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LEVERAGING MACHINE LEARNING TECHNIQUES TO FORECAST MARKET VOLATILITY IN THE U.S

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ABSTRACT
U.S. financial markets grow more intricate each day, so investors turn to machine learning models for better market volatility predictions. This research reviews Machine Learning models that predict market volatility by looking at their approaches and measuring how effectively they forecast volatility. The review starts with the examination of traditional time-series models and demonstrates their weaknesses in recognizing complex market volatility movements. The analysis then focuses on advanced Machine Learning models. Each model's strengths and weaknesses are scrutinized in the context of volatility forecasting. The paper explores the pivotal role of feature selection and engineering in enhancing the predictive power of ML models for volatility forecasting. Feature sets encompassing financial indicators, macroeconomic variables, sentiment analysis from news articles, and social media data are analyzed for their impact on forecasting accuracy. The review examines how accurate these prediction models are at spotting market volatility. This review explains how machine learning models predict market volatility by showing the various methods used while discussing their strengths and weaknesses. The insights from our research benefit Machine Learning scientists, business experts, and investors who plan to use Machine Learning methods to better handle market volatility. The outcome of this research points towards the need for continual developments in machine learning models for better prediction of volatility.
KEYWORDS: *Market Volatility, Stock Market Forecasting, Machine Learning*

INTRODUCTION
Research on volatility forecasting remains central within financial literature as multiple investigations are conducted on statistical and econometric models according to Dhingra et al. (2024). The volatility domain has used GARCH and its derivative models as its foundational measuring tools since their conception (Rohilla, 2023). The financial crisis of 2007-2008 revealed major limitations within traditional modeling approaches which led researchers to explore sophisticated alternatives (Ramos-Pérez et al., 2019; Adebayo et al., 2025; Amoako et al., 2025).

Investors need accurate market volatility predictions to make good investment choices while reducing exposure to risks and creating reliable trading plans. In recent years, machine learning techniques have improved how well market volatility is predicted (Rouf et al., 2021; Adebayo et al., 2025; Sadhukhan et al., 2022). Researchers must tackle multiple moving elements to predict market volatility with confidence. Traditional approaches predicting market volatility failed because financial markets remain unpredictable and volatile (Rouf et al., 2021; Christensen et al., 2023). As a result, there has been growing interest in employing Machine Learning to enhance volatility forecasting as Machine Learning technology proves more effective than prior methods as Zhang and Lei (2022) explained. Recent studies show that integrating Machine Learning into volatility forecasting will upgrade the field with stronger and more exact predictive tools (Kumar et al., 2022; Sen & Chaudhuri, 2017; Soni et al., 2022).

Empirical research shows strong interest in using machine learning methods to forecast market asset prices (Kumar et al., 2022; Rouf et al., 2021). Machine learning has shown better real-world results than standard statistical and financial models (Sarker, 2021; Christensen et al., 2023; Narteh-Kofi, et al., 2025). The U.S. capital market requires accurate volatility forecasting for successful investment decisions across investors, banks, and policymakers (Agbeve et al., 2025). Investors use this information to spot risks ahead and build safe strategies for their money (Yao et al., 2022). Financial institutions depend on correct volatility estimates to plan their fund allocations and set up secure investment systems (Janabi, 2021; Atisu et al., 2024). Policymakers evaluate market stability through volatility forecasts to take smart actions that keep the financial market balanced (Demirer et al., 2020).

Predicting volatility using Machine Learning is on the rise because it can handle extensive data while recognizing complex patterns that standard statistical methods cannot handle (Zhang & Lei, 2022; Sarker, 2021; Agbadamasi et al., 2025). ML algorithms show better predictive performance than standard forecasting techniques (Christensen et al., 2023). The integration of deep learning algorithms and recurrent neural networks delivers promising performance in understanding market volatility dynamics (Oyewole et al., 2024; Pattanayak, et al., 2024; Ramos-Pérez et al., 2019).
Machine Learning can leverage market volatility forecasting to improve results better than conventional methods while delivering more trustworthy predictions. Market participants in the U.S. financial system can use this technology to make better trading decisions in today's fast-changing market. This research explores the volatility forecasting capabilities of advanced machine learning approaches while collecting data from recent studies and investigating the ability of distinct predictive techniques to boost accuracy and reliability in volatility forecasting.

