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Gated Recurrent Unit Model with Untrained Heteroscedasticity Element in Modelling Forecast of Bursa Malaysia Stock Return Volatility

Aida Nabilah Sadon¹, Shuhaida Ismail^{2,*}, Azme Khamis¹

¹ Faculty of Applied Science and Technology, Universiti Tun Hussein Onn Malaysia, Parit Raja, 86400 Batu Pahat, Johor, Malaysia

² Faculty of Computer and Information Technology, Universiti Tun Hussein Onn Malaysia, Parit Raja, 86400 Batu Pahat, Johor, Malaysia

ABSTRACT

Heteroscedasticity effects are useful for forecasting future stock return volatility. Stock volatility forecasting can provide business insight into the stock market, making it valuable information for investors and traders. Predicting stock volatility is a crucial task and challenging. This study proposes a hybrid model that can predict the future stock volatility value by considering the heteroscedasticity element of the stock price. The proposed model is a combination of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and a well-known algorithm of Recurrent Neural Network (RNN) which is Gated Recurrent Unit (GRU). This proposed model is referred to as GARCH-GRU model. The proposed model is expected to improve the prediction accuracy by considering the heteroscedasticity element. First, GARCH model is used to find the model estimation. Then, residual obtained from the model is tested using ARCH effect test. This step is crucial in finding any untrained heteroscedasticity element. The hypothesis of the ARCH test yielded a p -value less than 0.05 indicating there is valuable information remained in the residual where it is also known as heteroscedasticity element. Next, the dataset with heteroscedasticity element undergoes modelling step using GRU model. The experimental results revealed that hybrid GARCH-GRU was able to improve the directional forecast accuracy based on Mean Directional Accuracy (MDA) performance measurement. The proposed hybrid GARCH-GRU model has potential to improve the directional forecasting accuracy by 87% based on the MDA scores obtained in single GRU and hybrid GARCH-GRU. This finding proved that GARCH-GRU model is highly reliable in predicting the stock price and able to assist the investors in making decisions on regards to stock price.

Keywords:

GRU Model; GARCH Model; Stock price forecasting; Hybrid GARCH-GRU

1. Introduction

The stock market is a marketplace where people can buy and sell shares or ownership stakes in any publicly traded companies. It is a vital component of the financial system and serves as a mechanism for companies to raise capital and for investors to potentially profit from their investments. In contrast, stock price refers to a stock's current market value. It reflects the supply and demand for the stock and is influenced by numerous factors, such as the financial performance

* Corresponding author.

E-mail address: shuhaida@uthm.edu.my

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of the company, macroeconomic factors, international events, political events, social behaviour, and investor's sentiment [1-3]. Clearly. Inflationary pressures and interest rates have a complex political-economic relationship [4].

Stock prices fluctuate constantly and can rise, or fall based on a variety of factors, making them a significant indicator of a company's financial health. Current stock prices are essential information for investors, especially in terms of the future value of shares [5]. Every investor, from novices to seasoned professionals, seeks the ideal time and decision to trade stocks where an brilliant choice can result in substantial gains and losses for investors [6].

Stock price prediction is an attempt to determine the future value of a company's stock or stock index. This is an important aspect of investing because it allows investors to make informed decisions regarding the optimal time to buy or sell a specific stock. Predicting stock prices is crucial in the financial and economic world [7]. Predicting changes or movements in stock price has increased investors' and traders' interest and demand [8,9]. Numerous parties, including individual investors, stockbrokers, fund managers, and financial institutions, can benefit from accurate stock price forecasts. An accurate prediction of stock price trends is essential for traders and investors to trade profitably [10]. The profitability of stock market investments has been shown to be substantially correlated with the predictability of stock price changes [11].

Predicting stock price is a difficult task due to various influence factors that affect the stock price [12,13]. The highly nonlinear structure of stock price time series makes it very difficult to make accurate predictions. As time series are noisy, non-stationary, nonlinearity, and heteroskedastic, predicting volatility for various forms of financial assets is one of the mathematically challenging tasks in time series forecasting [14].

There are several predictive approaches that have been applied in predicting stock prices and volatility. These approaches consist of either a single method or a hybrid method, such as a combination of mathematical and machine learning techniques. One of the most frequently used method in stock price and volatility forecasting is Box-Jenkins family of models, including Autoregressive Moving Averages (ARMA) and ARIMA models [15,16].

Given the uncertainty and multitude of factors influencing the stock market, predicting the volatility of stock returns can be more valuable than predicting stock prices directly [14,17]. Stock return volatility provides vital information about the state and behaviour of the stock market, which is of particular interest to investors. Information like this is crucial as it will help investors make the best decisions when trading stocks to maintain profitability in the long term.

