Do Machine Learning Approaches Have the Same Accuracy in Forecasting Cryptocurrencies Volatilities?

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Abstract

The emergence of cryptocurrencies as digital investments drives scholars to explore their predictive prices. Intriguingly, most research focuses on its price and returns prediction using various models, leaving out the importance of persistent risk for portfolio management. This is not to mention that most research focuses only on Bitcoin, neglecting other altcoins and stablecoins. Therefore, this study comprehensively examines the cryptocurrency investment's persistent risk from the forecasting point of view. We focus on comparing the best forecasting methods because they are vital for volatility-targeting and risk-parity in portfolio strategy. Four time-series model performances will be compared to select a suitable volatility prediction model: Machine Learning-Based GARCH, Machine Learning-Based SVR-GARCH, Neural Network, and Deep Learning. Using six different cryptocurrencies proxies: Bitcoin, Ethereum, Ripple, USD Coin, Tether, and Binance Coin, we found that ML-Based SVR-GARCH outperformed the peers in volatility forecasting. However, the prediction accuracy differences among all models are not significant. Finally, our paper provides new insights into machine learning methods' applications in cryptocurrency market volatility prediction, which is helpful for academics, policy-makers, and investors in forming portfolio strategies.

Keywords: Volatility Forecasting; Cryptocurrencies; Bitcoin; SVR-GARCH; Neural Network; Deep Learning

JEL: G17; G32; C53

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1. Introduction

Finance literature has extensively investigated financial asset prediction using machine learning (Refer to Table I), focusing on finding the best pricing prediction model with various methods, from Neural Networks to Fb Prophet methods. This surging literature is driven by the algo fund or ML-based investment used by the industry, like the case of the Rennaisance Fund. From the theoretical side, the use of historical price in predicting future price challenge the efficient market hypothesis, arguing that the market is predictable by combining historical prices and best machine learning (Wimalagunaratne & Poravi, 2018). Unfortunately, those empirical findings have left three shortcomings: (1) no consensus on the best accuracy model (Henrique et al., 2019; Mosavi et al., 2019), (2) weak in forming portfolio strategies (Huang et al., 2020; Mirete-Ferrer et al., 2022), and (3) neglecting the tenet in investing strategy: the noise effect from volatility (Jia et al., 2019; Rasekhschaffe & Jones, 2019). Those shortcomings are driven by price fluctuation, usually captured by its standard deviation. Intriguingly, less research focuses on volatility prediction, especially the volatility prediction of cryptocurrencies.

Cryptocurrencies are unregulated digital currencies, led by bitcoin as the most liquid and famous digital currency. It has received significant attention from institutional and retail investors and regulators. The sudden surge of its prices during COVID-19's lockdown attracted researchers' attention and drove several corporations to engage in cryptocurrencies as part of their business investment (Yermack, 2015). The debate among researchers arose in the argument of whether cryptocurrencies can be part of a portfolio. Kristoufek (2015) shows that cryptocurrencies are speculative assets driven without theoretical price, and Yermack (2015) surmises that cryptocurrencies, specifically BTC, are typical high-risk assets waiting to burst.

Intriguingly, most cryptocurrency research focuses more focusing on portfolio diversification. The existing literature has focused on proving whether it is a speculative asset (Baur et al., 2018), volatility dynamics (Katsiampa et al., 2019), price inefficiency (Sensoy, 2019), or the portfolio "cocktail" for optimum profit (Kajtazi and Moro, 2019). With the surging topic of machine learning, many attempts to explore the price prediction of cryptocurrencies (refer to Table I). However, the plate for volatility prediction remains empty, a gap this research aims to tackle.

Nevertheless, the volatility prediction of cryptocurrencies is important for investors in forming investing strategies. Volatility prediction is useful for risk-adjusted investing strategies, especially those that employ asset allocation (bottom-up), risk-parity, and volatility-targeting strategies. Understanding the volatility prediction provides a robust portfolio framework, especially in building the portfolio's value-at-risk (Louzis et al., 2014). Building on these theoretical and empirical gaps, this research aims to empirically exploit the best volatility prediction of cryptocurrencies by using four different predictive models on the top six cryptocurrencies.

The motivation of this research is to exploit the best predictive method that is capable of predicting cryptocurrency volatility. This is important to better understand the future behavior of cryptocurrencies as asset class, which, as already mentioned, is vital in many investment portfolios. It seeks to achieve this through various modern machine learning techniques, comparing their prediction assessment from historical prices in three different periods.

With this in mind, this research utilizes four different volatility prediction techniques: ML-Based GARCH, ML-Based SVR-GARCH (hereafter SVR), Neural Network (NN), and Deep Learning (DL). Instead of taking the price or the returns as the tested and trained data, this research uses the volatility, measured by the standard deviation (five-days rolling standard deviation). Subsequently, the predictive values are calculated, and the model fit is checked. This research also plots the trend lines between the actual and predicted volatility to portray how large the gap between those two values is. Finally, the model accuracy is calculated using the RMSE score.

