Machine Learning-based Quantitative Cryptocurrency Trading

Student: Jose De Los Santos
School of Computer Science
The University of Adelaide

Supervisor: Haiyao Cao
Australian Institute for Machine Learning
The University of Adelaide

Supervisor: Jinan Zou
Australian Institute for Machine Learning
The University of Adelaide

ABSTRACT

Current automated trading systems oversimplify the factors which impact the stock market. The complex relationship of fundamental factors, technical indicators and stock market prices often require expert intervention for profitable returns. By leveraging machine learning models in the fundamental-less environment of cryptocurrencies, key impact factors as technical indicators are extracted easier. Integrating these models into quantitative trading platforms result in above-market profitable returns.

1 INTRODUCTION AND MOTIVATION

The stock market is, by and large, the tug of war between supply and demand [1]. The price of a share increases when there are more buyers than sellers, and contrarily, the price of a share decreases when there are more sellers than buyers. The behaviour of the stock market is the result of a complex combination of various factors, including individual, industrial, economic, political, national, and global reasons which affect the value of shares. Consequently, investors attempt to profit from the stock market by predicting price movements [1].

In recent decades, the rise of alternative currencies hosted digitally known as cryptocurrencies have introduced a new trading instrument for investors to capitalise on. Cryptocurrencies are not backed by an underlying asset or a central authority such as a government [2], and therefore lack intrinsic value unlike typical stocks. Due to this nature, cryptocurrencies have been extremely volatile in their young lifespan and their value is mostly speculatory. For example, the largest cryptocurrency as of writing, Bitcoin, has had rapid upward movements in 2017 and 2021, but similarly devalued significantly in the following year [3].

Traditional techniques for predicting stock market behaviour include fundamental analysis and technical analysis. Fundamental analysis relies on determining the true intrinsic value of a share to capitalise on discrepancies with current market prices. On the other hand, technical analysis assumes patterns in stock price repeat and thus utilise the statistics on the past performance of a share to create models to predict future behaviour. While both cater to different trading styles and investment goals, it is generally beneficial for investors to utilise both [4].

Improved technology has increased the tools available to investors for analysing the behaviour of the stock market. However, due to the complex nature of the stock market, existing models oversimplify the underlying relationship between the stock market and affecting factors, and thus human intervention is often required for desirable results. Thus, cryptocurrencies have been selected over traditional stocks as their nature puts focus more into technical indicators rather than fundamentals, which will be easier for current technology to analyse and automate.

This project aims to explore the success of classifier models and sequence models within the environment of cryptocurrency trading. While minimising model error and improving accuracy during ML training is one avenue for increasing profit, focus is also placed on the quantitative trading strategies used to effectively utilise the models.

Ultimately, this project leverages machine learning models to assess cryptocurrency returns. Through QuantConnect, this model will be integrated into an automated investment algorithm that responds to real-time updates to produce above-market profits.

2 LITERATURE REVIEW

2.1 CLASSIFIER AND SEQUENCE MODELS

CLASSIFIER MODELS

Classifier models are a type of machine learning model that predict the class label of a new data point. In the context of cryptocurrency forecasting, this model can be used to predict whether at timestep t the cryptocurrency will have an upwards movement or downwards movement in price to the next timestep, $t + 1$. In other words, classifier models can be used to classify whether a cryptocurrency is profitable.

One specific type of classifier model is the gradient boosting classifier. This is an ensemble method, which means it combines the predictions of multiple weaker models to create a single, more accurate prediction. Gradient boosting works by iteratively building decision trees, one at a time. Each new tree is built to correct the errors of the previous trees, resulting in a more robust model [5].

SEQUENCE MODELS

Sequence models are a type of machine learning model that are specifically designed to handle sequential data, which is data that has an inherent order, such as time series data of cryptocurrencies. In the context of cryptocurrency trading, sequence models can learn the relationships between the elements in a sequence and use that knowledge to predict the next timestep.

One powerful type of sequence model is the Long Short-Term Memory (LSTM) network. LSTMs are a type of recurrent neural network (RNN) that are specifically designed to address the vanishing gradient problem that can plague traditional RNNs.