Heteroskedasticity, which refers to the uncertainty of variance, is one of the characteristics of stock market volatility. Heteroscedasticity in the volatility series explains the measured volatility transmission of the stock indices [18]. Stock return volatility provides vital information about the state and behaviour of the stock market, which is of particular interest to investors [19]. Information like this is crucial as it will help investors make the best decisions when trading stocks to maintain profitability in the long term. The complexity and volatility of stock market make it difficult to accurately predict the future values [20]. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which is part of the Box-Jenkins family, has been widely employed to develop an accurate forecasting model in financial field, particularly in volatility forecasting [21-24]. The variance of the current error term is a function of the variances of prior error terms, as predicted by the GARCH model.

The GARCH model is applied to a case that often exhibits fluctuating conditions, followed by a brief period of relative quiet and could respond to fluctuation sequences better. The model can accurately reflect the regular fluctuations in financial data volatility [25]. Previous study by Ng, Chin and Chong [26] showed the heteroskedasticity component of stock market returns can be employed

to forecast future market value. Factors such as political events and general economic conditions could affect the stock price movements and these factors only can be measures through news and bulletin. Instead of taking risk full step by extracting the qualitative variables, GARCH model can capture the information and news reported within the historical trading days. Despite the ability to capture the volatility in stock price return, GARCH has shown to have limitations in its ability to catch abrupt changes in volatility and an inability to capture non-linear relationships [27,28].

With the advancement of soft computing, Deep Learning (DL) algorithm has received massive rise in popularity for forecasting [29]. DL is a learning algorithm derived from neural network. The algorithm comprises of several layers that transform input data to outputs while learning progressively higher-level features. The DL algorithm also comprises a hidden layer. Hidden layers are located in between input and output layer, containing multiple hidden layers. An algorithm with multiple hidden layers is referred to as deep neural network or deep learning. There are two commonly used approaches in DL which are Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN). CNN is a DL algorithm that deals with spatial data such as images, while RNN is suitable for sequential and temporal data [30,31]. RNN were applied in various area such as in industry of automotive & transportation, healthcare & medicine, retail and more [32].

Given that the stock market is a field that deals with financial time series, DL algorithm based on RNN is more suitable compared to CNN. RNN can process sequential and temporal data before the advent of attention models. Algorithm from RNN neural network excellent fit for regression problems [33]. RNN has demonstrated its capability in predicting two different leading stock markets in the world which is National Stock Exchange (NSE) and New York Stock Exchange (NYSE) [15]. When predicting stock return volatility, RNNs have been shown to have some benefits over conventional statistical models such as GARCH.

Known as modified RNN, GRU has outperformed in many fields and has proven in better performance compared to traditional RNN [34]. GRU demonstrated its superiority in forecasting such as wind power forecasting [35], aquaculture [36], air quality [37] and etc. GRU were also applied in predicting financial time series data. A study conducted on applicability of DL approach on predicting BANKEX data proved that GRU is capable in providing a day-ahead and four-steps ahead of all stock for S&P BSE-BANKEX trends with least error accuracy [10]. Other than that, GRU is also applied in sentiment classification cases since it is able to preserve semantics over time. Previous study by Singh and Shakya showed that GRU able to capture sentimental relationship. However, these RNN algorithms also have limitations such as overfitting, intricacy, and inability to handle long-term dependencies [38].

In recent years, rather than depending solely on mathematical and traditional statistical methods, researchers have proposed a hybrid model that combines statistical methods and Machine Learning (ML) or DL methods for predicting stock prices. Hybrid models have been found to be effective for dealing with linear and non-linear characteristics in many cases [39]. Hybrid models are preferable not only in terms of prediction results, but also in terms of robustness and extrapolation capabilities [40]. Hybrid model has proven to be better than single model such as in stock price prediction [41,42], consumer price index forecasting [39] and many other.

Recent works in forecasting stock volatility suggested that combination of volatility forecast model such as GARCH model given better forecasting performance with the combination of other forecasting models such as Artificial Neural Network (ANN) [43]. Previous study also suggested that GARCH model unable to be the single forecasting model [44]. Due to this, hybridization of both RNN and GARCH is expected to overcome the weakness of GARCH model as well as increase the forecasting performance compared to single model.

In this study, a hybrid model which combine RNN and GARCH model is proposed to capture the fluctuation and volatility of the daily Bursa Malaysia stock return and provide a precise forecasting value for trading purposes. This research has two aims:

- i. to design a new hybrid model known as GARCH-GRU
- ii. to evaluate the performance of the proposed model in predicting future stock prices relative to a single GRU model.

It is anticipated that the proposed GARCH-GRU model will outperform the single LSTM model since the proposed model has an additional heteroscedasticity element. It is expected that the findings of this study will aid investors and economists in making stock trading decisions.

