ORIGINAL PAPER

DOI: 10.26794/2587-5671-2025-29-2-154-165
JEL G12, G15, G17

Predicting Financial Market Volatility with Modern Model and Traditional Model

R.G. Aldeki
Al-Sham Private University, Damascus, Syria

ABSTRACT

The major **topic** investigates how classical methods (ARCH and GARCH) and well-known machine learning algorithms, support vector regression, and hybrid methods. This paper **aims** to predict and forecast volatility to develop a two-stage forecasting approach the volatility of the Amman Stock Exchange Index (ASE) effectively. Additionally, the effectiveness of the machine learning techniques' selection and utilization of information in stock data is evaluated. **Methods** the semiparametric estimating technique known as support vector regression (SVR) has been widely used for the prediction of volatility in financial time series. By integrating SVR with the GARCH model (GARCH-SVR) application with various kernels (Radial Basis Kernel Function (RBF), Polynomial Kernel Function (PF), and Linear Kernel Function (LF)). The suggested learning approaches are compared to two well-known statistical time series models, Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH), in order to assess the assertion that they can properly anticipate ASE volatility. To compare their **results**, RMSE is employed as an error metric. There is evidence that the GARCH-SVR model performs best for predicting volatility time series, and classical volatility model techniques have an enormous predictive performance better than machine learning models.

Keywords: volatility forecasting; classical volatility models; ARCH; GARCH; machine learning models; support vector regression; hybrid model; GARCH-SVR

For citation: **Aldeki R.G. Predicting financial market volatility with modern model and traditional model. *Finance: Theory and Practice*. 2025;29(2):154-165. DOI: 10.26794/2587-5671-2025-29-2-154-165**

INTRODUCTION

Volatility is an important factor in risk management, asset pricing, and portfolio selection since it measures how much a financial return fluctuates and acts as a proxy for risk [1]. The functional shape of the data generation process and the error distribution are presumptions made by both linear and nonlinear parametric generalized autoregressive conditional heteroscedasticity (GARCH) models. Additionally, empirical investigations [2–5] show that GARCH has poor predicting performance. Because of this, suggestions have been made for changes to the prediction assessment criteria [6], the model's design and estimate, and the use of different proxies for volatility. Since SVR can capture non-linear characteristics of financial time series, such as volatility clustering, leptokurtosis, and leverage effect, without making assumptions about the properties of the data distribution, it has been suggested in the literature as a way to overcome these limitations. Due to its capacity to capture the dynamic and nonlinear behavior of financial time series, SVR exhibits superior results on volatility forecasting compared to GARCH models, as demonstrated by [6–8]. The choice of kernel function has a significant impact on the SVR's forecasting performance because it is a kernel-based technique. It is feasible to build hybrid kernels by linear or non-linear combination of kernels in order to enhance the SVR learning and generalization capacity and benefit from multiple kernel functions [9]. According to empirical data, the hybrid kernel outperforms the SVR with a single kernel in terms of predicting accuracy [9]. Additionally, the Structural Risk Minimization Principle is implemented using the SVR, a machine learning approach based on statistical learning theory, which enhances generalization performance [10]. For the purpose of forecasting financial time series, researchers have recently coupled the GARCH model and artificial intelligence-based methods. [11] created the nonparametric model known as support vector machines (SVMs), which has been applied to financial forecasting [12, 13] based on the GARCH (1, 1) model and demonstrates that it can produce better volatility estimates than the traditional GARCH model. They substitute the SVR for the maximum likelihood (ML) estimation procedure as a nonlinear nonparametric tool. SVR has an advantage over ML estimation since it does not assume that a probability density function exists across the return's series. The GARCH-based SVR approach is developed by [14] to study the relationship between information volume and trading volume volatility. The SVR-GARCH model is the way [15] models the conditional volatility in Turkish financial markets. Peng et al. (2018) [16] assess the SVR-GARCH model's ability to forecast the hourly and daily volatility of three different cryptocurrencies and three different exchange rates. The majority of the research on SVR-GARCH model parameter estimation has been concentrated on using the SVR model rather than the conventional ML approach to directly estimate the GARCH model parameters. The issue of financial time series volatility forecasting is complicated and time-varying, though. Any one model could have a limit on how well it can represent various time series aspects, leading to the associated inaccuracy. The main aim of the current research in this regard is to provide a two-stage strategy combining the GARCH-SVR estimate procedure to enhance the capacity to anticipate financial time series volatility. When compared to conventional volatility models, machine learning techniques can dramatically improve prediction accuracy, especially during periods of higher average volatility. The hybrid technique falls short and is significantly impacted by the market's quick fluctuations. Overall, the out-of-sample forecasting of volatility using learning approaches shows considerable promise for prediction and the extraction of significant information from additional data.

The remainder of this research is structured as follows. First, a methodology section is presented, which consists of an introduction to volatility, followed by statistical time series methods; the ARCH, GARCH, the machine learning methods; support vector machines, and finally the hybrid GARCH-SVR model with a kernel function. Furthermore, in this section the metric of root mean squared error (RMSE) and tests used to evaluate the data and the performance of the models are presented.

