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LATIN AMERICAN MARKET ASSET VOLATILITY ANALYSIS: A COMPARISON OF GARCH MODEL, ARTIFICIAL NEURAL NETWORKS AND SUPPORT VECTOR REGRESSION

Abstract

The objective of this research was to compare the effectiveness of the GARCH method with machine learning techniques in predicting asset volatility in the main Latin American markets. The daily squared return was utilized as a volatility indicator, and the accuracy of the predictions was assessed using root mean square error (RMSE) and mean absolute error (MAE) metrics. The findings consistently demonstrated that the linear SVR-GARCH models outperformed other approaches, exhibiting the lowest MAE and MSE values across various assets in the test sample. Specifically, the SVR-GARCH RBF model achieved the most accurate results for the IPC asset. It was observed that GARCH models tended to produce higher volatility forecasts during periods of heightened volatility due to their responsiveness to significant past changes. Consequently, this led to larger squared prediction errors for GARCH models compared to SVR models. This suggests that incorporating machine learning techniques can provide improved volatility forecasting capabilities compared to the traditional GARCH models.

1. INTRODUCTION

Volatility is a concept used in finance to indicate the level of fluctuation in the price of an asset, which reflects the uncertainty in that price. This measure is of great relevance both in academia and in the financial sector. Volatility is not only an indicator of risk in itself, but also a component of other indices, such as the Sharpe ratio, in risk management and performance analysis. Markowitz (1952) used volatility to quantify the risks of individual assets and the total risk of a portfolio in portfolio theory, where it is used as an input and optimization objective.

In Latin American markets, where economies can be particularly susceptible to factors such as exchange rate volatility, asset volatility can have a significant impact on

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investment strategies and financial decision making. Understanding and predicting volatility is essential to assessing the risk and return of financial assets in this region.

In recent years, the field of machine learning has experienced significant advancements in various domains, including financial analysis (Feng & Xiao, 2011; Monfared & Enke, 2014; Melike & Özgür, 2014; Rodríguez, 2020; Verma, 2021; Zahid et al., 2022; Satria, 2023). In particular, the study and prediction of asset volatility have greatly benefited from the application of machine learning techniques. In this area, numerous models and forecasting methods have been proposed and evaluated in the financial literature. Among these, GARCH (generalized autoregressive conditional heteroscedasticity) models have been extensively employed to model the volatility of financial returns. On the other hand, machine learning-based approaches, such as Artificial Neural Networks (ANN) and Support Vector Regression (SVR), have also been employed to analyze asset volatility. These machine learning methods offer significant advantages in analyzing asset volatility in Latin American markets. Their ability to identify non-linear patterns and adapt to changes in market conditions can provide better understanding and prediction of volatility compared to traditional approaches such as GARCH models. By using historical data and relevant variables, machine learning models can generate more accurate forecasts and therefore contribute to more informed and effective financial decision making.

In this study, our focus is on comparing the performance of machine learning models (ANN and SVR) with traditional models (such as GARCH models) in predicting asset volatility in Latin American markets. We utilize historical data from the MERVAl (Argentina), BOVESPA (Brazil), IPC (Chile), IPSA (Mexico), and IGBVL (Peru) assets to evaluate and compare the accuracy and predictive capabilities of these models.

The research has two standout contributions. First, it uniquely combines the comparison of the GARCH, EGARCH, ANN, and SVR methods within a single study, something that is not common in existing studies. While others have compared traditional methods with only one machine learning techniques separately (Karasan & Gaygısız, 2020), this unified and carefully structured analysis fills a notable gap, offering a broader understanding of their interactions and competitive dynamics.

Second, the study adds significant value to this field by focusing exclusively on the financial markets of Latin America. While most previous studies have used data from global markets or developed economies, the authors have chosen to explore a region that has been relatively less studied but is vital to the global economy. This exhaustive approach not only enriches the understanding of financial market volatility in this field but also provides valuable insights that could extend beyond the Latin American focus of the study.

The findings of this study provide a clearer understanding of the effectiveness of machine learning models in predicting volatility. These insights will have important implications for investors and financial professionals, helping them make more informed decisions and enhance risk management in their operations in Latin American markets.

The following sections of this article address the theoretical underpinnings of the methodologies used in the study, the datasets employed, and the comparative analysis of the results obtained from the SVR ANN and GARCH models. In addition, the implications of these findings and their potential applications in the financial sector are discussed.

