Algorithm Trading & Portfolio Management

Hybrid Strategy: Deep Learning and SMA for Trading Optimization

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Objective

The objective of this report is to evaluate a dynamic trading strategy using Deep learning (LSTM-based price prediction) combined with technical analysis indicators (e.g., SMA, RSI, ATR) and assess its performance in individual asset backtesting. Performance is measured against key financial metrics and compared to a buy-and-hold strategy.

Methodology

Data Preparation

- **Assets:** Data from various asset classes (e.g., BTC, ETH, COCOA) was used for testing. Historical prices and technical indicators were computed.
- **Training**: Data from BTC is used for training the model which is split into 80:20 for training and testing.
- **Features:** Included indicators like SMA, RSI, ATR, MACD, and Volatility.
- **Normalization:** Data was scaled using MinMaxScaler to improve LSTM performance.

Modeling

- **Model:** LSTM Neural Network for time-series prediction.
- **Input:** Sequences of 48 past time steps (features) to predict the next 5 closing prices.
- **Output:** Predicted prices scaled back to the original range for actionable insights.

Strategy Implementation

Our objective is to implement a hybrid strategy that combines predictions from an LSTM model with a momentum strategy based on SMA crossovers, allowing both approaches to complement one another.

ATR Threshold:

We have established a threshold for ATR(14 windows) to assess whether the asset is experiencing high volatility. To define this volatility threshold, we calculate the mean ATR and the standard deviation of the ATR:
Volatility Threshold = Mean ATR +2 *Standard standard deviation of ATR

If the current ATR exceeds this threshold, we will employ a strategy based on SMA crossovers; otherwise, we will utilize the LSTM-based strategy.

SMA Crossover Based Strategy:

Short-term Moving Average: Utilizes a 20-hour window.
Long-term Moving Average: Utilizes a 140-hour window.

Buy Signal: A Buy signal is triggered when the 20-hour Simple Moving Average (SMA20) exceeds SMA140.

Sell Signal: A Sell signal occurs when SMA20 falls below SMA140 or when the predicted price using LSTM is less than three times the Sell Threshold (to be discussed further below).

Cooldown Period: Following the generation of a Sell signal in this strategy, a cooldown period is established for the momentum strategy. During this period, which lasts for 21 periods, no Buy signals will be generated.

LSTM Based strategy:

1. LSTM Model for Price Prediction

- LSTM is a type of recurrent neural network (RNN) that is well-suited for time series data, like price movements, because it can capture long-term dependencies and trends over time.
- The model is trained on historical price data to forecast the price at a future time step (e.g., 5 hours ahead).

2. Dynamic Threshold Based on Rolling Volatility

- The volatility of the market is measured over a rolling window of 20 hours, and it is used to adjust the thresholds for triggering buy or sell signals.
- Rolling Volatility: The standard deviation of price changes over a 20-hour window is calculated, which helps capture the market's recent fluctuations.
- Dynamic Threshold: This volatility is then used to define a threshold that must be exceeded by the predicted price movement (either increase or decrease) to trigger a trade.
    - High Volatility: The threshold is set higher to avoid false triggers during periods of high fluctuation.
    - Low Volatility: The threshold is set lower when market fluctuations are less significant.

3. RSI (Relative Strength Index) Indicator

- RSI is used to measure whether the market is overbought or oversold.
    - Overbought: RSI > 70 (likely to reverse, suggesting a sell).
    - Oversold: RSI < 30 (likely to reverse, suggesting a buy).
- Mean RSI: The historical mean RSI is calculated, and its quartiles (upper and lower) are used to define thresholds for overbought and oversold conditions:
    - Mean RSI - 15: If the current RSI is below this value, it signals oversold conditions (suggesting a buy).
    - Mean RSI + 15: If the current RSI is above this value, it signals overbought conditions (suggesting a sell).

4. Combining LSTM Predictions with RSI and Dynamic Thresholds for Entry and Exit

- **Entry Conditions:**
    - Predicted Price > Dynamic Threshold: If the LSTM model predicts a significant price increase (above the dynamic threshold), it signals a buy.
    - RSI(current sequence) < (Mean RSI) - 15: If the current RSI is below the lower quartile of the historical RSI (indicating oversold conditions), it adds a buy signal.
    - The combination ensures that you only buy when both the LSTM model's predicted future price and the market momentum (via RSI) indicate favorable conditions for a price increase.
- **Exit Conditions:**
    - Predicted Price < Dynamic Threshold: If the LSTM model predicts a price decrease (below the dynamic threshold), it signals a sell.
    - RSI(current sequence) >(Mean RSI) + 15: If the current RSI is above the upper quartile of the historical RSI (indicating overbought conditions), it adds a sell signal.
    - The combination ensures that you exit the position when both the LSTM model and market momentum (via RSI) indicate a potential price drop.