The main contributions of this study are twofold. First, it exploits the best predictive model for cryptocurrency volatility. To the best of our knowledge, this type of application has rarely been conducted, primarily to forecast volatility. Thus, it enriches the portfolio management literature, especially selecting cryptocurrency as part of the portfolio. Although several papers attempt to investigate the volatility, it is more on a single cryptocurrency (bitcoin) or neglecting the economic shocks such as COVID-19. Moreover, those empirical findings do not compare the volatility assessment with the well-known traditional volatility measurement: the GARCH model. For this reason, this study also provides a new perspective regarding this type of implementation.

Secondly, it enriches the portfolio management studies by showing that most models in volatility prediction have high accuracy despite the economic shocks existing, not existing, or a combination of both (the entire period). These ML-based models, such as SVR, NN, and DL, can be the base for the value-at-risk model of portfolio management. Interestingly, the SVR, NN, and DL have no statistically significantly different in terms of predicted values. However, the traditional GARCH model is relatively not good for the volatility prediction of cryptocurrency. These results can be used to better predict the future, especially the volatility behavior of an asset such as cryptocurrencies.

The rest of the paper is outlined as follows. Next section reviews the literature. Section 3 describes the data and methodology. Section 4 reports the empirical results and the discussion. Section 5 concludes the paper with the suggestion for future research.

2. Literature

The volatility prediction literature is hugely dominated by the GARCH model. The application is extensive by aiming at the price volatility prediction of commodities (Musunuru, 2014), Gold (Kristjanpoller & Minutolo, 2015), energy price (Chan & Grant, 2015), Stock market (Lin, 2018), and derivatives market (Fang et al., 2018). Other related studies were conducted by extending and modifying the method into machine learning assessment. The tenet is that the machine-learning model has better accuracy than the traditional GARCH model. For example, Panella et al. (2012) use a neural network to forecast energy commodity prices. Panella et al. (2013) use the neuro-fuzzy method in modeling crude oil prices. In addition, several scholars use a similar method to predict ESG scores (D'Amato et al., 2022, D'Amato, 2021), stock prices (Nikou et al., 2019), and bond yield (Bianchi et al., 2021). In the context of cryptocurrencies, many have utilized machine learning to exploit the best predictive model (Refer to Table I).

The literature then extends by exploiting the volatility prediction. The objective is to reveal the optimum portfolio benefits based on risk parity (Clarke et al., 2013; Xiong et al., 2022). Volatility is crucial in portfolio management because it measures the uncertainty of the return on assets. The higher the volatility, the higher the uncertainty of the return of the assets. This makes volatility a parameter for pricing and portfolio allocation (Harvey & Whaley, 1992; Xiong et al., 2022). Predicting volatility will help investors determine the market timing, investment size, and asset allocation strategy (Cerqueti et al., 2021). However, given the importance of volatility prediction in investing, scholars move forward by assessing the volatility prediction.

D'Ecclesia & Clementi (2021), for instance, forecast the stock market volatility under the neural network approach. Lu et al. (2022) also predict volatility by using oil future prices as the sample. They found that the Machine Learning-based model is suitable for predicting the risk of oil futures prices. However, as reported in Table I, most research on volatility prediction focuses on stock markets. Rarely found a cryptocurrency volatility prediction amid several bitcoin attempts from Seo and Kim (2020) and D'Amato et al. (2022).

On the one hand, traditional research uses GARCH as the predictive model (e.g., Herwartz, 2017; Jotanovic & D'Ecclesia, 2019; 2021). It argues that the traditional approach can still earn the best predictive value. Meanwhile, other scholars exploit machine learning and use SVM, NN, or DL to predict volatility. The proponents of SVM (i.e., Chen et al., 2010) argue that this technique significantly outperforms the competing models in most situations of one-period-ahead volatility forecasting, which confirms the theoretical advantage of SVM. Meanwhile, the proponents of Neural Networks (i.e., Kristjanpoller & Minutolo, 2015) argue that the technique surpassed the traditional GARCH model in predictive ability. They argue that supervised learning from NN is an excellent complement used to improve the effectiveness of volatility prediction. It allows the model to predict the volatility, focusing on the contribution to explain the behavior out-of-sample and not in-sample as in the classical model fit. In addition, D'Amato et al. (2021) and Petrozziello et al. (2022) argue that deep learning outperforms the traditional approach for volatility prediction due to its multiple layers of trained data. Unfortunately, there is no consensus about the best predictive model for volatility. The compilation for the titles of research doing volatility prediction study from selected journal are in Table I.

