International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 03 March 2025
Page No: 615-621
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0086

Non-Linear Stock Market Prediction with Support Vector Machines

Amshavalli M[1], Paramesh Kumar S[2], Purusothaman R[3], Tharun M[4]
[1]Assistant Professor, Department of CSE, Erode Sengunthar Engineering College, Perundurai, Erode, India.
[2,3,4]Student, Department of Computer Science and Engineering, Erode Sengunthar Engineering College, Perundurai, Erode, India.
Emails: *amshavalli1494@gmail.com[1], purusothaman9952@gmail.com[3], tharunmbecse@gmail.com[4]*

Abstract
In forecasting financial markets using time series data, predicting Future in the financial market data such as Stock prices, currency exchange commodity price, and rates is a difficult but crucial endeavor. We introduced the Support Vector Machine (SVM) technique for financial market trend prediction using TSA. Because of their intricate patterns and inherent dynamic character, financial market time series data pose a challenge to traditional forecasting methods. The SVM algorithm, which is well-known for its robustness and ability to handle high-dimensional data, is used to estimate future market patterns based on historical price and volume data. The study evaluates the effectiveness of SVM in capturing non-linear correlations in financial time while accounting for shifting market and economic conditions. Through in-depth empirical investigation and performance comparison with other forecasting models, this study sheds light on the suitability and precision of SVM in anticipating movements in financial markets. For traders, investors, and scholars studying algorithmic trading and quantitative finance, it has significant ramifications.

Keywords: *Financial Market, Forecasting, Financial Time Series, Machine Learning.*

1. Introduction

Machine learning-based financial market forecasting is transforming how traders and investors make decisions in today's dynamic markets. With big data and advanced computing techniques, machine learning models analyze past price and trading data, identify trends, and predict future market movements. These algorithms help financial institutions, traders, and investors gain a competitive edge by optimizing investment strategies. Time series forecasting models are particularly crucial in finance, enabling stakeholders to make data-driven decisions and react faster to market changes. By integrating various market variables and analyzing historical trends, these models assist with price predictions, risk assessment, and portfolio optimization. As markets grow more complex and volatile, machine learning's predictive capabilities are reshaping risk and investment management, offering stakeholders valuable tools to improve performance and make informed decisions.

2. Literature Review

Stock market forecasting has seen significant advancements through various innovative models. A hybrid approach combining LSTM and DNN enhances prediction accuracy by integrating temporal learning with pattern recognition, effectively adapting to market fluctuations and demonstrating superior performance across multiple datasets [1]. Addressing the complexities of multivariate time series, a double Q-learning-based ensemble framework improves precision by selecting optimal actions for dynamic data, enhancing decision-making in volatile environments [2]. Another robust model integrates Bi-LSTM with an improved transformer and temporal convolutional networks, capturing bidirectional patterns, long-range dependencies, and generalizing well for reliable forecasts [3]. Deep learning frameworks utilizing pre-trained CNN models like VGGFace2 and ResNet-50, coupled with optimization techniques, improve feature extraction and prediction accuracy while mitigating underfitting risks [4]. Incorporating social media sentiment analysis into stock price predictions offers improved accuracy by addressing class imbalances and integrating sentiment data with financial metrics [5]. High-frequency trading benefits from reinforcement learning-based dynamic parameter optimization, enhancing flexibility and trading performance in rapidly changing markets [6]. For emerging markets, GRU-based models effectively capture sequential data and adapt to volatile conditions, providing reliable forecasting tools [7]. Integrating LSTM networks with sentiment analysis from platforms like Twitter enhances predictive insights, especially during macroeconomic uncertainties affecting North American and European banks [8]. Hybrid models using hierarchical frequency decomposition and clustering algorithms uncover underlying market patterns, significantly improving forecast accuracy [9]. Enhancements in multivariate time series forecasting through CNN-BiLSTM models with attention mechanisms address dynamic variability and nonstationarity challenges [10]. Incorporating investor sentiment with optimized deep learning techniques reduces investment risks and enhances returns by merging sentiment indices with fundamental data [11]. Medium-term forecasting models leverage adaptive feature subsets and dynamic trend indicators, employing machine learning techniques and rolling windows for accurate market movement predictions [12]. Cost-sensitive learning approaches, such as FL Light GBM, address the practical aspects of trading by minimizing costs, though their assumptions may limit flexibility for diverse strategies [13]. Integrated models combining decomposition techniques with neural networks capture fluctuating stock index states across frequencies, improving risk management and returns [14]. Further validation across diverse datasets highlights the need for robust models capable of generalizing beyond single datasets, as seen in hybrid LSTM-DNN frameworks tested on real-life data [15]. Shown in Table 1.