6. Summary of the Trading Logic

- **Entry (Buy):**
  - The predicted price increase from the LSTM model exceeds the dynamic threshold.
  - The current RSI value is below the lower quartile of the mean historical RSI (indicating oversold market conditions).
- **Exit (Sell):**
  - The predicted price decrease from the LSTM model exceeds the negative dynamic threshold.
  - The current RSI value is above the upper quartile of the mean historical RSI (indicating overbought market conditions).

Backtesting Results

Individual Asset Performance

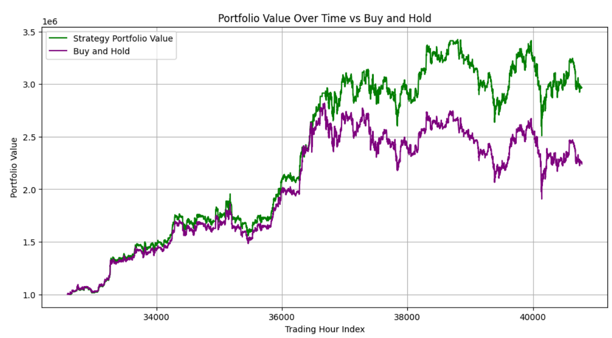

Fig 1: Strategy vs Buy and Hold BTC

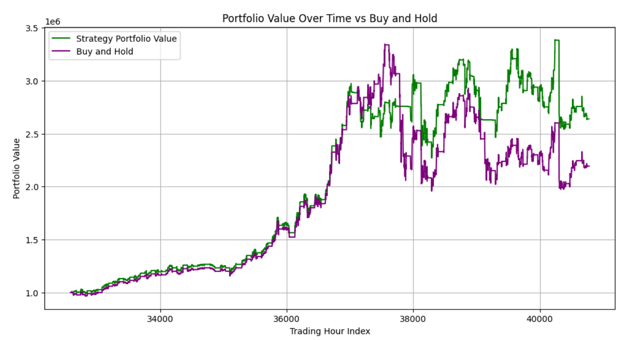

Fig 2: Strategy vs Buy and Hold Cocoa

	Trading Window	No. of Trades	Sharpe Ratio	Sortino Ratio	LSTM + SMA	LSTM	Buy & Hold
BTC	11 Months	815	2.59	3.32	196.82%	156.57%	123.90%
COCOA	11 Months	1642	2.16	1.19	163.88%	131.13%	118.27%
ETH	11 Months	815	0.91	1.12	44.75%	52.89%	58.11%

Findings

Outperformance vs Buy-and-Hold:

- The strategy consistently outperformed the buy-and-hold benchmark for BTC and COCOA, showing higher returns and better risk-adjusted performance.

High Volatility Management:

- Dynamic ATR thresholds allowed for trading in volatile conditions while reducing false signals.

Risk and Return:

- BTC and COCOA contributed significantly to portfolio growth.
- ETH had the lowest Sharpe ratio, suggesting room for optimization in the weighting scheme.

Number of Trades:

- The high frequency of trades (1642 for COCOA) indicates substantial activity. Transaction costs and slippage were accounted for but might need further evaluation.

Insights and Future Optimizations

Optimization Opportunities:

- Dynamic Weight Adjustment: Implement strategies for adaptive rebalancing based on market trends, volatility, asset performance, and predicted price increases.
- Diversify Across Asset Classes: Optimize for uncorrelated assets to enhance diversification benefits.

Drawdown Management:

- Introduce hedging strategies (e.g., options or futures) to mitigate large drawdowns, especially in high-volatility assets like ETH.

Feature Engineering:

- Additional features like sentiment analysis or macroeconomic indicators could improve predictive accuracy.

Further Testing:

- Test the strategy on a larger dataset across different asset classes to ensure generalization.

Conclusion

This strategy demonstrates the potential of combining LSTM-based predictive modeling with technical analysis indicators for automated trading. While the strategy shows strong performance on BTC and COCOA, ETH's underperformance suggests further optimization. Future iterations can enhance risk management, diversify features, and expand testing datasets for more robust insights.