LITERATURE REVIEW

Stock Market Forecasting

Financial market dynamics such as investor sentiment, economic conditions, and industry trends make forecasting market volatility a difficult task (Hu et al., 2018; Gite et al., 2021). Advanced technology now supports volatility prediction more precisely using artificial intelligence and machine learning despite the traditional theories suggesting that markets move randomly (Guidi et al., 2011; Srivastava et al., 2021). Historical market volatility data helps train models to make forecasts of upcoming patterns according to Yao et al. (2022). Market data combined with sentiment analysis significantly boosts volatility prediction accuracy particularly when deep learning is employed according to Gumus and Sakar (2021). Multiple researchers such as Khedr et al. (2017) and Pathak and Pathak (2020) have explored different methods for volatility forecasting including machine learning methods alongside news sentiment analysis and analytical models. Lin et al. (2022) found that Long Short-Term Memory (LSTM) and Gradient Recurrent Units (GRU) excel at detecting volatility patterns through their experimental research.

Researchers have studied many different methods to measure and forecast market volatility levels. Wang et al. (2019) introduced a hybrid time-series machine learning system to forecast U.S. equity market returns showing similar accuracy to traditional regression methods. Another research used time series decomposition with machine learning and deep learning to predict stock market movements with the finding showing that good results depend on suitable variable selection and model optimization (Chatterjee et al., 2021).

Traditional Time-Series Models for Volatility Forecasting

Analysis of market volatility stands as an essential element that aids multiple financial systems while enabling managers to create effective risk control methods across portfolios and risk assessments. Financial time series models have traditionally become the standard industry technology for predicting stock market and financial market volatility. Using previous market data, these approaches develop models that identify volatility patterns to offer predictions spanning future times (Christensen, 2023).

Among forecasting applications of time-series models the Autoregressive Conditional Heteroskedasticity model stands out widely by utilizing such as the Generalized ARCH model (Rohilla, 2023). These forecasting models were created with the intent to capture financial time series heteroscedasticity which produces variable data variance across different period periods. Research demonstrates the effectiveness of the GARCH models for volatility modeling because it handles volatility clusters and the leptokurtic distributions characteristic of financial returns (Rohilla, 2023; Bhowmik & Wang, 2020).

Traditional volatility forecasting tools such as GARCH models in forecasting volatility in financial markets have been extensively researched in prior studies (Ampountolas, et al., 2024; Mademlis et al., 2021). Financial time series analysis using these models enables volatility prediction which supports both investment decisions and risk oversight approaches (Olukoya et al., 2023)

The Autoregressive Integrated Moving Average (ARIMA) time series model remains the key approach to forecasting volatility**.** In order to attain stationarity, the methodology uses differencing to represent the correlation between volatility observations and their lags (Alshraideh & Runger, 2013)**.** While ARIMA demonstrates strong forecasting performance with financial data a study by Yahaya et al. (2021) shows its inability to handle nonlinear volatility and seasonal patterns.

Conflicting results about which approach provides superior volatility forecasting emerge from studies comparing ARIMA and ARCH/GARCH models (Bhowmik & Wang, 2020). ARCH/GARCH models prove better than ARIMA models for volatility forecasting and simulating non-constant financial data volatility (Setyowibowo et al., 2022).

Advanced Machine Learning Models for Volatility Forecasting
Machine learning models handle volatility forecasting better than traditional methods. Support Vector Machines are effective in market volatility forecasting because of their ability to handle complex data sets with non-linear patterns (Kurani et al., 2023). According to Omar et al., (2022), Support Vector Machines have successfully predicted market volatility patterns and have been helpful when merged with hybrid machine learning techniques. Artificial Neural Networks (ANN) technology stands out in volatility prediction because it analyzes market data patterns to uncover their complex nonlinear relationships. ANNs are very good at identifying patterns, but to avoid overfitting, they need a lot of training data. Random Forests show high accuracy for forecasting realized stock market volatility according to Demirer et al. (2020).

Feature Selection and Engineering for Volatility Forecasting
The fundamental building blocks of volatility forecasting systems are feature engineering and selection. Financial indicators combined with economic factors alongside social media sentiment analysis produce the most accurate results for volatility prediction according to Kelotra and Pandey (2020). According to the findings of Kuosmanen and Vataja (2011), market volatility is associated with changes in economic indicators such as GDP growth, inflation rates, and interest rates. The inclusion of sentiment analysis from news and social media is a useful measure for measuring market sentiment and its role in market volatility.

Volatility forecasting models now integrate alternative data sources regularly to improve their results (Alkhatib et al., 2021). These alternate data sources enhance market outlooks and provide new insights into market dynamics (Sheu et al., 2017). Research shows adding alternative data to financial and macroeconomic indicators enhances volatility forecasting results (Sheu et al. 2017). Studies continue into how multiple data sources affect their predictions and especially their ability to forecast US market volatility.

