

Machine Learning and Statistical Model Hybrid Approach to Optimizing Financial Data Prediction

Babikir M. O. Elsheikh^a, Ahmed Edris Abdo^a, Nagat Hamid^b, Abdelsamie Eltayeb Tayfor^c,
Abdelgalal O.I. Abaker^{d,*}, & Hiba A. A. A. Hussin^e

^aDepartment of Business Administration, College of Business Administration, Najran University, Najran, Saudi Arabia

^bDepartment of Accounting, College of Business Administration, Najran University, Najran, Saudi Arabia

^cDepartment of Economics, Applied College, King Faisal University, Al-Ahsa, Saudi Arabia

^dDepartment of Administrative Sciences, Applied College in Khamis Mushait, King Khalid University, Abha, Saudi Arabia

^eDepartment of Finance, Faculty of Business, Imam Mohammed Ibn Saudi Islamic University, Riyadh, Saudi Arabia

Abstract

Accurate price volatility prediction is a cornerstone of sound investment decisions and effective dynamic risk management in financial markets. This study addresses a significant research gap: the limited number of studies exploring the systematic integration of traditional statistical models and artificial intelligence techniques within emerging financial markets, despite their high levels of instability and volatility. The research aims to develop a hybrid predictive framework that combines the flexibility of linear models, specifically ARIMA, with the ability of machine learning algorithms to grasp the complex, nonlinear patterns inherent in financial time series. Furthermore, the study highlights an application gap: the underutilization of advanced volatility estimators. The Garman-Class estimator was adopted as a more efficient and accurate alternative to traditional estimators for measuring daily volatility, due to its reliance on four-part price information (open, close, high, and low). The proposed framework was applied to data from Savola Group, listed on the TASI. The results demonstrated the superiority of the proposed hybrid model in improving forecast accuracy and reducing predictive error measures, particularly the MAE, and RMSE, compared to traditional single-model models. The scientific value of this research lies in its contribution to bridging the knowledge gap related to the integration of statistical models and artificial intelligence techniques in the emerging markets environment. Furthermore, it provides an advanced analytical tool that can enhance asset allocation efficiency and support decision-makers and portfolio managers in navigating the dynamics of highly volatile markets.

Keywords: Accurate analytical tools, artificial intelligence techniques, Garman-Class estimator, hybrid predictive framework, Predicting daily volatility.

Received: 1 February 2026

Revised: 7 March 20246

Published: 30 April 2026

1. Introduction

Financial data analysis challenges are becoming increasingly complex, especially with the ever-growing volume of data. This necessitates sophisticated models and algorithms capable of rapidly processing massive datasets and finding optimal solutions. However, no single method or algorithm is perfect; all have limitations that can be mitigated or eliminated by combining the skills of different methodologies. In this way, the development of hybrid algorithms is anticipated, one that can leverage the capabilities and characteristics of each method (optimization and machine learning) to integrate methodologies and enhance efficiency. This paper presents a comprehensive systematic and literature review of linear, nonlinear, and hybrid models that combine linear and nonlinear components, incorporating optimization and machine learning techniques for clustering and classification. The paper aims to develop a hybrid model that combines linear and nonlinear models to improve the accuracy of forecasting financial market behavior. The proposed model relies on integrating the characteristics of each model type, capitalizing on the simplicity of linear models in interpreting relationships and the power of nonlinear models in capturing complex patterns and hidden

* Corresponding author.

E-mail address: aoadrees@kku.edu.sa

interactions between variables. This model is expected to contribute to enhancing the effectiveness of financial forecasting tools and supporting investment decisions based on historical and contemporary data.

Study Saberironaghi & Saberironaghi (2025), confirm the existence of a methodological gap in which advanced models lack transparency and traditional models lack accuracy, which necessitates the development of hybrid frameworks that efficiently handle big data. Ge (2025), addresses the topic of stock market forecasting, a vital aspect of the financial markets. It focuses on designing highly accurate predictive models aimed at forecasting stock price movements, given their crucial importance in minimizing losses and maximizing profits, especially considering the unpredictable and constantly fluctuating nature of the financial market. Recent study Darwish et al (2025), confirm a deficiency in the balance between prediction accuracy and explanatory capability, which necessitates the development of hybrid models that integrate linear methodologies and artificial intelligence to bridge the gap between technical efficiency and practical application. Recent study Rai & Soltanisehat (2025) emphasize the need to integrate explainable artificial intelligence techniques with hybrid models to bridge the gap between high prediction accuracy in big data and reliability in investment decision-making. Chilukuri et al. (2025), conclude that it is necessary to move from single approaches to hybrid frameworks that integrate statistical interpretation with the flexibility of artificial intelligence to ensure the reliability of prediction in volatile financial markets. The author developed a set of ten deep learning-based regression models to accurately and reliably predict the stock price of a leading Indian automotive company. Detailed stock price data collected at five-minute intervals from December 31, 2012, to December 27, 2013, was used for training. The testing phase utilized data from December 30, 2013, to January 9, 2015. Bustos et al. (2025) review the need to link market efficiency to model accuracy, proposing a broad comparative methodology that goes beyond prevailing practices that focus on limited markets to ensure the generalizability of predictive results globally.

