Application of time series models in stock market volatility forecasting: a review of the literature in the past decade

Qi Yu[1*]

[1]Australian National University, Canberra, Australia

Abstract. Accurately forecasting stock market volatility has become crucial, especially as financial markets become more complex and unpredictable. In the past decade, researchers have significantly advanced forecasting methods, moving from basic statistical tools towards sophisticated machine learning and hybrid solutions. Initially, classical models such as GARCH and stochastic volatility proved effective, particularly in capturing asymmetrical patterns, yet these models often fell short in handling complex nonlinear market behaviors. To address this gap, recent approaches involving neural networks and support vector machines (SVMs) have shown notable improvements, largely because of their adaptability to volatile market changes. However, these advanced methods come with their own practical challenges. Hybrid approaches, which combine econometric models with deep learning techniques, have also emerged as powerful tools, although their implementation can be challenging. This review critically evaluates these diverse methodologies, highlighting their practical strengths and limitations. By synthesizing current empirical findings and theoretical insights, the review identifies key challenges, including data scarcity, parameter complexity, and issues related to real-time forecasting and proposes future research directions. Emphasis is placed on integrating multiple data sources and adopting flexible optimization techniques, which could significantly enhance predictive capabilities in dynamic financial environments.

1 Introduction

Researchers have reshaped volatility forecasting over the past few decades. They first relied on classical econometric tools. They now turn to machine-learning and hybrid methods. This shift mirrors the mounting complexity of financial markets. It also reveals a stronger demand for precise predictive tools. Market dynamics keep changing. Data sources keep multiplying. Analysts therefore need advanced forecasting methods. These methods support risk management. They guide investment decisions. They help regulators monitor market stability.This paper maps the current landscape of volatility forecasting. It also sketches future directions. The discussion compares traditional and modern approaches. It evaluates each method in several market settings. The analysis covers four themes. The first theme reviews Support Vector Machines and highlights

* Corresponding author: u8082152@anu.edu.au

their edge over legacy models. The second theme assesses neural networks and other deep-learning tools. The third theme revisits stochastic-volatility and GARCH variants. The fourth theme explores hybrid models and optimisation techniques. This review offers clear insights. It pinpoints the most effective tools for forecasting volatility today. It also identifies open questions for future research in this fast-moving field.

2 Traditional Time Series Models

2.1 ARCH/GARCH Family Models

The rise of GARCH models marks a major breakthrough in the forecasting of financial market volatility. These advance signals a clear evolution from earlier and simpler statistical routines toward more sophisticated modelling techniques. Sahiner reviews this journey in careful detail [1] . The author shows that basic averaging and smoothing could not capture the rich dynamics of financial time series. Volatility clustering remained especially elusive for those early approaches. Engle introduced ARCH models in 1982 and opened a new path. Bollerslev extended that work in 1986 by presenting GARCH models, which offered stronger frameworks for volatility analysis. Yet the first GARCH forms failed to reflect volatility asymmetry, also called the leverage effect, described by Black in 1976. Researchers responded quickly and crafted more advanced variants. Nelson's EGARCH, Ding et al.'s PGARCH, and Zakoian's TGARCH each addressed a specific facet of market behaviour. The progressive refinement of these models demonstrates the field's agility in meeting empirical challenges and in pursuing higher forecasting accuracy. This steady evolution signals a deeper understanding of market dynamics and underscores the need for increasingly sophisticated tools that map complex volatility patterns. Consequently, GARCH-family models stand today as fundamental instruments in modern financial analysis and risk management.