Model Evaluation Metrics for Volatility Forecasting
Several key metrics are needed to analyze machine learning models that forecast U.S. market volatility. Volatility prediction accuracy requires both Mean Absolute Error (MAE) and Mean Squared Error (MSE) assessment according to Orth (2012)**.** MSE is ideal for forecasting volatility because it assigns more weight to big errors. Moreover, precision, recall, and F1 Score help understand how well the model performs (Naidu et al., 2023)**.** According to Bhambu et al. (2025), effective volatility forecasting needs multiple accuracy standards to check how well each model performs.

High levels of noise in U.S. market data make overfitting a major problem when trying to forecast volatility. According to Demšar & Zupan (2021), this happens when models get used to training data and focus excessively on market noise which results in inaccurate and weak generalization. Several strategies can be adopted to help solve this problem. L2 regularization stands out as an effective method to stop overfitting because it makes models avoid unnecessary complexity according to Kotsilieris et al. (2022)**.** Effective volatility forecasts depend on feature selection according to Zhang et al. (2022), because this technique helps to focus on the best market metrics.

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Comparative Analysis of Volatility Forecasting Models

Investors need market return predictions to properly allocate their asset holdings. Leung et al. (2021) suggested a hybrid machine learning and time series approach to predict long-term U.S. stock market returns which showed results comparable to standard regression techniques.

Comparing U.S. market volatility forecasting models from both traditional and machine learning fields requires a review of historical performance results and a careful assessment of essential success factors. The Popular traditional statistical techniques perform poorly when market volatility fluctuates unpredictably during times of market stress (Zhang et al., 2022). However, Machine Learning techniques perform better than standard models when measuring complex volatility according to both Qiu and Shen (2016) and Guan et al. (2018).

Research by Qiu and Shen (2016) and Zhang et al. (2022) demonstrate that improved artificial neural networks and support vector regression excel at forecasting financial market volatility. Neural network models excel at removing market noise and delivering more precise volatility forecasts according to Guan et al. (2018). The advent of Generative adversarial networks (GANs) and meta-learning approaches has further enhanced the modeling of intricate volatility patterns (Dael et al., 2023; Zhao et al., 2023).

To effectively predict volatility, markets must use various indicators along with traditional volatility data like trading volumes, daily price ranges, and market cross-market factors (Guan et al. 2019). Combining wavelet decomposition with N-BEATS improves forecasting accuracy according to recent research by Singhal et al. (2022). Financial networks can predict market volatility better, thus emphasizing their relevance when dealing with interconnected markets according to Magner et al. (2020).

Challenges and Opportunities in Volatility Forecasting

U.S. market volatility forecasting faces key implementation hurdles with regards to Machine Learning (Olubusola et al., 2024)**.** The major difficulty involves discovering which features have the strongest effect on how Machine Learning models predict volatility**.** Market volatility is inherently non-linear and dynamic making forecasting harder (Olubusola et al., 2024; Behera et al., 2024)**.** Another major obstacle is analyzing how analysts' biases affect their forecasting performance (Baird, 2019; Olubusola et al., 2024).

There are various paths to improve volatility forecasts using machine learning despite the current difficulties. Advanced Machine Learning methods demonstrate solid potential according to previous research findings (Christensen et al., 2023; Shah et al., 2019). Scholars focus on forecasting the trends of market volatility (Gunnarsson et al., 2024). Hybrid ML algorithms extend the possibilities for better volatility prediction (Kumar, et., 2025). Ensemble learning models and deep learning algorithms hold great potential to increase forecast accuracy according to Liu et al. (2019)

Volatility forecasting requires ethical standards and ways to avoid biases. According to Baird (2019), the relationship between market volatility and consensus predictions coupled with the biases of analysts creates ethical problems that need to be addressed. Improving these issues helps in building forecasting models that produce reliable results for every stakeholder in the U.S. capital market.

The recent developments in volatility forecasting methods indicate a shift towards advanced techniques that help explain the complexities in the U.S. capital market dynamics better while maintaining high ethical standards and fixing outcome bias problems.

Systematic Analysis of Literature on Stock Market Forecasting Using Machine Learning