Table I *Publication in Volatility Prediction in Selected Reputable Journals*

Authors	Year	Title
Volatility Prediction in General - Journal articles		
Atkins et al.	2018	Financial news predicts stock market volatility better than close price
Félix et al.	2020	Implied volatility sentiment: a tale of two tails
Lee et al.	2022	Trend Prediction Model of Asian Stock Market Volatility Dynamic Relationship Based on Machine Learning
Lu et al	2022	Oil futures volatility predictability: New evidence based on machine learning models1
Nayak & Suresh	2022	Forecast and Analysis of Stock Market Volatility using Deep Learning Algorithms
Nayak & Misra	2020	Extreme learning with chemical reaction optimization for stock volatility prediction
Rouf et al.	2022	Impact of Healthcare on Stock Market Volatility and Its Predictive Solution Using Improved Neural Network
Tissaoui et al.	2022	Does Uncertainty Forecast Crude Oil Volatility before and during the COVID-19 Outbreak? Fresh Evidence Using Machine Learning Models
Zhang et al.	2021	Predicting stock market volatility based on textual sentiment: A nonlinear analysis
Cryptocurrenies Prediction		
Barnwal et at.	2019	Stacking with Neural Network for Cryptocurrency investment
Da Silva et al.	2020	Multi-step ahead Bitcoin Price Forecasting Based on VMD and Ensemble Learning Methods
Mjoska et al.	2022	Predicting Bitcoin Volatility Using Machine Learning Algorithms and Blockchain Technology
Shah et al.	2022	Bitcoin Investment Classifier using Machine Learning and Sentimental Analysis
Wimalagunaratne & Poravi	2018	A predictive model for the global cryptocurrency market: A holistic approach to predicting cryptocurrency prices
Ahamed & Ravi	2021	Study of swarm intelligence algorithms for optimizing deep neural network for bitcoin prediction
Chowdhury et al.	2020	An approach to predict and forecast the price of constituents and index of cryptocurrency using machine learning
Erfanian et al.	2022	Predicting Bitcoin (BTC) Price in the Context of Economic Theories: A Machine Learning Approach
Mallqui & Fernandes	2019	Predicting the direction, maximum, minimum and closing prices of daily Bitcoin exchange rate using machine learning techniques
Mudassir et al.	2020	Time-series forecasting of Bitcoin prices using high-dimensional features: a machine learning approach
Nagula & Alexakis	2022	A new hybrid machine learning model for predicting the bitcoin (BTC-USD) price
Rathore et al.	2022	Real-world model for bitcoin price prediction

3. Methods and Materials

This research takes six cryptocurrencies as the samples, which are bitcoin (BTC), Ethereum (ETH), ripple (XRP), tether (USDT), USD coin (USDC), and Binance coin (BUSD). The rationale is that these six cryptocurrencies are the biggest in the market. Further, hedge funds also utilize it as part of the investment class. Moreover, this research takes USDT, USDC, and BUSD as the sample because these three coins represent stablecoins. The daily data retrieved from the yahoo finance library (yfinance) from 14 March 2018 to 14 March 2022, except for USDC and BUSD, and two coins were launched on September 2018 (USDC) and September 2019 (BUSD).

The period of study is divided into three sub-periods. The first period is the full period, from 2018 to 2022, then the other sub-periods are from 2018 to 14 March 2020, which was the pre-COVID-19 era. The last period is 14 March 2020 to 14 March 2022 to represent the COVID-19 era, and this sub-period approach is important because it will reveal whether the prediction accuracy will change due to the shocks.

In the following process, this research calculates the returns and volatility, then predict the cryptocurrencies under four different approaches: the GARCH model, SVR model, Neural Network, and Deep Learning. The following section contains a technical description of the four time-series models employed in this study.

3.1 Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model

One seminal way to model volatility is Generalized Autoregressive Conditional Heteroskedasticity (GARCH), an improved version of the ARCH model by adding lagged conditional variance. GARCH is fit to predict the volatility of returns on cryptocurrencies, especially its ability in volatility clustering. Further, it is formulated as an autoregressive moving average model for time-varying conditional variance with p number of lagged squared return and q number of lagged conditional variance. The GARCH (p,q) formulation is as follows.

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

Note that ω, β, and α are the parameters to be estimated. Meanwhile, p and q are the maximum lag in the model, and in the GARCH model, it is crucial to have the following conditions: $\omega > 0$, $\beta \geq 0$, $\alpha \geq 0$, and $\beta+\alpha<1$.

3.2 Support Vector Regression (SVR) GARCH model

The second ML-based approach is Support Vector Regression (SVR) – GARCH. It is a supervised learning algorithm that can predict volatility by aligning the *classification* and the *regression*. It is essential to understand the support vector machine (SVM) before describing the SVR. SVM is a supervised learning technique used to identify two distinct classes. Given a collection of training examples, each designated as belonging to one of two categories, it assigns new examples to one of two categories, resulting in a non-probabilistic binary linear classifier. SVM maps the training example, creating a *hyperplane*. In linear algebra, the *hyperplane* maximizes the distance between the points closest to the hyperplane but belonging to different classes, known as *support vectors*—the distance between the two points is called a margin. In the SVM approach, we maximize the margin between the support vector.

In SVR, it takes the volatility as the base for the support vector and then predicts its hyperplane that minimizes the error and maximizes the margin. Simply put, SVR is an SVM that applies to the GARCH model in predicting volatility.