LSTMs have internal mechanisms that allow them to learn long-term dependencies in sequences, making them well-suited for tasks that require understanding the context of a sequence [6]. For this project, the context aimed to be captured is the cryptocurrency market.

2.2 AUTOMATED TRADING

Approaches to automated stock market trading can be classified into two fields derived from the two types of stock market analysis and the data observed: technical methods and fundamental methods. Technical methods rely solely on market data. In the context of cryptocurrencies, market data includes the price of cryptocurrencies, their volume, and other derived features. Alternatively, fundamental methods draw information from other sources, such as company reports, social media, and news articles. Due to the decentralised nature of cryptocurrencies, fundamentals are limited, but are nonetheless present. Different machine learning techniques can be applied to implement the two methods.

Research by Anghel [7] find similar results from various purely technical analysis methods and machine learning methods. In addition to similar returns, machine learning methods generally underperform while also trading more often without additional benefits. This project aims to improve the abilities of machine learning in the field of cryptocurrency trading.

AI TECHNICAL METHODS IN CRYPTOCURRENCY

Previous work by Lucarelli and Borrotti [8] research reinforcement learning tested on Bitcoin, specifically Double Deep Q-Network and Dueling Double Deep Q-Network. Reinforcement learning systems work by introducing an agent to an environment in which it then learns to make decisions and achieve a goal or maximise rewards. Lucarelli and Borrotti [8] use several reward functions based on profits and Sharpe ratio. The experimental results vary with the most profitable trading system having an average return of 5.81% and the worst performing an average return of 1.82%.

Based on box theory and the K-means clustering algorithm, Wang and Lai [9] propose a trading system for Ethereum. The box theory suggests financial prices oscillate within a box, but once the price breaks through either the upper or lower boundary, the price switches to another higher or lower oscillation box. Wang and Lai [9] utilise the K-means clustering algorithm to determine the upper and lower boundaries of the oscillation box. Furthermore, the system implements a sliding window method to adapt to the market and generate reasonable upper and lower box boundaries. Across a training set of four months, the trading system achieved the highest result of a 33% profit in consolidation markets (a market of relatively sideways movement).

AI FUNDAMENTAL METHODS IN CRYPTOCURRENCY

Chheda et. al. [10] treat Twitter (now X) as a psychological database. The research team employ supervised machine learning to perform sentimental analysis on tweets related to Bitcoin and track the relationship between tweet sentiments and Bitcoin price movements. Chheda et. al. [10] observed an increase in Bitcoin prices when positive sentiments outnumbered the negative and Bitcoin prices decreased when negative sentiments were the majority. The results of the experiment are still in its infancy but may provide future groundwork for integrating sentimental analysis within an automated trading system.

Lamon, Nielsen and Redondo [12] predict the movements of Bitcoin and Ethereum using news and social media sentiment.[1] The learning algorithm provided the novelty of labelling news and social media sentiment using the actual price changes of the cryptocurrency one day in advance. Through this method the research team was able to predict 43.9% of price increases and 61.9% of price decreases in Bitcoin and 75.8% of price increases and 16.1% of price decreases in Ethereum.

Previous research into the automated trading of cryptocurrency has had varying results but technical methods outperformed the fundamental methods. Furthermore, there is a lack of automated trading systems utilising solely fundamental data. This is likely due to the highly non-fundamental-based nature of cryptocurrencies. Therefore, this project will leverage technical methods.

2.3 FactorVAE

One alternative to traditional classifier and sequence models is FactorVAE. Developed by Duan et. al. [13], FactorVAE is a probabilistic dynamic factor model based on variational autoencoder (VAE) see (see Figure 1).

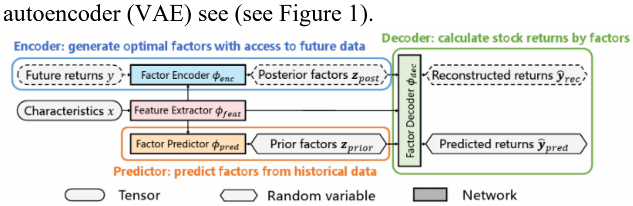

Figure 1: "The overall framework of FactorVAE. All the modules with dotted lines, involving the future data, are only used in the training phase, and would be removed in the test phase or in prediction." From Duan et. al. [13].