A comparative review of GARCH model variants shows clear differences in their ability to capture asymmetric volatility and leverage effects in stock markets. Traditional GARCH models still struggle when they try to explain the leverage effect. This effect is the negative link between stock returns and their variability [2]. The limitation arises because the baseline framework assumes that conditional variance reacts to market shocks in a balanced way, no matter whether the shock is positive or negative. The EGARCH model appears as a direct upgrade. This model builds in an asymmetric response to market shocks and so overcomes the earlier weakness [3]. Researchers show that negative shocks usually provoke stronger market reactions. Greater financial leverage and higher perceived risk in issued stocks amplify those reactions. Further support comes from Alexander and Beegam [4]. These authors confirm, with fresh data, that EGARCH (1,1) combined with a Student’s-t distribution beats competing variants in tracking asymmetric volatility patterns in futures markets. The edge of EGARCH rests on its capacity to embed psychological forces inside a statistical structure. Investors often fear losses more than they welcome gains. That bias drives extra volatility when markets fall. A deeper grasp of these asymmetric responses matters for risk management and investment planning. Better models improve volatility forecasts, especially during downturns.

2.2 Stochastic Volatility Models

Stochastic volatility models now stand out as sophisticated tools for predicting stock market volatility. These models give analysts a clear theoretical framework that captures the complex and ever-changing nature of financial markets. Beckmann and Schüssler advance this field by presenting a comprehensive approach that relies on predictive density [5]. Their method blends

conditional density with both a normal distribution and an inverse gamma component. That dual structure lets the model track volatility as it evolves over time. This solid mathematical base offers a more refined view of volatility patterns. It especially helps analysts describe the way market fluctuations change from one period to the next. Koo and Kim outline the core of this framework in a straightforward time-series form. They express returns as $y_t = \mu_t + \sigma_t z_t$. In that equation, μ_t captures the mean process, while $\sigma_t z_t$ packages volatility as the product of a changing scale term and a random shock. Volatility at any moment therefore depends on past market information. Oikonomikou stresses why this accuracy matters [6]. Volatility, in her view, signals how well markets guide capital toward productive investments. Strong modelling thus aids investment decisions, risk management, and even regulatory oversight. The joint use of normal and inverse gamma pieces gives practitioners a flexible platform. It lets them build richer strategies for portfolio design and for assessing systemic risk. Regulators can also apply these models when they test market stability and efficiency.

Empirical studies bring further insight into how these models behave in the real world. Recent work by Ahammed and Mariyappan shows a mixed picture [7]. GARCH models often shine during high-volatility spells. Stochastic volatility models, by contrast, deliver uneven results that depend on the setting. This outcome highlights the need to choose models with care. Aït-Sahalia adds another piece to the puzzle [8]. He demonstrates that stochastic volatility frameworks estimate correlations across asset classes with notable success. His study on the S&P 500 and gold prices illustrates how these tools aid portfolio optimisation and risk control. They examine the Dow Jones Euro STOXX 50 and achieve calibration errors under five basis points. Such precision underscores the practical value of stochastic volatility models in European markets. Taken together, the empirical record shows that these models offer powerful insights but also carry clear limits. Their performance hinges on market conditions, asset features, and the chosen task. Practitioners must weigh these factors before selecting a model. A keen grasp of each model's strengths and weaknesses will enhance portfolio management and bolster risk frameworks in complex financial landscapes.

3 Machine Learning Approaches

3.1 Neural Networks and Deep Learning

Neural network architectures now play a key role in forecasting stock market volatility. They mark a major step in financial prediction. Recent studies test many paths to optimise these structures. Chaudhuri and Ghosh designed a broad testing framework [9]. Their work used two distinct neural architectures. The team varied hidden neuron counts at 20, 30, and 40. They also compared nine learning algorithms. The researchers adopted tan-sigmoid and purelin transfer functions. These choices aimed to lift prediction accuracy. Reisenhofer et al. built on this base [10]. They unveiled the HARNet architecture. HARNet stacks hierarchical dilated convolutional layers. These layers scan several time horizons. The design mirrors the weekly and monthly blocks of the classic HAR model. The authors also set explicit initialisation schemes. These schemes strengthen model stability. Fraszka-Sobczyk and Zakrzewska pushed the design further [11]. They created a Multi-Layer Perceptron network with specialised activation functions. Their model gives extra weight to recent data through weighted recent-data prioritisation. Such priorities help the network track fast market shifts. These upgrades show clear progress. Basic neural networks have grown into refined systems that read market dynamics better. The steady change in design highlights two lessons. First, temporal dependencies matter. Second, cross-market influences shape volatility. Future work should keep these insights. Researchers must add richer market interactions yet protect efficiency and transparency.

