Bachelor's Thesis

in the Bachelor's Program 'Applied Mathematics and Computer Science'

Backtesting and Live-Testing of Classic and AI-Powered Trading Strategies

by

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Submitted on: 21st July, 2025

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Monheim am Rhein, 21st July, 2025

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Abstract

Contents

List of Figures

List of Tables

Code Listing

List of Abbreviations

ETH	Ethereum
USDC	USD Coin
AI	Artificial Intelligence
API	Application Programming Interface
LSTM	Long Short-Term Memory
CNN	Convolutional Neural Network
CFD	Contract For Difference
EU	European Union
UTC	Coordinated Universal Time
EMA	Exponential Moving Average
SMA	Simple Moving Average
MACD	Moving Average Convergence/Divergence
ATR	Average True Range
TR	True Range
RSI	Relative Strength Index
PCA	Principal Component Analysis
PM	Post Meridiem
RRR	Risk Reward Ratio
1D	One Dimensional
FNN	Feedforward Neural Network
MLP	Multilayer Perceptron
ReLu	Rectified Linear Unit
RNN	Recurrent Neural Network
GRU	Gated Recurrent Unit
Min	Minimum
Max	Maximum
No	Number
TA	Technical Analysis
MDD	Maximum Drawdown
DD	Drawdown
SPI	Service Provider Interface
JAR	Java Archive

1 Introduction

1.1 Motivation

In recent years, the cryptocurrency market has emerged as a highly dynamic and rapidly evolving financial ecosystem. Trading pairs such as ETH/USDC M1on minute-level (M1) intervals provide vast amounts of high-frequency data, reflecting extreme volatility and market shifts. This creates challenges and opportunities for traders and researchers.

The availability of detailed tick and minute data, combined with direct API access from crypto brokers, creates new opportunities for developing data-driven trading systems. Advances in machine learning and deep learning offer promising tools to identify patterns in market movements. This motivates an exploration of AI-based trading systems specifically designed for the ETH/USDC M1pair, aiming to leverage technical features and advanced models to improve performance in the volatile cryptocurrency environment.

On the other hand, classical trading strategies also could perform well in this environment, especially if the strategies are adapted to specific market regimes. Techniques such as moving averages, Bollinger Bands, or momentum indicators have the advantage of simplicity and transparency, allowing traders to understand and trust their decision-making process.

1.2 Aim of this Paper

The primary goal of this paper is to develop and evaluate AI-powered and classical trading strategies focused on the ETH/USDC M1cryptocurrency pair. This paper will:

1. Retrieve historical ETH/USDC M1data via a broker API and process it for analysis.
2. Perform exploratory data analysis and feature engineering, including trend, volatility, and momentum indicators.
3. Identify and classify distinct market regimes to provide adaptive trading decisions.
4. Apply risk and money management techniques to realistically simulate trading performance.
5. Design, train, and benchmark multiple deep learning architectures such as LSTM, CNN, and hybrid models for forecasting the price and classify trading decisions.
6. Develop algorithmic trading strategies based on AI model predictions and compare them with classical technical trading approaches.
7. Build a modular trading engine capable of backtesting trading strategies and live execution using real broker connections.
8. Execution of the final best trading strategy in live operation on a demo account with a real broker.

By focusing on the ETH/USDC M1pair, this paper aims to provide insights into the effectiveness of deep learning and classical strategies in cryptocurrency trading and contribute practical tools for automated, adaptive trading in this challenging asset class.

2 Data Source and Broker Selection

Cryptocurrency brokers (also called crypto brokers) play an important role in cryptocurrency trading. Among other things, they act as intermediaries between different market participants. Their key tasks include:

1. **Providing access:** Individuals can participate in the market through a broker and thereby trade various cryptocurrencies. This includes executing orders such as buying cryptocurrencies at the lowest available price or selling them at the highest available price.
2. **Security, and Compliance:** They also provide customers with a secure platform for executing transactions and adhere to the financial regulations established by authorities.
3. **Leveraging:** Brokers offer customers the opportunity to borrow money, and thus trade with more capital than they actually have in their account.

This has the advantage that trading with cryptocurrencies is much easier and safer, but one of the biggest disadvantages is the fees that are incurred when using [1].

2.1 Broker Selection

For this paper, one broker must be selected for data retrieval and live testing. Since the process is fully automated in short time-frames, the broker must meet certain requirements.

The API must be able to stream market data, request historical data, the current account balance, closed trades, and currently open positions, placing orders, and positions, as well as canceling unfilled orders.

Apart from the API, the broker must support leveraged long/short products like CFDs or margin trading, with the lowest possible fees. They also must provide data in high quality as well as a demo depot.

Table 1 summarizes the required features for some potential brokers. All listed there meet the API functionality requirements.[1]

Broker	Tradable assets	Fees		Leverage
		Maker	Taker	
ByBit	Spot, Spot with leverage, Futures, Options	0.02%	0.055%	10:1
IG	CFDs, Knock-out-Options	Spread (approx. $1.30)		2:1
Capital.com	CFDs	Spread (approx. $1.75)		2:1

Table 1: Broker Comparison

Taking into account Table 1, ByBit is the best broker because it has the lowest fees, high quality data, as well as the highest possible leverage.

[1]Sources: [2], [3], [4], [5], [6], [7]

2.2 API Connection and Data Retrieval Process

Before starting with the Machine Learning process, and the backtests, the first step is to download historical ETH/USDC M1data via the ByBit API. The request was executed on the `/v5/market/kline` API-Endpoint [8] with the category `linear`, symbol `ETHPERP`, and interval `1` at 17th June, 2025, 11:30 UTC+2. Since ByBit only returns 1000 candlesticks per request, the same request with different start-, and end-times was executed until the ByBit API does no longer return older candlestick data. This resulted in a candlestick data pool with data on a minute basis from 5th August, 2022, 10:00 UTC+2to 17th June, 2025, 11:30 UTC+2. Chapter 3.1 will go into more detail about the data.

3 Exploratory Data Analysis

3.1 Statistics

3.2 Dividing the Data

Unlike classic machine learning processes, where data is split in three subsets, named train-, validation-, and test-set, here the data is split in four subsets. The fourth data-set is used for backtesting the real trading strategy, and is therefore not part of the machine learning process but plays an important role in developing the final trading strategy.

