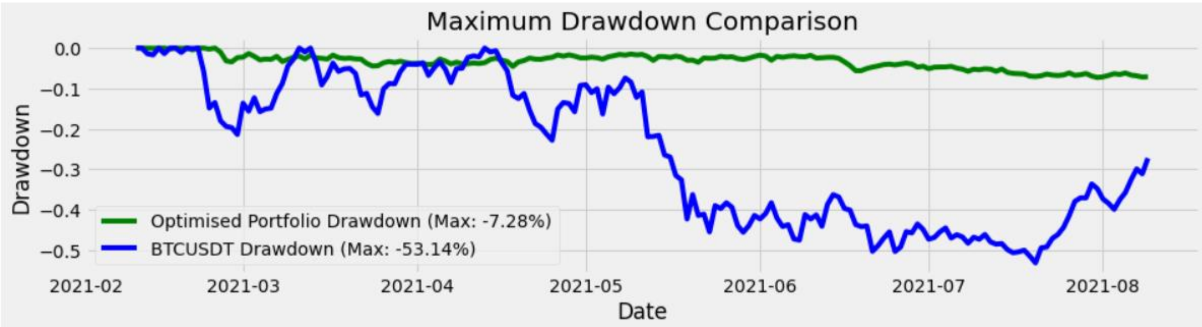


Figure 21 Drawdown Comparison Dataset 1

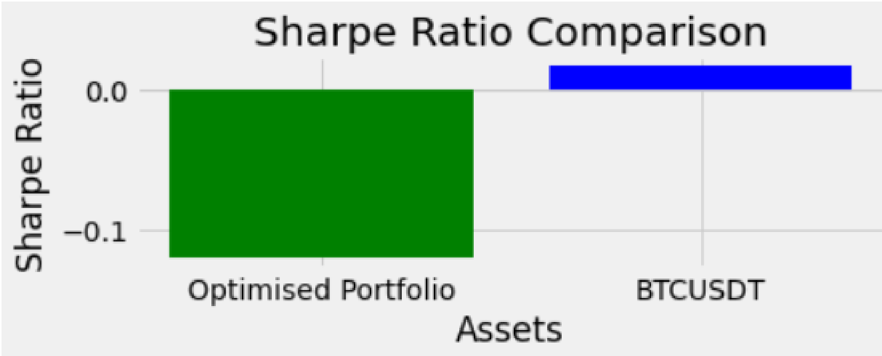


Figure 22 Sharpe Ratio Comparison Dataset 1

For this dataset, the algorithm recommended all weights to be allotted to just 1 cryptocurrency, AUDUSDT.

7.1.2 Dataset 2: 2021-2022

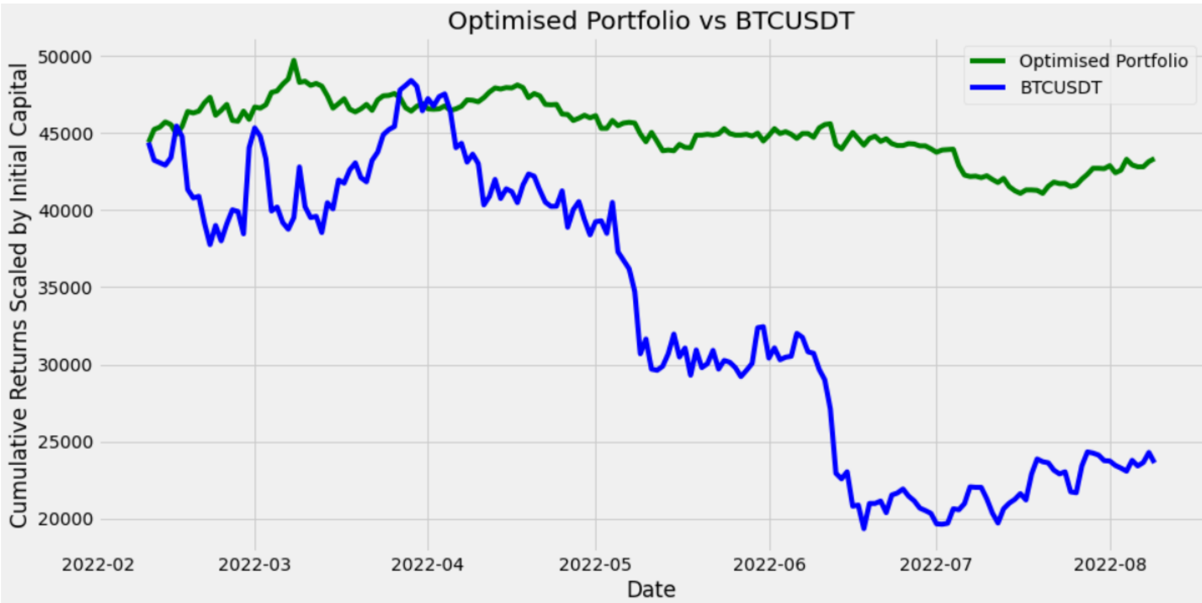


Figure 23 Portfolio Performance Chart Dataset 2

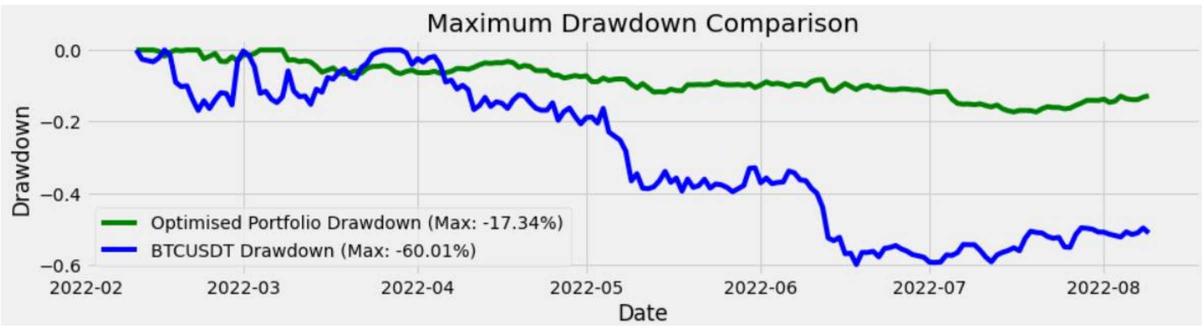


Figure 24 Drawdown Comparison Dataset 2

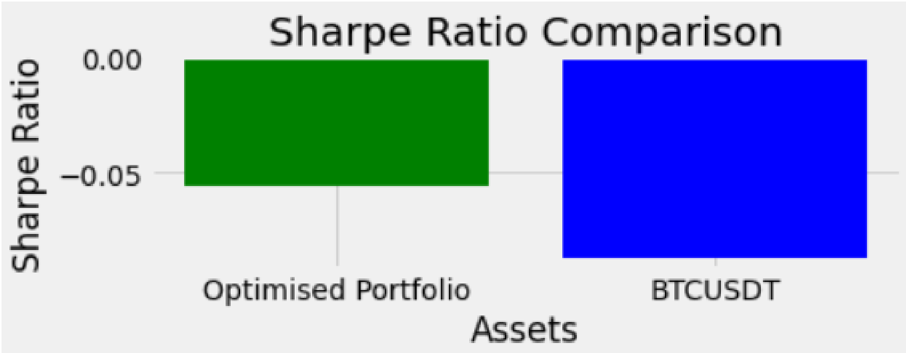


Figure 25 Sharpe Ratio Comparison Dataset 2

Entire capital of the portfolio was allotted to PAXGUSDT.