Empirical tests now compare these deep models with older econometric tools. Results often favour neural networks. Terraza et al. provide strong evidence [12]. They linked VAR-DCC-EGARCH with artificial neural networks to form hybrid models. These hybrids forecast volatility for Bitcoin, gold, and stock indexes. The hybrids excel, especially when they map Bitcoin's excess volatility patterns. Sahiner et al. present similar findings [13]. Their study covers Asian markets. Machine-learning algorithms beat traditional benchmarks. The edge comes from two skills. The models capture asymmetric relationships. They also grasp long-memory properties. Graph-based models have also shown promise, cutting average forecast errors by a notable margin when compared to standard HAR models. This gain underscores a vital point. Neural networks see complex, non-linear ties and cross-market interdependence that older models miss. The collective evidence is clear. Deep learning does more than add small gains. It changes how analysts predict volatility. The consistent outperformance across markets and assets suggests a shift in practice. These tools now allow investors, risk managers, and regulators to foresee market swings with higher precision and confidence.

3.2 Support Vector Machines

The performance of Support Vector Machine (SVM) algorithms in stock-market volatility prediction rests on two pillars. The first pillar is kernel-function choice. The second pillar is parameter optimisation. Recent studies test many kernels and record mixed results. Zahid et al. compare three kernels under high volatility. Their tests show that the Radial Basis Function (RBF) kernel reaches 62 % prediction accuracy. The linear kernel reaches 53 %. The polynomial kernel reaches 46 %. Their work trims the gamma parameter for the RBF kernel and drives Root Mean Square Error (RMSE) values to almost zero. Researchers link the RBF kernel's strength to its skill in tracing non-linear patterns in volatile data. Parameter tuning, especially for gamma, pushes this strength higher. The evidence therefore signals one lesson. Practitioners must marry smart kernel selection with careful parameter tuning that echoes specific market traits. When analysts meet those conditions, the RBF kernel offers the best path for volatility prediction in difficult markets.

Support Vector Machines (SVMs) also stand above traditional econometric models when they forecast volatility. Several features explain this lead. SVMs tackle high-dimensional data with ease. They also expose subtle patterns that classic models often miss. The core SVM mechanism searches for an optimal hyperplane. This hyperplane widens the margin between classes of market states and sharpens prediction. The kernel trick adds power. It lets SVMs address non-linear links without a costly move into higher-dimensional space. This design keeps large-scale analysis efficient. SVMs further adapt to shifting market regimes and resist outliers. Classical methods such as GARCH models or linear regression show less resilience. SVMs reduce empirical risk and structural risk at the same time. Better generalisation follows, which is vital in the turbulent stock-market setting. These combined advantages turn SVMs into a reliable tool for risk managers, traders, and analysts who demand precise volatility forecasts.

4 Hybrid Models and Future Directions

4.1 Integration Frameworks

Integration frameworks that join different volatility-forecasting models now mark a crucial advance in stock-market analysis. These frameworks supply broader and more precise predictions. Recent studies confirm the power of hybrid approaches to overcome the limits of single models. Brik and El Ouakdi present a GARCH-LSTM hybrid model [14]. This model captures sophisticated market features and long-term dependencies. Their evidence shows that model

integration builds sturdier forecasting structures. They design hybrid models that link Realized GARCH with neural networks. The design targets the weaknesses of traditional models when those models describe stylised facts in financial data. Each hybrid deals with many facets of volatility at once. It handles asymmetry. It also addresses long-term memory. The fundamental principle of hybridization has been well established in the literature. Researchers should combine several forecasting methods. The aim is to harness their strengths and soften their weaknesses. This strategy proves highly effective. It yields forecasts that stay reliable and accurate, especially when two complementary methods work together. The rise of these frameworks marks a major step in volatility prediction. Hybrid systems now offer a richer and more complete view of market dynamics than any single model can provide. Each added layer of integration deepens insight and sharpens risk assessment.