Factor models use various factors, such as fundamentals and technical indicators, to describe the variances in the stock market. Dynamic factor models improve performance by treating the relationship between stock returns and factors as evolving over time. The challenge with dynamic factor models occurs when extracting factors from market data for the model. Researchers have explored the use of machine learning to determine these factors, but noisy data has interfered with ML learning. Variational autoencoders encode input x to a lower-dimensional latent space z. A decoder neural network returns an original data space reconstruction of x from z [14]. By treating factors as the latent random variables in VAE, FactorVAE can extract effective factors from noisy market data and is thus capable of modelling

[1] The team had also used Litecoin, but the model performed poorly and the percentages of correct predictions was not presented.

noisy data, which surpasses other dynamic factor models and ML-based prediction models on cross-sectional returns prediction. Duan et. al. [13] research FactorVAE in the Chinese stock market, using the CSI300 index as the benchmark, and received exceptional returns compared to other ML models. This project originally aimed to utilise FactorVAE but was unable to due to time restrictions. Thus, this model is presented as possible future work to explore within the context of cryptocurrencies.

4 METHODOLOGY

In this section, machine learning models are established to predict relevant information for quantitative cryptocurrency trading. This strategy falls under the broader scope of time series forecasting, where historical data is used to predict future values. In this context, a simple model at time t at some interval aims to generate or make a prediction that reflects the state of a cryptocurrency at time $t+1$.

4.1 DATA COLLECTION

This project retrieves raw cryptocurrency historical data from Binance, containing minute-, hour-, and day-level price-volume data. The Binance platform was chosen due to their high-quality data. To gather an extensive amount of data. all spot pairs of cryptocurrencies trading against USDT were collected. In general, necessary values include the opening, closing, high and low prices, and trading volume. In regular use, these values are represented in candlestick data.

- Opening Price: The price at which the cryptocurrency begins trading during the interval.
- Closing Price: The price at which the cryptocurrency ends trading during the interval.
- High Price: The highest price reached during the interval.
- Low Price: The lowest price reached during the interval.
- Trading Volume: The total amount of cryptocurrency traded during the interval.

4.2 DATA PREPROCESSING

Before training a model, data must be prepared into a suitable format for accurate results. Missing values are addressed using forward filling, which propagates the last valid observation forward to the next missing value, ensuring continuity in the dataset. Additionally, any NaN values that could not be forward filled are removed to maintain dataset integrity.

Numerical features must be scaled to ensure they contribute equally to the model's learning process. This was achieved through Min-Max scaling for simplicity. This methodology scaled all numerical values to a range of 0 to 1.

As part of the process, datasets are split into training, validation, and testing sets. This is usually in a ratio of 70-15-15.

4.3 FEATURE ENGINEERING

Additional features are calculated to better capture the state of cryptocurrencies. The features chosen were:

Simple Moving Average (SMA): The average price over a specified number of periods, providing a smoothed price trend.

$$SMA_n = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i}$$

$$n = number\ of\ periods$$
$$P_{t-i} = Price\ at\ the\ time\ t-i$$

For this project, an SMA period of 5 timestamps was chosen.

Exponential Moving Average (EMA): The EMA is similar to the SMA, but gives weight to prices, making it more responsive to new or old information.

$$EMA_t = \alpha \cdot P_t + (1-\alpha) \cdot EMA_{t-1}$$

$$P_t = Price\ at\ time\ t$$
$$EMA_{t-1} = EMA\ value\ at\ previous\ period$$
$$\alpha = Smoothing\ factor\ ranging\ between\ 0\ and\ 1$$

An α value closer to 0 will put more importance on older values whereas an α value closer to 1 will put more importance on newer values. For this project, an EMA period of 10 timestamps was chosen.