Author(s)	Year	Methodology	Theory (if any)	Findings
Ajiga et al.	2024	Review of ML models in stock forecasting	N/A	Compared various ML algorithms including SVM, RF, and LSTM. Found deep learning models perform better in complex market scenarios.
Alkhatib et al.	2021	Time series forecasting and regional analysis	N/A	COVID-19 had a significant impact on GCC markets. ARIMA and VAR models are useful in short-term forecasting.
Alshraideh & Runger	2013	Hidden Markov Models (HMM) for process monitoring	Markov process theory	HMM effectively detects structural changes and anomalies in time-series data. Applicable to financial forecasting.
Ampountolas	2024	GARCH and Support Vector Regression (SVR)	Time-series econometrics	GARCH-SVR hybrid models enhance forecasting accuracy in financial and commodity markets.
Ansari et al.	2022	Deep Reinforcement Learning (DRL)	Reinforcement learning theory	Developed DRL-based decision support for automated trading. Significantly outperformed traditional strategies.
Atsalakis et al.	2015	Neuro-fuzzy systems	N/A	Neuro-fuzzy models improve prediction in turbulent markets, capturing nonlinear patterns effectively.
Baird	2019	Quantitative analysis	N/A	Investors often fail to correct for biases in analyst forecasts, indicating inefficiency in recognizing forecasting errors.
Behera et al.	2024	Comparative analysis of ML models for volatility	N/A	ML models like LSTM and RF provide better volatility prediction than traditional statistical methods.
Bhambu et al.	2025	Neural network-based volatility forecasting	Model conditional heteroscedasticity theory	Neural networks enhance high-frequency volatility forecasting, beneficial for intraday trading and risk analysis.
Bhowmik & Wang	2020	Systematic literature review	N/A	Synthesized insights from volatility-return literature. Identified increasing shift toward ML methods in volatility modeling.
Bhuvaneshwari	2020	Multi-agent deep reinforcement learning	N/A	Integrates multiple data sources for robust stock forecasting. Deep RL improves adaptability and decision-making.
Chatterjee et al.	2021	Comparative study of forecasting models	N/A	Found deep learning (especially LSTM) to outperform classical time-series models for stock price prediction.
Christensen et al.	2023	Comparative study of machine learning algorithms	N/A	Applied various ML algorithms to volatility forecasting. Random Forest and XGBoost delivered strong results.
Demirer et al.	2020	Random Forecasts (ML technique)	N/A	Industry-specific returns offer predictive value for market-wide volatility. Boosted forecasting accuracy.
Demšar & Zupan	2021	Educational analysis on overfitting	Machine learning theory	Emphasized practical implications of overfitting in model generalization. Valuable for financial data modeling.

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Author(s)	Year	Methodology	Theory (if any)	Findings
Dhingra et al.	2024	Systematic literature review	N/A	Reviewed volatility forecasting techniques; ML methods were found superior in dynamic environments.
Feuerriegel & Gordon	2018	Time Series Analysis	Information theory	Used text disclosures for long-term stock index prediction. Textual data was found to be a strong leading indicator.
Ghamdi	2019	Technical analysis with R programming	N/A	Analyzed Saudi equity market using TA indicators. Found indicators like RSI and MACD effective for trend detection.
Gite et al.	2021	Sentiment analysis with NLP	N/A	Combined financial news and ML for stock prediction. Sentiment features improved forecast accuracy and interpretability.
Guidi et al.	2011	Market efficiency testing in Eastern Europe	Efficient Market theory	Found weak-form inefficiency and calendar anomalies in multiple Eastern European equity markets.
Gumus & Sakar	2021	Hybrid of price data and sentiment analysis	N/A	The fusion of technical indicators and sentiment scores improves market movement prediction accuracy.
Gunnarsson et al.	2024	Literature review on AI in volatility forecasting	N/A	Surveyed AI/ML tools in predicting implied and realized volatility. Identified potential in hybrid model approaches.
Hu et al.	2018	Ensemble learning with market data	N/A	Used attention mechanism and ensemble deep learning to extract predictive features from noisy financial data.
Janabi	2021	ML-based portfolio analytics under liquidity constraints	Optimization theory	Presented optimization models that adapt to time-varying liquidity. ML enhances asset selection and risk balancing.
Jishtu et al.	2022	Sentiment and ML for price prediction	N/A	Sentiment from news combined with ML algorithms led to better short-term price prediction accuracy.

Future Outlook and Emerging Trends in Volatility Forecasting

In recent years, technological advancement has transformed the forecasting of U.S. capital market volatility**.** Researchers have now focused on investigating modern techniques such as deep reinforcement learning-based decision support systems and text mining of regulatory disclosures to help forecast market volatility (Feuerriegel & Gordon, 2018; Ansari et al., 2022). Moreover, conducting sentiment analysis of social media data now provides useful insights into market turbulence before it happens**.** According to Bhuvaneshwari (2020) and Ajiga (2024), the use of multi-source data with tolerance-based multi-agent deep reinforcement learning improves the prediction of intricate volatility patterns.

Neuro-fuzzy systems consistently deliver better results when predicting market volatility during times of turbulence according to Atsalakis et al. (2015)**.** The analysis of important market trends using technical tools and market events is crucial in predicting volatility behavior in markets (Ghamdi, 2019). Support vector classification and regression have been very successful when forecasting the directional changes in market volatility according to Li and Liu (2014) whereas fuzzy logic models produce superior results when predicting short-term market volatility movements according to Koirala and Aabhas (2021).