LITERATURE REVIEW

Volatility has been the focus of an extensive body of study for the past three decades due to its significance in finance and the difficulties associated with anticipating it. The distribution of volatility time series includes fat tails, and stock shocks have a significant influence on volatility, among other features that set them apart from other time series, according to research. Two qualities are particularly important for the study that was done for this thesis. Firstly, there is an enormous amount of evidence for volatility clustering, which is the concept that a high volatility period is probably to be followed by another high volatility period and vice versa for a low volatility period. Several investigations, including those by [17, 18], provide empirical support for this. Furthermore, the presence of volatility persistence in financial time series is supported by [19, 20], which means that the volatility in many future periods is influenced by the stock return today. Several models have been created and put into use to address the problem of forecasting volatility in an effort to take various stylized facts into account. The Autoregressive Moving Average Model, its extension ARIMA, and ARCH class models are suitable for estimating the conditional variance [20], some of the biggest contributions to the field after simple historical volatility models and linear regression. The parameters of the ARCH class models are often calculated using the parametric estimating approach, assuming that the return's series has a probability density function. Due to their capacity to detect volatility persistence or clustering, the ARCH class models are favorable [21]. To give superior forecasting performance, the ARCH class models must be changed, according to several current research studies [5]. For the purpose of forecasting financial time series, researchers have recently combined the GARCH model and artificial intelligence-based methods. Vapnik (1997) [11] created the nonparametric support vector machine (SVM), which has been used to financial forecasting [6]. Support vector regression (SVR) is a technique that [13] suggest and demonstrate may produce better volatility forecasts than the conventional GARCH model. It is based on the GARCH (1, 1) model. They substitute the SVR for the maximum likelihood (ML) estimation procedure as a nonlinear nonparametric tool. SVR has an advantage over ML estimation since it does not assume that a probability density function exists across the return's series. The GARCH-based SVR approach is developed by [14] to simulate the relationship between the volatility of trading volume and information volume. In order to predict the financial volatility of three important ASEAN stock markets, [22] fitted the least-squares support vector machine (LSSVM) based on the traditional GARCH (1, 1), EGARCH (1, 1), and GJR (1, 1) models. A recurrent SVR method is suggested by [6] and used to predict the conditional variance equation of the GARCH model. The SVR-GARCH model is how [15] model the conditional volatility in Turkish financial markets. When the data are skewed Student-t distributed, employs the SVR-based approach to estimate and predict volatility in the asymmetric power ARCH type of model. In order to increase prediction accuracy, [23] offer a mixture of Gaussian kernels in the SVR based on GARCH (1, 1) (with a linear combination of one, two, three, and four Gaussian kernels). Peng et al. (2018) [16] assess the SVR-GARCH model's ability to forecast the hourly and daily volatility of three different cryptocurrencies and three different exchange rates.

To estimate the GARCH parameters, the SVR estimation method (SVR-GARCH) is used in place of maximum likelihood estimation. By integrating the GARCH model with SVR, [24] creates a two-stage forecasting volatility approach called GARCH-SVR. To examine the impact of innovations in various distributions, they offer the GARCH-SVR and GARCH-t-SVR models, based on the standard normal distribution and the standard Student's t distribution, respectively. To account for asymmetric volatility effects, they additionally consider the GJR-(t)-SVR models. The forecasting performance of the GARCH-(t)-SVR and GJR-(t)-SVR models is assessed using the daily closing price of the S&P 500 index as well as the daily exchange rate of the British pound versus the US dollar. The empirical results for one-period forecasts show that the GJR-(t)-SVR and GARCH-(t)-SVR models improve the accuracy of volatility forecasting. Given that empirical evidence shows that the stock market oscillates between several possible regimes in which the overall distribution of returns is a mixture of normal, [23] we attempt to find the optimal number of mixtures of Gaussian kernels that improve one-period-ahead volatility forecasting of SVR based on GARCH(1,1). The forecast performance of a mixture of one, two, three, and four Gaussian kernels is compared to SVR-GARCH with Morlet wavelet kernel, standard GARCH, Glosten-Jagannathan-Runkle (GJR), and nonlinear EGARCH models with normal, student-t, and generalized error distribution (GED) innovations using the mean absolute error (MAE), root mean squared error (RMSE), and robust Diebold-Mariano test. A variety of Gaussian kernels used in SVR-GARCH, according to out-of-sample predictions, can better capture regime-switching behavior and anticipate volatility. Nõu et al. (2021) [25] show which approach — econometric or machine learning — is more effective in forecasting the returns and volatility of the Baltic stock market. There hasn't been much study done on using econometric or machine learning models to forecast the Baltic stock market. However, there are no comparison studies that fairly compare the various strategies for the Baltic stock market. The findings show that the support vector regression model has a symmetric mean absolute percentage error of 61.90% compared to the autoregressive moving average model's symmetric mean absolute percentage error of 165.43%. The symmetric mean absolute percentage error of the GARCH-ANN model is 61.65%, while that of the GARCH model is 51.05%. Machine learning models outperform econometric models in most of the studied measures. However, the outcomes of the machine learning and econometric models are typically comparable.

The majority of the research on SVR-GARCH model parameter estimation has been concentrated on using the SVR model rather than the conventional ML approach to directly estimate the GARCH model parameters. The issue of financial time series volatility forecasting is complicated and time-varying, though. Any one model could have a limit on how well it can represent various time series aspects, leading to the associated inaccuracy. The major goal of the current research is to provide a two-stage strategy that combines the SVR procedure with the GARCH-ML estimate process to increase the accuracy of forecasting financial time series volatility.

