Machine Learning Swing Trading Model

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1. INTRODUCTION

The objective of this project is to develop a profitable machine learning swing trading model that can be implemented using Trading Views PineScript. I have been involved in various markets for 5+ years now and have observed that crypto markets tend to be more volatile than stock and commodity markets. Furthermore, crypto seems to be less driven by news and business activities such as earnings reports. For this reason I believe that this strategy will be most suitable for crypto trading since the majority of price action occurs due to technical analysis. Furthermore, crypto is very flexible to trade with leverage and there is much more opportunity to trade due to the 24/7 nature of markets. For this project, the main features that I will base my strategy off of are **Exponential Moving Average (EMA)** bands as well as the **Relative Strength Index (RSI)**. To further confirm the validity of my indicator signals, I will be using a logistic regression machine learning model in order to classify the signals as 1 : valid or 0 : invalid.

2. INDICATOR SELECTION AND STRATEGY FOUNDATION

2.1 Exponential Moving Average (EMA)

The core of this trading algorithm is built on the use of multiple Exponential Moving Averages (EMAs), collectively referred to as EMA bands. These bands form a "ribbon" of moving averages ranging from very short-term (5 periods) to medium-term (100 periods), allowing the strategy to detect both the direction and strength of price trends.

In total, the strategy calculates EMAs for the following periods: 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, and 100. The color-coding of these ribbons (green/lime for bullish signals and red/maroon for bearish signals) is determined by the slope and relative position of each EMA compared to the longest-term EMA (100-period).

The algorithm uses a simple thresholding approach to define trading signals. A buy signal is triggered when at least 13 out of 18 EMA bands (approximately 72%) are showing bullish alignment. Conversely, a sell signal is triggered when at least 9 bands (50%) display bearish alignment. This multi-layered approach provides a robust confirmation of price direction, filtering out minor fluctuations and emphasizing trend consensus.

2.2 Relative Strength Index (RSI)

The Relative Strength Index (RSI) is employed as a momentum and overbought/oversold filter to enhance the reliability of the signals generated by the EMA bands. The strategy uses a standard RSI length of 14 periods, which measures the magnitude of recent price changes to identify potential reversal points.

The RSI values are then combined with the EMA band signals to confirm trade entries. A buy trade is only executed if the bullish EMA band setup coincides with an RSI reading below 30, indicating that the asset is oversold and may be primed for upward movement. Conversely, a sell trade is executed when bearish EMA band alignment occurs alongside an RSI reading above 70, suggesting the asset is overbought and may be ready for a downward correction.

This dual-layered filter — combining trend-based confirmation with momentum-based signals — helps reduce false signals and improves the probability of high-quality trade entries.

2.3 Strategy

The strategy will compute both long and short signals which are determined by the value of the inputs mentioned in 2.1 and 2.2.

In order to receive a long signal, 3 conditions must be true:

1. The EMA Ribbon must be showing a buy signal, meaning that at least 13 of the EMA periods must be trending upwards (green). This will ensure that the market is trending in a bullish direction both short and long term.
2. The RSI must be oversold (<30). If the relative strength index is < 30 it is considered by traders to be in the oversold region, implying that the current price is the result of a extreme move that has exaggerated the typical price action
3. The machine learning model must output a long signal

In order to receive a short signal, 3 conditions must be true:

1. The EMA Ribbon must be showing a sell signal, meaning that at least 9 of the EMA periods must be trending downwards (red). This will ensure that the market is trending in a bearish direction both short and long term.
2. The RSI must be overbought (>70). If the relative strength index is >70 it is considered by traders to be in the overbought region, implying that the current price is the result of a extreme move that has exaggerated the typical price action
3. The machine learning model must output a short signal

After receiving the signal from the model the following strategy will be implemented regarding take profit and stop-loss in order to ensure maximum profit.

1. Set a take profit of 1 % and a stop loss of 1%
2. If the open trade is at a profit of 0.5% move the stop loss to 0.5% to lock in profit

3. MACHINE LEARNING SIGNAL CONFIRMATION

To enhance the reliability of trade signals, I implemented a machine learning classification layer using logistic regression. The model takes as input the derivatives (directional slopes) of the EMA bands along with the RSI value at each given point in time.