Set	From	To	No. of Datapoints	% of All Data
Complete	08/05/2022 10:00 UTC+2	06/17/2025 11:30 UTC+2	$1,507,598$	
Train	08/05/2022 10:00 UTC+2	04/30/2024 23:59 UTC+2	$913,684$	60.6%
Validation	05/01/2024 00:00 UTC+2	09/30/2024 23:59 UTC+2	$220,320$	14.6%
Test	10/01/2024 00:00 UTC+2	12/31/2024 23:59 UTC+2	$132,482$	8.8%
Backtest	01/01/2025 00:00 UTC+2	06/17/2025 11:30 UTC+2	$241,111$	15.9%

Table 2: Data Split

After the splitting, the four subsets have the following summaries:

	Open	High	Low	Close	Volume
	Open	High	Low	Close	Volume
count	913684.0	913684.0	913684.0	913684.0	913684.0
mean	1933.4	1933.95	1932.85	1933.4	7.58
std	619.6	619.92	619.28	619.6	105.09
min	1074.35	1077.45	1064.05	1074.35	0.0
25%	1578.44	1578.89	1577.99	1578.44	0.0
50%	1801.52	1801.81	1801.13	1801.52	0.05
75%	2083.4	2083.84	2083.05	2083.4	2.02
max	4098.5	4099.48	4096.35	4098.5	31350.65

Table 3: Train Data

	Open	High	Low	Close	Volume
count	220320.0	220320.0	220320.0	220320.0	220320.0
mean	3050.36	3051.3	3049.4	3050.36	2.89
std	473.4	473.45	473.34	473.4	21.45
min	2111.8	2160.4	2088.13	2111.8	0.0
25%	2617.31	2618.04	2616.71	2617.31	0.0
50%	3063.4	3064.31	3062.43	3063.4	0.12
75%	3462.22	3463.29	3461.21	3462.22	1.32
max	3974.68	3976.96	3969.94	3974.68	4972.18

Table 4: Validation Data

	Open	High	Low	Close	Volume
count	132482.0	132482.0	132482.0	132482.0	132482.0
mean	3093.93	3095.27	3092.58	3093.94	4.42
std	531.85	532.29	531.4	531.85	18.42
min	2309.01	2311.73	2307.73	2309.01	0.0
25%	2541.8	2542.65	2540.94	2541.8	0.08
50%	3143.69	3145.38	3142.02	3143.7	0.68
75%	3487.9	3489.46	3486.33	3487.9	2.92
max	4107.28	4112.68	4102.6	4107.28	1341.05

Table 5: Test Data

	Open	High	Low	Close	Volume
count	241111.0	241111.0	241111.0	241111.0	241111.0
mean	2432.57	2433.77	2431.35	2432.57	7.0
std	574.72	574.95	574.49	574.72	32.11
min	1386.6	1395.8	1382.99	1386.6	0.0
25%	1887.22	1888.28	1886.1	1887.22	0.18
50%	2510.29	2511.4	2509.1	2510.29	1.26
75%	2732.0	2733.21	2730.7	2732.0	4.94
max	3742.33	3745.13	3739.65	3742.33	2534.66

Table 6: Backtest Data

3.3 Using Log-Returns

In the summary statistics of the subsets (Table 3, Table 4, Table 5, Table 6) it is noticeable that the mean values change over time. This becomes also clear when visualizing the data (Figure 1).

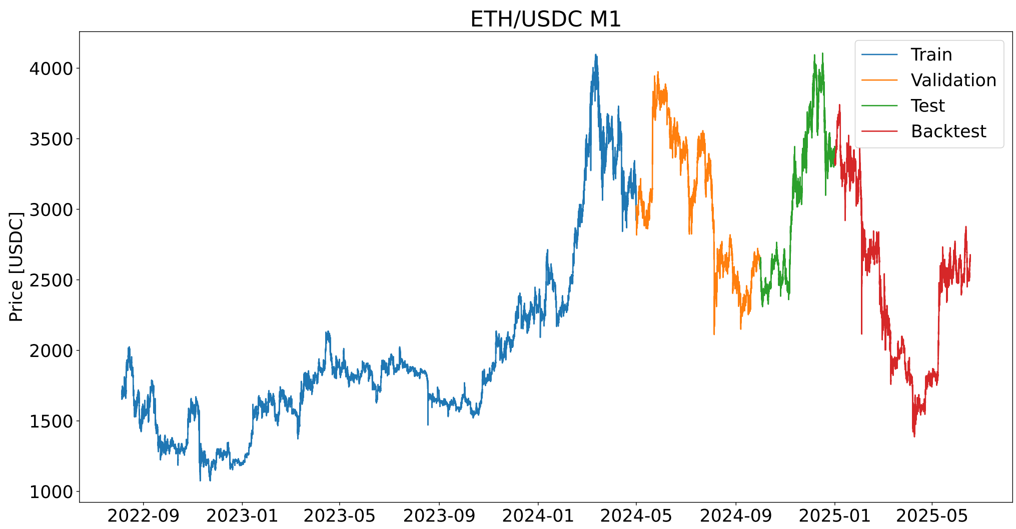

Figure 1: Price Fluctuation of ETH in USDC

To avoid this data drift, the price is transformed to its logarithmic returns (also called log-returns). These are calculated as follows:

$$LogReturn_t = ln(\frac{Price_t}{Price_{t-1}}) \tag{1}$$

After the transformation, the means and standard deviations in the subsets are very similar, and the data does no longer drift over time. Table 7 shows the means and standard deviations after the logarithmic return transformation. Additionally, Figure 2 shows visually, that the data drift is eliminated.

Data Set	Mean	Standard Deviation
Train	6.5E-7	8.7E-4
Validation	-6.1E-7	9.4E-4
Test	1.8E-6	9.4E-4
Backtest	-9.5E-7	1.1E-3

Table 7: Statistics after Logarithmic Returns Transformation

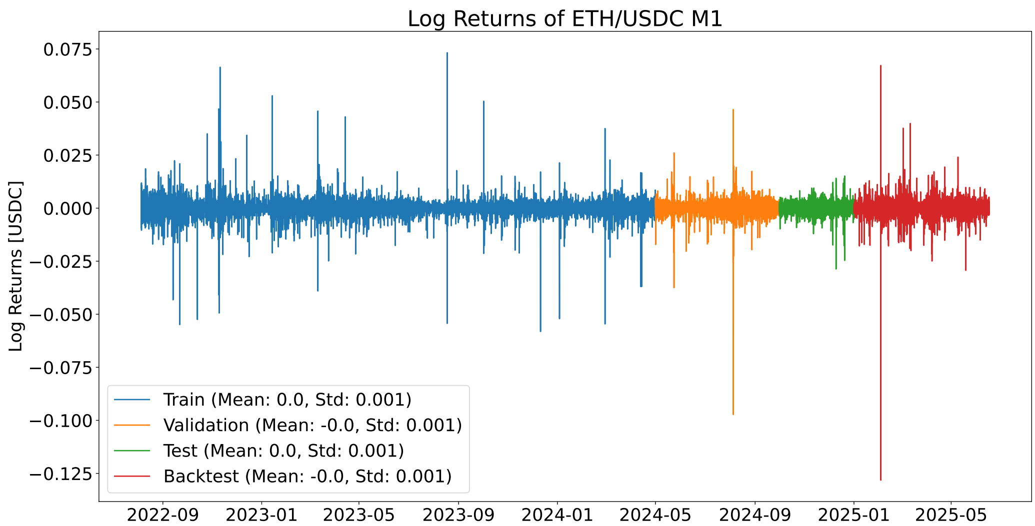

Figure 2: Log Returns of ETH in USDC

The transformation is applied to the open, high, low, and close prices, and the original prices are replaced by the logarithmic returns, so that all subsequent actions are carried out with the prices on the logarithmic returns.

