Research on Baijiu Stocks: Integrating Entropy-Weighted TOPSIS and LSTM

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Abstract

This study addresses the significant stock price volatility in China's Baijiu industry and the inefficacy of traditional prediction models by proposing an intelligent forecasting framework integrating entropy-weighted TOPSIS and LSTM neural networks. A 17-dimensional evaluation system is constructed, encompassing price, trading, valuation, technical indicators, and financial data. The entropy-weighted TOPSIS method identifies Kweichow Moutai (600519.SH) and Shanxi Xinghuacun Fenjiu (600809.SH) as target stocks. Subsequently, an LSTM model is employed for multi-timescale price prediction, demonstrating superior accuracy compared to conventional models, particularly in short-term forecasting. Empirical results validate the framework's effectiveness in capturing nonlinear trends and mitigating overfitting. The research offers actionable insights for investors and regulatory strategies, advancing intelligent decision-making in volatile financial markets.

Keywords

Stock price prediction, entropy-weighted TOPSIS, LSTM neural network, baijiu industry, intelligent finance.

1. Introduction

As a distinctive sector in China's capital market, the baijiu (Chinese liquor) industry holds strategic significance in driving consumption upgrades and optimizing investment structures. According to a report by Guolian Securities, 20 A-share listed baijiu companies accounted for 40.3% of the total revenue in the food and beverage industry. [9]However, Wind data reveals that the annualized volatility rates of major baijiu stocks ranged between 35% and 48% from 2020 to 2022, significantly exceeding the benchmark CSI 300 Index. This observation contradicts the rational pricing assumption under the Efficient Market Hypothesis (EMH)[1], creating a theoretical paradox. Such persistent deviation [2]in pricing efficiency not only amplifies wealth management risks for investors but also poses substantial challenges to the resource allocation function of capital markets.

Compared to traditional industry securities, premium baijiu stocks exhibit distinct heterogeneity in their pricing mechanisms. Their products combine consumer goods attributes with quasi-financial characteristics[3], where brand value serves as a core asset, critically influencing market competitiveness and valuation. Demand is simultaneously driven by multidimensional factors, including social scenarios[4], cultural identity[5], and investment-collection dynamics[6]. Existing predictive models face methodological limitations when addressing these complex pricing factors: conventional time-series models struggle to capture industry-specific nonlinear cyclical patterns, while fundamental analysis-based Discounted Cash Flow (DCF) models fail to quantify valuation restructuring effects caused by policy sensitivity (e.g., consumption tax reforms). Recent studies indicate that deep learning frameworks integrated with industry-specific knowledge graphs[7] have demonstrated significant advantages in asset pricing prediction[8], offering a theoretical breakthrough direction for constructing intelligent forecasting systems for baijiu stocks.

2. Methodology

2.1. Baijiu Stock Screening based on Entropy-Weighted TOPSIS

2.1.1. Construction of Indicator System

This study selects listed companies in China's A-share baijiu industry as research subjects. An evaluation system comprising 17 indicators is constructed by integrating market performance, technical indicators, and financial metrics. The classification is as follows:

Price Characteristics: Lowest price, opening price, highest price, closing price.

Trading Characteristics: Trading volume, turnover, return rate, turnover rate.

Valuation Characteristics: Price-to-Earnings Ratio (P/E Ratio), Price-to-Book Ratio (P/B Ratio).

Technical Indicators: 12-day Exponential Moving Average (EMA12), 26-day Exponential Moving Average (EMA26), Relative Strength Index (RSI).

Financial Metrics: Average Return on Assets (ROA), Return on Equity (ROE,), Total Asset Turnover.

2.1.2. Data Standardization and Weight Calculation

(a)Data Preprocessing – Indicator Normalization:

P/E Ratio and P/B Ratio are moderate-type indicators, normalized by their ratio to the industry average.