Rezaei et al. (2025), investigated the application and evaluation of a variety of machine learning models, including linear regression, decision trees, random forests, AdaBoost and XGBoost techniques, as well as the nearest neighbor (K) model, vector support machine, and the long-term short-term memory (LSTM) model. The performance of these models was measured using precise evaluation indicators such as root mean squared error (RMSE), mean absolute error (MAE), and error measure (ME) to determine their accuracy and the stability of their results. However, they did not address hybrid models. Bellaly et al. (2025), aims to address a research gap by proposing and implementing an analytical methodology focused on evaluating the accuracy of stock market forecasting models compared to market efficiency. Wang, S.'s (2024) study showed that machine learning models such as random forests and recurrent neural networks (LSTM) excel at stock prediction, but it did not adequately address the effect of incorporating external indicators on the stability of hybrid models. It evaluates the effectiveness of intelligent algorithms in predicting trading market trends by comparing a range of machine learning methods. These methods include random forests, the nearest neighbor (KNN) algorithm, XGBoost, decision trees, and a deep learning methodology based on long-term short-term memory networks (LSTM). The study by Phuoc et al. (2024) was limited to only three major technology companies, which limits the possibility of generalizing the results to other sectors or financial markets. It also neglected to integrate unstructured data such as sentiment analysis, news, and macroeconomic factors that significantly affect price volatility. The study also did not use the hybrid model.

The research gap in the study by Chaudhary & Mirani (2025) is that it compares ARIMA, SARIMA and LSTM without integrating them into a hybrid model that takes advantage of the advantages of both linear and nonlinear models, and it does not test the effect of external factors or economic variables on the accuracy of price prediction. The research by Cayzer & Bau (2025) focuses on using only one-day delayed variables without incorporating external economic and financial factors, and it does not explore hybrid or advanced models that might improve the accuracy of stock price predictions. Therefore, there remains a need for studies that integrate deep learning models with macroeconomic variables to enhance the predictive power of financial markets. Azevedo et al. (2024) relies on simple time variables (1-day lag) and traditional machine learning models without incorporating macroeconomic factors or using hybrid and advanced models, leaving a gap in the development of more accurate forecasting models that combine market data and external factors. Ibrahim et al. (2022) despite the remarkable progress in employing artificial intelligence algorithms for prediction, research output still tends towards single-model approaches, with a gap in the development of integrated hybrid frameworks capable of accommodating the complexity and instability inherent in the data. Liu et al. (2023), focuses on a comparative analysis of three of the most widely used machine learning and time series models: The Autoregressive Integrated Moving Average (ARIMA), the Seasonal Autoregressive Integrated Moving Average (SARIMA), and the Long-Term Short-Term Memory (LSTM), to predict the stock prices of Indian banks. However, the study did not explore the potential of hybrid models to improve the accuracy of the results. Ampountolas (2023). aims to provide accurate financial forecasts and clear insights to support investment decisions and risk management in the volatile cryptocurrency market. The research concludes that combining traditional statistical analysis with artificial

intelligence offers a robust framework for understanding complex time patterns in modern financial markets. The scientific value of Stempień & Ślepaczuk (2025). lies in addressing the knowledge gap regarding the responsiveness of European equities and digital assets to macroeconomic fluctuations. From a practical standpoint, the methodology employed provides a framework enabling analysts to develop advanced risk management models, thereby enhancing the quality of investment decisions in volatile markets. Qureshi et al. (2024), highlights the pivotal role of hybridization mechanisms in enhancing the efficiency of machine learning and deep learning models, especially when balancing linear and non-linear elements independently of traditional correlation assumptions. This conclusion forms a practical foundation that enables researchers and traders to design flexible investment strategies that are adaptable to volatile market dynamics. Fozap (2025), examines advanced statistical modeling aimed at improving the accuracy of Bitcoin/US Dollar price predictions.