3.4 Additional Features

To provide the machine learning models with more context about the price, additional features from different categories were added to the raw data.

3.4.1 Trend Following Indicators

In financial analysis trend following indicators play an essential role while modeling a predicting future price movements. This occurs because markets move in trends that are repeatedly interrupted by outliers. This results in a zigzag movement that nevertheless moves in one direction. Trend-following indicators can be used to filter out these outliers [9].

The exponential moving average (EMA) is one type of trend following indicator. It is a variation of the classic simple moving average (SMA), placing more emphasis on newer prices. It is often used by traders in length of 10-, 50-, and 200-period. One limitation is that many trades believe that new data better reflects the current trend, where many others believe that overweighting recent prices creates a bias [10].

Because the EMA reacts faster to price changes than the SMA, and the aim of this paper are short-term predictions, the EMA could provide more relevant context for the model. The EMA was added in 5, 10, 20, 30, 50, and 200 period to the data.

Another Trend following indicator is the moving average convergence/divergence (MACD) which does not only help to identify price trends, but also helps to measure the trend momentum. It shows the relationship between two exponential moving averages. To calculate the MACD line, an EMA(12) is subtracted from an EMA(26). Additionally, a signal line is calculated as an EMA(9) of the MACD line.

Although the MACD can signal possible reversals, it is also known for creating many false positives. This often happens if the market moves sideways [11].

3.4.2 Volatility Indicators

To measure volatility, there are other indicators and techniques to measure the volatility, in addition to those described in subsection 4.2.

One indicator is the average true range (ATR) which decomposes the entire range of an asset price for a period. It is calculated by determining the so-called true range (TR) for each candlestick - the maximum of: current high minus low; distance from the previous closing price up, and down. The ATR is then the moving average of these TR values, usually over 14 periods.

The ATR has two main limitations. The first is that an ATR value must always be set into comparison to previous ATR values, because one single value is not enough to tell if a trend is going to reverse. The second limitation is that the ATR does not tell anything about the direction of the price [12]. The ATR was added in 5, 7, 10, 14, and 18 periods to the data.

Another volatility indicator are Bollinger Bands, which consist of three lines. The middle line is a SMA of the closing prices, the lower line is calculated by subtracting a certain number of standard deviations from the middle line, and the upper line is calculated by adding a certain number of standard deviations to the middle line. Usually the double of the standard deviation is added, and subtracted from the middle line.

The higher the volatility of the market is in the last closing prices, the wider the band gets. If the price of the market rises near the upper band, traders see the market as overbought. Similarly, if the market falls near the lower band, the market could be oversold. This allows to generate possible entry and exit signals [13]. The three Lines where added to the data with a 15, 20, and 25 period SMA.

3.4.3 Momentum Indicators

Momentum measures the strength and direction of a price movement over a certain period of time. Momentum indicators are useful because they give insights into the strength of trending prices. Therefore, they can indicate possible reversals in the trend direction [14].

A common momentum indicator is the relative strength index (RSI). It measures the speed and magnitude of an asset price by comparing the average gains and losses of the asset, and can be used to detect overbought and oversold conditions. The RSI ranges between zero and 100. Usually an RSI over 70 indicates an overbought, and an RSI below 30 indicates an oversold market. Commonly the default RSI period to compare the average gains, and losses is 14 [15]. The RSI was added in periods 7, 14, and 20 to the data.

To depict relative trend strength, a sophisticated momentum indicator was constructed that compares the log returns of two different time frames. This feature allows the model to distinguish phases of accelerating price movements from stable or declining trends. The use of logarithmic returns simultaneously achieves scale independence, and improved comparability, which is particularly advantageous for modeling financial market-related time series. This indicator was added for time frames M2, M3, M6, M9, and M12.

3.4.4 Price Transformation Indicators

Apart from the mentioned indicators shifted logarithmic returns for the last six minutes have been added to provide additional context about the last price movements in a compact form. This could help the models to recognize trend reversals, volatility changes or short-term patterns.

Lastly, the logarithmic returns of other time frames (M2, M3, M6, M9, and M12) have been added to the data providing another more stable trend context which helps to correctly classify short-term price movements. This creates a balanced feature set that takes into account both rapid reactions and long-term patterns.

3.5 Scaling the Data

Scaling data is an important step in exploratory data analysis. This is because, on the one hand, machine learning models perform better with scaled data [16], and, on the other hand, principal component analysis (subsection 3.6) is sensitive to unscaled data [17].

The use of the scikit-learn `MinMaxScaler` [18], which scales data date in a fixed range of $[0; 1]$ is useful and widely used. Neural networks, especially those with activation functions such as ReLU, which is introduced in **??** benefits greatly from inputs with a uniform range of values. The scaling stabilizes the gradient flow, shortens training time and reduces vanishing gradients [19].

For these reasons, all features were scaled with the `MinMaxScaler` and are used exclusively in the scaled form in all steps related to machine learning.

3.6 Principal Component Analysis

The principal component analysis (PCA) is a process for dimensional reduction, by linearly transforming high dimensional datasets to a small number of uncorrelated principal components (directions of the new coordinate system). During the transformation, it can be specified how much variance in the data can be eliminated. After a transformation using PCA, it is ensured that at least the specified variance is retained [20].

Especially when processing numerous technical indicators or derived features in financial data, the high dimensionality can become problematic - a phenomenon known as the course of dimensionality. This term describes the increasing challenges in modeling as the number of dimensions or features increases. Data points become increasingly sparsely disturbed, computational costs increase, and many models lose their ability to generalize. Applying PCA allows redundant or correlated information to be condensed, making the model more robust, faster, and easier to interpret. At the same time, the risk of overfitting is reduced because the model focuses on the most important structures in the dataset [21].

Figure 3 shows the cumulative explained variance for the 56 added features in subsection 3.4 for each quantile market regime. It shows that the cumulative variance increases rapidly at the beginning. In this case, the reduction of the project to just 3 to 6 principal components already explains at least 80% of the variance. This means that the majority of the statistically relevant structures in the dataset are retained, even though the number of features has been massively reduced. Even if 20% of the variance is lost, the benefit outweighs this: The remaining principal components capture the statistical essence of the original feature space in a significantly more compact and robust form, which is particularly well-suited for machine learning.

