Federal University of Piauí
Center for Natural Sciences
Graduate Program in Computer Science

Scalper Major: A Computational Solution for Automated Trading in High-Volatility Environments

José Jeovane Reges Cordeiro

Teresina-PI, February of 2026

José Jeovane Reges Cordeiro

Scalper Major: A Computational Solution for Automated Trading in High-Volatility Environments

Master's Dissertation submitted to the Graduate Program in Computer Science at UFPI (concentration area: Intelligent Computing), as part of the requirements for obtaining the Master's Degree in Computer Science.

Federal University of Piauí – UFPI

Center for Natural Sciences

Graduate Program in Computer Science

Advisor: Dr. Arlino H. Magalhães de Araújo

Co-advisor: Dr. Guilherme Amaral Avelino

Teresina-PI

February of 2026

Ficha elaborada de acordo com o Código de Catalogação Anglo-Americano AACR2

C794s

Cordeiro, José Jeovane Reges.
Scalper Major: a computational solution for automated trading in high-volatility environments. / José Jeovane Reges Cordeiro. – Teresina, PI, 2026.
88 f.: il. (alg. color.)

Dissertação (Mestrado em Ciência da Computação) – Universidade Federal do Piauí, Centro de Ciências da Natureza, Programa de Pós-Graduação em Ciência da Computação, 2026.

Orientador: Prof. Dr. Arlino H. Magalhães de Araújo.
Coorientador: Prof. Dr. Guilherme Amaral Avelino.

1. Inteligência artificial - Aplicações financeiras. 2. Mercado financeiro. 3. Câmbio. 4. Sistemas de computação. I. Araújo, Arlino H. Magalhães de. II. Avelino, Guilherme Amaral. III. Título.

CDU: 004.8:336.76
CDD: 006.31

Ficha elaborada pelo Serviço de Catalogação da Biblioteca Prof. Queirois, IFMA, Campus Caxias
Ianna Torres Lustosa (Bibliotecária) CRB-13/687

José Jeovane Reges Cordeiro

Scalper Major: A Computational Solution for Automated Trading in High-Volatility Environments

Master's Dissertation submitted to the Graduate Program in Computer Science at UFPI (concentration area: Intelligent Computing), as part of the requirements for obtaining the Master's Degree in Computer Science.

Approved work. Teresina-PI, February 23, 2026:

Documento assinado digitalmente
gov.br ARLINO HENRIQUE MAGALHAES DE ARAUJO
Data: 18/03/2026 09:24:45-0300
Verifique em https://validar.iti.gov.br

Dr. Arlino H. Magalhães de Araújo
Advisor

Documento assinado digitalmente
gov.br GUILHERME AMARAL AVELINO
Data: 18/03/2026 10:19:00-0300
Verifique em https://validar.iti.gov.br

Dr. Guilherme Amaral Avelino
Co-Advisor

Documento assinado digitalmente
gov.br RAIMUNDO SANTOS MOURA
Data: 18/03/2026 11:10:13-0300
Verifique em https://validar.iti.gov.br

Dr. Raimundo Santos Moura
Internal Evaluator

Documento assinado digitalmente
gov.br ANGELO RONCALLI ALENCAR BRAYNER
Data: 20/03/2026 09:50:43-0300
Verifique em https://validar.iti.gov.br

Dr. Angelo Roncalli Alencar Brayner
External Evaluator

Teresina-PI
February of 2026

My family, my wife Taiane dos Santos Siebra and my son José Raví Siebra Cordeiro, for always being by my side.

Acknowledgements

First, I thank God for making my journey to this point possible and for granting me strength in moments of difficulty.

To my wife, Taiana dos Santos Siebra, for her invaluable love, encouragement, and understanding throughout this entire process. To my son, José Raví Siebra Cordeiro, who, even without fully understanding my absence at various times, displayed a surprising and inspiring maturity.

To my parents, Maria Joelma Ferreira Reges and Pedro Henrique Cordeiro, for the gift of life and the educational foundation they provided me. To my siblings, for their constant support, concern, and encouragement over the last two years.

To my advisor, Teacher Dr. Arlino H. Magalhães de Araújo, and my co-advisor, Teacher Dr. Guilherme Amaral Avelino, for their wise guidance, patience, and valuable contribution to my academic and professional growth during this period.

I also wish to register my sincere gratitude to my friend and teacher, André Wallas da Silva Sousa, for his generosity in opening the doors of his home and welcoming me at different times during this journey. I also thank the friends from our apartment "WAKANDA" in Coelho Neto, affectionately known as the "Wakandanos", for their encouragement.

To the Federal Institute of Maranhão (IFMA), for granting my leave of absence, enabling me to dedicate myself fully to this master's program.

"It is an extremely pleasant feeling to reach the end of a stage with the awareness of duty fulfilled."

(Unknown Author)

Abstract

This work addresses the complexity and challenges of manual trading in the Forex market, a high-volatility environment where decisions are often compromised by emotional biases and the human limitation in processing information and executing orders promptly. To overcome these difficulties, Scalper Major, an automated trading system (Expert Advisor), was developed. The solution is based on a modular architecture composed of a signal processor, a risk manager, and a money manager. These components apply technical criteria, specialized heuristics, and strict management rules to operate with minimal human intervention. The validation of Scalper Major was conducted in two distinct scenarios. In the simulated environment, using historical data from January 2016 to December 2023 with an initial capital of \$20,000.00, the system obtained a net profit of \$751,533.23, with an overall win rate of 82.54% across 11,571 executed trades. In the live environment, operating from June 2024 to September 2025, the system started with a capital of \$20,000.00 and generated a net profit of \$19,673.82, achieving a win rate of 78.58% in 1,886 trades. The results from both scenarios demonstrate the robustness and effectiveness of the proposed solution, which proved to be profitable and resilient even in the face of events of significant market instability.

Keywords: Forex Market. Algorithmic Trading. Evaluation Metric.

List of Figures

List of Tables

List of Abbreviations and Acronyms

ADV	Average Daily Volume
AI	Artificial Intelligence
ANN	Artificial Neural Network
AR	Annualized Return
BIS	Bank for International Settlements
B&H	Buy and Hold
CM	Capital Manager
CNN	Convolutional Neural Network
CPI	Consumer Price Index
CR	Cumulative Return
DEA	Signal Line
DIF	MACD Line
DNN	Deep Neural Network
DRL	Deep Reinforcement Learning
EA	Expert Advisor
EMA	Exponential Moving Average
EP	Expected Payoff
EU	European Union
Forex	Foreign Exchange Market
GDP	Gross Domestic Product
GP	Genetic Programming
IMF	International Monetary Fund
KPI	Key Performance Indicators

MACD	Moving Average Convergence Divergence
MDD	Maximum Drawdown
ML	Machine Learning
MPT	Markowitz's Portfolio Optimization Theory
MQL5	MetaQuotes Language 5
MT4	MetaTrader 4
MT5	MetaTrader 5
OSC	MACD Histogram
PF	Profit Factor
PnL	Profit and Loss
PPI	Producer Price Index
QT	Quantitative Trading
RF	Recovery Factor
RL	Reinforcement Learning
RM	Risk Manager
RNN	Recurrent Neural Network
RSI	Relative Strength Index
SMA	Simple Moving Average
SLR	Systematic Literature Review
SP	Signal Processor
US	United States
USD	US Dollar

Contents

1 Introduction

Trade among people has existed since ancient civilizations. However, the pillars of the modern foreign exchange market began to consolidate in the 19th century with the emergence of the gold standard system, which the Bretton Woods Agreement later reinforced in 1944 (BORDO, 1993). The idea underlying the gold standard dates back to David Hume in 1752, who argued that international trade should be balanced through the flows of precious metals (CAFFENTZIS, 2001). The gold standard was in effect until 1914 and was later replaced in 1944 by the Bretton Woods Agreement, which pegged exchange rates to the U.S. dollar.

As part of this agreement, institutions such as the International Monetary Fund (IMF) and the World Bank were created to promote global economic stability (BORDO, 1993). However, in 1971, the United States abandoned the convertibility of the dollar to gold, ending the Bretton Woods system and ushering in the era of floating exchange rate regimes, which characterize the modern foreign exchange market (MELTZER, 1991).

The foreign exchange market, also known as Forex (Foreign Exchange Market), stands out as the largest and most liquid in the world. Besides this one, there are other markets, such as the stock market (equities), cryptocurrencies, futures, and derivatives, among others. These segments handle billions and even trillions of dollars daily. For example, on August 12, 2025, data from NASDAQ[1] showed that the volume of shares traded on the Composite index was approximately US$ 372.4 billion. In the cryptocurrency market, data from July 2025 show that the total monthly trading volume was approximately US$ 1.77 trillion[2], which represents an average of US$ 57.1 billion per day. In turn, data published by the CME Group[3], one of the world's largest derivatives exchanges, recorded an average daily volume (ADV) of US$ 1.1 trillion for stock index futures.

Although the values presented above are high, they do not surpass the trading volume of the Forex market. The latest report released by the Bank for International Settlements (BIS)[4], with data collected in April 2022, shows that the average daily trading volume in Forex was US$ 7.5 trillion – a figure higher than that of any other market. This significant volume is a direct consequence of the unique characteristics of the foreign exchange market, such as high liquidity and decentralization, which involve the buying and selling of currencies among governments, financial institutions, corporations, and individual investors (MAHJOUBY et al., 2024; OLORUNSHEYE; MEENAKSHI, 2024).

1 <https://www.nasdaqtrader.com/Trader.aspx?id=DailyMarketSummary>
2 <https://www.theblock.co/post/365199/crypto-exchange-volume-july>
3 <https://br.tradingview.com/cme/>
4 <https://www.bis.org/statistics/rpfx25_announcement.htm>

The combination of these characteristics, along with its continuous operation – 24 hours a day, 5 days a week – offers significant profit opportunities, particularly for short-term strategies such as scalping and day trading (ZAFEIRIOU; KALLES, 2021). However, although accessible and with potential for gains, this market is influenced by various exogenous factors, including geopolitical events, economic announcements, and natural disasters, which significantly increase volatility and contribute to a volatile environment (CHANTONA; PURBA; HALIM, 2020). Furthermore, due to its noisy, non-stationary, chaotic, and deterministic nature, predicting exchange rates represents a significant challenge for researchers and investors (MAHJOUBY et al., 2024; ISMAIL et al., 2022).

1.1 The Research Problem

In this scenario, the performance of the manual trader[5] is often compromised by human limitations, as trading decisions are susceptible to emotional biases, such as fear, greed, and impatience, which can lead to significant losses. Furthermore, the speed required to capitalize on opportunities in short-term strategies, such as scalping, exceeds the human capacity to process information and execute orders in a timely manner (ISMAIL et al., 2022).

To overcome these difficulties, many traders resort to technical indicators; however, Povitukhin e Karmanova (2020) points out that these tools are, for the most part, lagging – that is, they react to price movements that have already occurred instead of accurately predicting them. This characteristic often results in the generation of false or delayed signals, leading the trader to make errors and, consequently, suffer financial losses.

Additionally, the relevance of this challenge is reinforced by the finding that, despite its economic importance, the Forex market remains an underexplored area in the scientific literature on algorithmic trading, as evidenced in a recent Systematic Literature Review (SLR) performed by (CORDEIRO; ARAúJO; AVELINO, 2025). In addition to the limited number of studies, the existing ones present significant methodological limitations, such as the lack of risk metrics and the absence of robust validation.

The studies by Povitukhin e Karmanova (2020) and Luangluewut e Thiennviboon (2023) base their evaluation solely on cumulative return. This approach is inadequate, as it completely ignores risk. The works by Chinprasatsak, Niparnan e Sudsang (2020), Chantona, Purba e Halim (2020), and Farooghi e Khaloozadeh (2024), on the other hand, represent an advancement by including Maximum Drawdown (MDD), a crucial risk metric. However, the analysis remains incomplete, as the absence of risk-adjusted metrics limits the evaluation of the quality of the returns.

[5] Trader: a human operator who buys and sells assets seeking profit from price variations.

Despite the low researchs engagement on the foreign exchange market, automated trading systems emerge as a promising solution to overcome the difficulties of manual *trading*, executing strategies consistently and efficiently, reducing the influence of emotional biases, and optimizing operational performance.

1.2 Proposed Solution

The solution to the problem raised in the previous section (Section 1.1) lies in creating a tool that automates the decision-making process based on objective criteria and specialized heuristics. This tool must also consider essential evaluation metrics, such as Return, Risk, and Risk-Adjusted Return, in order to ensure a disciplined and systematic execution of trades, even under adverse market conditions.

To this end, the present work introduces Scalper Major, an *Expert Advisor* (EA) developed based on objective technical criteria, strict risk management rules, specialized heuristics, and a modular architecture, to operate automatically and with minimal human intervention in the Forex market. To achieve this goal, the following specific objectives were established:

- Design a modular architecture composed of specialized components, such as a signal processor, risk manager, and money manager.
- Integrate technical and managerial heuristics to identify trading opportunities.
- Establish a risk and money management model that promotes judicious control of exposure and resource allocation in trades.
- Implement and validate the system in a simulated environment through *backtests* with real historical data, using appropriate metrics.
- Prepare Scalper Major for testing in a live environment to verify its adaptability to dynamic market conditions.

The strategy adopted by Scalper Major was validated in two distinct scenarios: (1) through a backtesting (simulation) process and (2) through the execution of trades in a live account to gauge its performance under actual market conditions. The following summarizes the main results obtained in each of these environments, highlighting profitability metrics, trading volume, and success rates.

- **Test Scenario:** This process that covered the period from January 2016 to December 2023. At this stage, an initial capital of $20,000.00 was utilized, and the system generated a total net profit of $751,533.23. This resulted from a gross profit of

$1,060,523.23 and gross losses of $308,991.00, which include trades closed with a negative balance and operational costs. In total, 11,571 trades were executed, of which 7,217 (62.37%) were *Long* (buy) trades and 4,354 (37.63%) were *Short* (sell) trades. The overall win rate was 82.54%, with an 83.66% rate for Long trades and an 81.42% rate for Short trades.

- **Real Scenario:** This process covered the period from June 2024 to September 2025. In this stage, an initial capital of $20,000.00 was used, and the system generated a total net profit of $19,673.82. This result stemmed from a gross profit of $29,830.00 and gross losses of $8,987.63, which include trades closed with a negative balance and operational costs. In total, 1,886 trades were executed, of which 1,057 (56.04%) were *Long* (buy) trades and 829 (43.96%) were *Short* (sell) trades. The overall win rate was 78.58%, with a rate of 80.61% for Long trades and 76% for Short trades.

1.2.1 Research Hypothesis

In this dissertation, we propose the following research question:

- How can an automated trading system be developed that overcomes the limitations of manual *trading*, by operating in an agile and objective manner and with strict risk management in a high-volatility environment such as the Forex market?

1.3 Contributions

The main contributions of this work are as follows:

1. Unpublished compilation of the main trading metrics used to evaluate automated trading systems.
2. A set of technical and managerial heuristics aimed at identifying trading opportunities and executing orders efficiently, with strict risk control and money management.
3. A modular architecture composed of specialized components that enables the implementation of the proposed approach.
4. A functional implementation of the proposed architecture and approach, validated through extensive simulations with historical data.

1.4 Publications

1. We authored and presented the paper "Beyond Profit: An Analysis of Risk and Return Metrics in Automated Trading Systems." This work was presented at the

35th Brazilian Conference on Intelligent Systems (BRACIS) (CORDEIRO; ARAúJO; AVELINO, 2025). The content of this work, which is the first article to address its subject matter, represents one of the contributions of my dissertation.

2. We authored and submitted the paper "Scalper Major: A Computational Solution for Automated Trading in High Volatility Environments" to the 22nd Brazilian Symposium on Information Systems (SBSI) (CORDEIRO; MAGALHãES; AVELINO, 2026).

1.5 Work Organization

This work is organized into chapters to detail the problem and the proposed solution. Chapter 2 establishes the conceptual and technological foundations necessary for understanding the work. Chapter 3 presents a review of the related research, contextualizing the study within the current scientific landscape. Chapter 4 details the methodology, computational resources, and experimental procedures used in the development, implementation, and validation of the proposed system. Chapter 5 details the architecture, strategies, and evaluation criteria of the Scalper Major automated trading system. Chapter 6 presents and analyzes the performance of the Scalper Major system in two distinct scenarios: simulated and real. Finally, the Conclusions and Future Work chapter presents the study's contributions and highlights future research directions.

2 Background

This chapter covers the conceptual and technological foundations necessary to understand this work.

2.1 The Financial Market Context

This section offers an overview of the financial market context. Initially, the historical evolution of the global financial market is explored, highlighting the phases of financial globalization. Next, the focus shifts to the Forex market, detailing its origin, decentralized structure, and its unique characteristics as the world's largest and most liquid market. Finally, the main participants in this market are presented, including financial institutions, corporations, and individual investors. Their different motivations and operational strategies are also analyzed.

2.1.1 The Global Financial Market

The first era of financial globalization, which extended until 1913, was characterized by the free movement of capital and by the hegemony of financial centers such as London, New York, and Paris. The modern version of international financial markets, on the other hand, dates back to the late 1950s with the emergence of the Eurodollar market (BULJEVICH; PARK, 1999). Starting in the 1980s, a new significant phase of integration in global financial markets began, often referred to as the modern era of financial globalization (BEKAERT; MEHL, 2019).

According to Bekaert e Mehl (2019), global financial integration follows a "swoosh" shaped pattern; that is, it showed high levels before 1913, a sharp decline during the interwar period, and a continuous recovery after the 1990s, reaching even higher levels in the modern era. The liberalization of capital accounts strengthened this so-called second wave of financial globalization, characterized by the intensification of international investment flows and the globalization of equity and credit markets.

Buljevich e Park (1999) also highlights that the accelerated pace of financial innovation is characteristic of this market. These innovations, which were more pronounced in international than in domestic markets, improved efficiency by offering a broader and more flexible range of instruments. The main participants in this market include financial institutions – such as central, local, and regional banks –, hedge funds, multinational corporations, and individual investors. Each of these agents acts with specific motivations – central banks, for example, may intervene with the aim of economic stabilization, while investors and speculators seek profits from currency fluctuations (ZHANG; KHUSHI, 2020).

2.1.2 The Forex Market

According to Abraham, Chowdhury e Petrovic-Lazarevic (2003), the modern Forex market was established in 1973 with the deregulation of the exchange rate in the United States and other developed countries. Before that, the fixed exchange rate regime was established by the 1944 Bretton Woods agreement, in which the US dollar served as an anchor for other currencies, based on the gold standard. However, global economic crises and inflation in the late 1960s and early 1970s made the gold standard unsustainable for the US. Although the process of abandoning the gold standard began in August 1971 with the "Nixon Shock" – an event in which US President Richard Nixon suspended the convertibility of the dollar into gold – the floating exchange rate system was only implemented in 1973.

This market is recognized as the largest and most liquid financial market in the world (DYMOVA; SEVASTJANOV; KACZMAREK, 2016). It has unique and important characteristics that distinguish it from other financial markets, playing a crucial role in facilitating payments between countries, transferring funds from one currency to another, and determining the exchange rate (ABRAHAM; CHOWDHURY; PETROVIC-LAZAREVIC, 2003). These characteristics make it a market of vital importance, as they affect the international balance of payments and the development of the domestic real economy, thereby impacting national security and social stability (WANG et al., 2021).

Unlike other financial markets, Forex is decentralized; that is, it does not have a central trading location (ABRAHAM; CHOWDHURY; PETROVIC-LAZAREVIC, 2003). It is an over-the-counter market that operates continuously 24 hours a day, five days a week, from Monday to Friday (WANG et al., 2021). Forex holds the most significant trading volume and liquidity among all financial markets, with a daily trading volume of $7.5 trillion, according to the Bank for International Settlements (BIS). Its high liquidity, along with high leverage and low trading costs, is the main attraction for traders.

The main trading centers in the world include London, New York, Singapore, Hong Kong, and Tokyo. Abraham, Chowdhury e Petrovic-Lazarevic (2003) highlights that in this market, the US dollar (USD) is the dominant currency, accounting for approximately 80% of all global foreign exchange transactions. He is often used to quote most exchange rates for two reasons: (1) to simplify trades (avoiding a considerable number of direct trading markets between each pair) and (2) to avoid the possibility of triangular arbitrage. Each currency in this market has a bid price (the price at which it is bought) and an ask price (the price at which it is sold) (ABRAHAM; CHOWDHURY; PETROVIC-LAZAREVIC, 2003).

Transactions in this market always occur in pairs; that is, the purchase of one currency simultaneously implies the sale of another. The exchange rate is primarily determined by the interaction of supply and demand, as well as the economic conditions of the issuing countries. Its volatility, however, also depends on other factors, such as the financing of government deficits, changes in capital ownership in companies, and employment issues.

Due to this volatility and the scale of the foreign exchange market, four currency pairs are generally used to represent the market as a whole. These pairs – EUR/USD, USD/JPY, GBP/USD, and AUD/USD – are the most traded and account for more than half of the activity in the foreign exchange markets (KARBALAEE, 2012). Furthermore, it is estimated that around 85% of all Forex trades occur between market makers, which creates room for speculative gains and losses (ABRAHAM; CHOWDHURY; PETROVIC-LAZAREVIC, 2003).

2.1.3 Market Participants

As previously mentioned, the primary participants in this market include financial institutions, hedge funds, multinational corporations, and individual investors, each with distinct motivations:

- **Financial Institutions:** Compared to other agents, they hold the most significant volumes and maintain longer-term positions. Their primary motivation is to facilitate international trade and investment for their clients, while also hedging their own balance sheet risks and earning revenue through spreads and fees.
- **Hedge Funds:** Have a significant participation in the foreign exchange market. According to Melvin e Prins (2015), this type of investment has gained increasing relevance since the 2009 financial crisis, particularly in the area of portfolio management. The main objective for these funds is to generate high absolute returns for their investors, often by employing speculative strategies and leveraging their positions.
- **Multinational Corporations:** On the other hand, turn to the foreign exchange market to hedge the currency risk arising from their activities (CRABB, 2002). The primary motivation for their participation is associated with managing risk exposure; therefore, their transactions are relatively small, and their positions are held for short periods.
- **Individual Investors:** Hold positions for the shortest periods, typically less than a day. These agents began to have greater participation in the foreign exchange market around the beginning of the 21st century, driven by the evolution of trading

platforms, which facilitated access (MWAMTAMBULO, 2021). These traders are driven almost entirely by speculation, aiming to profit from short-term fluctuations in currency prices.