Jishtu et al. (2022) posits that volatility patterns are easily predicted when sentiment analysis is employed together with machine learning technology. Combining different sources of data such as regulatory disclosure and social media opinions helps forecast volatility better than past methods**.** Models that forecast volatility better during market turbulence emphasize the need for forecasting techniques that can adjust to changing market conditions.

CONCLUSIONS

This research into machine learning for U.S. capital market volatility prediction delivers important findings. Traditional time-series techniques lack effectiveness in understanding market volatility patterns yet modern machine learning approaches such as Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) outperform them in pattern detection. Key components of Machine Learning are feature selection and engineering, especially when it relates to the integration of data from different sources such as sentiment analysis and financial metrics.

The research points towards the need for continual developments in machine learning models dedicated to better prediction of volatility**.** Integrating financial knowledge with machine learning models produces accurate volatility forecasting results**.** It will be beneficial for finance experts and players in the financial industry to understand the strengths of multiple models used to predict market volatility so they can make better choices for their practice.

Recommendations

The research suggests that investors should carefully evaluate the strengths and weaknesses of machine learning volatility predictions**.** To make sound decisions, investors need full disclosure of how models work and accurate information about prediction reliability.

Moving forward, based on the findings of this research, the following key issues need to be addressed:

i. Further development of volatility forecasting models that work better in unstable market environments.
ii. Enhanced integration of real-time sentiment analysis and market signals into volatility models
iii. Improved techniques for early detection of volatility regime changes
iv. Development of more robust feature selection methods for volatility prediction

The result of this review shows that successful volatility forecasting depends on ongoing teamwork between professionals and researchers in the development and implementation of machine learning models**.** The focus needs to be to develop models that forecast U.S. market volatility based on clear pattern recognition while staying reliable during all market situations.

REFERENCES

1. *Adebayo, O., Mensah, N., Adukpo, T. K. (2025). Beyond Cash Flow Management: How Machine Learning and Scenario Planning Drive Financial Resilience. EPRA International Journal of Economics, Business and Management Studies (EBMS), 12(3), 81-89. https://doi.org/10.36713/epra20503*
2. *Adebayo, O., Mensah, N., Adukpo, T. K. (2025). Navigating Liquidity Management Challenges in the Era of Digital Banking in the United States. World Journal of Advanced Research and Reviews, 25(2), 2711-2719. https://doi.org/10.30574/wjarr.2025.25.2.0576*
3. *Agbeve, V., Adukpo, T. K., Mensah, N., Appiah, D., Atisu, J. C. (2025). Comparative Analysis of Digital Banking and Financial Inclusion in the United States: Opportunities, Challenges and Policy Implications. Asian Journal of Economics, Business and Accounting, 25(3), 452-467. https://doi.org/10.9734/ajeba/2025/v25i31722*
4. *Ajiga, D. I., Adeleye, R. A., Tubokirifuruar, T. S., Bello, B. G., Ndubuisi, N. L., Asuzu, O. F., & Owolabi, O. R. (2024). Machine learning for stock market forecasting: a review of models and accuracy. Finance & Accounting Research Journal, 6(2), 112-124.*
5. *Alkhatib, K., Almahmood, M., Elayan, O., & Abualigah, L. (2021). Regional analytics and forecasting for most affected stock markets: the case of GCC stock markets during the COVID-19 pandemic. International Journal of Systems Assurance Engineering and Management, 13(3), 1298-1308. https://doi.org/10.1007/s13198-021-01445-9*
6. *Alshraideh, H., & Runger, G. (2013). Process monitoring using hidden markov models. Quality and Reliability Engineering https://doi.org/10.1002/qre.1560 International, 30(8), 1379-1387.*
7. *Amoako, E.K.W., Boateng, V., Ajay, O., Adukpo, T.K., Mensah, N. (2025). Exploring the Role of Machine Learning and Deep Learning in Anti-Money Laundering (AML) Strategies within U.S. Financial Industry: A Systematic Review of Implementation, Effectiveness, and Challenges. Finance & Accounting Research Journal, 7(1). https://doi.org/10.51594/farj.v7i1.1808*
8. *Ampountolas, A. (2024). Enhancing forecasting accuracy in commodity and financial markets: Insights from garch and svr models. International Journal of Financial Studies, 12(3), 59.*
9. *Ansari, Y., Yasmin, S., Naz, S., Zaffar, H., Ali, Z., Moon, J., … & Rho, S. (2022). A deep reinforcement learning-based decision support system for automated stock market trading. IEEE Access, 10, 127469-127501. https://doi.org/10.1109/access.2022.3226629*
10. *Atisu, J. C., Mensah N., Alipoe, S. A., Rahman, S. A. (2024). The Effect of Non-Performing Loans on the Financial Performance of Commercial Banks in Ghana. Iosr Journal of Economics and Finance, 15(5), 42-48.*

