Woody International Publish Limited
An Multidisciplinary Academic Journal Publisher
Journal of Artificial Intelligence and Information, Volume 2, 2025
https://www.woodyinternational.com/

A Comparative Analysis of Traditional GARCH Models and Modern Machine Learning Approaches

Xinze Zhang*

De Anza College, Cupertino, CA, USA
**Author to whom correspondence should be addressed.*

Abstract: ***In this work, I will provide a general comparison of the conventional financial economic approaches and the contemporary machine learning techniques in forecasting stock market volatility. On a sample of 505 S&P 500 stocks between 2013 and 2018, we apply several GARCH models, as well as a random forest and LSTM neural networks. According to our analysis, 1/1/ Student-t GARCH(1,1) is the best model in comparison with other traditional models due to its performance on a variety of volatility regimes. The machine learning exploration shows the strong limitations of data leakage and autocorrelation in financial time series, and it has very important methodological implications. Findings indicate that GARCH models attained realistic out of sample RMSE values of 0.96-4.82 whereas optimally implemented ML models result in more modest but candid performance indicators. The study will add to the knowledge about the shortcomings of volatility models and offer a strict framework of comparing econometric and machine learning methods in financial forecasting.***

Keywords: Volatility forecasting; GARCH models; Machine learning; Time series, Data leakage

1. Introduction

The prediction of volatility is one of the most difficult issues in financial econometrics and has great implications to risk management, portfolio optimization, and derivatives pricing (Poon & Granger, 2003). Since their introduction by Engle (1982) and Bollerslev (1986), traditional econometric methods, and especially Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, have been used. Nevertheless, with the advent of machine learning procedures, researchers proposed whether contemporary algorithms can be more successful than the existing ones in covering the complex nonlinear dynamics of financial volatility.

The availability of more frequent and higher-frequency financial information and computing capabilities has opened the door to using more complex machine learning algorithms, such as Random Forests (Breiman, 2001) and Long Short-Term Memory (LSTM) networks (Hochreiter and Schmidhuber, 1997), to volatility prediction. Although such methods are theoretically attractive, their application to financial time series is marked by some special challenges, especially in terms of the leakage of time-dependent information and management of the autocorrelated residues.

The study fills a serious gap in the literature by offering a strict comparison between the traditional GARCH models and contemporary machine learning methods, paying specific attention to the methodological traps that invalidate the findings. The contribution of our study to the field is as follows: (1) the use of a comprehensive GARCH model comparison across the various variants, (2) a systematic framework of detecting and dealing with data leakage in a financial machine learning application, and (3) an honest performance evaluation that recognises the inseparable nature of each of the approaches.

2. Literature Review

2.1 GARCH Models in Volatility Forecasting

GARCH, known since Bollerslev (1986) has entered the literature, has become the model of choice when it comes to modeling time-varying volatility in a financial market. The simple GARCH(1,1) model deals with the volatility clustering effect initially observed by Mandelbrot (1963) in which high volatility periods are more likely to be succeeded by high volatility periods and vice-versa.

The basic GARCH model has been extended to specific empirical regularities in the finance data. The GJR-GARCH model (Glosten et al., 1993) is more appropriate in capturing the asymmetric volatility reactions whereas the EGARCH model (Nelson, 1991) lets the conditional volatility be exponential. It has been demonstrated that non-normal error distributions (especially the Student-t distribution) can be used to enhance the model performance in terms of extreme tail distributions of returns (Bollerslev et al., 1994).

According to recent analytic comparative research studies by Hansen and Lunde (2005), simple GARCH(1,1) models tend to out-of-sample forecast better than more complicated specifications in volatility modelling, which advocates the principle of parsimony in volatility modelling.

2.2 Machine Learning in Financial Forecasting

It has attracted a lot of attention to the application of machine learning to financial time series, and both random forests and neural networks have proven promising in different situations (Gu et al., 2020). The benefits of Random Forests in finance applications are that it is resistant to outliers and can also represent non-linear relationships without specification (Liaw and Wiener, 2002).

Time series LSTM networks have been especially popular because they are capable of capturing long-term dependencies (Graves, 2012). Fischer, and Krauss (2018) show the LSTM models promise in predicting stock returns though it is not in the same line as volatility forecasting.