7.1.3 Dataset 3: 2022-2023

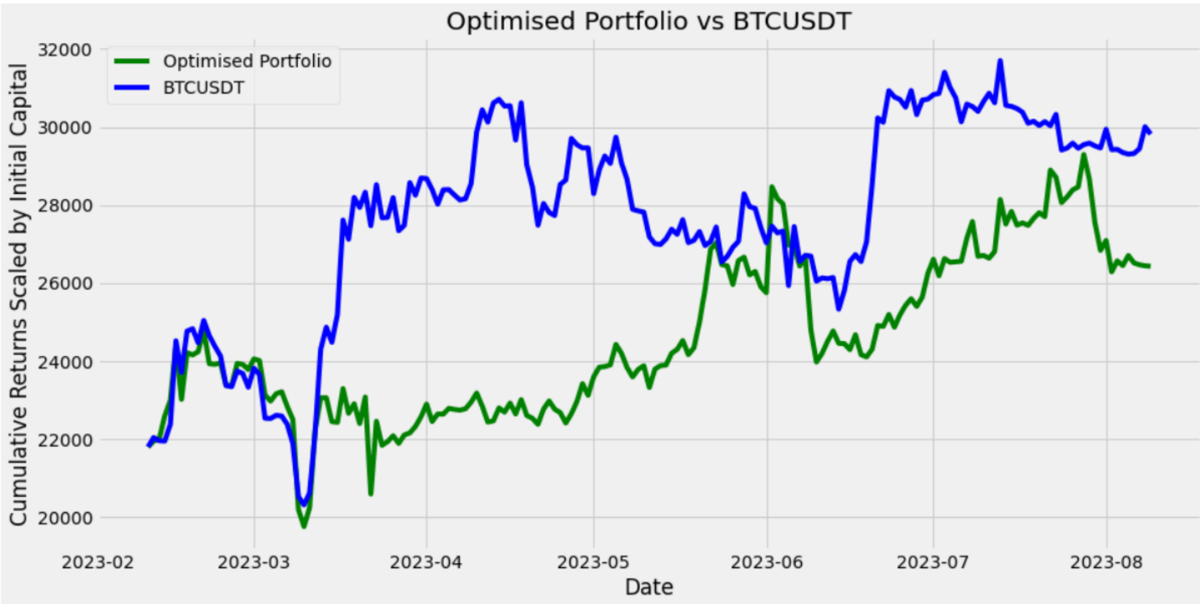


Figure 26 Portfolio Performance Chart Dataset 3

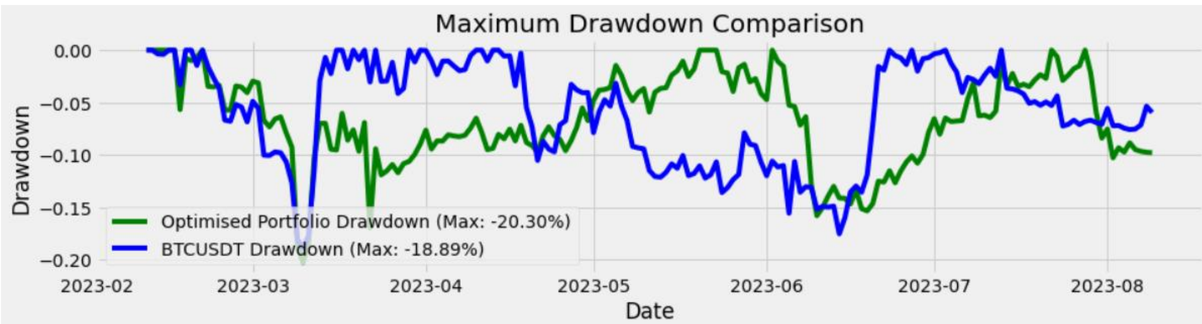


Figure 27 Drawdown Comparison Dataset 3

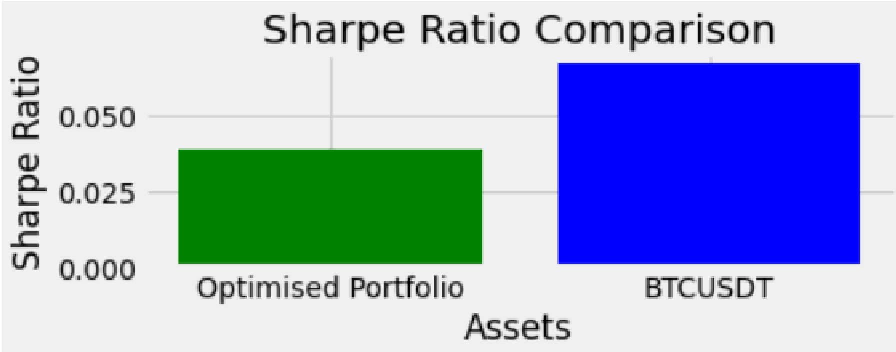


Figure 28 Sharpe Ratio Comparison Dataset 3

The portfolio weights were divided among TRXUSDT, FUNUSDT and GHSTUSDT

Asset	Dataset1		Dataset2		Dataset3	
	Returns	Drawdowns	Returns	Drawdowns	Returns	Drawdowns
Optimised Portfolio	-4.45%	-7.28%	-2.35%	-17.34%	21.25%	-20.30%
BTCUSDT	3.23%	-53.14%	-46.78%	-60.01%	36.79%	-18.89%

Figure 29 Comparison Table 1- Investment Strategy

Overview:

Figure 20, Figure 23 and Figure 26 show the performance of the weighted portfolio of each dataset against the buy and hold position of BTCUSDT. The initial capital of both these positions equal to generalise the results. The performance is for the test time period.

Figure 21, Figure 24 and Figure 27 show the drawdowns of individual datasets against the drawdowns demonstrated by BTCUSDT during the same time period.

Figure 22, Figure 25 and Figure 28 show the Sharpe ratio for the recommended portfolio in comparison to that of BTCUSDT for the same period.

Table 1 shows an overview of the total returns obtained and maximum drawdowns suffered by each recommended portfolio and BTCUSDT for that corresponding period.

Explanation:

By having a look at table 1, we see the optimised portfolio consistently having lower drawdowns compared to the drawdowns shown by BTCUSDT. Dataset1 shows returns mildly negative compared to the mildly positive returns shown by BTCUSDT. Dataset2 shows negative returns very close to zero while those shown by BTCUSDT has an almost 50% loss of investment in that time period. Dataset3 shows positive returns. However, the returns obtained by BTCUSDT are almost 70% more than those obtained by the optimised portfolio during that period. Their corresponding drawdowns is also an interesting phenomenon. The higher the returns by the optimised portfolio, the larger is the returns. But that is not the case for the buy and hold for BTCUSDT. The Sharpe ratio spread for the portfolio in dataset 1 shows consistent underperformance to the risk-free rate. However, the Sharpe ratio of BTCUSDT outperformed the risk-free rate by a very small amount. In dataset2, the Sharpe ratio spread shown by both BTCUSDT and the optimised portfolio underperform the risk-free rate. However, the optimised portfolio's Sharpe ratio is still better than that of BTCUSDT. The Sharpe ratio of dataset3 for both BTCUSDT and the optimised portfolio consistently outperforms the risk-free rate. However, BTCUSDT has outperformed the portfolio in terms of Sharpe ratio.

7.2 Trading:

7.2.1 Mean Reversion Trading:

5 minutes timeframe:

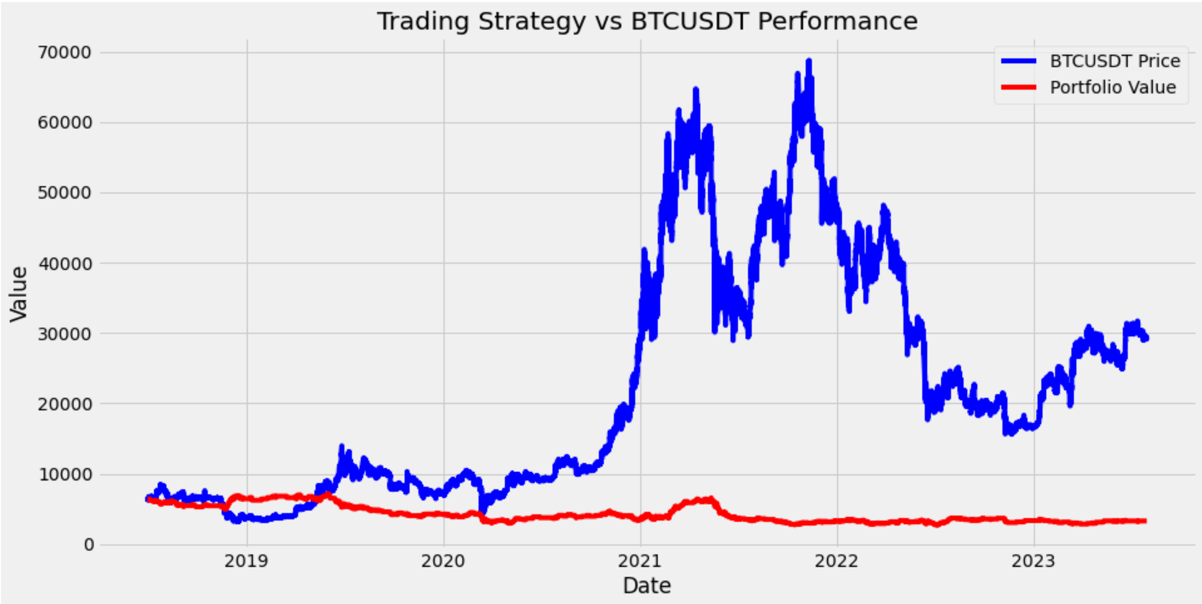


Figure 30 Mean Reversion Performance - 5 minutes

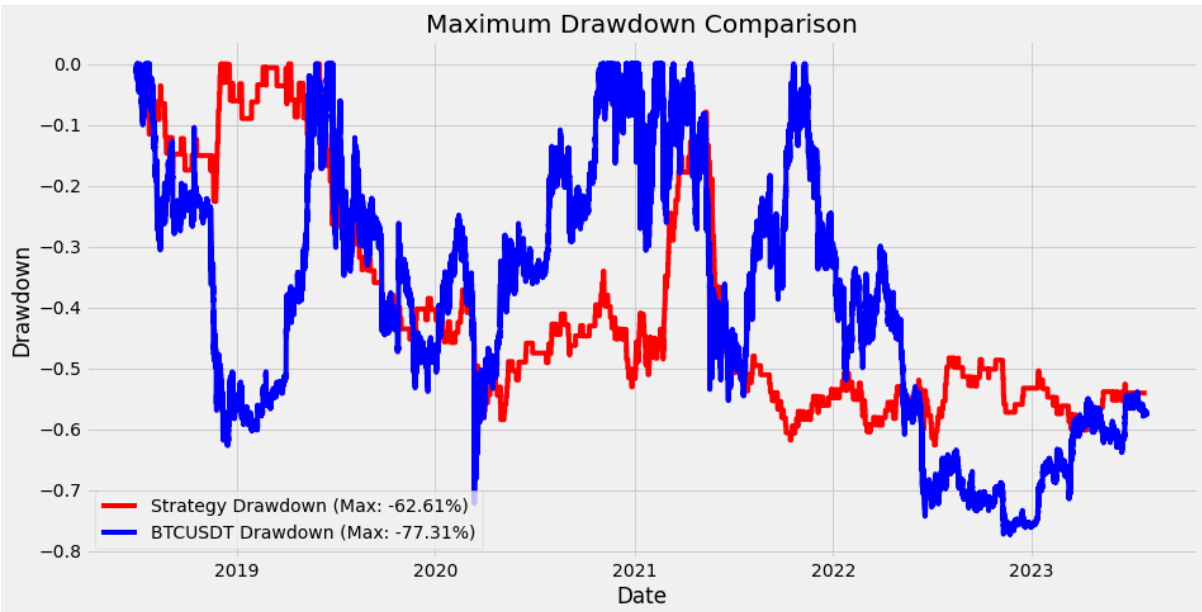


Figure 31 Mean Reversion Drawdown - 5 minutes

15 minutes timeframe:

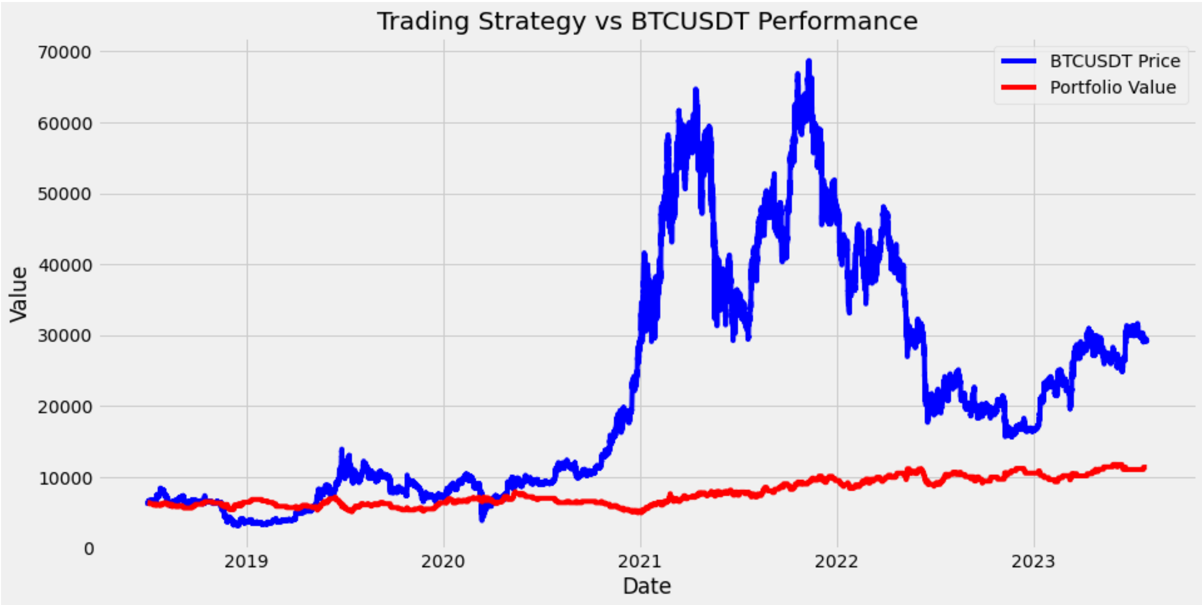


Figure 32 Mean Reversion Performance - 15 minutes

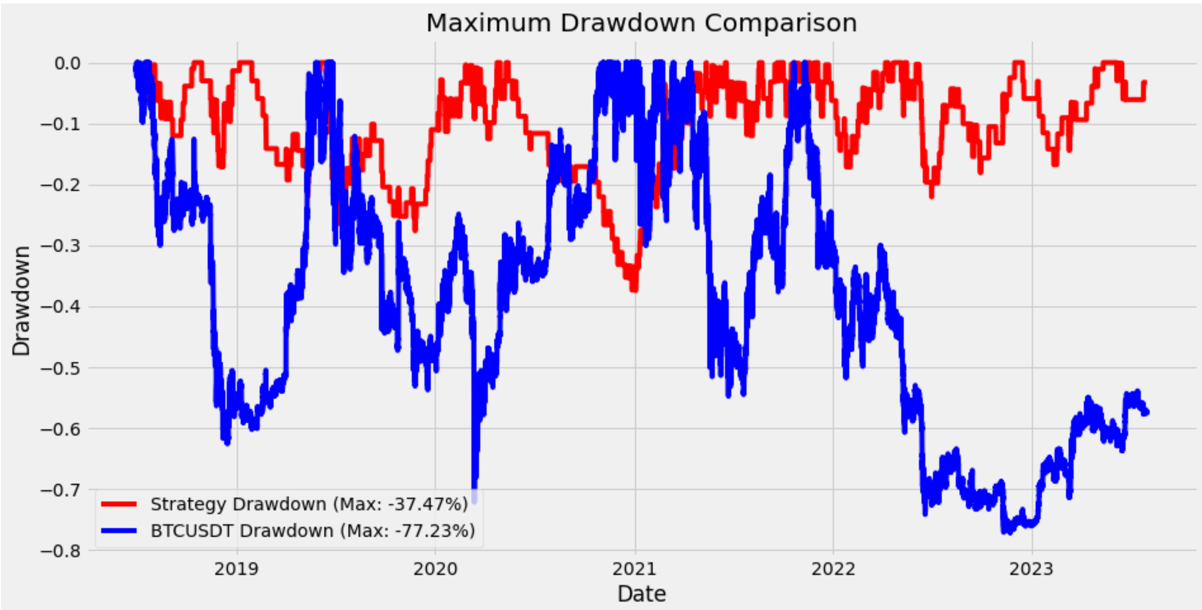


Figure 33 Mean Reversion Drawdown - 15 minutes

1 hour timeframe:

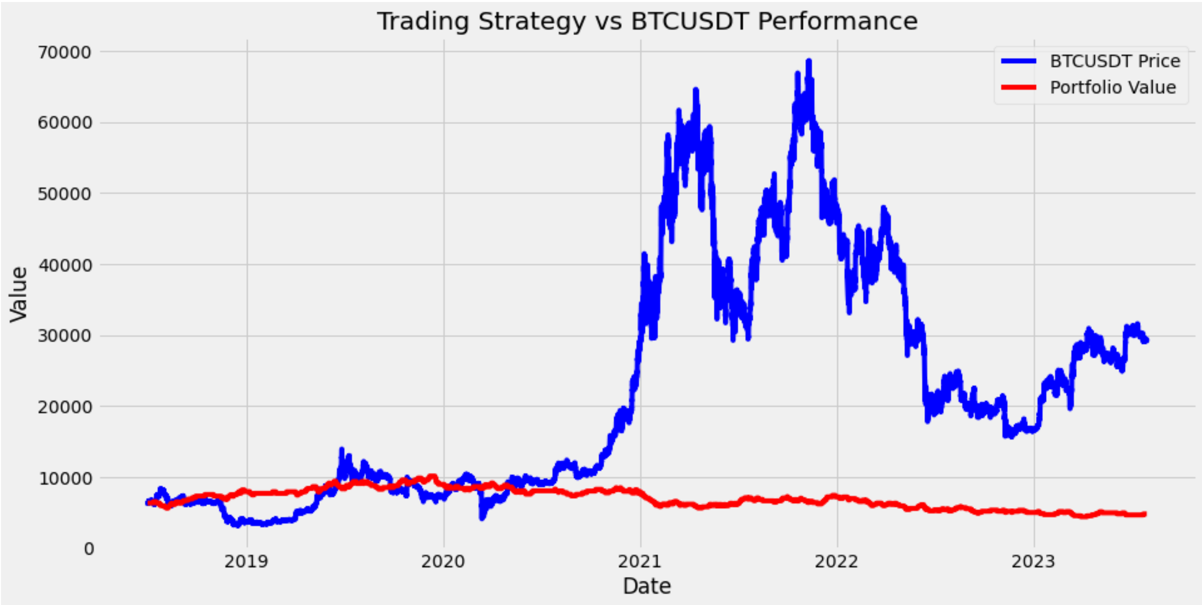


Figure 34 Mean Reversion Performance - 1 Hour

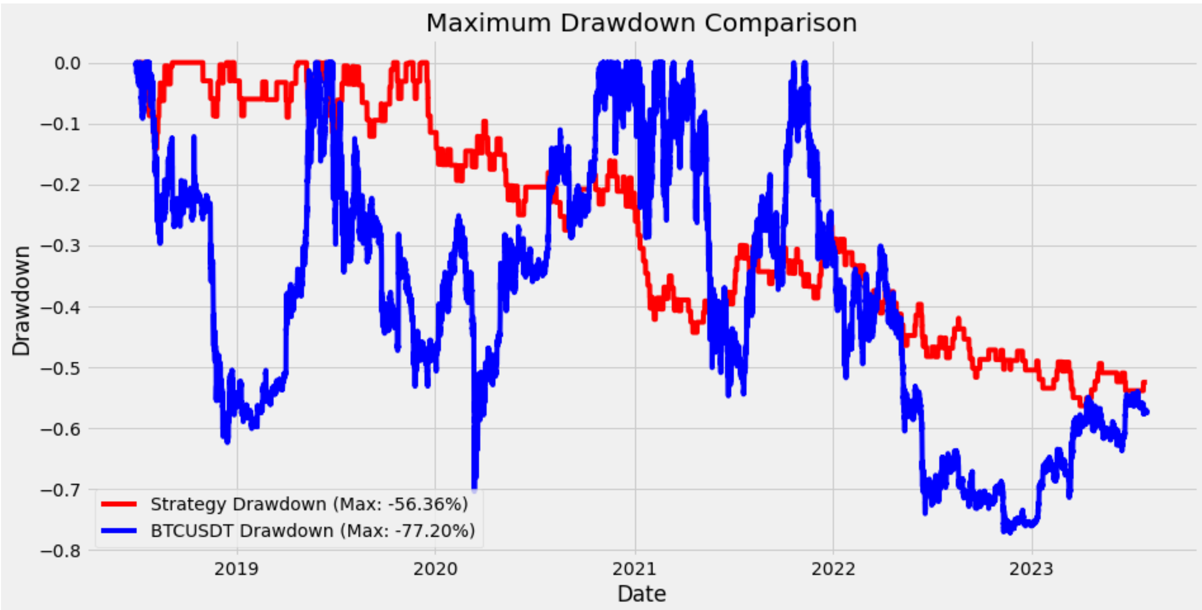


Figure 35 Mean Reversion Drawdowns - 1 Hour

Mean reversion						
Time period	5 mins		15 mins		1 hour	
Asset	Return	Drawdown	Returns	Drawdown	Returns	Drawdowns
Strategy	-48.82%	-62.61%	77.52%	-37.47%	-24.24%	-56.36%
BTCUSDT buy & hold	375.12%	-77.31%	355.25%	-77.23%	362.35%	-77.20%

Figure 36 Comparison Table 2 - Mean Reversion

Mean reversion						
	5 mins		15 mins		1 hour	
	Total Trades	Success percentage	Total Trades	Success percentage	Total Trades	Success percentage
Strategy	689	49.06%	526	52.47%	351	49.30%

Figure 37 Comparison Table 3 - Mean Reversion

Overview:

Figure 30, Figure 32 and Figure 34 show the performance of the strategy for the 5 mins, 15 mins and 1 hour timeframes against the Buy and Hold strategy of BTCUSDT for the same period.

Figure 31, Figure 33 and Figure 35 show the drawdowns of the strategy compared to the drawdowns of the BTCUSD buy and hold for the 5 mins, 15 mins and 1 hour timeframes.

Table 2 provides an overall view of the returns and drawdowns for each timeframe. Table 3 provides the details about the number of trades taken within each timeframe and its corresponding success percentage.

Explanation:

Having a look at the performance graphs of the strategy compared to the buy and hold for BTCUSDT, we see that the mean reversion strategy has shown some sort of success in the 15 minute time frames. However, it is important to note that these returns are very small compared to those obtained by the BTCUSDT buy and hold method. Having a look at table 3, it can be seen that the success ratio for any time period is just around 50% which can be credited to chance or probability. Additionally, having a total of 526 trades in a total of 5 years is very low when their risk to reward ratio is 1:1.