Relative Strength Index (RSI): Measures the speed and change of price movements, indicating overbought or oversold conditions. The RSI value typically ranges between 0 and 100. It is generally interpreted as values below 30 are potentially oversold condition and values above 70 are potentially overbought condition.

$$RSI = 100 - \left(\frac{100}{1+RS}\right)$$

$$RS = \frac{Average\ Gain\ Over\ n\ Timestamps}{Average\ Loss\ Over\ n\ Timestamps}$$

For this project, an RSI period of 14 timestamps was chosen.

Average True Range (ATR): Measures market volatility by decomposing the entire range of an asset price for that period.

$$ATR_t = \frac{1}{n}\sum_{i=0}^{n-1} TR_{t-i}$$

$$TR_t = max[(H_t - L_t), |H_t - C_{t-1}|, |L_t - C_{t-1}|]$$
$$H_t = High\ Price\ of\ Timestamp$$
$$L_t = Low\ Price\ of\ Timestamp$$
$$C_{t-1} = Closing\ Price\ of\ Previous\ Timestamp$$
$$TR_t = True\ Range$$

For this project, an ATR period of 14 timestamps was chosen.

Commodity Channel Index (CCI): Identifies cyclical trends by measuring the current price level relative to an average price over a specific period.

$$CCI = \frac{P_t - SMA_t}{0.015 \cdot Mean\ Deviation}$$

$$P_t = Typical\ Price\ at\ Time\ t = \frac{H + L + C}{3}$$

$$SMA_t = Simple\ Moving\ Average\ of\ P_t\ Over\ n\ Timestamps$$

$$Mean\ Deviation$$
$$= Average\ of\ Aboslute\ Differences\ Between\ P_t\ and\ SMA_t$$

For this project, a CCI period of 20 timestamps was chosen.

Overall, these indicators are chosen because they provide a comprehensive view of the market conditions and help in capturing the momentum, trend, and volatility of cryptocurrencies.

4.4 CLOSING PRICE PREDICTION

One prominent approach to utilising machine learning models in quantitative trading is predicting the closing price of a cryptocurrency. By accurately forecasting the closing price, algorithms can generate buy and sell signals, thereby enhancing trading profitability.

This project utilises the TensorFlow (v2.16) Python library to train a long short-term memory (LSTM) model to handle sequence learning. The popular Adam optimiser was used alongside a loss function of Mean Squared Error. For better generalisation, a dropout layer with a rate of 0.2 was applied after LSTM. The model is trained iteratively over multiple cryptocurrency historical datasets for better generality.

4.5 MOVEMENT PREDICTION

One drawback of only predicting the closing price is the possibility of inconsistency and no extra information is available to guide the generation of buy and sell signals. Therefore, a utility model which predicts only the movement of a cryptocurrency is trained. The assumption is that models will be more accurate if only direction needs to be predicted and not the magnitude of it as well. The model predicts whether at time $t + 1$ the cryptocurrency will be higher or lower than the current time t.

This project utilises the scikit-learn library to train a gradient boosting classifier (GBC) model and a random forest classifier (RF) model. These two models are simple and only use the current time t to predict the direction of time $t + 1$. A third LSTM model was created to leverage sequence data. This model has a dropout layer with a rate of 0.2 and uses the Adam optimizer and a Binary Crossentropy loss function.

5 EXPERIMENTAL SETUP AND RESULTS

In this section, the various models are tested for effectiveness. Therefore, the following research questions are raised:

- **RQ1:** Which model is the most effective in making predictions?
- **RQ2:** Can these models be integrated into a trading strategy and outperform the cryptocurrency market?
- **RQ3:** Can these models be integrated into a trading strategy and outperform non-machine learning-based strategies?

Due to restrictions in time and resources, only the best models in each step were considered.

Models were not trained on minute-level data as preliminary tests often found fees outweighed the returns due to the shorter trading window. Additionally, it was found that generally models converge similar when using around 10 "top" cryptocurrencies and training on more data had marginal returns or may lead to overfitting. In this case, "top" refers to a higher market cap. This group refers to both traditional cryptocurrencies like Bitcoin and Ethereum but also meme coins such as Shiba Inu coin or Dogecoin. These results require further testing for validation.

