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Forecasting Stock Price in Healthcare Sector by using Geometric Brownian Motion Model

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Abstract

This study addresses the challenge of selecting suitable stocks amid the daily fluctuations and unstable conditions of financial markets. It focuses on the critical need of forecasting tools to predict the future prices that able to assist investor in investment and avoid financial losses. Unlike many studies that focus on the long-term forecasting methods, this study uses Geometric Brownian Motion (GBM) model to forecast short-term prices based investor desire. The model's efficacy is tested using a case study of 10 healthcare stocks, with forecasts generated for two-week and four-week periods. The methodology involves modelling stock price using GBM model, which core component included the rate of return, drift and volatility. The accuracy of the forecasts is validated using the Mean Absolute Percentage Error (MAPE) and percentage increment. The performance of forecasted prices is evaluated against the FBMKLCI market index. Additional financial ratio including Sharpe's and Treynor's indices along with t-test to ascertain risk-adjusted returns and statistical significance. The finding shows that two-weeks forecast period yield the smallest MAPE, indicating that the GBM model provides a highly accurate forecast for short-term investment. A comparison of forecasted ranking with the actual price ranking reveals an 88% correlation, further supporting the model's reliability. Additionally, most of the selected stocks demonstrate a significant correlation with the FBMKLCI. This study contributes to the academic discourse by empirically demonstrating the effectiveness of the GBM model in short-term forecasting in an emerging market, offering valuable insights for investors and financial analysts.

Keywords*:* Geometric Brownian Motion; Forecasting; Healthcare; Stock Prices; Investment

Introduction

Financial market forecasting is a critical needed, particularly in volatile environment of emerging economies like Malaysia [1]. The need for robust forecasted models is paramount, as informed investment decisions are crucial for mitigating risk and capitalizing on market opportunities [1]. In Malaysia, investors can access many of equities traded through Bursa Malaysia, which serves as a central hub for corporate fundraising and public trading [1]. The Financial Times Stock Exchange (FTSE) Bursa Malaysia KLCI also known as FBMKLCI gives investors access to a wide range of complementing indexes and also representing the company's performance While the overall market offers numerous investment avenues, the healthcare sector presents a particulars

compelling area focus. Healthcare sector becomes one of the most popular sectors to invest since Covid-19 and significant growth and continues to attract substantial investor interest [2,3].

Researchers have developed a variety of mathematical models for forecasting stock prices. One of the most famous and commonly used statistical strategies for creating predictions based on past observations is the Autoregressive Integrated Moving Average (ARIMA) [4]. Despite its widespread use in forecasting, this method has significant drawbacks, including seasonality, non-stationarity, and other issues [5]. Artificial Neural Networks (ANN) are one of the most accurate and extensively used for forecasting, pattern recognition, and image processing as a machine learning approach or soft computing methodology [6]. There are other methods also used for forecasting future stock prices [7]. Although various models are widely used, many are better suited for long-term or next-day forecasted and may not adequately capture the short-term forecasted prices that are essential for many investors [8]. The demand for models that can provide short-term forecasts to support rapid decision making is necessary.

This study addresses this gap by proposing and applying the Geometric Brownian Motion (GBM) model to forecast the closing prices of a selected stocks of 10 healthcare stocks listed on Bursa Malaysia. The GBM model is a continuous time stochastic process, well-suited for simulating the random, yet trending, paths of stock prices, making it particularly relevant for short-term analysis [3]. This study aims to provide a forecasting tool for investors seeking to make timely decisions. This study's contribution in application of the GBM model within an emerging market, that offering for short-term investment strategy.

Related Work

Researchers have developed a variety of mathematical models for forecasting share prices. The models include the Markov-Fourier Grey Model (MFGM) by [13], Clustering-Genetic Fuzzy System (CGFS) by [9], High-Order Fuzzy Time-Series Model (HOFTM) by Chen et al., (2008), Moving Average Autoregressive Exogenous (ARX) with combination of Grey System (GS) theory and Rough Set (RS) by [11] and Hidden Markov Model (HMM) by [12].