Table 1 Comparative Table

S No	Authors Name	Publication Year	Title of Paper	Methodology	Merits	Demerits
1.	Khorshed Alam	IEEE 2024	Enhancing Stock Market Prediction: A Robust Lstm-Dnn Model Analysis On 26 Real-Life Datasets.	Use ML-GAT on stock market graph for trend forecasting and evaluation.	Fine-grained access control ensures data security, while ABAC centralization simplifies policy management and reduces workload	Existing methods for early MTS classification face issues with data length and faults, which this approach addresses.
2.	Ali Peivandizade	IEEE 2024	A Sentiment Analysis and Temporal Dynamics- Based Stock Market Prediction Approach.	The methodology combines sentiment analysis and stock data using PPO to address class imbalance and TLSTM to capture temporal patterns.	The method enhances stock prediction by integrating social sentiment, addressing class imbalance, and prioritizing relevant data.	The abstract omits disadvantages, but reliance on social media data poses challenges with noise and sentiment classification.
3.	Santosh Kumar	IEEE 2024	Early MTS Forecasting for Dynamic Stock Prediction: A Double Q-Learning Ensemble Approach	The methodology uses a double Q-learning ensemble with Q-learning agents, Gaussian Process Classifiers, and ARIMA for early	The framework attains 99.89% accuracy by tackling non-linearity, non-stationarity, and faulty MTS data.	Existing MTS classification methods struggle with data length and faults, which this method mitigates.

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 03 March 2025
Page No: 615-621
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0086

				MTS forecasting and classification.		
4.	Shuzhen Wang	IEEE 2024	A Stock Price Prediction Model Based on Investor Sentiment and Optimized Deep Learning	The methodology introduces BiLSTM-MTRAN-TCN, combining BiLSTM, an enhanced transformer (MTRAN-TCN), and TCN to improve stock price prediction accuracy and generalization.	The method outperforms others, fitting 85.7% of stock datasets, reducing RMSE by 24.3%-93.5%, and increasing R^2 by 15.6%, ensuring high accuracy and stability.	The abstract omits limitations of the BiLSTM-MTRAN-TCN model, leaving concerns about computational complexity and scalability unaddressed.
5.	Fathe Jeribi	IEEE 2024	A Sentiment Analysis and Temporal Dynamics- Based Stock Market Prediction Approach.	The methodology combines MSMA with stock data, using PPO to address class imbalance and TLSTM to capture temporal patterns and sentiment relationships.	The method enhances stock prediction accuracy by integrating social media sentiment, addressing class imbalance, and focusing on relevant temporal data.	The abstract doesn't mention explicit disadvantages, but reliance on social media data may lead to challenges with noise and sentiment mis-classification.
6.	Weipeng Zhang	IEEE 2024	Reinforcem ent Learning for Stock Prediction and High- Frequency Trading With T+1 Rules	The methodology optimizes stock predictions and strategies using reinforcement learning and T+1 rules.	The framework adapts to market conditions, optimizing trading strategies for improved accuracy and profitability in the Chinese stock market.	The model addresses adaptation to market conditions, but dynamic parameter tuning may increase computational overhead.
7.	Yi Li, Lei Chen	IEEE 2024	Accurate Stock Price Forecasting Based on Deep Learning and Hierarchica l Frequency Decomposi tion	The methodology presents HDFM, combining CEEMDAN, K-means clustering, VMD, and GRU for accurate stock price prediction.	The model enhances stock price forecasting by decomposing time-series data and using GRU, outperforming other methods across multiple stock markets.	The abstract doesn't mention explicit disadvantages, but the hierarchical decomposition process may introduce computational overhead, especially with multiple layers.
8.	Luca Bacco	IEEE 2022	Investigatin g Stock Prediction Using LSTM Networks and Sentiment Analysis	The paper uses LSTM networks and FinBERT for stock price prediction by integrating	The incorporation of sentiment analysis with traditional metrics enhances model accuracy, especially during	The European market is more fragmented, making prediction models less accurate compared to the more

