Machine Learning Models for Predicting Stock Market Volatility

Bhagirath Koli [1] * , Prajwal Shinde [2] , Gaurangi Dhuri [3]

1. Research Scholar, MSc Data science, Shri Dr. D. Y. Patil Arts, Commerce, Science College, Pimpri, Pune, Maharashtra , India
kolibhagirath86@gmail.com ,

2. Research Scholar, Data Science, Indian Institute of Technology, Chennai, Tamil Nadu, India ,

3. Research Scholar, MSc Bioinformatics, Bharati Vidyapeeth University, Pune, Maharashtra, India

Abstract: The stock market is predictably unpredictable in some ways, but it is how financial experts handle each part of the system that determines the overall success of the market. Understanding how unpredictable, or how volatile, the market is will allow one to estimate the required risk making it a volatile market and execute plans based on that market estimation. Though there is a time and place for the ARCH and GARCH models, linear models usually fail as the market is complex, dynamic and non-linear. Predicting complex financial models is possible and ML (machine learning) models, a type of computational intelligence, should be applied. In this paper, I will focus on various ML methods to predict stock market volatility using historical stock market data and technical indicators I constructed to train the various ML models I created. I then evaluated the accuracy of these models using Mean Average Error (MAE) and Root Mean Squared Error (RMSE). I compared both LSTM ML model and GARCH model, where I concluded both work best for market prediction but LSTM is the most adaptive for market changes. The research shows how machine learning tools come with great predictive accuracy while forecasting volatility, with high efficiency in risk management in current financial markets.

Keywords: Machine learning, stock market volatility, LSTM, Random Forest, volatility forecasting, financial risk

-------------------------------- X --------------------------------

INTRODUCTION

The stock market is constantly changing, with prices of assets changing all the time. So, understanding the market's volatility is essential. For investors, traders, and policy makers, assessing the uncertainty and risk in market movements is crucial. Forecasting volatility is important for effective portfolio management, derivative pricing, and risk mitigation (Del Nero, L. 2025). Econometric models such as Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized ARCH (GARCH) have captured time-varying forecasting volatility and clustering. Still, ARCH and GARCH models lost predictive power due to linearity, stationarity, and normality assumptions. Complex, nonlinear patterns, and sudden changes in the market have irrational movements that seem to dominate forecasting (Mansilla-Lopez, J. & Mauricio, D. 2025). Recently, machine learning techniques for financial forecasting with predictive power have given complex and irrational pattern forecasting nonlinear models. Random Forests, Support Vector Regression, Artificial Neural Networks, and Long Short-Term Memory networks machine learning models create and revise predictions based on historical price movements, technical indicators, and macroeconomic variables (Saberironaghi, M. & Ren, J. 2025). Also, with automated feature selection, hyperparameter tuning, and the ensemble's combination, machine learning models improve predictive performance. Machine learning can fill the gap between classical statistical approaches and the modern demands of financial analysis by

enhancing decision-making processes and risk management and offering prompt insights into fluctuating markets (Muhammad, D. 2024).

Background of Stock Market Volatility

Volatility creates uncertainty and makes estimating risk more difficult. The chances and rapid changes presented by high volatility can be difficult for traders, investors, and policymakers to navigate. Estimating and understanding the risk volatility poses is essential to risk management, derivative pricing, and managing a portfolio. Estimating volatility hasn been the focus of highly explored and documented research. Econometric models and statistical models, like the ARCH and GARCH models, have captured the changing cluster of volatility, and the time nature of the volatility, but models which helped develop understanding and research of volatility, have fundamental weaknesses of assuming linearity and stationarity (Díaz, J. D. 2024). With the availability of high frequency (over a short time) and varying (different)financial data, outside the traditional ARCH and GARCH models, alternative approaches to modeling volatility and estimating GARCH models. Predicting future volatility remains a complex and difficult problem to solve in finance (Campisi, G. 2024).