The researchers compared eight different models, including machine learning and traditional time-based models, and proposed a hybrid model combining these approaches using a weighted average methodology. The results showed that this proposed hybrid model clearly outperformed the individual models in reducing error rates and increasing the accuracy of financial forecasts. presents a hybrid deep learning model combining short-term long-term memory networks (LSTMs) and convolutional neural networks (CNNs) to predict the long-term movement of the S&P 500 index. The study integrates technical indicators and historical data to enhance forecast accuracy, with the LSTM component focusing on time-based trends and the CNN component analyzing spatial patterns and short-term fluctuations. The results show that this hybrid model outperforms traditional methods such as ARIMA and SVM, providing an effective balance between understanding historical patterns and adapting to market changes. Alanazi (2025), published in the International Journal of Analysis and Applications, provides a comprehensive evaluation of the effectiveness of artificial intelligence in predicting stock prices compared to traditional statistical methods. Researcher Bader Al-Anzi demonstrated the ability of advanced models such as Long Short-Term Memory (LSTM) and random forests to analyze historical S&P 500 index data with an accuracy exceeding that of linear regression. Martinez (2025). presents a hybrid prediction model that combines ARIMA statistical techniques with artificial neural networks (ANNs) to improve the accuracy of predictions in complex time series. This innovative framework aims to handle both linear and nonlinear patterns simultaneously, reducing error rates by 12% to 18% compared to single models. Kadkhoda & Amiri (2024), explores the use of complex network analysis and machine learning models to predict the occurrence of financial distress in small and medium-sized enterprises (SMEs). By constructing networks based on similarity and correlation between enterprises, the researchers extracted structural features such as proximity centrality and clustering coefficients to enhance the accuracy of predictive models. The results showed that integrating these network features with traditional financial data significantly improves the ability of algorithms, such as random forests, to identify potential risks.

2. Methods

To develop a robust framework for predicting daily volatility in stock markets, this study adopted a comparative modeling approach combining statistical and machine learning techniques. The methodology consisted of the following key phases:

2.1. Data source and preprocessing

The source of this data is the daily share prices (open, close, high, low) of Savola Group, listed on the Saudi Stock Exchange (Tadawul), for the period from April 1, 2024 to August 1, 2024.

Daily volatility was calculated using the Jarman-Class estimator, Jarman & Boyland (2011), using the following formula:

Daily volatility:

$$\sigma_{GK} = \sqrt{\sigma_{GK}^2} \quad (1)$$

$$\sigma_{GK}^2 = \frac{1}{2} \left(\ln \left(\frac{H}{L} \right) \right)^2 - (2 \ln 2 - 1) \left(\ln \left(\frac{C}{O} \right) \right)^2 \quad (2)$$

where, H: High, L: Low, C: Close, O: Open

2.2. Model selection

For evaluation, three predictive models were selected.

a. ARIMA

The ARIMA model is a statistical forecasting model used to analyze time series data and predict future values based on past data Albeladi et al. (2023). The model combines Autoregressive integrated Moving Average to provide accurate predictions for data that changes over time Abdulrahim et al. (2025).

Let Z_t a time series data, which represents an integer index and Z_t is a real number, then:

$$Z_t = Z_{t-1} + a_t ; a_t \sim WN(0, \sigma^2) \tag{3}$$

$$Z_t - Z_{t-1} = a_t ; a_t \sim WN(0, \sigma^2) \tag{4}$$

$$(1 - B) Z_t = a_t \tag{5}$$

$$Z_t = \frac{1}{(1 - B)} a_t \tag{6}$$

$$\psi(B) = \frac{1}{(1 - B)} \tag{7}$$

Where the weighed $\psi_1, \psi_2, \psi_3, \dots$

$$\psi(B)(1 - B) = 1 \tag{8}$$

$$(1 + \psi_1 B + \psi_2 B^2 + \psi_3 B^3 + \dots)(1 - B) = 1 \tag{9}$$

$$B : \psi_1 - 1 = 0 \Rightarrow \psi_1 = 1 \tag{10}$$

$$B^2 : \psi_2 - \psi_1 = 0 \Rightarrow \psi_2 = \psi_1 = 1 \tag{11}$$

$$B^3 : \psi_3 - \psi_2 = 0 \Rightarrow \psi_3 = \psi_2 = 1 \tag{12}$$

:
:
:

$$B^j : \psi_j - \psi_{j-1} = 0 \Rightarrow \psi_j = \psi_{j-1} = 1 \tag{13}$$

That is, the weights for the random walk model is

$$\psi_j = 1, j \geq 1 \tag{14}$$

b. Radial Basis Function

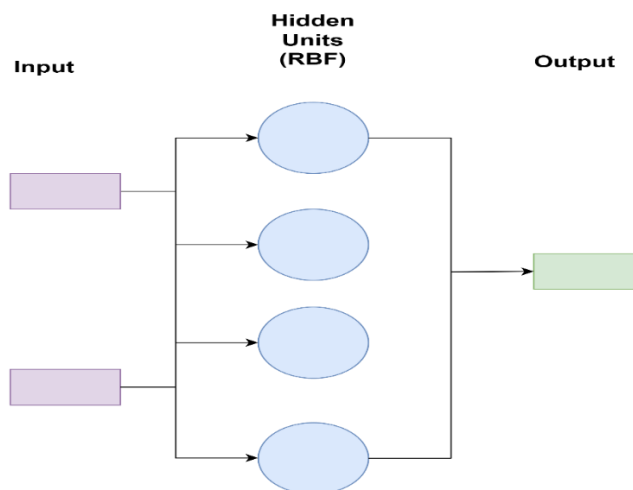


Figure 1. The RBF Network architecture

A radial basis function (RBF) network is a type of artificial neural network that uses radial basis functions as activation functions in the hidden layer and employs point-centered basis functions to approximate complex functions Zholamanov et al. (2025). Gaussian formulas are widely used due to their smooth performance and infinite differentiability, which facilitates superior approximation properties and faster computations. A radial basis function (RBF) is defined as a three-layer neural network architecture consisting of an input layer, a hidden layer, and an output layer Zhang et al. (2022).

