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Research on Silver Futures Trading Strategy Based on Support Vector Machine

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Abstract: With the continuous development of financial markets, silver futures trading has become increasingly significant in the investment sector. In recent years, the application of machine learning techniques in finance has provided novel perspectives for futures trading. This paper focuses on silver futures and proposes an effective trading strategy framework based on machine learning. The research proceeds through the following steps: Background Analysis, Model Selection, Model Training and Evaluation, and Strategy Implementation. Experimental results demonstrate that machine learning-based strategies can significantly enhance trading returns while mitigating risks. This research provides a reference framework for developing strategies in other financial derivatives markets.

Keywords: Silver futures; Machine learning; Trading strategy

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1. Research background

Since the silver futures market was launched on the Shanghai Futures Exchange in 2013 in China, its trading volume has continued to expand with growing investor participation, becoming an indispensable part of the capital market.

In recent years, an increasing number of studies have explored the application of machine learning algorithms in financial market forecasting and trading strategy optimization. Ma et al. revealed the "nighttime effect" in intraday trading [1]. Parente and Rizzuti designed trading strategies for the cryptocurrency market using neural network models [2]. Wang discussed the application of machine learning in developing and dynamically adjusting quantitative investment strategies [3]. Chu conducted systematic research on AI-driven quantitative investment and risk control [4]. Lin et al. verified the reliability of neural networks in financial forecasting through model stability analysis [5]. Yang noted that deep learning models in financial forecasting need to be combined with multiple validation methods to improve reliability [6]. These researches provides a theoretical foundation and technical support for this study.

2. Fundamental principles of machine learning

Machine learning is a crucial branch of artificial intelligence, whose core goal is to train models using data so that computers can automatically learn and improve performance without explicit programming. As a supervised learning algorithm in Machine learning, the Support Vector Machine (SVM) is a type of generalized linear classifier that performs binary classification on data in a supervised learning manner. It is a high-accuracy classifier capable of building highly accurate predictive models for non-linear data and boasts excellent generalization ability. This paper selects the Support Vector Machine (SVM) to predict the binary classification problem of silver futures price movements and conducts historical simulated trading backtesting based on the prediction results.

3. Model training and parameter tuning

The data input section primarily relies on historical price data and trading volumes. These datasets undergo standardization and normalization to eliminate the impact of dimensional differences on the model [7].

According to research by Bustarviejo et al., multi-modal information fusion technology can effectively improve the accuracy of financial forecasts [8]. Therefore, this study considers the diversity of data features during model selection and optimizes model performance by integrating cross-attention mechanisms and calibrated uncertainty methods.

For the SVM model, optimization focuses on the kernel function type, regularization parameter C, and kernel function parameters. A combination of Grid Search and Random Search is used to comprehensively explore the parameter space, ultimately determining the optimal parameter combination.

Drawing on research by Wang Mingzhu et al., this study further validates the model's feasibility in real-world trading scenarios, laying a solid foundation for subsequent strategy backtesting and optimization [3].

4. Strategy backtesting and simulated trading

To validate the effectiveness and stability of machine learning-based silver futures trading strategies, this paper designs a systematic backtesting scheme and conducts simulated trading experiments. A backtesting framework is constructed based on strategic logic, with historical data used as input [9]. Trading signals are generated via the algorithm model, and trading operations are executed in accordance with preset rules. During the backtesting process, strict adherence to actual trading scenarios is maintained, covering key factors such as handling fees, slippage, and market liquidity to ensure the authenticity and reliability of results.

Multi-dimensional analysis is performed on the strategy's performance across different time periods, incorporating core indicators including return rate, maximum drawdown, and Sharpe ratio to evaluate its risk-return characteristics. Experimental data is sourced from daily silver futures data spanning from January 1, 2020, to December 31, 2025, encompassing 1,455 trading days. This dataset covers multiple market cycles, including bull markets, bear markets, and sideways markets, to comprehensively test the strategy's adaptability and robustness [10].

The backtesting phase employs historical data for simulated trading tests to ensure the strategy's stability in dynamic market environments. This paper uses the RQAlpha Plus backtesting framework from the Ricequant quantitative platform for model training and backtesting [11]. To mitigate the impact of gaps caused by rollover of silver futures front-month contracts, pre-adjusted continuous front-month contract data is adopted. The dataset is divided into an 80% training set (January 1, 2020, to October 31, 2024, 1,140 trading days) for model training and a 20% test set (November 1, 2024, to December 31, 2025, 285 trading days) to verify the model's generalization ability. A total of 30 feature indicators are employed to fully explore volume and price information, as presented in **Table 1**.