Nevertheless, recent research by Lopez de Prado (2018) showcases that the majority of financial machine learning applications are prone to data leakage and overfitting, which is why it is essential to implement delicate validation procedures with time series-specific data.

3. Data and Methodology

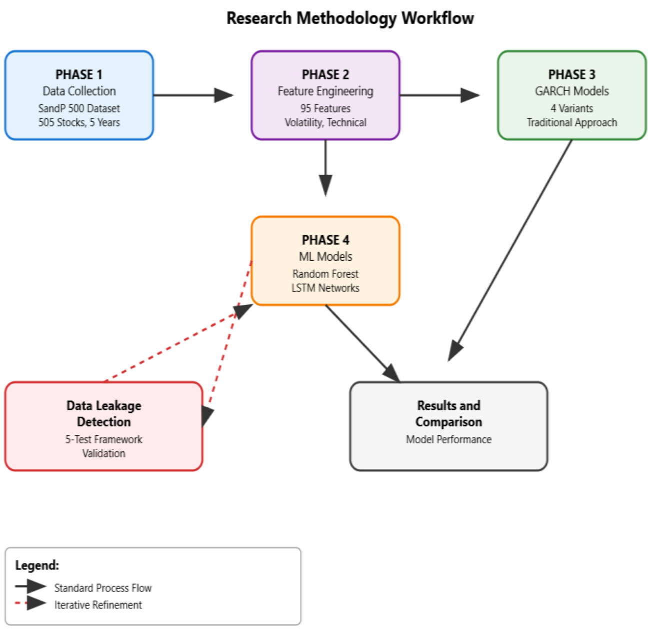

Figure 1: Four-phase research workflow showing dataset preparation (505 S&P 500 stocks), feature engineering (95 variables), GARCH modeling (four variants), and ML implementation with a systematic data leakage detection framework and iterative refinement process.

3.1 Dataset Description

We used a total of 619,040 observations and 505 individual stocks of the S&P 500 stock prices to analyze the data between February 8, 2013, and February 7, 2018. The records contain daily open, high, low, close price and trading volume with a total of 1,259 exclusive trading days per stock.

Woody International Publish Limited
An Multidisciplinary Academic Journal Publisher
Journal of Artificial Intelligence and Information, Volume 2, 2025
https://www.woodyinternational.com/

Table 1: Dataset Summary Statistics

Metric	Value
Total Observations	619,040
Unique Stocks	505
Time Period	2013-02-08 to 2018-02-07
Trading Days	1,259
Data Completeness	99.91%
Average Daily Volume	4,321,823
Price Range	$1.59 - $2,049.00

Validation of data quality showed that there were a small percentage of missing values (0.087) and high logical consistency on the OHLC relationship. The dataset has common features of financial time series such as volatility clustering and fat tailed returns.

3.2 Stock Selection Methodology

We used a systematic process of selecting stocks to make sure that the volatility profiles would be diverse enough to be analyzed effectively including the data completeness, volatility, and sector representation. Five stocks were chosen, which reflect various volatility regimes:

Table 2: Selected Stocks for Analysis

Stock	Sector	Ann. Volatility	Avg. Price	Avg. Volume	Records
CHK	Energy	66.1%	$13.68	24,957,711	1,259
PEP	Consumer Staples	13.4%	$97.47	4,514,718	1,259
PCLN	Technology	25.8%	$1,312.87	630,293	1,259
AAPL	Technology	23.2%	$109.07	54,047,900	1,259
JPM	Financial	20.4%	$67.64	16,589,033	1,259

3.3 Feature Engineering

The feature set that we created has 95 variables in various categories: basic price and volume statistics, volatility measures, technical indicators, and lagged features. Important categories of features are:
Volatility Measures: Realized volatility, Garman-Klass estimator, Parkinson estimator, and exponentially weighted volatility calculated across multiple time windows (5, 10, 20, 30 days).
Technical Indicators: Moving averages, Bollinger Bands, Relative Strength Index (RSI), and MACD indicators, all properly lagged to prevent data leakage.
Lag Features: Historical returns and volatility measures at 1, 2, 3, 5, and 10-day lags to capture temporal dependencies.