7.2.2 Momentum Trading:

5 minutes timeframe:

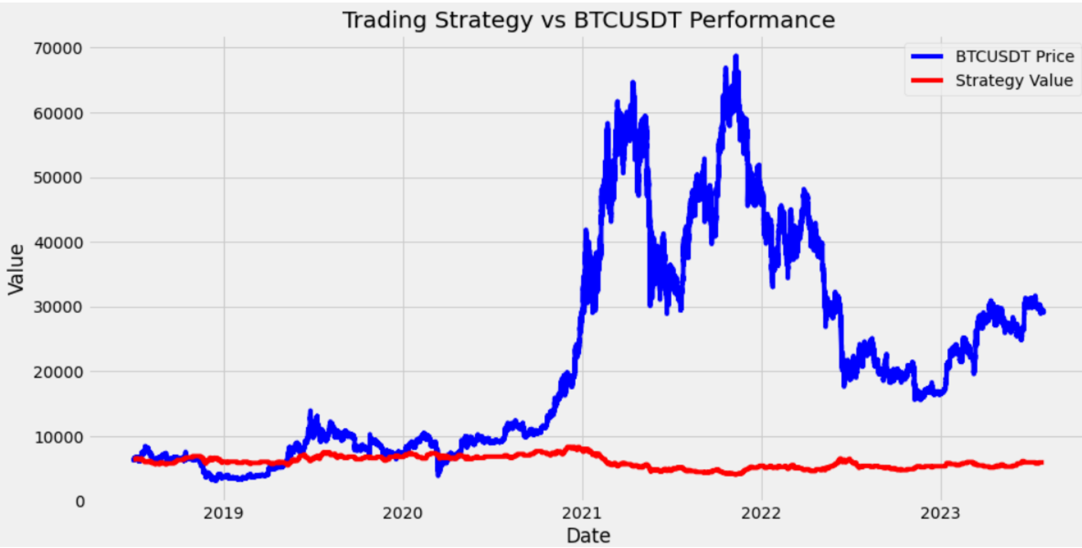


Figure 38 Momentum Trading Performance - 5 minutes

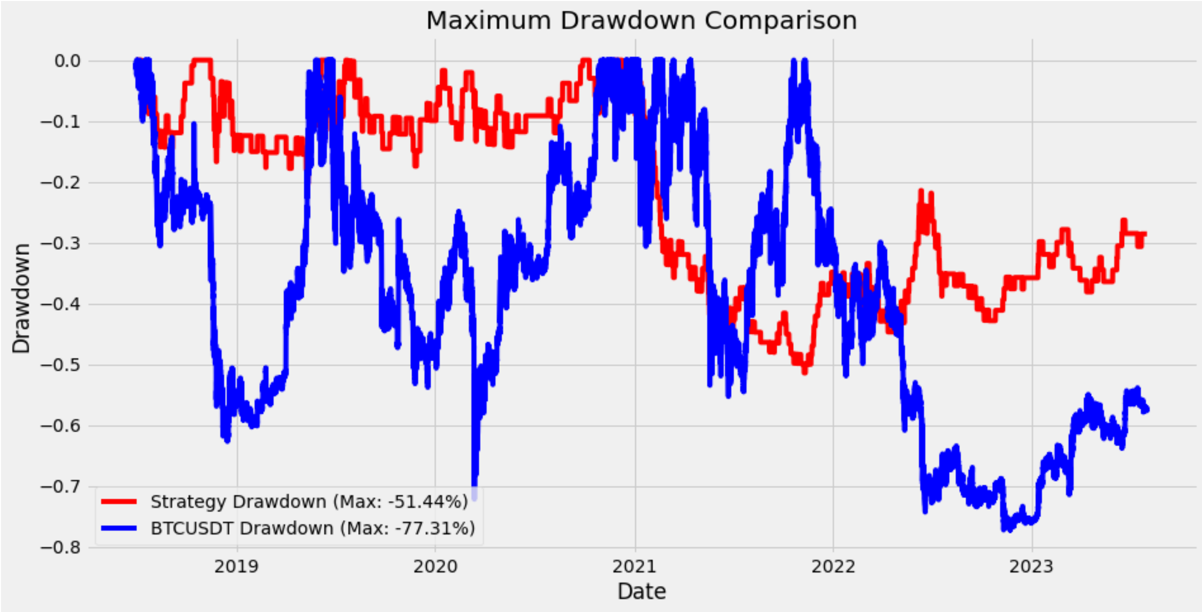


Figure 39 Momentum Trading Drawdowns - 5 minutes

15 minutes timeframe:

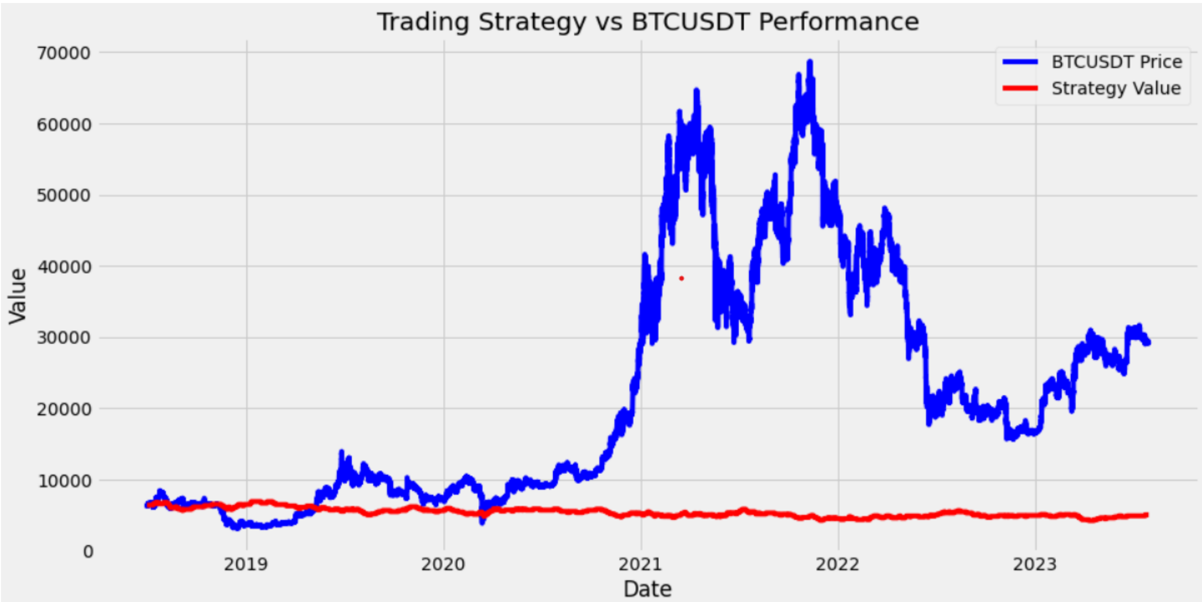


Figure 40 Momentum Trading Performance - 15 minutes

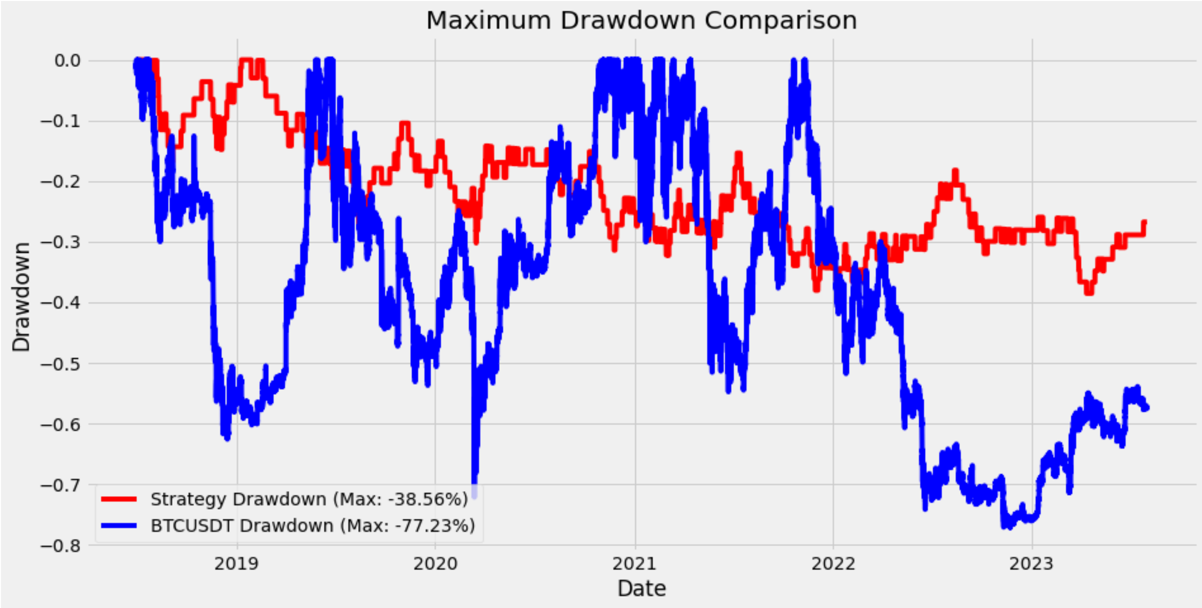


Figure 41 Momentum Trading Drawdowns - 15 minutes

1 hour timeframe:

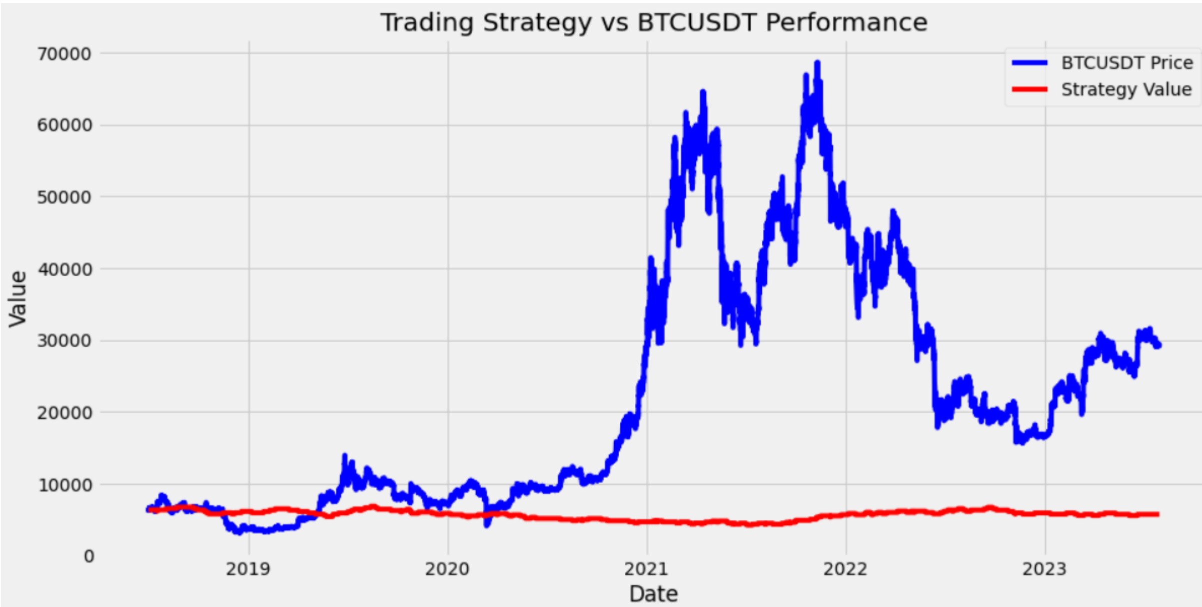


Figure 42 Momentum Trading Performance - 1 hour

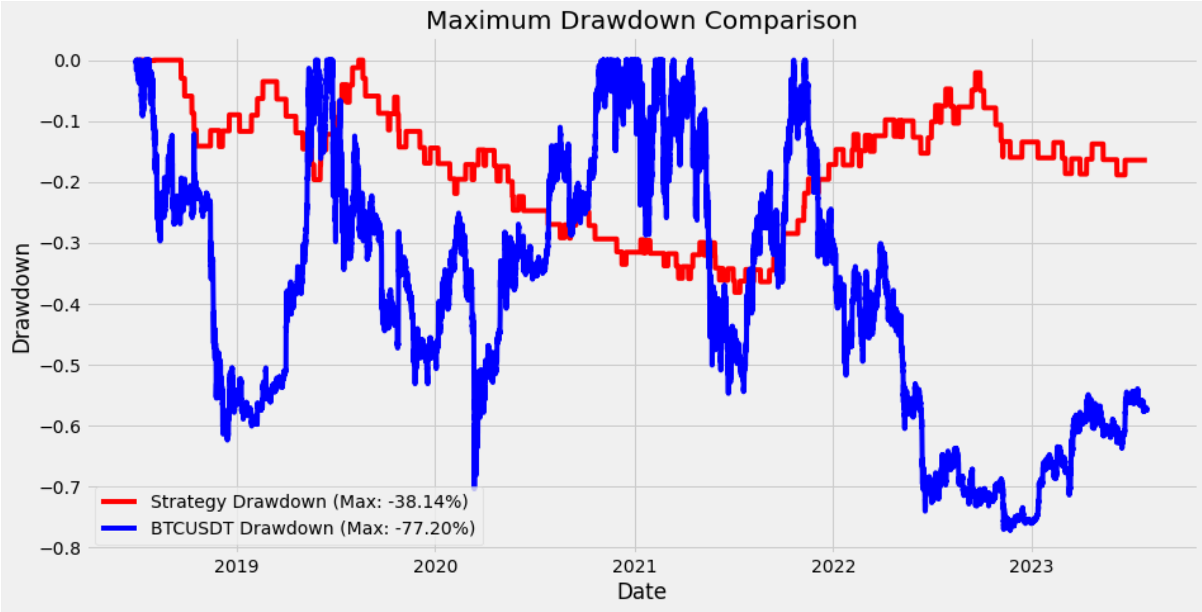


Figure 43 Momentum Trading Drawdowns - 1 hour

Momentum trading						
Time period	5 mins		15 mins		1 hour	
Asset	Return	Drawdown	Returns	Drawdown	Returns	Drawdowns
Strategy	-6.77%	-51.44%	-21.05%	-38.56%	-9.90%	-38.14%
BTCUSDT buy & hold	357.12%	-77.31%	355.25%	-77.23%	362.35%	-77.20%

Figure 44 Comparison Table 4 - Momentum Trading

Momentum trading						
	5 mins		15 mins		1 hour	
	Total Trades	Success percentage	Total Trades	Success percentage	Total Trades	Success percentage
Strategy	490	50.41%	326	49.40%	166	49.40%

Figure 45 Comparison Table 5 - Momentum Trading

Overview:

Figure 38, Figure 40 and Figure 42 demonstrate the performance of the momentum strategy against the buy and hold for BTCUSDT buy and hold for the 5 minutes, 15 minutes and 1 hour timeframe.

Figure 39, Figure 41 and Figure 43 show the drawdown of the strategy compared to the drawdowns suffered by the buy and hold of BTCUSDT during the 5 minutes, 15 minutes and 1 hour timeframes.

Table 4 shows the drawdowns and returns for various timeframes for the strategy as well as BTCUSDT for the corresponding timeframes. Table 5 shows the number of trades taken and their corresponding success ratios.

Explanation:

The performance graphs of the momentum trading system hardly show sustenance of level. This is because the success ratio is around 50%. This makes it impossible for it to generate returns. Having a look at table 4, we see the strategy isn't profitable in any timeframe. It has a lower level of drawdown compared to BTCUSDT. However, the absence of positive returns makes this strategy unfruitful. Adding to this, the number of trades executed are too low for a period of 5 years.

7.2.3 Contrarian Trading:

5 minutes timeframe:

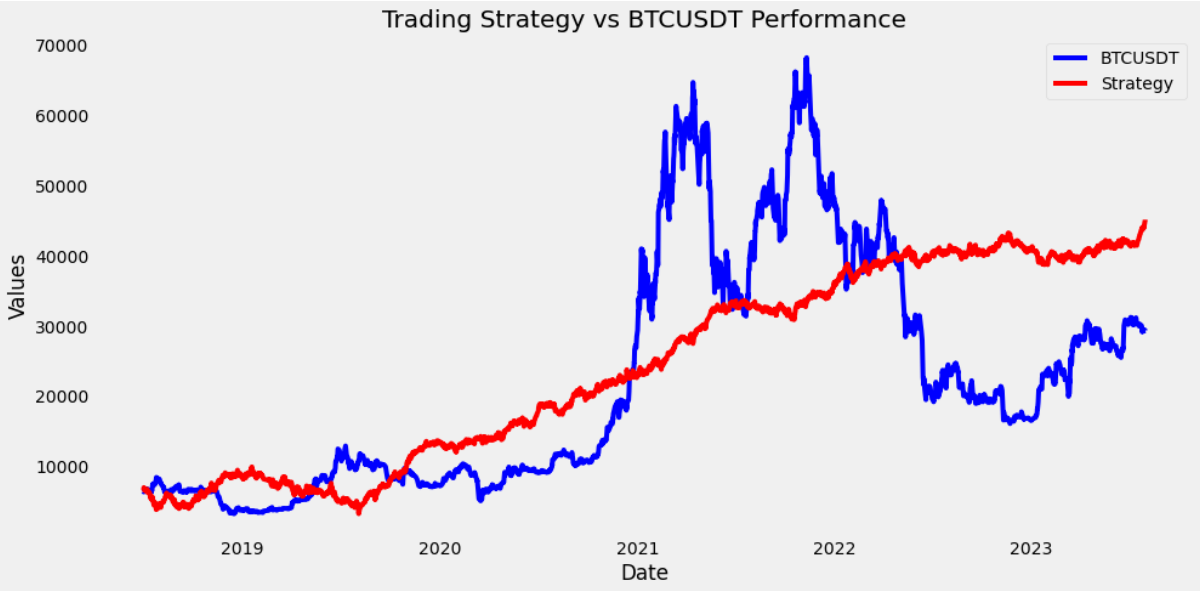


Figure 46 Contrarian Trading Performance - 5 minutes

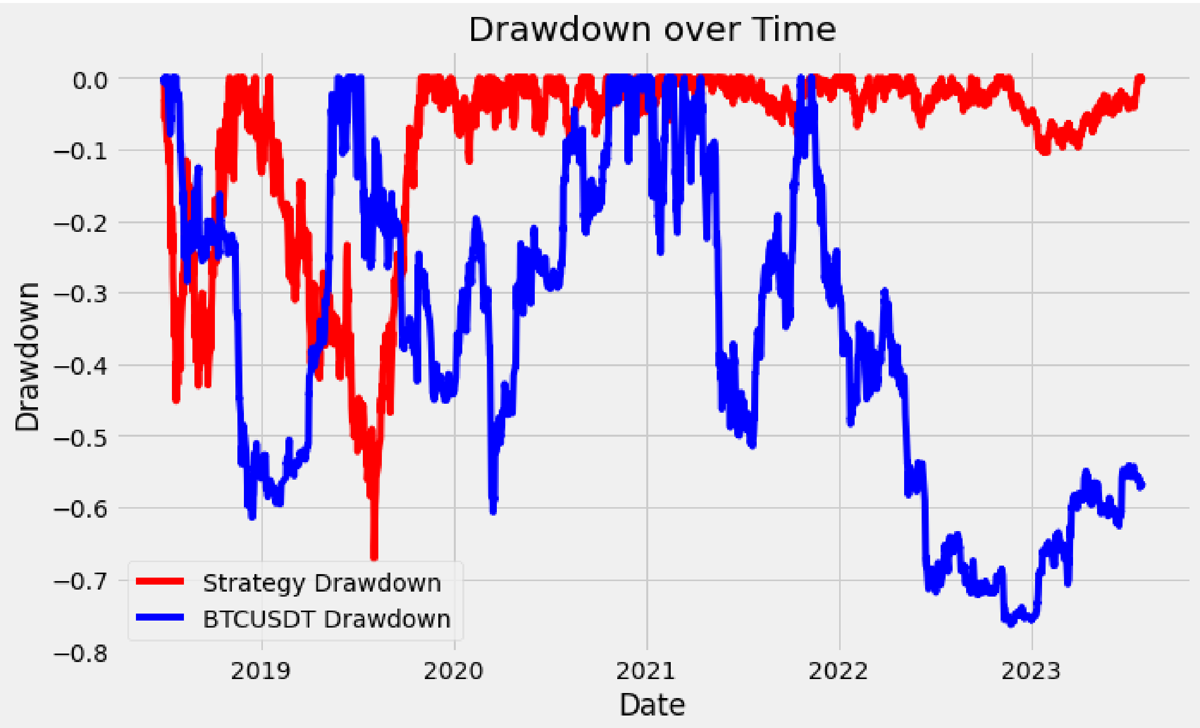


Figure 47 Contrarian Trading Drawdowns - 5 minutes

15 minutes timeframe:

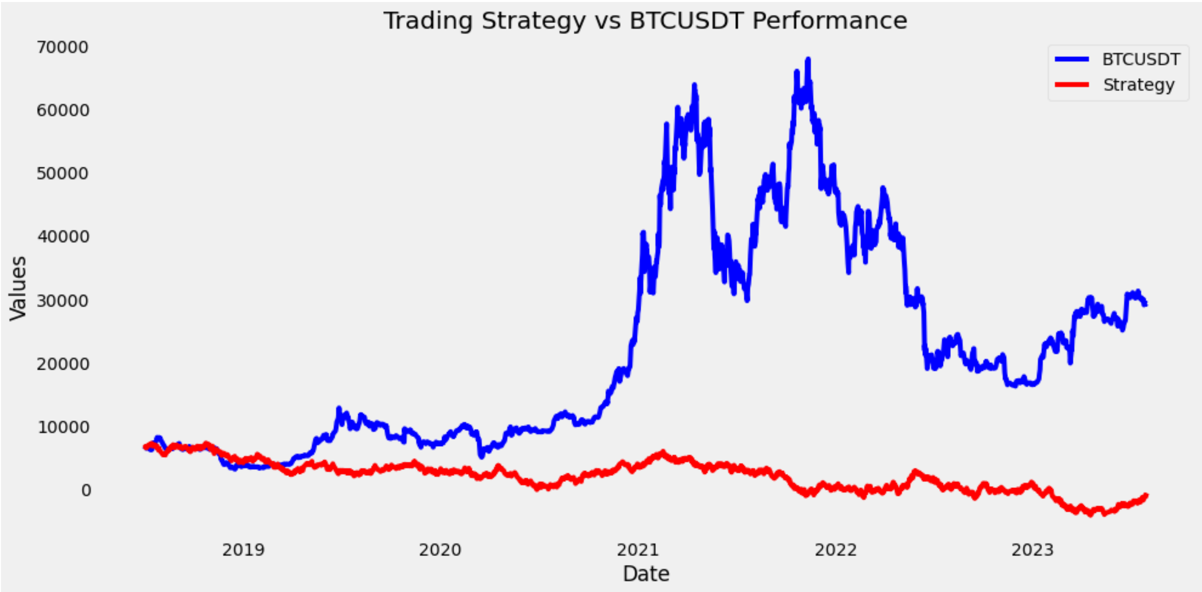


Figure 48 Contrarian Trading Performance - 15 minutes

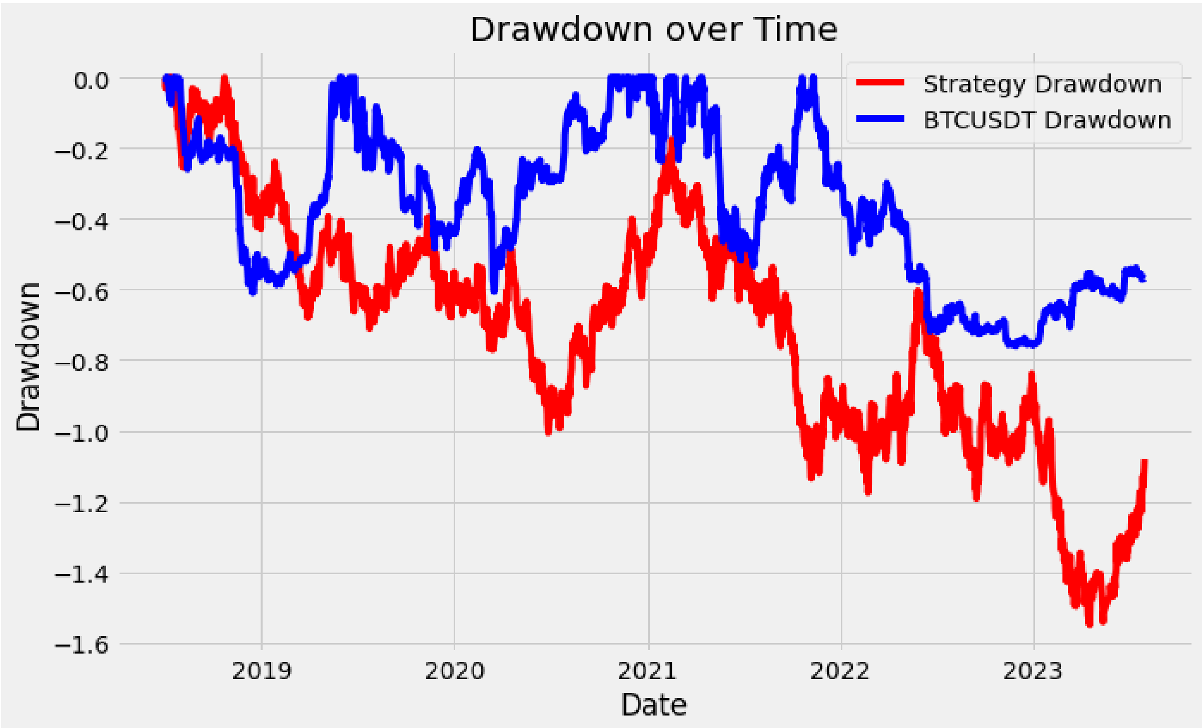


Figure 49 Contrarian Trading Drawdowns - 15 minutes

1 hour timeframe:

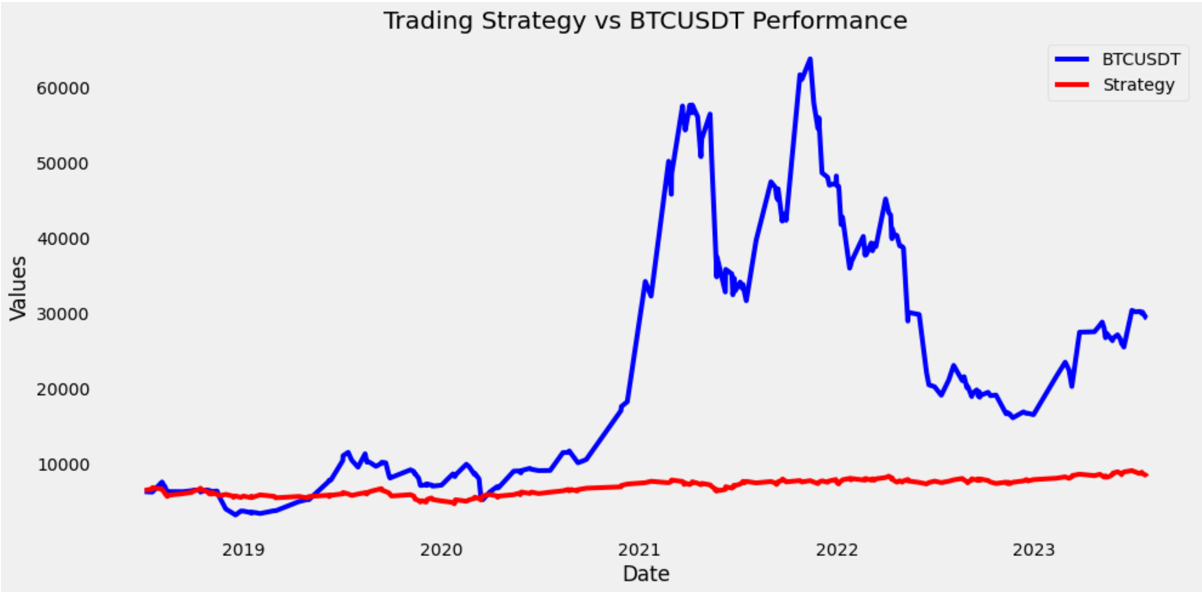


Figure 50 Contrarian Trading Performance - 1 hour

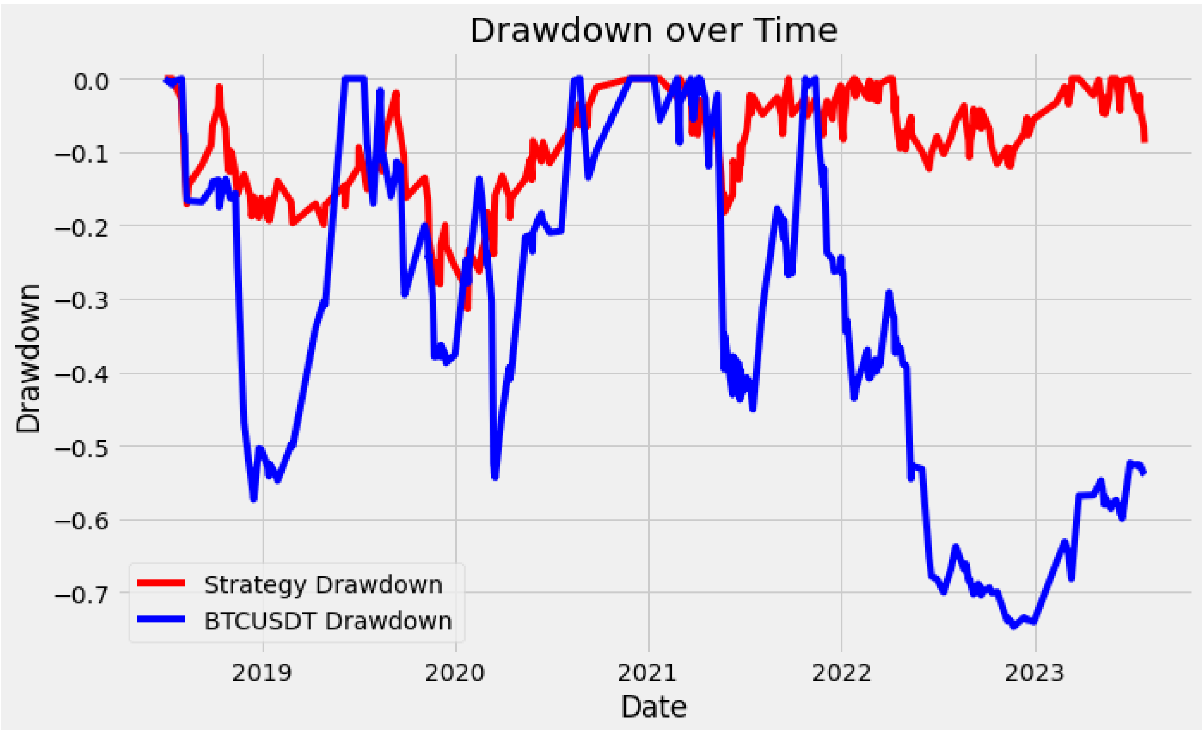


Figure 51 Contrarian Trading Drawdowns - 15 minutes

Contrarian trading								
Time period	5 mins		15 mins		1 hour		5 mins - 1year	
Asset	Return	Drawdown	Returns	Drawdown	Returns	Drawdowns	Returns	Drawdowns
Strategy	606.27%	-67.25%	-109.21%	-154.98%	30.83%	-31.37%	109.40%	-34.75%
BTCUSDT buy & hold	358.03%	-76.42%	362.27%	-76.02%	362.35%	-77.20%	37.65%	-25.73%

Figure 52 Comparison Table 6 - Contrarian Strategy

Contrarian trading								
	5 mins		15 mins		1 hour		5 mins - 1year	
	Total Trades	Success percentage	Total Trades	Success percentage	Total Trades	Success percentage	Total Trades	Success percentage
Strategy	2886	55.13%	1872	50.69%	252	53.57%	825	53.80%

Figure 53 Comparison Table 7 - Contrarian Strategy

Overview:

Figure 46, Figure 48 and Figure 50 showcase the robustness of the results obtained by the contrarian approach as compared to the buy and hold strategy of BTCUSDT during the same time period.

Figure 47, Figure 49 and Figure 51 elaborate on the drawdowns the trading strategy suffers from while comparing it to the drawdowns in the corresponding valuation of BTCUSDT.

Table 6 shows the drawdowns and returns for various timeframes for the strategy as well as BTCUSDT for the corresponding timeframes. Table 7 shows the number of trades taken and their corresponding success ratios.

The extra column titled '5 mins – 1 hour' is intended for comparison purposes with the LSTM results.

Explanation:

Having a look at the performance graphs, we can see that the contrarian trading strategy shows promise in the 5 minutes timeframe and the hourly timeframe. It has major drawdowns in the 15 minutes timeframe. While looking at Table 6, we see that the drawdowns suffered by the trading strategy are low compared to those achieved by the BTCUDT buy and hold. Table 7 shows us that the 5 minutes timeframe has a healthy number of trades with a highest success ratio out of the three timeframes. Table 6 shows us that the returns obtained by the strategy exceed those achieved by the BTCUSDT buy and hold. Figure 46 shows a spike in BTCUSDT during the years 2021 and 2022. However, this gain wasn't sustainable. The gains obtained by the contrarian strategy look linear in nature as well.