2. LITERATURE REVIEW

Recent studies on financial market volatility have compared the use of traditional econometric models with machine learning methods, such as neural networks, support vector machines, and long short-term memory.

Contemporary research on financial market volatility has juxtaposed the use of traditional econometric models with machine learning methods, like neural networks, support vector machines, and long short-term memory. Sun & Yu (2020) concluded that the GARCH-(t)-SVR and GJR-(t)-SVR models enhance volatility forecasting, and Karasan & Gaygısız (2020) have corroborated more precise financial risk management using an SVR-GARCH model on S&P 500 stocks. However, the superiority is not uniform; Shen et al. (2021) and Christensen et al. (2022) observed that machine learning methods do not always efficiently capture extreme market events. On the other hand, several authors have emphasized the efficacy of these methods, such as Kristjanpoller et al. (2014), Filipovic & Khalilzadeh (2021), and D'Ecclesia & Clementi (2021), who stressed the ability of neural networks to uncover complexities in the volatility of stock returns.

In additional studies, Fraz et al. (2022) and Zhang & Qiao (2021) explored various facets of volatility, while Satria (2023) identified GRU as an effective predictor in the context of Indonesia. Chhajer et al. (2022) and Xiaoxing et al (2023) took a step forward by introducing an advanced model to predict volatility, demonstrating superiority over conventional models.

The world of cryptocurrency has also been a fertile field for innovation, with Zahid et al. (2022) developing hybrid techniques to forecast the volatility in Bitcoin's price, and Yamaka et al. (2020) comparing models in the ASEAN-5 stock markets.

Together, these studies illustrate a dynamic and evolving understanding of volatility in financial markets, where machine learning methods are playing an increasingly prominent and nuanced role.

3. METHODOLOGY

In this study, the authors analyze the volatility data across various financial markets, using both traditional and machine learning approaches, including GARCH models, Support Vector Regression (SVR), and Artificial Neural Networks (ANN). This approach not only provides a solid foundation for understanding asset volatility but also seeks to explore how machine learning techniques can be applied in predicting the volatile behavior of assets in Latin American markets. The application of this methodology represents a significant contribution to the study of the subject and promises to open new perspectives in the research of volatility in financial markets.

The datasets in these methods have been separated into specific percentages for training, validation, and testing. This data splitting was done in Python using the corresponding split model.

Using a training sample and a test sample in machine learning analysis is an essential practice in scientific research that simulates the process of verification and validation. The training sample allows the model to learn patterns and relationships, while the test sample serves to evaluate its performance on unseen data, providing a realistic measure of how the model is expected to perform in practical situations. This split helps to prevent overfitting and ensures that the model has captured genuine relationships, strengthening the credibility and robustness of the findings. This approach is a vital component for validity and replicability in scientific research.

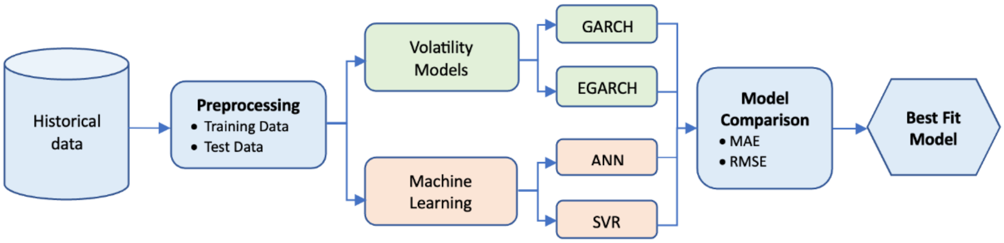

Fig. 1. Proposed Methodology

This research falls within a predictive research model, with the primary objective of comparing GARCH models with Machine Learning techniques to forecast volatility in financial markets. The adoption of quantitative methods and metrics such as MAE and RMSE emphasizes its predictive nature, highlighting the study's focus on accurately anticipating trends in the financial domain.

In summary, our approach in this research follows the following steps, leading to a suitable prediction model for volatility in financial markets:

1. Training: apply a machine-learning algorithm to the training data set for the model to learn and use it to estimate the GARCH and EGARCH volatility models.
2. Validation: evaluate the error of the statistical models using new data and by comparing the MAE and RMSE metrics.
3. Prediction approach: employ the trained and validated models to anticipate volatility in different financial markets.