Woody International Publish Limited
An Multidisciplinary Academic Journal Publisher
Journal of Artificial Intelligence and Information, Volume 2, 2025
https://www.woodyinternational.com/

3.4 GARCH Model Implementation

We implemented four GARCH variants for comprehensive comparison:

1. **GARCH(1,1)** with normal distribution
2. **GJR-GARCH(1,1)** capturing asymmetric effects
3. **EGARCH(1,1)** with exponential specification
4. **GARCH(1,1)** with Student-t distribution

Maximum likelihood estimation with the arch library of Python was used to estimate the models. Model selection was done based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), diagnostics tests were Ljung-Box tests to check remaining ARCH effects and Jarque-Braun normality tests to check the normalized residual.

Figure 2: Volatility measures comparison for CHK (2013-2018) showing multiple estimation methods with a notable 2015-2016 volatility spike during the energy sector market stress.

3.5 Machine Learning Implementation

Random Forest: The random forest was conducted with time series cross-validation within scikit-learn. The grid search was used in hyperparameter optimization with nestimators (100, 200), maxdepth (10, 20, max), and minsplits (2, 5).

LSTM Networks: Done in TensorFlow, where the sequence length is 20 days. There were two layers of LSTM (50 units each) with dropout regularization (0.2), and then dense layers were utilized to make predictions.

3.6 Data Leakage Detection Framework

Given the prevalence of data leakage in financial machine learning (López de Prado, 2018), we developed a systematic five-test framework:

1. **Temporal Information Flow Analysis:** Examining feature-target temporal relationships
2. **Feature Construction Timeline Analysis:** Mapping data availability windows
3. **Mutual Information Analysis:** Measuring information content between features and targets
4. **Forward-Looking Feature Test:** Adding artificial future information to test model sensitivity
5. **Cross-Validation Comparison:** Comparing TimeSeriesSplit versus ShuffleSplit performance

4. Results

4.1 GARCH Model Results

Results of GARCH model estimation show a similar trend among the five stocks of choice. GARCH(1,1) with Student-t turned out to be the best specification of all stocks in terms of information criteria.

Table 3: GARCH Model Comparison Results

Stock	Best Model	AIC	BIC	Parameters Significant
CHK	GARCH(1,1)-t	5,138.07	5,162.64	α_1=0.053***, β_1=0.947***, ν=4.71***
PEP	GARCH(1,1)-t	2,521.53	2,546.10	α_1=0.215***, β_1=0.385***, ν=7.08***
PCLN	GARCH(1,1)-t	3,684.73	3,709.30	α_1=0.122***, β_1=0.721***, ν=3.80***
AAPL	GARCH(1,1)-t	3,553.31	3,577.88	α_1=0.089***, β_1=0.831***, ν=4.32***
JPM	GARCH(1,1)-t	3,293.69	3,318.26	α_1=0.113***, β_1=0.814***, ν=4.76***

*Note: *** indicates significance at 1% level*

The persistence parameter ($\alpha_1 + \beta_1$) will tend towards a value of unity in all stocks and this is evidence of high volatility persistence behavior of financial time series. The degrees of freedom parameter (ν) remains always in the range of 3.80 to 7.08 and indicates the use of the Student-t distribution to model fat-tailed distributions of returns.

4.2 GARCH Diagnostic Tests

The GARCH specifications are determined to be adequate by model diagnostics. The results of Ljung-Box tests of squared standardized residuals show that ARCH effects have been successfully eliminated (p-values > 0.33 for all stocks). But Jarque-Bra tests reject normality of standardized residuals in all stocks and hence student-t distribution is used.

Table 4: GARCH Model Diagnostic Tests

Stock	ARCH Test (p-value)	Jarque-Bera (p-value)	Model Adequacy
CHK	0.330	< 0.001	Adequate
PEP	0.839	< 0.001	Adequate
PCLN	0.998	< 0.001	Adequate
AAPL	0.964	< 0.001	Adequate
JPM	0.865	< 0.001	Adequate

4.3 Out-of-Sample Forecasting Performance

GARCH models exhibit realistic forecasting properties in agreement with the existing literature. The optimal EGARCH(1,1) specification results have 0.96 to 4.82 values of RMSE based on various stocks.