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 03 March 2025
Page No: 615-621
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0086

			of Tweets Under High Uncertainty : A Case Study of North American and European Banks	traditional financial metrics with sentiment analysis of tweets, particularly targeting banks in North America and Europe under volatile economic conditions.	periods of high uncertainty, with market-specific insights for the US and EU.	correlated US banking market.
9.	Mahbubul Haq Bhuiyan	IEEE 2024	Enhancing Stock Market Prediction: A Robust LSTM- DNN Model Analysis on 26 Real- Life Datasets	The methodology presents a hybrid LSTM-DNN model for predicting stock closing prices, validated on 26 real-world datasets for robustness and scalability.	The model achieves an R^2 score of 0.98606, outperforming other DL models, proving its accuracy and robustness for stock prediction.	The paper highlights high accuracy but doesn't address potential limitations like overfitting or performance during extreme market volatility.
10.	An Luo	IEEE 2024	Short-Term Stock Correlation Forecasting Based on CNN- BiLSTM Enhanced by Attention Mechanism	The methodology presents a CNN-BiLSTM-Attention (CLATT) model for short-term stock forecasting, optimizing accuracy feature extraction, time series processing.	The CLATT model improves stock correlation prediction accuracy by 57.32% and 33% over single LSTM models, making it robust for short-term forecasting.	While highly accurate, the study doesn't address how the model handles extreme market conditions or outliers, which could affect its robustness in unpredictable environments.
11.	Guangyu Mu	IEEE 2024	A Stock Price Prediction Model Based on Investor Sentiment and Optimized Deep Learning	The MS-SSA-LSTM model combines sentiment analysis and Sparrow Search Algorithm for LSTM optimization to predict stock prices using multi-source data.	The MS-SSA-LSTM model shows a 10.74% R^2 increase over standard LSTM, highlighting the benefits of integrating sentiment indices and optimized hyperparameters.	The focus on short-term predictions may limit the model's applicability for long-term investment strategies, particularly in volatile markets.

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 03 March 2025
Page No: 615-621
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0086

12.	A.Bareket, Parva	IEEE 2024	Adaptive Feature Subset and Dynamic Trend Indicators for Medium- Term Stock Market Predictions : A 70 Trading Days Forecasting Approach	This study focuses on MTSMF (70 trading days) using various traditional and novel input features, combined with machine learning techniques like ANN and SVM, to optimize predictions for dynamic market conditions.	The approach improves prediction of market movements and identifies periods of high and low predictability for informed investment decisions.	The reliance on multiple sub-models and complex feature selection may hinder model interpretability and increase computational resource requirements.
13.	Xiaosong Zhao	IEEE 2024	Cost Harmonizat ion LightGBM -Based Stock Market Prediction.	The CHL-LightGBM model dynamically adjusts error costs for stock prediction, addressing the limitations of equal treatment for false positives and negatives.	CHL-LightGBM achieved the highest annual return across stock exchanges, making it potentially more beneficial for investors than traditional models.	The model showed no significant differences in accuracy or winning rate compared to others, raising questions about its precision.
14.	Sibo Li	IEEE 2024	Stock Index Forecasting Using a Novel Integrated Model Based on CEEMDA N and TCN- GRU-CBAM	The methodology presents a novel stock price prediction model combining CEEMDAN with TCN, GRU, and CBAM to enhance forecasting accuracy.	The CEEMDAN-TCN-GRU-CBAM model outperforms traditional models in robustness, universality, and accuracy across stock indices in developed markets.	The abstract does not mention specific limitations or challenges, which could provide a more balanced view of the model's applicability.
15.	Kun Huang	IEEE 2024	ML- GATA Multilevel Graph Attention Model for Stock Prediction	The study introduces a ML-GAT for stock forecasting, integrating news, events, and complex stock relationships.	ML-GAT achieves state-of-the-art performance, improving F1-score by 11.82%, accuracy by 12.6%, average daily return by 5.06%, and Sharpe ratio by 94.81% compared to existing models.	The abstract lacks details on the model's limitations, challenges, or potential weaknesses, which could offer a more comprehensive understanding of its applicability.