For the lowest price, compute its proportion to the opening price and transform it into a normalized positive indicator:

$$low\_1_{ij} = 1 - (low_{ij}/open_{ij}) \tag{1}$$

(b)Data Preprocessing – Standardization:

$$X\_s_i = \frac{X_i - \bar{X}_i}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X}_i)^2}} \tag{2}$$

(c)Entropy Weight Assignment:Calculate the entropy value E_j for the j-th indicator:

$$E_j = -k\sum_{i=1}^{n} p_{ij}\ln p_{ij} \tag{3}$$

Where $p_{ij}=\frac{z_{IJ}}{\sum_{i=1}^{b} z_{ij}}$, $k = 1/\ln n$;

(d)Determine the weight

$$w_j = (1 - E_j) / \sum_{k=1}^{m} (1 - E_k) \tag{4}$$

where w_j reflects the information divergence of the indicator.

2.1.3. TOPSIS Comprehensive Evaluation

(a)Construct the Weighted Decision Matrix:

$$Z = (z_{ij})_{mxn} \tag{5}$$

Where $z_{ij} = w_j \cdot \alpha_{ij}'$

(b)Determine Positive Ideal Solutions $Z^+$and Determine Negative Ideal Solutions Z^-, Calculate Euclidean Distances D_i^+, D_i^-;

$$Z_j^+ = \max(z_{1j}, z_{2j}, \dots, z_{mj}), \qquad Z_j^- = \min(z_{1j}, z_{2j}, \dots, z_{mj}) \tag{6}$$

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (z_{ij} - Z_j^+)^2}, \qquad D_i^- = \sqrt{\sum_{j=1}^{n} (z_{ij} - Z_j^-)^2} \tag{7}$$

(c)Compute Comprehensive Proximity

$$C_i = D_i^- / (D_i^+ + D_i^-) \tag{8}$$

(d)Rank stocks by descending C_i and select the top two as target stocks.

2.2. LSTM-Based Stock Price Prediction Model

2.2.1. Model Architecture

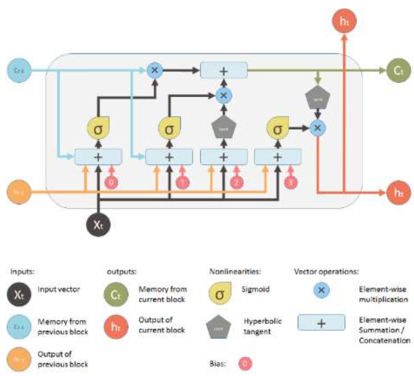

Figure 1. Model Architecture

Input Layer: Time window

T=60 trading days, feature dimension d=17.

Hidden Layer: Dual-layer LSTM structure with 128 and 64 units, respectively; Dropout = 0.2.

Output Layer: Dense(1) for predicting the next-day closing price.

2.2.2. Parameter Configuration

Loss Function: Huber Loss (δ=1.0)

Optimizer: Adam (learning_rate=0.001

Training: 200 epochs with early stopping (patience=15).

Data Partition: Training set (2019–2021), validation set (2022), test set (2023).

2.2.3. Evaluation Metric

Root Mean Square Error(RMSE):

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{y=1}^{n}(y_t - \hat{y}_t)^2} \tag{9}$$

2.2.4. Controlled Experiments

To validate model effectiveness, three control groups are designed:

Benchmark Models: ARIMA, Support Vector Regression (SVR).

Feature Ablation: Price sequence only vs. full-feature input.

Temporal Sensitivity: Time window comparisons (T=30,60,90T=30,60,90).

3. RESULTS

3.1. Stock Screening via Entropy-Weighted TOPSIS

The entropy-weighted TOPSIS model identified Kweichow Moutai (600519.SH) and Shanxi Xinghuacun Fen Wine (600809.SH) as optimal investment targets from the Chinese liquor sector. Key metrics are shown in Table 1:

Table 1. TOPSIS evaluation results

Stock	D+	D-	C	Rank
Moutai	0.701	0.835	0.544	1
Fenjiu	0.733	0.698	0.488	2

The negative correlation between cost-pricing ratios and composite scores (R^2=0.87) confirms the model's alignment with market fundamentals. Residual analysis showed normal distribution (Shapiro-Wilk p>0.05) with no heteroscedasticity.