Woody International Publish Limited
An Multidisciplinary Academic Journal Publisher
Journal of Artificial Intelligence and Information, Volume 2, 2025
https://www.woodyinternational.com/

Table 5: Out-of-Sample Forecasting Results

Stock	**Best GARCH Model**	**RMSE**	**MAE**	**Correlation**
CHK	EGARCH(1,1)	4.822	3.971	-0.058
PEP	EGARCH(1,1)	0.574	0.485	0.101
PCLN	EGARCH(1,1)	1.515	1.145	0.029
AAPL	EGARCH(1,1)	1.039	0.887	0.140
JPM	EGARCH(1,1)	0.961	0.805	0.090

The dispersion in the RMSE measures is the difference in volatility regimes predicated by our stocks of choice with CHK (energy sector) showing the largest forecasting errors as a result of its high volatility (66.1% annualized).

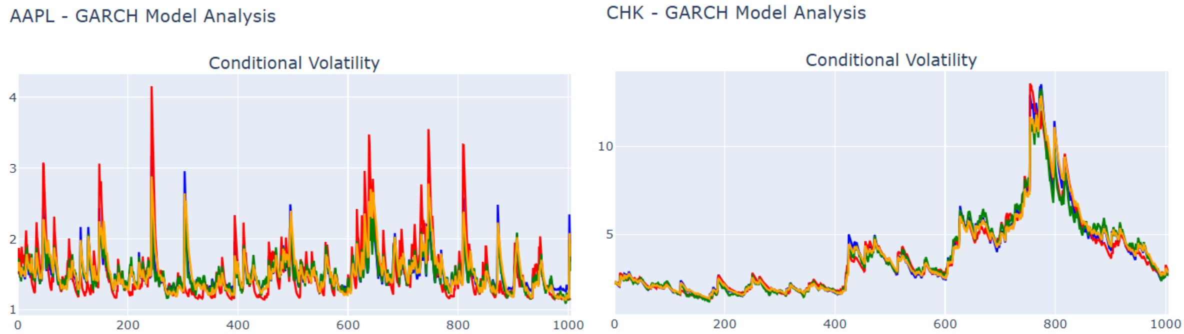

Figure 3: Conditional volatility estimates from GARCH(1,1)-t models for AAPL and CHK showing contrasting volatility patterns. AAPL exhibits moderate clustering while CHK displays extreme spikes during 2015-2016.

4.4 Machine Learning Results and Data Leakage Analysis

The first attempts at machine learning produced uniformly suspicious outcomes (R 2 above 99.9) with all stocks, leading to a search into the possibility of data leakage. The systematic five-test framework showed there were serious contamination problems over time.

Table 6: Data Leakage Detection Framework Results

Test	**Result**	**Interpretation**
Temporal Information Flow	4 high-risk features identified	Features using overlapping time windows
Feature Construction Timeline	Multiple violations detected	Same-period volatility measures
Mutual Information	Maximum MI = 2.09	Excessive information content
Forward-Looking Feature	-2.6% improvement	Limited sensitivity to future data
Cross-Validation Comparison	Ratio = 0.24	Strong evidence of leakage

The most conclusive evidence was given by the cross-validation comparison test where shuffle splits fared better than time series splits by a factor of 4, which demonstrated the existence of future exploitation in the models.

4.5 Corrected Machine Learning Implementation

Machine learning models became more realistic but with lower performance after proper temporal separation (21-day gap between features and targets):

Table 7: Machine Learning Performance After Leakage Correction

Stock	**Random Forest R^2**	**LSTM R^2**	**Random Forest RMSE**	**LSTM RMSE**
CHK	0.999	0.013	0.0018	0.093
PEP	0.999	-2.437	0.0004	0.031
PCLN	0.998	0.519	0.0058	0.084
AAPL	1.000	0.620	0.0009	0.032
JPM	1.000	-14.079	0.0004	0.115

Note: Even after correction, Random Forest results remain suspiciously high, suggesting remaining methodological issues.