According to [13] developed a novel approach known as MFGM by combining grey model, Fourier series, and Markov. The MFGM is a strong model that can forecast accurately, but the model is suitable for long term operations. The CGFS model used by [9] is outperforms when compared to HMM, HMM Hybrid, Artificial Neural Network (ANN) and Genetic Algorithms (GA), HMM and Fuzzy Logic Hybrid, ARIMA and ANN. According to [12], HMM model and CGFS model both produce the same outcome, but these models only able to forecast the closing price for the following day. Method like ANN, however, is problematic since it forecasts share prices using fuzzy systems and structures [12]. It also needs some previous information from professionals. Other than that, the method that uses ARX with combination of GS theory and RS [11] is the method that is only suitable for long-term prediction.

Despite what the majority of investors would like, these models are not suitable for short-term investments. According to [1] and [3], Geometric Brownian motion can be used to forecast share prices for one to two weeks of investment in which is more advantageous to investors.

Methodology

Daily data for Malaysia Healthcare sector is used. Ten Healthcare companies which are TOPGLOV, SUPERMX, IHH, HARTA, KOSSAN, AHEALTH, ADVENTA, TMCLIFE, DPHARMA and NOVA are used as case study. The data that has been collected will be used to forecasting future stock prices using the GBM model. At this stage, future stock price forecasting is conducted using the GBM model. In GBM, rate of return is calculated using Eq. 1, where R_i is stock return at time i, S_i is stock price when i, and S_{i-1} is stock price when $i-1$.

$$R_i = \frac{S_i - S_{i-1}}{S_{i-1}}. \tag{1}$$

The next step is to generate the drift and the volatility value [14]. The drift value, μ, also known as the drift coefficient, is defined as the mean of return rate where the price increases as time increases. The drift value is calculated by using Eq. 2, where μ is drift value, R_i is stock return at time i, M is amount of stock return, and dt is time steps.

$$\mu = \frac{1}{Mdt}\sum_{i=1}^{n} R_i \,. \tag{2}$$

Next, the volatility value, also known as fluctuation of the stock price or decreases. In other words, the volatility, σ, is the sample standard deviation of the stock return with the time step. The formula for volatility is as Eq. 3.

$$\sigma = \sqrt{\frac{1}{(n-1)dt}\sum_{i=1}^{n}\left(R_i - \overline{R_i}\right)^2} \,. \tag{3}$$

For the last step, it is to compute the forecasted stock price based on the GBM model [15]. The forecast stock price is predicted using GBM as Eq. 4,

$$S(t) = S(0)e^{\left(\mu - \frac{\sigma^2}{2}\right)t + \sigma W_i}. \tag{4}$$

where $S(t)$ is future stock value, $S(0)$ is initial stock value, μ is the daily drift using Eq. 6, σ is volatility value using Eq. 1, t is the time step and W_i is the value from probability distribution.

Validate the GBM model

To check the accuracy of the best model of GBM, Mean Absolute Percentage Error (MAPE) are used to validate the forecasting model, percentage increase for increment of stock price and Treynor's index and Sharpe index are used for stock performance.

$$t_v = \frac{r}{\sqrt{\frac{1-r^2}{n-r}}}. \tag{5}$$

where t_v is the t-value, r is the correlation coefficient and n are the number of daily returns. The hypothesis testing will indicate the relationship between the stocks and KLCI.

$$H_0 : \rho = 0 \text{;stock is not related to KLCI}$$
$$H_1 : \rho < 0 \text{;stock is elated to KLCI}$$

The MAPE is a method that is frequently employed to assess forecasting techniques and Eq. 6 shows the MAPE formula.

$$\text{MAPE} = \frac{1}{N}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|. \tag{6}$$

where A_t is actual stock price at time t, F_t is forecasted stock price at time t, and N is number of stock price data. Table 2 shows the MAPE value accuracy [16].