These participants, regardless of the category they fall into, generate gains or losses by speculating on the appreciation or depreciation of one currency against another. They can be classified into two types of investors: (1) reactive investors, whose transactions depend on events related to the economic situation and political decisions, and (2) speculative investors, who base their investments on the prediction of future events.

2.2 Trading Foundations

The first part of this section examines the four primary trading strategies, categorized by the holding period of the trades. The second part details the assets traded in the Forex, classified into three distinct categories.

2.2.1 Price Quotation, Leverage, and Profit Calculation in Forex

Although the economic logic of buying and selling in the Forex market resembles retail currency exchange operations – where profit is derived from the differential between entry and exit prices – the operational structure of the institutional market presents fundamental distinctions regarding precision and leverage.

For instance, it is common for currency exchange bureaus to quote the Brazilian Real (BRL) with only two decimal places. Conversely, in the Forex market, the USD/BRL pair (US Dollar vs. Brazilian Real) is quoted with an extended precision of four decimal places.

This granularity, in addition to making the quantification of financial results (Profit and Loss - PnL) different, also allows for the capture of minute price variations, which is essential for high-frequency and scalping strategies. To better understand how this granularity affects market profits and losses, consider the two scenarios described below.

1. If an investor purchased $1,000.00 at R$5.39 at a currency exchange bureau, aiming to profit from the dollar's appreciation against the real, R$5,390.00 would be required (excluding fees). If, days later, he sold these $1,000.00 after the dollar rose to R$5.42, the investor would profit a total of R$30.00.

2. In the Forex market, due to the introduction of leverage—which allows traders to trade with a larger amount than their deposit—the quantification of the financial result (Profit and Loss - PnL) would differ from that observed in the physical market.

If the investor deposited the same \$1,000.00 invested in "Scenario 1"with a Forex broker allowing 500:1 leverage, this would be equivalent to trading with a capital of \$500,000.00. Thus, if a purchase of 1 lot (100,000 units of the base currency) were executed at a rate of 5.3900 and a sale at a rate of 5.4200, the final profit would be \$3,000.00, as illustrated below.

$$\Delta P = P_{\text{opening}} - P_{\text{closing}}$$
$$\Delta P = 5.4200 - 5.3900$$
$$\Delta P = 0.0300$$

The PnL equation, when applied to this volume, demonstrates the leverage of the nominal result relative to the asset's variation:

$$PnL = \Delta P \times V_{\text{units}}$$
$$PnL = 0.0300 \times 100.000 \text{ USD}$$
$$PnL = \$3.000, 00$$

2.2.2 Trading Modalities

Trading strategies are typically classified based on the position holding period, that is, the time interval between the opening and closing of each trade. According to Coloma-Carmona et al. (2025), there are four main types of trading:

- **Scalping:** This trading modality seeks to profit from small price movements within short time intervals, typically within minutes or even seconds. It is the trading style with the shortest position duration in the market.
- **Day Trading:** In day trading, transactions are carried out within a single trading session, and positions are generally closed before the market closes. This modality is often considered a speculative activity, characterized by high uncertainty and a higher risk of losses on positions.
- **Swing Trading:** This strategy involves holding positions for several days to capitalize on price fluctuations. The duration of the trades is intermediate between day trading and position trading.
- **Position Trading:** Position trading focuses on maintaining positions for weeks or even months, making it the strategy with the most extended duration among those analyzed.

2.2.3 Types of Assets and Currency Pairs

The essence of transactions in the Forex market lies in the trading of currency pairs, in which the first is called the base currency and the second, the quote currency (KOTHIWAL; RAJIYAN, 2019). When buying a pair, one buys the base currency and sells the quote currency; when selling, one sells the base currency and buys the quote currency (ISMAIL et al., 2022). Currency pairs are generally classified into three categories: (1) major pairs or big pairs, (2) minor pairs or cross pairs, and (3) exotic pairs.

2.2.3.1 Major Pairs

Kothiwal e Rajiyan (2019) highlight that major currency pairs are consistently recognized as the most traded in the world. A characteristic of this category is the involvement of the US Dollar (USD) in all pairs. According to Luangluewut e Thiennviboon (2023), this class is distinguished by its high market depth, which helps to prevent price manipulation.

Weithers (2011) highlight that the magnitude of the daily transaction volume in these pairs is substantially higher than in other financial markets, such as the stock market, which underlines their central importance to the liquidity and functionality of the Forex market. The main assets in this category are listed below:

- AUD/USD – Australian Dollar vs. US Dollar;
- EUR/USD – Euro vs. US Dollar;
- GBP/USD – British Pound vs. US Dollar;
- NZD/USD – New Zealand Dollar vs. US Dollar;
- USD/CAD – US Dollar vs. Canadian Dollar;
- USD/CHF – US Dollar vs. Swiss Franc; and
- USD/JPY – US Dollar vs. Japanese Yen.

2.2.3.2 Minor Pairs

Minor currency pairs, also known as cross pairs, are those that generally do not involve the USD (QI; KHUSHI; POON, 2020; MAHJOUBY et al., 2024). Although they are less studied than major pairs in specific contexts, they are recognized and used. Weithers (2011) highlights that analyzing pairs belonging to this class is also fundamental for identifying triangular arbitrage opportunities in the spot market. Among the frequently cited minor pairs are:

- AUD/JPY – Australian Dollar vs. Japanese Yen;
- CAD/CHF – Canadian Dollar vs. Swiss Franc;
- EUR/GBP – Euro vs. British Pound;
- EUR/JPY – Euro vs. Japanese Yen;
- GBP/JPY – British Pound vs. Japanese Yen; and
- NZD/JPY – New Zealand Dollar vs. Japanese Yen.

2.2.3.3 Exotic Pairs

According to Weithers (2011), in the context of the Forex market, the terminology "exotic currency pairs" is used to refer to pairs that involve currencies with lower liquidity or limited use in the global market. Weithers (2011) also highlights that, unlike major and minor pairs, which dominate trading volume and are the focus of most analysis in the foreign exchange market, exotic pairs are characterized by more limited market depth. Among the most cited exotic pairs are:

- EUR/TRY – Euro vs. Turkish Lira;
- USD/BRL – US Dollar vs. Brazilian Real;
- USD/MXN – US Dollar vs. Mexican Peso;
- USD/TRY – US Dollar vs. Turkish Lira; and
- USD/ZAR – US Dollar vs. South African Rand.

2.3 Negotiation Approaches in the Financial Market

Predicting market trends and financial asset prices represents a constant challenge for investors and researchers (KUMAR; RIZK; SANTOSH, 2024; MEHRKIAN; DAVARI-ARDAKANI, 2025). Throughout history, various approaches have been developed with the objective of understanding and profiting in these markets, which can be broadly categorized into traditional methods and, more recently, quantitative methods. Traditional trading methods rely heavily on human analysis and judgment, which are often subject to emotions and biases (MA et al., 2022). Among the most widely used approaches are fundamental analysis and technical analysis.

2.3.1 Fundamental Analysis

Namdari e Li (2018) highlight that the central premise of fundamental analysis is that securities can be mispriced, and that their actual value can be identified through an in-depth evaluation of economic and financial fundamentals. In the foreign exchange market, fundamental analysis seeks to identify and anticipate market movements by evaluating the monetary policies adopted by governments, as well as analyzing statements from central bank meetings and other relevant factors. To analyze a country's financial health, a set of indicators is used that illustrate the current state of the economy based on specific areas of economic activity. These indicators are published regularly by government agencies and the private sector. According to Moya (2024), the leading indicators include: interest rates, Gross Domestic Product (GDP), the Consumer Price Index (CPI), the Producer Price Index (PPI), employment indicators, and monetary and fiscal policy measures.

2.3.2 Technical Analysis

According to Almeida e Vieira (2023), technical analysis originated in the 18th century with the use of candlestick charts and was later consolidated with Dow Theory, which seeks to identify the primary market trend (uptrend, downtrend, or sideways), helping investors make more informed decisions. Unlike fundamental analysis, which focuses on a company's or currency's financial health and intrinsic value, technical analysis is based mainly on historical price and trading volume data to identify trends and predict future market dynamics (SHENDE et al., 2022; ALMEIDA; VIEIRA, 2023). Another notable characteristic of this approach is the use of technical indicators to assist in identifying trends and market entry or exit signals. Furthermore, although technical analysis simplifies manual analysis, it can be limited by the subjectivity in pattern interpretation and by the non-stationary and noisy nature of financial data (VINITNANTHARAT et al., 2019; LI; XU; LAI, 2022).

2.3.2.1 Candlestick Chart

Candlestick charts, also known as "Japanese Candlesticks", represent a fundamental and visually powerful tool in the technical analysis of financial markets (SANTUR, 2022). Although their origin dates back to the 18th century in Japan with Munehisa Homma – a rice trader who used charts to track price fluctuations – the technique was only popularized in the Western world in the 1990s by Chen e Tsai (2020). However, it was only after 1991 that their application in the financial markets – especially in stocks, futures, and foreign exchange – gained significant prominence (SANTUR, 2022).

Each candlestick can be understood as a concise graphical representation of an asset's price variations over a specific period – as hourly, daily, weekly, monthly, or yearly (VARGHESE; KRISHNADAS; KUMAR, 2023). As illustrated in Figure 1, each candlestick encapsulates four main pieces of information for each trading session: the open, high, low, and close (HEINZ et al., 2021).

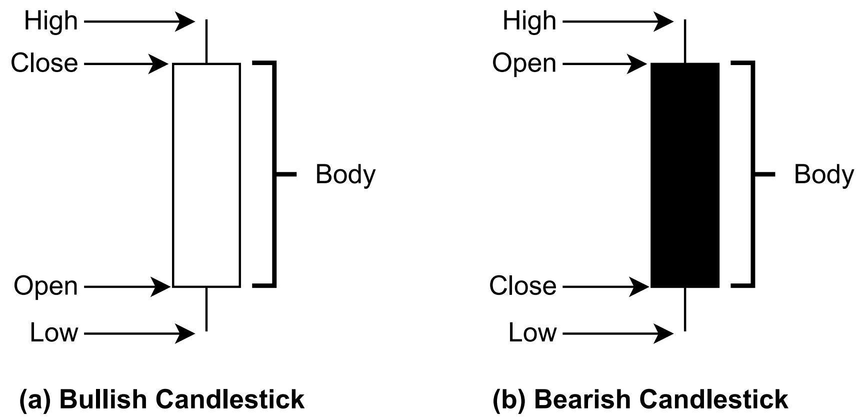

Figure 1 – Candlestick Example.

According to Santur (2022), the primary visual components of a candlestick are:

- **Real Body:** This is the rectangular part of the candlestick that represents the range between the opening and closing price. By convention, as illustrated in Figure 1, a white or green body (a) indicates that the closing price was higher than the opening price, while a black or red body (b) indicates the opposite – that is, that the close was lower than the open in the analyzed period.
- **Shadows or Wicks:** These are the vertical lines that extend from the real body. The upper shadow (Figure 1(a)) goes from the top of the body to the highest price reached in the period. The lower shadow (Figure 1(b)) extends from the bottom of the body to the period's lowest price.

The length of the body and the shadows, along with their relative position, provide insights into price dynamics and the balance of power between buyers and sellers (ALAGDEVE; KARULE; PALSODKAR, 2024). For example, a long body indicates a strong price movement, while long shadows can suggest volatility or a potential reversal (HU et al., 2019).

2.3.2.2 Candlestick Patterns

According to Mersal, Karaoğlan e Kutucu (2025), the actual utility of candlesticks lies in the formation of specific patterns, which consist of recurring combinations of one or more candlesticks interpreted to predict future price movements. Although there is no consensus on the effectiveness of these patterns, their use is widespread among professionals and investors (HEINZ et al., 2021).

The literature presents a large number of candlestick patterns, with references varying between 103 and 105 different types (VARGHESE; KRISHNADAS; KUMAR, 2023). These candlestick patterns can be categorized in various ways, with one of the most common being based on the number of candles that compose them – such as one, two, three, four, or five (or more) candle patterns (HU et al., 2019). The following are some examples of widely known patterns:

- **Hammer:** A bullish reversal pattern that usually appears after a downtrend. It is characterized by a small body (either light or dark), a long lower shadow – generally two to three times the size of the body – and a very short or absent upper (NOERTJAHYANA et al., 2019).
- **Engulfing Pattern:** A pattern formed by two consecutive candlesticks that signals a possible trend reversal. In a bullish engulfing pattern, after a downtrend, a large white body completely engulfs the previous black body. In a bearish engulfing pattern, after an uptrend, a large black body fully engulfs the white body that precedes it (CHEN; TSAI, 2020).
- **Doji:** A candlestick with opening and closing prices that are very close or the same, forming a tiny body or a horizontal line. It signals indecision in the market, and its meaning depends on its location within the trend (PIASECKI; HANćKOWIAK, 2020).
- **Morning Star:** A three-candlestick bullish reversal pattern, indicating the end of a downtrend and the beginning of an uptrend. It consists of a large black body, followed by a small body (which can be black or white) that usually gaps down, and then a large white body that closes well within the body of the first day (ALAGDEVE; KARULE; PALSODKAR, 2024).
- **Marubozu:** This pattern is identified as a bullish Marubozu when the low price is equal to or close to the opening price, and the high price is equal to or close to the closing price. On the other hand, a bearish Marubozu is identified when the high price is equal to or close to the opening price and the low price is equal to or close to the closing price. This pattern also has the following characteristics: (a) it indicates strong buying or selling pressure, (b) it represents a potential trend continuation signal, and (c) it is a clear and easily identifiable visual pattern (CORDEIRO et al., 2025).

2.3.2.3 Technical Indicators

Almeida e Vieira (2023) highlight that among the most widely used technical indicators in technical analysis, the following stand out: the Simple Moving Average

(SMA), the Exponential Moving Average (EMA), the Relative Strength Index (RSI), and the Moving Average Convergence Divergence (MACD) indicator.

2.3.2.3.1 Moving Averages

Moving averages are among the leading indicators used in technical analysis to anticipate future price movements in the financial market (K et al., 2021; ALMEIDA; VIEIRA, 2023). Their primary function is to smooth out price variations and assist in identifying trend direction (PICASSO et al., 2019). In general, moving averages help investors confirm the direction of an asset's trend, whether it is upward, downward, or sideways. Almeida and Vieira (ALMEIDA; VIEIRA, 2023) highlight two of the most common and widely used types:

- **Simple Moving Average:** The SMA is calculated as the arithmetic average of prices (P) over a specific number of periods (n). It is used to identify the general direction of a trend over time by smoothing out short-term fluctuations. The formula for calculating the SMA is given in Equation 2.1.

$$\mathrm{SMA} = \frac{S_t + S_{t-1} + \cdots + S_{t-(n-1)}}{n} \tag{2.1}$$

  Where:

  - S_t represents the current value (e.g., the closing price on day t, or the displacement at time t);
  - $S_{t-1}, S_{t-2}, \ldots, S_{t-(n-1)}$ represent the values from previous periods within the calculation window; and
  - n is the number of observations (or "periods") considered for the calculation of the average.

- **Exponential Moving Average:** Unlike the SMA, the EMA assigns greater weight to more recent prices, which makes it more sensitive and responsive to market changes. The formula for calculating an EMA is represented in Equation 2.2.

$$\mathrm{EMA}_x(t) = \alpha \cdot P(t) + (1 - \alpha) \cdot \mathrm{EMA}_x(t-1) \tag{2.2}$$

  In the equation above, $P(t)$ represents the sequence of observations over time t (e.g., closing price, bandwidth, or displacement), and α (alfa) is the smoothing coefficient, calculated as $2/(N+1)$, where N is the number of observations considered in the period (WU et al., 2021). Smaller values of N result in a larger α, making the EMA more sensitive to slight variations in the observed samples (VU; MASHAL; AND, 2017).

2.3.2.3.2 Relative Strength Index (RSI)

The RSI is one of the most prominent and widely used technical indicators in technical analysis by traders and investors (KULSHRESTHA; SRIVASTAVA, 2020). Developed by J. Welles Wilder Jr., the indicator's primary function is to measure the magnitude of recent price changes to evaluate overbought or oversold conditions for a given asset. Cordeiro et al. (2025) highlight that the RSI's main capabilities include: (a) identifying potential trend reversal points; (b) measuring the strength of the momentum; (c) adapting to different time horizons; and (d) having wide acceptance and support in academic studies.

The general formula for calculating the RSI is illustrated in Equation 2.3. The variable RS (Relative Strength) represents the ratio of the average gains to the average losses over a given period n (COCCO; TONELLI; MARCHESI, 2019). In this context, n corresponds to the number of time units considered (e.g., days, if the timeframe is daily) (CORDEIRO et al., 2025). The resulting value ranges on a scale from 0 to 100.

$$\mathrm{RSI}(n) = 100 - \left[\frac{100}{1 + \mathrm{RS}(n)}\right] \tag{2.3}$$

Wilder (1978) classic interpretation defines the RSI as follows: (a) "overbought" when the value surpasses 70. This may indicate that the asset is overvalued and due for a bearish reversal, signaling a selling opportunity; and (b) "oversold" when the value falls below 30. This may indicate that the asset is undervalued and about to undergo a bullish reversal, signaling a buying opportunity.

2.3.2.3.3 Moving Average Convergence Divergence (MACD)

The MACD is a widely recognized technical indicator, developed by Gerald Appel in the late 1970s (WANG; KIM, 2018). Initially created for the analysis and prediction of price movements in financial markets, such as stocks and foreign exchange, the MACD has become a popular tool among market analysts and traders for identifying reversal points and generating buy and sell signals (WU et al., 2021). Like the RSI, the MACD is classified as a momentum indicator, as it measures both the speed and the direction of price changes (ALMEIDA; VIEIRA, 2023).

Picasso et al. (2019) highlight that this indicator analyzes the relationship between two exponential moving averages (EMAs) of different periods for a financial asset. Its calculation is done by subtracting the long-period EMA (slower moving average) from the short-period EMA (faster moving average) (WILES; ENKE, 2015). According to the specialized literature, the main components of the MACD are:

- **MACD Line (DIF):** The MACD is defined as the difference between the short-period EMA and the long-period EMA (HUNG; KIEN, 2020). Generally, 12 periods ($N_f = 12$) are used for the short-term EMA and 26 for the long-term EMA ($N_s = 26$), although these values can be adjusted depending on the analyzed asset (WILES; ENKE, 2015). The formula expressed in Equation 2.4 is used to calculate MACD_t, where m is the short period and n is the long period.

$$\mathrm{MACD_t} = \mathrm{DIF_t} = \mathrm{EMA_m}(S_t) - \mathrm{EMA_n}(S_t) \tag{2.4}$$

- **Signal Line (DEA):** This is an EMA applied to the MACD line itself, with a period typically set to 9 days (WU et al., 2021). Equation 2.5 gives its formula, where p is the period of the EMA applied to the DIF line, commonly set to $p = 9$.

$$\mathrm{DEA_t} = \mathrm{EMA_p}(\mathrm{DIF_t}) \tag{2.5}$$

- **MACD Histogram (OSC):** The MACD histogram represents the difference between the MACD line (DIF) and the signal line (DEA). It oscillates above and below the zero line, indicating the relative strength of the movement. Its formula is expressed in Equation 2.6:

$$\mathrm{OSC_t} = \mathrm{DIF_t} - \mathrm{DEA_t} \tag{2.6}$$

2.4 Quantitative and Algorithmic Trading

This section provides a detailed analysis of Quantitative Trading and Algorithmic Trading, explaining how these approaches utilize mathematical models and computational systems to identify opportunities and execute trades in the financial market.

2.4.1 Quantitative Trading

Quantitative trading (QT) represents a paradigm shift in how investment decisions are made (ZHANG, 2023). QT uses mathematical models, statistical methods, and computational technology to identify investment opportunities and execute trades automatically (WANG; LUO, 2021).

Since the 1970s, QT has been a topic of interest in both academia and the financial industry (SUN; WANG; AN, 2023). However, with the advent of cloud computing and big data, this approach has become more popular and effective (TIAN, 2022). Sun, Wang e An (2023) highlight that in 2020, QT accounted for more than 70% of the trading volume in developed markets (such as the United States and Europe) and approximately 40% in emerging markets (such as China and India).

In general, a quantitative trading system is composed of several integrated modules that form a systematic workflow, including:

- **Data Collection and Preprocessing:** Market data (such as prices, volumes, and technical indicators), fundamental data, macroeconomic data, and sentiment data are collected from multiple sources (ZHANG, 2023). According to Ta, Liu e Tadesse (2020), the handling and preprocessing of this data are crucial to ensure its reliability and accuracy.

- **Feature Engineering:** Raw data is transformed into more meaningful features for model training and analysis, directly influencing its performance (LI; XU; LAI, 2022).

- **Model Building:** Algorithmic models are built to predict and generate trading signals. According to Zhang (2023), the selection and optimization of these model parameters are essential.

- **Backtesting:** Shi e Xu (2020) emphasize that strategies based on this approach must be rigorously tested with historical data in order to verify their viability and optimize their respective parameters before real-time implementation.

- **Trade Execution:** Based on the model's prediction results, buy and sell signals are generated and executed. Factors such as transaction costs and liquidity are considered to ensure the efficiency of the operation (ZHANG, 2023).

- **Risk Management:** Risk control modules are implemented to ensure the robustness and security of the trading strategy, minimizing drawdowns and managing risk exposure (TA; LIU; TADESSE, 2020).

2.4.2 Advantages of Quantitative Trading Over Traditional Techniques

QT offers a series of significant advantages compared to traditional trading approaches, which drives its growing adoption in the global financial market. These advantages include:

- **Objectivity and Discipline:** According to Zhu, Han e Li (2025), the main advantage of QT is the elimination of the influence of human emotions—such as greed, fear, overconfidence, and behavioral biases—in trading decisions. Strategies are rigorously tested and implemented by computer programs, which ensures discipline and consistent execution.