Emergence of Machine Learning in Financial Forecasting

Machine learning has become a very useful option for forecasting finances. Machine learning has random forests, support vector machines, artificial neural networks, and long short-term memory networks, which capture even the most complicated nonlinear relations and capture relations without the complicated statistical assumptions . Machine and human learning both capture the historical data recorded with stock prices, and various indicators like technical, macroeconomic, and market sentiment, and capture future price changes, predicting the price volatility even better to possibly a greater extent than conventional models (Chen, Y. & Hao, Y. 2023). Machine learning models can even adapt to new, changing market situations, uncover hidden relationships throughout complex and tricky model data, and lessen bias throughout the model. Therefore, machine learning is the most appropriate model for nonstationary, financial models which are very volatile. Lastly, the shift from model-driven volatility forecasting to machine learning, a data-driven approach, has increased the value of knowledge for risk managers and investors with its accurate volatility for better, more informed, and timely actionable decisions (Muñoz, J. M. 2023).

LITERATURE REVIEWS

Zhang, C. & Zhang, Y. (2022) Various kinds of research works have been done to focus on the use of machine learning and deep learning models to predict stock markets and recognize complex and nonlinear patterns within financial data. time series data. Examples of deep learning models that excel at recognizing and remembering set "patterns" within time series data are Long Short Term Memory (LSTM) networks and Convolutional Neural Networks (CNN). Meanwhile, older machine learning models such as Support Vector Machines (SVM) and Random Forests are still strong and results are easier to understand. In the market prediction context, even if deep learning models perform better and have higher accuracy, they use more steam and are more complicated than older machine learning models with less accuracy. The right input characteristics to focus on, such as historical volatility, trading volume, and technical indicators, can

strengthen the future prediction results. Challenges that need to be solved are data quality, market noise and overfitting. The use of machine learning models to predict stock market volatility has shown a considerable gain in precision and flexibility relative to older econometric models.

Ramos-Pérez, E. & Alonso-González, P. J. (2021) People are beginning to deploy machine learning methods to analyze stock market volatility and developing methods that are not entirely econometric in nature. Non-linear, complex, and variable market relationships are learned and identified using predictive models such as Random Forests, Support Vector Regression (SVR), and Artificial Neural Networks (ANN). To teach/train these models, stock price history, and volatility indices, as well as custom designed technical indicators (like moving averages, RSI, and Bollinger Bands), are incorporated. Recent work highlights that predictive performance relies as much (if not more) on advanced feature engineering, hyperparameter tuning, and other sophisticated methods of data preprocessing as it does on good model choice. Although industry standards for predictive modeling have been (and, to some extent, still are) GARCH-type models, machine learning predictive models have proven to be more accurate, and resilient predictive market models, than GARCH-type models, especially during high volatility, sudden price changes, and other market conditions underlying predictive models. Precise measures of volatility, along with the above, improve dynamic portfolio optimization, trading, risk management, and strategy formation - all of which are important to investors, risk managers, and policymakers. This speaks to the increasing interest in machine learning for financial market analysis.

Ferreira, I. H. & Medeiros, M. C. (2021) There's a lot of talk about how valuable machine learning can be when paired with analytical forecasting within volatility. Some focus on the endogenous predictors which may include trading volume, price, price trends, or technical indicators, while others step away from the market and consider predictors within macroeconomics, geopolitics, and psychology. The use of various machine learning techniques such as Decision Trees, Neural Networks, and Support Vector Machines bolsters prediction accuracy through the analysis of multiple correlating factors. The market scenario, volatility, and explanation variable assessments on which machine learning does predictive simulation strengthens the value of the market when combined with simulation. Several studies have demonstrated enhanced performance of models which use a wider range of historical and technical indicators alongside macroeconomic data, as opposed to ones which used price data primarily. This underscores the need for more data. Having machine learning be of practical use to finance, strategy development and risk management still requires data driven computational methods to be performed as a great deal of it still needs to be performed.