RBF Networks Figure 1 are an excellent choice when we need speed in training or when we are dealing with real-time applications, such as dynamic system control or time series prediction, because they do not suffer from gradient vanishing problems as severely as deep networks.

3. Results and Discussion

This section presents the tables and graphs as analytical tools that contribute to interpreting the results and clarifying the main trends of daily market fluctuations using the Garman-Klass

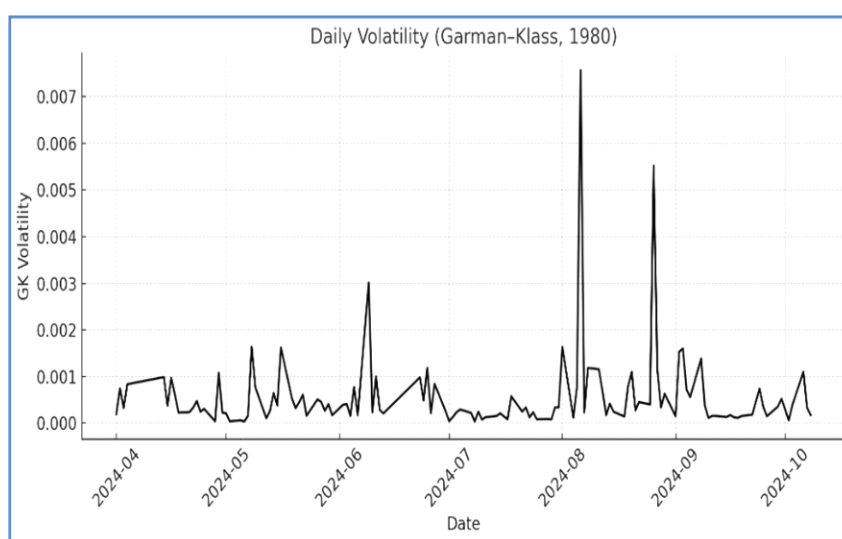


Figure 2. Savola Group stock performance According to the Garman-Klass 1980 methodology

Figure 2 shows relatively low daily volatility (Garman-Klass) ranging between 0.000 and 0.007, with occasional sharp peaks (particularly in August). There is no clear upward or downward trend, but rather random fluctuations with sudden changes, which may reflect unexpected market events during that period. The reason for the sharp fluctuations is the nature of the Garman-Klass methodology itself, which is calculated daily and exhibits high sensitivity to sudden price changes within the day (such as opening or closing gaps, or sharp intra-session moves). These peaks do not necessarily reflect major economic events but may be the result of daily technical or trading fluctuations, especially in markets with fluctuating liquidity or during data release periods.

Figure 3 shows a daily volatility distribution (Garman-Klass), where most of the data is concentrated around the mean, indicating a near-normal distribution. The frequency peaks at approximately 0.022, with a gradual decrease in frequency to the right and left. The distribution ranges from 0.000 to 0.080, with a slight tail to the right, which may indicate a slight positive bias.

3.1. ARIMA (1,0,1) Model

This analysis on Table 1 presents the ARIMA model for estimating daily volatility.

Table 1 shows that the AR (1) and MA (1) coefficients are highly significant ($p = 0.000$), indicating a strong dependence on the previous value (autoregressive) and the previous shock (moving average). The constant is also significant, suggesting a stable series average of approximately 0.02225. High T-statistic values (9.27 and 4.89) further enhance

the confidence of the estimates. Since all significant coefficients are highly significant and there are no signs of instability, this RIMA (1,0,1) model is reliable and dependable for short-term forecasting.