METHODOLOGY

Firstly, it begins by describing the basic ideas of volatility, then goes on to cover the statistical techniques used as a benchmark, the machine learning techniques, and lastly the hybrid approach. The tests utilized and assessment metrics put in place to compare and evaluate the results are discussed at the end. In that it enables us to assess the uncertainty, volatility prediction is essential to comprehending the dynamics of the financial market. As a result, many financial models, particularly risk models, use it as an input. These details underline how crucial it is to estimate volatility accurately. In the past, parametric approaches like ARCH, GARCH, and their extensions have been widely employed; however, these models have the drawback of being rigid. This study seeks to employ data-driven models, such as Support Vector Machines and the hybrid approach GARCH-SVR, in order to address this problem. It turns out that data-driven models perform better than parametric models.

Volatility Measures

Volatility plays a significant role in risk management, asset allocation, and derivatives pricing. The standard deviation or variance of returns from a financial instrument or market index is widely used to measure it. This section discusses realized volatility and implied volatility, the two historical measures of volatility. While implied volatility represents market expectations for a company's future price, previous volatility measures stock movement based on previous prices. It analyzes changes in a certain stock or index over a defined period of time. Implied Volatility in its purified state. The two sources of implied volatility, also known as the ex-ante measure of volatility (model-free estimate), are the Black-Scholes' options pricing model from Black and Scholes (model-based estimation) or the formula for the options market price. These metrics rely on a number of factors, including the number of days till expiry, the stock price, put options, the risk-free rate of interest, and the actual call/put price. As a result, changes in these factors will cause an adjustment in the implied volatility. According to [26], purified implied volatility (PV) is utilized to lessen the impact of stock price fluctuations.

By applying historical volatility (realized volatility) in this paper, which is calculated using the stock return standard deviation. Because it is a non-observable, the amount that cannot be accurately measured but can only be retrieved with an acceptable margin of error, volatility prediction remains a challenging issue. More proxies, such as realized volatility, might be used to better understand the use of machine learning and hybrid models in volatility forecasting. This measure of volatility is used in the literature [26].

$$R_t = \log\left(\frac{S_t}{S_{t-1}}\right), \quad (1)$$

$$R_m = \frac{\sum_{t=1}^{n} R_t}{n}, \quad (2)$$

$$HV = \sqrt{\frac{\sum_{t=1}^{n}\left(R_t - R_m\right)^2}{n-1}}, \quad (3)$$

where HV — historical volatility; R_t — stock return; R_m — average stock return; S_t — stock's price at current day: S_{t-1}: stock's price at previous day; n — number of listed companies. To calculate the return market, it takes the average stock return through dividing the sum of return companies by a number of listed companies.

Statistical Methods

In order to better understand and approach the uncertainty, modeling volatility is essentially modeling uncertainty. This allows us to have a good enough approximation to the actual world. We must compute the return volatility, sometimes referred to as realized volatility, in order to determine how well the suggested model captures the actual scenario. The square root of realized variance, which is the total squared return, is realized volatility. In order to determine how well the volatility prediction approach performs, realized volatility is employed. The reliability and quality of the related analyses are unquestionably impacted by how volatility is calculated. The purpose of this study is to demonstrate the superior prediction performance of ML-based models by discussing both traditional and ML-based volatility prediction strategies. We begin by simulating the traditional volatility models in order to compare the brand-new ML-based models. ARCH-GARCH is only one of several well-known classical volatility models.

Classical Volatility Models

1. ***ARCH model***

ARCH Model One of the early attempts to model the volatility was proposed by [27] and it is known as ARCH model. ARCH model is a univariate model and it is based on the historical asset returns.

Let ϵ_t represent the model's unexpected returns so that the model may be expressed mathematically. The error components are divided into a time-dependent standard deviation (y) and a stochastic portion (z_t), which is a white-noise process. The error term is so defined as follows:

$$\varepsilon_t = \sigma_t z_t .$$

Since the previous squared error terms determine the current value of the model's variance of errors, the ARCH (*p*) model may be defined as the variance of the series, σ_t^2, and is modelled by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}{}^2. \tag{4}$$

where σ_t^2 is the current variance of errors, α_0; a positive constant, $\alpha_i \geqslant 0$ and $\varepsilon_{t-i}{}^2$ represents the squared errors for the period *t — i*. where *p* denotes the number of included. With the knowledge that ARCH effects exist in the time series, an LM test for ARCH effect had been carried out.

All of these equations indicate that the ARCH model is univariate and non-linear and that volatility is calculated using the square root of historical returns. One of ARCH's most distinguishing characteristics is its ability to model the volatility clustering phenomenon, which is defined by [17] as the tendency for large changes to be followed by larger changes of either sign and for smaller changes to be followed by smaller changes. So, when a significant announcement reaches the market, there may be a lot of volatility. A positive shock has the same impact on the conditional variance as a negative shock of the same size since the ARCH model is symmetric.

Bollerslev in 1986 found that the ARCH model needed a long lag length to be able to capture and explain the financial data (the excess kurtosis in data), in which GARCH model allows for a more flexible lag structure.