3. Methodology

This paper examines the application of SVM to financial market time series forecasting. Data cleaning and feature engineering are part of the study's preparation of historical financial data. An SVM model is constructed once the dataset has been divided into training and testing datasets, with a focus on hyperparameter adjustment and appropriate kernel selection. The trained SVM model is then used to predict values using the testing set, and the model's performance is evaluated using metrics like Mean Squared Error. The study emphasizes the importance of rolling forecast origin, normalization, and potential ensemble techniques to increase anticipated accuracy. It is crucial to acknowledge the inherent intricacy of financial markets and the necessity of continuous model evaluation and enhancement to adapt to changing market conditions, Shown in Figure 1.

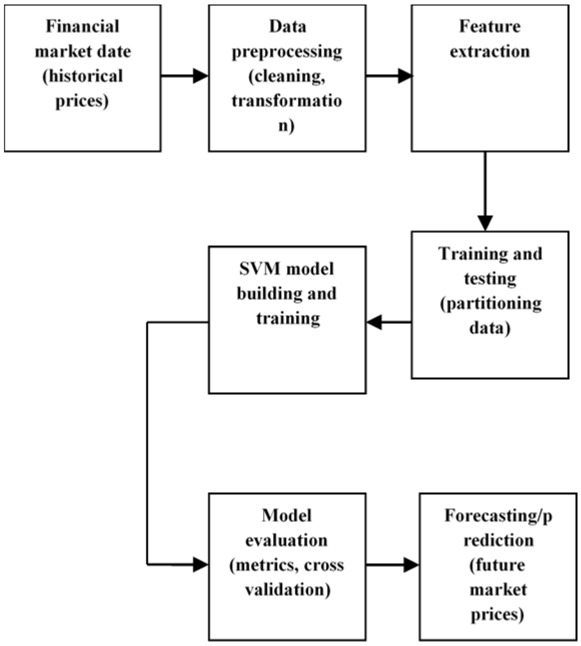

Figure 1 Flow Chart

Conclusion

In conclusion, the integration of the SVM algorithm into the time series forecasting system for financial markets offers a comprehensive and dynamic approach to predicting market movements. The systematic process of feature selection, preprocessing, loading data, and training the model ensures that the system can identify and interpret complex patterns in past financial data. The input modules' thoughtful design enhances user engagement and makes the system more approachable and instructive. Comprehensive testing, both throughout development and after deployment, validates the system's accuracy, robustness, and adaptability. The forecasting model will always be dependable and successful in navigating the complexities of constantly changing market conditions because of the intrinsic nature of financial markets, which makes continuous system improvements possible through ongoing system monitoring and refining.

References

[1]. Li, L. Chen, C. Sun, G. Liu, C. Chen, and Y. Zhang, "Early Mts Forecasting for Dynamic Stock Prediction: A Double Q-Learning Ensemble Approach," IEEE Access, vol. 12, pp. 49878-49894, 2024.