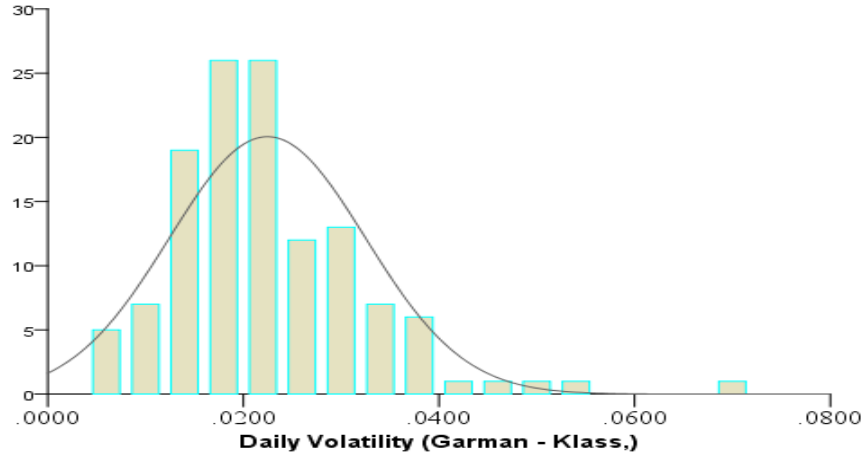


Figure 3. Daily volatility distribution according to the Garman-Klass methodology

Table 1. ARIMA(1,0,1) model estimates daily volatility: coefficients and diagnostic statistics

Final Estimates of Parameters			T-Value	P-Value
Type	Coef	SE Coef		
AR (1)	0.8753	0.0944	9.27	0
MA (1)	0.6890	0.1410	4.89	0
Constant	0.0028	0.0003	10.59	0
Mean	0.0223	0.0021		
Number of Observations: 126				

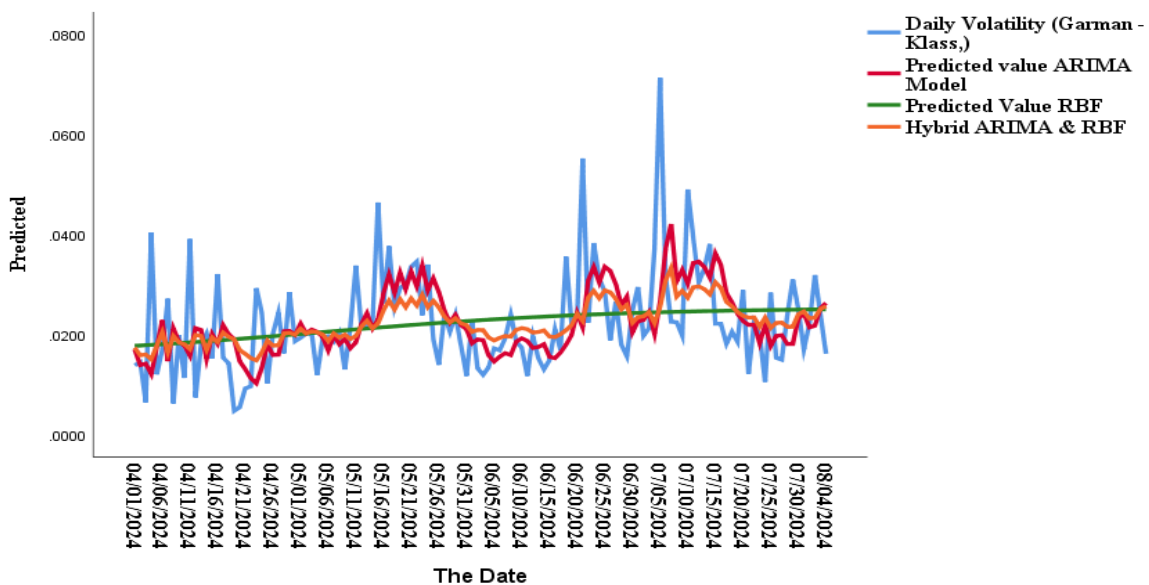


Figure 4. Comparison of the performance of prediction models: ARIMA, RBF, and the hybrid model

Figure 4. compares actual daily volatility (Garman-Klass) in blue, with three predictive models: ARIMA (red), RBF (green), and an ARIMA-RBF hybrid (orange). The hybrid model performs very closely with actual volatility, particularly in tracking peaks and troughs, demonstrating its superiority in capturing nonlinear dynamics. The ARIMA

model follows the overall trend but fails to capture sharp swings, while the RBF model produces a very stable line that does not reflect daily changes. This suggests that combining the two models (linear and nonlinear) improves predictive accuracy. The hybrid model is most effective for use in risk management or trading strategies that require an accurate assessment of intraday volatility.