- **Large-Scale Data Processing Capability:** Chao et al. (2019) highlight that QT is capable of analyzing large volumes of historical and real-time data—including technical, financial, and sentiment indicators—that would be infeasible to process manually.
- **Profitability and Risk Control:** Empirical studies and simulations, such as those by Zhu et al. (2022) and Wang, Zhuang e Feng (2022), demonstrate that quantitative trading strategies can generate significantly higher returns than traditional strategies. Furthermore, many of these strategies incorporate robust risk control mechanisms aimed at minimizing drawdowns and protecting capital (SHARMA et al., 2022).
- **Reduction of Information Asymmetry:** According to Rossi e Tinn (2021), quantitative systems are capable of incorporating public information more quickly and effectively, thereby allowing investors to obtain a more accurate interpretation of price data and order flow.

In summary, QT represents a significant advancement in financial market trading by enabling large-scale data analysis, objective decision-making, and high-speed trade execution. Although traditional techniques still play a relevant role, the complexity and volume of modern financial markets make quantitative approaches increasingly indispensable for maximizing returns and effectively managing risks.

2.4.3 Algorithmic Trading

Algorithmic trading, also known as automated trading or algo-trading, is a technique that uses computer programs and algorithms to execute trades in the financial markets (BHATIA et al., 2023; ANSARI et al., 2024). These techniques emerged as an alternative to the challenges associated with manual trading and the variability of traditional approaches, aiming to enhance precision and efficiency in financial operations (ISMAIL et al., 2022).

Such systems utilize computer programs – commonly called Expert Advisors or bots – to process large volumes of data and execute trading orders automatically, based on predefined algorithms and parameters (ZHANG; KHUSHI, 2020). One of the primary advantages of algorithmic trading is its ability to operate continuously, reacting promptly to market fluctuations without requiring continuous supervision from a human operator.

2.4.4 Benefits of Algorithmic Trading

- **Elimination of human emotions and biases:** Unlike human traders, who can be influenced by emotions such as greed and fear, algorithmic systems operate logically, precisely, and free from emotion (ANSARI et al., 2024; CHEN et al., 2024;

JONGPERMWATTANAPOL et al., 2024). The absence of these factors can result in performance superior to that of decisions made manually (ANSARI et al., 2024).

- **Speed and precision:** Algorithmic trading systems are capable of analyzing large volumes of data and executing orders at speeds unattainable for human operators, allowing for rapid responses to market variations and greater precision in trades (WU et al., 2019; SALKAR et al., 2021; CHEN et al., 2024).

- **Pattern detection:** Algorithmic systems can identify and exploit complex market patterns that would often go unnoticed by human traders (ANSARI et al., 2024).

- **Greater discipline and consistency:** By following predefined rules, algorithmic trading promotes greater discipline and uniformity in the execution of operational strategies (POVITUKHIN; KARMANOVA, 2020).

2.4.5 Challenges of Algorithmic Trading

- **Market volatility and non-stationarity:** Modeling financial markets is a challenging task due to the non-stationary and non-linear nature of the dynamic processes that govern them (CARTA et al., 2021; JONGPERMWATTANAPOL et al., 2024). Furthermore, Jongpermwattanapol et al. (2024) emphasize that external factors such as natural disasters, government policies, and international relations also exert a significant influence on their behavior.

- **Data noise and unpredictability:** Financial time series contain a high level of noise, which complicates the extraction of effective market representations and compromises the generalization capability of the models (LI; ZHENG; ZHENG, 2019a; AZIMIFAR; ARAABI; MORADI, 2020; CARTA et al., 2021). Jongpermwattanapol et al. (2024) emphasize that minor prediction errors can lead to substantial losses, particularly in high-volatility markets, such as the Forex market.

- **Rule definition and feature extraction:** Formulating trading strategies and selecting relevant attributes (features) represent some of the main challenges in ensuring the long-term performance of algorithmic trading (BHATIA et al., 2023).

- **Risk management:** Minimizing losses while seeking to maximize returns is one of the most significant challenges for profitable trading (HUANG et al., 2024). To do this, a sound management system must be able to handle the inherent volatility and non-stationary nature of financial markets, which makes it challenging to profit from static rules (ANSARI et al., 2022).

2.4.6 Modern Portfolio Theory (Markowitz)

Markowitz's Portfolio Optimization Theory (MPT), introduced by Harry Markowitz in 1952, is widely recognized as the foundation of modern quantitative finance and is often cited as the origin of algorithmic trading (THUANKHONRAK; RATTAGAN; PHOOMVUTHISARN, 2019; HUANG; GONG; DUAN, 2023). Markowitz's work established the Mean-Variance model, which seeks to optimize a portfolio by simultaneously considering expected return and risk (WANG; REDDY, 2022).

According to Wang e Reddy (2022), the central objective of MPT is to find the optimal weights for each asset in order to maximize the portfolio's return and minimize its risk. This focus led to the study of diversification in asset allocation, demonstrating that the combination of assets – especially those with low correlation – can reduce overall risk (THUANKHONRAK; RATTAGAN; PHOOMVUTHISARN, 2019).

The most significant concept of MPT is the Efficient Frontier, which can be understood as the set of "most efficient" portfolios that offer the lowest possible level of risk for a given level of expected return. The solution of the mean-variance model in the context of automated trading systems can be seen as the first algorithmic trading technique. This is because, once the portfolio is constructed, the trading strategy (the number of shares to buy or sell) is determined by the difference between the optimal weights and the current weights (HUANG; GONG; DUAN, 2023).

Blažiūnas e Raudys (2019) highlights that although the real-world portfolio selection problem is complex due to the uncertainty and chaotic nature of the markets, MPT remains an indispensable theoretical pillar for quantitative risk management and the formulation of profitable strategies.

2.5 Evaluation Metrics in Algorithmic Systems

The validation of automated strategies requires the integrated consideration of return, risk, and risk-adjusted metrics, since each group provides a distinct and complementary perspective on the strategy's performance. Regarding these metrics, Cordeiro, Araújo e Avelino (2025) highlight that:

- **Return Metrics:** They are widely used to measure the profitability and consistency of strategies over time.
- **Risk Metrics:** They are essential for quantifying maximum losses and measuring risk exposure.
- **Risk-Adjusted Metrics:** They play a fundamental role in measuring the relationship between return and risk, differing from risk metrics in how they treat downside

volatility.

To identify the primary metrics used in the evaluation of automated trading systems, a complementary study was conducted (CORDEIRO; ARAúJO; AVELINO, 2025). In that study, the primary metrics identified were: Annualized Return (AR), Cumulative Return (CR), Maximum Drawdown (MDD), and the Sharpe Ratio. In addition to these metrics, Cordeiro, Magalhães e Avelino (2026) conducted a comprehensive investigation within specialized forums and the MQL5 language documentation, identifying three relevant secondary indicators for the evaluation process: Profit Factor (PF), Expected Payoff (EP), and Recovery Factor (RF). Technical details about these metrics are presented in Section 5.4.

2.6 Final Considerations

In this chapter, the theoretical foundation necessary for understanding the present work is presented, providing a comprehensive overview of the fundamentals that underpin the financial market, with a special focus on the Forex market. Starting from the market structure and its various participants, we explored the evolution of trading methodologies, from traditional approaches to the most modern and computationally intensive ones.

3 State of the Art

In recent decades, a growing number of studies have focused on investigating computational techniques for modeling and automating trading strategies. The approaches explored range from classic techniques, such as Machine Learning (ML) and Artificial Neural Networks (ANN), to more sophisticated methods, including Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), Reinforcement Learning (RL), and Deep Reinforcement Learning (DRL). To provide further context on this topic, the following chapter presents a review of related works.

3.1 Related Work

In their research on the development of profitable trading strategies, Povitukhin e Karmanova (2020) proposed a methodology that integrates technical analysis indicators with machine learning algorithms, applied to the foreign exchange market. The work is based on the premise that traditional trading systems, which rely exclusively on technical indicators, often yield unsatisfactory financial results due to the inherent lag of these indicators, which cannot keep up with real-time price movements.

To overcome this limitation, the authors frame day trading as a classification problem, the objective of which is to predict a "buy" or "sell" signal at the beginning of each day. The study's central approach is based on the use of supervised learning, in which the authors introduce the concept of a "teacher". This "teacher" corresponds to an idealized model designed to generate stable, low-noise trading signals.

For the practical implementation, a historical dataset of the EUR/USD currency pair was used, spanning the period from 1999 to 2015, with data collected at five-minute intervals and subsequently aggregated into a daily series. The authors used the R language and packages such as *xts*, *TTR* e *Caret* to process the data, generate a wide range of technical indicators, and, after filtering to remove collinearity and near-zero variance. Furthermore, they trained different classification models, including K-Nearest Neighbors (KNN), Classification and Regression Trees (CART), Naive Bayes (NB), Support Vector Machines (SVM), Random Forest (RF), Neural Networks (NNET), and AdaBoost (ADA).

One of the most relevant insights of the study is the critique of the accuracy metric as the sole criterion for evaluating a trading system's effectiveness. The authors argue that the true measure of success is profitability, calculated in pips. This is because, although a system may show high accuracy in predicting signals, it might still not be profitable due to the magnitude of the price movements. The testing period with unseen data corresponded to the period from 2016 to 2020, and the results showed that the model based on the CART algorithm, despite having a lower accuracy than the other models (between 70% and 77%) – possibly due to its lower sensitivity to small price corrections – achieved profitability almost twice as high as the average of the others. The authors conclude that the proper choice of the "teacher"and the strategy's evaluation criterion is decisive for performance.

In a complementary approach, Chinprasatsak, Niparnan e Sudsang (2020) focused on predicting the daily high and low prices in the foreign exchange market, specifically for the EUR/USD pair. To achieve this, they compared various artificial neural network architectures, including traditional models and the variants they proposed. A central contribution of the work is the evaluation of forecasting models not through standard error metrics, such as Mean Squared Error (MSE), but through a trading simulation system that measures investment effectiveness in terms of "Total Return" and "Drawdown".

To do this, the research conducts a comparative analysis between four neural network architectures existing in the literature and two new ones proposed by the authors themselves. The selected baseline models were: the Backpropagation Neural Network (BPNN), Bayesian Regularized Neural Network (BRNN), Empirical Mode Decomposition Stochastic Time Strength Neural Network (EMD-STNN), and Random Data-time Effective Radial Basis Function Neural Network (RT-RBFNN). The two new proposals are hybrid models that combine the existing techniques: the Empirical Mode Decomposition Random Data-time Effective Radial Basis Function Neural Network (EMD-RT-RBFNN) and the Empirical Mode Decomposition Random Data-time Effective Bayesian Regularized Neural Network (EMD-RT-BRNN).

The main innovation of the proposed models lies in the use of Empirical Mode Decomposition (EMD). This process separates the original time series into multiple simpler components, known as Intrinsic Mode Functions (IMFs). The authors hypothesized that by decomposing the noisy signal, the neural networks could improve their predictive performance. These new data series (IMFs) were then used as input for the advanced neural networks, which incorporate Bayesian regularization to prevent overfitting and a stochastic time strength function to weigh the importance of more recent data.

In the experiment, all networks were trained with historical data from the EUR/USD currency pair, covering the period from 2005 to 2016 for the training phase and from 2017 to 2019 for the testing phase. The networks were fed 15 input variables, including the high and low prices of the previous five days, EMAs, Bollinger Bands, and the current day's opening price. The network's output consisted of two numbers: the forecast for the current day's high and low prices. The performance metric considered both total return and drawdown, reflecting the practical effectiveness of the forecasts in a real investment context.

The trading simulation results demonstrated that the proposed models significantly outperformed the baseline models, with the EMD-RT-BRNN standing out by achieving a total return of 21.27% with a drawdown of 8.48%. In comparison, the traditional BRNN model showed a return of 13.74% with a drawdown of 12.28%. The authors concluded that EMD's ability to extract relevant information from the signal significantly improved the performance of the neural networks. The success of the EMD-RT-BRNN model was attributed to the combination of EMD with the overfitting reduction from Bayesian regularization, coupled with the effectiveness of the stochastic time strength function.

Therefore, the study reinforces the potential of neural networks when combined with preprocessing and regularization techniques in modeling complex financial markets. Furthermore, it highlights the importance of evaluating predictive models based on realistic trading simulations, rather than relying exclusively on traditional statistical metrics. This represents a significant contribution to the advancement of predictive strategies and automated decision-making in the foreign exchange market.

Expanding on the application of artificial intelligence in the financial market, Chantona, Purba e Halim (2020) address a fundamental limitation of Reinforcement Learning (RL) models applied to trading. The authors argue that most trading systems existing up to 2020, based on RL, exclusively used historical technical data (such as prices and indicators) as the state input for the decision-making agent. However, the authors emphasize that external factors, such as news, can drastically alter market sentiment and influence price movements – something that technical data alone cannot capture.

To overcome this gap, the authors propose a hybrid model that enables the trading agent to process and understand both technical and fundamental data in the form of news headlines. The proposal is based on the use of DRL techniques, specifically the Deep Recurrent Q-Network (DRQN) architecture, combined with Recurrent Convolutional Neural Networks (RCNN), Word2Vec, and Long Short-Term Memory (LSTM).

The model's evaluation was performed on seven major currency pairs – AUD/USD, EUR/USD, GBP/USD, NZD/USD, USD/CAD, USD/CHF, and USD/JPY –, using data from 2009 to 2019, covering various timeframes (15, 30, 60, and 240 minutes). Performance was measured using financial metrics, including net profit, annualized return, the Sharpe Ratio, the Ulcer Performance Index, and Maximum Drawdown. The results demonstrated that the proposed model, which combines technical and fundamental data – referred to as Mix Data – outperformed those that used only technical data, especially on shorter timeframes. A noteworthy example is the significant reduction in the strategy's maximum drawdown for the GBP/USD pair, which dropped from 7.9% to 3.32%, representing an improvement of 57.9%. Thus, the primary innovation of this work lies in integrating news sentiment analysis into the decision-making process.

Addressing the complexity of machine learning models, the research by Aloud

(2020) investigates the role of feature selection in the development of a financial trading system. The author argues that while many forecasting models are designed with complex architectures, this complexity can increase the risk of overfitting and compromise performance consistency. Furthermore, such complexity can hinder the precise identification of the features or rules that truly influence the profitability of trading strategies.

The work, therefore, seeks to demonstrate that a simple Deep Artificial Neural Network (D-ANN) system can generate profitable results, provided that the selection and weighting of the input features are done appropriately. To achieve this, the author proposed a methodology for a multi-agent D-ANN system, in which multiple input features – such as technical analysis indicators, intraday seasonality, and fundamental analysis – serve as individual "agents", each providing a trading recommendation: buy, sell, or hold.

The central innovation of the study lies in the way the recommendations from these agents are combined. Instead of assigning equal weights to all features, the author employs a Genetic Algorithm (GA) to evolve and optimize the weights of each input feature. This process enables the system to learn, over time, which agents are more effective and, therefore, should exert greater influence on the final trading decision. This decision is determined by a type of weighted majority vote: the action (buy or sell) with the highest sum of weights from the features that recommend it is executed.

The D-ANN system was tested using high-frequency data corresponding to the period from 2006 to 2009, specifically for the EUR/USD and EUR/CHF currency pairs. Its performance was compared against that of four other baseline strategies, including the Buy-and-Hold (B&H) approach and a system based on Genetic Programming (GP). The results showed that the D-ANN system outperformed all other strategies, achieving the highest average return and the highest Sharpe Ratio. Specifically for the EUR/USD pair, the Sharpe Ratio was 0.48 and the average win rate was 66%, outperforming the GP system. The research thus concludes that the automatic selection and weighting of features via a GA are crucial and allow even a simple D-ANN system to become a robust and profitable forecasting tool.

In an approach focused on the complete automation of the trading process, Ismail et al. (2022) developed an automated trading system (EA) to predict movements in the foreign exchange market. The primary objective of this work was to eliminate the human emotional factors – such as greed and impatience – that often lead manual traders to significant losses. To achieve this, the authors propose a strategy that combines Technical Analysis (TA) indicators and an Artificial Neural Network (ANN) to create a system that operates independently on the MetaTrader 4 (MT4) platform.

The study's methodology focused on optimizing an Artificial Neural Network (ANN) to predict the direction of the GBP/USD currency pair on the 4-hour (H4) chart. For this purpose, the work uses historical data from 2015 to 2019 for the training and validation phases (Sets A and B), while the EA's performance test is simulated over the period from 2017 to 2022. The authors conducted a systematic and large-scale exploration, testing 7,200 different network configurations to identify the most effective architecture. To achieve this, they varied the architecture (Elman vs. Feedforward), the number of hidden layers, the activation functions (such as Tanh, Sigmoid, and Ramp, among others), the training methods (Backpropagation, Nelder-Mead, and Resilient Propagation, among others), and the output normalization techniques.

The technical indicators used included moving averages (MA), the relative strength index (RSI), and candlestick patterns. They were tested in multiple combinations. One of the study's methodological differentiators was the use of 'equilateral normalization' for the ANN's output layer. This technique represents the three market classes – uptrend, downtrend, and sideways – with two output neurons, which, according to the authors, simplifies and accelerates the network's training.

The results of the exploration phase revealed that the combination of three MAs with the RSI, without bias neurons, and with the Tanh activation function, produced the best classification results. Furthermore, the Bullish Engulfing (BLE) and Bearish Engulfing (BRE) candlestick patterns were the most effective for training and validating the ANN. The performance of the optimized EA was validated through a five-year backtest simulation (from 2017 to 2022). The simulation demonstrated that the system was able to generate a consistent profit, turning an initial balance of $10 into $185.43, which proves the viability of the proposed approach.

The study demonstrates that the adoption of ANN-based strategies, when combined with carefully selected technical indicators, can offer substantial benefits in predicting market trends and automating trading strategies. Furthermore, it emphasizes the importance of systematic experimentation in determining the optimal neural network configurations, tailored to the specific behavior of the analyzed financial assets.

A distinct approach to trend prediction in the Forex market is presented by Luangluewut e Thiennviboon (2023), who propose converting price time series into images to be processed by a CNN. The study is based on the observation that, although machine learning models are widely used, they can have significant limitations when dealing with financial data. Furthermore, the authors highlight that some research indicates that complex Deep Learning (DL) models may not be effective due to the visual similarity between graphs of different trends, which compromises the models' generalization capability.

Unlike traditional approaches that use price time series as numerical input for ML algorithms, the authors propose converting these series into images (charts) with a 1-minute resolution, generating 256x256-pixel figures. These images were used as input for a CNN with a simple architecture, designed to perform a binary classification: predicting whether the segment represents an uptrend or a downtrend based on the last 26 minutes of data from the EUR/USD pair.

One of the most innovative contributions of the study is the method used to label the training data. Instead of using traditional indicators, such as moving average crossovers, which can generate ambiguous and noisy trend signals, the authors developed an algorithm based on the Martingale investment strategy. This strategy, traditionally used to increase the value of bets after consecutive losses, was adapted to identify and label trend events clearly and objectively. In this context, an event is classified as an uptrend or a downtrend if the Martingale algorithm detects a sequence of at least four consecutive buy or sell orders, respectively.

The proposed model was trained on data from the EUR/USD pair from 2013 to 2015 and tested using data from the years 2016 to 2018 and 2020. The experimental results demonstrated the model's high effectiveness, as it achieved an accuracy of 93% in predicting trends on the test set. This performance significantly surpassed that of traditional techniques such as simple moving average, exponential moving average, and MACD, whose accuracies ranged between 78% and 80%.

In addition to the predictive evaluation, the authors conducted trading simulations with a simple algorithm to investigate the practical applicability of the model as a trend indicator. In the scenarios tested, using historical data from the EUR/USD and GBP/USD currency pairs, the proposed model achieved returns between 6% and 422% higher than those achieved with traditional technical indicators. This demonstrates the promising potential of treating time series as images for trend prediction in the Forex market.

Farooghi e Khaloozadeh (2024) presents an innovative approach in the field of algorithmic trading, proposing a cooperative Multi-Agent Deep Reinforcement Learning (MADRL) system for the Forex market. The main contribution of the study lies in the functional specialization between two distinct agents: one agent is exclusively responsible for opening positions (the Trade Opener). At the same time, the other is dedicated to closing those positions (the Trade Closer).

The system is built on the Proximal Policy Optimization (PPO) algorithm, an actor-critic policy gradient technique known for its stability, which makes it particularly advantageous for volatile markets like Forex. To handle the sequential nature of market data, including prices and technical indicators, both agents use LSTM neural networks. Additionally, the model also implements the Generalized Advantage Estimation (GAE) to balance immediate rewards and long-term consequences, increasing learning efficiency.

Cooperation between the agents is encouraged through a shared reward function. A reward, based on the transaction's profit or loss, is only generated when a trade is closed. Its value is distributed equally between the two agents. This mechanism incentivizes the opening agent to initiate trades with high profit potential and the closing agent to end them at opportune moments.

The experiments were conducted using data from the EUR/USD pair on the 1-hour (1H) timeframe, covering the period from April to June 2024. This dataset was used for training (April 1, 2024, to May 22, 2024), validation (May 23, 2024, to June 6, 2024), and testing (June 7, 2024, to June 14, 2024). On the test set, the system executed a total of 150 trades, achieving profits ranging from 3.5% to 6.9%. The maximum observed drawdown was 2.9%, indicating a consistent and risk-controlled performance. The authors report that a comparable single-agent system, using the same LSTM architecture and PPO algorithm, was unable to generate profits on the same dataset, highlighting the superiority of the cooperative multi-agent structure. The study concludes that the methodology is promising for developing profitable and risk-controlled trading systems.

In a recent study on the impact of noise and non-stationarity on the stability of trading agents, Nalmpantis, Passalis e Tefas (2025) proposed a hybrid architecture termed Deep Gaussian Filtering (DGF). The method introduces layers of trainable Gaussian filters that can be integrated into any neural network, enabling the model to autonomously learn the optimal bandwidth for each asset via backpropagation. In addition to noise reduction, DGF employs high-order derivatives to generate multiple representations of the input signal, enabling the agent to robustly handle the non-stationarity of financial data.