Advanced optimisation techniques now act as key parts of hybrid models for volatility prediction. Recent studies test several optimisation tools. Their list includes genetic algorithm, grey-wolf optimisation, and biogeography-based optimisation. The last method stands out. It posts coefficient-of-determination scores above 0.99 for HSI, Dow Jones, and KOSPI markets. Such accuracy highlights the promise of nature-inspired optimisation in finance. The Adam optimiser has been effectively applied in similar computational contexts. Adam blends gradient descent, momentum, moving average, and RMSprop. The blend creates a sturdier optimisation framework for hybrid models. Recent empirical findings push the concept even further. They build a pretraining–finetuning system. The system combines an Attention-based CNN-LSTM architecture with XGBoost fine-tuning. This design shows that optimisation can act at many stages, from early feature extraction to the final forecast refinement. The combined use of these techniques lifts model accuracy. It also boosts the robustness and flexibility of hybrid models when they track complex market behaviour. This ongoing evolution in optimisation signals a strong advance. The field now moves toward more sophisticated and efficient hybrid-modelling systems for future volatility prediction.

4.2 Research Challenges

Methodological gaps in stock-market volatility forecasting still pose serious hurdles. Recent studies draw attention to several pressing issues that slow progress and weaken model trustworthiness. One clear problem shows that short sample periods, often only five years, hurt artificial neural networks. These networks usually need large datasets to learn well. Hyperparameter optimisation and variable selection add another layer of difficulty. Researchers still rely on subjective judgement because no accepted protocols exist. Real-world complexity raises the bar even higher. Messy data and intricate financial ecosystems as major obstacles. These imperfections ripple through every modelling step. Sentiment analysis methods suffer too. Relying on one sentiment stream can bias results because it fails to represent all market voices. Together, these problems call for tougher, more systematic solutions. Scholars must craft frameworks that tackle technical fine-tuning and practical deployment at the same time. They must also guard data integrity and representativeness across markets, timeframes, and conditions.

Looking ahead, the field faces both daunting tasks and exciting openings. Hybrid models and fresh research paths may offer the next leap. One research path involves incorporating alternative data, such as social-media sentiment and satellite imagery into market inputs. This mix could capture richer signals driving price swings. Market behaviour remains stochastic, non-stationary, and non-linear. Other studies underscore that fact. Their work pushes for hybrid designs able to map these tangled patterns. Yet practical barriers remain. Limitations in back testing procedures and real-time implementation have been widely acknowledged in recent literature. Unplanned noise and abrupt price jumps still cloud forecasts. Future studies therefore need adaptive hybrid systems that shift with market regimes. These systems should blend methods, draw on live

feedback, and keep forecasts sturdy. Success here may reshape how analysts see volatility. Even so, every new model will need ongoing validation and thoughtful, hands-on implementation to earn lasting trust.

5 Conclusion

This broad review of stock-market volatility-forecasting methods yields several key insights. First, machine-learning approaches especially SVMs and neural networks repeatedly outperform traditional econometric models. They manage non-linear links and tangled market dynamics with greater skill. Their flexible structures let them map patterns that linear tools miss. Second, the steady evolution of GARCH models and their many variants now supplies analysts with sharper instruments. These models track asymmetric volatility and leverage effects more precisely than before. Each new variant adds a layer of nuance that improves risk estimates. Third, hybrid models and advanced optimisation techniques have become promising bridges. They merge the strengths of multiple methods while softening their separate flaws. Techniques such as genetic algorithms, Adam, and grey-wolf optimisation refine model parameters and lift accuracy. These findings point to clear paths for further work. Researchers should build richer hybrid frameworks that blend alternative data, such as social-media sentiment or satellite imaging with classic price information. Developers must keep computational efficiency in view so that models run in real time. Practitioners also need to tackle deployment hurdles, including noisy data and sudden regime shifts. In addition, the field would gain from standardised rules for hyperparameter tuning and variable selection. Shared protocols would speed comparison and replication across studies. Progress on these fronts will sharpen volatility forecasts, strengthen risk-management tools, and support more stable financial markets.