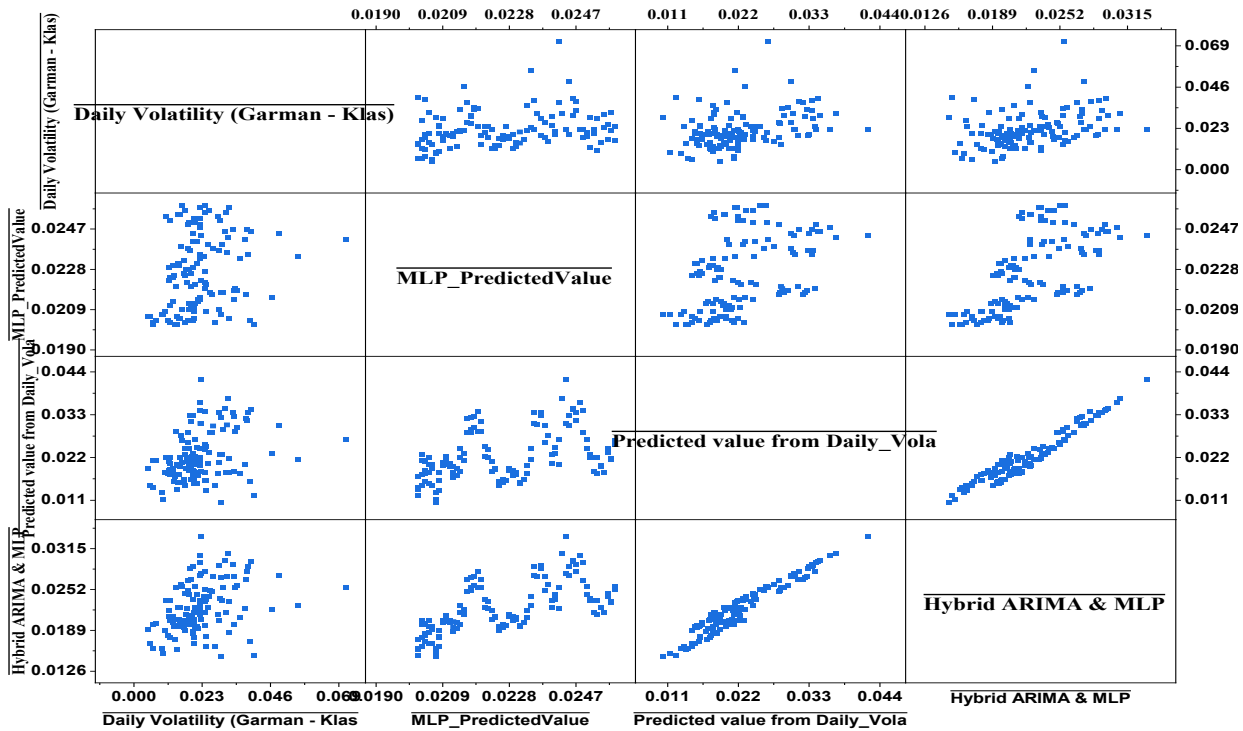


Figure 5. Visual correlation matrix between estimated daily fluctuations and predicted values

A thorough Figure 5 analytical comparison between the actual daily volatility values estimated by the Garman-Klass scale and those predicted by three forecasting methodologies—the MLP neural network model, the ARIMA-MLP hybrid model, and predictions based directly on daily volatility indicators—is shown in the accompanying figure, which displays a dispersion plot matrix. This graphic comparison makes it possible to see exactly how well each model captures the financial market's movements. Plots of the MLP model's performance reveal a somewhat good correlation with real values, but there is also a considerable amount of dispersion, especially at high volatility levels. This illustrates the model's versatility in learning from nonlinear patterns as well as its capacity to identify the general direction of volatility movement. However, when working with intricate and quickly shifting financial time series, neural models frequently encounter the problem of "predictive noise" appearing at extreme levels. However, the quality of forecasts greatly increases when previous daily volatility data is added as a direct explanatory variable within the "Daily Vola Prediction" framework. When compared to utilizing MLP alone, the regularity of the link between anticipated and actual values improves, strengthening the model's explanatory dimension and lowering the margin of error that comes from depending just on machine learning without a supporting temporal context. The ARIMA-MLP hybrid model, on the other hand, shows a distinct quasi-linear alignment of points around a perfect line of congruence in the lower right plot. This is clear visual proof that there is a substantial drop in dispersion, particularly at extreme values, and a high correlation coefficient between predictions and actual values. This demonstrates how the hybrid model can handle nonlinearity and abrupt volatility because it systematically combines MLP's ability to handle complicated nonlinear interactions with ARIMA's ability to simulate linear components and time trends. In light of this, the visual and statistical analysis results validate that the combination of methods (Hybridization) and the addition of contextual information, such as historical volatility, to models significantly improves their predictive power, making the ARIMA-MLP hybrid model the best option for real-world risk management and investment decision-making applications. Meanwhile, pure neural models continue to develop predictive noise handling mechanisms to improve their performance in extremely volatile market conditions.

3.2. Evaluation Metrics

A wide range of evaluation measures can be applied in the case of assessing the performance of prediction models of machine learning. To evaluate our models, we have utilized the following metrics: RMSE, MAPE, and MAE Ghojogh & Ghodsi (2023) and Chen et al. (2025), if the error metrics (RMSE, MAPE, and MAE) are smaller, the model performs better.

The formula:

$$APE = \frac{1}{n} \sum_{i=1}^n \left| \frac{A_t - F_t}{A_t} \right| \tag{15}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (A_t - F_t)^2}{n}} \tag{16}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |A_t - F_t| \tag{17}$$

Where F_t , A_t and n represented the forecasted value, actual value, and the fitted points number respectively.