https://doi.org/10.9790/5933-1505054248
11. *Atsalakis, G., Protopapadakis, E., & Valavanis, K. (2015). Stock trend forecasting in turbulent market periods using neuro-fuzzy systems. Operational Research, 16(2), 245-269. https://doi.org/10.1007/s12351-015-0197-6*
12. *Baird, P. (2019). Do investors recognize biases in securities analysts' forecasts?. Review of Financial Economics, 38(4), 623-634. https://doi.org/10.1002/rfe.1094*
13. *Behera, I., Nanda, P., Mitra, S., & Kumari, S. (2024). Machine Learning Approaches for Forecasting Financial Market Volatility. Machine Learning Approaches in Financial Analytics, 431-451.*
14. *Bhambu, A., Bera, K., Natarajan, S., & Suganthan, P. N. (2025). High frequency volatility forecasting and risk assessment using neural networks-based heteroscedasticity model.*
15. *Bhowmik, R., & Wang, S. (2020). Stock Market Volatility and Return Analysis: A Systematic Literature Review [Review of Stock Market Volatility and Return Analysis: A Systematic Literature Review]. Entropy, 22(5), 522. Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/e22050522*
16. *Bhuvaneshwari, C. (2020). Stock market forecasting from multi-source data using based tolerance-based multi-agent deep reinforcement learning. International Journal of Engineering and Advanced Technology, 9(3), 3492-3499. https://doi.org/10.35940/ijeat.c6293.029320*
17. *Chatterjee, A., Bhowmick, H., & Sen, J. (2021). Stock Price Prediction Using Time Series, Econometric, Machine Learning, and Deep Learning Models. In 2021 IEEE Mysore Sub Section International Conference (MysuruCon) (p. 289). https://doi.org/10.1109/mysurucon52639.2021.9641610*
18. *Christensen, K., Siggaard, M., & Veliyev, B. (2023). A machine learning approach to volatility forecasting. Journal of Financial Econometrics, 21(5), 1680-1727.*
19. *Demirer, R., Gupta, R., & Pierdzioch, C. (2020). Forecasting realized stock-market volatility: do industry returns have predictive value?. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3744537*
20. *Demšar, J., & Zupan, B. (2021). Hands-on training about overfitting. PLOS Computational Biology, 17(3), e1008671. https://doi.org/10.1371/journal.pcbi.1008671*
21. *Dhingra, B., Batra, S., Aggarwal, V., Yadav, M., & Kumar, P. (2024). Stock market volatility: a systematic review. Journal of Modelling in Management, 19(3), 925-952.*
22. *Feuerriegel, S., & Gordon, J. (2018). Long-term stock index forecasting based on text mining of disclosures. Decision Support Systems, 112, 88-97. https://doi.org/10.1016/j.dss.2018.06.008*
23. *Ghamdi, M. (2019). The role of technical analysis indicators over equity market (nomu) with R programing language. International Journal of Advanced Computer Science and Applications, 10(6). https://doi.org/10.14569/ijacsa.2019.0100660*
24. *Gite, S., Khatavkar, H., Kotecha, K., Srivastava, S., Maheshwari, P., & Pandey, N. (2021). Explainable stock prices prediction from financial news articles using sentiment analysis. In PeerJ Computer Science (Vol. 7). PeerJ, Inc. https://doi.org/10.7717/peerj-cs.340*
25. *Guidi, F., Gupta, R., & Maheshwari, S. (2011). Weak-form market efficiency and calendar anomalies for eastern Europe equity markets. Journal of Emerging Market Finance, 10(3), 337-389. https://doi.org/10.1177/097265271101000304*
26. *Gumus, A., & Sakar, C. (2021). Stock market prediction by combining stock price information and sentiment analysis. International Journal of Advances in Engineering and Pure Sciences, 33(1), 18-27. https://doi.org/10.7240/jeps.683952*
27. *Gunnarsson, E. S., Isern, H. R., Kaloudis, A., Risstad, M., Vigdel, B., & Westgaard, S. (2024). Prediction of realized volatility and implied volatility indices using AI and machine learning: A review. International review of financial analysis, 103221.*
28. *Hu, Z., Liu, W., Bian, J., Liu, X., & Liu, T. (2018). Listening to chaotic whispers. https://doi.org/10.1145/3159652.3159690*
29. *Janabi, M. (2021). Optimization algorithms and investment portfolio analytics with machine learning techniques under time-varying liquidity constraints. Journal of Modelling in Management, 17(3), 864-895. https://doi.org/10.1108/jm2-10-2020-0259*
30. *Jishtu, P., Prajapati, H., & Fiaidhi, J. (2022). Prediction of the stock market based on machine learning and sentiment analysis. https://doi.org/10.36227/techrxiv.21692852*
31. *Kelotra, A., & Pandey, P. (2020). Stock market prediction using optimized deep-convlstm model. Big Data, 8(1), 5-24. https://doi.org/10.1089/big.2018.0143*
32. *Khedr, A., Salama, S., & Yaseen, N. (2017). Predicting stock market behavior using data mining technique and news sentiment analysis. International Journal of Intelligent Systems and Applications, 9(7), 22-30. https://doi.org/10.5815/ijisa.2017.07.03*
33. *Koirala, J., & Aabhas, S. (2021). Forecasting stock market momentum in Nepal: application of fuzzy logic model. International Research Journal of Management Science, 6(1), 17 28. https://doi.org/10.3126/irjms.v6i1.42335*
34. *Kotsilieris, T., Anagnostopoulos, I., & Livieris, I. (2022). Special issue: regularization techniques for machine learning and their applications. Electronics, 11(4), 521. https://doi.org/10.3390/electronics11040521*