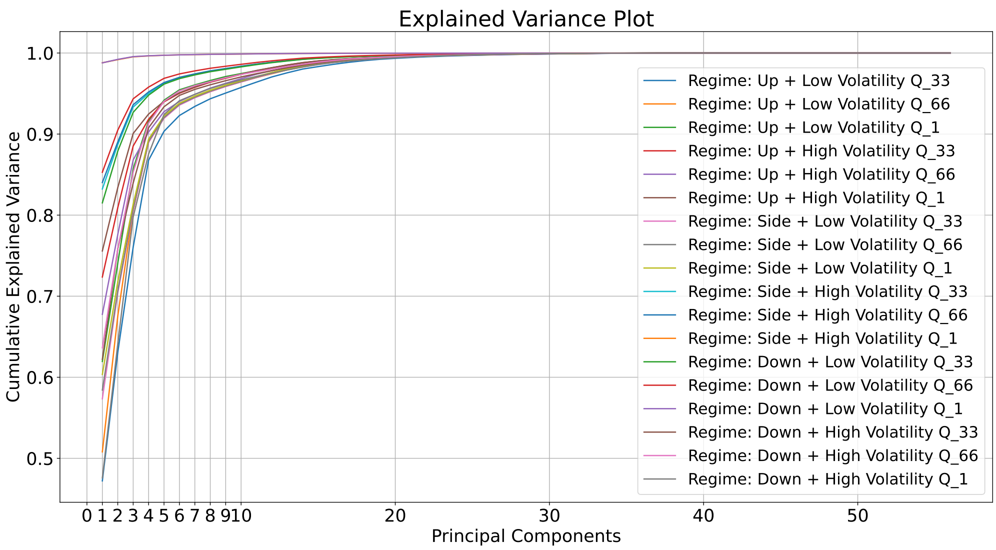

Figure 3: Cumulative Explained Variance

4 Market Regimes

Cryptocurrency markets are subject to constant change, which is reflected not only in price movements but also in the underlying structures and dynamics. In quantitative analysis and algorithmic trading, understanding these changes is essential for developing and adapting robust trading strategies. A central concept in this context is market regimes.

4.1 Introduction to Market Regimes

Market regimes describe phases with distinct statistical and economic characteristics, such as volatility, and trend behavior. They can be understood as different "states" of the market in which certain trading patterns dominate. Distinguishing between, for example, upward, sideways, and downward trends or high, and low volatility enables more targeted strategy selection and adaption. Accordingly, the identification and classification of market regimes plays an increasingly important role in modern trading analysis. For example, a strategy that performs well in a stable uptrend may fail in a sideways movement or in periods of high volatility [22].

Understanding market regimes leverages traders and analysts to design strategies that are adaptive, and therefore more robust. Through targeted adaptation of the parameters or the selection of different models, the performance can be increased, and the risk can be reduced.

4.2 How to Categorize the Market?

Categorizing different market characteristics is a common step in identifying market regimes. In literature and practical applications, there exist different approaches to classifying markets. A fundamental categorization is often made by the following dimensions:

1. **Trend behavior:** Markets can be categorized trend following (bullish/ bearish) or trendless (sideways).

2. **Volatility:** The volatility of a market is often an indicator for insecurity or stability. High volatility can indicate periods of stress, while low volatility indicates calm markets.

3. **Liquidity:** In illiquid markets, pricing processes can be different compared to liquid markets which has effect on strategies.

According to the analysis goal, the categorization can be binary (e.g. bullish vs. bearish) or granular (e.g. a combination of trend behavior, and volatility). Also, a combination of multiple indicators, named regime scores, is possible to capture more complex market structures.

In the current context, the market is categorized by trend behavior, and volatility. This results in six categories:

1. Downtrend + Low Volatility

2. Downtrend + High Volatility

3. Sideways Trend + Low Volatility

4. Sideways Trend + High Volatility
5. Uptrend + Low Volatility
6. Uptrend + High Volatility

This takes into account the two most central aspects that lead traders to different trading decisions. However, the market is not divided into too many small segments, which can lead to overfitting.

4.3 Recognizing Market Regimes

As described in subsection 4.2, the market will be divided into six categories which are the result of combinations of two individual categories. This makes it possible to categorize the two individual categories individually, and finally merge them.

4.3.1 Recognizing Trend Behavior

The first step is to categorize the market into uptrends, downtrends, and sideways trends. Commonly, a combination of a short-term moving average (e.g. SMA(50)), and a long-term moving average (e.g. SMA(200)) is used to identify superior trends. The SMA(200) is considered the classic boundary between bullish and bearish market phases. If the short-term moving average is above the long-term moving average, the market is considered bullish. Vice versa, if the short-term moving average is below the long-term moving average, the market is considered bearish [23].

For the purpose of the current context, a modified combination of SMA(50), and SMA(100) was chosen. This decision is based on two considerations:

1. **Faster reaction:** The SMA(100) is intended to achieve faster reaction to medium-term trend changes without heavily weighting short-term volatility.
2. **Inertia of trend definition:** A shorter trend window, compared to the SMA(200) reduces the inertia of trend definition, which can be particularly advantageous for more refined classification into uptrends, downtrends, and sideways trend.

Additionally, a minimum slope threshold over the last 15 minutes was integrated for the SMA(50) to avoid that minimal direction changes are mistakenly interpreted as a meaningful trend. This short time span ensures that current market movements are adequately incorporated into the trend classification without being dominated by short-term noise (e.g., individual volatility peaks), and therefore increases the robustness of the trend recognition, and addresses the weaknesses of moving averages in sideways phases. A slope above +0.05 signals a significant short-term uptrend, while a slope below -0.05 suggests a clear downtrend. Values in between are interpreted as ambiguous, and are included in the sideways classification accordingly.

The market can therefore be divided into three trend phases based on the following criteria:

1. **Uptrend:** The SMA(50) is above the SMA(100), and the slope of the SMA(50) in the last 15 minutes is greater than 0.05.

2. **Downtrend:** The SMA(50) is below the SMA(100), and the slope of the SMA(50) in the last 15 minutes is less than -0.05.

3. **Sideways trend:** The market currently does not meet condition 1 or 2.

Figure 4 shows an example of trend classification of ETH/USDC M1for 700 minutes.