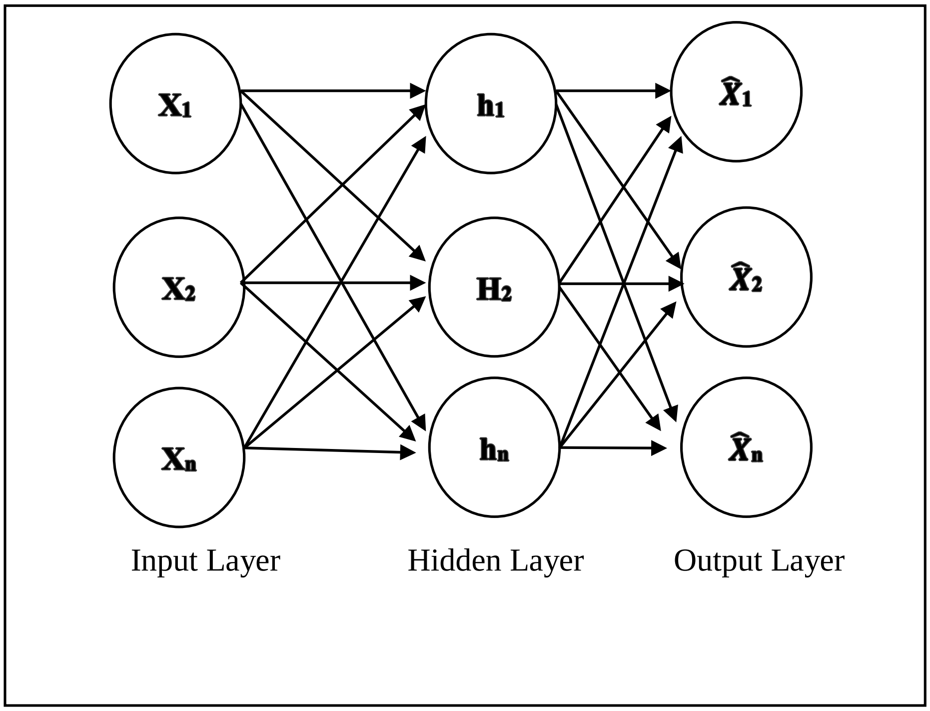
3.3 Neural Network model

The third approach is Neural Network (NN) model. It processes the data in multiple stages to make a decision, creating layers consisting of small individual units called a neuron. Each neuron takes a result of a dot product as input and uses it in an activation function to make a decision:

$$z = w_1 x_1 + w_2 x_2 + b$$

Where b is bias, w is weight, and x is input data. The NN model has three layers: input, hidden, and output. The input layer includes raw data, which is the cryptocurrencies volatility. This input data is mathematically manipulated in hidden and output layers. In the hidden layers, the input is predicted by performing a nonlinear transformation via activation functions. Finally, the predicted value is produced as output layers. Note that this research predicts the volatility of cryptocurrencies based on the weight from the training phase from 200 epochs. Figure I shows the structure.