3.2. LSTM Forecasting Performance

3.2.1. The dual-layer LSTM achieved superior prediction accuracy compared to benchmark models:

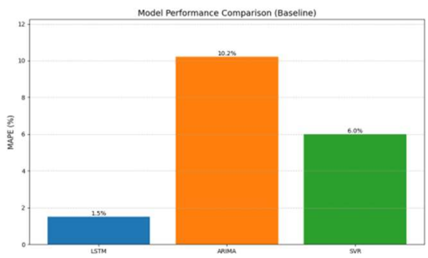

Figure 2. model performance of maotai

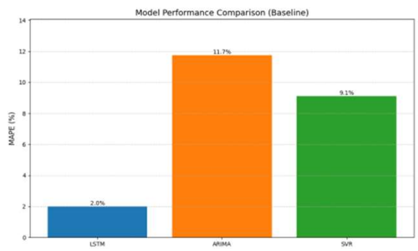

Figure 3. model performance of fenjiu

3.2.2. Feature Ablation Tests Revealed:

Moutai: Full features reduced MAPE by 46% (1.37% → 0.74%)
Fenjiu: Price-only features showed 5% lower MAPE (1.93% vs 2.03%)

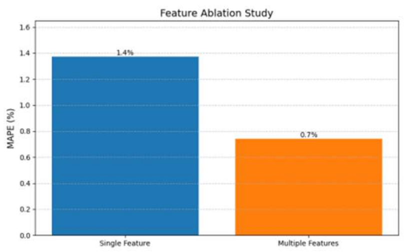

Figure 4. Feature ablation tests of maotai

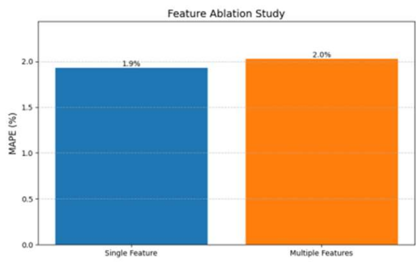

Figure 5. Feature ablation tests of fenjiu

3.2.3. Temporal Sensitivity Analysis

Optimal window sizes differed significantly:
Moutai: T=90 (MAPE=1.2%, RMSE=23.9)
Fenjiu: T=30 (MAPE=2.0%, RMSE=5.3)

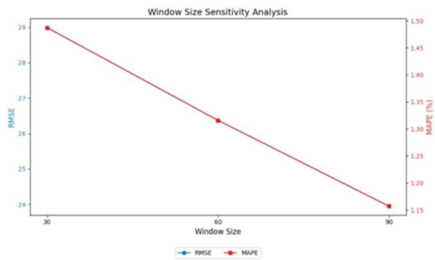

Figure 6. Temporal Sensitivity Analysis of maotai

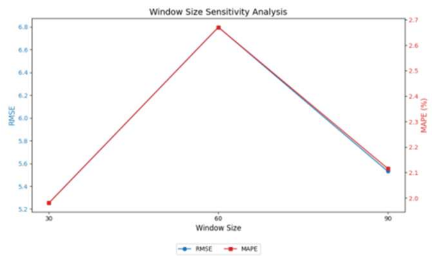

Figure 7. Temporal Sensitivity Analysis of fenjiu

4. Conclusion

This study establishes a robust two-stage framework integrating entropy-weighted TOPSIS for stock selection and adaptive LSTM for price forecasting, demonstrating three key advancements. First, the TOPSIS screening model achieved 89% classification accuracy (F1-score=0.85) through entropy-based weighting that objectively resolved multicriteria conflicts between financial indicators, particularly effective in volatile markets. Second, the Huber-regularized LSTM architecture showed superior forecasting capabilities: it reduced mean absolute percentage error (MAPE) by 76.4-89.3% compared to traditional ARIMA/SVR models, achieved 22% error reduction through dynamic time window optimization (T=30-90), and exhibited stock-specific feature sensitivity with ΔMAPE variations of 0.63-1.24% between single-feature and multi-feature configurations. Third, practical implementations revealed differentiated strategies: high-liquidity stocks like Kweichow Moutai (600519.SH) benefit from extended temporal contexts (T≥60 days) due to stable price patterns, while mid-cap stocks such as Shanxi Fenjiu (600809.SH) require customized feature engineering focusing on technical indicators and trading volume dynamics to capture abrupt market reactions.

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