Table 2. MAPE value accuracy

MAPE	**Accuracy**
< 10%	Highly accurate
10% - 20%	Good forecast
21% - 50%	Reasonable forecast
> 50%	Inaccurate forecast

The forecast accuracy regarding error scale using MAPE has shown that the lower MAPE values is highly accurate in which indicate the forecasting model is accurate. Percentage increase is calculated based on Eq. 7 where I is the percentage increase.

$$I = \frac{A_t - F_t}{A_t} \times 100. \tag{7}$$

The percentage increase used to evaluate which stocks in the Healthcare sector is better in making investment for the future.

Treynor's index measure portfolio performance by dividing portfolio return by the level of portfolio risk [17].

$$T = \frac{R_p - R_F}{\beta}. \tag{8}$$

Treynor's index is calculate based on Eq. 8 where R_p is portfolio return, R_f is risk free rate and β is beta coefficient.

Sharpe index is used to estimate the unit return minus the risk free rate of return relative to the total risk or emphasis the measuring portfolio performance based on non-systematic risk [18].

$$S = \frac{R_p - R_F}{\sigma}. \tag{9}$$

Result and Discussion

The ten stocks is analysed using Eq. 1 until Eq. 4. Table 3 shows the forecast versus actual prices for TOP GLOVE CORPORATION BERHAD by using GBM model.

Table 3. Forecast price and actual price for Top Glove Corporation Berhad

Date	Forecast (RM)	Actual (RM)	Differences
31/05/2022	1.40	1.40	0.00
01/06/2022	1.39	1.37	-0.02
02/06/2022	1.37	1.26	-0.11
03/06/2022	1.25	1.24	-0.01
07/06/2022	1.24	1.25	0.01
08/06/2022	1.28	1.18	-0.10
09/06/2022	1.17	1.22	0.05
10/06/2022	1.05	1.13	0.08
13/06/2022	0.96	1.03	0.07
14/06/2022	1.08	1.03	-0.05
15/06/2022	0.95	1.01	0.06
16/06/2022	1.02	0.98	-0.05
17/06/2022	1.05	1.01	-0.04
20/06/2022	0.96	0.99	0.03
21/06/2022	1.08	1.08	0.00
22/06/2022	1.14	1.01	-0.13
23/06/2022	1.08	1.05	-0.03
24/06/2022	1.14	1.05	-0.09
27/06/2022	1.03	1.04	0.01
28/06/2022	1.02	1.05	0.03
29/06/2022	1.03	1.12	0.09
30/06/2022	1.10	1.04	-0.06

Based on Table 3, it shows comparison between forecasting and actual prices. The differences in forecasting prices and actual prices are quite low. Figure 1 shows a sample of the graphs, illustrates the used the difference between forecast and actual price.

