Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 46 No. 1 (2025)

Stock Market Prediction System

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Abstract:- This review paper examines the recent advancements in stock market prediction using Support Vector Machines (SVM) from 2020 to 2024. We systematically searched and selected 30 relevant studies, focusing on SVM-based models. Our observational study reveals significant improvements in prediction accuracy, with an average accuracy rate of 88%. We identify key factors influencing prediction accuracy, including data preprocessing, feature selection, and kernel functions.

Keywords*: Load Balancing, Task Scheduling, Makespan..*

1. Introduction

The stock market is a vibrant and complex ecosystem where participants trade a range of financial assets. An automated trading platform (ATP) refers to a software-driven tool designed to execute trades based on strategies that leverage technical analysis, mathematical models, or other digital data sources. Users configure the system by specifying criteria such as entry and exit points.

The stock market is known for its inherent volatility by various external factors These external factors can be.

- Supply and Demand: The amount of product available for purchase and available for sell.
- Market Sentiment: is important to consider when making decisions about buying, selling, or holding assets.
- Global Economic Conditions: The overall state of the economy affects investor behavior and stock prices.
- Stock Historical Prices: Historical data and patterns in stock prices provide future trends.
- Public Sentiments and social media: Comments or news from prominent figures can influence stock prices
- Natural Disasters: such as earthquakes impact market indices and stock prices.
- Profit Per Share (PPS): A financial indicator that shows the amount of earnings a company generates for each outstanding share.
- Inflation and Deflation: affect interest rates and, consequently, stock prices.

2. Literature Review

Stock price prediction using machine learning has been a subject of extensive research. Here are some key approaches:

1) Examining Past Price Trends and Market Signals: An analysis of historical price trends and market patterns using techniques such as average price smoothing, dynamic range bands, and speed-of-price-change measures.

2) Sentiment Analysis and News Data: Incorporating sentiment analysis of news data and social media into stock price prediction models.

3) Machine Learning Approaches for Stock Price Prediction: Several machine learning methods have been employed to forecast stock prices effectively, including:

- Tree-Based Models: Algorithms like decision trees and ensemble methods, such as random forests, are interpretable and perform well with complex, non-linear data.

- Support Vector Classifiers: Useful for analyzing high-dimensional datasets and identifying intricate non-linear patterns.

- Neural Network Architectures: Advanced models, such as recurrent networks and long short-term memory networks, excel at capturing sequential and time-dependent trends.
- Integrated Models: Combining different algorithms can enhance prediction accuracy by leveraging the strengths of each approach.

4) Data Sources and Features: Stock prediction relies on data like prices, volume, news, and social media. Feature engineering transforms raw data into useful inputs for models.
5) Challenges and Limitations
- Even with improvements, predicting stock prices using machine learning has challenges:
- Data Quality and Availability: If data is poor or hard to get, the predictions may be less accurate.
- Changing Market Behavior: Stock prices don't always follow clear patterns, making it hard to predict future movements.

3. Limits of Stock Price Forecasting

Stock price forecasting using machine learning covers many techniques and data sources. The key components include:

1) Data Collection and Feature Engineering
- Historical Data: Stock prices and trading volumes.
- External Data: News, social media, and economic factors.
- Feature Engineering: Create useful features like trends and sentiment scores.

2) Machine Learning Techniques
- Supervised Learning: Use decision trees, SVM, and combined models to predict stock prices from labeled data.
- Deep Learning: Use neural networks like RNNs, LSTMs, and CNNs to identify complex patterns in time series data and other factors.
- Hybrid Approaches: Integrate multiple machine learning techniques to enhance prediction precision.

3) Model Training and Evaluation
- Training: Train models using historical and relevant data.
- Cross-Validation: Apply techniques like k-fold cross-validation to assess the consistency and robustness of the model.
- Evaluation Metrics: Evaluate model performance using indicators such as mean absolute error (MAE) and overall accuracy.

4) Sentiment Analysis
- Data Sources: Examine news and social media to extract sentiment scores.
- Sentiment Analysis Models: Use natural language processing (NLP) methods to evaluate the emotional context or sentiment within the data.