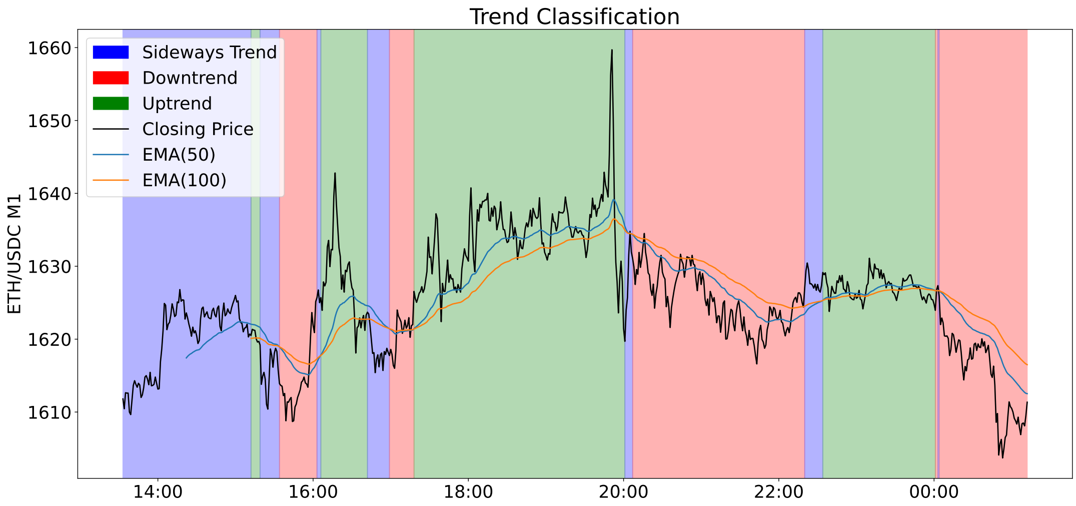

Figure 4: Trend Classification

4.3.2 Recognizing Volatility

The second step is to categorize the market into phases with high and low volatility. The volatility is calculated as the standard deviation of the logarithmic returns over the last 30 minutes [24]. This locally calculated volatility depicts short-term fluctuation intensity, and enables a context-dependent assessment of current market behavior.

To classify this local volatility, a comparison is made with the median of all available volatilities in the training dataset which was used for fitting the volatility classification indicator. If the current volatility is greater than the median, the market is classified as highly volatile. Otherwise, the market is classified as low volatility.

This threshold definition is deliberately based on a dynamic, data-dependent approach rather than using a fixed absolute threshold. This automatically adapts the volatility classification to each specific market, and can therefore theoretically be applied to other financial markets.

Figure 5 shows the volatility classification on the same base data used in Figure 4.

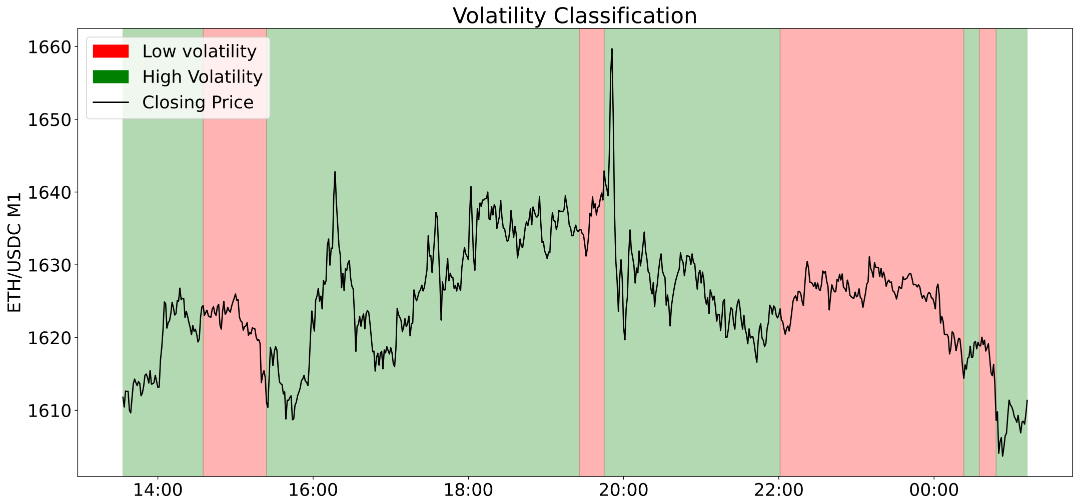

Figure 5: Volatility Classification

4.3.3 Combining Trend and Volatility Classification

After the two separate classifications in subsubsection 4.3.1 and subsubsection 4.3.2 the results can be combined. The results of the combination can be seen in Figure 6.

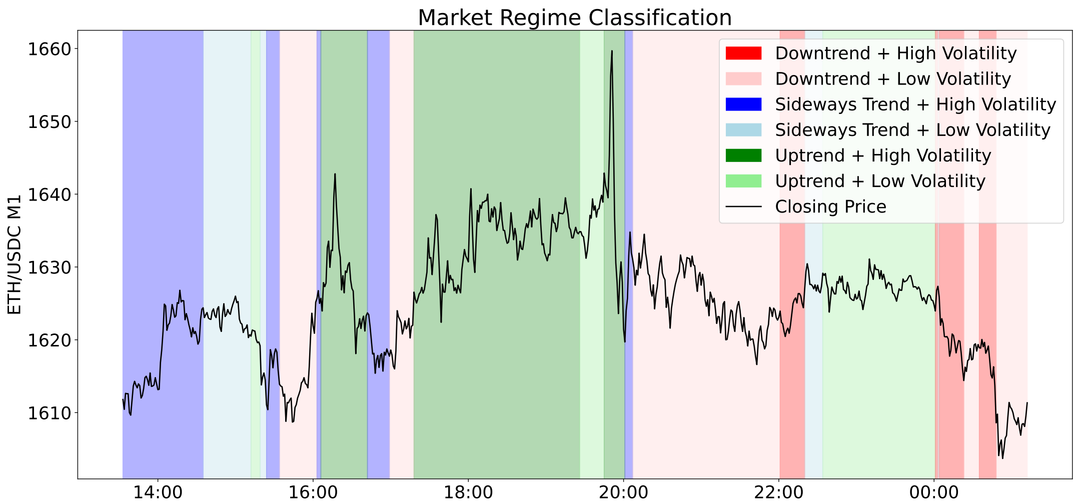

Figure 6: Regime Classification

While classification of the market regimes some discrepancies may occur in individual cases between the algorithmically determined category and the visually perceived category. Such misclassifications are particularly possible during transition phases or in the case of short-term outliers. For example, the downtrend, highly volatile market regime after 10:00 PM, the algorithm detected a downtrend, but visually, an uptrend is perceived. At this time, the market is in a transition, which causes this misclassification.

Crucially, the classification distinguishes consistently and meaningfully, which is the case when viewed as a whole. The robustness and usefulness of the approach does not arise from absolute freedom from errors, but rather from the systematic reduction of uncertainty compared to a purely visual or subjective assessment.

4.4 Dividing Market Regimes in Durations

Based on the combination of trend direction and volatility level, the duration of each market regime is also taken into account to enable a more differentiated classification. The regime duration is divided into three quantiles (33%, 66%, 100%) based on its distribution, allowing for classification into short-term, medium-term, and long-term phases. The notation in the current work for the respective regime durations is $Q_{0.33}$, $Q_{0.66}$ and Q_1.

