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Design and Implementation of a Multi-Strategy Algorithmic Trading Bot

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The financial markets require speed and accuracy, and thus, the quick take-up of algorithmic trading systems has ensued. This study presents a hybrid trading bot based on machine learning algorithms and technical indicators such as Moving Average (MA) and Relative Strength Index (RSI). The integration of Random Forest significantly improved signal accuracy and reduced false positives. Back testing over 1 year showed a win rate of 73.2% and a return on investment (ROI) of 42.5%, confirming the effectiveness of the hybrid model. The bot is designed to analyze the market in real-time, and it makes trades autonomously, regulates risk, and adjusts to volatile markets.

Keywords: Algorithmic Trading; Machine Learning; RSI; Moving Average; Risk Management; Strategies.

Introduction:

Algorithmic trading revolutionized custom trading techniques by offering automation that can process at faster speeds. With artificial intelligence and technical analysis, traders can avoid emotional prejudices, detect profitable opportunities, and streamline decision-making using multiple strategies [1]. In this paper, an algorithm-based trading bot is proposed to work across various financial assets while maintaining adaptability and reliability in changing markets. Meta Trader 5 (MT5) is one of the most popular and widely adopted trading platforms in the financial industry. It is known for its multi-asset capabilities and robust support for automated trading systems [2]. It uses the concept of Expert Advisors (EAs), custom-coded bots that execute trades based on predefined strategies without requiring manual intervention. Trading bots like these play an important role in reducing human error, improving executional speed, and maintaining discipline under emotional or volatile market conditions. By integrating a bout with MT5, traders gain access to real-time data, efficient back testing tools, and seamless execution pipelines [3]. The main purpose of our trading bot is to harness these capabilities by combining the machine learning algorithms with classical technical indicators to facilitate rule-based trading with minimal oversight.

Literature Review:

Numerous prior studies have demonstrated the potential of machine learning for financial forecasting. In [4], author(2020) show the complementarity of AI with signal processing to analyze markets, and in [5], authors(2021) proposed a framework that is based on reinforcement learning to dynamically adjust strategies. These studies basically point to the advantages of combining different strategies with machine learning for greater accuracy and greater profits [6].

While [4] and [5] explore general AI applications in trading, our approach uniquely fuses RSI, MA, and Random Forest in a real-time MQ5 bot, aiming for higher risk-adjusted returns. Other studies like [7] and [8] focus solely on traditional indicators, which our hybrid bot enhances through intelligent signal validation.

Problem Statement:

In extremely volatile markets, Inexperienced human traders are facing difficulties in making timely decisions, resulting in below-optimal trades and higher risk that eventually ends up as a loss. This paper seeks to create a self-driving trading bot that constantly monitors market conditions, reduces human error, and maximizes trade execution by means of automatic strategies.

Methodology:

Introduction to Meta Trader 5 (MT5) and Algorithmic Trading:

Over the past few decades, financial markets have undergone a dramatic transformation, driven by technological advancements that provide traders with increasingly sophisticated tools. Meta Trader 5 (MT5) is one of the most widely used and popular trading platforms available today. Meta Trader 5 (MT5), developed by Meta Quotes Software Corp., is a multi-asset trading platform designed for trading forex, stocks, commodities, and more. What truly sets MT5 apart from other platforms is its use of Expert Advisors (EAs), which enable automated trading based on custom algorithms. The platform supports both manual and algorithmic trading, with automation achieved through Expert Advisors (EAs). These EAs allow traders to encode their strategies into the system, enabling fully automated trading where the platform executes trades on their behalf. As a result, traders can simply set up their strategies and let the system manage the trading process independently.

Data Acquisition:

For this study, we utilized historical market data from the EUR/USD forex pair, retrieved through the Meta Trader 5 (MT5) platform and Binance API. The dataset spans a

period of 10 years (January 2013 – December 2023), covering a wide range of market conditions including bullish, bearish, and sideways trends

Preprocessing:
Data was cleaned and technical features such as RSI, MA were extracted.

Strategy Design:
Hybrid algorithms implementation *was done* using Demand & Support, RSI, MA, Price Action, Back testing, etc.

Signal Generation:
Fully automated trade signals were generated based on fused technical and machine learning signals.

Deployment:
Back-end integration into trading platforms was done by supporting low-latency, seamless execution.