The experiments were conducted on six Forex currency pairs (AUD/NZD, AUD/USD, EUR/CAD, EUR/GBP, GBP/JPY, and GBP/USD), employing the Proximal Policy Optimization (PPO) algorithm. The results demonstrated that the incorporation of DGF enabled agents based on Multilayer Perceptrons (MLP) and Long Short-Term Memory (LSTM) to significantly outperform conventional preprocessing methods, such as input standardization and Layer Normalization. The study concludes that the proposed methodology demonstrates superior efficacy compared to traditional data processing approaches for training trading agents in the Forex market.

3.1.1 Evaluation of Existing Approaches in the Literature

Table 1 presents an overview of the currency assets and time periods used by the studies discussed in this chapter. A predominance of the EUR/USD pair is observed, which appears as the central asset in practically all works, either exclusively or in combination with other pairs. Regarding the data period, there is significant variation in the length and temporal depth of the experiments. Some studies use extensive and robust windows, capable of capturing different market regimes, which demonstrates concern about the generalization of the data.

On the other hand, the work of Farooghi e Khaloozadeh (2024) stands out negatively due to its extremely problematic temporal approach. The study employs absurdly short observation windows, which, from a scientific standpoint, render the time frame completely inadequate for any automated trading strategy that aims to identify relevant patterns, evaluate robustness, or ensure replicability. The dataset is so limited that it makes it unfeasible to detect volatility cycles, structural changes, seasonalities, or even typical market conditions.

Works	**Asset(s)**	**Train**	**Validation**	**Test**
Povitukhin and Karmanova	EUR/USD	1999–2015	–	2016–2020
Chinprasatsak et al.	EUR/USD	2005–2016	–	2017–2019
Chantona et al.	AUD/USD, EUR/USD, GBP/USD, NZD/USD, USD/CAD, USD/CHF, and USD/JPY	–	–	2009–2019
Aloud	EUR/USD and EUR/CHF	–	–	2006–2009
Ismail et al.	GBP/USD	2015–2019	–	2017–2022
Luangluewut and Thiennviboon	EUR/USD	2013–2015	–	2016–2020
Farooghi and Khaloozadeh	EUR/USD	04.01–05.22	05.23–06.06	06.07–06.14
Nalmpantis, Passalis, and Tefas	AUD/NZD, AUD/USD, EUR/CAD, EUR/GBP, GBP/JPY, and GBP/USD	2015–2019	–	2020

Table 1 – Summary of the Periods and Data Used in the Analyzed Works.

In turn, the Table 2 compares the analyzed studies based on the metrics defined in Section 2.5 and discussed in detail in Section 5.4. The column headings for the table are: Annualized Return (AR), Cumulative Return (CR), Maximum Drawdown (MDD), Profit Factor (PF), Expected Payoff (EP), and Recovery Factor (RF). The purpose of this comparison, in addition to contextualizing the "Proposed Solution", is to identify the performance metrics used to evaluate each of the approaches documented in the literature. This initial survey is crucial for conducting a subsequent comparative analysis to evaluate the effectiveness and robustness of the proposed solution in comparison to others.

Work/Metrics	**AR**	**CR**	**MDD**	**Sharpe**	**PF**	**EP**	**RF**
Povitukhin e Karmanova (2020)	No	Yes	No	No	No	No	No
Chinprasatsak, Niparnan e Sudsang (2020)	Yes	Yes	Yes	No	No	No	No
Chantona, Purba e Halim (2020)	Yes	Yes	Yes	Yes	No	No	No
Aloud (2020)	No	No	No	Yes	No	No	No
Ismail et al. (2022)	Yes	Yes	No	No	No	No	No
Luangluewut e Thiennviboon (2023)	No	Yes	No	No	No	No	No
Farooghi e Khaloozadeh (2024)	Yes	No	Yes	No	No	No	No
Nalmpantis, Passalis e Tefas (2025)	No	No	No	No	No	No	No

Table 2 – Comparison between the Works

As the analysis of the table above shows, many works adopt a limited view by not using an adequate set of metrics. Consequently, the reliability and robustness of their conclusions are compromised. The studies by Povitukhin e Karmanova (2020) and Luangluewut e Thiennviboon (2023) base their evaluation solely on Cumulative Return (CR). This approach is inadequate, as it completely ignores risk. A strategy can show a high cumulative return but with unacceptable risk (massive drawdowns), making it unfeasible in practice. Although Povitukhin e Karmanova (2020) critiques the isolated use of accuracy and argues for profitability as a more suitable measure of success, they do not measure the risk associated with that profitability.

The works by Chinprasatsak, Niparnan e Sudsang (2020), Chantona, Purba e Halim (2020), and Farooghi e Khaloozadeh (2024) represent an advancement by including Maximum Drawdown along with return metrics. However, the analysis remains incomplete, as the absence of risk-adjusted metrics, such as the Sharpe Ratio, limits the evaluation of the quality of the returns. Thus, it is not possible to determine whether the profits resulted from an efficient strategy or simply from exposure to excessive risk. The work by Ismail et al. (2022) also presents a similar limitation, focusing only on return metrics (AR and CR), despite its objective being to create a profitable EA.

The study by Aloud (2020) employs a distinctive approach, utilizing only the Sharpe Ratio. Although the Sharpe Ratio is a powerful metric for evaluating risk-adjusted return, its use in isolation is also problematic, as it does not inform the investor about the magnitude of potential losses (MDD) or operational efficiency (PF). A strategy can exhibit a good Sharpe Ratio but still have an unacceptable Drawdown from both a psychological and financial standpoint for an investor.

Finally, the work of Nalmpantis, Passalis e Tefas (2025) presents a critical methodological gap by disregarding all financial performance metrics presented in Table 2. Unlike the other studies analyzed in this chapter, which adopt at least one return or risk indicator, the authors restrict their validation solely to Profit and Loss (PnL). This myopic approach is insufficient, as the isolated observation of nominal profit can mask inefficient strategies operating under unacceptable levels of risk exposure.

3.2 Final Considerations

As can be observed in Table 2, the works discussed in this chapter present significant methodological gaps due to the neglect of one or more essential evaluation metrics, which limits the validity and robustness of their automated trading strategies. In contrast, Scalper Major, by employing an evaluation framework that provides a balanced integration of return, risk, and risk-adjusted metrics, offers a much more complete and reliable analysis of its performance.

4 Materials and Methods

This chapter details the methodology, computational resources, and experimental procedures employed in the development, implementation, and validation of Scalper Major.

4.1 Software and Hardware Resources

The development and testing of the proposed system required specific hardware and software resources, as detailed in the following sections.

4.1.1 Development and Execution Environment

For the development and implementation of Scalper Major, the MetaQuotes Language 5 (MQL5) programming language, which is native to the MetaTrader 5 (MT5) trading platform, was used. The MT5 platform itself was employed for programming, executing backtests, and operating in a live environment. The entire backtesting phase was conducted on a computer with the Windows 11 operating system. Regarding the hardware, the equipment featured an Intel(R) Core(TM) i7-10700K CPU @ 3.80GHz processor, with eight cores and 16 threads, in addition to 128 GB of RAM with a speed of 2133 MT/s.

4.1.2 Historical Data Acquisition

To ensure maximum precision in the system validation tests (backtests), the historical data used was obtained through the Quant Data Manager tool[1]. This tool was chosen because it offers:

- **Speed and Quality:** Super-fast download of high-quality data, in both tick and minute formats.
- **Data Analysis:** Functionalities to analyze data quality and identify gaps.
- **Export:** Ability to export data to platforms such as MetaTrader 4 and 5, allowing for high-precision backtests.
- **Flexibility:** Ability to clone data for any time period and export to virtually any trading platform.

The data was downloaded in tick format because it records each price change, providing the most granular and faithful representation of market dynamics. Additionally,

[1] <https://strategyquant.com/pt/quantdatamanager/>

the use of data in this format offers relevant methodological advantages compared to aggregated data (per minute or hour), among which the following stand out:

- **Maximum Temporal Precision:** Essential for high-frequency and short-duration strategies, such as scalping.
- **Greater Realism in Tests:** Allows for the faithful reconstruction of market micro-variations.
- **Reduction of Interpolation Errors:** Ensures that variations in spread, slippage, and execution delays are correctly reproduced.
- **Greater Statistical Reliability:** Performance metrics are calculated on real data, without the use of candle-based approximations.

It is important to note that other sources for downloading historical data (tick data) are available on the market, such as Yahoo Finance, Tickstory, TickData, and HistData.com. However, Quant Data Manager was chosen for its combination of tick quality and ease of integration with the MT5 environment.

4.2 Experimental Procedures and Scenarios

This section details all the experimental procedures and test scenarios used for the performance evaluation of Scalper Major.

4.2.1 Definition of Assets and Test Periods

1. **Assets (Currency Pairs):** Scalper Major was configured to operate on the four main tested currency pairs: EUR/USD, GBP/USD, USD/CAD, and USD/CHF. The selection of these pairs was based on their high liquidity and the positive results obtained in a preliminary testing phase that covered 24 currency pairs.
2. **Backtesting Period (Simulated):** The system was validated with historical data from January 2016 to December 2023. This interval was intentionally chosen to subject Scalper Major to a variety of extreme market conditions, including:
    - **Geopolitical Events:** The Brexit referendum, the US Presidential Elections in 2016 and 2020.
    - **Global Crises:** The COVID-19 health crisis.
    - **International Tensions:** The start of the war in Ukraine.

- **Monetary Policy Shifts:** The transition from an expansionary monetary policy to a restrictive cycle of quantitative tightening. quantitativo).

3. **Live Environment:** For validation in real market conditions, Scalper Major has been in testing since June 2024. However, the data presented in Section 6.2 is restricted to the period up to September 2025.

4.2.2 Simulation Parameters (Backtesting)

The experiments were conducted on the MetaTrader 5 platform in a controlled environment. To ensure the backtest approximated real market conditions as closely as possible, the following operational variables were included:

- **Initial Capital:** $20,000.00.
- **Commission:** A commission fee of $7 per lot was considered.
- **Swap (Rollover Fee):** A swap fee exemption was applied.
- **Execution Latency:** An execution delay of 50 ms was considered.
- **Modeling Mode:** Tick-by-tick with a variable spread.

These configurations ensured the reproducibility of the tests and the comparability of the results with real trading environments.

4.3 Trading Architecture and Strategy

This section details the technical architecture and operational logic of Scalper Major.

4.3.1 Scalper Major Modular Architecture

The proposed solution adopts a modular architecture composed of three specialized components (detailed in Section 5.1), which are essential for the execution of the trading strategy:

1. **Signal Processor (SP):** Responsible for evaluating the feasibility of a new trade based on two heuristics: the Technical Signals Heuristic and the Candlestick Identification Heuristic (Marubozu Pattern).

2. **Risk Manager (RM):** Acts as a safety filter, applying the Risk Heuristic to protect capital. Its drawdown control rules include a maximum floating loss limit of 10% per asset and a global drawdown of 25%, which suspends the opening of new trades.

3. **Capital Manager (CM):** Determines the optimal lot size for the new trade. The CM applies the Capital Heuristic with a Progressive Rebalancing lot-sizing model (detailed in Section 5.3).

This modular structure allowed each component to be tested and validated independently, ensuring greater control and transparency in the development process.

4.3.2 Trading and Recovery Strategy

The Scalper Major strategy uses a hybrid Grid approach combined with an adapted Martingale strategy, aiming for the recovery of unfavorable positions, which operates under the following conditions:

- **Order Entry:** A new order in the grid is opened only if the SP identifies a new valid entry signal.

- **Lot Scaling:** The lot progression is moderated, as the system opens two consecutive positions with the same lot size before doubling it.

- **Risk Limitation:** A maximum limit of 14 simultaneously open positions has been established per asset and per direction.

  Profit Target in Recovery: When the Grid and Martingale system is active, the set of positions is closed when the total profit from the winning positions reaches a value three times greater than the accumulated loss from the losing positions (a 3:1 ratio), ensuring a favorable risk-return for the recovery.

This approach made it possible to balance the potential for capital recovery with more prudent risk management. By imposing strict conditions for adding new positions and defining an asymmetric profit target, the strategy aims to reverse unfavorable scenarios while maintaining risk within predefined limits efficiently.

4.4 Evaluation Metrics

The strategy's robustness was evaluated based on an integrated set of seven financial metrics highlighted in Table 3 and detailed in Section 5.4. This set focuses on metrics of return, risk, and risk-adjusted return.

Category	Metric	Acronym	Description
Return	Cumulative Return	CR	Total profit from the strategy in relation to the initial capital.
	Annualized Return	AR	Compound growth rate of the investment over one year.
Risk	Maximum Drawdown	MDD	Largest observed loss from peak to trough before a recovery.
	Profit Factor	PF	Ratio between gross profit and gross loss.
	Expected Payoff	EP	Average expected profit or loss per trade.
	Recovery Factor	RF	Indicator of the system's ability to overcome drawdown.
Adjusted Risk	Sharpe Ratio	Sharpe	Excess return obtained per unit of risk assumed.

Table 3 – Evaluation Metrics

4.5 Final Considerations

The adopted methodology, which included using tick data for rigorous simulations, defining a backtesting period that covered multiple market crises, and applying a modular architecture with a progressively conservative lot-sizing model, allowed for a robust validation of Scalper Major. The choice of a comprehensive set of evaluation metrics ensures a balanced analysis of the performance, encompassing profitability, risk assumed, and operational efficiency of the proposed solution.

5 Proposed Solution

Having established the theoretical foundation, the related works, and the relevance of the problem, this chapter is dedicated to detailing the proposed solution and the criteria for its evaluation. First, the architecture of the proposed system is described, detailing its design and operation. Next, the adopted strategies for managing new trades when the market moves against already open positions and for scaling the lot size are presented. Finally, a systematic survey of the most commonly used financial evaluation metrics in the literature is presented, which not only guides the analysis of the results of this study but also establishes itself as a reference for future research in the area.

5.1 Scalper Major Architecture

Scalper Major is an automated trading system developed to operate in the Forex market, implementing short-term strategies with minimal human intervention. It was implemented using the MQL5 programming language, which is native to the MetaTrader 5 platform. The system's operation is based on a set of rules derived from technical criteria (the signal processor), combined with a strict risk and money management system, as outlined in the architecture presented in Figure 2.

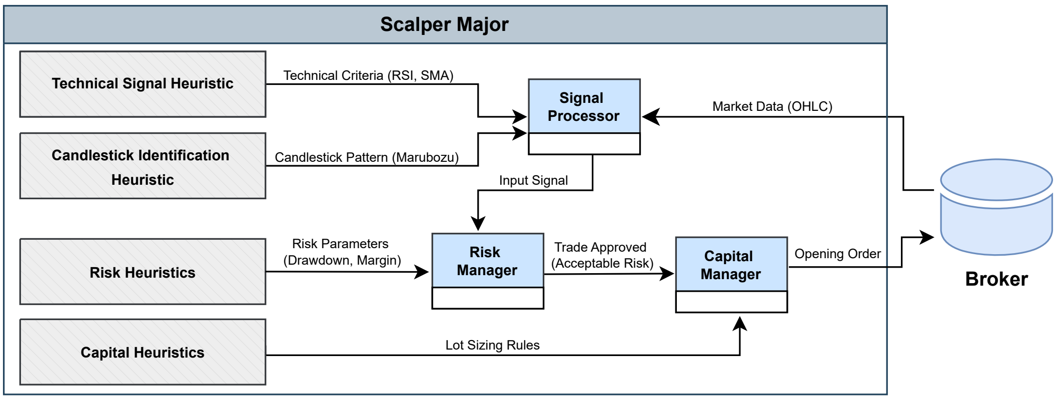

Figure 2 – Scalper Major Architecture.

5.1.1 Signal Processor

The operational flow of Scalper Major begins with the receipt of market data (OHLC – open, high, low, close) provided by the broker. This data is directed to the Signal Processor (SP), the first component in the decision-making process. The SP evaluates the feasibility of a new trade using two main heuristics, analyzed at the beginning of each new hour based on the newly closed H1 (1-hour) candle: the Technical Signals Heuristic and the Candlestick Identification Heuristic, which are detailed below.

- **Technical Signals Heuristic:** This heuristic uses a combination of two indicators, the details of which are presented in Section 2.3.2.3: the RSI and the SMA. During the testing phase, it was found that the best buy signals were generated when the RSI was below 30, while the best sell signals occurred when it was above 70. Furthermore, it is required that the closing price of the candlestick be at a significant distance from the 20-period Simple Moving Average (SMA-20): below it for buy trades and above it for sell trades. Similar to the 30 and 70 levels for the RSI, the SMA-20 was selected because it yielded the best results in the tests performed. A sharp distance of the price from this average reinforces the hypothesis of an excessive extension of the downward or upward movement, increasing the probability of a correction.

- **Candlestick Identification Heuristic:** This heuristic focuses on recognizing the Marubozu pattern, the characteristics of which are detailed in Section 2.3.2.2. During the testing phase, the combination of this pattern with the RSI was found to be a robust confirmation for trade entries. A sell signal is generated when a bullish Marubozu occurs with the RSI in an overbought condition (above 70), indicating a likely exhaustion of the uptrend. On the other hand, a buy signal is generated when a bearish Marubozu is identified with the RSI in an oversold condition (below 30). Figure 3 presents an example of a sell trade executed on the EURUSD asset. It is observed that the RSI of the candle prior to the sell trade is above 70. Furthermore, it is noted that this same candle closed at a considerable distance from the SMA-20 (the white line below the candlesticks). These two conditions, combined with the bullish Marubozu, resulted in a successful sell trade. The process for a buy trade occurs analogously.

Figure 3 – Example of a sell trade.

5.1.2 Risk Manager

Once both of the SP's heuristics indicate a trading opportunity, the Risk Manager (RM) is triggered. This component acts as a safety filter, applying the Risk Heuristic to evaluate the strategy's sustainability and protect the capital from excessive losses. Its primary function is to ensure that risk exposure remains within predefined and acceptable limits. This heuristic considers data such as the available free margin and implements a maximum loss (drawdown) control at two levels: individual (per asset) and global. A new trade on a specific asset is blocked if the open trades show a negative float greater than 10%.

Additionally, the system ceases to open any new trades if the overall account drawdown (the sum of all floating losses) exceeds 25%. These 10% and 25% limits were set empirically during the testing phase, aiming to strike an optimal balance between allowing the strategy to operate without excessive restrictions while rigorously protecting capital. It is essential to note that the Risk Manager's decision takes precedence over that of the Signal Processor; that is, even if the entry conditions are perfectly met, the operation will be canceled if the Risk Heuristic indicates an exposure that exceeds the defined safety parameters.

5.1.3 Capital Manager

After the operation is validated and approved by the RM, control is transferred to the Capital Manager (CM), the last component in the flow before the execution of a new trade (position). The CM's primary responsibility is to size the lot for new trades, a fundamental step in capital management. To achieve this, the CM employs the Capital Heuristic to determine the optimal lot size. The lot size is automatically adjusted based on the risk parameters defined in the EA and the total capital available in the account.

This mechanism ensures that the exposure level adapts to the growth or decline of the account equity, promoting the scalability of returns in favorable scenarios and, crucially, capital preservation during periods of loss, thereby avoiding disproportionate risk exposures. Unlike the Risk Heuristic, which acts as a veto mechanism, the Capital Heuristic does not block the trade.

Finally, once the lot size is defined, the CM sends the request to open the new position to the broker, completing the automated cycle. The joint application of these criteria, from signal identification to capital sizing, allowed the implemented strategy to achieve promising results in tests using historical data, as demonstrated and discussed in Chapter 6.

5.2 Trading and Recovery Strategy

However, if the market moves against the initial position, the EA activates a recovery mechanism that combines the grid and martingale strategies. The grid strategy consists of opening new positions at predefined price intervals as the market moves against the original position. The martingale strategy, in turn, involves increasing the lot size of the subsequent trade. Nevertheless, its isolated use is high-risk.

To mitigate the inherent risk of the martingale strategy, Scalper Major adopts a hybrid and innovative approach. Before applying the martingale, the system opens two consecutive positions with the same lot size, then doubles the lot size of the last position. For example, the lot sequence would follow the pattern 0.02, 0.02, 0.04, 0.04, 0.08, 0.08, and so on, until the maximum number of openable positions is reached.

Table 4 presents a set of trades executed on the EUR/USD pair using the combined *grid and martingale* strategy. The data presented corresponds to a series of five consecutive sell trades. The "Price" column shows the different price levels at which the new positions were opened. The "Volume" column illustrates the geometric scaling of the lot sizes as the price moves against the initial position. The other columns provide contextual information, such as the time ("Time"), asset ("Symbol"), type ("Type"), and direction ("Direction") of each trade.

Time	**Symbol**	**Type**	**Direction**	**Volume**	**Price**
2023.12.15 20:00:00	EURUSD	sell	in	0.02	1.08995
2023.12.18 21:00:00	EURUSD	sell	in	0.02	1.09195
2023.12.19 06:00:00	EURUSD	sell	in	0.04	1.09277
2023.12.20 14:00:00	EURUSD	sell	in	0.04	1.09607
2023.12.20 16:00:00	EURUSD	sell	in	0.08	1.09739

Table 4 – Grid and Martingale Strategy.

Furthermore, a new order in the grid is opened only if the SP identifies a new valid entry signal, according to the criteria already detailed. This prevents the indiscriminate opening of positions that occurs in pure martingale systems. Additionally, to limit risk exposure, a maximum of 14 simultaneously open trades has been set per asset for each direction (14 buy and 14 sell). When the grid and martingale system are active, the profit target is met when the total profit from the winning positions reaches a value three times greater than the accumulated loss from the losing positions, ensuring a favorable risk-return ratio for recovery.

Table 5 provides a complete example of managing a "grid + martingale" operation, encompassing both the position accumulation phase and the profit-taking phase. The initial phase shows the opening of five sell positions at different price levels, with a scaling in lot sizes ("Volume"). The second phase demonstrates the strategic closing of all open positions, which were liquidated as soon as the aggregate profit from the positive positions ($55,92 + $9,72) exceeded three times the aggregate loss of the negative positions ($2,32 + $7,12 + $10,94). The "Commission" column details the costs of each transaction, which are added to the losses in calculating the aggregate loss.