3.1. Volatility Models

Volatility studies commonly use Bollerslev (1986) GARCH models. GARCH models assume that volatility, or error variance, is a stochastic process that depends on its own and the shocks' prior values. Conditional heteroskedasticity is what sets GARCH models apart. Many financial time series vary with market events and conditions. Heteroskedasticity occurs. A GARCH(p,q) model can be formulated as:

$$e_t = \sigma_t \epsilon_t \tag{1}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{\{t-1\}}^2 + \dots + \alpha_q e_{\{t-q\}}^2 + \beta_1 \sigma_{\{t-1\}}^2 + \dots + \beta_p \sigma_{\{t-p\}}^2 \tag{2}$$

e_t, the disturbance term of the mean equation, is usually an ARMA process, and e_t follows an i.i.d distribution with mean 0 and standard deviation 1. In financial time series, "volatility clustering", periods of high volatility that follow each other, is captured by GARCH models.

EGARCH, or exponential GARCH, improves market scenarios. Positive shocks affect volatility less than negative shocks. Capture the "leverage effect" volatility asymmetry. In many financial markets, negative returns (price drops) tend to increase volatility more than positive returns of the same amount.

EGARCH models also specify conditional variance logarithms. This feature guarantees that variance forecasts (volatility squared) will always be non-negative, regardless of model parameters.

The form of the EGARCH(p, q) model is:

$$e_t = \sigma_t \epsilon_t \quad (3)$$

$$ln\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \left[\frac{|e_{t-j}|}{\sigma_{t-j}} - E\frac{|e_{t-j}|}{\sigma_{t-j}}\right] + \sum_{i=1}^{p} \beta_i ln\, \sigma_{t-i}^2 + \sum_{i=1}^{p} \gamma_i \frac{|e_{t-j}|}{\sigma_{t-j}} \quad (4)$$

In an EGARCH model, there are no non-negativity constraints on the coefficients, unlike in GARCH models. This is because the model is specified in terms of the log of the conditional variance, which is always positive. As with GARCH models, the parameters of EGARCH models are generally estimated by maximizing the likelihood function.

3.2. Machine Learning

3.2.1. Support Vector Regression (SVR)

SVR is a machine learning algorithm for regression tasks that predicts continuous variables in various domains. It robustly handles outliers by identifying support vectors for linear bounds. Combining SVR with GARCH models in finance captures nonlinear relationships and heteroscedasticity, improving accuracy in volatility forecasting and risk management. It utilizes kernel functions to find the best linear or hyperplane fit, effectively handles high-dimensional data, and avoids overfitting. Proper selection of kernel functions and regularization parameters is crucial for optimal performance (Chen et al.,2008).

In the context of the SVR discussion, a linear decision function is defined as $f(x) = w'x + b$ where x is a vector, and w and b are a weighting vector and bias parameter used to estimate the scaler vector of Y. However, the main distinction between an SVR and a conventional regression analysis is that, in an SVR, the decision function is selected so that it deviates from the insensitivity parameter ε as little as possible (see Fig. 2). This means that SVR uses slack variables (x_i) to determine the best hyperplane while disregarding the mistake caused by data contained within the ε margins (Gholami & Fakhari, 2017).

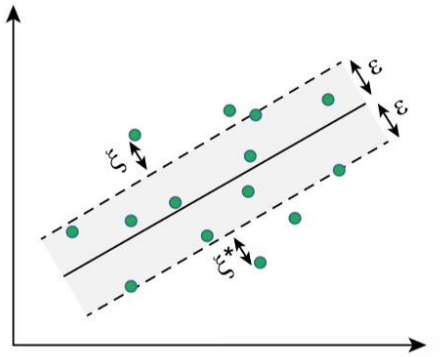

Fig. 2. SVR Graphical Representation

SVR algorithms use kernel functions to map data points to higher dimensions, reducing the computational cost. A margin value ε is set, and the algorithm performs regression in the higher dimension, obtaining a minimum error hyperplane with margin width ε. Values inside ε-tube are not penalized, while those outside are. The most common kernels are the linear, polynomial and radial basis function (RBF) (Scholkopf, 2018).

- **Linear:** Is a commonly used and simple kernel for SVR, suitable for datasets with low noise, as it can fit a regression line to the data points.
- **RBF:** Is a nonlinear kernel that measures the similarity of two data points by calculating the Euclidean distance between them. Using the RBF kernel, SVR can find a nonlinear decision boundary that is more accurate than a linear decision boundary.
- **Polynomial:** Is able to capture nonlinear relationships between data points. However, it is important to choose the right degree. The SVR model with the polynomial kernel is trained on the data points and then used to predict the output of new data points.