Live Testing:
This bot was tested and optimized with both historical back testing and live market conditions.
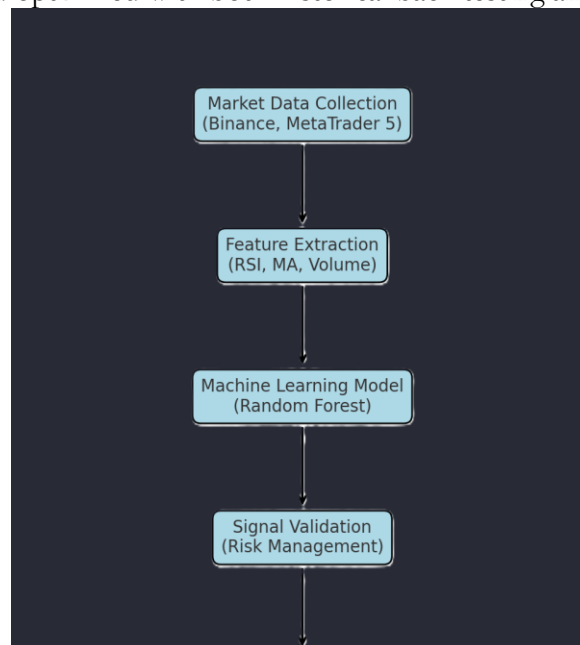

Figure 1. Trading Bot System Architecture

The structure of an AI-based trading bot consists of multiple integrated modules that must operate in seamless coordination to enable effective real-time financial trading. It starts with data scraping from APIs (for instance, Binance and Meta Trader 5), then feature extraction routines computing technical indicators such as RSI and Moving Averages. A machine learning model, such as Random Forest, processes the extracted data to generate trade predictions. These signals are tested via risk management protocols prior to sending buy/sell orders to the linked trading platform. Performance indicators are continuously tracked for optimization of strategy.

Results and Evaluation:
The bot exhibits superior performance compared to individual strategies due to its hybrid design. By integrating traditional technical indicators (such as RSI and Moving Averages) with machine learning algorithms (e.g., Random Forest), the system benefits from both historical rule-based logic and adaptive learning. The inclusion of machine learning significantly reduced the number of false signals by learning complex patterns in historical price data that are often missed by static indicators. Meanwhile, the use of conventional indicators such as RSI and MA provided interpretable validation for signal accuracy, ensuring that trades were aligned with established market principles.
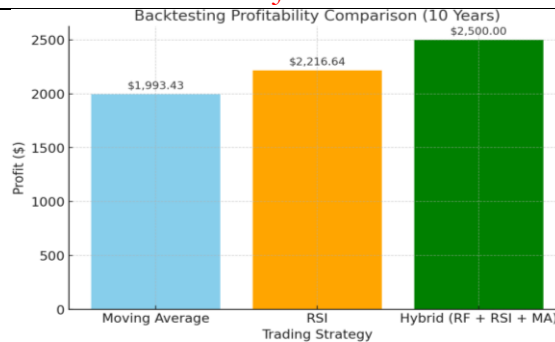
Figure 2. Back Testing Profitability Comparison

Figure 2 shows a comparative study of the profitability of various trading strategies over a period of 10 years of back testing. The Moving Average strategy, the RSI strategy, and the Hybrid strategy (incorporating Random Forest, RSI, and Moving Average) are compared as shown in Figure 2. The Hybrid strategy performed the best, with the highest total profit while maintaining stability under different market conditions. This shows the strength of combining machine learning with conventional technical indicators to achieve maximum long-term returns and minimum trading risks.

Setting Up a Real-World MQ5 Trading Bot:

Diving into algorithmic trading, you've likely come across Meta Trader 5 (MT5), a trading platform that allows traders to apply multiple strategies. It is a robust platform for creating and running trading bots. An MQ5 bot is essentially a script or algorithm that automates trading decisions based on predefined strategies. It can be configured using various techniques such as RSI, Moving Averages, Support and Resistance levels, Price Action, and Volume Analysis.

Figure 3. Buy And Sell Signals on a Meta Editor 5

The Trading Dashboard:

Multi-screen setup that displays candlestick charts and technical indicators aligned with price action, where the bot is configured to execute trades in real-time. These elements (MA, RSI) are designed to function collectively, allowing the bot to operate in a way that may reduce emotional influence on trading decisions.

Working:

An MQ5 bot was composed of several technical indicators to make rational trading decisions. It analyzed market conditions using tools like RSI, Moving Averages, support and resistance levels, and volume. For example, when the RSI dropped below 30, indicating an oversold market—and the price approached a strong support level, the bot interpreted this as a signal to buy. Conversely, if the RSI rose above 70, signaling an overbought condition and the price neared a resistance level, the bot considered it a cue to sell. Additionally, a bullish crossover

of Moving Averages served as confirmation for initiating long trades. The bot also monitored volume spikes, which indicated intense buying or selling pressure, helping it filter out weaker or misleading signals for more accurate decision-making. The bot continuously scanned the market and responded to developments at a speed far beyond human capability.