2. Methodology

2.1 Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

The Autoregressive Conditional Heteroscedastic (ARCH) model developed by Engle in 1983 for univariate regression [45,46]. In 1986, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model that uses squared daily log returns to solve conditional volatility problems was introduced. In contrast to the ARCH model, GARCH model considers past conditional variance, also known as volatility. Therefore, volatility remains the same regardless of whether the return is negative or positive [47]. The stock return volatility also known as realized volatility (RV_t) on t day are computed by using following equation:

$$RV_t = \frac{1}{T} \sum_{j=t}^{j=t+T-1} (R_j - \bar{R})^2 \quad (1)$$

where, T is number of trading days after day, R_j is return on day j , \bar{R} is an average return on day j , and RV_t is actual return volatility. By using closed values from Bursa stock price data, set of daily realized volatility are created and used in training and testing the forecasting models proposed in this study.

Due to the nature of financial asset returns and their highly persistent volatility, simple GARCH models turn out to be very effective for modelling and predicting the scale terms [48]. A simple GARCH (p, q) is explained as follow:

$$\begin{aligned} \varepsilon_t &= \eta_t \sigma_t \\ \sigma_t^2 &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \dots + \alpha_q \varepsilon_{t-q}^2 \\ &+ \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \dots + \beta_p \sigma_{t-p}^2 \end{aligned} \quad (2)$$

where, ε_t is lagged squared residuals, η_t is sequence of independent and identically distributed random variables with zero mean and unit variance, α_q is non-negativity constraints, and β_p is measure the extent to which volatility. As this study is working on heteroscedasticity effect, the ARCH effect test derived by Engle is used to identify ARCH elements in residuals generated by GARCH model estimation. The H_0 for the test indicating there is no ARCH effect found, while H_A indicate there are significant ARCH effects in the dataset.

2.2 Gated Recurrent Unit (GRU)

Gated Recurrent Unit (GRU) is known as one of algorithm in Recurrent Neural Network (RNN) also known as upgraded model based on Long Short-Term Memory (LSTM) model.

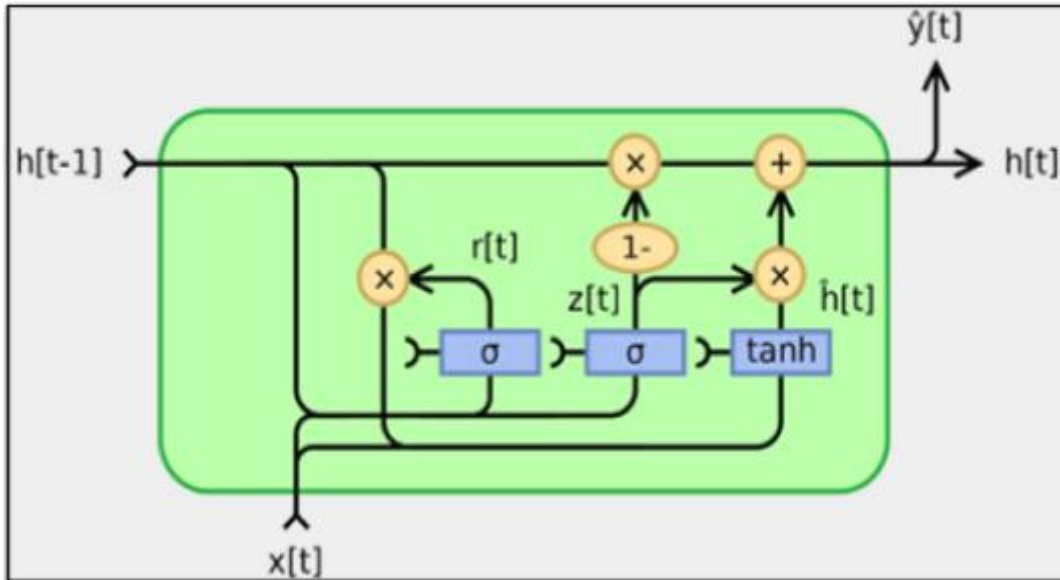


Fig. 1. GRU block diagram

The mathematical formula from behinds GRU as follow:

$$z_t = \sigma(W_z X_t + U_z h_{t-1}) \quad (3)$$

$$r_t = \sigma(W_r X_t + U_r h_{t-1}) \quad (4)$$

$$\hat{h}_t = \tanh(W_h X_t + (r_t \odot h_{t-1}) U_h) \quad (5)$$

$$h_t = (Z_t \odot \hat{h}_t) + ((1 - Z_t) \odot h_{t-1}) \quad (6)$$

where, X_t is input at time t , z is the update gate, r is reset gate, \hat{h}_t is candidate hidden state, and h is hidden state. Eq. (3) denotes as update gate, Eq. (4) as reset gate, Eq. (5) as candidate hidden state and Eq. (6) denotes as hidden layers. GRU architecture is known to be the simpler one compared to LSTM.