2. ***GARCH Model***

GARCH model is an extension of ARCH model incorporating lagged conditional variance by [21]. So, ARCH is improved by adding p number of delayed conditional variance, which makes GARCH model a multivariate one in the sense that it is an autoregressive moving average model for conditional variance with p number of lagged squared returns and *q* number of lagged conditional variance. GARCH (*p, q*) can be formulated as:

$$\sigma_t^2 = \omega + \sum_{k=1}^{q} \alpha_k^2 \varepsilon_{t-1}^2 + \sum_{k=1}^{p} \beta_k^2 \sigma_{t-1}^2 , \tag{5}$$

where σ_t^2 is the current variance of errors, ω; a positive constant, $\alpha_k \geq 0; \varepsilon_{t-1}{}^2$ represents the previous squared errors for the period *t* – 1; σ_{t-1}^2 represents the previous variance of errors for the period *t* – 1 coefficient (β) is called the GARCH term.

p denotes the number of previous σ^2 terms and *q* denotes the number of previous ε^2 terms.

In order to have consistent GARCH, following conditions should hold:

$$\omega > 0;\ \beta \geqslant 0;\ \alpha \geqslant 0;\ \beta + \alpha < 1.$$

The restrictions for model parameters used level of persistence of volatility as was shown by Engle and Bollerslev (1986).

The ARCH model is unable to account for the effects of previous advancements. However, GARCH models are a denser model that may explain the change in historical inventions since they can be expressed as an infinite-order ARCH. Due to its symmetrical character, which is similar to the ARCH model, the GARCH model has the disadvantage of not allowing for different responses to positive or negative shocks.

The two main benefits of GARCH in modeling volatility are that it does not need independent returns, allowing modeling of the leptokurtic aspect of returns, and that returns are well fitted by the GARCH model in part as a result of volatility clustering.

Machine Learning Methods

The following paragraphs are structured as follows: first a short introduction on the machine learning framework is presented, followed by a description of Support Vector Machines selected machine learning method applied to forecast the volatility of the ASE.

Machine Learning Framework

The process of computer algorithms that can interact with and learn from their environment with the aim of improving predictions through structural adaptation is known as machine learning. These learning techniques are frequently used when it is challenging to develop precise forecasting models and are quite beneficial when dealing with high-dimensional data [28, 29]. These machine learning techniques excel at effectively modeling complicated patterns by choosing just the descriptive variables from highly dimensional data. A number of promising approaches are chosen to estimate the

ASE volatility with the aim of analyzing the forecasting ability of machine learning algorithms in financial time series. Contrary to the GARCH-type models that try to estimate volatility through the conditional variance σ_t^2, these machine learning methods try to predict the ASE volatility.

Support Vector Machines

Boser et al. (1992) [30] created the support vector machine (SVM), a supervised learning technique, for classification issues. The SVM algorithm's objective is to build a hyperplane with the greatest possible margin between data points from distinct classes in order to categorize them. When building the support vectors for the model using linear equations, these dividing hyperplanes may be thought of as decision boundaries that specify the categorization of the data points. The approach was further developed as support vector regression (SVR), which can be used with time series data, by [11] for the application on regression issues. By using kernel functions, support vector regression is anticipated to generate comparatively enormous advantages as compared to conventional models in terms of capturing the nonlinear dynamics contained in financial time series data [31]. With the help of these kernel functions, it is possible to convert data from a nonlinear decision plane to a linear equation in a higher dimension. The capacity of SVR to effectively choose information from extra data to improve predictive performance is another advantage of using SVR in volatility forecasting compared to previous approaches.

The kernel function, which is the essential component of SVM, is typically used to transform primitive characters and enhance their dimension in order to solve linear non-separable problems and improve the prediction accuracy of the model during the SVM modeling process. The optimum kernel function for model prediction should be chosen by testing each one and comparing the outcomes one at a time since different kernel functions have distinct benefits and drawbacks. There are three primary kernel functions in SVM:

1 — Polynomial Kernel Function (PF):

$$K\left(x, x_i\right)=\left[\left(x . x_i\right)+1\right]^q \tag{6}$$

In which, q is the parameter.

2 — Radial Basis Kernel Function (RBF):

$$K\left(x, x_i\right)=\exp \left\{\frac{x-x_i}{-2\sigma^2}\right\} \tag{7}$$

In which, σ is the real parameter.

3 — Linear Kernel Function (LF):

$$K\left(x, x_i\right)=\left(x . x_i\right). \tag{8}$$

The Hybrid Model

The GARCH and SVR models that were discussed in the preceding section fall under two categories of estimation methods: parametric estimation and nonparametric estimation. Several researchers have suggested utilizing the SVR model instead of the ML technique to estimate GARCH parameters (SVR-GARCH), taking advantage of nonlinear regression estimation. According to [32], the realized volatility matches more closely with the actual volatility theoretically during the day. Although it is conceivable that using a different proxy may change the findings provided here, this problem is outside the scope of the present research. In fact, predictions made using this type of model can be more accurate than those made using the ML method. The difficulty of predicting the volatility of financial time series is usually complicated, and it's possible that no single model will be able to accurately capture all of its various characteristics. In this study, we propose a two-stage method combining the SVR model and the GARCH model (GARCH-SVR) to forecast the returns volatility. The forecasting value can be obtained by combining the linear GARCH model and the nonlinear SVR model, rather than replacing the ML method directly with the SVR model to estimate the GARCH parameters.