Trading with an MQ5 Bot in Action:

This is how the trades are made automatically while a trader is watching it.

Entry: The bot waits for all the conditions to meet (RSI, MA cross, support/resistance).

Stop Loss: Placed below the support to limit risk.

Take Profit is Placed when the price reaches near the subsequent resistance or when the bot realizes there is diminishing momentum. This strategy works day and night, responding to market dynamics and making accurate trades, even while the trader is resting.

The bot opened a total of 42 trades, out of which 28 closed in profit, yielding a win rate of approximately 66.7%. The average trade duration was around 1–2 hours, and the system maintained low latency with near-instant order execution. This hands-on testing confirmed that the hybrid strategy performs effectively in live environments and can adapt to market volatility without requiring manual intervention.

A real MQ5 trading bot is more than just automation; it creates a balanced system that combines several indicators to increase accuracy. If done properly, it can assist in eliminating emotional reactions in trading and aid traders in following their strategies.
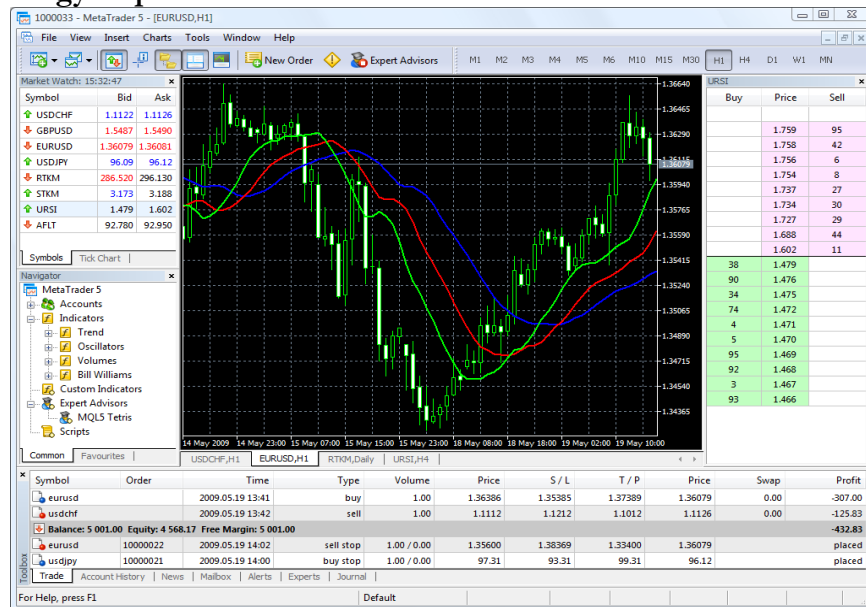
Detailed Strategy Explanations:

Figure 4. Different Strategies Implemented on an MQL5 Bot

Relative Strength Index (RSI):

The Relative Strength Index (RSI) is a popular momentum oscillator that compares the magnitude of recent price movements to identify overbought or oversold levels. RSI was first created by J. Welles Wilder in 1978, and its accuracy ranges from 0 to 100 [9]. In which 70 is generally considered an overbought market, while below 30 is considered an oversold market. RSI helps traders in knowing if a security price is moving too far, too quickly, and if a reversal could be on the horizon. One of the advantages of RSI is its ability to adjust to various market conditions, ranging from trending to ranging markets.

For instance:

If the targeted market is following the bull trend, RSI could remain above 30 and often move into overbought levels. If there is a bearish trend, RSI will stay below 70 and repeatedly drop into oversold levels.

Bot Implementation:

RSI is also used as a filter to confirm entries from other strategies. For example, in a strong support area, the bot can enter a buy trade only if RSI signals the bot about oversold conditions, like making the trade setup more reliable.

Moving Averages (MA):

Moving Averages (MAs) are a strategy tool used to level out fluctuations in price data and determine the direction of the underlying trend. This strategy helps traders in identifying whether the market is trending, declining, or trending sideways. Author(2002) highlights that moving average crossovers serve not only as trend identifiers but also as psychological levels for market participants, reinforcing their role in bot decision logic [8], [10], [11]. Following are the most widely used strategies:

Simple Moving Average (SMA): It is an "Average closing price over a given period".

Exponential Moving Average (EMA): A better version of SMA, but with more emphasis on recent prices and is even more sensitive to recent market action.