With the chosen kernel, the SVR algorithm works by creating a hyperplane that separates the data into two classes and then optimizing the hyperplane parameters to minimize the distance between the data points and the hyperplane. Once the hyperplane is optimized, the predicted output can be calculated from the data points that lie on the hyperplane

3.2.2. Artificial Neural Network (ANN)

An ANN is a machine learning algorithm that consists of interconnected artificial neurons. It is designed to mimic the structure and function of the human brain, enabling it to learn and make predictions from input data. Each neuron performs calculations by combining weighted inputs and applying an activation function, allowing the network to model complex nonlinear relationships. A fundamental architecture of ANNs is the multilayer perceptron, which consists of three layers: an input layer, one or more hidden layers, and an output layer (Fig. 3). In regression problems, the multilayer perceptron is designed to predict continuous-valued outputs (Chhajer et al., 2022).

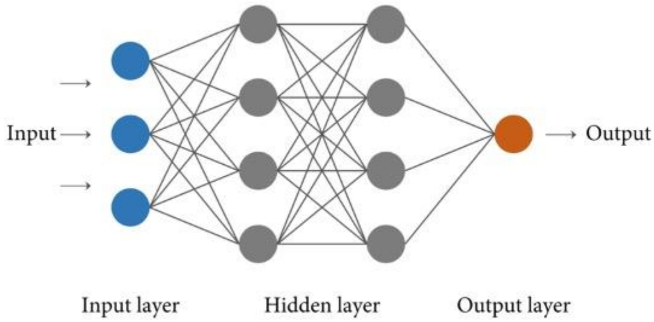

Fig. 3. ANN Architecture

Backpropagation is a crucial process in training Artificial Neural Networks (ANNs). It plays a vital role in enabling the network to learn and make adjustments by computing gradients of the cost function with respect to the synaptic weights. The backpropagation algorithm consists of two main phases: forward propagation and error backpropagation. During forward propagation, the input data is passed through the network, activating each neuron and producing an output. Then, during error backpropagation, the error between the predicted output and the actual output is propagated backward through the network, updating the weights based on the calculated gradients. This iterative process of forward and backward passes allows the network to adjust its weights, minimizing the error and improving its predictive capabilities.

4. RESULTS

4.1. Data and Variables

The authors analyzed the daily values of the BOVESPA (Brazil), IGBVL (Peru), IPC (Chile), IPSA (Mexico) and MERVAL (Argentina) indexes for the period from 04/01/2012 to 12/29/2021, which were obtained from Yahoo Finance. Daily returns were calculated as logarithmic differences of closing prices as follows:

$$r_t = [lnP_t - lnP_{t-1}] \times 100 \quad (5)$$

4.2. Descriptive Statistics

According to the descriptive statistics that are provided in Table 1, the empirical distributions of asset returns have a leptokurtic form. This shape is distinguished by a rising excess kurtosis. In terms of kurtosis, MERVAL has the highest value (50.40), while IPC has the lowest value (4.19). In addition, every return series exhibits skewness and is skewed to the left. This suggests that the distributions are more likely to have significant negative returns than they are to have big positive returns. The empirical moments of the assets, notably the kurtosis, are quite excessive in comparison to the global benchmarks, which indicates that the diversification effects within each asset are not as strong as they could be. This exemplifies the relatively considerable risks that are associated with investing in these markets, which are underscored by the previous sentence. In addition to the moments' non-normal appearance, the return sequence demonstrates autocorrelation, with the exception of MERVAL. Both the ARCH test and the Ljung-Box (LB) test demonstrate that the hypothesis that the squared returns do not exhibit autocorrelation is false.

Tab. 1. Summary statistics of asset returns

	IGBVL	BOVESPA	IPSA	IPC	MERVAL
Returns					
Mean	0.0022	0.0259	0.0009	0.0158	0.1604
Standard Deviation	1.1465	1.6747	1.1692	1.0082	2.6634
Asymmetry	-0.7218	-0.6469	-1.4773	-0.4079	-2.7896
Kurtosis	10.4875	10.1786	22.0923	4.1936	50.4019
Minimum	-11.0094	-15.9930	-14.0150	-6.6381	-47.6922
Maximum	8.2616	13.0223	7.4941	6.3371	14.2680
Square Returns					
Mean	1.3140	2.8040	1.3665	1.0162	7.1164
Standard Deviation	4.6382	9.7591	6.7001	2.5213	50.9591
Ljung-Box (r=20)	68.6723	49.2749	71.8558	30.2044	29.7599
	(0.000)	(0.000)	(0.000)	(0.067)	(0.074)
ARCH LM (q=2)	85.1737	11.1046	420.3846	94.296	11.1046
	(0.000)	(0.004)	(0.000)	(0.000)	(0.004)
ARCH LM (q=10)	182.0439	841.8176	432.73	399.2309	18.1029