Table 1. Feature indicators used in the model

No.	Indicator Category	Indicator Code	Indicator Meaning
1	Return-related	returns	Daily return
2		log_returns	Logarithmic daily return
3	Moving Average (MA)	ma_ratio_5	5-day MA ratio (Price / MA5)
4		ma_ratio_10	10-day MA ratio (Price / MA10)
5		ma_ratio_20	20-day MA ratio (Price / MA20)
6		ma_ratio_30	30-day MA ratio (Price / MA30)
7		ma_5_10_ratio	Short-term MA ratio (MA5 / MA10)
8		ma_10_20_ratio	Mid-term MA ratio (MA10 / MA20)
9		price_position	Price position relative to the 20-day MA
10	Price Pattern	high_low_ratio	Intraday amplitude ratio (High price / Low price)
11		close_open_ratio	Price change ratio (Closing price / Opening price)
12		close_high_ratio	Closing price position relative to the intraday high
13		close_low_ratio	Closing price position relative to the intraday low
14	Volatility	volatility_5	5-day volatility (Standard deviation of returns)
15		volatility_10	10-day volatility
16		volatility_20	20-day volatility
17	Bollinger Bands	bb_position	Bollinger Band position (0 = Lower band, 1 = Upper band)
18		bb_width	Bollinger Band width (Reflects market volatility)
19	Volume-related	volume_ratio	Volume ratio (Current day volume / 5-day average volume)
20	MACD	macd	MACD line / DIF line
21		macd_signal	MACD signal line / DEA line
22		macd_diff	MACD histogram (Difference between MACD line and signal line)
23	RSI	rsi	Relative Strength Index (Range: 0–100)
24		rsi_overbought	RSI overbought signal (RSI > 70)
25		rsi_oversold	RSI oversold signal (RSI < 30)
26	Momentum	momentum_5	5-day momentum (Price change over 5 days)
27		momentum_10	10-day momentum
28		momentum_20	20-day momentum
29		momentum_acceleration	Momentum acceleration (Difference between 5-day and 10-day momentum)
30	Price Channel	price_channel_position	Price channel position (0 = 20-day low, 1 = 20-day high)

Grid search was conducted on the training set to identify the optimal hyperparameter combination of C×ϵ×kernel×gamma. The best-performing parameters were determined as: {C: 0.1, epsilon: 0.1, gamma: scale, kernel: rbf}.

During backtesting simulations, the trained SVM model was used to predict the next trading day's return. The trading rules were defined as follows:

Position Opening: Enter a long position if the predicted next-day return exceeds the threshold of 0.08%, and enter a short position if the predicted return falls below the threshold of -0.08%.

Position Holding/Closing: Maintain the current position if the next-day prediction aligns with the existing position direction. Close the position immediately if the prediction contradicts the current position.

Position Sizing: Fix the position at 1 contract without any additional scaling. All trades were executed using the daily closing price for simulation purposes.

Profit-taking and Stop-loss Rules: Trigger profit-taking when the realized profit reaches 3%, and execute stop-loss when the realized loss reaches 2%.

Risk Control Mechanism: Pause all trading activities for 5 consecutive trading days after 3 consecutive losing trades occur.

Capital and Cost Setup: The initial capital was set at 100,000 RMB, accounting for the contract value, margin requirements, and fixed position size of silver futures. Market frictions were calculated based on the exchange-standard commission rate and a one-tick transaction slippage.

Benchmark Comparison: The strategy performance was benchmarked against the China Securities Index Commodity Futures Index (CCICFI) for relative performance evaluation.

5. Strategy performance evaluation

A comprehensive performance evaluation was conducted on the silver futures trading strategy built on the SVM machine learning framework to verify its effectiveness and stability [12]. The assessment spanned multiple dimensions, including yield, risk management capability, and the Sharpe ratio, to ensure the strategy's practical feasibility and reliability in live trading.

As the core indicator to measure profitability, the strategy's performance was evaluated by calculating both cumulative and annualized returns over the backtesting period. Empirical results demonstrated that the strategy achieved a cumulative return of 194.808% during the testing phase (2020–2025), which significantly outperformed the benchmark index's cumulative return of 28.224%, indicating robust profit generation potential. The yield curve is illustrated in **Figure 1**.

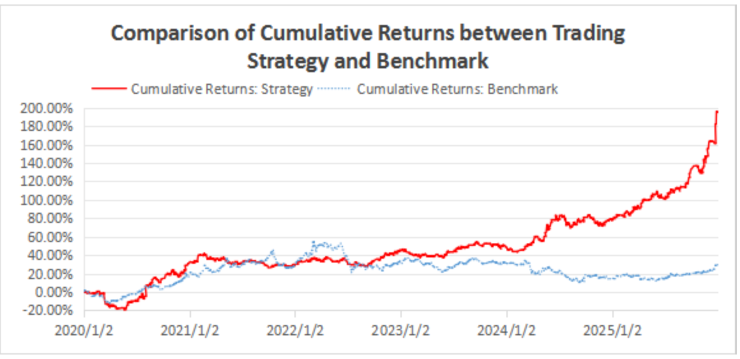

Figure 1. Comparison of cumulative return between trading strategy and benchmark

The strategy achieved an annualized return of 20.593% during the backtesting period, which outperformed the benchmark index's annualized return of 4.4% by a significant margin. A detailed comparison of the annualized returns between the strategy and the benchmark is presented in **Table 2**.