5.1 BACKTESTING (PREDICTIONS)

The errors and accuracies of the models were tested by comparing predictions made on historical data with the ground truth values.

Closing Price Predictions	
Model | Interval | Sequence	**Mean Squared Error**
LSTM | 1h | 24	0.0000134719
LSTM | 1h | 168	0.00001469763
LSTM | 1d | 7	0.00033714476
LSTM | 1d | 30	0.0004816649
Movement Predictions	
Model | Interval | Sequence	**Accuracy**
GBC | 1h | 1	0.56066247251
GBC | 1d | 1	0.53574206956
RF | 1h | 1	0.5325935773
LSTM | 1h | 24	0.54757634401

Table 1: Errors and Accuracies of Trained Models.

The closing price LSTM models using hourly data had less error than the models using daily data. This is likely due to the lower price difference between hourly price points compared to those of the daily. Additionally, the models with the longer sequence length failed to capture more meaningful data and performed worse than their alternative. The LSTM model trained on hourly data with 168 timesteps in a sequence had a larger error than the model trained on hourly data with only 24 timesteps. Likewise, the LSTM model trained on daily data with 30 timesteps in a sequence had a larger error than the model trained on daily data with only 7 timesteps.

All models trained to predict movement had accuracies above 50% but only by a marginal amount. Over the tested cryptocurrencies, the models overall only gained at most a ~6% advantage over randomly guessing whether the cryptocurrency would increase or decrease in price. This may indicate that cryptocurrencies can be defined by the random walk theory. As there is little intrinsic value held by most, if not all, cryptocurrencies, then technical analysis and machine learning is unable to predict winning trades as these technical indicators do not define anything meaningful in the asset. Conversely, these results may indicate that cryptocurrencies have more value than previously thought. The slightly above average performance of the machine learning models using only technical indicators may imply the need of fundamentals in the prediction model.

Despite this, all of the movement models had a higher prediction accuracy for Bitcoin at around 64-73%. Since the GB model for predicting hourly movement performed the best in terms of Bitcoin (0.7299), a gradient boosting classifier model was trained to predict daily movement. However, the accuracy decreased, with the model having a correct prediction for Bitcoin only 49.59% of the time.

To answer RQ1, out of the models trained for predicting closing prices, the most effective one was an LSTM using 1h intervals and a sequence length of 24. Out of the models trained for predicting price movements, the most effective one was a Gradient Boosting Classifier using 1h intervals.

5.2 BACKTESTING (SIMULATION)

To test the application of these models in the real world, simulated trading backtesting was performed on the QuantConnect platform. This platform was chosen due to the accuracy of its backtesting feature to imitate live trading. Although slower than other platforms, QauntConnect treats simulated backtesting as if it were live trading and feeds in historical data accordingly and trades in a sped-up environment. This means that backtesting simulations are translatable to live trading. An abstracted diagram of the trading system is shown in Figure 2.

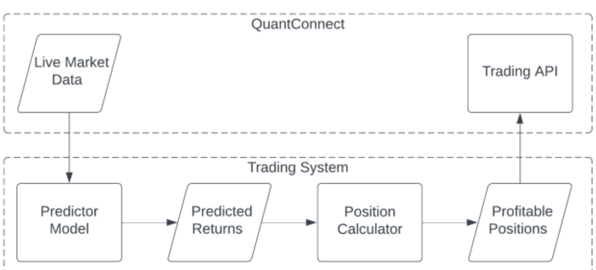

Figure 2: Automated trading system.

TRADING STRATEGY (CLOSING PRICE PREDICTION)

Various trading strategies were explored using closing price prediction, and the top performing ones were tuned to find optimal trading parameters. Using the LSTM Closing Price Model with an hourly interval and a sequence length of 24, the top performing strategy had an average monthly return of 33%. This strategy employs a static portfolio of ten cryptocurrencies and every hour makes a prediction on the closing price of each cryptocurrency. If the predicted closing price is 0.5% greater than the current price, then the cryptocurrency is bought with 20% of the starting equity (e.g., if the starting equity is $10,000, then all trades, even if the equity increases, will be $2,000). Additionally, the last 100 errors per cryptocurrency are stored and is subtracted from the predicted closing price for a more accurate prediction. This strategy does not utilise the model to generate a sell signal, but instead employs a trailing stop loss of 1.5%. When a held cryptocurrency falls by 1.5% from the local maximum, half of the position is sold.