Figure 4 shows the daily closing prices and asset returns. It shows the rises and falls of the variables during the analysis period. Regarding the closing prices, the IGBVL, BOVESPA and IPSA assets presented a downward trend in the period 2012-2016, and then went up. In addition, a break point is seen in 2020. This is reflected in the volatility of the assets. From this previous analysis, it is concluded that volatility is autocorrelated.

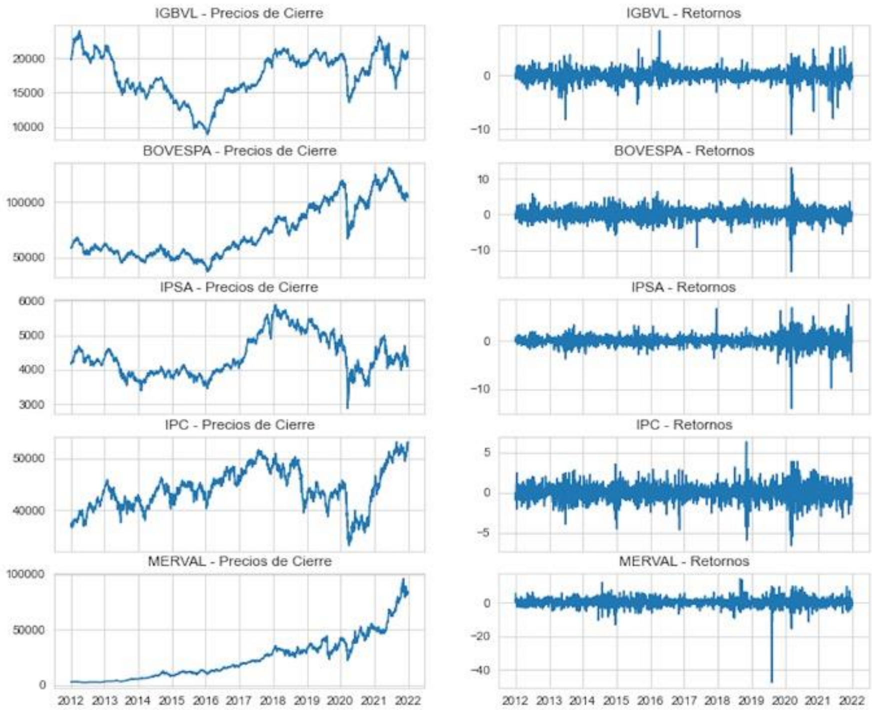

Fig. 4. Asset Price and Return Behavior

4.3. Empirical Results

The purpose of this study was to develop an accurate model to predict asset volatility in the main Latin American markets, using the daily squared return as a volatility indicator.

First, the authors estimated the GARCH and EGARCH models using the training sample, obtaining the coefficients shown in Table 2, all of which were significant.

For the purpose of measuring the error, measures such as the mean absolute error (MAE) and the root mean squared error (RMSE) were utilized. The outcomes are presented in Table 3 in the form of MAE as well as RMSE.

As for the MAE and RMSE measures, the prediction errors that correlate with MERVAL are the largest, while those corresponding to IPC are the smallest. As a consequence, the volatility of the daily return of these assets is the highest and lowest, respectively (see Table 1). Due to the sensitivity of RMSE to outliers, its value is higher than those of MAE.

In general, the Linear SVR-GARCH models present the lowest values of MAE and MSE in the test sample for the different assets. In the case of the IPC asset, the SVR-GARCH RBF model shows the lowest values of MAE and RMSE (0.0005 and 0.0007, respectively).