Support Vector Regression-GARCH

The supervised learning method known as Support Vector Machines (SVM) may be used for both classification and regression. To identify a line dividing two classes is the goal of SVM. Although it seems simple, the following is difficult: The number of lines that may be used to separate the classes is practically unlimited. However, we have been looking for the best path that will allow for the most accurate classification of the classes. The hyperplane, also known as the best line in linear algebra, maximizes the distance between the points that are closest to it but belong to different classes. Margin is the separation between the two points, or the support vectors. So, in SVM, our goal is to increase the space between the support vectors. Support Vector Classification, or SVC, is the name given to SVM used for classification. It is applicable to regression while maintaining all SVM properties. Once more, the goal of regression is to identify the hyperplane that maximizes margin while minimizing error. In this section, we will use the Support Vector Regression (SVR) approach to analyze the GARCH model. These two models are combined to form the SVR-GARCH.

Measuring Errors

Since the study focuses on predicting both the direction and the size of the realized volatility, we utilized the following metrics to evaluate each model.

Root Mean Squared Error (RMSE):

It is calculated by taking the square root of the square of the difference between the actual value and the target value that was predicted. It is also known as the standard deviation of errors.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{Y}_i - Y_i\right)^2}, \quad (9)$$

where N is the number of observations.

$\hat{Y}_i$ and Y_i are the predicted and observed value of asset on the i day.

Results and Discussion

Volatility prediction is a difficult endeavor. Several theories have been developed in an effort to produce more precise projections due to the unique characteristics of volatility and its significant effects on financial markets. In the current study, some of them are contrasted. Machine learning was used because it can be used to do difficult regression problems and has been used well in the literature on the subject when paired with other models.

It is demonstrated that the algorithms do not outperform the conventional, while having minimal errors in the majority of forecast horizons and being able to capture the main structure of the series. This could be as a result of the algorithms' absence of volatility-specificity. It is possible that predictions would be more accurate if one took volatility time series features into account. Machine learning algorithms have the drawback of being taught to detect correlations between values in a series and will do so even in situations where there are none, which may lead to incorrect forecasts.

The ARCH model's accuracy is a little unexpected. Despite being a less complicated model than those used by the other methods, it generates the most accurate projections. This demonstrates the idea that model complexity does not always translate into increased forecast accuracy. The flexibility of ARCH is one of its benefits. The optimal sequence of parameters that reduce mistakes can be found by fitting the data. In contrast to machine learning methods, time series models have the drawback of making more assumptions about the incoming data. The forecasts generated if machine learning is adjusted for volatility and integrated with time series models would probably be more accurate than their independent predictions.

It is crucial to compare and evaluate the output of various techniques in order to use the learning machine algorithm to create the most accurate predictions possible. One of the important components in algorithms' success is evaluation using appropriate criteria.

Evaluation Data

Using Google Colab notebooks as financial instruments for analysis in the Amman Stock Exchange, the data was gathered from January 2nd, 2018, until October 6th, 2022. There are 1147 samples in the data. The first COVID-19 infection in Jordan happened on March 2, 2020. To study volatility before and during the COVID-19 pandemic, the full sample data from January 2nd, 2018, until October 6th, 2022. In addition, according to literature, Bezerra & Albuquerque (2016) and Sun & Yu (2019) used daily data in the volatility modeling of hybrid models (SVR-GARCH), so the author applies the daily price index in the Amman Stock Exchange.

Zero-valued data is removed using noise removal techniques, and the data is then normalized. Using validation techniques in line with research on financial series forecasting using machine learning algorithms, the assessment statistics are split into two groups: Algorithms are trained on the training set before being tested on the test set. You should be aware that in order to evaluate

Table 1

The Number of Train and Test Sample

Total sample	Train set	Test set
1147	917	230

Source: Compiled by the author.

the training amounts that result from train figures, the train set itself is divided into two categories: validation and train. Based on the results of the evaluation, only the best training set is selected. There is little doubt that the assumptions made from the study of training data won't apply generally.

However, the accuracy of the algorithm on forecasting samples that fall into the test set category is what is meant as a consequence of the algorithm precision evaluation. Each share's test and try sets are determined by allocating 20% of the data to the test set and 80% of the data to the training set, respectively (*Table 1*) according to study Gholamy et al, (2018) empirical studies show that the best results are obtained if we use 20–30% of the data for testing, and the remaining 70–80% of the data for training [32].

Series of realized volatility can be obtained, as shown in *Table 2* in details.

Figure 1 is a line chart illustrating the Price Index trend over time. The index declines from 2018 to early 2020, followed by a sharp drop in 2020. Subsequently, it begins to recover, showing volatility before reaching a peak in 2022, with noticeable fluctuations.