***Figure I**. NN Structure*

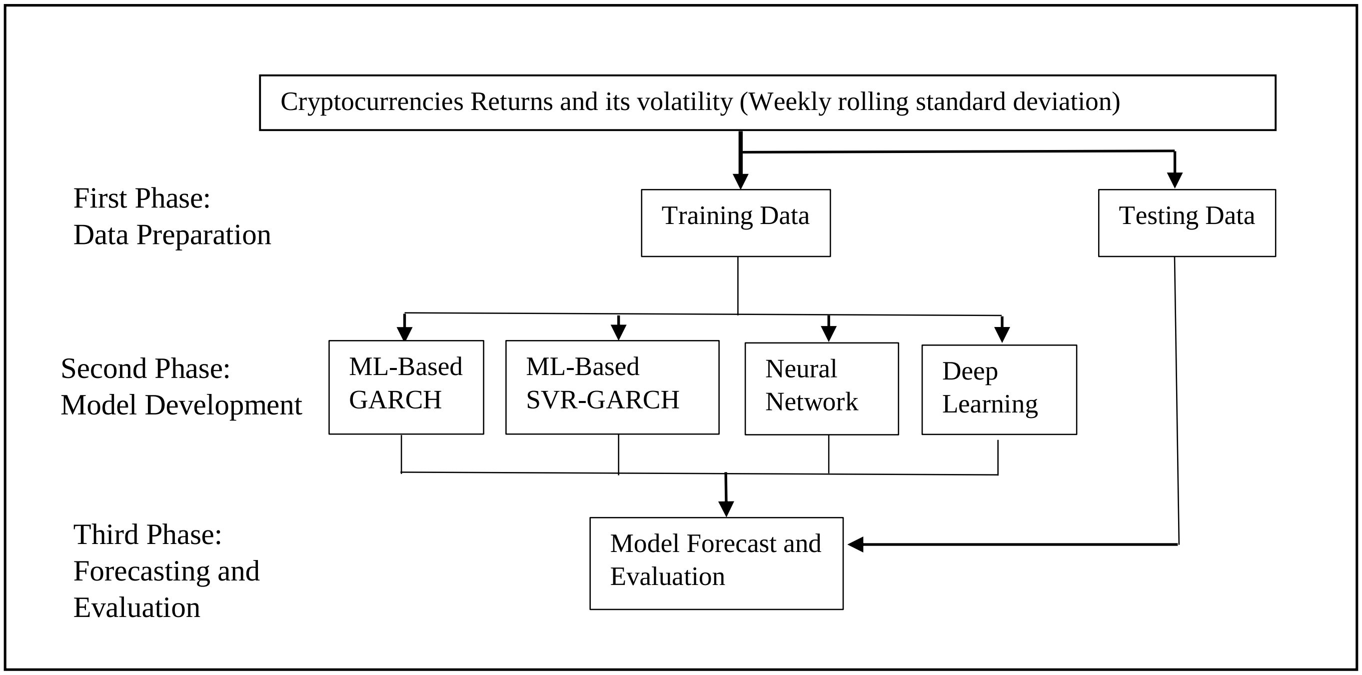


3.4 Deep Learning (DL) model

The final ML-based approach is deep learning, an extended version of NN. If previously NN contained 2-3 hidden layers, DL can have as many as 150 layers, making it a theoretical robust predictive model. DL models are trained using a large set of labeled data and multiple layers of NN architectures. In my research, the DL starts from the configuration of the network structure by deciding the number of layers and neurons to find the optimum hidden layers. Then, it continues with the compilation of the loss and optimizer and deciding the epoch and batch size. This researc runs the volatility data by fitting it first and followed by volatility prediction based on the weight from the training phase.

In sum, a three-stage research methodology is adopted (see Figure II). In the first stage, cryptocurrencies' returns and volatilities are calculated to produce a training and testing set. The second stage is model development. ML-Based GARCH, SVR, Neural Network (NN), and Deep Learning (DL) are developed inside the python environment using arch, pandas, NumPy, statsmodels, scipy, numba, sklearn, and keras libraries.

Figure II. Research Methodology



4. Results

4.1 Descriptive Statistics

Table I shows the summary of the descriptive statistics. As this research is about volatility, the descriptive emphasizes return and risk. The returns were calculated using daily and monthly returns, even though the persistent volatility is based on daily returns. The objective of showing monthly returns is to reveal the risk-reward relationship. Note that all figures in Table I are in percentage.

In the full period timeframe, XRP has the highest return daily (0.2226) and monthly (7.9075). As expected, the standard deviation is also the highest among the coins. This tallies with the research from Elender et al. (2018), who surmise that altcoins usually have a higher risk than BTC. Meanwhile, stablecoins have the lowest returns and standard deviation. Specifically, USDC has the lowest daily return (-0.0005), and BUSD has the lowest monthly return (-0.0172). Therefore, it is no surprise considering those stablecoins like USDC, USDT, and BUSD are pegged to stable fiat money such as the US dollar. This also explains why the standard deviation of those three stablecoins in the full period is significantly lower than BTC, ETH, and XRP.

Before the COVID-19 pandemic, BTC offered the highest daily (0.0194) and monthly returns (1.4028). Intriguingly, the standard deviation of BTC (3.7622) is relatively lower than ETH (4.9026) and XRP (4.9271) during the pre-COVID even though the returns were higher. Meanwhile, BUSD had the lowest daily return (-0.0038) and monthly return (-0.2434) before COVID-19, with the lowest risk being on USDT (0.5068).

Additionally, the highest returns during the COVID-19 pandemic went to ETH for daily returns (0.5386) and XRP for monthly returns (18.548). The highest returns among stablecoins were USDT for daily returns (0.0002) and BUSD for monthly returns (0.0025). In fact, the return differences among stablecoins are not significant. In terms of volatility, XRP has the highest standard deviation, with a value of 7.030 (based on daily returns) and 61.6582 (based on monthly returns).

In sum, this descriptive statistic shows that each cryptocurrency has a unique risk reward with different standard deviation levels. For example, due to risk compensation, adding BTC and/or altcoins (ETH and XRP) may generate higher returns for the portfolio. Meanwhile, introducing stable coins into the portfolio may not generate optimum portfolio benefits due to their static prices. Therefore, we proceed with the research by taking the volatility as the basis for the prediction.