35. *Kumar, D., Sarangi, P. K., & Verma, R. (2022). A systematic review of stock market prediction using machine learning and statistical techniques. Materials Today: Proceedings, 49, 3187-3191.*
36. *Kumar, S., Rao, A., & Dhochak, M. (2025). Hybrid ML Models for Volatility Prediction in Financial Risk Management. International Review of Economics & Finance, 103915.*
37. *Kuosmanen, P., & Vataja, J. (2011). The role of stock markets vs. the term spread in forecasting macrovariables in Finland. The Quarterly Review of Economics and Finance, 51(2), 124-132. https://doi.org/10.1016/j.qref.2011.01.005*
38. *Kurani, A., Doshi, P., Vakharia, A., & Shah, M. (2023). A comprehensive comparative study of artificial neural network (ANN) and support vector machines (SVM) on stock forecasting. Annals of Data Science, 10(1), 183-208.*
39. *Leung, E., Lohre, H., Mischlich, D., Shea, Y., & Stroh, M. (2021). The Promises and Pitfalls of Machine Learning for Predicting Stock Returns. In The Journal of Financial Data Science (Vol. 3, Issue 2, p. 21). https://doi.org/10.3905/jfds.2021.1.062*
40. *Li, X., & Liu, P. (2014). Prediction of the moving direction of google inc. stock price using support vector classification and regression. Asian Journal of Finance & Accounting, 6(1), 323. https://doi.org/10.5296/ajfa.v6i1.5485*
41. *Lin, Z., Tian, F., & Zhang, W. (2022). Evaluation and analysis of an LSTM and GRU based stock investment strategy. 1615-1626. https://doi.org/10.2991/978-94-6463-052-7_179*
42. *Liu, J., Lin, C., & Chao, F. (2019). Gradient boost with convolution neural network for stock forecast. 155-165. https://doi.org/10.1007/978-3-030-29933-0_13*
43. *Mademlis, D. K., & Dritsakis, N. (2021). Volatility forecasting using hybrid GARCH neural network models: the case of the Italian stock market. International Journal of Economics and Financial Issues, 11(1), 49.*
44. *Naidu, G., Zuva, T., & Sibanda, E. M. (2023, April). A review of evaluation metrics in machine learning algorithms. In Computer science on-line conference (pp. 15-25). Cham: Springer International Publishing.*
45. *Narteh-Kofi, E., Asamoah, E., Adukpo, T. K., Mensah, N. (2025). Mergers and Acquisitions in the U.S. Capital Market: Theoretical Foundations, Market Dynamics and Strategic Implications. EPRA International Journal of Economics, Business and Management Studies (EBMS), 12(3), 71-80. https://doi.org/10.36713/epra20500*
46. *Olubusola, O., Mhlongo, N. Z., Daraojimba, D. O., Ajayi-Nifise, A. O., & Falaiye, T. (2024). Machine learning in financial forecasting: A US review: Exploring the advancements, challenges, and implications of AI-driven predictions in financial markets. World Journal of Advanced Research and Reviews, 21(2), 1969-1984.*
47. *Olukoya, O. (2023). Time series-based quantitative risk models: enhancing accuracy in forecasting and risk assessment. International Journal of Computer Applications Technology and Research, 12(11), 29-41.*
48. *Omar, A., Huang, S., Salameh, A., Khurram, H., & Fareed, M. (2022). Stock market forecasting using the random forest and deep neural network models before and during the covid-19 period. Frontiers in Environmental Science, 10. https://doi.org/10.3389/fenvs.2022.917047*
49. *Orth, W. (2012). The predictive accuracy of credit ratings: measurement and statistical inference. International Journal of Forecasting, 28(1), 288-296. https://doi.org/10.1016/j.ijforecast.2011.07.004*
50. *Oyewole, A. T., Adeoye, O. B., Addy, W. A., Okoye, C. C., Ofodile, O. C., & Ugochukwu, C. E. (2024). Predicting stock market movements using neural networks: a review and application study. Computer Science & IT Research Journal, 5(3), 651-670.*
51. *Pathak, A., & Pathak, S. (2020). Study of machine learning algorithms for stock market prediction. International Journal of Engineering Research, V9(06). https://doi.org/10.17577/ijertv9is060064*
52. *Pattanayak, A. M., Swetapadma, A., & Sahoo, B. (2024). Exploring Different Dynamics of Recurrent Neural Network Methods for Stock Market Prediction-A Comparative Study. Applied Artificial Intelligence, 38(1), 2371706.*
53. *Ramos-Pérez, E., González, P. J. A., & Núñez-Velázquez, J. J. (2019). Forecasting volatility with a stacked model based on a hybridized Artificial Neural Network. In Expert Systems with Applications (Vol. 129, p. 1). Elsevier BV. https://doi.org/10.1016/j.eswa.2019.03.046*
54. *Rohilla, A. (2023). Exploring Volatility: Evolution, Advancements, Trends, and Applications. Indian Journal of Economics and Finance (IJEF), 3(2), 73-79.*
55. *Rouf, N., Malik, M. B., Arif, T., Sharma, S., Singh, S., Aich, S., & Kim, H. C. (2021). Stock market prediction using machine learning techniques: a decade survey on methodologies, recent developments, and future directions. Electronics, 10(21), 2717.*
56. *Sadhukhan, S., Gopaliya, S. M., & Jain, P. (2022). A novel approach to quantify volatility prediction. In arXiv (Cornell University). Cornell University. https://doi.org/10.48550/arxiv.2211.00528*
57. *Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. SN computer science, 2(3), 160.*
58. *Sen, J., & Chaudhuri, T. D. (2017). A Robust Predictive Model for Stock Price Forecasting.*
59. *Setyowibowo, S., As' ad, M., Sujito, S., & Farida, E. (2022). Forecasting of daily gold price using arima-garch hybrid model. Jurnal Ekonomi Pembangunan, 19(2), 257-270.*
60. *Shah, D., Isah, H., & Zulkernine, F. (2019). Stock market analysis: a review and taxonomy of prediction techniques. International Journal of Financial Studies, 7(2), 26. https://doi.org/10.3390/ijfs7020026*