Time	**Symbol**	**Type**	**Direction**	**Volume**	**Price**	**T/P**	**Commission**	**Profit**
2023.12.21 12:00:00	EURUSD	sell	in	0.02	1.09799	1.09699	-0.12	
2023.12.21 20:00:00	EURUSD	sell	in	0.02	1.09990	1.09699	-0.12	
2023.12.22 14:00:00	EURUSD	sell	in	0.04	1.10288	1.09699	-0.24	
2023.12.27 12:00:00	EURUSD	sell	in	0.04	1.10589	1.09699	-0.24	
2023.12.27 15:00:00	EURUSD	sell	in	0.08	1.11045	1.09699	-0.48	
2023.12.29 21:11:00	EURUSD	buy	out	0.08	1.10346	1.09699		55.92
2023.12.29 21:11:00	EURUSD	buy	out	0.02	1.10346	1.09699		9.72
2023.12.29 21:11:00	EURUSD	buy	out	0.04	1.10346	1.09699		-2.32
2023.12.29 21:11:00	EURUSD	buy	out	0.02	1.10346	1.09699		-7.12
2023.12.29 21:11:00	EURUSD	buy	out	0.02	1.10346	1.09699		-10.94

Table 5 – Complete Negotiation Cycle.

Figure 4 provides a visualization of the price dynamics and of the execution points corresponding to the trades in Table 5. The candlestick chart shows the opening of five sell positions – the five "SELL"markers – triggered at ascending price levels during an unfavorable market movement. The closing of all positions was executed at a single point, identified as "TAKE PROFIT", after a market reversal that allowed the weighted average price of all orders to reach the established profit target, ensuring a consolidated profit for the set of trades, as per the data in Table 5.

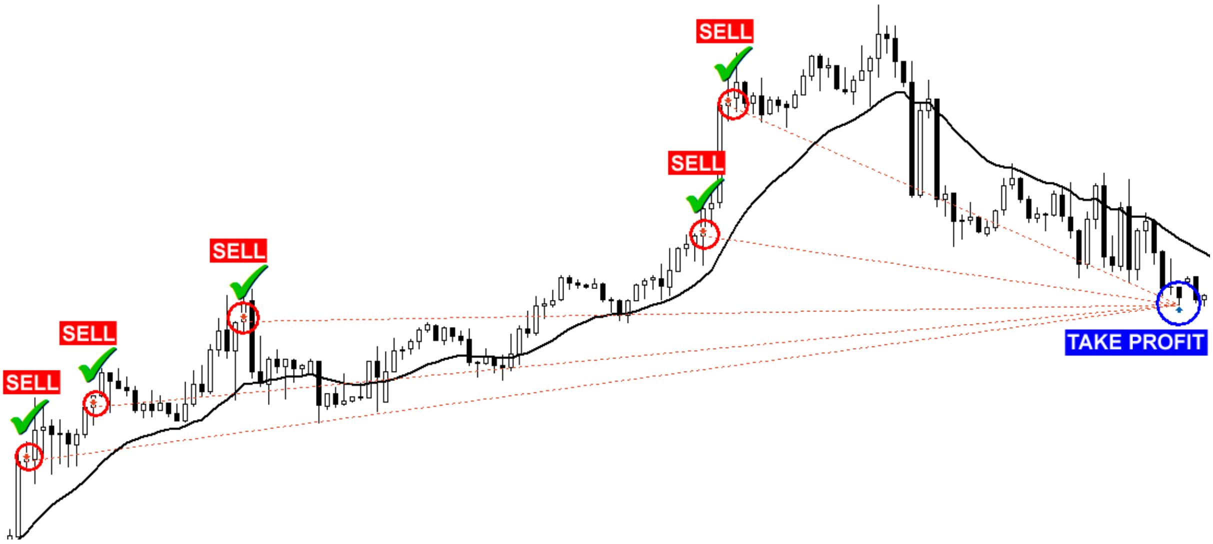

Figure 4 – Grid and Martingale Strategy.

5.3 Lot Sizing Model with Progressive Rebalancing

The logic for the dynamic calculation of the lot size is formalized through a series of equations presented below. These equations adjust the trading volume based exclusively on the account's accumulated historical profit, P_h.

5.3.1 Rebalancing Factor Calculation (Q_b)

Equation 5.1, presented below, indicates the number of times that the historical profit (P_h) has surpassed the rebalancing threshold R. The factor Q_b is an integer that represents the number of rebalancing events.

$$Q_b = \begin{cases} \left\lfloor \dfrac{P_h}{R} \right\rfloor, & \text{se } R > 0 \\ 0, & \text{se } R \leq 0 \end{cases} \tag{5.1}$$

5.3.2 Adjustment of Reference Capital Base (B'_x)

The reference base capital, B_x, establishes the profit threshold necessary to justify increases in the base lot size. This threshold is dynamic, adjusted at each rebalancing event (Q_b) by adding a constant C (empirically defined as US\$1,000). This arithmetic progression renders the criterion for lot increase (L) increasingly stringent. Consequently, for historical profit (P_h) to authorize higher exposure, a progressively higher accumulated amount (B'_x) must be reached, requiring greater consistency from the trading system.

What happens if the value of the constant C is increased? Increasing the value of C makes the EA significantly more conservative, dampening the progression of traded volume relative to account growth. By mitigating financial exposure, the system tends to exhibit a lower Maximum Drawdown (MDD) and a more robust Recovery Factor. Conversely, there is a reduction in total net profit, as the system underutilizes the potential of compounding to leverage returns during winning phases. Equation 5.2 shows how this criterion is calculated.

$$B'_x = B_x + (C \cdot Q_b) \tag{5.2}$$

5.3.3 Calculation of Final Lot Size (L)

Finally, the final lot size to be returned by the variable L is calculated, as represented in Equation 5.3. The equation determines how many multiples of the adjusted base capital (B'_x) are contained within the historical profit (P_h). This result is then multiplied by the base lot size corresponding to B_x, L_{base} (e.g., 0.01). The use of the floor function ($\lfloor \cdot \rfloor$) ensures that the lot is only incremented after the profit has fully covered the new threshold.

$$L = \begin{cases} L_{base} \cdot \left\lfloor \dfrac{P_h}{B'_x} \right\rfloor, & \text{se } P_h \geq B'_x \\ 0, & \text{se } P_h < B'_x \end{cases} \tag{5.3}$$

5.3.4 Case Study

To illustrate the behavior of the lots-sizing model described above, a hypothetical case study is presented in this section. The configuration parameters to be considered are as follows:

- **Reference Base Capital** (B_x)**:** \$10,000
- **Basic Lot** (L_{base})**:** 0.01
- **Rebalancing Limit** (R)**:** \$10,000
- **Adjustment Constant** (C)**:** \$1,000

Based on the data defined above, the final lot size (L) will be calculated for different levels of profits (P_h) by applying Equations 5.1, 5.2, and 5.3. Table 6 presents the evolution of the lot size calculation in six distinct profitability scenarios.

Scenario	**Historical Profit** (P_h)	**Rebalancing Factor** (Q_b)	**Adjusted Capital Base** (B'_x)	**Final Lot** (L)
A	\$9,999	$Q_b = \left\lfloor \frac{9{,}999}{10{,}000} \right\rfloor = 0$	$B'_x = 10{,}000 + (1{,}000 \cdot 0) = 10{,}000$	$L = 0$
B	\$10,000	$Q_b = \left\lfloor \frac{10{,}000}{10{,}000} \right\rfloor = 1$	$B'_x = 10{,}000 + (1{,}000 \cdot 1) = 11{,}000$	$L = 0.01 \cdot \left\lfloor \frac{10{,}000}{11{,}000} \right\rfloor = 0$
C	\$23,999	$Q_b = \left\lfloor \frac{23{,}999}{10{,}000} \right\rfloor = 2$	$B'_x = 10{,}000 + (1{,}000 \cdot 2) = 12{,}000$	$L = 0.01 \cdot \left\lfloor \frac{23{,}999}{12{,}000} \right\rfloor = 0.01$
D	\$24,000	$Q_b = \left\lfloor \frac{24{,}000}{10{,}000} \right\rfloor = 2$	$B'_x = 10{,}000 + (1{,}000 \cdot 2) = 12{,}000$	$L = 0.01 \cdot \left\lfloor \frac{24{,}000}{12{,}000} \right\rfloor = 0.02$
E	\$38,999	$Q_b = \left\lfloor \frac{38{,}999}{10{,}000} \right\rfloor = 3$	$B'_x = 10{,}000 + (1{,}000 \cdot 3) = 13{,}000$	$L = 0.01 \cdot \left\lfloor \frac{38{,}999}{13{,}000} \right\rfloor = 0.02$
F	\$39,000	$Q_b = \left\lfloor \frac{39{,}000}{10{,}000} \right\rfloor = 3$	$B'_x = 10{,}000 + (1{,}000 \cdot 3) = 13{,}000$	$L = 0.01 \cdot \left\lfloor \frac{39{,}000}{13{,}000} \right\rfloor = 0.03$

Table 6 – Rebalancing Scenarios for Adjusted Capital and Final Lot Calculation

The analysis of Table 6 reveals the progressively conservative nature of the model. The following details three key observations: the nature of the activation threshold, the non-linear scale for lot increments, and the consequent tightening of exposure criteria.

1. **Threshold Activation:** In scenarios A and B, although the historical profit (P_h) has reached the base reference capital (B_x), the final lot (L) remains zero. This occurs because the adjusted capital base (B'_x) is recalculated before the final lot. In scenario B, with P_h = \$10,000, the rebalancing factor Qb becomes 1, raising the B'_x threshold to \$11,000. Since $P_h < B'_x$, the condition for lot allocation is not met.
2. **Non-Linear Scaling:** In a simple linear model (where the lot size increases every \$10,000 in profit), the second lot increment (to 0.02) would occur with a profit of

\$20,000. However, the proposed model requires a profit of \$24,000 to reach the same exposure level (Scenario D). This is due to the tightening of the increment criterion: with P_h above \$20,000, Q_b is 2, and the adjusted base capital B'_x rises to \$12,000. The lot is only incremented when the historical profit is a multiple of this new value.

3. **Increasing Conservatism:** The effect becomes even more pronounced at higher profit levels. The third lot increment (to 0.03) does not occur at a \$30,000 profit, as in a linear model, but only when P_h reaches \$39,000 (Scenario F). At this point, B'_x has already been adjusted to \$13,000, and the system requires the profit to cover three times this amount to justify the allocation of a 0.03 lot size.

The principle of Scalper Major's lot scaling method is based on the premise that the trading volume should be a function directly proportional to the accumulated profit. This non-linear scaling approach, triggered by the rebalancing threshold R, makes the system progressively more conservative: as profits increase, the capital requirement for the next lot increment also grows. From a risk management perspective, this methodology aims to mitigate the impact of large drawdowns that can occur after periods of significant profit.

5.4 Financial Assessment Metrics

Next, each metric used for evaluating the strategy's performance will be detailed. It is crucial to highlight that the consolidation of these metrics is the result of an extensive and complex survey conducted in the specialized literature.

- **Annualized Return (AR):** Represents the compound growth rate of an investment over one year. It is an essential metric for evaluating the long-term performance of a strategy, allowing direct comparisons across different periods and asset classes, even when referring to distinct investment horizons (HUANG et al., 2024).

- **Cumulative Return (CR):** Represents the percentage change in capital from the beginning of the investment to the present moment (HUANG et al., 2024). This metric is widely used to measure the total profitability of an investment or trading strategy over a specific time horizon (LI et al., 2024). A high cumulative return may indicate significant growth of the invested capital, but it does not necessarily reflect the stability of the gains.

- **Maximum Drawdown (MDD):** Measures the maximum observed loss from the peak value of an investment or strategy to its lowest point before a recovery (SHAHSAFI; NADERKHANI, 2024). It is also often interpreted as the maximum exposure to risk or the most significant possible capital loss (OLORUNSHEYE;

MEENAKSHI, 2024). Rahimpour et al. (2024) highlights that this metric is essential for assessing the risk associated with a trading or investment strategy, as it reveals the magnitude of losses during adverse market periods. Strategies with a high MDD may be considered riskier, as they require significant recovery to return to their previous level.

- **Sharpe Ratio:** Evaluates the risk-adjusted return of an investment or trading strategy (RAHIMPOUR et al., 2024). It helps investors interpret risk-adjusted performance by measuring the excess return obtained per unit of risk taken and is widely used to assess the effectiveness of trading strategies (LI; ZHENG; ZHENG, 2019b). Values greater than 1 indicate a more favorable risk-return relationship for the strategy, which is why traders extensively use it to evaluate the efficiency of trading systems (BLAžIūNAS; RAUDYS, 2019; CARTA et al., 2021).
- **Profit Factor (PF):** According to the MQL5 documentation[1], the PF can be understood as the ratio of gross profit to gross loss, where a value of 1 indicates that the sum of profits is equivalent to the sum of losses. Huang e Martin (2019) explains that the PF, which can be understood as the annualized rate of return per unit of risk, is a crucial metric for evaluating the performance of leveraged trading strategies.
- **Expected Payoff (EP):** The MQL5 documentation defines EP as a statistical indicator that represents the average profit or loss per trade. For Qin e Li (2011), EP is a practical tool for evaluating and comparing trading strategies in scenarios of uncertainty, offering a way to quantify expected outcomes even when historical data is scarce or inadequate.
- **Recovery Factor (RF):** According to the MQL5 documentation, the RF is an indicator that reflects the strategy's risk level, representing the amount the system is willing to risk to obtain a profit. Nasution et al. (2024) points out that values above 1 indicate that the EA has good recovery capability, while values below 0.3 reveal that the EA has difficulty overcoming the Drawdown.

5.5 Final Considerations

In comparison with related works in the literature, the proposed solution addresses recurring limitations in previous approaches, including the lack of risk-related indicators and the lack of transparency in money management. By integrating a realistic empirical evaluation with a comprehensive set of metrics, Scalper Major represents an advancement

[1] MQL5 Documentation: https://www.mql5.com/en/docs

in the state of the art of automated trading, making a significant contribution to the development of computational tools that support decision-making in the financial market.

6 Results and Discussion

This chapter presents the results achieved by Scalper Major in both controlled (simulated) and real (live) environment. Scalper Major was developed using Quantitative Trading techniques (detailed in Section 2.4.1) and was configured to operate specifically on the currency pairs EUR/USD, GBP/USD, USD/CAD, and USD/CHF. The selection of these assets was based on the results obtained from tests conducted on 24 currency pairs, with an average duration of 8 hours per asset. Throughout the evaluation process, the performance metrics described in Section 5.4 were applied to ensure a consistent and objective evaluation in both environments.

6.1 Performance in Simulated Environment

The EA's backtesting period corresponds to the interval between January 2016 and December 2023. This period was methodologically chosen to subject the proposed strategy to various market conditions. The inclusion of these distinct scenarios, as listed below, aims to validate the strategy's robustness and generalization capability, evaluating its performance not only in favorable market conditions but also during periods of stress and systemic market uncertainty.

- The Brexit referendum and the US presidential elections of 2016 and 2020.
- The global COVID-19 health crisis catalyzed one of the fastest bear markets in history.
- The start of the war in Ukraine, with consequent stress on commodity markets.
- The subsequent abrupt transition from an environment of expansionary monetary policy to a restrictive cycle of quantitative tightening to combat global inflation.

To better approximate the results to real market conditions, the following factors were considered: (a) a commission rate of $7 per lot, (b) an exemption from the swap fee (although it is common for some brokers to charge it), and (c) an execution delay of 50 ms. In the simulation process, an initial capital of $20,000.00 was used, and the system achieved a total net profit of $751,533.23. This resulted from a gross profit of $1,060,523.23 and gross losses of $308,991.00, which include trades closed with a negative balance and commissions. In total, 11,571 trades were executed, of which 7,217 were long (buy) trades and 4,354 were short (sell) trades. The overall win rate was 82.54%, with an 83.66% rate for long trades and an 81.42% rate for short trades.

Figure 5 presents the grouped distribution of the trades made in each month of the analyzed years. A relatively uniform distribution is observed, with values varying approximately between 800 and 950 entries. March stands out with the highest number of entries, surpassing the 900 mark, while April recorded the lowest quantity, showing a slight decrease compared to the other months. Figure 6 presents the monthly distribution of profits and losses throughout the analyzed period, enabling a more detailed analysis of seasonality and financial performance patterns. It is observed that profits, represented by the blue bars, consistently exceed losses, indicated by the red bars, in all analyzed months. The months of May, June, and July stand out as those with the highest profitability, with an absolute peak recorded in June, when profits surpassed $130,000.00. On the other hand, the months of February and December recorded the lowest profit.

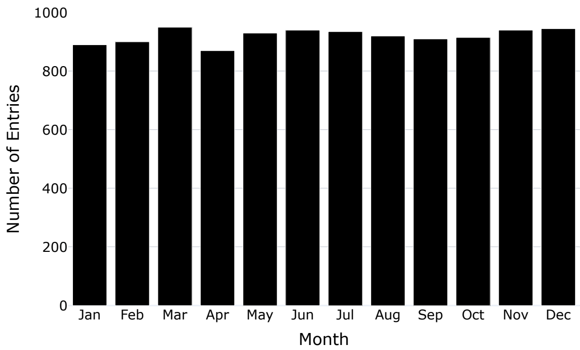

Figure 5 – Negotiations per Month.

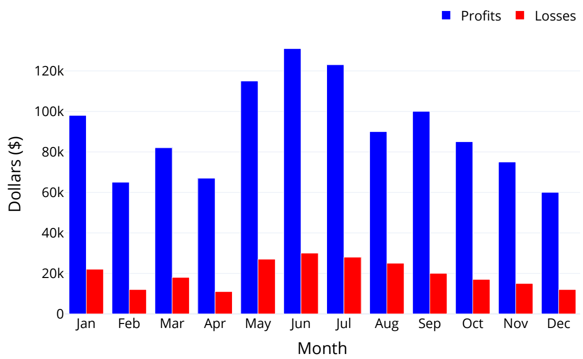

Figure 6 – Profits and Losses.

Figure 7 presents the risk graph, in which the blue line represents the account's growth, and the green line represents the drawdown. The graph also demonstrates robust and consistent growth over time, underscoring the effectiveness of the strategy. A notable point in the trading history occurred in July 2023, when the system experienced its most significant drawdown, reaching a value of 9.43%. The curve also shows that, immediately after this setback, the system not only reversed the losses but also quickly resumed its upward trajectory, continuing to generate new profits, which attests to the soundness and recovery capability of the employed strategy.

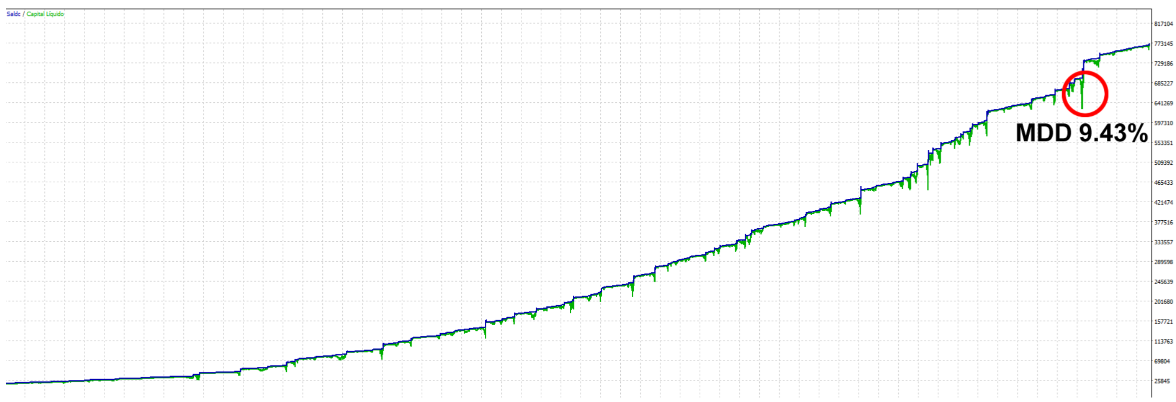

Figure 7 – Risk and Robustness.

6.2 Performance in Real Environment

This section presents the preliminary results obtained in a real-world environment, covering the period from June 2024 to September 2025. These results demonstrate the robustness and consistency of Scalper Major in terms of both profitability and risk control. Figure 8 presents a quantitative summary of the trading strategy's performance through a set of key performance indicators (KPIs).

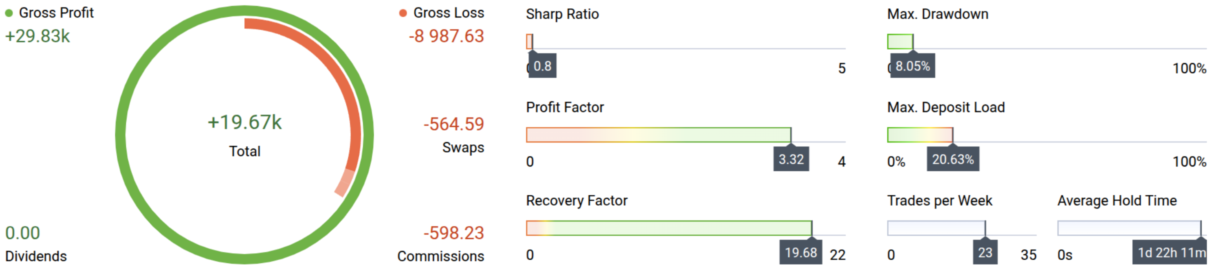

Figure 8 – General Information on Strategy in a Real Environment.

In the figure above, the main circle chart details the composition of the financial result, showing a Gross Profit of $29,830.00 and a Gross Loss of $8,987.63. After the deduction of operational costs, such as Swaps ($564.59) and Commissions ($598.23), the total net profit achieved was superior to $19,673.82. The strategy's robustness is highlighted even more significantly by the Recovery Factor of 19.68 and the Profit Factor of 3.32, which relates the gross profit obtained to the gross loss. The latter, the "Max. Drawdown", was limited to 8.05%, indicating efficient risk control. Other metrics complete the profile of a consistently profitable strategy with managed risk exposure.

Figure 9 offers a detailed analysis of the strategy's historical performance over the period from June 2024 to September 2025. The bar chart highlights the volatility of the results, with peaks of profitability and losses in adjacent periods. The black line overlaid on the bars represents the net result for each period, allowing for a clear visualization of the alternation between periods of gain and loss.