Figure 3: Strategy Equity for Closing Price Prediction Strategy.

A benchmark for the strategy has been set to buying an equal portion of each cryptocurrency at the start of the backtesting period and holding until the end. The starting equity is $10,000.

Figure 4: Benchmark for Closing Price Prediction Strategy.

Backtest Results			
Start Equity (USD$)		$10000.00	
End Equity (USD$)		$13307.60	
Net Profit		33.076%	
Compounding Annual Return		2791.845%	
Total Fees (USDT)		₮1261.89	
Total Orders		1336	
Maximum Drawdown		2.77%	
Total Drawdown		4.300%	
PSR		99.880%	
Sharpe Ratio		62.295	
Win Rate	Average Win	52%	0.10%
Loss Rate	Average Loss	48%	-0.04%
Profit-Loss Ratio		2.77	

Table 2: Backtest Results for Closing Price Prediction Strategy.

TRADING STRATEGY (MOVEMENT PREDICTION)

Due to the movement predictor models having a higher accuracy (72.99%) when predicting Bitcoin movement, the first movement-based strategy utilises the Gradient Boosting Classifier model with an hourly interval to make Bitcoin-only trades. The strategy, every hour, predicts the movement of Bitcoin. If the predicted movement is an increase in price, the strategy buys Bitcoin using all available funds. Using a trailing stop loss, half of the held Bitcoin is sold whenever Bitcoin dips by 1.5%. This strategy had an average return of 28%.

Figure 5: Strategy Equity for Bitcoin Movement Strategy.

A benchmark for the strategy has been set to buying Bitcoin at the start of the backtesting period and holding until the end. The starting equity is $10,000.

Figure 6: Benchmark for Bitcoin Movement Strategy.

Backtest Results			
Start Equity (USD$)		$10000.00	
End Equity (USD$)		$12819.42	
Net Profit		28.194%	
Compounding Annual Return		1762.351%	
Total Fees (USDT)		₮946.76	
Total Orders		176	
Maximum Drawdown		3.99%	
Total Drawdown		7.400%	
PSR		98.082%	
Sharpe Ratio		30.638	
Win Rate	Average Win	57%	0.62%
Loss Rate	Average Loss	43%	-0.25%
Profit-Loss Ratio		2.49	

Table 3: Backtest Results for Bitcoin Movement Strategy.

Due to the Bitcoin Movement Strategy performing relatively similar to the more complex Closing Price Prediction Strategy, this project explored a movement strategy using more cryptocurrencies. This strategy has a set portfolio of ten cryptocurrencies and every hour buys an equal portion of all cryptocurrencies predicted to increase in price using all available funds. Using a trailing stop loss, when a cryptocurrency dips by 1.5% from a local maximum, half of the held cryptocurrency is sold. This strategy was able to outperform the other two proposed strategies with an average monthly return of around 35%.

Figure 7: Strategy Equity for Portfolio Movement Strategy.

A benchmark for the strategy has been set to buying an equal portion of each cryptocurrency at the start of the backtesting period and holding until the end. The starting equity is $10,000.

Figure 8: Benchmark for Portfolio Movement Strategy.

Backtest Results			
Start Equity (USD$)		$10000.00	
End Equity (USD$)		$13423.12	
Net Profit		34.231%	
Compounding Annual Return		3101.632%	
Total Fees (USDT)		₮1457.47	
Total Orders		5115	
Maximum Drawdown		2.17%	
Total Drawdown		4.800%	
PSR		99.781%	
Sharpe Ratio		53.533	
Win Rate	Average Win	50%	0.05%
Loss Rate	Average Loss	50%	-0.02%

Profit-Loss Ratio	2.53

Table 4: Backtest Results for Portfolio Movement Strategy.