References

1. M. Sahiner, Forecasting volatility in Asian financial markets: Evidence from recursive and rolling window methods. SN Business & Economics, 2. https://doi.org/10.1007/s43546-022-00329-9 (2022)
2. S. Zahid, H. Mujtaba, N. Saleem, P. Scholar, Stock Volatility Prediction Using Machine Learning during Covid-19. Statistics, Computing and Interdisciplinary Research. https://doi.org/10.52700/scir.v5i2.135 (2023)
3. Y. Bakkali, M. El Merzguioui, A. Akharif, Enhancing Volatility Prediction: Comparison Study Between Persistent and Anti-persistent Financial Series. Statistics, Optimization & Information Computing. https://doi.org/10.19139/soic-2310-5070-2021 (2024)
4. A. M. Alexander, S. Beegam, Modeling Symmetric and Asymmetric Volatility in Nifty 50 Index Futures Market. Commerce & Business Researcher, 15(1), 89–102. https://doi.org/10.59640/cbr.v15i1.89-102 (2023)
5. J. Beckmann, R. Schüssler, Forecasting Equity Premia using Bayesian Dynamic Model Averaging. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2502356 (2014)
6. L. E. Oikonomikou, Modeling financial market volatility in transition markets: A multivariate case. SSRN: Volatility (Topic). https://doi.org/10.2139/ssrn.2743567 (2015)
7. M. S. R. S. I. Ahammed, Mariyappan. Volatility Modeling and Forecasting in Stock Markets: A Comparative Analysis. European Economic Letters, 13(5). https://doi.org/10.52783/eel.v13i5.870 (2023)

8. Y. Aït-Sahalia, R. Kimmel, Maximum likelihood estimation of stochastic volatility models. *Journal of Financial Economics*, 83(2), 413-452. https://doi.org/10.1016/j.jfineco.2005.10.006 (2007)
9. T. Chaudhuri, I. Ghosh, Forecasting Volatility in Indian Stock Market using Artificial Neural Network with Multiple Inputs and Outputs. arXiv. https://doi.org/10.5120/21245-4034 (2015)
10. R. Reisenhofer, X. Bayer, N. Hautsch, HARNet: A Convolutional Neural Network for Realized Volatility Forecasting. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4116642 (2022)
11. E. Fraszka-Sobczyk, A. Zakrzewska, The Impact of Foreign Stock Market Indices on Predictions Volatility of the WIG20 Index Rates of Return Using Neural Networks. Computational Economics. https://doi.org/10.1007/s10614-024-10662-w (2024)
12. V. Terraza, A. B. İpek, M. M. Rounaghi, The nexus between the volatility of Bitcoin, gold, and American stock markets during COVID-19: Evidence from VAR-DCC-EGARCH and ANN. Financial Innovation, 10(1). https://doi.org/10.1186/s40854-023-00520-3 (2024)
13. M. Sahiner, D. McMillan, D. S. Kambouroudis, Do artificial neural networks provide improved volatility forecasts: Evidence from Asian markets. Journal of Economics and Finance. https://doi.org/10.1007/s12197-023-09629-8 (2023)
14. H. Brik, J. El Ouakdi, Interplay of Volatility and Geopolitical Tensions in Clean Energy Markets: A GARCH-LSTM Forecasting Approach. International Journal of Energy Economics and Policy. https://doi.org/10.32479/ijeep.16075 (2024)