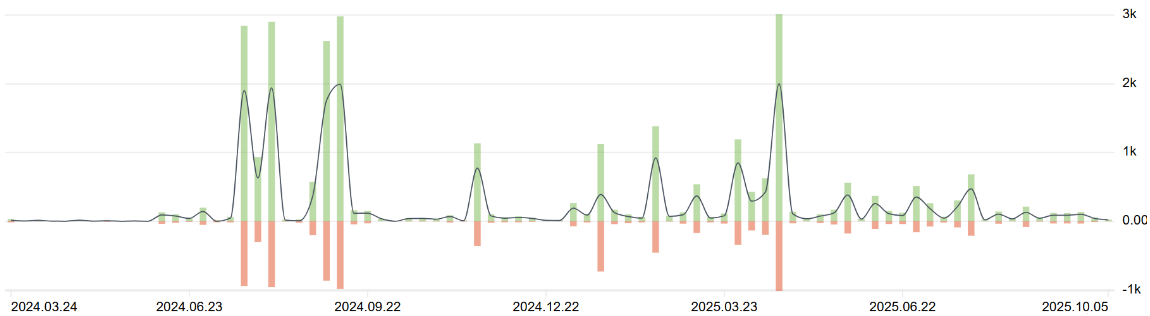

Figure 9 – Peaks of Gains and Losses.

Table 7 quantifies the historical performance of the strategy, as illustrated in the previous charts, by summarizing the monthly net profit throughout the years 2024 and

2025. The data demonstrates the month-to-month performance, with 2024 covering the period from June to December and 2025 from January to September – profitability peaks in September 2024 (3.99k) and April 2025 (3.63k). The table consolidates annual results of 10.52k in 2024 and 9.16k in 2025, confirming the strategy's accumulated profitability with a total of 19.68k at the end of the period.

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Year Total
2024						207.16	2.1k	2.94k	3.99k	126.65	929.66	162.15	**10.51k**
2025	790.34	1.11k	598.18	3.63k	630.96	805.13	847.97	373.61	324.5				**9.16k**
Total													**19.67k**

Table 7 – Annual Metrics Summary for 2024 and 2025

Figure 10 summarizes the main operational statistics of the strategy, based on 1,886 trades, of which 56.04% (1,057) were buy trades and 43.96% (829) were sell trades. The overall performance reached a net profit of $19,673.82 and a win rate of 78.58%. Although buy trades had a higher win rate (80.61% versus 76% for sells), sell trades were, on average, more profitable, with an average profit per trade of $12.26 compared to $9.01 for buys. This higher profitability meant that sell positions contributed $10,160.27 to the total net profit, a value slightly higher than the contribution from buy positions ($9,519.91).

Although 17 trades appear as manual in the image, they were opened by the EA itself but closed manually for system adjustments. Additionally, the bar chart in the center of the figure details the days of the week with their respective daily trading volume. The days from Wednesday to Friday have the highest number of executed trades. These days coincide with the release of the most important economic data from the United States (US) and the European Union (EU). In contrast, activity is significantly reduced at the beginning of the week.

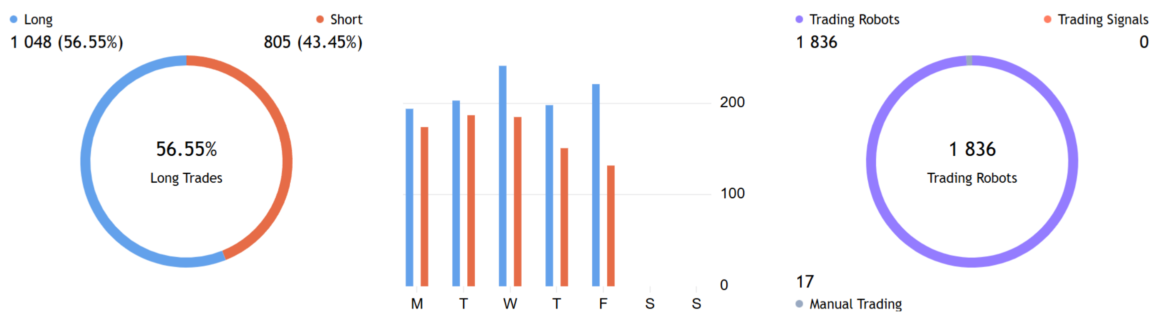

Figure 10 – Distribution and Performance of Strategy Operations.

Figure 11 details the contribution of each currency pair to the overall performance of the strategy. Although the trading volume was distributed relatively uniformly among the four main assets – with 489 trades (26.39%) for the EUR/USD pair, 501 (27.04%) for GBP/USD, 412 (22.23%) for USD/CAD, and 451 (24.34%) for USD/CHF – the financial results varied significantly. The GBP/USD pair was the main profit generator, accumulating $8,480.94. The EUR/USD, USD/CAD, and USD/CHF pairs had returns of $2,281.43, $4,222.75, and $4,688.70, respectively. In terms of efficiency, as measured by the Profit Factor, the EUR/USD pair stood out with a ratio of 3.56, despite not being among the top performers in total net profit. The other assets – GBP/USD, USD/CAD, and USD/CHF – had ratios of 3.08, 3.08, and 2.77, respectively. Thus, all pairs proved to be efficient, both in terms of profitability and operational efficiency.

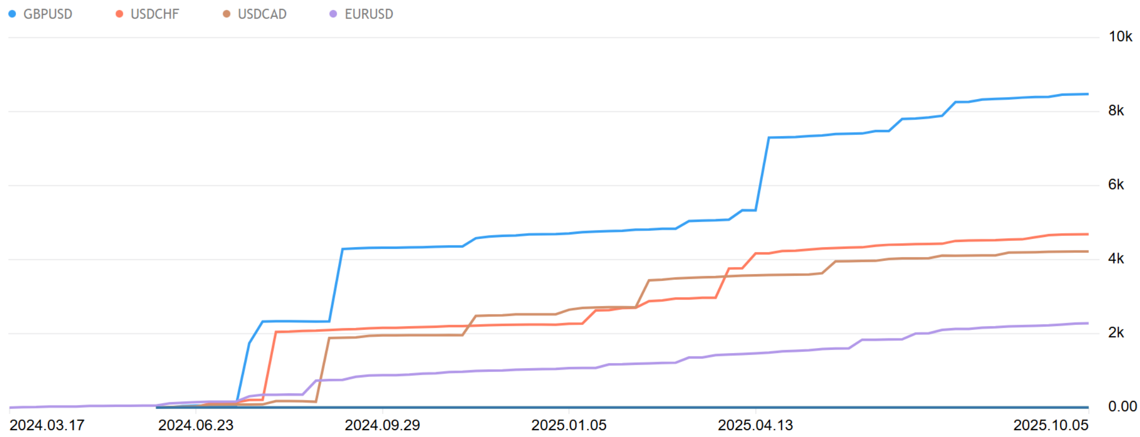

Figure 11 – Distribution of Income by Assets.

Figure 12 illustrates the capital progression (blue line) in juxtaposition with the percentage drawdown of the account (red line). The equity curve demonstrates consistent growth over the period, resulting in a final balance of $39,673.82. The risk analysis, represented by the drawdown, indicates that the most significant unfavorable fluctuation was 8.05% relative to the previous equity peak. Other important data, although not available in the Figure 12, reveal a positive asymmetry between the best result ($2,123.24) and the worst result (-$189.44) in a single trade. Furthermore, the strategy achieved a maximum sequence of 38 consecutive wins, against a maximum of 10 consecutive losses, reinforcing its consistency.

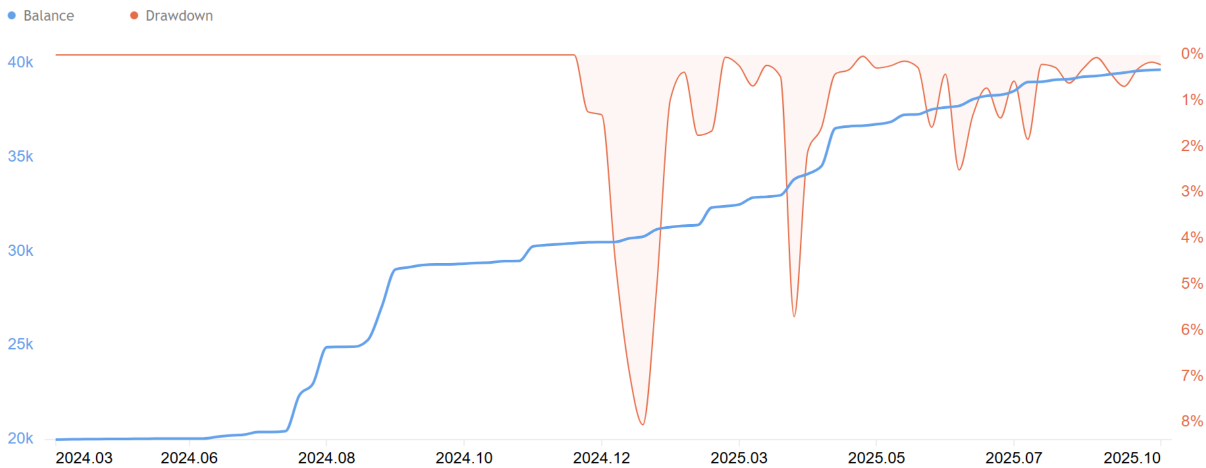

Figure 12 – Growth and Decline Curves.

6.3 Analysis of Results in the Context of Related Literature

In this section, the performance of Scalper Major is evaluated and contextualized through a direct comparative analysis. This analysis contrasts the results of the proposed solution (in simulation and in a live environment) with the works discussed in Chapter 3. The objective is to demonstrate the effectiveness and robustness of the proposed strategy through key metrics of return, risk management, and operational consistency. However, it is essential to highlight that the studies used in the comparative analysis were tested in different scenarios, as indicated in the data presented in Table 1. However, this does not invalidate the comparison, given that there are metrics whose evaluation is time-independent.

Table 8 compares the performance of Scalper Major with that of related works, using the metrics made available in the respective studies. The data presented demonstrate that the results of Scalper Major are notably superior across most of the analyzed metrics. The initial analysis of this comparison, focusing on the simulation results, demonstrates that Scalper Major's performance is notably superior across most of the analyzed metrics.

Work/Metrics	**Deposit**	**Maximum Drawdown**	**Sharpe Ratio**	**Annual Return**	**Cumulative Return**	**Accuracy**
Scalper Major (*simulation*)	**$20,000.00**	**9.43%**	**1.63**	**57.87%**	**$751,533.23**	**82.82%**
Scalper Major (*live*)	**$20,000.00**	**8.05%**	**0.80**	**67.83%**	**$19,673.82**	**78.58%**
Povitukhin and Karmanova	-	-	-	-	$1,171.15	70.0%
Chinprasatsak et al.	$10,000.00	7.72%	-	9.75%	$2,925.00	-
Chantona et al.	$21,200.00	3.67%	1.26	11.64%	$71,182.62	-
Aloud	-	-	0.42	-	-	68.5%
Ismail et al.	$10.00	-	-	79.32%	$175.43	79.7%
Luangluewut and Thiennviboon	-	-	-	-	$76,713.37	93.0%
Farooghi and Khaloozadeh	$1,000.00	2.90%	-	-	$58.00	-

Table 8 – Scalper Major vs Other Works

According to the table above, the most significant indicator is the Cumulative Return, which reached $751,533.23 from an initial deposit of $20,000.00. This superiority is also reflected in the risk-adjusted return metric. The Sharpe Ratio of 1.63 is the highest among the studies that reported it. This suggests that the strategy was more efficient at generating return for each unit of risk assumed. Additionally, its win rate of 82.82% is among the highest, highlighting its robust operational consistency.

The robustness achieved in the testing phase was not only replicated but also surpassed in the live environment, which demonstrated excellent results in risk and return metrics. The Annualized Return obtained in the live environment reached 67.83%, exceeding the simulation's result of 57.87%. Furthermore, risk management showed superior performance in the live environment, registering a Maximum Drawdown of only 8.05%, a value lower than that observed in the simulation (9.43%). The Sharpe Ratio (0.8) and the win rate (78.58%), although lower, remained at robust and competitive levels.

This transparency regarding risk, demonstrated by the inclusion of these essential evaluation metrics, becomes even more apparent when compared to some works listed in Table 2, such as that of Ismail et al. (2022). This study, despite presenting a higher Annualized Return, does not report the Maximum Drawdown of its strategy. The absence of this metric seriously compromises the validity of the presented results, as a high return may have been achieved at the cost of very high and potentially unacceptable risk for an investor. Our solution, on the other hand, offers complete transparency regarding its risk.

This lack of a comprehensive view is not restricted to the work of Ismail et al. (2022). The last two works listed in the table present some good metrics in isolation, but they fail to provide a complete overview of their performance. For example, the work by Luangluewut e Thiennviboon (2023) reports the lowest Maximum Drawdown among those analyzed. However, this risk control is presented without crucial risk-adjusted return metrics, such as the Sharpe Ratio, making it impossible to evaluate the strategy's efficiency in generating profit relative to the risk assumed. The same occurs with the study by Farooghi e Khaloozadeh (2024), which reports the highest win rate among all works, reaching 93.0%. Nonetheless, the study omits essential risk data, such as the MDD and the Sharpe Ratio. A high win rate, although desirable, does not guarantee a strategy's profitability or safety if the few losses are significantly larger than the gains, or if the risk of ruin (drawdown) is not controlled.

Although not listed in the previous table, other relevant data obtained by Scalper Major are presented in Table 9, which directly compares the results of the proposed solution in the testing phase and in the live environment. Furthermore, additional data obtained during the simulation phase, which were not presented in this work, can be accessed through the report available at the following link: <https://zenodo.org/records/16983868>. At the same link, the EA is available, along with the instructions on how to replicate the results.

Work/Metrics	**Maximum Drawdown**	**Recovery Factor**	**Sharpe Ratio**	**Profit Factor**	**Expected Payoff**	**Annual Return**	**Cumulative Return**
Simulation	9.43%	$11.47	1.63	3.43	$64.95	57.87%	$751,533.23
Live	8.05%	$19.68	0.80	3.32	$11.35	67.83%	$19,673.82

Table 9 – Overall Performance of Scalper Major in Simulated and Real Environments

6.4 Comparison with Benchmarks

To conduct a rigorous validation of the robustness and competitive advantage of the Scalper Major strategy, a comparative performance analysis was implemented against three benchmarks. This step is fundamental to ensure that the obtained results are not merely stochastic. The tests were segmented into two categories: passive benchmarks and an active competitor strategy.

1. **Passive Benchmarks**: Two classic benchmarks were used to represent the market's performance and an optimized asset allocation.

    - **S&P 500**: The performance of the S&P 500 index served as a proxy for the aggregate return of the US stock market, utilizing a passive buy-and-hold (B&H) strategy.
    - **Markowitz Portfolio (MPT)**: Based on Modern Portfolio Theory, as detailed in Section 2.4.6, a minimum-variance portfolio was constructed using the ten most extensive market capitalization stocks – extracted from the Companies Market Cap website[1] on October 15, 2025 – from the S&P 500 index. The B&H performance of this optimized portfolio served as the second passive benchmark, representing a diversified and theoretically-grounded risk allocation.

2. **Competing Active Strategy**: The third test consisted of applying an alternative (competing) trading strategy to the same of stocks as the MPT portfolio. This strategy was treated as a classification problem, in which the model had to determine whether the stock should be bought or not. For this purpose, different classification algorithms were used to identify the model with the best predictive capability. The rule stipulated that if a purchase was made, it should occur on Monday, and the sale would be executed on the following Friday. The objective of this test was to compare the Scalper Major not only against passive metrics but also against another active trading approach, allowing for a relative performance evaluation under similar conditions of complexity.

A methodological pillar of this validation was the temporal alignment of the data. All three comparative tests were executed using strictly the same period as the Scalper Major testing phase in the live production environment. This data synchronization is imperative to ensure the direct comparability of the results, mitigate survivorship bias or look-ahead bias, and ensure that all strategies are operated under identical market conditions.

The top ten stocks selected for the MPT are listed in Table 10. The selection criterion adopted was the maximization of the Sharpe ratio, which seeks to select the portfolio with the highest risk-adjusted return within the efficient frontier. Of the stocks listed in the table below, the selected ones are those highlighted in bold. The "Tickers" column presents the trading symbols as used on the Yahoo Finance data platform, which served as the primary source for extracting the price time series for this testing phase.

[1] https://companiesmarketcap.com/

Rank	Stock	Ticker	Marketcap (Trillions)
1	**NVIDIA**	**NVDA**	**$4.386**
2	Microsoft	MSFT	$3.819
3	Apple	AAPL	$3.706
4	Alphabet	GOOG	$3.034
5	Amazon	AMZN	$2.293
6	Meta	META	$1.803
7	**Broadcom**	**AVGO**	**$1.666**
8	Saudi Aramco	2222.SR	$1.610
9	Taiwan Semiconductor	TSM	$1.579
10	**Tesla**	**TSLA**	**$1.442**

Table 10 – Market Cap of the Ten Largest Companies Listed on the S&P 500

The performance evaluation of each strategy was conducted through the analysis of the performance indicators presented in Section 5.4. It is important to note that these metrics are not limited to observing absolute profitability, but primarily seek to measure the efficiency and operational robustness of the systems in the face of the risks they assume. The adoption of these metrics fulfills a dual methodological function. First, it validates the sustainability of each strategy individually, enabling the identification of asymmetric or unsustainable risk profiles. Second, it establishes the quantitative basis for a direct and objective comparison between the results obtained and the performance of Scalper Major. The results of the comparison for each metric are presented below.

Figure 13 presents a direct comparison of the Maximum Drawdown (MDD) metric between the market benchmarks (S&P 500 and MPT), the competing strategy (MPT + ML), and the proposed solution. The MDD, defined as the most significant percentage decline from a previous peak to a subsequent trough, serves as the primary indicator of tail risk and the strategy's vulnerability to adverse market shocks.

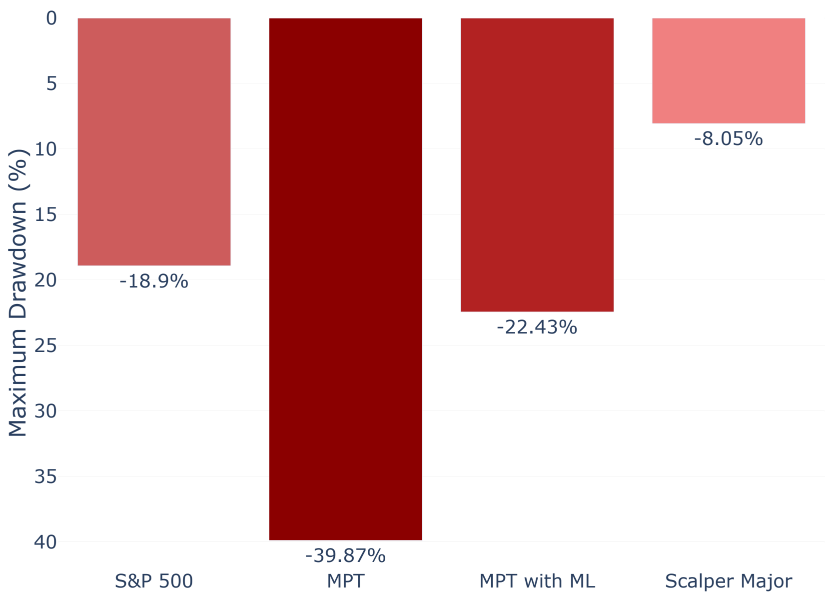

Figure 13 – Comparison of the Maximum Drawdown of the Strategies.

The analysis of the data in Figure 13 reveals a significant disparity in risk exposure among the tested approaches. The portfolio based on Markowitz Optimization (MPT) exhibited the highest vulnerability, with an MDD of -39.87%, indicating that the theoretical diversification among the top 10 stocks was insufficient to shield the portfolio from systemic volatility. The competing strategy (MPT + ML) and the S&P 500 index recorded drawdowns of -22.43% and -18.90%, respectively, remaining at considerable risk levels for conservative or moderate profiles. On the other hand, Scalper Major demonstrated superior resilience, decoupled from general market behavior. By registering an MDD of only -8.05%, the proposed strategy not only outperformed all benchmarks by a wide margin but also proved its capital preservation capability in adverse scenarios.

Figure 14 presents the comparative analysis of the Recovery Factor among the evaluated strategies. This metric, defined as the ratio of total net profit to the absolute maximum drawdown, is a performance indicator that assesses how efficiently a trading strategy recovers from losses. It quantifies the strategy's ability to recover from periods of loss (troughs) and resume capital growth. In practical terms, the higher the ratio, the faster the strategy recovers from its worst historical periods.

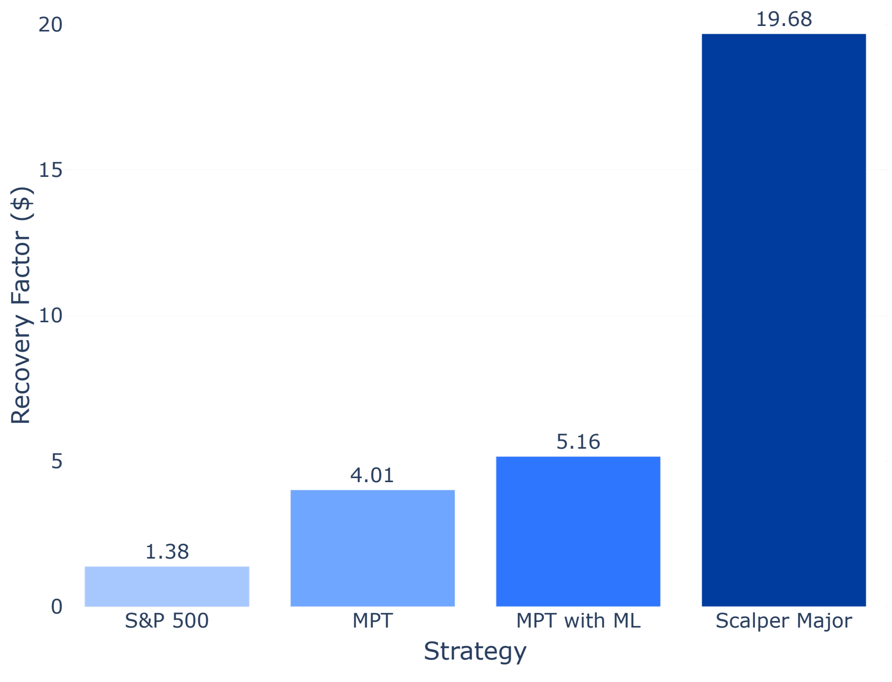

Figure 14 – Comparison of the Recovery Factor of the Strategies.