The combination of these three dimensions results in a total of 18 different market regimes. This fine-grained segmentation makes it possible to more precisely capture and differentiate different market conditions. For example, a short-term, volatile uptrend from a long-term, calm downtrend.

Even through this makes the market appear more fragmented, and regimes can change more frequently, this finer subdivision is analytically useful. It allows for context-sensitive market behavior to be examined, and differences in the dynamics of effectiveness of trading strategies in specific regime types to be systematically analyzed.

Instead of smoothing out reality with overly broad categories, a more nuanced picture is deliberately drawn that takes into account both the direction, intensity, and stability of market behavior. The resulting increased complexity is not a disadvantage, but rather a prerequisite for more meaningful, context-based analyses.

5 Money- and Risk-Management

Successful trading is not only based on a good strategy, but also on a disciplined management of capital and risk. Even the best prediction is useless if losses grow uncontrolled or a majority of the capital is risked by a few wrong decisions. This is where money and risk management come into play. They define clear rules regarding how much to invest per trade, what level of risk is acceptable, and how losses can be limited. The goal is to protect capital over the long term, minimizing drawdowns, and profit from positive expected values in a controlled manner. This chapter introduces fundamental concepts, metrics, and methods helping to make rational and sustainable decisions.

5.1 Calculating the Position Size

An important part of risk management is calculating the position size. It is helpful to maximize the potential returns, as well as minimizing the financial risk. Many traders are only willing to risk 1% or 2% of the available capital per trade, to prevent a series of losing trades from decimating the available capital too much.

The distance between the estimated entry price and the estimated stop-loss price represents the maximum distance a market can move in an unprofitable direction before a position is automatically closed.

This allows the calculation of the position size to be carried out in three steps:

1. **Determining the risk per trade:** First, it must be determined how much of the available capital should be risked. If 1% of $10,000 is to be risked, the maximum risk is $100. It is important to note that the fraction of 1% does not have to be fixed. Thus, it is possible to risk more if the entry signal is very clear. If the entry signal is less clear, it can also be risked less. Only a fixed upper limit should be defined.

2. **Calculating the risk per unit:** To calculate the risk per share the absolute distance between the estimated entry price, and the estimated stop-loss price must be calculated. This represents the risk per unit.

3. **Calculate the position size:** Dividing the risked capital by the risk per unit represents the number of units to buy or sell.

In total, these three steps can be combined into one formula [25]:

$$PositionSize = \frac{AvailableBalance * RiskPerTrade}{RiskPerUnit}$$

So if the available account balance is $10,000.00, the risk per trade is 1%, and the distance from the estimated entry price to the stop-loss is $5. The position size is calculated by:

$$PositionSize = \frac{\$10.000 * 1\%}{\$5} = \frac{\$100}{\$5} = 20[Units]$$

It is important to note that numbers can result with many decimal places, and many brokers only allow positions with a certain number of decimal places. If this is the case, the position size must be subsequently rounded to the maximum number of decimal places supported.

5.2 Validating an Entry Signal

Not every entry signal generated by a trading strategy is necessarily profitable. To be profitable in the long term, it is important to ensure that entry signals that are too risky or unrealistic in advance are filtered out, thus preventing positions from being opened. This chapter presents some techniques that can be used to validate entry signals.

5.2.1 Risk-Reward-Ratio

The risk reward ratio (RRR) is a fundamental key figure in trading. It describes the ratio between the potential profit (reward), and the potential loss (risk) of a single trade. The RRR helps in deciding whether an entry signal is too risky or not. It ensures that not only the hit rate determines the success of a strategy, but also the ratio of profit to loss in each individual trade.

The RRR is calculated by:

$$RRR = \frac{PossibleProfit}{PossibleLoss} = \frac{|OpenPrice - TakeProfitPrice|}{|OpenPrice - StopLossPrice|}$$

For example, if a long trade is opened at \$100, with a take-profit at \$110, and a stop-loss at \$95, the result is:

$$RRR = \frac{|\$100 - \$110|}{|\$100 - 95\$|} = \frac{\$10}{\$5} = 2$$

This means that for every dollar risked, a potential profit of two dollars is targeted.

A RRR greater 1 is generally considered positive because the expected profit is higher than the potential loss. However, the RRR should not be viewed in isolation. The essential factor is the combination of RRR, and hit rate:

1. **High RRR, low hit rate:** e.g. $RRR = 3$ with only a 30% probability of winning $\Rightarrow$ potentially profitable.
2. **Low RRR, high hit rate:** e.g. $RRR = 0.5$ with an 80% hit rate $\Rightarrow$ also potentially profitable.

The following rule of thumb clarifies when a strategy has a positive expected value in the long term:

$$ExpectedValue = PossibleProfit * HitRatio - PossibleLoss * (1 - HitRatio)$$

Only when this expected value is above zero, a trading strategy is statistically profitable.

The RRR is not only a mathematical metric, but a central component of risk management. It helps traders systematically plan how much they are willing to lose per trade, relative to the expected profit. By consistently applying a minimum RRR (e.g.≥ 1.5), many inefficient setups can be eliminated in advance [26].

5.2.2 Maximum Account Risk

(Nicht mehr als 10% des Riskieren in Summe)

5.2.3 Minimum Take-Profit

In every trading strategy, transaction fees play an important role. Especially in short-term trading, transaction fees can turn seemingly profitable trades negative if they are not adequately considered. A common mistake is setting the take-profit level too narrowly, resulting in a profit that is smaller than the costs incurred. To trade profitably and sustainably, it is therefore essential that the take-profit at least covers the fees incurred, but ideally, significantly higher.

5.3 Dealing with Trading Fees

As shown in Table 1 ByBit charges two different fees named maker-, and taker-fee. The maker fee is charged when a limit order is placed in the order book, thereby creating liquidity. In contrast, the taker fee is charged when a market order is executed. This removes liquidity from the market. It is better for a broker if a market is as liquid as possible. Therefore, maker orders incur lower fees than taker orders.

Especially in higher-frequency trading, it is better to charge as few fees as possible. Therefore, it is better for a trader to execute as many limit orders as possible. Two orders are required for a complete trade: one for entry, and one for exit. But typically, three orders are placed (entry, stop-loss, take-profit), with either the take-profit or stop-loss order being executed.

If a market order is to be executed as an entry order, it is possible to convert it into a limit order by setting the order price slightly below (for long positions) or slightly above the current price (for short positions). The same procedure can be followed for the take-profit order.

However, this procedure should not be used for a stop-loss order. If this is converted to a limit position, there is no longer any guarantee that the stop order will be executed at all, as there is no longer any guarantee that the price will rise above or below the order level. This means that a position may remain open significantly longer than intended. If the price then continues to move in an unprofitable direction, the worst-case scenario is that the position is automatically closed by the broker because there is no longer any capital in the account.