MAs can even serve as a dynamic level of support and resistance, with price often reversing off these averages in trending markets. The integration of machine learning with traditional technical indicators such as RSI and Moving Averages provides strong trend confirmation, as emphasized in classical technical analysis frameworks [7], [12], [13]. However, crossover systems are favored by traders:

A bullish crossover is when a short-term MA (50-period) moves above a long-term MA (200-period). A bearish crossover tends to happen when the short-term MA goes below the long-term MA.

Bot Implementation:

MAs are utilized both for confirmation of the trend and as entry/exit signals in the bot's logic. As an example, the bot would only enter into long (buy) positions if the price is over the 200 EMA to make sure trades are in the direction of the prevailing trend.

Demand and Support Zones:

Demand and support zones are a key part of price structure study. Support prices are levels where buying interest was previously strong enough to stop falling, and demand zones are locations where intense buying has entered the market, pushing prices significantly.

These areas are mapped from past price responses, typically at prior swing lows (support) or consolidation levels ahead of strong uptrends (demand). When price returns to these areas, traders expect similar responses, and thus they are high-probability trading setups.

This bot detects major historical support and demand levels by examining past lows and consolidation ranges. Buy orders are set to trigger when price reaches these levels, particularly if validated by other signals from RSI, MAs, or bullish price action patterns. This multi-layered verification eliminates false signals and enhances trade accuracy.

Price Action:

Price Action trading is centered on interpreting raw price action without excessive dependence on lagging indicators. It is based on analyzing candlestick patterns, trendlines, and support/resistance levels to predict future price action. Price Action techniques are based on the idea that all information is contained in the price.

Some typical price patterns are:

Pin Bars: Long-wick candles, indicating rejection of specific price levels.

Engulfing Patterns: Reversal patterns where one bigger candle completely engulfs the prior one.

Inside Bars: Times of consolidation, commonly succeeded by breakout activity.

Price Action also prominently relies on market structure, locating higher highs and higher lows in bull markets, or lower lows and lower highs in bear markets. These candlestick-based setups, including Pin Bars and Engulfing patterns, align closely with the price action

methodology taught by author(2009), which focuses on raw price interpretation without lagging indicators [14], [15].

Bot Implementation:

The bot looks for certain candlestick patterns around major support or demand areas. If there is a bullish engulfing pattern at a demand area where the RSI has convalidation of oversold levels, then the bot places a buy trade. This strategy enables the bot to trade in sync with the natural movements and psychology of the market.

Volume Analysis:

Volume strategies are one of the most important strategies used in bot implementation. Volume is an essential indicator since it shows the degree of strength supporting the movement of price. Volume strategies have been influenced by foundational works such as author(1963) [16], [17], [18]. If a price moves with high volume, it signifies strong market participation and belief. On the other hand, if it moves on the light volume, then it might lack the support necessary to sustain the move.

Most of the Volume indicators include On-Balance Volume (OBV) and Volume Weighted Average Price (VWAP); these assist a trader in understanding whether buying pressure or selling pressure prevails.

Most used Volume Strategy includes:

Volume Divergence: It is a Situation when price direction contrasts with the direction of volume and suggests a probable reversal.

Bot Implementation:

Volume strategy filters help prevent trades during times of low liquidity and when to validate breakouts. For example, if the bot recognizes a price breakout through resistance but the volume is not high, it will avoid taking the trade to minimize the threat of a false breakout and prevent any loss to the trader.

By integrating these tools, the bot provides a solid, rule-based system that can respond to varied market conditions. The multi-strategy structure conserves dependence on one particular indicator, reduces the influence of spurious signals, and delivers improved trading performance.

Applications:

Retail Trading: Trades automated without continuous monitoring.

Institutional Trading: Large-scale and high-frequency trade automation.

Crypto Markets: Controlling erratic price movements.

Forex Markets: Rapid execution of currency trades.

Portfolio Management: Automating passive income strategies.

Conclusion:

This study sets the effectiveness of the integration of AI with technical indicators for algorithmic trading. The hybrid trading bot enhances profitability and risk mitigation as well as provides emotional independence from trading decisions. Further development will investigate sophisticated reinforcement learning integrations and cross-market flexibility.

The trading bot consolidates a few key technical analysis approaches, each serving to solve distinct aspects of market behavior:

- RSI serves to gauge momentum and possible reversals.
- Moving Averages validate direction of trend and serve as dynamic support/resistance.
- Demand and Support Zones determine strategic entry price levels.
- Price Action interprets the structure of the market through candlestick patterns.
- Volume Analysis confirms the power behind price action.

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Author's Contribution:

It is acknowledged that all authors have contributed significantly and that all authors agree with the content of the manuscript.

Conflict of interest:

There exists no conflict of interest for publishing this manuscript in IJIST.

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