61. *Sheu, S., Lin, C., Lu, S., Tsai, H., & Yanchun, C. (2017). Forecasting the volatility of a combined multi-country stock index using GWMA algorithms. Expert Systems, 35(3). https://doi.org/10.1111/exsy.12248*
62. *Smith, G., & Dyakova, A. (2013). African stock markets: efficiency and relative predictability. South African Journal of Economics, 82(2), 258-275. https://doi.org/10.1111/saje.12009*
63. *Soni, P., Tewari, Y., & Krishnan, D. (2022). Machine learning approaches in stock price prediction: a systematic review. Journal of Physics Conference Series, 2161(1), 012065. https://doi.org/10.1088/1742-6596/2161/1/012065v*
64. *Srivastava, A., Srivastava, A., Singh, S., Sugandha, S., & Gupta, S. (2021). Design of machine learning classifier for stock market prediction. SN Computer Science, 3(1). https://doi.org/10.1007/s42979-021-00970-5*
65. *Wang, H., Ahluwalia, H., Aliaga-Díaz, R., & Davis, J. H. (2019). The Best of Both Worlds: Forecasting US Equity Market Returns using a Hybrid Machine Learning – Time Series Approach. In SSRN Electronic Journal. RELX Group (Netherlands). https://doi.org/10.2139/ssrn.3497170*
66. *Yahaya, A., Etuk, E., & Amos, E. (2021). Comparative performance of arima and garch model in forecasting crude oil price data. Asian Journal of Probability and Statistics, 251-275. https://doi.org/10.9734/ajpas/2021/v15i430378*
67. *Yao, W., Zhang, Y., Chang, S., Li, J., Zhao, Q., & Ge, F. (2022). Stock price analysis and forecasting based on machine learning. https://doi.org/10.1117/12.2662176*
68. *Zhang, J., & Lei, Y. (2022). Deep reinforcement learning for stock prediction. Scientific Programming, 2022, 1-9. https://doi.org/10.1155/2022/5812546*