The strategy's alpha relative to the benchmark reached 17.33%, proving its ability to generate excess return. With a beta coefficient of 23.22%, which is less than 1, the strategy exhibited notably lower systematic risk compared to the broader market.

Table 2. Comparison of annualized return between trading strategy and benchmark

Year	Annualized Return: Strategy	Annualized Return: Benchmark
2020	31.07%	17.19%
2021	-1.93%	10.38%
2022	13.10%	2.78%
2023	2.26%	-1.60%
2024	19.26%	-12.64%
2025	66.30%	12.19%
Average Annualized Return	20.593%	4.400%

Max Drawdown and volatility were employed as the primary metrics to assess the strategy's risk management capability. Max Drawdown quantifies the peak-to-trough loss over a given period, while volatility measures the consistency of returns. The backtesting results showed the strategy's Max Drawdown was 19.629%, remaining within a reasonable range. Its annualized volatility reached 0.1356, indicating stable returns under market fluctuations [13].

As a critical measure of risk-adjusted returns, the strategy's Sharpe Ratio was calculated as 1.2365. A value exceeding 1 demonstrates the strategy can generate higher returns per unit of risk, reflecting strong adaptive ability in dynamic markets. The Sortino Ratio is 1.9152, and the Information Ratio is 1.4823.

To evaluate the strategy's robustness comprehensively, classification metrics, including confusion matrices, accuracy, recall, and F1-scores, were separately computed on the training and test sets. They are presented in **Tables 3** to **5**.

Table 3. Confusion matrice for training set

Training Set	Predicted Rise	Predicted Fall
Actual Rise	512	81
Actual Fall	354	193

Table 4. Confusion matrice for test set

Test Set	Predicted Rise	Predicted Fall
Actual Rise	136	27
Actual Fall	103	19

Table 5. Results comparison between training set and test set

Dimension	Training Set	Test Set
Accuracy Rate	0.6184	0.5439
Recall Rate	0.6081	0.495
F1 Score (Harmonic Mean)	0.586	0.4514
Total Number of Trades	221	48
Win Rate	54.75%	70.83%
Cumulative Return	141.67%	103.43%
Annualized Return	20.29%	85.44%
Annualized Sharpe Ratio	0.9572	3.4638
Maximum Drawdown (Peak-to-Trough)	-30.46%	-5.78%
Profit-to-Loss Ratio	1.44	3.5

The strategy's key classification metrics, including accuracy, recall, and F1 score, showed moderate declines on the test set compared with the training set. However, the test set outperformed the training set in terms of annualized return and profit-to-loss ratio.

Overall, the strategy demonstrated stable profitability and consistent risk control across varied market conditions. This SVM-based silver futures trading strategy delivered strong performance on multiple core indicators, maintaining stability even under volatile market environments and exhibiting robust risk resilience during periods of high fluctuation [14]. With high theoretical feasibility and verified practical effectiveness, it stands out as a reliable quantitative trading framework.

Further analysis revealed that the strategy's performance is highly sensitive to model parameter tuning and feature selection. It is therefore recommended to conduct dynamic optimization in line with real-time market changes during live deployment to enhance adaptive capacity and profit generation potential [15]. This study validated the strategy's effectiveness and stability through systematic backtesting and simulated trading experiments, providing solid theoretical and technical support for its application in real-world trading scenarios.

6. Limitations and improvements of the trading strategy

Following the preliminary design and backtesting evaluation of the trading strategy, a systematic analysis was conducted based on the assessment results. It was identified that the current model exhibits high return volatility and insufficient risk control capabilities under certain market conditions. Issues include a large maximum drawdown, unstable performance across both training and test sets, and potential overfitting risks. This paper proposes targeted optimization directions to further enhance the strategy's stability and profitability.

Feature Engineering Enhancement: Additional predictive financial indicators can be introduced and integrated with market sentiment data to construct multi-dimensional features, improving the model's sensitivity to market changes.

Model Optimization: Multiple machine learning algorithms, including Random Forest and LSTM, can be tested.

Risk Control Mechanism: Dynamic stop-loss mechanisms and position management rules can be incorporated.

Data Granularity Upgrade: Current backtesting relies solely on daily-level data. Increasing data granularity to hourly or minute-level could improve testing accuracy.

Implementation of the above optimization measures is expected to further enhance the overall performance of the trading strategy.

Disclosure statement

The authors declare no conflict of interest.

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