Table 2. Comparison of the performance of volatility prediction models

	APE	RMSE	MAE
ARIMA (1,0,1)	0.367298	0.009849	0.007002
Hybrid ARIMA-RBF	0.344652	0.008718	0.00638
RBF	0.358589	0.009327	0.006603

Table 2 compares the performance of three models in volatility prediction using error metrics. The results indicate that the ARIMA-RBF hybrid model outperforms all three metrics. Lowest APE (0.3447), Lowest RMSE (0.008718), Lowest MAE (0.00638). This demonstrates that combining the linear (ARIMA) and nonlinear (RBF) models improves forecasting accuracy compared to using either model alone.

4. Conclusion

This research explores the shortcomings of single-model models—whether linear statistical or AI-based—in simulating the dynamics of highly volatile emerging financial markets. To bridge this gap, we present a hybrid predictive framework that combines the ARIMA model, with its ability to model linear components, and the Basic Vector Function (RBF) network, with its flexibility in accommodating complex nonlinear patterns. The model was applied to Savola stock data in the Saudi market, utilizing the advanced Garman-Klass estimator to extract price volatility with greater accuracy by integrating opening, closing, and price range data.

The experimental results demonstrated the statistical superiority of the hybrid (ARIMA-RBF) model over single-model models, recording the lowest error values, with a relative mean error (APE) of 0.3447 and a root mean square error (RMSE) of approximately 0.0087, compared to the reference models. This performance is attributed to the proposed framework's ability to balance statistical stability with dynamic adaptation to market shocks. The theoretical contribution of this work lies in presenting an integrated protocol that enhances forecasting accuracy in low-efficiency financial environments, providing a strategic tool for portfolio managers and decision-makers to improve risk management and derivatives pricing.

However, the research is not without some limitations. First, the application is limited to a single stock within a specific food sector, which may restrict generalizability without further testing across diverse sectors and markets. Second, the hybrid model relies on specific RBF network settings (such as the number of central units and the diffusion function), which may require fine-tuning depending on the nature of the data. Third, the research did not compare with other modern hybrid models such as LSTM-ARIMA or Transformer-based hybrids, which may affect the evaluation of relative performance in more complex environments.

Therefore, several avenues for future research are recommended: (1) Expanding the study to include a wider range of stocks and sectors within and outside the Saudi market, including similar emerging markets; and (2) Integrating the hybrid model with modern deep learning techniques to enhance its ability to capture long-term dependencies. (3) Developing an automated mechanism to dynamically adjust the parameters of the hybrid model in response to changes in market structure; and (4) testing the framework's applicability in real-time forecasting within a real trading

environment. This research thus opens promising avenues for developing smarter and more adaptive financial forecasting tools in an increasingly complex world.

Acknowledgements

The authors extend their appreciation to the Deanship of Research and Graduate Studies at King Khalid University for funding this work through Large Research Project under grant number RGP/2/492/46