Stationarity, which is the state in which statistical parameters like mean and variance do not change over time, is typically required for time series modeling. The first step in figuring out whether the time series is stationary is to take a look at the information given for time-dependent characteristics like trend or seasonality. A test statistic, an essential value for varying levels of confidence, and a p-value are all included in the test result. The p-value must be less than the significance threshold of 0.05 and the time series must be assumed to be stationary in order for it to be significant. When the test is applied to the volatility dataset with the first difference, H0 has been ruled out since the p-value is below 0.05 and below the values for each confidence level. *Figure 2* shows the auto-correlation chart for the volatility. The actual scenario is as follows: Realized volatility has a very long memory, as seen by its autocorrelation characteristics, which are strong in the first step and positive throughout the first 30 steps. To do this, a realized volatility model based on the volatility's long memory attribute is created in order to generate forecasts for short-term volatility. The adoption of daily price limitations for stock prices on ASE may be the reason for the high autocorrelation levels (Chiang & Doong). 2001).

In *Table 3*, the maximized log-likelihood function value and information criteria values are presented. The results unanimously select the GARCH model as best fitted model to the training set by exhibiting the largest likelihood in combination with the lowest values of the information criteria. This finding is in line with the expectation that due to the asymmetrical behavior of the financial return series, the models that allow for asymmetry and leverage effects, which is the GARCH model, are likely to fit better to the series compared to the symmetrical ARCH model.

The models are fitted with daily volatility. In *Table 4* the estimated parameters are presented, where all parameters are significant for the ARCH-GARCH model all parameters are significant. This indicates that the GARCH model probably fits well to the data, which is coinciding with the previous results based on the likelihood and the information criteria.

From the practical standpoint, SVR-GARCH application with different kernels is not a labor-intensive process, all we need to switch the kernel name.

In *Table 5* the ARCH forecast shows some similarities to that of GARCH and the RMSE result obtained (ARCH

Table 2

Statistical Indicator Table for a Series of Realized Volatility

Mean Value	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
0.610770	1.784991	0.003492	0.715778	0.462620	1.424129

Source: Compiled by the author.

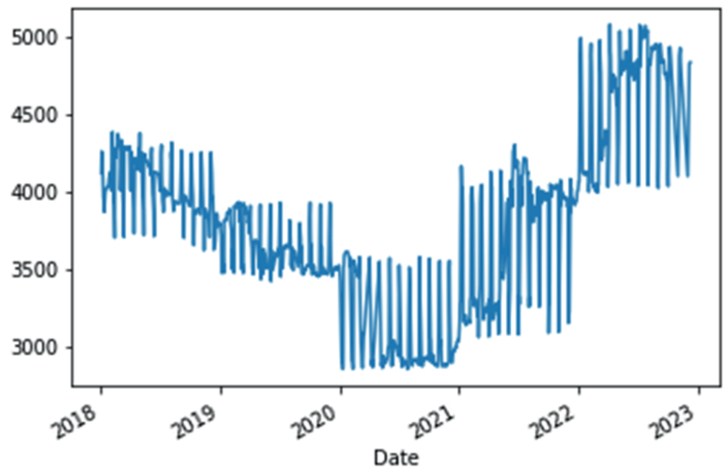

Fig. 1. **Price Index**

Source: Compiled by the author.

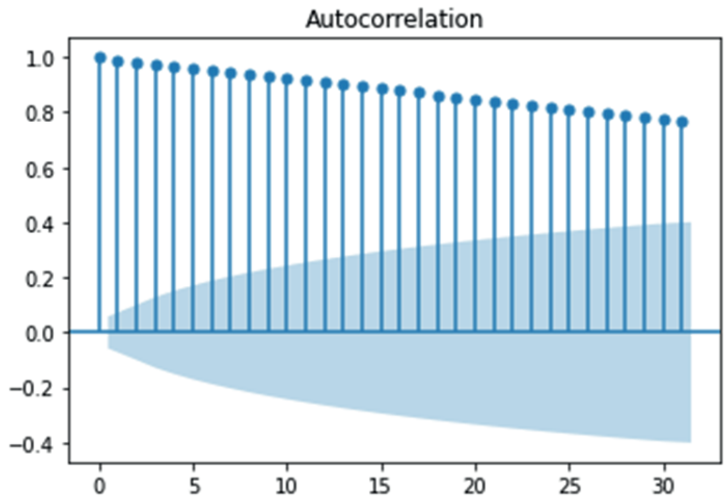

Fig. 2. **Auto-correlogram of the Realized Volatility**

Source: Compiled by the author.

Table 3

Log Likelihood and Information Criteria of the ARCH and GARCH Models

Log Likelihood and Information Criteria	ARCH	GARCH
Log L	−1001.46	−989.269
AIC	2014.92	1986.54
BIC	2045.19	2006.72

Source: Compiled by the author.

Table 4

Estimated Parameters of the ARCH and GARCH Models

Parameter	ARCH	GARCH
	Coefficient(p-value)	Coefficient (p-value)
ω	0.2355 (5.597e-24)***	0.0322 (5.104e-03)***
α	0.5301 (5.221e-08)***	0.2245 (1.102e-04)***
β		0.7136 (6.922e-27)***

Source: Compiled by the author.

Note: Three asterisks indicate significance at the 5% significance level.

Table 5

The RMSE Result Represented for Each Model

Model	RMSE
ARCH	0.0670
GARCH	0.0680
SVR kernel = "rbf"	1.150429603
SVR kernel = "linear"	0.887802733
SVR kernel = "poly"	0.701112386
SVR-GARCH kernel = "linear"	0.000784
SVR-GARCH kernel = "rbf"	0.001467
SVR-GARCH kernel = "poly"	0.001582

Source: Compiled by the author.