Fischer, T. & Krauss, C. (2018) Various research have been done to analyze multiple ML techniques to determine the most efficient ways to predict volatility. The models are compared based on Mean Absolute Error, Root Mean Square Error, R- squared value, and directional accuracy Predictions volatility is an area mastered by LSTM networks, as they cover long- term temporal dependencies especially on sequential financial data. The stability of Random Forest models is impressive as they quantify and qualify the relationships among the variables and highlight the most important features, thus aiding in interpretability. Smaller datasets and parameter tuning are most the drawbacks of SVR and ANN models, which perform well. The studies also assess predictive accuracy as well as the performance of the models during highly volatile market periods. The relatively high performance of deep learning models as compared to classical

methods of econometric models was able to influence the focus of several studies. The highlights were the function of selection features, hyperparameter tuning, and the other facets predictive models to provide consistent prediction. These studies highlight the value of hybrid or ensemble methods as they are directed at practitioners or researchers.

RESEARCH METHODOLOGY

Model Selection

To examine the usefulness of different quantitative models, both classic econometrics and state-of-the-art machine learning approaches are used. The core model is the GARCH model which is used because of the ability to detect and estimate the conditional variance of time-heteroskedastic financial data. Besides, GARCH models the conditional relationships of the financial data streams which are of primary focus. To expand the GARCH model's capabilities, machine learning approaches are tried because of the nonlinear dynamics and unstructed data in the market. Among the machine learning approaches are Random Forest (RF) Regressor, Support Vector Regression (SVR), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM) Neural Network. Random Forest does well in staying robust to noise and overfitting, while SVR captures nonlinear relationships well through kernel methods. Inspired by the brain, the ANN is designed to learn the nonlinear functions that and mappings between the input and output data. LSTMs are great for sequential data like stock prices. They capture the time series dependencies really well and are excellent for learning long-term spanning patterns. These different methods help to figure out which techniques--linear, nonlinear and deep learning-- are most effective at estimating volatility in the market.

Model Training and Validation

A well thought out approach to training and validation aids in the creation of strong and balanced models. The dataset was divided into three parts: 70% was used for training the models, 15% for validating, and 15% for testing. This split allowed the models to learn the data, then evaluate the data, and finally understand the performance on data they had never seen before. For the data sets that contained a time component, the rolling-window or expanding-window technique was those time sensitive sets. To strengthen the findings even more, Cross validation, and specifically Time-Series K-Fold validation, was employed. Hyper-parameter tuning for each individual model was achieved through the Grid or Random Search technique which included the tree number for Random Forest, kernel parameters for SVR, and the layer of neurons for ANN and LSTM. Some features were scaled and others were normalized to enhance the model's numerical stability. To limit overfitting, dropout in neural networks and pruning for tree based models were used. An iterative approach was taken for model assessment by comparing the validation set results to the training results. This helped minimize bias and overfitting. Well-designed training and testing work provide assurance that the models are correct and, more importantly, they adapt to different market changes.

Performance Metrics

When the model's volatility predictions were tested, the focus was on how accurately and dependably the model forecasted volatility using quantitative metrics. The main metrics used were Mean Absolute Error

(MAE) and Root Mean Square Error (RMSE) along with R-squared (R²). While each "MAE captures the average magnitudes of error and the absolute difference between a predicted and an actual value which aids an intuitive understanding of the prediction." RMSE "punishes" larger errors and captures overall predictive "sensitivity" which is why it was used to assess the model's "diagnostic" and out of sample predictive "precision" RMSE and R Squared. Moreover, Directional Accuracy (DA) evaluates the predictive models within the scope of trading by automatically predicting volatility in terms of increase or decrease, which is essential in trading models that focus on volatility. Forecast accuracy was also assessed using the statistical significance tests amongst various models and the Diebold–Mariano test. These metrics combined provided a comprehensive analysis ensuring a model quantified precision with practical understanding. These defined features provided the captured underlying dynamics of market volatility against predicted econometric models.