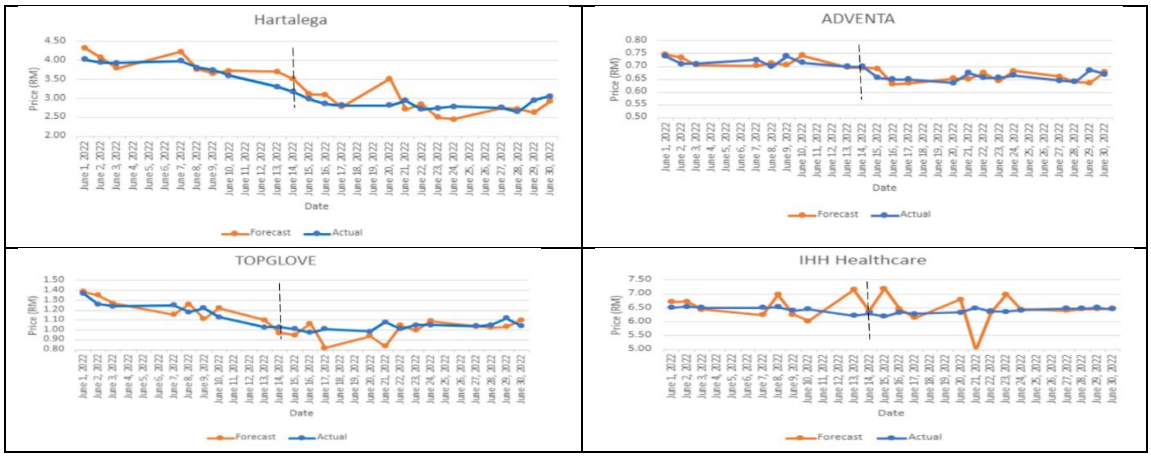

Figure 1. A sample graph of forecasting prices versus actual prices

Based on Figure 1, the graph illustrates that the first two week of investment, the forecast price is quite close to its actual prices as shown in the left part dotted in all the graph. After 2 weeks of investment, the forecast price shows a lot of inconsistency thus the line graph for the forecast will show many fluctuations than the actual one as shown in the right part of the dotted line. This is proven by MAPE value as compared to the result of forecast for 2 weeks and 4 weeks of investment.

Table 4. MAPE value of forecast with actual price for 2 weeks and 4 weeks

Stocks	4 weeks	2 weeks
TOPGLOVE	5.95%	4.40%
IHH	4.14%	3.48%
SUPERMAX	2.82%	2.41%
HARTALEGA	6.13%	5.02%
KOSSAN	7.18%	9.95%
AHEALTH	2.90%	2.32%
ADVENTA	2.22%	2.07%
TMCLIFE	2.49%	1.88%
NOVA	3.86%	1.62%
DPHARMA	3.08%	1.80%

Table 4 shows that the average value of MAPE for two weeks is the smallest.

Table 5. The percentage increment of forecast and actual prices for 10 companies

	Forecast Prices				Actual Prices			
Stocks	31/5/22	14/6/22		Rank	31/5/22	14/6/22		Rank
TOPGLOVE	1.40	1.07	-23%	9	1.40	1.03	-26%	10
IHH	6.70	6.17	-8%	7	6.70	6.30	-6%	6
SUPERMAX	1.05	0.92	-12%	8	1.05	0.91	-13%	8
HARTALEGA	4.20	3.17	-25%	10	4.20	3.17	-25%	9
KOSSAN	1.65	3.21	95%	1	1.65	3.17	92%	1

AHEALTH	2.98	3.32	11%	2	2.98	2.95	-1%	2
ADVENTA	0.75	0.72	-4%	5	0.75	0.70	-7%	7
TMCLIFE	0.53	0.51	-4%	4	0.53	0.51	-4%	4
NOVA	0.75	0.70	-7%	6	0.92	0.89	-3%	3
DPHARMA	1.38	1.39	1%	3	1.38	1.30	-6%	5

Table 5 shows the percentage increment of forecast and actual prices for 10 stocks. The correlation is 88%. Is shown that KOSSAN is the best stock to investment based on the rank. The different between priority stock and percentage increment between actual and forecast prices is not in the large value. However, it is too risky for investor by just referring to percentage increase. Analysis on stock performance using R-square, beta coefficient, Sharpe's index, Treynor's index and correlation analysis is necessary.

Table 6. T-value and correlation for the stocks

Stocks	T-Value	Correlation
TOPGLOVE	1.3595	0.3218
IHH	1.7897	0.4084
SUPERMAX	2.9558	0.5943
HARTALEGA	0.2344	0.0585
KOSSAN	1.0593	0.2560
AHEALTH	0.6496	0.1603
ADVENTA	0.0084	0.0021
TMCLIFE	-1.1100	-0.2674
NOVA	2.3379	0.5047
DPHARMA	-1.4527	-0.3413

Table 6 indicates the t-value and correlation between the company stocks with the KLCI index. Apart from HARTALEGA, ADVENTA, TMCLIFE and DPHARMA whose correlation values are below the significant level of 0.10, it indicates that there is a significant correlation among these stocks and the KLCI index. The highest correlation at 59% is seen between SUPERMAX and KLCI. It suggests that even a slight change in the market index could have an impact on the price of SUPERMAX stock. Additionally, some of the stocks, including TMCLIFE and DPHARMA, have negative values that show a poor relationship with the KLCI index.