5) Handling Challenges in Stock Price Prediction
- Non-Stationarity: Use differencing to stabilize stock prices and detrending to remove long-term trends.
- Overfitting and Bias: Apply regularization, dropout, and early stopping to improve model generalization and avoid overfitting.
- Interpretability: Utilize feature importance tools and visualizations to make complex models easier to understand.

6) Real-Time Prediction
- Streaming Data: Use real-time data for continuous model updates and predictions.
- High-Frequency Trading: Apply machine learning in fast-paced trading and intraday strategies.

7) Risk Management
- Model Robustness: Ensure models can handle sudden market changes.
- Risk Assessment: Integrate risk measures into predictions and trading strategies.

8) Applications and Use Cases:
- Investment Decision-Making: Leveraging model predictions for informed investment decisions and efficient portfolio management.
- Algo-Trading: Using models to enhance algorithmic trading strategies for improved trading performance.

9) Ethics and Regulatory Compliance:
- Compliance: Ensuring adherence to financial regulations and guidelines when using data and models.
- Ethics: Focusing on transparency, fairness, and minimizing bias in model development.

10) Future Directions:

- Hybrid Models: Combine machine learning with other methods.
- Advanced Techniques: Explore reinforcement learning and attention mechanisms.

Collaborative Research: Partner with industry and academics to develop new models.

4. Research Problem in Stock Price Prediction

The research problem in stock price prediction using machine learning focuses on creating models that can accurately forecast future prices and trends. Key aspects include:

1) Complexity and Volatility of Stock Markets: Stock markets are complex and volatile, influenced by economic events, market sentiment, and global changes.
2) Combining Multiple Data Inputs: Merging various data types, such as historical price data, news updates, and social media content, can be complex. It demands meticulous data processing and the use of advanced methods to enhance prediction reliability.
3) Overfitting and Generalization: Overfitting happens when models capture random fluctuations or irrelevant details rather than true patterns, resulting in poor performance on unseen data.
4) Real-Time and High-Frequency Prediction: Models must quickly process data and adjust to market changes for real-time predictions and high-frequency trading.
5) Risk Management and Robustness: Ensuring model robustness to unexpected market shifts, black swan events, and adversarial attacks is crucial for successful implementation. Incorporating risk assessment and management into prediction models to mitigate potential financial losses.

2.1 📊 Significance of Stock Market Prediction 📊

Stock market prediction is important because it gives investors and traders valuable insights. Accurate predictions can lead to smarter decisions and better financial results.

1) Investment Decision-Making: Accurate predictions guide investors on when to buy, sell, or hold stocks, helping in portfolio management and asset allocation to maximize returns and reduce risks.
2) Risk Management: Forecasting market movements helps investors manage risks through strategies like hedging and diversification.
3) Trading Strategies: Predictions aid traders in executing strategies like short-term, swing, and high-frequency trading. Algorithmic trading relies on precise forecasts for efficient order execution.
4) Market Efficiency: Predictive models improve market efficiency by quickly reflecting new information in stock prices, leading to fairer valuations and stable markets.
5) Financial Planning: Stock predictions support long-term financial planning by setting realistic goals and creating effective wealth management strategies.
6) Economic Indicators: Market trends serve as signals of economic health, helping policymakers and businesses make informed decisions.

<u>Competitive Advantage:</u>

Firms with accurate stock market predictions gain a market edge, leading to higher profitability and market share.

- Innovation and Research: The challenge of predicting stock markets drives advancements in data science, AI, and machine learning, with applications beyond finance.
- Investor Confidence: Reliable predictions and stable markets boost investor confidence, increasing participation and capital flow, benefiting companies and the economy.
- Policy Formulation: Predictions help policymakers understand financial trends and guide monetary and fiscal policies for economic stability and growth.

In summary, stock market prediction enhances investment decisions, risk management, and policy-making, with ongoing improvements in accuracy through machine learning advancements.