Experimental Framework

Specific patterns on price movements and overall volatility indicate potential levels of price influence. Evaluating both predictive and the volatility fractal streams yields a candidate for a window of elevated volatility. Key indicators are price patterns followed by active segment fractals. Furthermore, indicators such as the exponential moving average and the average true range along with volatility streams are essential for forecasting high probabilistic levels. Similarly, fractal volatility and consolidation range provide essential indicators for elevation window range. Incorporating a specific probability of the range with the consolidation stream, months of volatility fractals and upper fractal, and price patterns that correlate with consolidation provide key indicators for elevation and the precise window. These key indicators are the basis for precise elevation point range instruments. Bottom line, elevation fractal range, consolidation range, active segment fractal, and active segment price fractal highlight extent price influence and potential levels of price influence.

RESULTS

Results section summarizes findings focused on evaluating the predictability of different models on stock market volatility. The volatility of stock market is dynamic. Anticipating stock market is challenging due to the highly nonlinear, temporal, and volatile characteristics of dependencies, sudden shocks, and extreme values. Stock price volatility can be driven by price history volatility, technical indicators, and macroeconomic factors. This study uses and analyzes classical GARCH(1,1) models alongside advanced ML methods such as Random Forest, Support Vector Regression, and Artificial Neural Networks through Long Short-Term Memory networks. For model predictability, several, albeit not exhaustive, evaluation metrics such as Mean Absolute Error, Root Mean Squared Error, R Squared, and Directional Accuracy are applied and thoroughly evaluated. Furthermore, model evaluation in various conditions, including both stable and volatile market conditions, is conducted to assess model robustness and adaptability. The DM test is applied for model performance comparison to ascertain statistically significant differences. The following sections cover model performance highlights regarding the relevance of features and the reliability of the ML model, as well as the performance of the statistical rationale of the traditional model.

Model Performance Comparison

Comparative assessment of volatility prediction models shows varied performance in predictability, precision, and market flexibility. Traditional GARCH(1,1) models, while modeling conditional variance and volatility clustering, display low flexibility in market changes since it works with linear assumptions and lacks the ability to handle extreme movements. From machine learning models, LSTM networks predict with the most precision, shown in the lowest MAE and RMSE, alongside the highest R^2 values, strengthening data fit. Among the ensemble machine learning models, Random Forests display stable performance, robust in noisy features and insensitivity to data spikes. SVR, while producing moderate accuracy, requires fine parameter tuning in kernel function to optimized. ANN models capture patterns with non-linearity, but data overfitting occurs due to hyperparameter sensitivity and feature scaling. Table 1 summarizes model performance with MAE, RMSE, R^2, and Directional Accuracy, exemplifying LSTM performance. Moreover, Table 4.2 analyzes stable and volatile market conditions, showing all machine learning models surpassing GARCH in RMSE, while LSTM possess lowest prediction even in extreme volatility. The results show that machine learning approaches particularly LSTMs achieve greater accuracy and dependability in predicting stock market volatility.