0.0670, GARCH 0.0680) in the sense that it underestimates the level of changes in volatility and regression realized volatility with the SVM under different kernel functions, the RMSE result obtained ("rbf" 1.150429603, "linear" 0.887802733, "poly" 0.701112386) subsequently traditional model outperform more machine learning model.

While RMSE score suggests that SVR-GARCH with linear kernel outperforms SVR-GARCH with RBF kernel. The RMSE of SVR-GARCH with linear and RBF kernels are 0.000784 and 0.001467, respectively. So, SVR with linear kernel does performs well. Lastly, SVR-GARCH with polynomial kernel is employed but it turns out that it has the lowest RMSE implying that it is the worst performing kernel among these three different applications.

In this case hybrid model outperform more both the machine learning model and traditional statistical time series model.

CONCLUSION

The aim of this research was to investigate the power of machine learning models as well as a novel hybrid model in the out-of-sample volatility forecasting of the ASE based on data of the period of January 2nd, 2018 to October 6th, 2022. The proposed methods are support vector regression, and the hybrid method GARCH-SVR. In order to assess not only their relative performance but also substantiate these findings the models are compared to the traditional statistical time series models of the ARCH, GARCH.

Hybrid model techniques can therefore perform better than more traditional statistical time series models when applied to extremely nonlinear and complicated time series. They demonstrate to be particularly appropriate during periods of significant market volatility, when both the machine learning model and traditional models perform less well. According to the empirical findings, the GARCH-(t)-SVR model enhances the capability of volatility forecasting. In the future, we may expand the number of volatility models we use and examine how alternative volatility proxies can influence our results. Furthermore, it would be beneficial to expand the historical data as much as possible because having more training data is frequently advantageous to both the traditional time series approaches and the learning methods stated. To the greatest degree possible, the features of multi-variable financial data should be thoroughly investigated, and the test methods of nonlinear mixed-pure characteristics (correlation dimension, annoyance, index calculation technique, etc.) should be improved on. We can do an accurate assessment and thorough research on the mixing features of multivariate financial time series by seeking an original method to identify their mixing characteristics. It is another element that requires research and discussion in the examination of financial time series in the future. The updating judgment method is used to find the closest points, and the fast neighborhood search method is used to search and calculate the neighborhood, which makes the local prediction method more useful in real-world engineering applications and reduces the computational complexity of local prediction. The performance of a support vector machine is primarily affected by the choice of kernel parameters, type of kernel function, and quadratic programming parameter. These criteria are often chosen by researchers based on their limited research and previous experience. How to select their optimal kernel function and a set of optimal parameters for particular application challenges is still a pressing issue that requires more research. Only low-frequency financial data may be used with the financial time series model that was examined in this article. Some volatility models are presented based on high-frequency data as high-frequency and ultra-high-frequency financial data become more prevalent. One of the next study objectives will be how to enhance the high-frequency data models' ability to predict the future.

REFERENCES

1. Brownlees C.T., Gallo G.M. Comparison of volatility measures: A risk management perspective. *Journal of Financial Econometrics*. 2010;8(1):29–56. DOI: 10.1093/jjfinec/nbp009
2. Jorion P. Predicting volatility in the foreign exchange market. *The Journal of Finance*. 1995;50(2):507–528. DOI: 10.1111/j.1540–6261.1995.tb04793.x
3. Brailsford T.J., Faff R.W. An evaluation of volatility forecasting techniques. *Journal of Banking & Finance*. 1996;20(3):419–438. DOI: 10.1016/0378–4266(95)00015–1
4. McMillan D., Speight A., Apgwilym O. Forecasting UK stock market volatility. *Applied Financial Economics*. 2000;10(4):435–448. DOI: 10.1080/09603100050031561
5. Choudhry T., Wu H. Forecasting ability of GARCH vs Kalman filter method: Evidence from daily UK time-varying beta. *Journal of Forecasting*. 2008;27(8):670–689. DOI: 10.1002/for.1096
6. Chen S., Härdle W.K., Jeong K. Forecasting volatility with support vector machine-based GARCH model. *Journal of Forecasting*. 2010;29(4):406–433. DOI: 10.1002/for.1134
7. Li Y.Q., Tian M. A semi-supervised regression algorithm based on co-training with SVR-KNN. *Advanced Materials Research*. 2014;926:2914–2918. DOI: 10.4028/www.scientific.net/AMR.926–930.2914
8. Santamaría-Bonfil G., Frausto-Solís J., Vázquez-Rodarte I. Volatility forecasting using support vector regression and a hybrid genetic algorithm. *Computational Economics*. 2015;45(1):111–133. DOI: 10.1007/s10614–013–9411-x
9. Huang C., Gao F., Jiang H. Combination of biorthogonal wavelet hybrid kernel OCSVM with feature weighted approach based on EVA and GRA in financial distress prediction. *Mathematical Problems in Engineering.* 2014. DOI: 10.1155/2014/538594
10. Cao L.J., Tay F.E.H. Support vector machine with adaptive parameters in financial time series forecasting. *IEEE Transactions on Neural Networks*. 2003;14(6):1506–1518. DOI: 10.1109/TNN.2003.820556
11. Vapnik V.N. Statistical learning theory. New York, NY: John Wiley & Sons, Inc.; 1997. 768 p.
12. Rosillo R., Giner J., de la Fuente D. The effectiveness of the combined use of VIX and support vector machines on the prediction of S&P 500. *Neural Computing and Applications*. 2014;25(2):321–332. DOI: 10.1007/s00521–013–1487–7
13. Pérez-Cruz F., Afonso-Rodriguez J.A., Giner J. Estimating GARCH models using support vector machines. *Quantitative Finance*. 2003;3(3):163–172. DOI: 10.1088/1469–7688/3/3/302
14. Li N., Liang X., Li X.L., Wang C., Wu D.S.D. Network environment and financial risk using machine learning and sentiment analysis. *Human and Ecological Risk Assessment*. 2009;15(2):227–252. DOI: 10.1080/10807030902761056
15. Bildirici M., Ersin Ö.Ö. Support vector machine GARCH and neural network GARCH models in modeling conditional volatility: An application to Turkish financial markets. *SSRN Electronic Journal*. 2012. DOI: 10.2139/ssrn.2227747
16. Peng Y., Albuquerque P.H.M., de Sá J.M.C., Padula A.J.A., Montenegro M.R. The best of two worlds: Forecasting high-frequency volatility for cryptocurrencies and traditional currencies with support vector regression. *Expert Systems with Applications*. 2018;97:177–192. DOI: 10.1016/j.eswa.2017.12.004
17. Mandelbrot B. New methods in statistical economics. *Journal of Political Economy*. 1963;71(5):421–440. DOI: 10.1086/258792
18. Fama E.F. The behavior of stock-market prices. *The Journal of Business*. 1965;38(1):34–105. DOI: 10.1086/294743
19. Bollerslev T., Chou R.Y., Kroner KF. ARCH modeling in finance: A review of the theory and empirical evidence. *Journal of Econometrics*. 1992;52(1–2):5–59. DOI: 10.1016/0304–4076(92)90064-X
20. Bollerslev T., Engle R.F., Nelson D.B. ARCH models. In: Engle R.F., McFadden D., eds. Handbook of econometrics. Amsterdam: Elsevier; 1994;4:2959–3038. DOI: 10.1016/S 1573–4412(05)80018–2
21. Bollerslev T. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*. 1986;31(3):307–327. DOI: 10.1016/0304–4076(86)90063–1