2.3 Hybrid GARCH-GRU Model

Stock return volatility is considered key information and helpful for analysing the movements of the stock market. Predictability of stock market volatility has been noted as a challenging task [49]. Since economists have difficulty in predicting stock market volatility, investors may also find it difficult to analyse their stock markets. This hybrid model is proposed with the aim of helping economists analysing and forecasting the future stock return volatility scenarios by considering the heteroscedasticity effects contained by stock market that their working with.

Previous researchers believed residuals from the GARCH model contained untrained heteroscedasticity effects [49]. To assist investors in analysing and predicting stock market volatility

values more effectively, this study focuses on the development of a hybrid model that incorporates heteroscedasticity effects. Heteroscedasticity element is known as useful information in studying volatility movements.

Figure 2 shows the flowchart of the proposed model. First, the dataset collected from Yahoo Finance website with time interval in between January 2012 until December 2022 was analysed. Next, daily return volatility (RV_t) was calculated from the dataset. As for the first part, RV_t were trained and tested in GARCH model. Forecasted values produced by GARCH model is then tested using ARCH effect test to determine the heteroscedasticity element left in the residuals produced by the model. Once ARCH effect was detected, residuals from the GARCH model is considered to containing untrained heteroscedasticity by the GARCH model once again used as additional variable to be used in training the daily RV_t in GRU model. From now, GRU are training and training using two variables which are RV_t and residuals from the GARCH model.

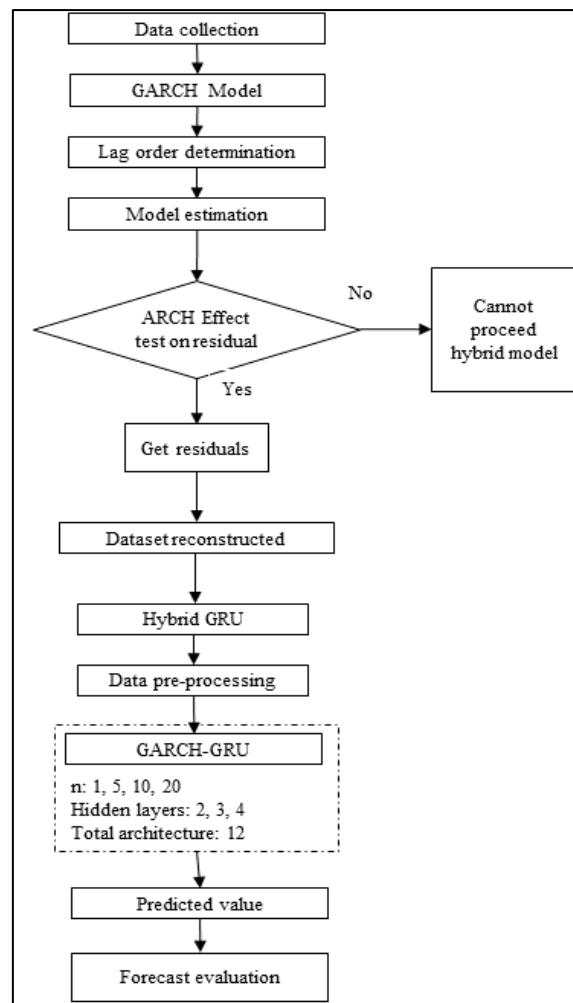


Fig. 2. Flowchart of proposed hybrid model GARCH-GRU

The hybrid GARCH-GRU proposed in this study was designed by incorporating uncaptured heteroscedasticity element known as residuals from GARCH model into the GRU architecture. Based on the pilot study, the number of hidden layers most optimum in terms of time and performance accuracy is four layers. This hybrid model validated with comparison of single GRU model that only used dataset of stock return volatility without heteroscedasticity element.

2.4 Accuracy Measurements

This study employs several performance evaluations as follows:

$$RMSE = \sqrt{\frac{(RV_t - \hat{v}_t)^2}{n}} \quad (7)$$

$$MAPE = \frac{100}{n} \left| \sum \frac{RV_t - \hat{v}_t}{RV_t} \right| \quad (8)$$

$$HMAE = \frac{1}{n} \sum |1 - \hat{v}_t / RV_t| \quad (9)$$

$$r^2 = \frac{\sum (RV_t - \hat{v}_t)^2}{\sum (RV_t - \bar{RV})} \quad (10)$$

$$MDA = \frac{1}{n} \sum 1 \text{sign}(RV_t) == \text{sign}(\hat{v}_t) \quad (11)$$

Where RV_t is the actual value at time t , \hat{v}_t is forecast value at time t and n is number of sample observation.