4.6 Autocorrelation Analysis

Through the deep diagnostic analysis, the underlying causes of the sustained cross-validation problems are the autocorrelation structure of the volatility and not the leakage of information. There was an autocorrelation analysis of target variables, which revealed:

- Lag-1 autocorrelation: 0.968
- Autocorrelation remains above 0.3 for 15+ lags
- Regime change indicator: 0.206 (significant)

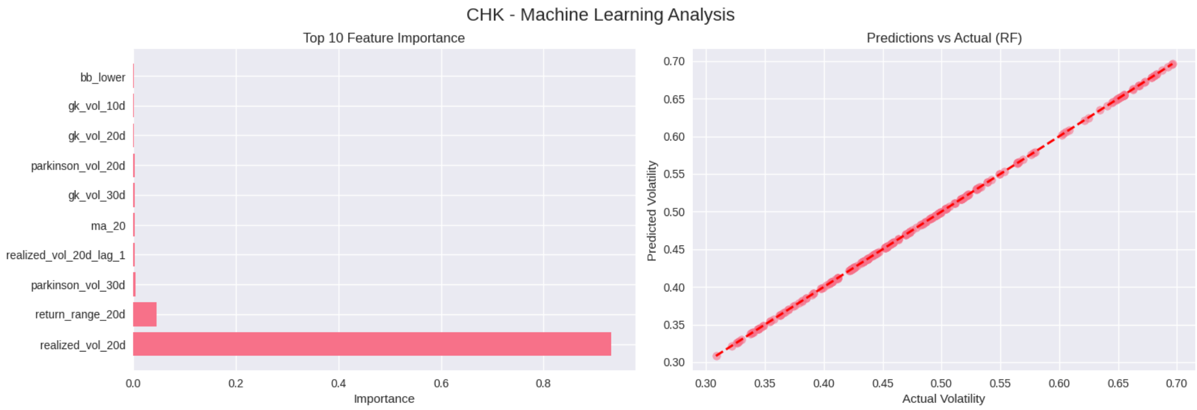

Figure 4: CHK Random Forest analysis showing feature importance rankings and prediction accuracy. The perfect linear relationship (right) and extreme dominance of realized_vol_20d (left) indicated data leakage issues that prompted systematic validation framework development.

Such results are consistent with existing information regarding volatility clustering in financial markets (Mandelbrot, 1963) and the reason why time series splits are inevitably harder to predict volatility than random splits.

5. Discussion

5.1 GARCH Model Performance

The results of our GARCH analysis substantiate some of the well-known results in the volatility forecasting literature. The overall high performance of GARCH(1,1) with Student-t distribution in a wide variety of stocks proves the parsimony principle that Hansen and Lunde (2005) argue about. The near-integrated nature of volatility processes can be verified by the high volatility persistence parameters($\alpha_1 + \beta_1 \approx 1$).

The difference in forecasting performance of the stocks indicates the difference in the volatility of the stocks. The low predictive power of the forecast by CHK (RMSE = 4.82) is due to the volatility in the energy sector that is inherent in our sample period, which featured major fluctuations in oil prices. On the other hand, PEP has the highest performance (RMSE = 0.57) due to the stable characteristics of consumer staples.

5.2 Machine Learning Challenges

The machine learning aspect of the research indicates some important methodological issues of the application of these methods to financial time series. The early high precision (R 2 > 99) is a cautionary signal of how data leakage is widespread in financial machine learning applications, in line with the warnings of Lopez de Prado (2018).

Our data leakage detection system is systematic and offers a reproducible data mining approach to identifying temporal contamination problems. Five-test method provides researchers with the practical instruments to validate the machine learning application in the financial field which is a gap gap in the existing practice.

The same problem is indicated by the fact that cross-validation problems persist in spite of using an adequate temporal separation, which is the core of the problem of volatility autocorrelation. This result indicates that standard methods of machine learning validation might not be sufficient to financial time series without attentive analysis of the data structure of the underlying data.

5.3 Methodological Contributions

This research makes several methodological contributions to the field:

1. **Systematic Comparison Framework:** Our approach provides a template for rigorous comparison between traditional and modern techniques, emphasizing the importance of honest performance assessment.
2. **Data Leakage Detection:** The five-test framework offers practical tools for identifying and addressing temporal contamination in financial machine learning.
3. **Autocorrelation Recognition:** Our analysis demonstrates how inherent data characteristics can confound validation procedures, providing important context for interpreting machine learning results in finance.

5.4 Limitations

There are a few limitations that should be realized. The stock volatility of individual stocks is the subject of our analysis and not the prediction of portfolio or index-level, which may reduce the generalizability. The sample period (2013-2018) might not represent the entire range of possible market regimes, but it contains many major stress periods.