Table II *Summary Statistic*

Cryptocurrencies	Period	Daily Returns (%)	Std. Dev	Cryptocurrencies	Period	Daily Returns (%)	Std. Dev
BTC	Full Period	0.1771	3.7863	USD-Coin	Full Period	-0.0005	0.4111
	Pre-COVID 19	0.0194	3.7622		Pre-COVID 19	-0.0012	0.5421
	During COVID 19	0.3442	3.8004		During COVID 19	-0.0001	0.0831
ETH	Full Period	0.2226	4.9628	Tether (USDT)	Full Period	0.0006	0.4061
	Pre-COVID 19	-0.0825	4.9206		Pre-COVID 19	0.0009	0.5068
	During COVID 19	0.5386	4.9841		During COVID 19	0.0002	0.2706
XRP	Full Period	0.1843	6.0767	Binance (BUSD)	Full Period	0.0005	0.3995
	Pre-COVID 19	-0.0833	4.9271		Pre-COVID 19	-0.0038	0.7488
	During COVID 19	0.4629	7.0330		During COVID 19	0.0001	0.0929
Cryptocurrencies	Period	Monthly Returns(%)	Std. Dev	Cryptocurrencies	Period	Monthly Returns(%)	Std. Dev
BTC	Full Period	5.8679	22.3270	USD-Coin	Full Period	0.0113	0.7286
	Pre-COVID 19	1.4208	22.7952		Pre-COVID 19	0.0421	1.1292
	During COVID 19	9.8912	22.2134		During COVID 19	-0.0018	0.0369
ETH	Full Period	7.9075	30.1105	Tether (USDT)	Full Period	0.0001	0.5208
	Pre-COVID 19	-0.5507	29.6276		Pre-COVID 19	-0.0022	0.7314
	During COVID 19	16.3584	28.7482		During COVID 19	-0.0116	0.1843
XRP	Full Period	8.5585	48.2251	Binance (BUSD)	Full Period	-0.0172	0.2067
	Pre-COVID 19	-1.7030	27.5233		Pre-COVID 19	-0.2434	0.6610
	During COVID 19	18.5458	61.6582		During COVID 19	0.0025	0.0432

4.2 Volatility Forecasting Assessment

My approach in selecting the best volatility prediction is straightforward: using RMSE value as the benchmark. Predictive models with the lowest RMSE scores imply the best-fit prediction. As aforementioned, the train and test data were run under three periods: full period (2018 to 2022), pre-COVID-19, and COVID-19. The epochs for the prediction of each model were 200. The RMSE results from each period in different sub-sections are also described.

4.2.1 *Full Period Forecasting Assessment*

This sub-section reveals the RMSE scores for each cryptocurrency with different predictive models. Table II reveals the RMSE scores.

RMSE values for the ML-Based GARCH are hugely different from the other models. It ranges from 0.0126 (predicting USDT volatility) to 0.5405 (predicting XRP volatility). In a more detailed analysis, SVR has the lowest RMSE in predicting BTC volatility with a value of 0.0022, followed by Deep Learning. It implies that SVR outperforms other models in the volatility prediction of BTC.

Similarly, the RMSE of SVR in ETH volatility prediction is also the lowest, with a score of 0.0022. Neural Network is the second predictive model with the lowest RMSE for ETH volatility prediction. This implies that SVR is the best predictive model in ETH volatility prediction. For the last altcoins, XRP, Table II also reveals that SVR- GARCH has the lowest RMSE score (0.0023). Based on that evidence, this research surmises that SVR has the best predictive model for volatility prediction.

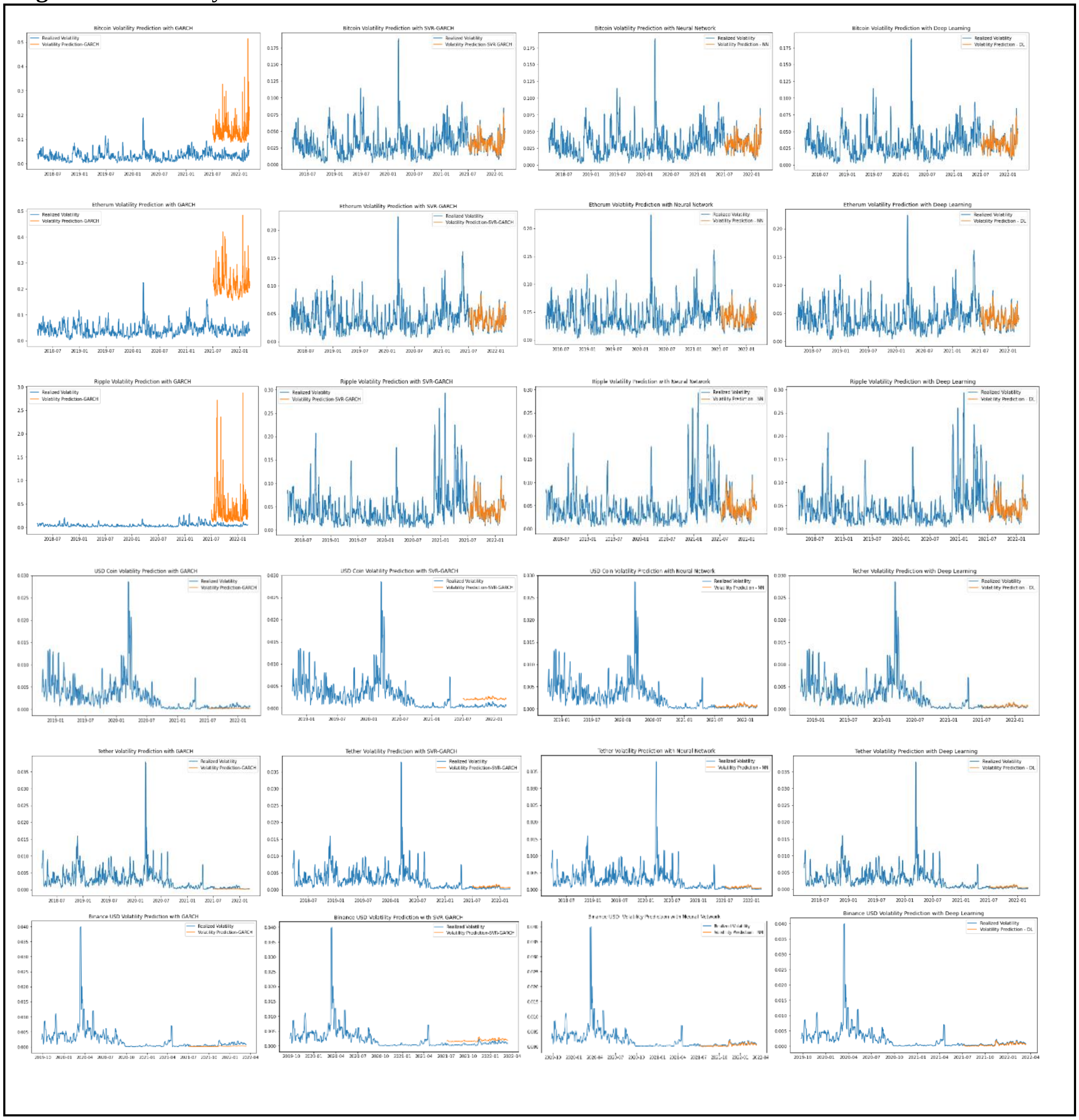
Meanwhile, the predictive model for stablecoins volatility shows that DL has the lowest RMSE scores. For instance, the RMSE score for USDT is 0.0001, which is lower than SVR (0.0004) and NN (0.0002). Further, the RMSE scores for USDC and BUSD using DL are 0.0002 and 0.0001, respectively. NN model has the second lowest RMSE, followed by SVR. Based on those RMSE scores, it is surmised that DL is the best model to predict the volatility of stablecoins.