Tab. 2. Coefficients of the Volatility Models

Stock	Parameters	GARCH		EGARCH	
		Coeficcient	Standar Error	Coeficcient	Standar Error
IGBVL	ω	0.0203*	0.009	0.0076	0.005
	α	0.0774**	0.020	0.1440**	0.032
	β	0.9066**	0.021	0.9832**	0.008
	γ	-	-	-0.0544**	0.013
BOVESPA	ω	0.1257**	0.040	0.0431**	0.016
	α	0.0822**	0.018	0.1459**	0.032
	β	0.8674**	0.025	0.9550**	0.015
	γ	-	-	-0.0891**	0.022
IPSA	ω	0.0198*	0.010	0.0022	0.005
	α	0.1022**	0.029	0.1724**	0.038
	β	0.8790**	0.035	0.9808**	0.007
	γ	-	-	-0.0630**	0.017
IPC	ω	0.0315**	0.018	0.0016	0.003
	α	0.0818**	0.017	0.0948**	0.028
	β	0.8848**	0.025	0.9737**	0.006
	γ	-	-	-0.1075**	0.016
MERVAL	ω	0.5216	0.291	0.2493*	0.108
	α	0.2871*	0.138	0.5665*	0.163
	β	0.6869**	0.119	0.8778**	0.056
	γ	-	-	0.0024	0.045

Note: * $p< 0.05$; ** $p < 0.01$

Figure 5 shows a comparison between the volatility predictions of the GARCH and linear SVR models. It is observed that the predictions of the GARCH models are superior to those of SVR in periods of high volatility. This is because GARCH models respond more quickly to previous significant variations in volatility compared to SVR models. As a result, squared prediction errors are higher for SVR models than for GARCH models. These general conclusions are also applicable to other energy products studied.

Tab.3. Evaluation of out-of-sample prediction

Stock	Model	Train		Test	
		MAE	RMSE	MAE	RMSE
IGBVL	GARCH	0.0919	0.0977	0.1296	0.1370
	EGARCH	0.0907	0.0958	0.1204	0.1253
	SVR-GARCH Lineal	**0.0005**	**0.0009**	**0.0009**	**0.0015**
	SVR-GARCH RBF	0.0006	0.0016	0.0015	0.0029
	SVR-GARCH Polynomial	0.0009	0.0017	0.0012	0.0026
	ANN	0.0006	0.0010	0.0009	0.0016
BOVESPA	GARCH	0.1422	0.1498	0.1342	0.1353
	EGARCH	0.1410	0.1471	0.1370	0.1390
	SVR-GARCH Lineal	**0.0010**	**0.0016**	**0.0008**	**0.0010**
	SVR-GARCH RBF	0.0011	0.0042	0.0008	0.0015
	SVR-GARCH Polynomial	0.0014	0.0031	0.0010	0.0017
	ANN	0.0023	0.0047	0.0020	0.0026
IPSA	GARCH	0.0843	0.0965	0.1338	0.1404
	EGARCH	0.0831	0.0921	0.1261	0.1299
	SVR-GARCH Lineal	0.0007	0.0013	**0.0010**	**0.0016**
	SVR-GARCH RBF	0.0008	0.0031	0.0017	0.0035
	SVR-GARCH Polynomial	0.0011	0.0024	0.0023	0.0019
	ANN	**0.0006**	**0.0011**	0.0012	0.0017
IPC	GARCH	0.0859	0.0898	0.0916	0.0926
	EGARCH	0.0853	0.0896	0.0849	0.0856
	SVR-GARCH Lineal	0.0006	**0.0009**	0.0009	0.0011
	SVR-GARCH RBF	**0.0005**	0.0011	**0.0005**	**0.0007**
	SVR-GARCH Polynomial	0.0008	0.0010	0.0007	0.0012
	ANN	0.0007	0.0010	0.0007	0.0009
MERVAL	GARCH	0.2346	0.2648	0.2237	0.2336
	EGARCH	0.2343	0.2795	0.2256	0.2369
	SVR-GARCH Lineal	**0.0006**	**0.0012**	**0.0009**	**0.0012**
	SVR-GARCH RBF	0.0020	0.0091	0.0012	0.0023
	SVR-GARCH Polynomial	0.0018	0.0029	0.0026	0.0024
	ANN	0.0085	0.0401	0.0072	0.0110