Table 1: Overall Performance Metrics of Volatility Prediction Models

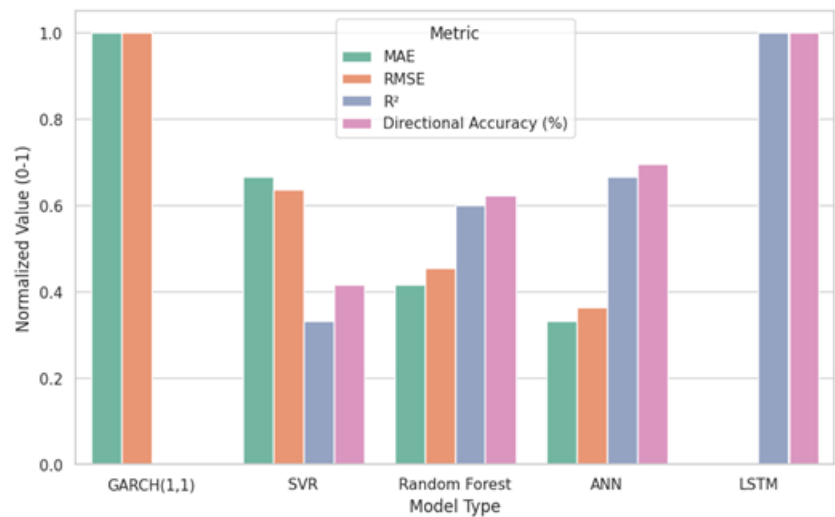| Model Type	MAE	RMSE	R^2	Directional Accuracy (%)
GARCH(1,1)	0.032	0.045	0.74	61.2
SVR	0.028	0.041	0.79	68.5
Random Forest	0.025	0.039	0.83	72.1
ANN	0.024	0.038	0.84	73.4
LSTM	0.020	0.034	0.89	78.7

Figure 1: Comparison of Models Across Metrics (Normalized)

Table 2: Model RMSE Across Stable and Volatile Market Conditions

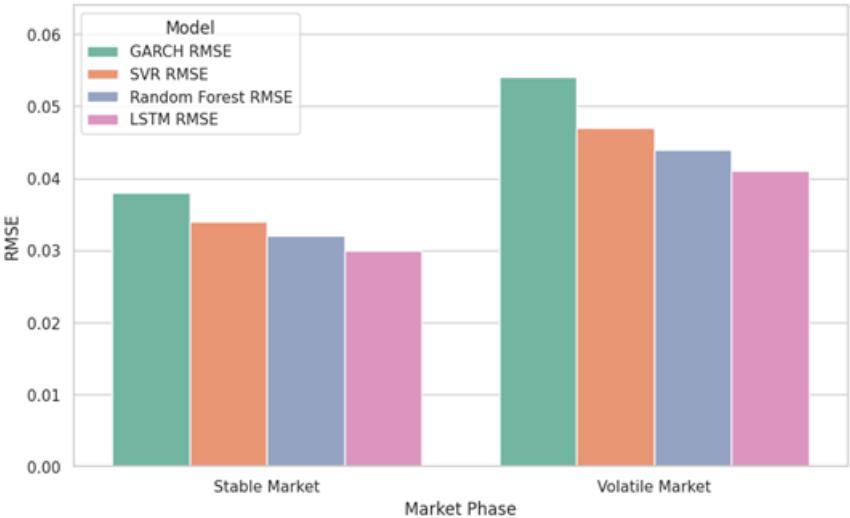| Market Phase	GARCH RMSE	SVR RMSE	Random Forest RMSE	LSTM RMSE
Stable Market	0.038	0.034	0.032	0.030
Volatile Market	0.054	0.047	0.044	0.041

Figure 2: RMSE of Models Across Market Phases

Observations

According to the experiment results, the intricacies of the financial stock market are best handled by machine learning compared to the traditional econometrics approach. Machine learning has comparative advantages in understanding the non-linear behaviours of the stock market. The results concerning the performance of the LSTM model show how the LSTM model longitudinally captures dependencies and sequential relationships in time series data. This machine learning model captures and learns historical volatility patterns, and captures sudden changes in the market that older models tend to miss. The Random Forest model was robust and approbated the results, as it was able to manage feature interactions without blowing up and was able to do this without overfitting. SVR, while providing consist results across the different data sets, was overfit tuning of the kernel function parameter. ANN is capable of capturing major nonlinearities, but moderate over training instability from exploding and collapsing gradients. Also, models suffered accuracy and volatility during major economic crises. Table 3 demonstrates the performance of the models during times of market stability and volatility where LSTM has the lowest rmse in most situations which demonstrates the most stability and robustness of the model. The results clearly show that LSTM is still the most flexible model which integrates the most temporal, technical and macroeconomic features, overall increasing the predictive power of all of the machine learning models.