2.5 Datasets

In this research, Malaysia stock market known as Bursa Malaysia (KLSE) stock index used as materials in models' development. This index contained the variable of Price, Open, High, Low, Vol, and Change%.

Based on the timeline event in Figure 3, the first COVID-19 pandemic outbreak was reported in March 2020. The figure shown KLSE stock index portrays growth from 2012 to 2014, then turned downward until 2016, and continues to grow every two years. There is significant downward trend by end of 2019 and mid of 2020. This is due to Covid-19 outbreak and the stock market was negatively impacted. As for the seasonal effects, there seems to be cyclical movements across the month of each year, yet it is hard to describe the dataset as random variation.

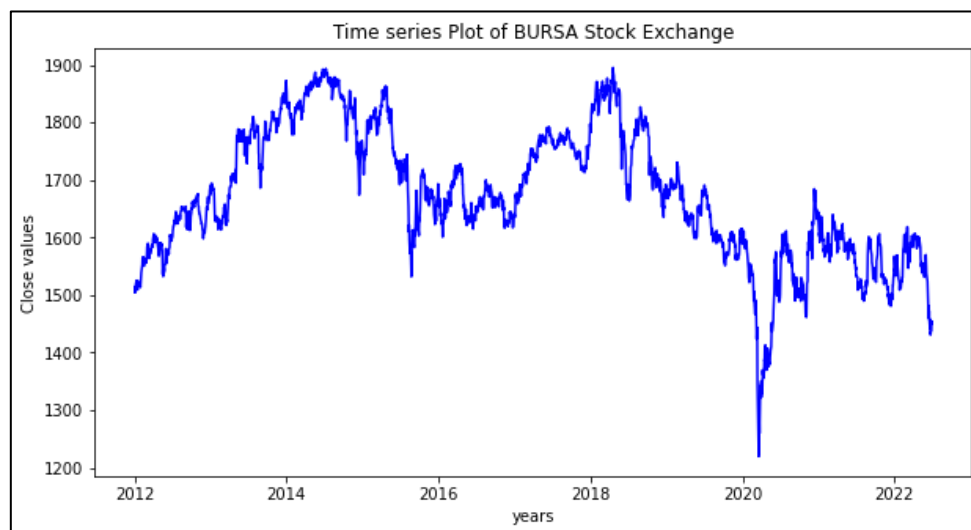


Fig. 3. Time series plot of Bursa Malaysia Index (KLSE)

Table 1 shows the excerpt of the dataset used in this study. The dataset is characterized as non-normal and non-stationary by visual inspections. Since financial time series dataset are expected to be this way, it is normal due to its seasonality effects.

Table 1

Excerpt Dataset of Daily KLSE stock Index

Date	Open	Close	Returns	RV_t	residual (GARCH)
2/2/2012	1526.61	1537.09	0.010332	0.073	-0.00147
3/2/2012	1537.59	1538.77	0.001092	0.073	-0.00152
8/2/2012	1542.27	1553.18	0.009321	0.074	-0.00057
9/2/2012	1555.15	1565.32	0.007786	0.075	0.000409
10/2/2012	1562.72	1561.66	-0.00234	0.076	0.001435
13/2/2012	1560.35	1562.82	0.000742	0.075	0.000413
14/2/2012	1565.25	1566.05	0.002065	0.075	0.000329
15/2/2012	1566.66	1561.3	-0.00304	0.076	0.00182
16/2/2012	1558.27	1550.49	-0.00695	0.081	0.006817

Figure 4 showed the realized volatility of KLSE stock return visual inspection revealed that the dataset has high pick volatility especially on early year of 2020 that the dataset has reached the abnormal pick of its usual volatility range.