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

References

- Albeladi, K., Zafar, B., & Mueen, A. (2023). Time series forecasting using LSTM and ARIMA. *International Journal of Advanced Computer Science and Applications*, 14(1), 313-320.
- Abdulrahim, H., Alshibani, S. M., Ibrahim, O., & Elhag, A. A. (2025). Prediction OPEC oil price utilizing long short-term memory and multi-layer perceptron models. *Alexandria Engineering Journal*, 110, 607-612.
- Alanazi, B. S. (2025). A comparative study of traditional statistical methods and machine learning techniques for improved predictive models. *International Journal of Analysis and Applications*, 23, 18-18.
- Ampountolas, A. (2023). Comparative analysis of machine learning, hybrid, and deep learning forecasting models and Deep Learning Algorithms. *JOIV: International Journal on Informatics Visualization*, 9(2), 510-527
- Azevedo, B. F., Rocha, A. M. A., & Pereira, A. I. (2024). Hybrid approaches to optimization and machine learning methods: a systematic literature review. *Machine Learning*, 113(7), 4055-4097.
- Bellaly, A., Belattar, S., & Haimoudi, E. K. (2025). Application of Artificial Intelligence in Stock Market Prediction. *Engineering Proceedings*, 112(1), 34
- Bustos, O., Pomares-Quimbaya, A., & Stellian, R. (2025). Machine learning, stock market forecasting, and market efficiency: a comparative study. *International Journal of Data Science and Analytics*, 20(7), 6815-6839.
- Cayzer, A. F., & Bau, Y. T. (2025). Predicting the Next Day's Closing Price of Stock Indices Using Machine Learning and Deep Learning Algorithms. *JOIV: International Journal on Informatics Visualization*, 9(2), 510-527.
- Chaudhary, T., & Mirirani, S. (2025). Machine Learning and Time Series Approaches for Stock Price Prediction: A Case Study of Indian Banks. *Procedia Computer Science*, 260, 626-634.
- Chen, W., Nguyen, K. A., & Lin, B. S. (2025). Rethinking evaluation metrics in hydrological deep learning: Insights from torrent flow velocity prediction. *Sustainability*, 17(19), 8658.
- Chilukuri, G. S. P., Nwanegbo, I. M., & Chiobi, N. F. (2025). Stock Price Prediction Using Machine Learning. Comprehensive Review. *Smart Cities*, 8(5), 153. *Conferences* (Vol. 196, p. 02007). EDP Sciences.
- Darwish, M., Hassanien, E. E., & Eissa, A. H. (2025). Stock Market Forecasting: From Traditional Predictive Models to Large Language Models. *Computational Economics*, 1-45.
- Fozap, F. M. P. (2025). Hybrid machine learning models for long-term stock market forecasting: Integrating technical indicators. *Journal of Risk and Financial Management*, 18(4), 201
- Ge, Q. (2025). Enhancing stock market Forecasting: A hybrid model for accurate prediction of S&P 500 and CSI 300 future prices. *Expert Systems with Applications*, 260, 125380.
- Ghojogh, B., & Ghodsi, A. (2023). Recurrent neural networks and long short-term memory networks: Tutorial and survey. *arXiv preprint arXiv:2304.11461*
- Hegazy, O., Soliman, O. S., & Salam, M. A. (2014). A machine learning model for stock market prediction. *arXiv preprint arXiv:1402.7351*.
- Ibrahim, K. S. M. H., Huang, Y. F., Ahmed, A. N., Koo, C. H., & El-Shafie, A. (2022). A review of the hybrid artificial intelligence and optimization modelling of hydrological streamflow forecasting. *Alexandria Engineering Journal*, 61(1), 279-303.

- Jarman, D. W., & Boyland, L. G. (2011). The Impacts of Budget Reductions on Indiana's Public Schools: The impact of Budget Changes on Student Achievement, Personnel, and Class Size for Public School Corporations in the State of Indiana. *Current Issues in Education*, 14(2).
- Kadkhoda, S. T., & Amiri, B. (2024). A hybrid network analysis and machine learning model for enhanced financial distress prediction. *IEEE Access*, 12, 52759-52777
- Liu, S., Wu, K., Jiang, C., Huang, B., & Ma, D. (2023). Financial time-series forecasting: Towards synergizing performance and interpretability within a hybrid machine learning approach. *arXiv preprint arXiv:2401.00534*.
- Martinez, A. (2025). Hybrid Forecasting Models: Integrating Statistical and Machine Learning Approaches for Enhanced Predictive Accuracy. Available at SSRN 5515260
- Phuoc, T., Anh, P. T. K., Tam, P. H., & Nguyen, C. V. (2024). Applying machine learning algorithms to predict the stock price trend in the stock market—The case of Vietnam. *Humanities and Social Sciences Communications*, 11(1), 1-18.
- Qureshi, M., Iftikhar, H., Rodrigues, P. C., Rehman, M. Z., & Salar, S. A. (2024). Statistical modeling to improve time series forecasting using machine learning, time series, and hybrid models: A case study of bitcoin price forecasting. *Mathematics*, 12(23), 3666.
- Rai, B., & Soltanisehat, L. (2025). A Multi-Model Machine Learning Framework for Daily Stock Price Prediction. *Big Data and Cognitive Computing*, 9(10), 248.
- Rezaei, A., Abdellatif, I., & Umar, A. (2025). Towards economic sustainability: A comprehensive review of artificial intelligence and machine learning techniques in improving the accuracy of stock market movements. *International journal of financial studies*, 13(1), 28.
- Saberironaghi, M., Ren, J., & Saberironaghi, A. (2025). Stock Market Prediction Using Machine Learning and Deep Learning Techniques: A Review. *Applied Math*, 5(3), 76.
- Stempień, D., & Ślepaczuk, R. (2025). Hybrid models for financial forecasting: combining econometric, machine learning, and deep learning models. *arXiv preprint arXiv:2505.19617*
- Wang, S. (2024). Machine learning and deep learning predictive models for the stock market. In *SHS Web of Conferences* (Vol. 196, p. 02007). EDP Sciences.
- Zhang, R., Li, Y., Gui, Y., & Zhou, J. (2022). Prediction of blasting induced air-overpressure using a radial basis function network with an additional hidden layer. *Applied Soft Computing*, 127, 109343
- Zholamanov, B., Saymbetov, A., Nurgaliyev, M., Bolatbek, A., Dosymbetova, G., Kuttybay, N., ... & Beyca, Ö. F. (2025). RSSI Fingerprint-Based Indoor Localization Solutions Using Machine Learning Algorithms: A Comprehensive Review. *Smart Cities*, 8(5), 153.