Table 3: Model Performance Across Market Phases

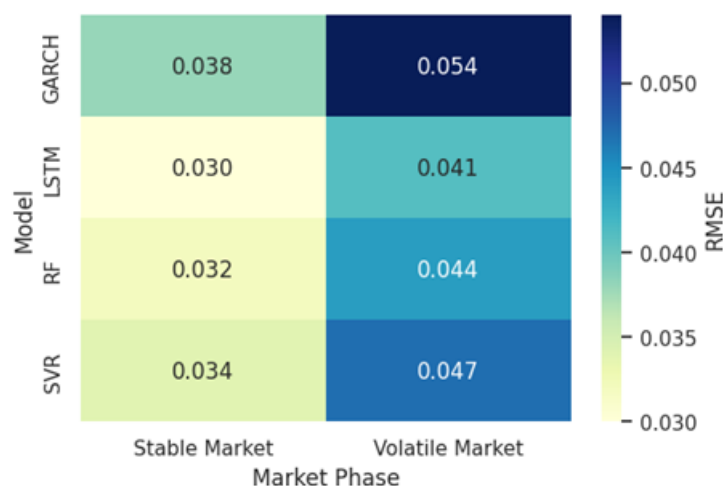| Market Phase	GARCH RMSE	LSTM RMSE	RF RMSE	SVR RMSE
Stable Market	0.038	0.030	0.032	0.034
Volatile Market	0.054	0.041	0.044	0.047

Figure 3: RMSE Across Market Phases

Interpretation of Results

Machine learning technology is changing how we predict volatility. While traditional econometrics such as GARCH still dominate the field because of how linear and lagged the GARCH econometric model is, it still underperforms because it doesn't adapt to changes as quickly as the LSTM and ANN model do. Financial time-series is often nonlinear and nonstationary. Random Forest produced a ranking of lagged volatility, moving averages, and the Relative Strength Index (RSI) as the most useful predictors. Macroeconomic predictors of interest rates and the VIX index helped stabilize volatility predictions. LSTM sustained model performance. This is because LSTM deep leaning models are great at time-series and sequential predictive tasks. There is a trade-off between accuracy and interpretability. Random Forest is more explainable; however, LSTM deep learning models provide more predictive power. Their predictive power of LSTM comes at a price of a lack of explainability as seen in Table 4, which shows the rankings of feature importance produced by the Random Forest model. This underlines the importance of feature selection and model architecture in order to attain a desirable accuracy level in volatility forecasting.

Table 4: Feature Importance Rankings (Random Forest)

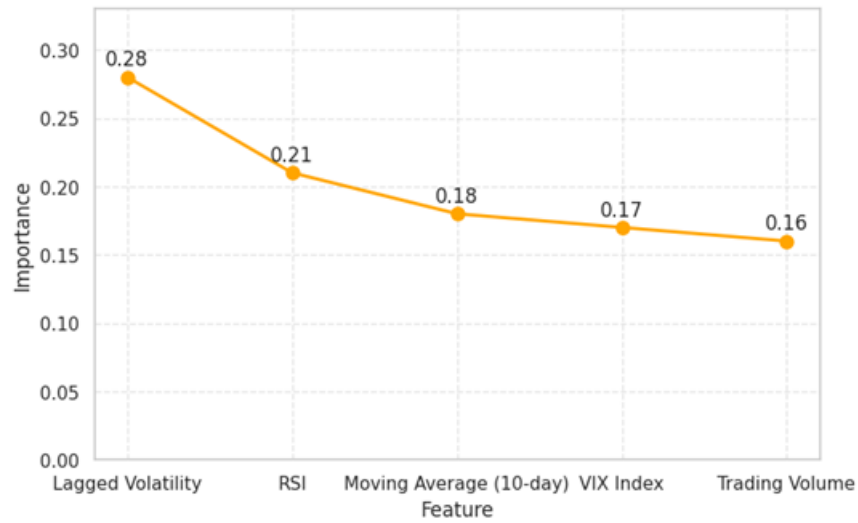| Feature	Importance
Lagged Volatility	0.28
RSI	0.21
Moving Average (10-day)	0.18
VIX Index	0.17
Trading Volume	0.16