The analysis of the data in Figure 14 reveals a notable performance disparity between the proposed model and the market benchmarks. In this context, the S&P 500 index showed the lowest performance, with a factor of 1.38, indicating that for every monetary unit of risk assumed during the worst decline, the return generated was marginally higher than one. Strategies based on Portfolio Theory presented intermediate results: the Markowitz portfolio (MPT) obtained 4.01, while its variant with Machine

Learning (MPT with ML) obtained 5.16. Although superior to the market index, these values still demonstrate a limited risk-return relationship compared to the proposed solution. Scalper Major demonstrated exceptional efficiency, achieving a Recovery Factor of 19.68. This value represents a magnitude approximately four times that of the best benchmark (MPT with ML) and more than fourteen times that of the S&P 500. This result demonstrates that the strategy not only avoids significant losses but also exhibits a profit-generating dynamic robust enough to neutralize any capital drawdowns quickly.

Figure 15 presents the comparative results of the Sharpe Ratio, a fundamental metric for evaluating the excess return generated per unit of total risk (volatility) assumed. A higher Sharpe Ratio indicates a more efficient capital allocation, in which the reward adequately compensates for the volatility borne.

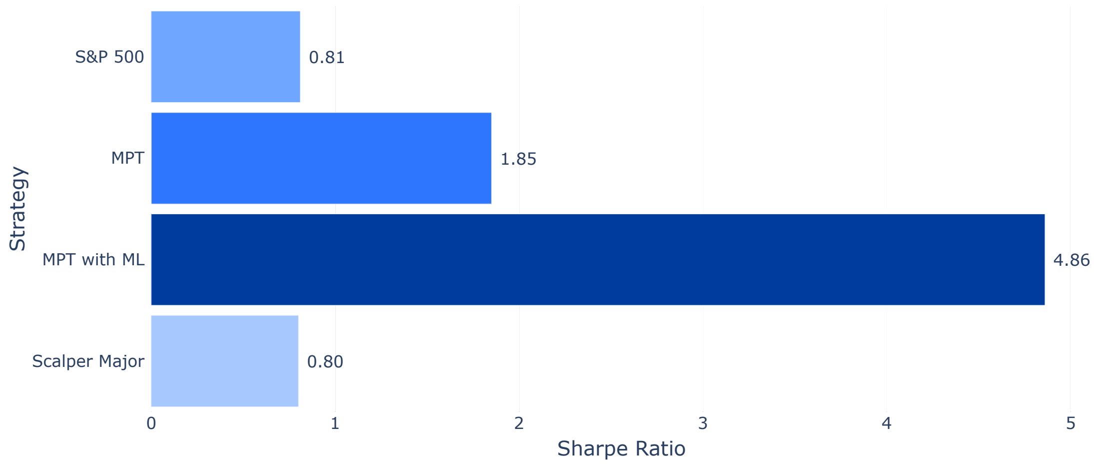

Figure 15 – Comparison of the Sharpe Ratio of the Strategies.

The analysis of the data in Figure 15 reveals distinct behaviors between the portfolio optimization approaches and the proposed strategy. Strategies based on Modern Portfolio Theory (MPT) demonstrated high efficiency, especially the strategy combining Markowitz optimization with Machine Learning (MPT with ML), with a Sharpe Ratio of 4.86. This result suggests that applying ML to stock selection maximizes the relationship between returns and portfolio volatility.

On the other hand, the Scalper Major strategy achieved a Sharpe Ratio of 0.80, which was inferior to that of the other strategies. At first glance, this result might suggest a lack of competitive advantage in terms of efficiency. However, the joint analysis of this indicator with the Drawdown and Recovery Factor presented earlier reveals the true nature of the proposed strategy. While the MPT with ML-based strategy seeks aggressive efficiency maximization (a high return/volatility ratio), Scalper Major demonstrates a profile of stability.

Figure 16 illustrates the comparison of the Profit Factor among the analyzed strategies. Mathematically defined as the ratio of total Gross Profit to total Gross Loss, this indicator serves as a direct measure of the "quality" of the trades. A value greater than 1.0 is a necessary condition for profitability, but high values indicate a strategy in which wins exceed losses with a substantial margin of safety.

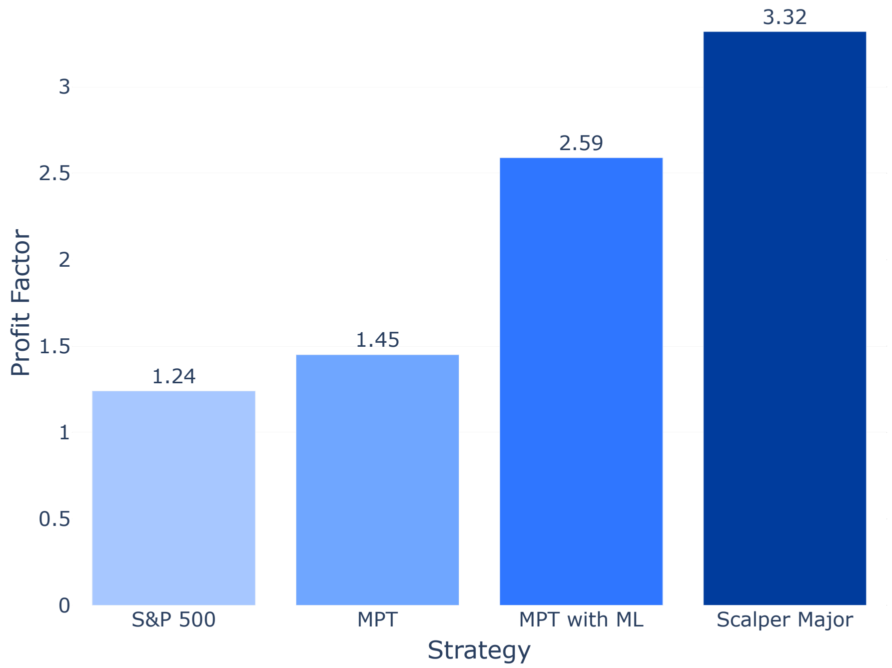

Figure 16 – Comparison of the Profit Factor of the Strategies.

The analysis of the data in Figure 16 reveals a clear hierarchy of operational efficiency, with the S&P 500 index presenting the lowest efficiency coefficient (1.24). The optimized portfolio (MPT) showed a slight improvement, rising to 1.45. These values, although positive, indicate systems with narrow margins of error, in which a sequence of losses can quickly compromise accumulated gains. On the other hand, the introduction of machine learning algorithms combined with the optimized portfolio (MPT with ML) significantly increased efficiency, resulting in a Profit Factor of 2.59. This quantitative leap validates the hypothesis that computational models can filter market noise more effectively than static allocations.

The proposed solution, however, stood out as the dominant strategy, achieving a Profit Factor of 3.32. This result is statistically significant. In practical terms, this means that for every monetary unit lost in losing trades, the strategy generated 3.32 units of gain in winning trades. This demonstrates that while the Sharpe Ratio analysis indicates a risk-return relationship similar to the market's, the Profit Factor of 3.32 reveals that the assumed volatility is extremely 'productive'. Furthermore, unlike the MPT with ML strategy, which may rely on large movements (high volatility) to generate returns, Scalper Major demonstrates surgical precision in extracting value from the market, minimizing the 'cost' of operational losses.

Figure 17 illustrates the comparison of the Expected Payoff across the strategies.

This metric is fundamental for assessing the quality of each trade, as it represents the average expected return (in monetary terms) for each trade opened in the market. Mathematically, it synthesizes the relationship between the win probability and the average size of gains and losses, indicating the "fair value"of each trade.

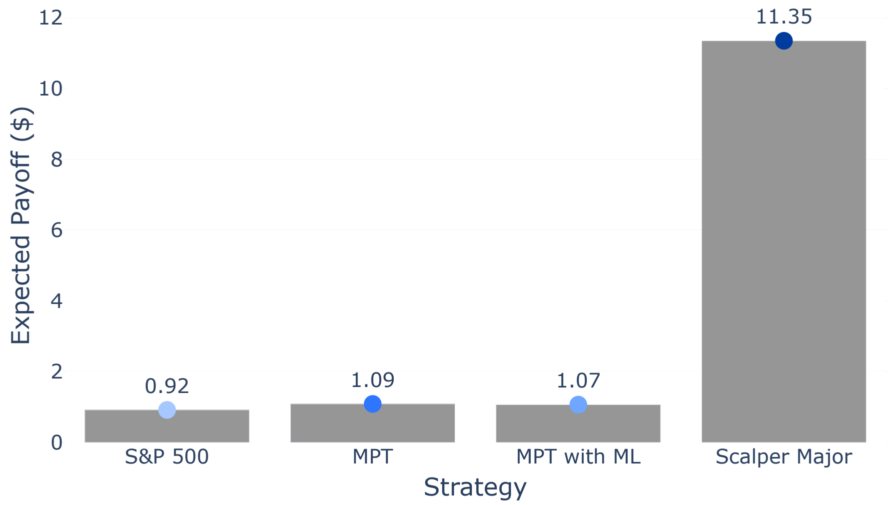

Figure 17 – Comparison of the Expected Payoff of the Strategies.

The visual analysis of the data in the figure above reveals a structural dichotomy between the traditional approaches and the proposed solution. Specifically, the benchmark strategies exhibited modest, homogeneous expected payoffs. The S&P 500 index recorded a value of 0.92, while the portfolios based on Portfolio Theory (MPT and MPT with Machine Learning) recorded 1.07 and 1.09, respectively. These values, close to unity, are characteristic of strategies that rely on exposure volume or passive diversification to accumulate returns, offering only marginal statistical advantages per individual trading event.

In stark contrast, Scalper Major presented an Expected Payoff of 11.35. This magnitude, more than 10 times the benchmark average, indicates a robust probabilistic advantage. That high mathematical expectation implies that the proposed system identifies windows of opportunity where the asymmetry in favor of profit is substantial. This validates the solution's efficiency in filtering out market "noise" and executing orders only when the statistical probability of return justifies the operational risk.

Additionally, whereas benchmarks rely on temporal asset appreciation, Scalper Major operates under a positive expectancy model, structured around active profit-taking algorithms. Coupled with the Signal Processor's selectivity – which mitigates indiscriminate order entry – the system ensures that each closed trade contributes robustly to the Expected Payoff, validating the strategy's efficacy in filtering market noise and capturing price asymmetries.

Figure 18 presents the comparative data on Annualized Return for the four strategies under analysis. This metric normalizes capital growth on an annual basis, enabling direct comparison across different timeframes and facilitating the projection of the Compound Annual Growth Rate (CAGR). Unlike absolute return, annualized return provides a view of the strategy's average velocity of wealth accumulation. Analysis of this data reveals three different levels of performance:

1. **Market Benchmark:** The S&P 500 index showed an annualized return of 19.20%. This value, although consistent with the long-term historical average, is the lowest among the analyzed strategies.

2. **Optimization Strategies (MPT):** The approaches based on Modern Portfolio Theory presented the highest nominal returns. The classic MPT portfolio reached 106.12%, while the version enhanced with Machine Learning (MPT with ML) achieved a peak profitability of 109.40%. Although impressive at first glance, these returns must be interpreted with caution. In the context of the risk data presented earlier (where MPT suffered drawdowns close to 40%), these values suggest a high-volatility strategy, in which the excess return is a premium demanded for the high risk of ruin assumed.

3. **Scalper Major Performance:** The proposed strategy recorded an annualized return of 67.83%. Although nominally lower than the MPT models, this result represents a return exceeding 3.5 times that of the S&P 500 index.

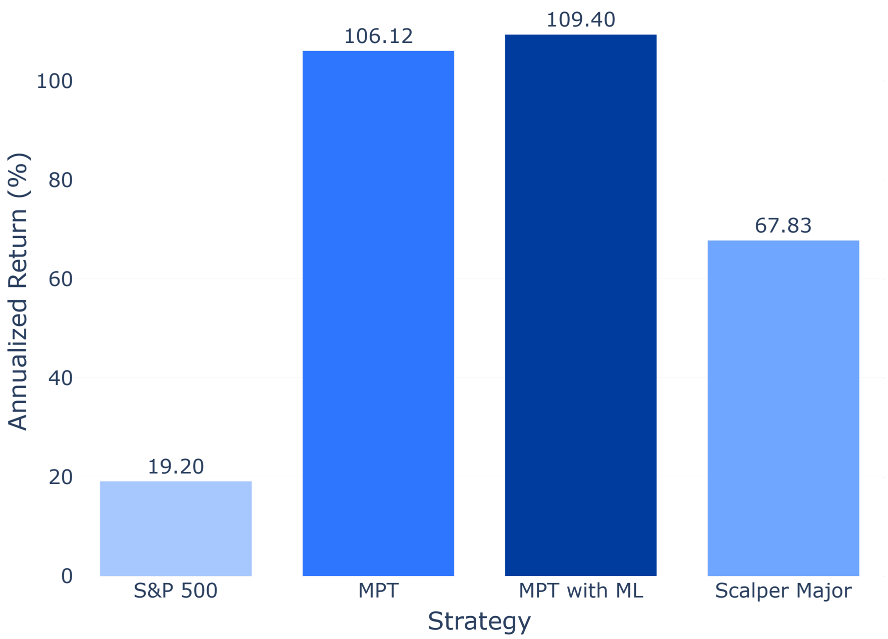

Figure 18 – Comparison of the Annualized Return of the Strategies.

However, an isolated analysis of the data presented in Figure 18 could lead to the erroneous conclusion that the MPT models are superior. However, when integrating this metric with robustness indicators (Drawdown and Profit Factor), Scalper Major position is solidified as the most balanced. After all, in quantitative finance, a consistent annualized return of 67% with a smooth equity curve is preferable to a 100% return subject to violent fluctuations, which can compromise investor psychology or trigger institutional stop-loss limits.

Finally, Figure 19 presents the consolidated financial result at the end of the testing period, expressed by Cumulative Return. This metric represents the total net gains, offering a view of each strategy's effectiveness in multiplying initial capital and generating absolute wealth.

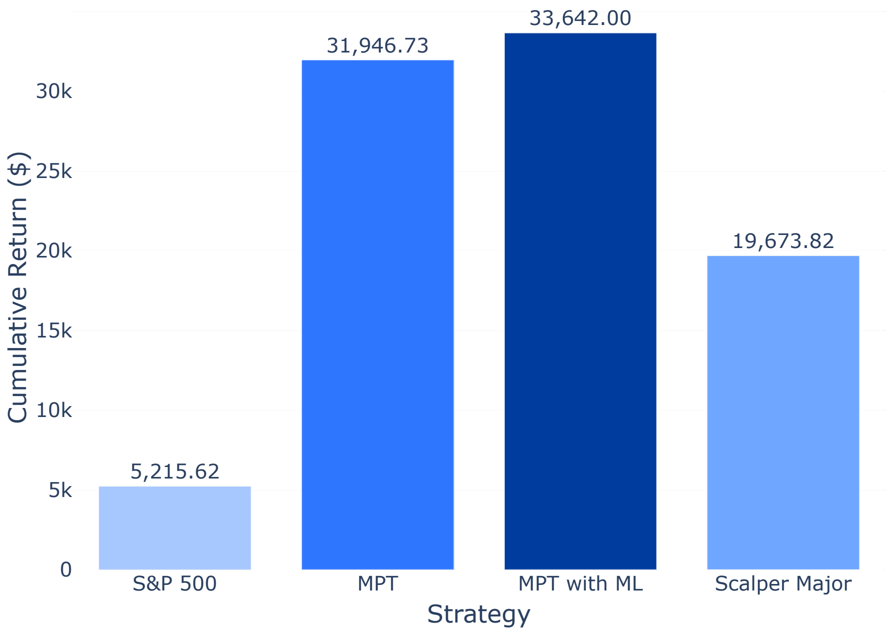

Figure 19 – Comparison of the Cumulative Return of the Strategies.

The analysis of the data in the figure above shows that the S&P 500 index ended the period with a cumulative return of $5,215.62, the lowest among the analyzed strategies, corroborating the data presented in Figure 18. The portfolio optimization strategies, in turn, demonstrated the most excellent gross accumulation capacity. The classic MPT portfolio reached $31,946.73, while the variant enhanced with Machine Learning (MPT with ML) achieved the maximum result of $33,642.00. These figures confirm the theoretical potential of optimized diversification; however, as discussed previously, this return was accompanied by severe volatility and deep drawdowns. Finally, the return achieved by Scalper Major was $19,673.82. Although nominally lower than the portfolio models, this result is notable from the perspective of active risk management.

6.5 Final Considerations

The results discussed in this chapter highlight the robustness and consistency of Scalper Major, demonstrating significant performance in both profitability and risk control. The financial metrics presented indicate the system's efficiency in capturing market opportunities while simultaneously mitigating losses in simulated environments. It is crucial to emphasize that when adequate and rigorous metrics are considered during the testing phase, the likelihood of the system performing similarly in the real trading environment increases. Although it is not possible to guarantee such equivalence due to the dynamic and unpredictable nature of the market, careful analysis in backtests and simulations serves as a strong indicator of the strategy's potential and soundness.

Conclusions and Future Work

Conclusions

The general objective of this work was to develop Scalper Major, an automated trading system capable of operating automatically with minimal human intervention in high-volatility environments, such as the Forex market, through an agile, objective approach with strict risk management. To achieve this purpose, specific objectives were outlined, including designing a modular architecture, integrating specialized heuristics, implementing a robust capital management model, and validating the system in both simulated and real scenarios.

The results obtained demonstrate that the objectives were fully achieved. The modular architecture, composed of the Signal Processor (SP), Risk Manager (RM), and Capital Manager (CM) components, proved to be effective in executing the proposed strategy. The combination of technical and managerial heuristics allowed for the consistent identification of trading opportunities, while the lot-sizing model with progressive rebalancing ensured prudent control of risk exposure. The system's validation, conducted over an extensive backtesting period (2016-2023) and in a live environment (2024-2025), confirmed the strategy's robustness, which proved to be profitable and resilient even in the face of significant market instability events.

The main contribution of this work lies in the demonstration that it is possible to develop an automated trading system capable of generating significant financial returns while maintaining transparent and methodologically sound risk control. From a theoretical standpoint, the research enriches the literature on algorithmic trading by proposing a hybrid approach that combines the grid strategy with an adapted version of the Martingale, conditioning the opening of new positions on valid technical signals and limiting maximum exposure.

Methodologically, the dissertation stands out for its novel compilation and rigorous application of a comprehensive set of evaluation metrics (return, risk, and risk-adjusted return), overcoming a gap identified in related works that often limit their analysis to profitability alone. In practice, Scalper Major is presented as a functional and validated tool, with its architecture and operational logic serving as a reference for developing other computational solutions in the financial market.

Despite the positive results, this research has limitations. Although the backtesting used high-quality tick data to simulate realistic conditions, factors such as network latency and slippage can vary in a real trading environment and impact the results. Finally, the strategy depends on technical parameters (such as the RSI levels and the SMA-20) that, although effective in the analyzed period, may require future recalibration to adapt to new market dynamics.

The research journey was marked by significant challenges, particularly during the Systematic Literature Review phase, which required considerable time and effort to identify the main evaluation metrics applied to automated trading systems. The testing phase also represented another major challenge, as it required extensive computational processing to evaluate dozens of configurations across different assets. Furthermore, debugging a system that operates in real time and ensuring the logical robustness of each component required discipline and methodological rigor. The main lesson learned was recognizing that in the development of trading systems, risk and capital management are not just auxiliary components, but the foundation that sustains the viability of any strategy in the long term.

Future Work

The research developed opens up the following possibilities for future work:

- **Individualized Optimization of Constant C:** We propose the investigation of specific values for this constant per currency pair, given that Forex market assets exhibit distinct profiles of volatility, liquidity, and range. To this end, we suggest the application of sensitivity tests and robust validation methods, such as Walk-Forward Analysis, aiming to identify the ideal C parameter for each financial instrument.

- **Expansion to other Markets:** Applying Scalper Major to other financial markets, such as futures, indices, and stocks, by adapting its heuristics and risk parameters.

- **Incorporation of Artificial Intelligence (AI):** Utilizing Machine Learning techniques, such as Recurrent Neural Networks (RNNs) or transformers, to enhance the identification of market patterns, and exploring Reinforcement Learning (RL) to optimize risk management.

- **Sentiment Analysis:** Integrating sentiment analysis based on news and social media as an additional heuristic to validate technical signals, especially during high-volatility events.

- **Automatic Parameter Optimization:** Developing a version of the system with continuous and automated optimization (*walk-forward optimization*) to ensure that it periodically readjusts to changes in the different market cycles.

References

ABRAHAM, A.; CHOWDHURY, M.; PETROVIC-LAZAREVIC, S. Australian forex market analysis using connectionist models. *Deakin University. Journal contribution*, 2003. Cited 2 times on pages 7 e 8.

ALAGDEVE, V.; KARULE, P.; PALSODKAR, P. Stock prediction using dual analysis of candlestick chart pattern. In: *2024 2nd International Conference on Emerging Trends in Engineering and Medical Sciences (ICETEMS)*. [S.l.: s.n.], 2024. p. 497–502. Cited 2 times on pages 14 e 15.

ALMEIDA, L.; VIEIRA, E. Technical analysis, fundamental analysis, and ichimoku dynamics: A bibliometric analysis. *Risks*, v. 11, n. 8, 2023. ISSN 2227-9091. Cited 4 times on pages 13, 15, 16 e 17.

ALOUD, M. E. The role of attribute selection in deep anns learning framework for high-frequency financial trading. *Intelligent Systems in Accounting, Finance and Management*, 2020. Cited 3 times on pages 27, 31 e 32.

ANSARI, Y. et al. A multifaceted approach to stock market trading using reinforcement learning. *IEEE Access*, v. 12, p. 90041–90060, 2024. Cited 2 times on pages 20 e 21.