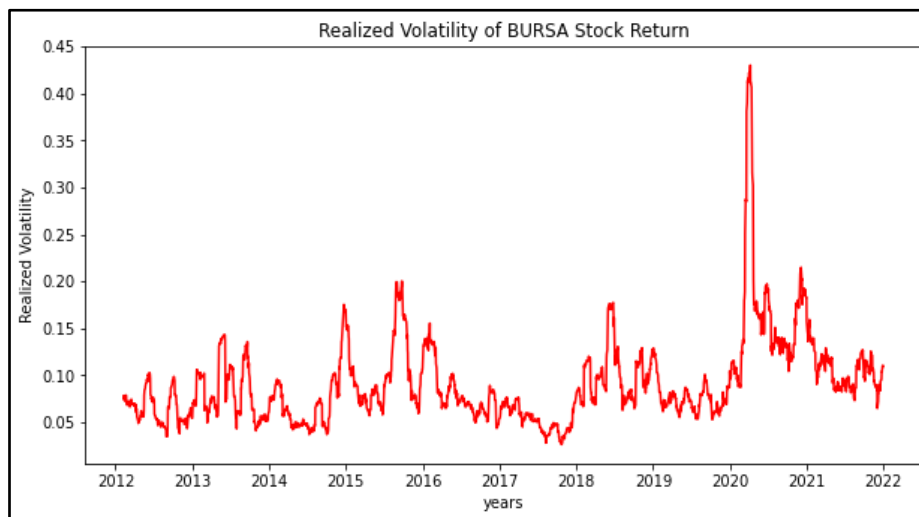


Fig. 4. Realized volatility of KLSE stock return

3. Results and Discussion

The dataset must undergo statistical testing to prove the normality and stationarity of the dataset. The results of preliminary study of Anderson Darling (AD) and Augmented Dickey-Fuller (ADF) tests indicated that the dataset is not normal and not stationary. These characteristics is common for financial time series as these data exhibit substantial fluctuations. AD test resulted in 9.54911 test statistics at 95% confidence interval, indicating the test statistics obtained was larger than critical value of 0.786. Therefore, null hypothesis failed to be rejected indicating the dataset is not normal. Meanwhile, the ADF test results showed a p -value of -0.2583 and critical value of 0.09654 where it is greater than 0.05, which indicates that null hypothesis of the test was not rejected. There is no stationary pattern in the sample dataset, indicating that it is non-stationary. Therefore, it does not vary consistently over time and proven has a time-dependent structure.

3.1 GARCH Model

Figure 5 displays the GARCH model estimation, demonstrating a good fit to the data with most parameters showing significant coefficients. This suggests that the model effectively captures the volatility dynamics and indicates strong persistence in volatility. The ARCH effect test of ARCH-LM test was conducted on the residuals produced by GARCH model estimation.

Constant Mean - GARCH Model Results					
Dep. Variable:	vol	R-squared:	0.000		
Mean Model:	Constant Mean	Adj. R-squared:	0.000		
Vol Model:	GARCH	Log-Likelihood:	4187.53		
Distribution:	Normal	AIC:	-8365.06		
Method:	Maximum Likelihood	BIC:	-8337.88		
Date:	Thu, Aug 04 2022	No. Observations:	1698		
Time:	02:53:17	Df Residuals:	1697		
		Df Model:	1		
Mean Model					
	coef	std err	t	P> t	95.0% Conf. Int.
mu	0.0695	7.453e-04	93.247	0.000	[6.803e-02, 7.096e-02]
Volatility Model					
	coef	std err	t	P> t	95.0% Conf. Int.
omega	2.1218e-05	4.618e-11	4.595e+05	0.000	[2.122e-05, 2.122e-05]
alpha[1]	0.1000	4.635e-02	2.157	3.097e-02	[9.152e-03, 0.191]
alpha[2]	0.1000	6.979e-02	1.433	0.152	[-3.678e-02, 0.237]
beta[1]	0.7800	1.339e-02	58.256	0.000	[0.754, 0.806]

Fig. 5. GARCH Model Estimation

Based on the *p*-value that was produced by ARCH-LM test, if the *p*-value is less than 0.05 at 95% confidence interval, null hypothesis is rejected. The ARCH effect test was tested on the residuals of GARCH model with lag is equal to 10. The full results of ARCH effect test as documented in Table 2.

Table 2
 ARCH Effect test

Lag	Score	C.V.	P-Value	Present
1	2479.02	3.84	0.0%	TRUE
2	4852.13	5.99	0.0%	TRUE
3	7105.29	7.81	0.0%	TRUE
4	9224.31	9.49	0.0%	TRUE
5	11178.65	11.07	0.0%	TRUE
6	12929.32	12.59	0.0%	TRUE
7	14479.41	14.07	0.0%	TRUE
8	15830.93	15.51	0.0%	TRUE
9	16995.38	16.92	0.0%	TRUE
10	17978.20	18.31	0.0%	TRUE

It can be seen from the above table that ARCH effect has been detected ever since the first lag of the observation was made. As the *p*-values obtained by the test are below 0.05, therefore the test failed to accept the null hypothesis of the statement. Therefore, the GARCH model did not fully eliminate the ARCH elements in the dataset. There is still useful information left in the residuals of

the GARCH model, which is the uncaptured heteroscedasticity element contained inside the residuals. This condition allows the study to proceed for the hybrid GARCH-GRU model development.