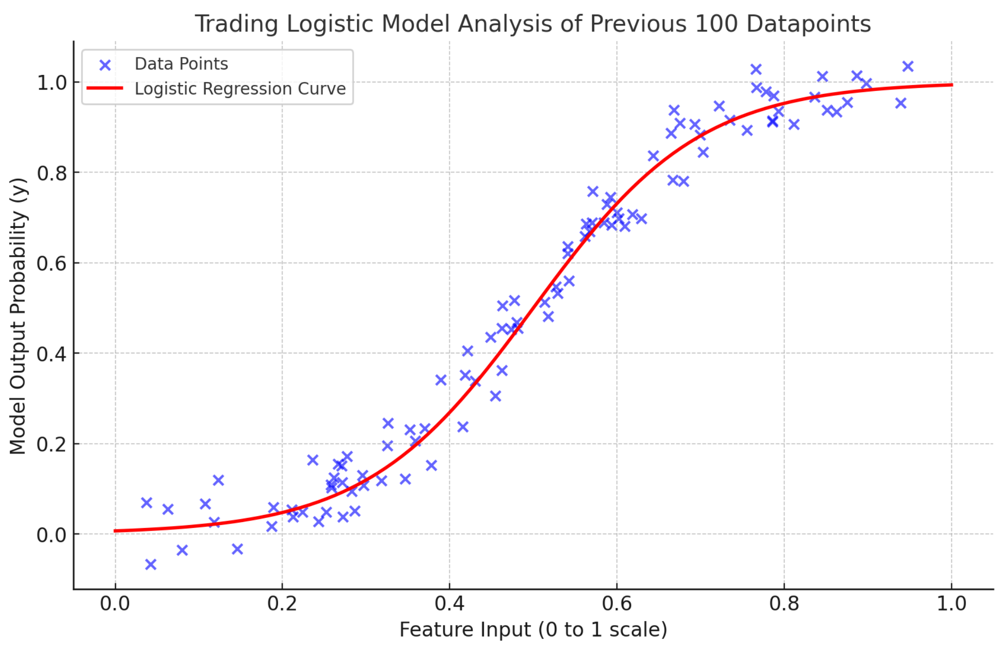
- The EMA band derivatives capture the momentum and directionality of each EMA period, providing the model with dynamic insight into price trends.
- The RSI value complements this by offering momentum and potential reversal context.

The logistic regression model is trained to output a value yy between 0 and 1:

- When yy is close to **1**, it indicates a strong likelihood of a valid **long** signal.
- When yy is close to **0**, it indicates a strong likelihood of a valid **short** signal.
- If the value is between these two extremes (around 0.2–0.8), it suggests that the conditions are not strong enough to place a trade, and the signal is disregarded.

This additional layer helps filter out false positives by ensuring that both the technical indicators and the model agree on market direction before executing trades.

As seen in the regression models graph below, the majority of the time, the output is not strong enough to suggest a short or a long on the market. The majority of the outputs fall in the range of 0.2-0.8 which are considered to be weak signals that should be ignored.



4. RESULTS AND BACKTESTING

I backtested this strategy on the Bitcoin 5-minute chart using historical price data. The results were encouraging:

- The strategy achieved an approximate 70% success rate on executed trades.
- It generated around 4-6 trade signals per week on BTC, providing a healthy balance of activity without overtrading. At the same time, this algorithm can be applied to various coins such as ETH, SOL, and XRP in order to maximize trades and thus maximize profits
- The combination of EMA alignment, RSI filtering, and machine learning signal validation effectively minimized false entries.
- The trade management rules (1% take profit and stop-loss, with trailing adjustment at +0.5%) allowed for consistent capital growth while controlling risk.

Overall, the backtest suggests that this approach is a promising starting point for automated crypto swing trading strategies.

5. CONCLUSION

This project successfully demonstrates the potential of combining traditional technical indicators with machine learning to create a profitable and disciplined crypto swing trading strategy. By leveraging EMA bands to identify trend direction, RSI to filter overbought and oversold conditions, and logistic regression as a signal validation layer, I was able to significantly reduce noise and false entries that often plague purely indicator-based strategies.

The backtesting results on Bitcoin's 5-minute chart — achieving a 70% success rate with consistent weekly trade frequency — strongly validate the model's effectiveness and reliability. Additionally, the integration of dynamic trade management rules ensures that profits are locked in while downside risk is minimized.

This strategy represents more than just a theoretical framework; it is a practical, implementable solution designed to thrive in the fast-moving, technically driven crypto markets. The combination of systematic technical analysis with machine learning refinement is a powerful formula for building confidence, consistency, and profitability in trading. Moving forward, this foundation can be continuously enhanced through more advanced models and broader market testing, but the current results already show clear potential for robust, automated trading performance.