7.2.4 LSTM + Contrarian trading style:

5 minutes timeframe:

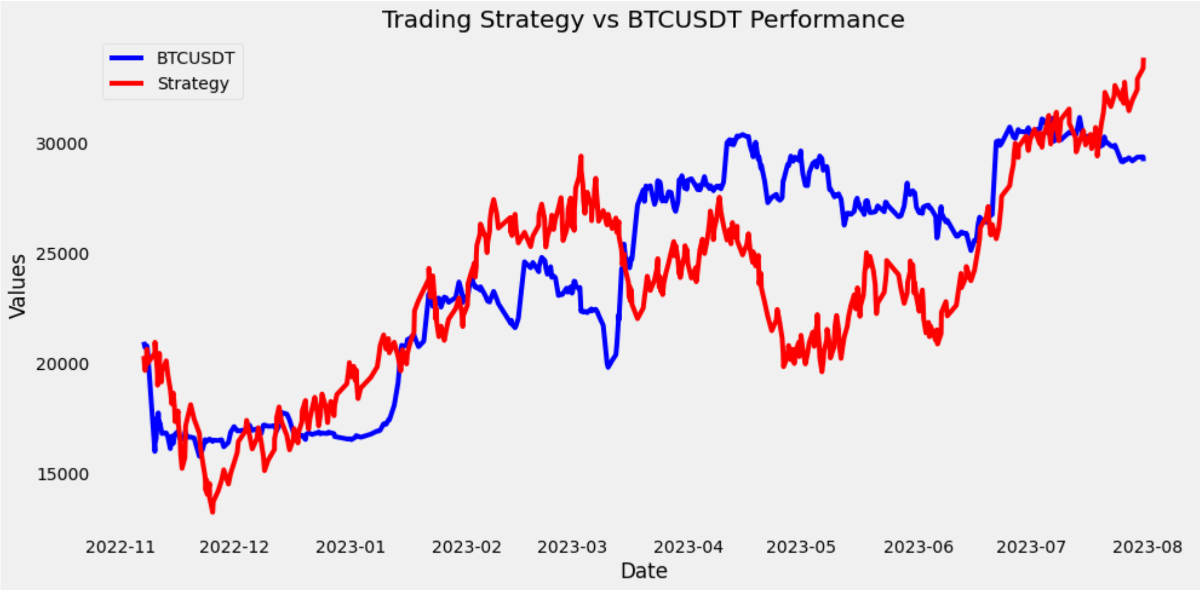


Figure 54 LSTM + Contrarian Performance -5 minutes

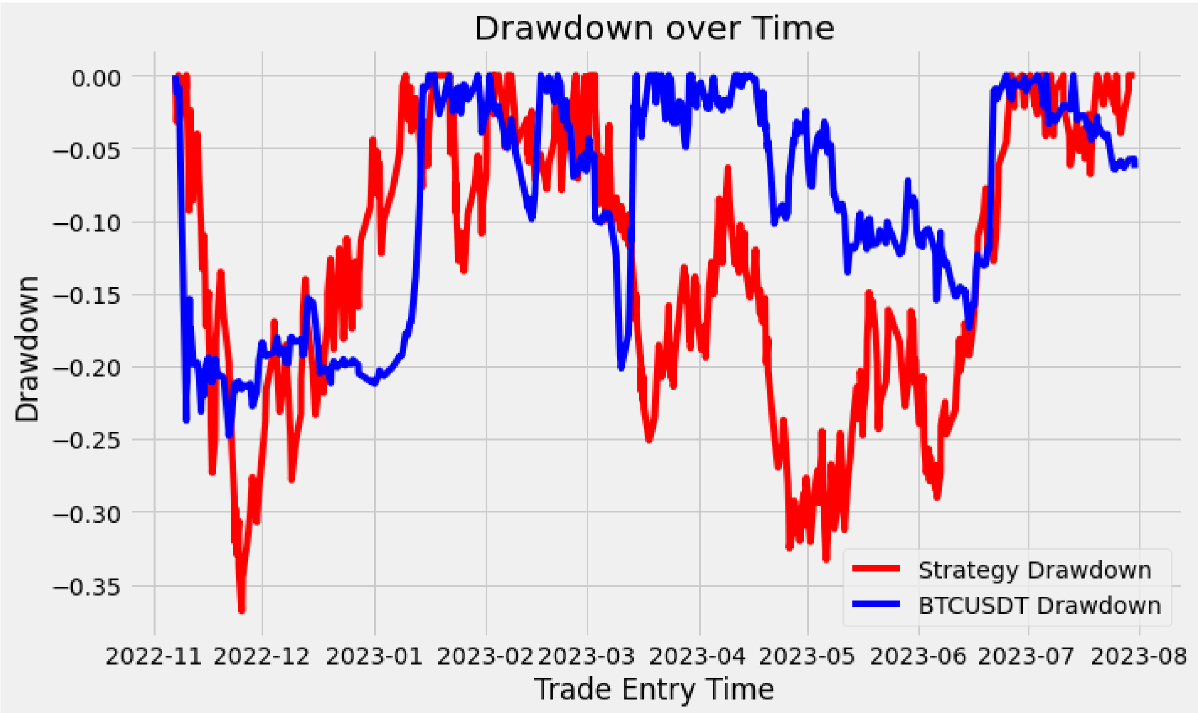


Figure 55 LSTM + Contrarian Drawdowns - 5 minutes

15 minutes timeframe:

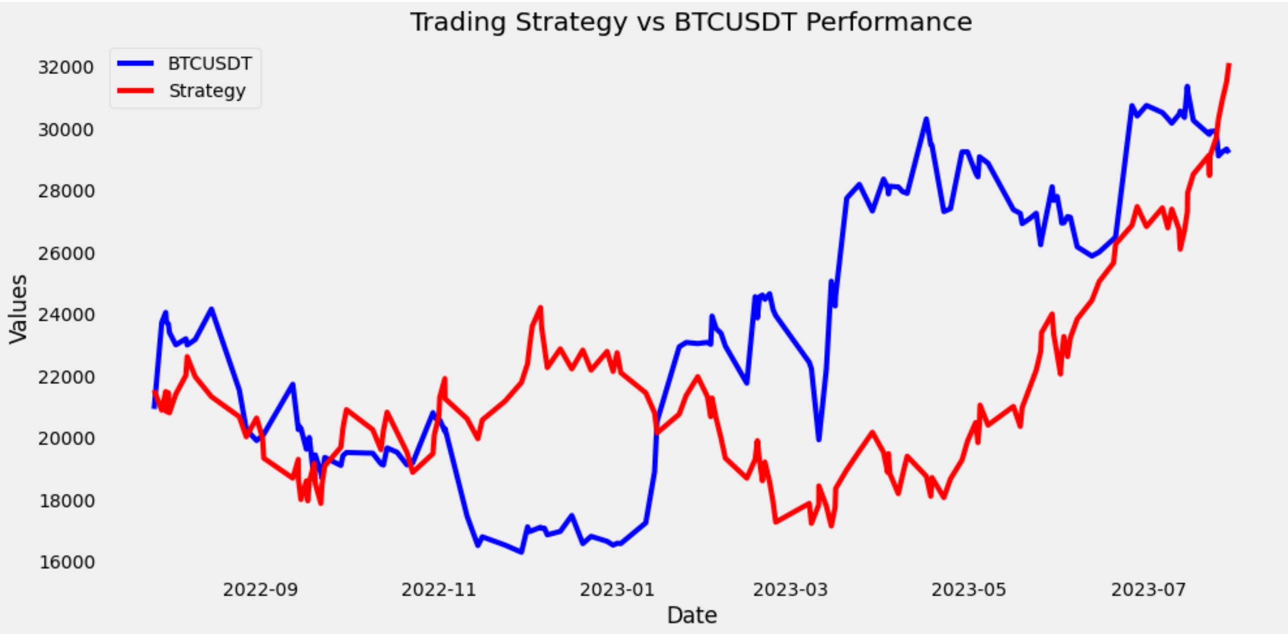


Figure 56 LSTM + Contrarian Performance - 15 minutes

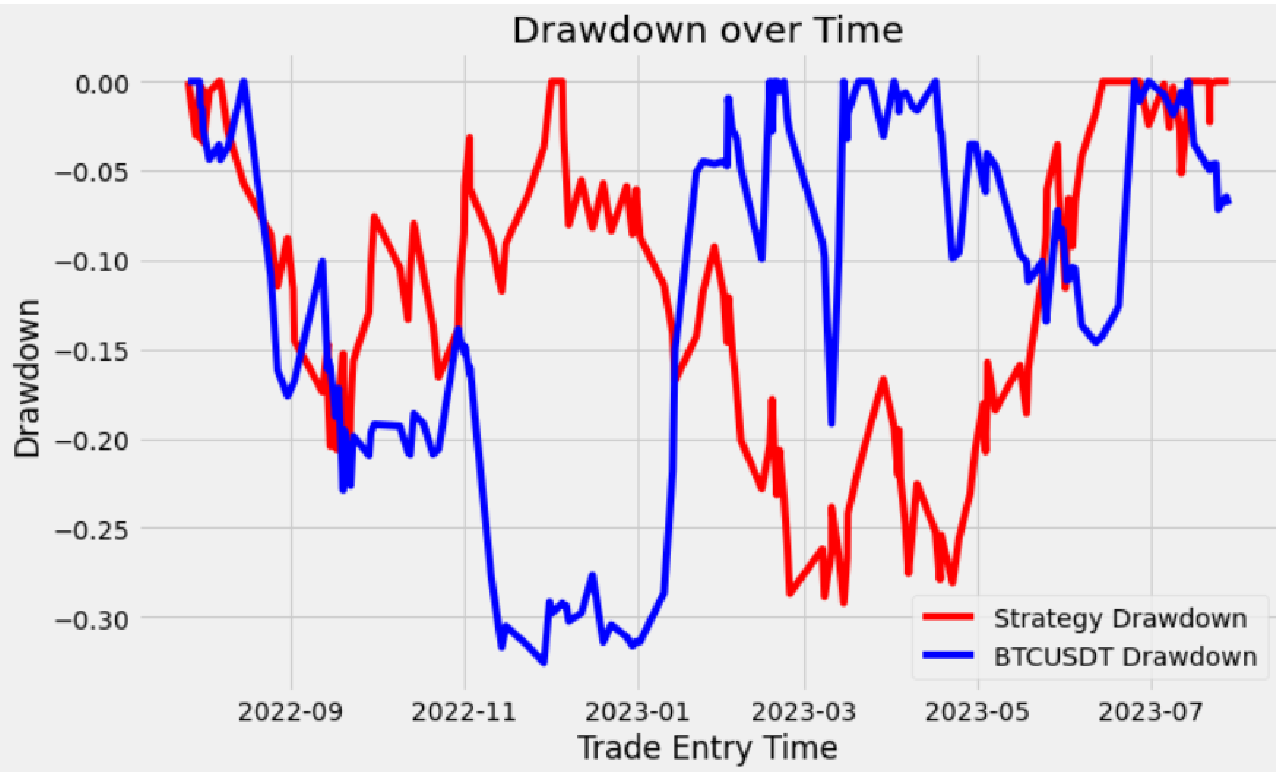


Figure 57 LSTM + Contrarian Drawdowns - 15 minutes

1 hour timeframe:

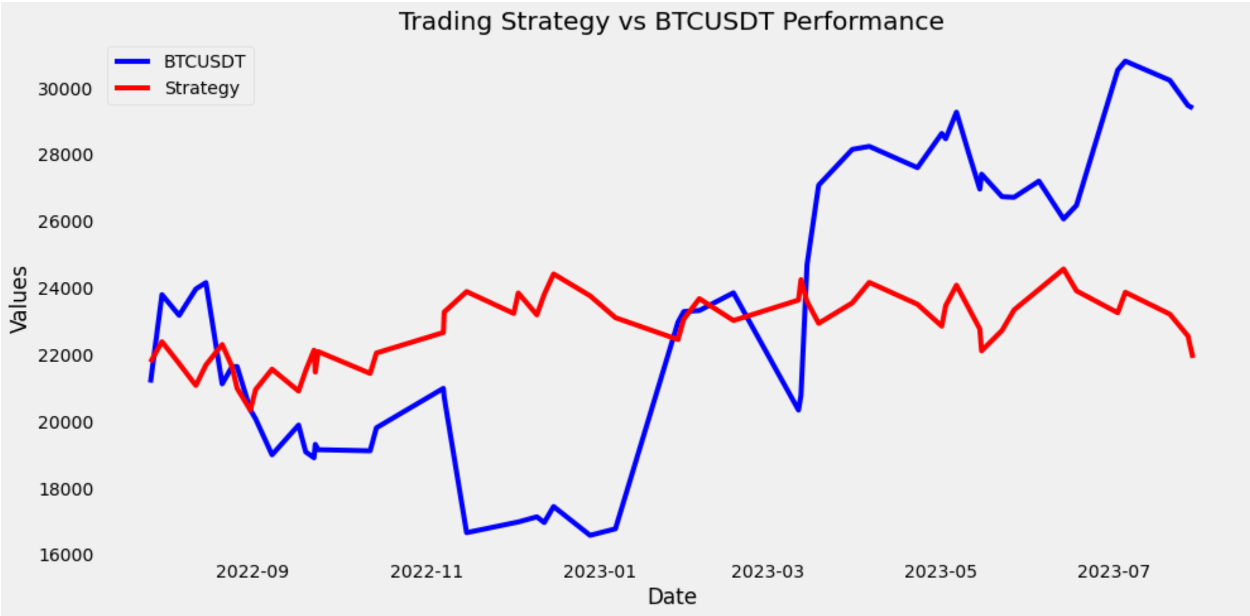


Figure 58 LSTM + Contrarian Performance - 1 hour

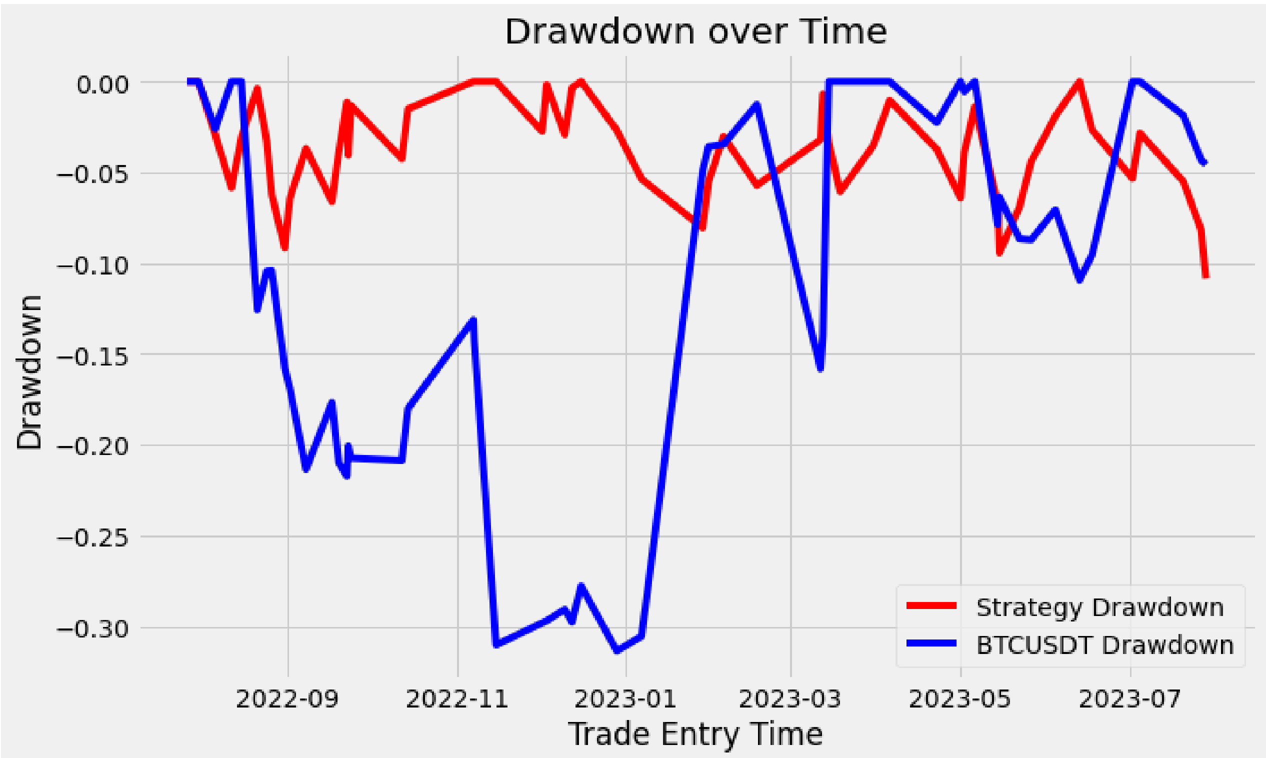


Figure 59 LSTM + Contrarian Drawdowns - 1 hour

LSTM+Contrarian trading						
Time period	5 mins		15 mins		1 hour	
Asset	Return	Drawdown	Returns	Drawdown	Returns	Drawdowns
Strategy	62.45%	-36.84%	52.47%	-27.05%	-0.46%	-10.85%
BTCUSDT buy & hold	39.09%	-24.78%	40.13%	-33.48%	38.90%	-31.37%

Figure 60 Comparison Table 8 - LSTM+Contrarian Strategy

	5 mins		15 mins		1 hour	
	Total Trades	Success percentage	Total Trades	Success percentage	Total Trades	Success percentage
Strategy	640	59.87%	228	55.70%	55	52.73%

Figure 61 Comparison Table 9 - LSTM+Contrarian Strategy

Overview:

Figure 54, Figure 56 and Figure 58 display the performance of the strategy against the buy and hold returns of BTCUSDT.

Figure 55, Figure 57 and Figure 59 show the drawdowns displayed by the strategy as well as BTCUSDT.

Table 8 shows the drawdowns and returns of various timeframes for the strategy and the buy and hold for BTCUSDT and Table 9 shows the number of trades and the success percentages of those trades.

Explanation:

Observing the performance graphs of the LSTM+ contrarian methodology, we see that the 5 minute timeframe has performed the best. There is an improvement in the 15 minutes timeframe performance compared to that achieved by the contrarian strategy without LSTM. By having a look at Table 8, we see a similar level of drawdowns compared to the contrarian-based approach, especially in the 5 minutes timeframe ('5 mins -1 year' column for the contrarian strategy). Table 9 shows an improved success ratio. However, the number of trades is too few to help make a good enough difference to the capital.

Note: An extra column by the name of '5 mins – 1 year' has been added in Table 6 and Table 7. This is done to make an accurate comparison between the performance of the LSTM based model and the contrarian approach. Inspite of using a 5 year dataset, the LSTM trains on 80% of the dataset and tests only on the remaining 1 year. Thus, the performance would be different. To enable a clear comparison, an extra dataset of 1 year, similar to the duration of the LSTM test data has been tested with the contrarian approach.

Chapter 8: Conclusion:

8.1 Investment:

The visualisations and the explanations derived from the result of the three datasets help us conclude that aiming for reduced risk can sometimes come at the expense of its corresponding reward. However, the portfolios created are defensive in nature. Meaning, even though their rewards are lower, they still greatly reduce the drawdowns, which are very close to 0. Additionally, their returns aren't zero when the market rises. Meaning, they are better compared to holding liquid cash. The downside of this however is that since the datasets extend upto one year and the test period obtained is six months, the assets in the recommended portfolio and their respective weights keep on changing. Meaning we need to keep checking and changing the portfolio assets and its weights periodically. However, that is outside the scope of this report.

8.2 Trading:

The explanations of the visualisations and tables obtained point to the contrarian strategy being the superior trading strategy generating returns in excess of even the buy and hold returns of BTCUSDT. The addition of the LSTM model helps improve the success percentages of the strategy. However, reduction of the number of trades executed bring the overall percentage returns obtained by the strategy lower than the contrarian strategy. It may also be pointing in the direction of reducing the timeframe even further like a 1 minute timeframe.

8.3 Overall:

Based on all the above results and their subsequent observations, it is evident that the contrarian approach to trading BTCUSDT yields the highest gains. Remarkably, it outperforms both, the buy and hold for BTCUSDT as well as the portfolio optimisation strategies when traded over a smaller timeframe.

It is however important to noted that the efficiency of investment strategies like buy and hold or portfolio optimisation largely depends on market timing. Meaning, these investments yield higher returns when investments are made in valleys (or market lows). Improper market timings could result in losses or capital lock-in.

In contrast, the contrarian approach offers a more consistent form of returns as evident in Figure 46. It is however, crucial to acknowledge that even though it is the most profitable methodology, it comes with one significant drawback: it had a maximum drawdown of around 67%. This high level of risk may not be suitable for risk averse people.

Final thoughts: Even though the study concludes that trading is better under certain conditions, it is of vital importance to understand that any form of optimal approach may depend on market conditions, investment horizon and an individual's risk appetite. With newer avenues opening up to real-time studies and increasingly sophisticated algorithms, a well-researched, data driven approach can help significantly improve returns by enhancing decision making for both trading and investment.

Chapter 9: Future Scope

Dataset: One of the major limiting factors for this study has been the scope of the dataset available. A larger range of data, especially one encapsulating various market cycles would give a broader overview.

Consideration of different assets: Consideration of various assets can prove to be insightful for both the parts of this report.

Different algorithms: While LSTM has proved to be helpful in the present-day scenario, various other methodologies like transformers and sentiment analysis algorithms could help improve accuracy by provided insight into public opinion regarding an asset.

Tailor making strategies: Strategies could be tailormade to fit traders according to their trading style (HFT, intraday, swing, etc).

Other parameters: The investment strategy could be optimised to enable its usage for people with high risk tolerance looking for higher rewards.

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