3.2 GRU Model

Since GRU model has many components to be considered such as number of hidden layers, number of hidden neurons, and number of inputs, this study proposed a simple framework to start developing GRU architecture that suits the dataset. The architecture of GRU model with different number of input lag or also known as input node which $n = 1, 5, 10, 20$ and number of hidden layers of 2, 3, 4. Based on pilot study, hidden layer more than four layers required longer time for model execution, yet the performance is equivalent to four hidden layers. It is also proved the model architecture of (10, 4, 1) has reached the highest error forecasting performance. This study used one output node as it is focused on one-day ahead forecasting.

Based on Table 3, the GRU model with architecture of (10, 2, 1) indicating ten input nodes, two hidden layers, and one output node is most sensitive in forecasting KLSE stock return volatility 0.0063 value of RMSE, 3.4421 value of MAPE, 0.0344 value of HMAE and 0.9582 value of correlation coefficient. As to Mean Directional Accuracy (MDA) here in GRU, the best MDA is obtained by GRU (10, 4, 1), this model only winning in only one performance measurement among others. To simplify, GRU (10, 2, 1) taken as the best architecture of GRU to be used in this study.

Table 3
 GRU Architectures and Performance Measurements

Input Nodes	Hidden Layers	Performance Measurements				
		RMSE	MAPE	HMAE	r2	MDA
1	2	0.007	4.3143	0.0431	0.9498	0.2582
	3	0.0069	3.9065	0.0391	0.9513	0.2643
	4	0.0071	4.1969	0.042	0.9493	0.2623
5	2	0.0067	3.5478	0.0355	0.9544	0.2705
	3	0.0069	3.8718	0.0387	0.9519	0.2725
	4	0.0067	3.6205	0.0362	0.9546	0.2828
10	2	<u>0.0063</u>	<u>3.4421</u>	<u>0.0344</u>	<u>0.9582</u>	0.2746
	3	0.0064	3.4589	0.0346	0.9581	0.2766
	4	0.0071	4.4731	0.0447	0.9478	<u>0.2807</u>
20	2	0.0064	3.498	0.035	0.953	0.2766
	3	0.0064	3.4786	0.0348	0.9534	0.2766
	4	0.0064	3.5598	0.0356	0.9524	0.2766

3.3 Hybrid GARCH-GRU

The hybrid model GARCH-GRU proposed in this study was designed by incorporating the uncaptured heteroscedasticity element known as residuals from the GARCH model into the GRU architecture. Even though GRU with architecture (10, 2, 1) is chosen as the best model, the same list of architectures is used in the hybridization process to find the best hybrid GARCH-GRU architecture to be used in this study.

It is expected that heteroscedasticity element will aid in forecast accuracy. Based on performance measurements scores showed in Table 4. As for RMSE, MAPE HMAE and r^2 even though the values obtained in GARCH-GRU is slightly higher than obtained in GRU model, but performance measurement of MDA can capture a big improvement made by hybrid GARCH-GRU model where 0.5147 value of MDA indicates that 51.47% of directional forecast accuracy has been achieved. Overall performance measurements scores, the GARCH-GRU seems more stable with all scores

indicating that GARCH-GRU (10-4-1) is the best architecture to be use in predicting the stock return volatility.

Table 4
 GARCH-GRU Architectures and Performance measurements

Input Nodes	Hidden Layers	Performance Measurements				
		RMSE	MAPE	HMAE	r2	MDA
1	2	0.0081	4.3377	0.0434	0.9364	0.5363
	3	0.0077	4.2749	0.0427	0.9418	0.4931
	4	0.0142	11.3694	0.1137	0.8047	0.5088
5	2	0.0079	4.3951	0.044	0.9398	0.4990
	3	0.0079	4.3858	0.0439	0.9401	0.4990
	4	0.0078	4.2904	0.0429	0.9415	0.5010
10	2	0.0079	4.4241	0.0442	0.9397	0.4990
	3	0.0077	4.1395	0.0414	0.9423	0.4892
	4	<u>0.0076</u>	<u>4.0099</u>	<u>0.0401</u>	<u>0.9443</u>	<u>0.5147</u>
20	2	0.0081	4.8124	0.0481	0.9352	0.4990
	3	0.0078	4.3529	0.0435	0.9401	0.4774
	4	0.008	4.5596	0.0456	0.9381	0.4990

3.4 Comparisons

This study focuses on analysing Malaysia stock return volatility using both GRU and GARCH-GRU. Table 5 illustrates the model’s performance and validated using five statistical performance measurements which are RMSE, MAPE, HMAE, r^2 , and MDA.