Figure III confirms our results, portraying the gap between actual volatility and predicted volatility of each cryptocurrency. It shows that ML-Based GARCH has a huge gap between actual and predicted volatility. Note that the RMSE values among SVR, NN, and DL are not hugely different. Therefore, this research provides the t-test differences test to reveal whether the RMSE scores among the model are significantly different or not. We discuss this matter in the last section of Results.

Table III *Cryptocurrencies Volatility Prediction with Different Models: RMSE Scores for Full Period*

	ML-Based GARCH	ML-Based SVR-GARCH	Neural Network	Deep Learning
BTC	0.3345	0.0022	0.0030	0.0027
ETH	0.4260	0.0022	0.0031	0.0035
XRP	0.5405	0.0023	0.0058	0.0062
USDT	0.0126	0.0004	0.0002	0.0001
USDC	0.0129	0.0016	0.0002	0.0002
BUSD	0.0134	0.0011	0.0003	0.0001

Figure III. Volatility Prediction in Full Period



4.2.2 Pre-COVID-19 Forecasting Assessment

For robustness reason, this research tests the predictive model by excluding the COVID-19 shocks. The argument is that the volatility of the shocks may disturb the trained and tested data, especially when the data used is the standard deviation. The time period is changed from 2018 to 2020. The cut-off is 14 March 2020, when most countries recognized COVID-19 as a pandemic and started the lockdown phase. The second week of 2020 was also the short-life fallen of cryptocurrencies.

The approaches remain the same, where ML-Based GARCH, SVR, NN, and DL are employed. The RMSE scores are utilized as the accuracy measurement, and Table III reveals the results.

Overall, the conclusions are similar, where SVR has the lowest RMSE score for the volatility predictions of four cryptocurrencies: BTC, ETH, XRP, and USDT. Meanwhile, NN has the lowest RMSE scores for the volatility prediction of USDC and BUSD, but unequivocally, RMSE scores from ML-Based GARCH are hugely distinct from the other models.

Notably, the volatility predictions of stablecoins were again close to zero. The low level of persistent volatility from those stablecoins may generate a better predictive model. We also can see Figure IV to support this, where the predicted volatility of all stablecoins was very close and aligned with the actual volatility.

Table IV *Cryptocurrencies Volatility Prediction with Different Models: RMSE Scores for Pre-COVID-19 period*

	ML-Based GARCH	ML-Based SVR-GARCH	Neural Network	Deep Learning
BTC	0.3474	0.0046	0.0063	0.0049
ETH	0.4270	0.0049	0.0072	0.0085
XRP	0.4240	0.0032	0.0046	0.0056
USDT	0.0494	0.0019	0.0022	0.0054
USDC	0.0433	0.0013	0.0008	0.0013
BUSD	0.0535	0.0020	0.0015	0.0058

Figure IV. Volatility Prediction Pre-COVID 19

4.2.3 During COVID-19 Forecasting Assessment

We proceed with the volatility prediction by taking a different cut-off period: the COVID-19 pandemic. Hence, the retrieved data was from 14 March 2020 to 14 March 2022. All approaches with their procedures remain the same. Table IV reports the RMSE values.