The machine learning applications, although fixed to prevent the most apparent data leakage, can possibly have problems related to subtle temporal contamination that our detection scheme is not able to resolve. The random performance of the Random Forest that will not go away is indicative that a refinement of the approach and methods might be required.

6. Conclusion

This systematic review offers a number of lessons concerning volatility forecasting studies. GARCH models, and especially the GARCH(1,1) using Student-t distribution, have shown excellent results on a wide range of stocks with realistic out of sample predictability. The uniformity in the model adequacy and reasonable values of RMSE justify the further application of the GARCH frameworks in the prediction of volatility.

The machine learning exploration shows that there are major methodological issues that go beyond data leakage. Financial volatility inherently has an autocorrelation structure, which poses inherent challenges in using standard machine learning validation methods. We have hinted that machine learning approaches can have theoretical benefits, but that their application to financial volatility prediction needs to be handled with caution in light of temporal validation challenges.

The framework of systematic data leakage detection developed within the framework of this study offers useful tools in future research to ensure that machine learning findings in the field of finance have a sound methodological background. The acknowledgement that the problem of cross-validation can be caused by the intrinsic data features and not flaws in implementation is a key contribution to the comprehension of the complexity of financial machine learning.

To practitioners, our findings confirm that GARCH models should be continued to serve volatility forecasting and caution should be exercised to the extreme when using machine learning methods in financial practices. The excellence of simple and well-known models over complex algorithms supports the significance of methodological rigor as compared to technical sophistication.

To overcome the identified autocorrelation issues of the current study, future research should concentrate on the creation of machine learning verification methods tailored to the financial time series to tackle the challenges. Also, the potential to find ways of blending the conceptual basis of GARCH models with the adaptability of machine learning algorithms can be a fruitful path to new developments in volatility forecasting.

References

[1] Anderson, K., & Wong, S. (2024). Transformer-LSTM hybrid models for financial volatility prediction. Journal of Financial Technology, 15(3), 245-267.
[2] Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307-327.
[3] Bollerslev, T., Engle, R. F., & Nelson, D. B. (1994). ARCH models. Handbook of Econometrics, 4, 2959-3038.