TRADING STRATEGY (NON-MACHINE LEARNING)

As a baseline for comparison, a non-machine learning-based strategy was developed. The strategy, every hour, allocates all available funds equally to 10 cryptocurrencies. No calculations are made, and these cryptocurrencies are bought every hour. Using a trailing stop loss, when a cryptocurrency dips by 1.5% from a local maximum, half of the held cryptocurrency is sold. This strategy had an average monthly return of 27%.

Figure 9: Strategy Equity for Non-ML Strategy.

A benchmark for the strategy has been set to buying an equal portion of each cryptocurrency at the start of the backtesting period and holding until the end. The starting equity is $10,000.

Figure 10: Benchmark for Non-ML Strategy.

Backtest Results			
Start Equity (USD$)		$10000.00	
End Equity (USD$)		$12699.27	
Net Profit		26.993%	
Compounding Annual Return		1566.900%	
Total Fees (USDT)		₮1194.34	
Total Orders		7641	
Maximum Drawdown		3.34%	
Total Drawdown		5.800%	
PSR		94.864%	
Sharpe Ratio		22.896	
Win Rate	Average Win	47%	0.07%
Loss Rate	Average Loss	53%	-0.03%
Profit-Loss Ratio		2.41	

Table 5: Backtest Results for Non-ML Strategy.

It must be noted that these strategies were also backtested over other periods to prevent overfitting and similar results were found. Therefore, to answer RQ2, the trained models are able to be integrated into quantitative trading algorithms to produce above market returns. Additionally, to answer RQ3, the machine learning models integrated into quantitative strategies outperformed the non-machine learning-based strategy.

5.3 LIVE TRADING

Due to limited time and resources, only one strategy could be tested with live trading. The Closing Price Prediction Strategy was chosen as it had the highest Sharpe Ratio out of the strategies presented in the previous section. This should optimise the profits against the risk.

As of writing, the live trading deployment has only been active for 6 days (from May 23, 2024, to May 29, 2024). Because of this, the results are limited. From this period, the strategy was given 250 USDT and is currently at ~245.5 USDT (see Figure 11). This results to around a -1.8% return.

Figure 11: Live Trading Results from May 23, 2024, to May 29, 2024.

In comparison, the benchmark had a 1.9% return (see Figure 12).

Figure 12: Live Trading Benchmark from May 23, 2024, to May 29, 2024.

Due to an error, the benchmark starts at 257.7 USDT and not 250 USDT.

6 DISCUSSION

The models trained in this project showed promising results that had predictions that were slightly more accurate than random guessing. However, the lack of conclusive precision and confident predictions indicate the drawbacks of using only technical indicators.

The experimental setup explores the uses of machine learning in quantitative trading. The top performing models from the methodology were chosen for integration due to limited time and resources to test all models created. The first top strategy leverages an LSTM model with a mean average error of 0.0000134719 to predict closing prices of a set portfolio of cryptocurrencies to create buy signals on an hourly level. The second top strategy uses a gradient boosting classifier model to predict the upwards or downwards movement of Bitcoin with an accuracy of 72.99% and buys the asset when the model predicts upwards within the hour. The final top strategy utilises the same gradient boosting classifier model to predict the upwards or downwards movement of a portfolio of 10 cryptocurrencies with an accuracy of 56.07% and buys an equal portion of assets which the model predicts has an upwards trend.

While the Portfolio Movement Strategy has the highest net profit over the backtesting period, other factors must be analysed. One consideration is the Sharpe Ratio. Expectedly, the Bitcoin Movement Strategy has the lowest Sharpe Ratio with a value of 30.638, indicating it is the riskier strategy of the three due to only one cryptocurrency ever being traded. This can be seen in it having the highest maximum drawdown and total drawdown. This reinforces the need to diversify the trading portfolio. This strategy also makes the least number of trades having only done 176, which resulted in fees of ₮946.76. Despite the Portfolio Movement Strategy having the higher net profit of 34.231%, it also has a lower Sharpe Ratio of 53.533 compared to the Closing Price Prediction Strategy which had a net profit of 33.076% and a Sharpe Ratio of 62.295. Depending on risk tolerance, a 16% increase in Sharpe Ratio may be better despite a ~1% loss in net profit. Furthermore, the Portfolio Movement Strategy, which used a Gradient Boosting Classifier model, required less pre- and post-processing of data compared to the Closing Price Prediction Strategy, which used an LSTM model. It also must be noted that these Sharpe Ratio values, and the compounding annual returns (annualised return) are disproportionately high compared to standard values in the market. There is likely an error in calculations or data handling on the side of QuantConnect as the project relies solely on the platform to do backtesting; the only external factors being the models used to make predictions in the strategies. Currently, the backtesting period should be outside the model training datasets. However, these inflated Sharpe Ratios and returns can still be used to compare the strategies with each other, although cannot be used to compare with other works.