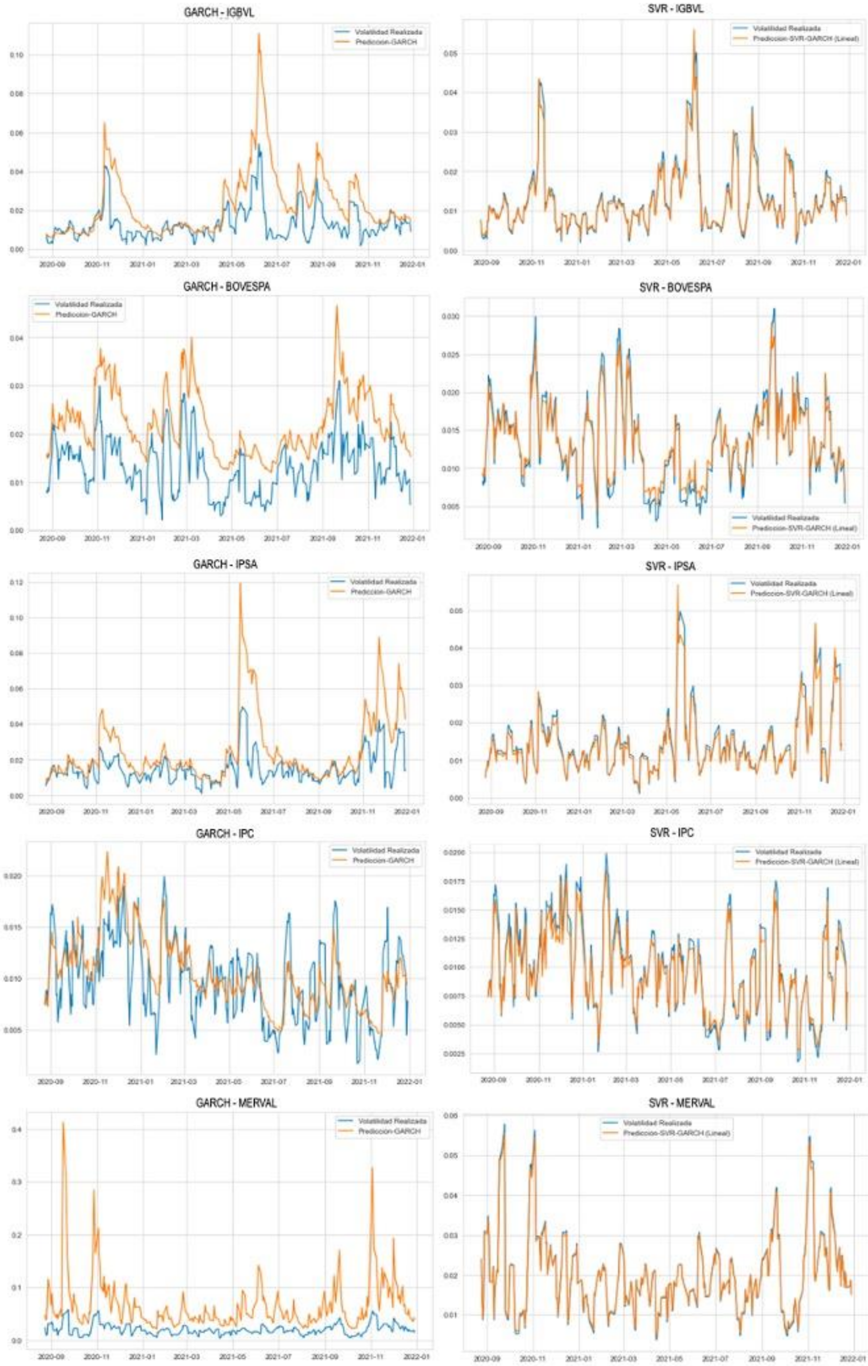

Fig. 5. Comparison of Predictions between GARCH and Linear SVR Models

Comparing SVR (Support Vector Regression) and ANN (Artificial Neural Networks) machine learning techniques with GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models in our research, we found that SVR-GARCH linear models provide better predictive performance in terms of MAE (Mean Absolute Error) and MSE (Mean Squared Error) in the test sample for different financial assets.

This result indicates that SVR-GARCH linear models are more accurate in predictions compared to ANN and GARCH techniques individually. The reason for this predictive superiority could be due to the ability of SVR-GARCH linear models to capture both linear relationship and volatility in the data, combining the advantages of both approaches (SVR and GARCH). (Sun & Yu, 2020 and Karasan & Gaygısız, 2022).

The lower MAE value in the SVR-GARCH linear models means that, on average, the differences between the predictions of these models and the actual observed values are smaller compared to ANN and GARCH. This implies that SVR-GARCH linear models have fewer errors in their predictions, which can lead to better decision making in practical situations, such as investing in the stock market (Bezerra & Alburqueque, 2017; Sun & Yu, 2020).

In addition, the lower value of MSE in the linear SVR-GARCH models suggests that these models succeed in reducing variability and dispersion in their predictions. Since the MSE penalizes larger errors by squaring the differences between predictions and actual values, a lower MSE indicates that SVRGARCH linear models are more consistent in their predictions and less prone to extreme errors.