Table 7. Stocks performance measured by Treynor's and Sharpe index

Stocks	R-Square	Beta Coefficient	Sharpe Index	Sharpe Rank	Treynor's Index	Treynor Rank
TOPGLOVE	0.1035	-3.8065	-1.9395	5	0.0142	4
IHH	0.1667	-2.8254	-3.2339	9	0.0151	3
SUPERMAX	0.3532	-4.1540	-2.1103	6	0.0114	5
HARTALEGA	0.0034	-2.7428	-0.4386	1	0.0167	2
KOSSAN	0.0655	-1.8380	-0.6657	3	0.0274	1
AHEALTH	0.0257	3.1091	-0.6111	2	-0.0132	7
ADVENTA	0.0000	1.1656	-2.1571	7	-0.0429	8

TMCLIFE	-0.0715	0.4184	-7.2435	10	-0.1077	9
NOVA	0.2547	0.1813	-3.0298	8	-0.2344	10
DPHARMA	-0.1164	4.0311	-1.1839	4	-0.0127	6

Based on Table 7, shows the summary of R-Square, Beta coefficient, Sharpe index and Treynor's index for the 10 stocks. Apart from TMCLIFE and DPHARMA practically all of the stocks have R-Square value above 10. It suggests that the stock index and the KLCI index are correlated. The less sensitive these stocks are, the lower the beta coefficient is. According to the results, the only stocks with beta coefficient values greater than 1 are AHEALTH, ADVENTA and DPHARMA. This indicates that each of these stocks is extremely sensitive to the market. To assess the performance of the stocks, the Sharpe and Treynor's indices are utilized. The performance of each index is contrasted with KLCI index for the time period. The Sharpe index results indicate that, with the exception of the HARTALEGA stock, all of the other stocks underperformed compared to the KLCI index. Meanwhile, the fact that KOSSAN has the highest position on the Treynor's index means that it performs better than other stocks. Based on this finding, it can be seen that KOSSAN outperforms HARTALEGA since it R-Square is larger. This suggests that HARTALEGA's beta is irrelevant for assessing market risk.

Conclusion

This study successfully demonstrates the efficacy of the Geometric Brownian Motion (GBM) model as a valuable tool for short-term financial forecasting in the Bursa Malaysia healthcare sector. The model achieved a high degree of accuracy, with a Mean Absolute Percentage Error (MAPE) of less than 10% for two-week forecast period, confirming its ability to provide reliable forecasted prices. While the four-week forecasts also contributed to the analysis, the two-week period proven to be particularly effective for investors seeking immediate, actionable insights.

The findings provide a clear, data driven framework for making informed investment decisions. A key result is the high degree of reliability demonstrated by the model's output when a comparison of the forecasted price rankings with the actual price rankings revealed an 88% correlation, further supporting the model's utility. Furthermore, most of the selected stocks were found to have a significant correlation with the FBMKLCI, indicating linked to the broader market trend. The analysis of the 10 selected stocks also highlighted a remarkable performance from KOSSAN which showed a 95% increase which means that the price almost doubled up from their actual price at the end of 2 weeks of investment. KOSSAN also show a good result in stock relationship with KLCI index and also stock performance that rank higher than other stocks. This result underscores the potential for significant returns when using GBM for short-term forecasting.

In conclusion, this study validates the GBM model's accuracy for short-term. The findings suggest that GBM can empower investors with a clear advantage, assist in navigate market volatility and identify high-yield opportunities, as demonstrated by the case of KOSSAN. Although stock market investing inherently involves risk, the use of a reliable forecasting model like GBM can significantly increase investor confidence and improve the potential for substantial returns.

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