The same problem can theoretically occur with a take-profit order. The difference here is that the set stop market order still defines the maximum risk. Thus, while this particular trade may not be profitable, it is impossible to lose all the capital. It is similar with the opening order. If it is not executed, the entire trade is not going to be executed. This means a missed potential profit, but there is no risk of losing capital.

If all orders are executed as planned, and the price moves in a profitable direction, the conversion of the orders will result in a reduction of fees by a factor of 2.75.

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7 Appendix

7.1 Backtesting Results

7.1.1 Classification AI Strategy Backtest Results

Regime	Downtrend + Low Volatility $Q_{0.33}$	Downtrend + Low Volatility $Q_{0.66}$	Downtrend + Low Volatility Q_1	Downtrend + High Volatility $Q_{0.33}$	Downtrend + High Volatility $Q_{0.66}$	Downtrend + High Volatility Q_1
Min. Probability for Entry	0.3	0.6	0.3	-	-	-
Trailing Stop Orders	false	false	false	-	-	-
Stop-Loss Delta	11	16	11	-	-	-
Take-Profit Delta	96	61	86	-	-	-
Number of Trades	29	30	20	-	-	-
Maximum Gain	518	371	803	-	-	-
Maximum Loss	-111	-95	-112	-	-	-
Profits Std.	212	108	199	-	-	-
Equity Minimum	-47	0	0	-	-	-
Equity Maximum	3833	7978	15144	-	-	-
Equity Last	3532	7978	15144	-	-	-
Maximum Drawdown	23	1	3	-	-	-
Win Ratio	48	96	95	-	-	-

Table 8: Classification AI Strategy Results I

Regime	Sideways Trend + Low Volatility			Sideways Trend + High Volatility		
	$Q_{0.33}$	$Q_{0.66}$	Q_1	$Q_{0.33}$	$Q_{0.66}$	Q_1
Min. Probability for Entry	0.3	0.3	0.4	-	-	-
Trailing Stop Orders	false	false	false	-	-	-
Stop-Loss Delta	11	11	6	-	-	-
Take-Profit Delta	81	81	76	-	-	-
Number of Trades	4	13	32	-	-	-
Maximum Gain	530	530	956	-	-	-
Maximum Loss	-109	-152	-139	-	-	-
Profits Std.	257	255	333	-	-	-
Equity Minimum	-65	-301	-463	-	-	-
Equity Maximum	701	1999	4583	-	-	-
Equity Last	592	1705	4583	-	-	-
Maximum Drawdown	15	14	18	-	-	-
Win Ratio	50	46	46	-	-	-

Table 9: Classification AI Strategy Results II

Regime	Uptrend + Low Volatility			Uptrend + High Volatility		
	$Q_{0.33}$	$Q_{0.66}$	Q_1	$Q_{0.33}$	$Q_{0.66}$	Q_1
Min. Probability for Entry	0.4	0.3	0.8	-	-	-
Trailing Stop Orders	false	true	false	-	-	-
Stop-Profit Delta	11	26	11	-	-	-
Take-Profit Delta	86	76	86	-	-	-
Number of Trades	23	58	56	-	-	-
Maximum Gain	568	250	469	-	-	-
Maximum Loss	-66	-53	-245	-	-	-
Profits Std.	279	125	268	-	-	-
Equity Minimum	-193	-819	-619	-	-	-
Equity Maximum	6275	6348	11467	-	-	-
Equity Last	6275	6348	9427	-	-	-
Maximum Drawdown	36	0	100	-	-	-
Win Ratio	60	68	55	-	-	-

Table 10: Classification AI Strategy Results III

7.1.2 Dual Simple Moving Average Strategy Backtest Results

Regime		Downtrend + Low Volatility $Q_{0.33}$	$Q_{0.66}$	Q_1	Downtrend + High Volatility $Q_{0.33}$	$Q_{0.66}$	Q_1
SMA Period	Short-Term	11	3	3	3	-	-
	Long-Term	13	19	5	5	-	-
Swing Order N		5	7	9	7	-	-
Swing Max Age		10	20	10	40	-	-
Trailing Stop Order		false	false	false	true	-	-
Take-Profit Delta		140	155	185	95	-	-
Stop-Loss Delta		65	50	35	65	-	-
Number of Trades		267	501	327	2	-	-
Maximum Gain		135	211	162	218	-	-
Maximum Loss		-81	-160	- 81	-41	-	-
Profits Std.		37	34	56	130	-	-
	Minimum	-11	-122	- 644	-41	-	-
Equity	Maximum	1146	2250	2123	177	-	-
	Last	1098	2044	2123	177	-	-
Maximum Drawdown		108	259	836	0	-	-
Win Ratio		52	49	49.5	50	-	-

Table 11: Dual Simple Moving Average Strategy Results I

	Regime	Sideways Trend + Low Volatility			Sideways Trend + High Volatility		
		$Q_{0.33}$	$Q_{0.66}$	Q_1	$Q_{0.33}$	$Q_{0.66}$	Q_1
SMA Period	Short-Term	3	3	3	3	5	3
	Long-Term	19	19	19	5	11	19
Swing Order N		1	3	5	9	3	1
Swing Max Age		30	10	30	30	10	10
Trailing Stop Order		false	false	false	false	false	true
Take-Profit Delta		155	125	200	65	155	110
Stop-Loss Delta		65	5	80	20	35	35
Number of Trades		94	111	19	1	1	1
Maximum Gain		124	357	54	3	4	25
Maximum Loss		-40	-67	-40	3	4	0
Profits Std.		23	37	20	0	0	0
Equity	Minimum	-11	-8	0	0	0	0
	Maximum	585	418	126	3	4	6
	Last	573	385	126	3	4	6
Maximum Drawdown		125	116	77	0	0	0
Win Ratio		45	33	57	100	100	100

Table 12: Dual Simple Moving Average Strategy Results II

Regime		Uptrend + Low Volatility			Uptrend + High Volatility		
		$Q_{0.33}$	$Q_{0.66}$	Q_1	$Q_{0.33}$	$Q_{0.66}$	Q_1
SMA Period	Short-Term	3	5	3	5	11	-
	Long-Term	19	11	19	11	13	-
Swing Order N		5	7	7	7	3	-
Swing Max Age		30	10	40	10	20	-
Trailing Stop Order		false	false	false	false	true	-
Take-Profit Delta		200	185	185	155	140	-
Stop-Loss Delta		80	50	20	50	35	-
Number of Trades		1468	526	152	1	1	-
Maximum Gain		189	234	337	160	83	-
Maximum Loss		-121	-114	-59	160	83	-
Profits Std.		27	52	46	0	0	-
Equity	Minimum	-149	-218	0	0	0	-
	Maximum	2860	5120	975	160	83	-
	Last	2490	5025	835	160	83	-
Maximum Drawdown		427	408	14	0	0	-
Win Ratio		48	53	42	100	83	-