22. Ou P., Wang H. Financial volatility forecasting by least square support vector machine based on GARCH, EGARCH and GJR models: Evidence from ASEAN stock markets. *International Journal of Economics and Finance*. 2010;2(1):51–64. DOI: 10.5539/ijef.v2n1p51
23. Bezerra P.C.S., Albuquerque P.H.M. Volatility forecasting via SVR-GARCH with mixture of Gaussian kernels. *Computational Management Science*. 2017;14(2):179–196. DOI: 10.1007/s10287–016–0267–0
24. Sun H., Yu B. Forecasting financial returns volatility: A GARCH-SVR model. *Computational Economics*. 2020;55(2):451–471. DOI: 10.1007/s10614–019–09896-w
25. Nõu A., Lapitskaya D., Eratalay M.H., Sharma R. Predicting stock return and volatility with machine learning and econometric models: A comparative case study of the Baltic stock market. *SSRN Electronic Journal*. 2021. DOI: 10.2139/ssrn.3974770
26. Rousan R., Al-Khouri R. Modeling market volatility in emerging markets: The case of daily data in Amman stock exchange 1992–2004. *International Journal of Applied Econometrics and Quantitative Studies*. 2005;2(4):99–118. URL: https://www.usc.gal/economet/Journals3/ijaeqs/ijaeqs248.pdf (accessed on 07.03.2025).
27. Engle R.F. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*. 1982;50(4):987–1007. DOI: 10.2307/1912773
28. Hansen P.R., Lunde A. A forecast comparison of volatility models: Does anything beat a GARCH (1,1)? *Journal of Applied Econometrics*. 2005;20(7):873–889. DOI: 10.1002/jae.800
29. Alpaydin E. Introduction to machine learning. Cambridge, MA: The MIT Press; 2020. 719 p.
30. Boser B.E., Guyon I.M., Vapnik V.N. A training algorithm for optimal margin classifiers. In: Proc. 5th Annu. workshop on computational learning theory (COLT'92). (Pittsburgh, PA, July 27–29, 1992). New York, NY: Association for Computing Machinery; 1992:144–152. DOI: 10.1145/130385.130401
31. Qu H., Zhang Y. A new kernel of support vector regression for forecasting high-frequency stock returns. *Mathematical Problems in Engineering*. 2016. DOI: 10.1155/2016/4907654
32. Andersen T.G., Bollerslev T. Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review*. 1998;39(4):885–905. DOI: 10.2307/2527343

ABOUT THE AUTHOR

Raneem Ghazi Aldeki — PhD, Assist. Prof., Department of Banks and Financial Institutions, Al-Sham Private University, Damascus, Syria
https://orcid.org/0000-0002-4370-971X
r.d.foas@aspu.edu.sy

Conflicts of Interest Statement: The author has no conflicts of interest to declare.

The article was submitted on 15.08.2023; revised on 18.10.2023 and accepted for publication on 27.02.2025.
The author read and approved the final version of the manuscript.

Translator V.I. Timonina