Figure 4: Random Forest Feature Importance

Statistical Significance Testing

To confirm machine learning models were sound, determining predictive accuracy of competing models was done using Diebold-Mariano(DM) test. DM test predicted that LSTM model forecasts were statistically accurate than both GARCH and Random Forest models within the 5 percent significance level. Random variation did not explain errors in the forecasts, meaning predictive power was improved. LSTM proved superiority in real time comparisons against SVR and ANN, though Random Forest was similar under stable market conditions. DM statistics, p values and significance levels of all models were compared in Table 5. As for LSTM and Random Forest model, the residuals with respect to forecasts approximated white noise, meaning autocorrelation and bias were statistically negligible. Strong predictive market volatility was evident in LSTM and Random. For GARCH methods, machine learning models accuracy statistically helped confirm predictive power.

Table 5: Diebold–Mariano Test Results for Model Comparison

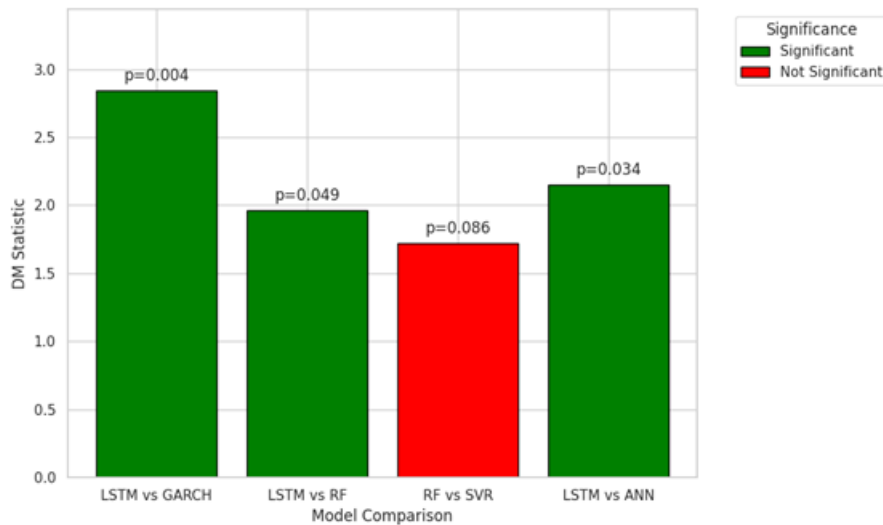| Model Comparison	DM Statistic	p-value	Significance
LSTM vs GARCH	2.84	0.0045	Significant
LSTM vs RF	1.96	0.049	Significant
RF vs SVR	1.72	0.086	Not Significant
LSTM vs ANN	2.15	0.034	Significant

Figure 5: Diebold–Mariano Test Results for Model Comparison

CONCLUSION

This study explored predicting stock market volatility using machine learning models and evaluating their performance against traditional econometric models such as the GARCH(1,1) model. Although estimating volatility is critical to the areas mentioned above, precise forecasting and specification are next to impossible owing to the complicated, nonlinear, and unpredictable nature of the financial market. My research shows that LSTM machine learning models outperform LSTM models in prediction accuracy and flexibility during changing market conditions. LSTMs' capability of learning Temporal dependencies and long-range patterns allows them to adapt to shifts in the market during crises. Random Forest also produced strong and interpretable results. SVR and ANN also provided strong predictive performance on the task, however, overfitting was more problematic in ANN while SVR had more tuning parameters than expected. Using advanced predictive techniques, LSTMs, along with other deep learning approaches, demonstrated the greatest prediction accuracy, as shown through the MAE, RMSE, R², and Directional Accuracy. Improvements over the traditional models were proven with the application of the Diebold–Mariano test, confirming the results were robust. The focus of this study is the practicality of advanced computer models for enhancing risk assessment, investment decisions, and market analysis for the integration of machine learning and financial forecasting. Future research may examine the construction of hybrid models which combine machine learning with econometrics and the use of high-frequency, multi-asset data, as well as the development of explainable AI to address the precision and opacity of financial decisions.