Table 13: Dual Simple Moving Average Strategy Results III

7.1.3 Triple Exponential Moving Average Strategy Backtest Results

Regime		Downtrend + Low Volatility			Downtrend + High Volatility		
		$Q_{0.33}$	$Q_{0.66}$	Q_1	$Q_{0.33}$	$Q_{0.66}$	Q_1
	Short-Term	3	9	7	7	5	-
EMA Period	Medium-Term	5	14	14	14	23	-
	Long-Term	10	25	40	40	45	-
Minimum EMA Slope		0.2	0.4	0.8	0.8	1.0	-
EMA Slope Window Length i		30	20	20	40	10	-
Trailing Stop Order		false	false	false	false	false	-
Stop-Loss Distance		10	40	30	10	50	-
Take-Profit Distance		140	130	130	100	150	-
Number of Trades		531	159	6	1	3	-
Maximum Gain		475	174	205	460	111	-
Maximum Loss		-90	-78	-60	460	111	-
Profits Std.		70	75	123	0	0	-
	Minimum	-568	0	-54	0	0	-
Equity	Maximum	2323	2471	357	460	335	-
	Last	800	2088	191	460	335	-
Maximum Drawdown		151	97	46	0	0	-
Win Ratio		28	44	33	100	100	-

Table 14: Triple Exponential Moving Average Strategy Results I

Regime		Sideways Trend + Low Volatility $Q_{0.33}$	$Q_{0.66}$	Q_1	Sideways Trend + High Volatility $Q_{0.33}$	$Q_{0.66}$	Q_1
EMA Period	Short-Term	9	5	9	9	3	-
	Medium-Term	14	23	14	14	5	-
	Long-Term	25	45	25	25	10	-
Minimum EMA Slope		0.4	1.0	0.4	0.4	0.2	-
EMA Slope Window Length i		20	30	40	40	30	-
Trailing Stop Orders		false	false	false	true	true	-
Stop-Loss Distance		20	10	30	10	30	-
Take-Profit Distance		150	150	150	20	150	-
Number of Trades		114	2	4	1	1	-
Maximum Gain		264	717	261	42	164	-
Maximum Loss		-75	-79	0	42	164	-
Profits Std.		79	398	106	0	0	-
Equity	Minimum	-627	0	0	0	0	-
	Maximum	916	717	347	42	164	-
	Last	561	637	347	42	164	-
Maximum Drawdown		2552	11	0	0	0	-
Win Ratio		35	50	100	100	100	-

Table 15: Triple Exponential Moving Average Strategy Results II

	Regime	Uptrend + Low Volatility			Uptrend + High Volatility		
		$Q_{0.33}$	$Q_{0.66}$	Q_1	$Q_{0.33}$	$Q_{0.66}$	Q_1
	Short-Term	7	7	7	7	-	-
EMA Period	Medium-Term	14	14	14	14	-	-
	Long-Term	40	40	40	40	-	-
Minimum EMA Slope		0.8	0.8	0.8	0.8	-	-
EMA Slope Window Length i		40	20	40	20	-	-
Trailing Stop Orders		false	false	false	false	-	-
Stop-Loss Distance		10	10	30	10	-	-
Take-Profit Distance		100	150	110	90	-	-
Number of Trades		2	43	2	1	-	-
Maximum Gain		484	875	170	488	-	-
Maximum Loss		484	-135	170	488	-	-
Profits Std.		0	290	0	0	-	-
	Minimum	0	-88	0	0	-	-
Equity	Maximum	968	2914	341	488	-	-
	Last	968	2075	341	488	-	-
Maximum Drawdown		0	58	0	0	-	-
Win Ratio		100	18	100	100	-	-

Table 16: Triple Exponential Moving Average Strategy Results III

7.1.4 Bollinger Bands Strategy Backtest Results

Regime	Downtrend + Low Volatility			Downtrend + High Volatility		
	$Q_{0.33}$	$Q_{0.66}$	Q_1	$Q_{0.33}$	$Q_{0.66}$	Q_1
Bollinger Band Period	14	18	13	20	15	25
No. of Standard Deviations	2.5	3.0	1.5	2	1.5	1.5
Trailing Stop Orders	true	false	true	false	false	false
Stop-Loss Distance	10	10	10	10	10	30
Take-Profit Delta	11	9	15	-1	1	19
Number of Trades	4	15	8	2	1	1
Maximum Gain	84	109	97	191	111	80
Maximum Loss	-27	-63	-56	127	111	80
Profits Std.	44	50	65	32	0	0
Equity Minimum	0	-9	0	0	0	0
Equity Maximum	174	250	226	319	111	80
Equity Last	174	250	179	319	111	80
Maximum Drawdown	33	98	57	0	0	0
Win Ratio	75	53	50	100	100	100

Table 17: Bollinger Bands Strategy Results I

Regime	Sideways Trend + Low Volatility			Sideways Trend + High Volatility		
	$Q_{0.33}$	$Q_{0.66}$	Q_1	$Q_{0.33}$	$Q_{0.66}$	Q_1
Bollinger Band Period	15	23	24	-	23	24
No. of Standard Deviations	2.0	2.5	1.5	-	1.5	1.5
Trailing Stop Orders	false	false	false	-	false	true
Stop-Loss Distance	10	10	10	-	10	10
Take-Profit Delta	-3	15	5	-	1	5
Number of Trades	2	25	7	-	1	1
Maximum Gain	73	142	140	-	75	-31
Maximum Loss	57	-64	-51	-	75	-31
Profits Std.	7	52	67	-	0	0
Equity Minimum	0	-64	0	-	0	-31
Equity Maximum	130	398	340	-	75	0
Equity Last	130	269	340	-	75	-31
Maximum Drawdown	0	52	51	-	0	0
Win Ratio	100	40	71	-	100	0

Table 18: Bollinger Bands Strategy Results II

Regime		Uptrend + Low Volatility			Uptrend + High Volatility		
		$Q_{0.33}$	$Q_{0.66}$	Q_1	$Q_{0.33}$	$Q_{0.66}$	Q_1
Bollinger Band Period		19	15	13	-	16	-
No. of Standard Deviations		1.5	1.5	1.5	-	1.5	-
Trailing Stop Orders		false	false	false	-	false	-
Stop-Loss Distance		30	10	10	-	10	-
Take-Profit Delta		9	1	15	-	9	-
Number of Trades		1	8	196	-	1	-
Maximum Gain		121	114	96	-	107	-
Maximum Loss		121	-57	-62	-	107	-
Profits Std.		0	66	25	-	0	-
	Minimum	0	-57	0	-	0	-
Equity	Maximum	121	253	521	-	107	-
	Last	121	253	128	-	107	-
Maximum Drawdown		0	59	90	-	0	-
Win Ratio		100	62	36	-	100	-

Table 19: Bollinger Bands Strategy Results III