The predictive results from COVID-19 are interesting. It has small values of RMSE, indicating that all models are rigorous in predicting volatility. The volatility predictions of BTC, for example, have small RMSE scores from SVR (0.0021), NN (0.0030), and DL (0.0047). For the first time, my ML-Based GARCH's RMSE is lower than 1 (0.3250). The results for ETH's volatility predictions also have a small RMSE score across all predictive models. SVR has the lowest RMSE (0.0021), followed by NN (0.0045). The RMSE from ML-Based GARCH is the highest, with a value of 0.4136. This implies that SVR is the best volatility prediction model during a shock like the COVID-19 pandemic. For the XRP's volatility prediction, SVR still has the lowest value (0.0018). NN and DL models still have a relatively low RMSE (0.0045 and 0.0059, respectively).

Additionally, the stablecoins volatility predictions are intriguing. All RMSE scores are near zero. The RMSE scores of SVR, NN, and DL are indifferent. In fact, the score from SVR for USDC is almost zero. The same results are found for the NN model for USDC and BUSD, where the RMSE scores are almost zero. ML-Based GARCH's RMSE is also very low in predicting the volatility of all stablecoins. In short, all predictive models have good volatility prediction during COVID-19.

Table V *Cryptocurrencies Volatility Prediction with Different Models: RMSE Scores During COVID-19 period*

	ML-Based GARCH	ML-Based SVR-GARCH	Neural Network	Deep Learning
BTC	0.3250	0.0021	0.0030	0.0047
ETH	0.4136	0.0021	0.0045	0.0059
XRP	0.5080	0.0018	0.0052	0.0069
USDT	0.0089	0.0001	0.0001	0.0001
USDC	0.0060	0.0000	0.0000	0.0002
BUSD	0.0083	0.0002	0.0000	0.0001

Figure V. Volatility Prediction During COVID-19

4.2.4 Is it significantly different?

Considering the RMSE scores from SVR, NN, and DL are not much different, One may argue that SVR may have the lowest RMSE score, but the predicted volatility may not be significantly different from other models. Therefore, this research examines it further by conducting ANOVA among predicted values from all models. The purpose is to reveal whether the volatility prediction from all models is significantly different. The results show no statistically significant difference between the predictive volatility values of SVR, NN, and DL. However, the predictive volatility from ML-Based GARCH is significantly different from others. These results surmise two important findings. First, even though SVR is the best predictive model for volatility prediction, the predicted values are not significantly different from the predictive values from NN and DL. Second, ML-Based GARCH has a low RMSE score for stablecoins during pandemic COVID-19, yet its predictive values are significantly different from those of SVR, NN, and DL.

5. Conclusion

Accurate volatility predictions are important for portfolio management to ensure the calculated risk-adjusted returns, especially those that employ asset allocation, risk-parity, and volatility-targeting strategies. The emergence of cryptocurrencies as part of the investment class in asset allocation has driven many finance research papers emphasizing the prediction of the price and returns of cryptocurrencies, specifically the bitcoin. This research attempts to fill in the lacuna by presenting a comparative assessment of cryptocurrencies' volatility predictions from four different models: ML-Based GARCH, SVR, NN, and DL. All four models were trained using three periods: full period, pre-COVID-19, and during COVID-19, using historical rolling standard deviation.

The results show that SVR has the lowest RMSE score, implying the best accuracy in volatility prediction. In contrast, ML-Based GARCH has the highest RMSE score. We further examine the results by having statistical inferences from the predicted values of each model. The results surmise that the predicted values of volatility prediction from ML-SVR, NN, and DL are statistically indifferent. However, the predicted values from ML-Based GARCH are statistically different from those three models, implying ML-Based GARCH is inferior as the predictive model of cryptocurrency volatility.

However, all findings need to be validated by further research from different angles, considering the limitation of this research. This study has focused on examining the best volatility prediction for cryptocurrencies, especially the significant three cryptocurrencies (BTC, ETH, and XRP) and the big three stablecoins (USDC, USDT, and BUSD). The volatility is calculated using daily returns, which may not capture the extensive fluctuation from intraday trading. Future research may test it on that intraday data. Moreover, this research only takes relatively "stable" cryptocurrencies, neglecting the other cryptocurrencies with higher volatility, such as penny coins (known as memecoin/shitcoins) and tokens. The assessment result might be different for those cryptocurrencies.

A few extensions can be further built upon this analysis. Firstly, more in-depth insight can be gained by examining different assessments such as LSTM, Bayesian Metropolis-Hastings, Markov-Chain Monte Carlo, or Recurrent Neural Networks. Secondly, some institutional characteristics such as volume, liquidity, sentiments, and government regulation news can be another exciting study extension for this analysis.

NOTE:

1. For our Python Coding: https://github.com/rayenda83/finance_research/blob/main/ML_volatility_prediction.ipynb

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