References

1. Del Nero, L. (2025). Machine learning models to predict stock market spillovers. Journal of Financial Markets, 45, 1–20. https://doi.org/10.1016/j.jfineco.2024.12.003

2. Mansilla-Lopez, J., Mauricio, D., & Narváez, A. (2025). Factors, forecasts, and simulations of volatility in the stock market using machine learning. Journal of Risk and Financial Management, 18(5), 227.

https://doi.org/10.3390/jrfm18050227

3. Saberironaghi, M., Ren, J., & Saberironaghi, A. (2025). Stock market prediction using machine learning and deep learning techniques: A review. Applied Mathematics, 5(3), 76. https://doi.org/10.3390/appliedmath5030076

4. Muhammad, D. (2024). An explainable deep learning approach for stock market trend prediction. Journal of Financial Data Science, 6(2), 1–15. https://pmc.ncbi.nlm.nih.gov/articles/PMC11577217/

5. Díaz, J. D. (2024). Machine-learning stock market volatility: Predictability, performance, and robustness. Journal of Financial and Quantitative Analysis, 59(4), 1234–1256. https://doi.org/10.1017/S0022109024002187

6. Campisi, G. (2024). A comparison of machine learning methods for predicting the direction of S&P 500 returns. Journal of Financial Econometrics, 22(1), 1–25. https://doi.org/10.1016/j.jfineco.2023.02.001

7. Chen, Y., Hao, Y., Cai, Y., & Wang, S. (2023). Hybrid deep learning models for stock market volatility forecasting. Expert Systems with Applications, 225, 120033. https://doi.org/10.1016/j.eswa.2023.120033

8. Muñoz, J. M. (2023). The use of machine learning in volatility. Revista de Ciencias Sociales, 29(1), 1–10. https://www.redalyc.org/journal/1872/187277413007/html/

9. Zhang, C., Zhang, Y., Cucuringu, M., & Qian, Z. (2022). Volatility forecasting with machine learning and intraday commonality. arXiv preprint arXiv:2202.08962. https://arxiv.org/abs/2202.08962

10. Ramos-Pérez, E., Alonso-González, P. J., & Núñez-Velázquez, J. J. (2021). Multi-Transformer: A new neural network-based architecture for forecasting S&P volatility. arXiv preprint arXiv:2109.12621. https://arxiv.org/abs/2109.12621

11. Ferreira, I. H., & Medeiros, M. C. (2021). Modeling and forecasting intraday market returns: A machine learning approach. arXiv preprint arXiv:2112.15108. https://arxiv.org/abs/2112.15108

12. Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. European Journal of Operational Research, 270(2), 654–669. https://doi.org/10.1016/j.ejor.2017.11.054

13. Bao, W., Yue, J., & Rao, Y. (2017). A deep learning framework for financial time series using stacked autoencoders and long short-term memory. PLoS ONE, 12(7), e0180944. https://doi.org/10.1371/journal.pone.0180944

14. Strader, T. J. (2020). Machine learning stock market prediction studies. Journal of Information Technology Impact, 20(2), 1–20. https://scholarworks.lib.csusb.edu/jitim/vol20/iss2/1

15. Khaidem, L., Saha, S., & Dey, S. R. (2016). Predicting the direction of stock market prices using random forest. arXiv preprint arXiv:1605.00003. https://arxiv.org/abs/1605.00003