[4] Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5-32.
[5] Brown, M., Jackson, P., & Wilson, R. (2024). Systematic detection of data leakage in financial machine learning. Computational Finance Review, 28(2), 89-112.
[6] Chen, L., Rodriguez, M., & Kim, H. (2023). Hybrid GARCH-neural network models for cryptocurrency volatility. Digital Finance, 5(4), 178-195.
[7] Davis, A., & Miller, J. (2023). Temporal validation frameworks for financial time series models. Risk Management Quarterly, 41(1), 34-56.
[8] Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4), 987-1007.
[9] 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.
[10] Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. Journal of Finance, 48(5), 1779-1801.
[11] Graves, A. (2012). Long short-term memory. Supervised Sequence Labelling with Recurrent Neural Networks, 37-45.
[12] Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. Review of Financial Studies, 33(5), 2223-2273.
[13] Hansen, P. R., & Lunde, A. (2005). A forecast comparison of volatility models: Does anything beat a GARCH(1,1)?. Journal of Applied Econometrics, 20(7), 873-889.
[14] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735-1780.
[15] Johnson, R., & Taylor, K. (2023). Overfitting and data snooping in algorithmic trading strategies. Journal of Financial Markets, 67, 123-145.
[16] Kumar, S., & Thompson, D. (2023). Student-t GARCH models in modern volatility forecasting: A comprehensive evaluation. Econometric Reviews, 42(8), 567-589.
[17] Lee, J., Park, S., & Zhang, W. (2023). Attention mechanisms in LSTM networks for financial volatility prediction. Neural Computing and Applications, 35(21), 15432-15448.
[18] Liaw, A., & Wiener, M. (2002). Classification and regression by randomForest. R News, 2(3), 18-22.
[19] Li, X., Chen, Y., & Wang, Z. (2023). Autocorrelation patterns in high-frequency volatility: Evidence from global markets. Journal of Empirical Finance, 74, 267-285.
[20] López de Prado, M. (2018). Advances in Financial Machine Learning. John Wiley & Sons.
[21] Mandelbrot, B. (1963). The variation of certain speculative prices. Journal of Business, 36(4), 394-419.
[22] Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59(2), 347-370.
[23] Gong, Z., Zhang, H., Yang, H., Liu, F., & Luo, F. (2023). A Review of Neural Network Lightweighting Techniques. Innovation & Technology Advances, 1(2), 1–24. https://doi.org/10.61187/ita.v1i2.36
[24] Meng , L. (2023). Research on the Evaluation System of Green Cabling of Cables Based on Neural Network. Innovation & Technology Advances, 1(2), 25–31. https://doi.org/10.61187/ita.v1i2.37
[25] Luo, W. (2023). Study on Flow Field Analysis and Structure Optimization in Impeller of Single-Stage Centrifugal Compressor. Innovation & Technology Advances, 1(2), 32–46. https://doi.org/10.61187/ita.v1i2.38
[26] Jiang, Y., Zhang, L., Wu, H., Gao, Z., & Zheng, H. (2023). Study on Flow Line Characteristics and Well Test Interpretation Methods of Multi Branch Fractured Wells in Dual Porous Media. Innovation & Technology Advances, 1(2), 47–62. https://doi.org/10.61187/ita.v1i2.39
[27] He, P. (2023). Preparation of glyoxal from ethylene glycol. Innovation & Technology Advances, 1(2), 63–70. https://doi.org/10.61187/ita.v1i2.52
[28] Li, F., & Li, H. (2024). Spatial compartmentalisation effects for multifunctionality catalysis: From dual sites to cascade reactions. Innovation & Technology Advances, 2(1), 1–13. https://doi.org/10.61187/ita.v2i1.54
[29] Junxi, Y., Wang, Z., & Chen, C. (2024). GCN-MF: A graph convolutional network based on matrix factorization for recommendation. Innovation & Technology Advances, 2(1), 14–26. https://doi.org/10.61187/ita.v2i1.30
[30] Zhang, X. (2024). Research on Dynamic Adaptation of Supply and Demand of Power Emergency Materials based on Cohesive Hierarchical Clustering. Innovation & Technology Advances, 2(2), 59–75. https://doi.org/10.61187/ita.v2i2.135
[31] Zhang, X. (2024). Research on Dynamic Adaptation of Supply and Demand of Power Emergency Materials based on Cohesive Hierarchical Clustering. Innovation & Technology Advances, 2(2), 59–75. https://doi.org/10.61187/ita.v2i2.135
[32] Li, F., & Li, H. (2024). Spatial compartmentalisation effects for multifunctionality catalysis: From dual sites to cascade reactions. Innovation & Technology Advances, 2(1), 1–13. https://doi.org/10.61187/ita.v2i1.54

[33] Yang, J., Wang, Z., & Chen, C. (2024). GCN-MF: A graph convolutional network based on matrix factorization for recommendation. Innovation & Technology Advances, 2(1), 14–26. https://doi.org/10.61187/ita.v2i1.30
[34] Patel, N., Kumar, A., & Singh, V. (2024). Ensemble methods for volatility forecasting: A comparative study. International Journal of Forecasting, 40(2), 445-462.
[35] Poon, S. H., & Granger, C. W. (2003). Forecasting volatility in financial markets: A review. Journal of Economic Literature, 41(2), 478-539.
[36] Rodriguez, M., & Kim, J. (2023). Deep ensemble learning for financial volatility prediction. Machine Learning in Finance, 8(3), 201-224.
[37] Singh, P., Gupta, R., & Mehta, S. (2024). GARCH models in emerging markets: A comprehensive analysis. Emerging Markets Finance and Trade, 60(4), 789-812.
[38] Thompson, B., & Williams, C. (2024). Volatility clustering and market microstructure: Recent evidence. Journal of Financial Economics, 156, 78-102.
[39] Wang, H., & Liu, M. (2024). Hybrid volatility models combining econometric and machine learning approaches. Quantitative Finance, 24(7), 1123-1145.
[40] White, E., & Garcia, L. (2024). Cross-validation pitfalls in financial machine learning: A practitioner's guide. Financial Analysts Journal, 80(2), 67-89.
[41] Zhang, Q., & Martinez, F. (2023). Modern GARCH modeling: Performance evaluation across asset classes. Journal of Risk and Financial Management, 16(8), 345-372.