In summary, the results suggest that SVR-GARCH linear models are superior in terms of predictive accuracy compared to ANN and GARCH approaches separately. This is due to their ability to effectively capture linear relationships and volatility in the data. However, when choosing an approach for practical applications, it is also critical to consider factors such as model complexity and computational requirements.

5. DISCUSSION

The research presented in this work adds to the growing field of studies aiming to understand and predict volatility in financial markets through the use of machine learning techniques. The findings in our study demonstrate that machine learning techniques such as Linear SVR-GARCH outperformed other methods in predicting volatility in Latin American financial markets. This is in line with the works of Sun & Yu (2020) and Karasan & Gaygısız (2020), who also emphasized the enhancement in volatility forecasting through combined models like GARCH-(t)-SVR and GJR-(t)-SVR.

Our observations regarding the non-uniform superiority of machine learning methods resonate with the findings of Shen et al. (2021) and Christensen et al. (2022), who noted limitations in capturing extreme market events. However, our study offers distinctive elements by focusing on specific markets in Latin America and on particular models like Linear SVR-GARCH, SVR-GARCH RBF, and SVR-GARCH Polynomial. This exclusive geographical focus provides a unique perspective and complements the body of research spanning a variety of global markets and economic contexts. The careful selection of parameters and data preprocessing ensures the robustness and accuracy of our results.

While the efficacy of machine learning methods in our study adds to the insights provided by researchers such as Filipovic & Khalilzadeh (2021) and D'Ecclesia & Clementi (2021), the world of cryptocurrency and innovations like those explored by Zahid et al. (2022) remain outside our scope. These variations underscore the complexity and dynamism of the field, where machine learning methods are playing an increasingly prominent and nuanced role.

We acknowledge that the exclusive geographical focus on Latin American markets in our study may limit the applicability and generalization of our findings. Future research could expand to markets outside Latin America and explore integration with other methods and emerging techniques in the field, such as those addressed by Fraz et al. (2022) and Satria (2023).

In conclusion, this discussion reflects an evolving landscape in the study of volatility in financial markets, where our research contributes to a deeper and more contextualized understanding. Through comparison with contemporary literature, our conclusions are confirmed, broadened, and nuanced, strengthening the understanding of this critical field and offering guidance for future academic and applied exploration.

6. CONCLUSIONS

The study of volatility in financial markets is an essential task that has gained considerable attention in academic research. In recent years, machine learning techniques such as Support Vector Regression (SVR), GARCH models and Artificial Neural Networks (ANN) have become popular in this field. This study aimed to compare the performance of these methods in predicting volatility in financial markets.

The findings of this study demonstrate that machine learning techniques are effective in predicting volatility in financial markets. Among the models evaluated, Linear SVR-GARCH outperformed other methods for several stocks such as IGBVL, BOVESPA, IPSA, IPC, and MERVAL, where the MAE in the test sample ranged between 0.0005 and 0.0009, and the RMSE values varied between 0.0007 and 0.0012. The SVR and ANN models were found to be particularly effective in enhancing the accuracy of volatility predictions compared to conventional GARCH models, which showed generally higher MAE and RMSE values.

This indicates that machine learning techniques can be a promising alternative to traditional economic models in volatility analysis. However, effectiveness varies with different models and data, as seen in the SVR-GARCH RBF and SVR-GARCH Polynomial models, which showed slightly higher errors compared to the Linear SVR-GARCH model.

However, it is important to consider that the performance of machine learning models may be highly dependent on parameter selection and data preprocessing. In this study, special care was taken with these aspects to ensure that the results were robust and accurate.

While the findings provide valuable insights into the volatility within these specific markets, the applicability and generalization of the insights to other global markets may be restricted. It is suggested that future research broaden the scope of applying the models developed in this study to other financial markets outside of Latin America. Such an expansion could not only enhance the robustness and generalization of the findings but also allow for a deeper understanding of how Machine Learning techniques and GARCH and EGARCH models perform across various economic and cultural contexts. This geographical expansion would contribute to a more holistic understanding of volatility in the global financial markets.

In summary, this study adds to the growing body of research supporting the use of machine learning techniques in volatility analysis in financial markets. Future research could expand this work by exploring the use of other machine learning techniques and analyzing the impact of different factors on the results. Overall, the findings of this study reveal the potential of machine learning techniques to enrich our understanding of volatility in financial markets and provide more accurate predictions in this field.

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