ANSARI, Y. et al. A deep reinforcement learning-based decision support system for automated stock market trading. *IEEE Access*, v. 10, p. 127469–127501, 2022. Cited on page 21.

AZIMIFAR, M.; ARAABI, B. N.; MORADI, H. Forecasting stock market trends using support vector regression and perceptually important points. In: *2020 10th International Conference on Computer and Knowledge Engineering (ICCKE)*. [S.l.: s.n.], 2020. p. 268–273. Cited on page 21.

BEKAERT, G.; MEHL, A. On the global financial market integration "swoosh" and the trilemma. *Journal of International Money and Finance*, v. 94, p. 227–245, 2019. ISSN 0261-5606. Cited on page 6.

BHATIA, S. et al. Algo-indicator based trading in stock market. In: *2023 4th International Conference on Smart Electronics and Communication (ICOSEC)*. [S.l.: s.n.], 2023. p. 1730–1734. Cited 2 times on pages 20 e 21.

BLAžIūNAS, S.; RAUDYS, A. Comparative study of neural networks and decision trees for application in trading financial futures. In: *2019 International Conference on Deep Learning and Machine Learning in Emerging Applications (Deep-ML)*. [S.l.: s.n.], 2019. p. 33–38. Cited 2 times on pages 22 e 46.

BORDO, M. *The Gold Standard, Bretton Woods and other Monetary Regimes: An Historical Appraisal*. [S.l.], 1993. (Working Paper Series, 4310). Cited on page 1.

BULJEVICH, E. C.; PARK, Y. S. *Project Financing and the International Financial Markets*. New York, NY: Springer, 1999. Hardcover edition published 31 July 1999. Softcover ISBN: 978-1-4757-8321-6 (published 21 March 2013). eBook ISBN: 978-0-585-31561-4 (published 27 August 2007). ISBN 978-0-7923-8524-0. Cited on page 6.

CAFFENTZIS, C. G. Hume, money, and civilization; or, why was hume a metallist? *Hume Studies*, Hume Society, v. 27, n. 2, p. 301–335, 2001. Cited on page 1.

CARTA, S. M. et al. Ensembling and dynamic asset selection for risk-controlled statistical arbitrage. *IEEE Access*, v. 9, p. 29942–29959, 2021. Cited 2 times on pages 21 e 46.

CHANTONA, K.; PURBA, R.; HALIM, A. News sentiment analysis in forex trading using r-cnn on deep recurrent q-network. In: *2020 Fifth International Conference on Informatics and Computing (ICIC)*. [S.l.: s.n.], 2020. Cited 4 times on pages 2, 26, 31 e 32.

CHAO, C.-H. et al. Opinion mining and the visualization of stock selection in quantitative trading. In: *2019 International Conference on Technologies and Applications of Artificial Intelligence (TAAI)*. [S.l.: s.n.], 2019. p. 1–6. Cited on page 20.

CHEN, J.-H.; TSAI, Y.-C. Encoding candlesticks as images for pattern classification using convolutional neural networks. *Financial Innovation*, Springer, v. 6, n. 1, p. 26, 2020. Cited 2 times on pages 13 e 15.

CHEN, X. et al. A stock market decision-making framework based on cmr-dqn. *Applied Sciences*, v. 14, n. 16, 2024. ISSN 2076-3417. Cited 2 times on pages 20 e 21.

CHINPRASATSAK, K.; NIPARNAN, N.; SUDSANG, A. Neural network for forecasting high price and low price on foreign exchange market. In: *2020 17th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*. [S.l.: s.n.], 2020. Cited 4 times on pages 2, 25, 31 e 32.

COCCO, L.; TONELLI, R.; MARCHESI, M. An agent-based artificial market model for studying the bitcoin trading. *IEEE Access*, 2019. Cited on page 17.

COLOMA-CARMONA, A. et al. Not all traders gamble, but some gamblers trade: a latent class analysis of trading and gambling behaviors among retail investors. *Public Health*, v. 244, p. 105742, 2025. ISSN 0033-3506. Cited on page 10.

CORDEIRO, J. et al. Redução da subjetividade na identificação da variação do nível de valores de ativos financeiros. In: *Anais do XL Simpósio Brasileiro de Bancos de Dados*. Porto Alegre, RS, Brasil: SBC, 2025. p. 222–235. ISSN 2763-8979. Cited 2 times on pages 15 e 17.

CORDEIRO, J. J. R.; ARAúJO, A. H. M. de; AVELINO, G. A. Beyond profit: An analysis of risk and return metrics in automated trading systems. In: *Proceedings of the Brazilian Conference on Intelligent Systems (BRACIS)*. Fortaleza, CE, Brasil: [s.n.], 2025. To be published. Cited 4 times on pages 2, 5, 22 e 23.

CORDEIRO, J. J. R.; MAGALHãES, A.; AVELINO, G. Scalper major: A computational solution for automated trading in high volatility environments. In: *Proceedings of the XXII Brazilian Symposium on Information Systems*. Porto Alegre, RS, Brasil: SBC, 2026. To be published. Cited 2 times on pages 5 e 23.

CRABB, P. R. Multinational corporations and hedging exchange rate exposure. *International Review of Economics & Finance*, v. 11, n. 3, p. 299–314, 2002. ISSN 1059-0560. Cited on page 8.

DYMOVA, L.; SEVASTJANOV, P.; KACZMAREK, K. A forex trading expert system based on a new approach to the rule-base evidential reasoning. *Expert Systems with Applications*, v. 51, p. 1–13, 2016. ISSN 0957-4174. Cited on page 7.

FAROOGHI, K.; KHALOOZADEH, H. Cooperative multi-agent deep reinforcement learning for forex algorithmic trading using proximal policy optimization. In: *2024 10th International Conference on Control, Instrumentation and Automation (ICCIA)*. [S.l.: s.n.], 2024. Cited 6 times on pages 2, 29, 30, 31, 32 e 54.

HEINZ, A. et al. Bullish and bearish engulfing japanese candlestick patterns: A statistical analysis on the s&p 500 index. *The Quarterly Review of Economics and Finance*, v. 79, p. 221–244, 2021. ISSN 1062-9769. Cited on page 14.

HU, W. et al. A formal approach to candlestick pattern classification in financial time series. *Applied Soft Computing*, v. 84, p. 105700, 2019. ISSN 1568-4946. Cited 2 times on pages 14 e 15.

HUANG, Y. et al. Improving algorithmic trading consistency via human alignment and imitation learning. *Expert Systems with Applications*, v. 253, p. 124350, 2024. ISSN 0957-4174. Cited 2 times on pages 21 e 45.

HUANG, Z.; GONG, W.; DUAN, J. Tbdqn: A novel two-branch deep q-network for crude oil and natural gas futures trading. *Applied Energy*, v. 347, p. 121321, 2023. ISSN 0306-2619. Cited on page 22.

HUANG, Z.; MARTIN, F. Pairs trading strategies in a cointegration framework: back-tested on cfd and optimized by profit factor. *Applied Economics*, Routledge, v. 51, n. 22, p. 2436–2452, 2019. Cited on page 46.

HUNG, N.; KIEN, T. Profitability of moving average convergence divergence and moving average on vietnamese stock: A comparison. *Advances and Applications in Statistics*, v. 60, p. 147–168, 02 2020. Cited on page 18.

ISMAIL, M. A. H. et al. Automated trading system for forecasting the foreign exchange market using technical analysis indicators and artificial neural network. In: *2022 IEEE 18th International Colloquium on Signal Processing & Applications (CSPA)*. [S.l.: s.n.], 2022. Cited 7 times on pages 2, 11, 20, 27, 31, 32 e 54.

JONGPERMWATTANAPOL, A. et al. A comprehensive approach of algorithmic trading system based on technical analysis. In: *2024 IEEE International Conference on Cybernetics and Innovations (ICCI)*. [S.l.: s.n.], 2024. p. 1–6. Cited 2 times on pages 20 e 21.

K, P. et al. Comparative study: Stock prediction using fundamental and technical analysis. In: *2021 IEEE International Conference on Mobile Networks and Wireless Communications (ICMNWC)*. [S.l.: s.n.], 2021. p. 1–4. Cited on page 16.

KARBALAEE, A. *Risk and Return in Retail Forex*. 2012. Cited on page 8.

KOTHIWAL, R.; RAJIYAN, A. Major currency pairs: Forex market. *International Journal of Recent Technology and Engineering (IJRTE)*, v. 8, n. 4S3, dez. 2019. ISSN 2277-3878. Cited on page 11.

KULSHRESTHA, N.; SRIVASTAVA, V. K. Synthesizing technical analysis, fundamental analysis & artificial intelligence – an applied approach to portfolio optimisation & performance analysis of stock prices in india. In: *2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*. [S.l.: s.n.], 2020. p. 1185–1188. Cited on page 17.

KUMAR, A.; RIZK, R.; SANTOSH, K. Transformer-based reinforcement learning model for optimized quantitative trading. In: *2024 IEEE Conference on Artificial Intelligence (CAI)*. [S.l.: s.n.], 2024. p. 1454–1455. Cited on page 12.

LI, L. et al. A risk-sensitive automatic stock trading strategy based on deep reinforcement learning and transformer. In: *2024 IEEE 20th International Conference on Automation Science and Engineering (CASE)*. [S.l.: s.n.], 2024. p. 468–473. Cited on page 45.

LI, P.; XU, J.; LAI, X. Lstm neural network with attention mechanism for stock timing in quantitative trading field. In: *2022 2nd International Conference on Intelligent Technologies (CONIT)*. [S.l.: s.n.], 2022. p. 1–7. Cited 2 times on pages 13 e 19.

LI, Y.; ZHENG, W.; ZHENG, Z. Deep robust reinforcement learning for practical algorithmic trading. *IEEE Access*, v. 7, p. 108014–108022, 2019. Cited on page 21.

LI, Y.; ZHENG, W.; ZHENG, Z. Deep robust reinforcement learning for practical algorithmic trading. *IEEE Access*, v. 7, p. 108014–108022, 2019. Cited on page 46.

LUANGLUEWUT, W.; THIENNVIBOON, P. Forex price trend prediction using convolutional neural network. In: *2023 20th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*. [S.l.: s.n.], 2023. Cited 5 times on pages 2, 11, 28, 31 e 54.

MA, R. et al. Research on quantitative trading strategy based on lstm and dynamic programming. In: *2022 International Conference on Computers, Information Processing and Advanced Education (CIPAE)*. [S.l.: s.n.], 2022. p. 282–285. Cited on page 12.

MAHJOUBY, M. E. et al. Machine learning algorithms for forecasting and categorizing euro-to-dollar exchange rates. *IEEE Access*, 2024. Cited 3 times on pages 1, 2 e 11.

MEHRKIAN, S. S.; DAVARI-ARDAKANI, H. An integrated model of sentiment analysis and quantitative index data for predicting stock market trends: A case study of tehran stock exchange. *Expert Systems with Applications*, v. 269, p. 126298, 2025. ISSN 0957-4174. Cited on page 12.

MELTZER, A. H. Us policy in the bretton woods era. *Federal Reserve Bank of St. Louis Review*, v. 73, n. 3, p. 54–83, 1991. Cited on page 1.

MELVIN, M.; PRINS, J. Equity hedging and exchange rates at the london 4p.m. fix. *Journal of Financial Markets*, v. 22, p. 50–72, 2015. ISSN 1386-4181. Cited on page 8.

MERSAL, E. R.; KARAOğLAN, K. M.; KUTUCU, H. Enhancing market trend prediction using convolutional neural networks on japanese candlestick patterns. *PeerJ Computer Science*, v. 11, p. e2719, 2025. Cited on page 14.

MOYA, E. *The Most Important Macroeconomic Indicators for Forex Trading*. 2024. Acesso em julho de 2025. Disponível em: <https://www.oanda.com/us-en/trade-tap-blog/analysis/technical/forex-trading-most-important-indicators/>. Cited on page 13.

MWAMTAMBULO, D. J. Factors influencing individual investor participation in stock market. In: JAJUGA, K. et al. (Ed.). *Contemporary Trends and Challenges in Finance*. Cham: Springer International Publishing, 2021. p. 57–74. Cited on page 9.

NALMPANTIS, A.; PASSALIS, N.; TEFAS, A. Explicit bandwidth learning for forex trading using deep reinforcement learning. *IEEE Signal Processing Letters*, v. 32, p. 686–690, 2025. Cited 3 times on pages 30, 31 e 32.

NAMDARI, A.; LI, Z. S. Integrating fundamental and technical analysis of stock market through multi-layer perceptron. In: *2018 IEEE Technology and Engineering Management Conference (TEMSCON)*. [S.l.: s.n.], 2018. p. 1–6. Cited on page 13.

NASUTION, M. A. et al. Perancangan dan pengujian kinerja expert advisor berbasis indikator rsi, ma, dan optimasi lot pada 10 pair forex populer dengan akun swap-free. *Jurnal Sains, Teknologi & Komputer*, v. 1, n. 2, p. 62–68, 2024. Cited on page 46.

NOERTJAHYANA, A. et al. Combination of candlestick pattern and stochastic to detect trend reversal in forex market. In: *2019 4th Technology Innovation Management and Engineering Science International Conference (TIMES-iCON)*. [S.l.: s.n.], 2019. Cited on page 15.

OLORUNSHEYE, A. O.; MEENAKSHI, S. Ai powered indicatorless algorithmic trading bot for cryptocurrency and financial market. In: *2024 International Conference on Emerging Technologies in Computer Science for Interdisciplinary Applications (ICETCS)*. [S.l.: s.n.], 2024. Cited 2 times on pages 1 e 46.

PIASECKI, K.; HANćKOWIAK, A. Łyczkowska. Representation of japanese candlesticks by oriented fuzzy numbers. *Econometrics*, v. 8, n. 1, 2020. ISSN 2225-1146. Cited on page 15.

PICASSO, A. et al. Technical analysis and sentiment embeddings for market trend prediction. *Expert Systems with Applications*, v. 135, p. 60–70, 2019. ISSN 0957-4174. Cited 2 times on pages 16 e 17.

POVITUKHIN, S.; KARMANOVA, E. Development of a profitable trading strategy with data mining techniques. In: *2020 International Multi-Conference on Industrial Engineering and Modern Technologies (FarEastCon)*. [S.l.: s.n.], 2020. p. 1–6. Cited 5 times on pages 2, 21, 24, 31 e 32.

QI, L.; KHUSHI, M.; POON, J. Event-driven lstm for forex price prediction. In: *2020 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE)*. [S.l.: s.n.], 2020. p. 1–6. Cited on page 11.

QIN, Z.; LI, X. Expected payoff of trading strategies involving european options for fuzzy financial market. *Iranian Journal of Fuzzy Systems*, University of Sistan and Baluchestan, v. 8, n. 3, p. 81–94, 2011. Cited on page 46.

RAHIMPOUR, S. M. et al. Algorithmic trading using technical indicators and extereme gradient boosting. In: *2024 11th IEEE Swiss Conference on Data Science (SDS)*. [S.l.: s.n.], 2024. p. 92–98. Cited on page 46.

ROSSI, S.; TINN, K. Rational quantitative trading in efficient markets. *Journal of Economic Theory*, v. 191, p. 105127, 2021. ISSN 0022-0531. Cited on page 20.

SALKAR, T. et al. Algorithmic trading using technical indicators. In: *2021 International Conference on Communication information and Computing Technology (ICCICT)*. [S.l.: s.n.], 2021. p. 1–6. Cited on page 21.

SANTUR, Y. Candlestick chart based trading system using ensemble learning for financial assets. *SIGMA JOURNAL OF ENGINEERING AND NATURAL SCIENCES-SIGMA MUHENDISLIK VE FEN BILIMLERI DERGISI*, v. 40, n. 2, p. 370–379, JUN 2022. ISSN 1304-7205. Cited 2 times on pages 13 e 14.

SHAHSAFI, S.; NADERKHANI, F. Enhancing stock trading performance with deep q-learning by addressing noisy data through advanced denoising techniques. In: *2024 27th International Conference on Information Fusion (FUSION)*. [S.l.: s.n.], 2024. p. 1–7. Cited on page 45.

SHARMA, D. et al. Quantitative trading toolkit. In: *2022 IEEE 3rd Global Conference for Advancement in Technology (GCAT)*. [S.l.: s.n.], 2022. p. 1–8. Cited on page 20.

SHENDE, S. D. et al. Stocks price prediction by fundamental analysis using machine learning algorithms. In: *2022 5th International Conference on Contemporary Computing and Informatics (IC3I)*. [S.l.: s.n.], 2022. p. 1515–1522. Cited on page 13.

SHI, W. Y.; XU, H. X. The driving engine of quantitative trading strategy based on event processing. In: *2020 4th Annual International Conference on Data Science and Business Analytics (ICDSBA)*. [S.l.: s.n.], 2020. p. 79–82. Cited on page 19.

SUN, S.; WANG, R.; AN, B. Reinforcement learning for quantitative trading. *ACM Trans. Intell. Syst. Technol.*, Association for Computing Machinery, New York, NY, USA, v. 14, n. 3, mar. 2023. ISSN 2157-6904. Cited on page 18.

TA, V.-D.; LIU, C.-M.; TADESSE, D. A. Portfolio optimization-based stock prediction using long-short term memory network in quantitative trading. *Applied Sciences*, v. 10, n. 2, 2020. ISSN 2076-3417. Cited on page 19.

THUANKHONRAK, P.; RATTAGAN, E.; PHOOMVUTHISARN, S. Machine trading by time series models and portfolio optimization. In: *2019 4th International Conference on Information Technology (InCIT)*. [S.l.: s.n.], 2019. p. 217–222. Cited on page 22.

TIAN, T. Analysis of stock market quantitative trading strategies based on machine learning. In: *2022 4th International Conference on Applied Machine Learning (ICAML)*. [S.l.: s.n.], 2022. p. 401–404. Cited on page 18.

VARGHESE, A. A.; KRISHNADAS, J.; KUMAR, R. S. Candlestick chart based stock analysis system using ensemble learning. In: *2023 International Conference on Networking and Communications (ICNWC)*. [S.l.: s.n.], 2023. p. 1–7. Cited 2 times on pages 13 e 15.

VINITNANTHARAT, N. et al. Quantitative trading machine learning using differential evolution algorithm. In: *2019 16th International Joint Conference on Computer Science and Software Engineering (JCSSE)*. [S.l.: s.n.], 2019. p. 230–235. Cited on page 13.

VU, V.-H.; MASHAL, I.; AND, T.-Y. C. A novel bandwidth estimation method based on macd for dash. *KSII Transactions on Internet and Information Systems*, v. 11, n. 3, p. 1441–1461, March 2017. Cited on page 16.

WANG, H. et al. Financial contagion and contagion channels in the forex market: A new approach via the dynamic mixture copula-extreme value theory. *Economic Modelling*, v. 94, p. 401–414, 2021. ISSN 0264-9993. Cited on page 7.

WANG, J.; KIM, J. Predicting stock price trend using macd optimized by historical volatility. *Mathematical Problems in Engineering*, v. 2018, n. 1, p. 9280590, 2018. Cited on page 17.

WANG, J.; ZHUANG, Z.; FENG, L. Intelligent optimization based multi-factor deep learning stock selection model and quantitative trading strategy. *Mathematics*, v. 10, n. 4, 2022. ISSN 2227-7390. Cited on page 20.

WANG, Q.; REDDY, M. P. K. Risk adapting stock trading system associated technical with macroeconomic indicators. *Mob. Inf. Syst.*, IOS Press, NLD, v. 2022, jan. 2022. ISSN 1574-017X. Cited on page 22.

WANG, Y.; LUO, C. An intelligent quantitative trading system based on intuitionistic-gru fuzzy neural networks. *Applied Soft Computing*, v. 108, p. 107471, 2021. ISSN 1568-4946. Cited on page 18.

WEITHERS, T. *Foreign Exchange: A Practical Guide to the FX Markets*. [S.l.]: Wiley, 2011. (Wiley Finance). ISBN 9781118046210. Cited 2 times on pages 11 e 12.

WILDER, J. W. *New concepts in technical trading systems*. [S.l.]: Greensboro, NC, 1978. Cited on page 17.

WILES, P. S.; ENKE, D. Optimizing macd parameters via genetic algorithms for soybean futures. *Procedia Computer Science*, v. 61, p. 85–91, 2015. ISSN 1877-0509. Complex Adaptive Systems San Jose, CA November 2-4, 2015. Cited 2 times on pages 17 e 18.

WU, J. et al. Quantitative trading on stock market based on deep reinforcement learning. In: *2019 International Joint Conference on Neural Networks (IJCNN)*. [S.l.: s.n.], 2019. p. 1–8. Cited on page 21.

WU, X. et al. Moving average convergence and divergence indexes based online intelligent expert diagnosis system for anaerobic wastewater treatment process. *Bioresource Technology*, v. 324, p. 124662, 2021. ISSN 0960-8524. Cited 3 times on pages 16, 17 e 18.

ZAFEIRIOU, T.; KALLES, D. Ultra-short-term trading system using a neural network-based ensemble of financial technical indicators. *Neural Comput. Appl.*, Springer-Verlag, Berlin, Heidelberg, abr. 2021. Cited on page 2.

ZHANG, P. Research into developing a data mining-based quantitative trading system for use with software and high performance computers. In: *2023 International Conference on Industrial IoT, Big Data and Supply Chain (IIoTBDSC)*. [S.l.: s.n.], 2023. p. 209–213. Cited 2 times on pages 18 e 19.

ZHANG, Z.; KHUSHI, M. *GA-MSSR: Genetic Algorithm Maximizing Sharpe and Sterling Ratio Method for RoboTrading*. 2020. Cited 2 times on pages 7 e 20.

ZHU, Q.; HAN, C.; LI, Y. Dual-market quantitative trading: the dynamics of liquidity and turnover in financial markets. *Data Science and Management*, v. 8, n. 1, p. 48–58, 2025. ISSN 2666-7649. Cited on page 19.

ZHU, Q. et al. Can low-carbon value bring high returns? novel quantitative trading from portfolio-of-investment targets in a new-energy market. *Economic Analysis and Policy*, v. 76, p. 755–769, 2022. ISSN 0313-5926. Cited on page 20.