Table 5
 Models Comparison

	GRU	GARCH-GRU
RMSE	0.0063	0.0076
MAPE	3.4421	4.0099
HMAE	0.0344	0.0401
r^2	0.9582	0.9443
MDA	0.2746	0.5147

Based on Table 5, both are used in forecasting stock price index of KLSE and found that model with heteroscedasticity element able to improve the directional forecasting accuracy. Model performance measurements scores obtained by GRU and GARCH-GRU are similar and close to each other values for RMSE, MAPE, HMAE and r^2 , but the major different can be captured by performance measurement of MDA which measures the true direction gives by the forecasting model.

Even though the error measurements (RMSE, MAPE, HMAE) in GRU is small with high value of correlation coefficient, GRU model still lack of giving true directional accuracy forecast values. As for GARCH-GRU model, the error measurement obtained is small with high value of coefficient correlation, and almost half of the forecast values given has been forecasted in true direction. Compared to GRU model, GARCH-GRU has the potential to increase the directional accuracy of forecasting by 87% based on the MDA scores obtained in both models.

Figure 6 shows the plot of standardized residuals of prediction produced by GARCH-GRU (10-4-1) model in modelling for KLSE stock return volatility. The plot visually displays a random pattern with most values lying between zero line. The high points in the plot that were thought to be outlier are sparsely and evenly dispersed throughout the zero line. The plot somewhat resembles a random, showing white noise pattern that lacks any patterns or clusters.

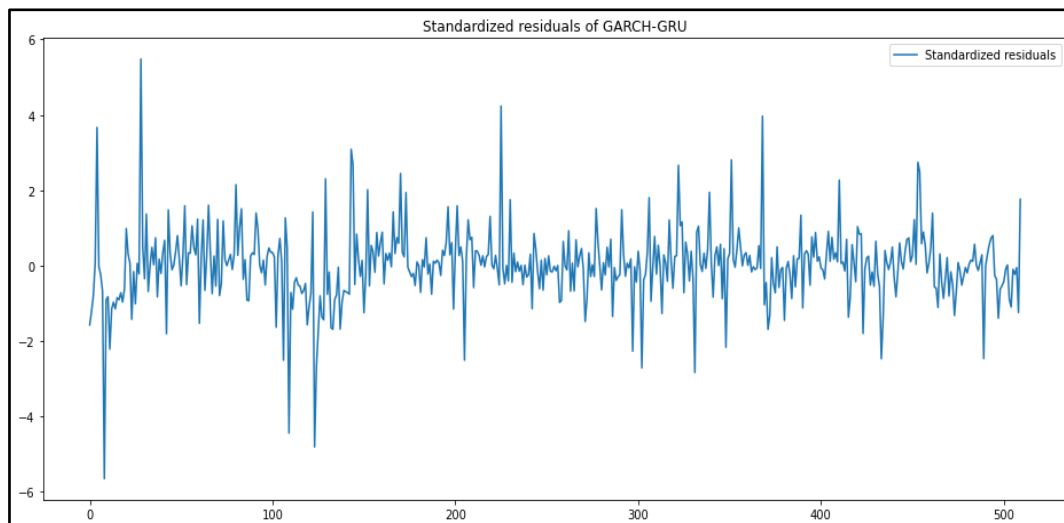


Fig. 6. Standardized residuals plot of GARCH-GRU Model

4. Conclusions

In conclusion, this study has shown that performance measurement with low error rates is not the only thing. The directional correctness is one of the key factors to take into account while forecasting financial time series. Even if a single GRU model may find the lowest scores for error measurements, the model still falls short in providing the predicted values' real direction.

The proposed model's performance has shown good results based on the performance measurements scores obtained, which is in line with the study's objectives of developing a new hybrid model known as GARCH-GRU and evaluating the model's performance in predicting future stock prices relative to a single GRU model. Despite the significantly higher error measurement values, it is marginally greater than those of single GRU model, the range disparity is minimal.

In order to determine whether model is more effective at forecasting stock return volatility, this study yielded an additional two performance measurements. According to correlation coefficients, both models' scores fall within a narrow range, or very close to 1, which shows that each model's prognosis may closely match the actual observation. The score generated by the GARCH-GRU model has demonstrated significant differences when compared to the single GRU model based on the most recent performance measurement, known as MDA.

GARCH-GRU has demonstrated its ability to provide true directional accuracy forecast values with a small margin of error. In future research, it is recommended to work with hyper parameter setting adjustments because this hybrid GARCH-GRU model works with more than one variable, and the settings may differ from those used in single GRU models.

The novelty of this study is offering a comprehensive guide for effectively integrating the GARCH and GRU models, emphasizing the sophistication of hybrid process to harness their complementary strengths. Additionally, this study has made significant contribution by providing precise and practical guidance on optimal parameters for practitioners to enhance model accuracy and robustness in financial analysis and modelling forecasting.

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