Despite the contradiction of the highly accurate platform of QuantConnect producing seemingly improbable results, the machine learning-based strategies had an increase (~7%) compared to the non-machine learning-based strategy. This indicates the effectiveness of machine learning within a cryptocurrency trading context. However, a 7% increase from an almost random strategy indicates either that there are relatively low hidden factors relating to the price fluctuations of cryptocurrencies, or the models used do not fully draw out the latent factors and make accurate enough predictions. A stronger machine learning model may provide higher returns when using the same quantitative strategies proposed in the experimental setup. Additionally, the strategies all used a trailing stop loss to sell the cryptocurrencies as that was found more effective than using the models to predict when to sell. This may hint that the models are better at predicting when to buy but not necessarily when to sell. Ultimately, the current proposed models and strategies show promising results and above market returns. It is important to note that the results seem disproportionate to current similar strategies and market trends. More research, especially in the field of live trading, is required to validate these results further.

Although the live trading deployment period is relatively short at only 6 days, the results show the strategy is able to keep a consolidating equity balance, fluctuating around the 245 and 250 USDT price points (or -1.8% and 0% returns). Unfortunately, this means the strategy is performing below the market as the strategy has a -1.8% return whereas the benchmark market has a 1.9% return. Furthermore, this is not consistent with the simulated backtests which had a ~30% return over a period of a month. Accounting for the time differences, the live trading should have had a return of approximately 6%, but it does not. This presents a factor that must be considered: the inherent differences between simulated trading and live trading. Although QuantConnect is accurate in effectively simulating a live trading environment during backtests, slight deviations in data handling may affect the effectiveness of a strategy, and volatile markets may result in trades not executing at desirable times. More time is required to fully analyse the effectiveness of the strategies proposed in a live trading context.

6.1 LIMITATIONS

The results of this project have heavy focus on simulated backtests. More time is required for live trading results to be recorded and consequently determine the effectiveness of the proposed models and strategies in real-world contexts.

The proposed strategies use a set portfolio of ten cryptocurrencies and often have periods where most of the equity is held in the stablecoin USDT, which means no movement in price occurs. A larger portfolio or a dynamic universe selection should increase the exposure of the strategies and may increase profits.

7 SYSTEM RELEASE

The version 1.3.1 release for the project can be accessed here: https://github.com/jose-dls/ML-Crypto-Public/releases/tag/v1.3.1

8 CONCLUSION

Much focus has been placed by researchers on stock market trading and machine learning quantitative strategies, however, cryptocurrency markets provide a different approach to trading. Cryptocurrencies often place more focus on technical factors and thus machine learning models may prove to be more effective. This project explored the use of classifier models and sequence models to predict the state of cryptocurrencies at certain times and thus create a quantitative strategy that provides above-market results. While promising results were received in backtesting simulations, more time is required for live trading results.

Gradient Boosting Classifier provide a simpler model for quantitative trading, however, may be riskier due to the limited amount of time sequence data used. On the other hand, LSTM models have stronger predictions, but require pre- and post-processing.

8.1 FUTURE WORK

The backtesting results should be validated to confirm the effectiveness of the results in live trading applications.

Future work should explore the differences between simulated backtests and live trading. Understanding and minimising the differences between the two during development should increase the profits and the accuracies of the quantitative strategies.

For the proposed strategies, implementing a dynamic universe should be explored instead of a set portfolio.

For the proposed strategies, it is recommended that other models are explored, such as the FactorVAE model discussed previously.

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