[2]. Ruke, S. Gaikwad, G. Yadav, A. Buchade, S. Namaskar, and A. Sonawane, "A Stock Price Prediction Method Using Bi LSTM and Improved Transformer," in Proceedings of the 4th International Conference on Informatics and Communication Systems (ICDECS), Bangalore, India, March 2024, pp. 1–6

[3]. Yang and J. Wang, "A deep learning-based expert framework for portfolio prediction and forecasting," Proc. Computer Sci., vol. 199, pp. 18-25, January 2022.

[4]. A. Chin and K. Najaf, "Stock Market Forecast Using Transudative Long Short-Term Memory and Social Media Sentiment Analysis," International Journal of Public Sector Performance Management, vol. 1, no. 1, pp. 100–114, 2020.

[5]. W. K. Cheng, K. T. Bea, S. M. H. Leow, J. Y.-L. Chan, Z.-W. Hong, and Y.-L. Chen, "Reinforcement Learning for Stock Prediction and High-Frequency Trading Using T+1 Rules," Mathematics, vol. 10, no. 14, pp. 2437, July 2022.

[6]. Y.-L. Lin, C.-J. Lai, and P.-F. Pai, "Emerging Stock Market Prediction Using the GRU Algorithm: Incorporating Endogenous and Exogenous Variables," Electronics, vol. 11, no. 21, pp. 3513, Oct. 2022.

[7]. C. Wimmer, "Accurate Stock Price Forecasting with Deep Learning and Hierarchical Frequency Decomposition," Johannes Kepler University, Linz, Austria,

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 03 March 2025
Page No: 615-621
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0086

Technical Report 9943, 2022.

[8]. H. Oukhouya, H. Kadiri, K. El Himdi, and R. Guerbaz, "Investigating Stock Prediction Using LSTM Networks and Sentiment Analysis of Tweets Under High Uncertainty: A Case Study for North American and European Banks." Statist., Optim. Inf. Comput., vol. 12, no. 1, pp. 200-209, Nov. 2023.

[9]. Z. Karevan and J. A. K. Suykens. "Short-Term Stock Correlation Forecasting Using CNN-Bi LSTM Enhanced with Attention Mechanism." Neural Networks, vol. 125, pp. 1–9, May 2020.

[10]. R. Li, B. Wang, T. Zhang, and T. Sugi, "A Stock Price Prediction Model Using Investor Sentiment and Optimised Deep Learning," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 31, pp. 1418-1428, 2023.

[11]. X. Zhu, D. Cheng, Z. Zhang, S. Lin, and J. Dai, "Adaptive Feature Subset and Dynamic Trend Indicators for Medium-Term Stock Market Predictions: A 70-Day Forecasting Approach," in Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), October 2019, pp. 6687-6696.

[12]. T. Swathi, N. Kasiviswanath, and A. A. Rao, "Cost Harmonisation: A Light GBM-Based Stock Market Forecast," Appl. Intell., vol. 52, no. 12, pp. 13675-13688, September 2022.

[13]. [P. N. Achyutha, S. Chaudhury, S. C. Bose, R. Kler, J. Surve, and K. Kaliyaperumal, "Stock Index Forecasting using a Novel Integrated Model Based on CEEMDAN and TCN-GRU-CBAM," Math. Problems Eng., vol. 2022, pp. 1-9, April 2022.

[14]. S. Harguem, Z. Chabani, S. Noaman, M. Amjad, M. B. Alvi, M. Asif, M. H. Mehmood, and A. H. Al-Kassem, "Improving Stock Market Prediction: A Robust LSTM-DNN Model Analysis of 26 Real-Life Datasets," in Proc. Int. Conf. Cyber Resilience (ICCR), Oct. 2022, pp. 1-

[15]. Kun Huang, Xiaoming Li, Fangyuan Liu, Xiaoping Yang, And Wei Yu “ML-GAT:A Multilevel Graph Attention Model for Stock Prediction”,pp.8640886422,doi.10.1109/ACCESS.2022.3199008, 2022.