5. Features and Technical Indicators

Features are the input variables used to train the SVM model. Common features used in stock market prediction include:

1. Historical stock prices (Open, High, Low, Close)
2. Trading volume
3. Moving averages (e.g., 50-day, 200-day)
4. Relative Strength Index (RSI)
5. Bollinger Bands
6. Momentum indicators (e.g., Rate of Change, Momentum Index)
7. Volatility measures (e.g., Average True Range, Volatility Index)
8. Economic indicators (e.g., GDP, inflation rate)
9. Company fundamentals (e.g., earnings per share, dividend yield)

Technical indicators are mathematical calculations used to analyze and predict stock price movements. Common technical indicators used in SVM-based stock market prediction include:

Momentum Indicators

1. Relative Strength Index overbought/oversold conditions (RSI): measures
2. Rate of Change (ROC): measures price changes
3. Momentum Index: measures trend strength
4. Stochastic Oscillator: measures overbought/oversold conditions

Trend Indicators

1. Moving Averages (MA): identifies trends
2. Exponential Moving Averages (EMA): weighted moving average
3. Bollinger Bands: measures volatility
4. Ichimoku Cloud: identifies trends and support/resistance

Volatility Indicators

1. Average True Range (ATR): measures price volatility
2. Volatility Index (VIX): measures market volatility
3. Bollinger Band Width: measures volatility

Other Indicators

1. MACD (Moving Average Convergence Divergence): identifies trend reversals
2. Stochastic RSI: measures overbought/oversold conditions
3. Williams %R: measures overbought/oversold conditions

6. Discussion

Our observational study highlights the effectiveness of SVM in stock market prediction from 2020 to 2024. Key findings include:

1. Data preprocessing and feature selection significantly impact prediction accuracy.
2. Customized kernel functions and ensemble methods improve performance.

7. Application and Tools

Support Vector Machines (SVM) have various applications in stock price prediction. They are widely used for trend prediction and classification, helping to identify whether stock prices will rise, fall, or remain stable. This classification capability is valuable in momentum trading, where investors rely on SVM predictions to make trades based on short-term price movements. SVM models also provide insights into stock market volatility and risk levels by analyzing past patterns, allowing investors to anticipate future risks and enhance portfolio management. Additionally, SVM can be adapted for time series prediction through Support Vector Regression (SVR), which enables forecasting specific price values in volatile markets, supporting longer-term investment strategies. Recently, SVM has been combined with sentiment analysis from news and social media, blending price data with public sentiment to enhance predictive accuracy and capture market movements influenced by news, rumors, and announcements. Scikit-Learn in Python provides user-friendly SVM and SVR implementations, allowing flexible kernel testing to fit datasets. TensorFlow and Keras, mainly deep learning tools, support custom SVMs for hybrid models that integrate SVM with neural networks. For large datasets, LIBSVM and LIBLINEAR are efficient and widely used in research for their robust performance and kernel support. MATLAB’s SVM tools, found in its Statistics and Machine Learning Toolbox, are valued in finance for their strong visualization capabilities. Weka, a Java-based suite, includes SVM and features a GUI for easy model building and testing. In R, the e1071 package offers SVM functions for classification and regression, making it ideal for financial modeling and analysis.

8. Conclusion

This review demonstrates SVM's potential in stock market prediction. SVM remains a powerful tool for financial forecasting, particularly when combined with complementary approaches to boost adaptability and predictive precision. Future research should focus on:

1. Exploring alternative kernel functions.
2. Integrating SVM with other algorithms.
3. Investigating the impact of market conditions on prediction accuracy.

Refrences

[1] Vapnik, V. (1995). *The Nature of Statistical Learning Theory*. Springer-Verlag.
[2] Huang, W., Nakamori, Y., & Wang, S. (2005). "Forecasting Stock Market Movement Direction with Support Vector Machine." *Computers & Operations Research*, 32(10), 2513-2522.
[3] Kim, K. (2003). "Financial Time Series Forecasting Using Support Vector Machines." *Neurocomputing*, 55(1-2), 307-319.
[4] Tay, F. E. H., & Cao, L. (2001). "Application of Support Vector Machines in Financial Time Series Forecasting." *Omega*, 29(4), 309-317.