Available online at
https://mijuitm.com.my

e-ISSN: 2735-0703

Mathematical Sciences and Informatics Journal 6(2) 2025, 22 – 32.

Mathematical Sciences and Informatics Journal

Forecasting Stock Market Prices using Geometric Brownian Motion by Applying the Optimal Volatility Measurement

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ARTICLE INFO

Article history:
Received 2 May 2025
Revised 22 June 2025
Accepted 20 July 2025
Online first
Published 30 July 2025

Keywords:
Geometric Brownian Motion
Forecasting
Volatility
Stock Prices
Investment

DOI:
10.24191/mij.v6i2.5794

ABSTRACT

Investing in the Malaysian stock market can be overwhelming due to the abundance of options, which necessitates informed decision-making to navigate the volatile market. This study addresses a common problem faced by investors venturing into the stock market, where instability and fluctuations pose significant risks, leading to financial losses stemming from inadequate knowledge about suitable stocks for investment. Unlike many studies that focus on long-term forecasting methods, this research adopts the Geometric Brownian Motion (GBM) model for short-term investment analysis. The study aims to identify the most effective volatility measurement model, develop a forecasting model using GBM based on the chosen volatility model, and evaluate the accuracy of the GBM model using Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Deviation (MAD). Four volatility models, which include simple, log, high-low, and high-low-closed volatility are analysed to determine the most effective volatility measurement model. Four months of daily stock data were collected to ensure accuracy excluding factors such as seasonality, politics, natural disasters, and wars. Findings indicate that the simple volatility model is the most suitable for forecasting stock market trends using the GBM model, demonstrating high accuracy based on MSE, MAPE and MAD. These results suggest that employing the simple volatility model within GBM model can offer a practical and accurate approach for short-term market analysis in Malaysia, potentially aiding investors in mitigating risks and optimizing their trading strategies.

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https://doi.org/10.24191/mij.v6i2.5794

1. INTRODUCTION

Stock is classified as a type of financial instrument that provides investors with a share of ownership in a company (Azizah et al., 2020; Hersugondo et al., 2022). Investors can either gain profits or incur losses in the company. However, insufficient understanding and lack of information regarding the best stock for investment may result in significant losses (Estember et al., 2016; Hersugondo et al., 2022). Additionally, there are several stocks traded in Malaysia that may cause confusion among investors, in selecting which ones are worthwhile investments that can provide better returns. Moreover, stock prices are highly volatile, characterized by the rate at which the price of a stock rises or drops over a particular period.

There are numerous methods for forecasting stock prices, but some of the methods have been utilized for modelling financial and economic predictions, security price movements, mortgage risk assessments, and investor behavior prediction, among others. Methods such as Decision Trees, Autoregressive Integrated Moving Average (ARIMA), and Artificial Neural Networks (ANN) have been employed to forecast stock prices, as explored by Estember et al. (2016), Tsai and Wang (2014), Adebiyi et al. (2014) and Abidin and Jaffar (2014). Nevertheless, the forecasting methods are suitable for long-term and next-day price predictions, yet they fail to fulfill the investors' expectations of achieving quick profits from their investments (Kowerski & Haniewska, 2022). A gap exists in the literature concerning effective short-term forecasting tools specifically tailored for the Malaysian stock market. Short-term forecasting methods that can capture the rapid fluctuations of stock prices are crucial for investors seeking timely insights.

To address this gap, this study employs the Geometric Brownian Motion (GBM) model for short-term investment forecasting. The GBM model is a stochastic process used to model the movement of stock prices over time (Ramadhan et al., 2024; Maulana et al., 2025). The GBM assumes that the logarithmic returns of a stock price follow a Brownian motion with constant drift and volatility (Ramadhan et al., 2024; Maulana et al., 2025). An optimal volatility measurement is crucial for accurate GBM forecasting as it quantifies the inherent risk associated with stock. Different volatility measures can yield varying estimates of risk, directly impacting the reliability of the GBM model (Abidin & Jaffar, 2014). This study analyses simple volatility, log volatility, high-low volatility, and high-low-closed volatility to determine the most effective measure.

Geometric Brownian Motion (GBM) model, as demonstrated by Abidin and Jaffar (2014), Mensah et al. (2023), Prasad et al. (2022), and Badriah (2018), indicates that the GBM model can forecast for short-term investments as early as two weeks of investment. Hence, this study proposes the GBM model for short-term investment forecasting. GBM effectively captures short-term data for making short-term forecasts (Prasad et al., 2022). GBM is also employed to forecast the upcoming market prices (Azizah et al., 2020). Thus, stock prices can be predicted using the GBM model, which will be validated using Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD) in this study. Therefore, this study aims to identify the most effective volatility measurement model for short-term stock price forecasting using the GBM model in the Malaysian stock market and to evaluate the accuracy of the resulting forecasts.

This paper is organized as follows: Section 2 presents the literature review, Section 3 outlines the methodology, Section 4 discusses the results, and Section 5 concludes the study.

2. LITERATURE REVIEW

There are several methods and metrics used to measure volatility, with the most widely recognized being simple volatility. Simple volatility calculates the average deviation of a series of prices or returns from their mean value, providing a measure of how much they tend to deviate from the average. A higher standard deviation indicates more volatility, signifying larger price swings and potentially higher risk (Abidin & Jaffar, 2012). There are four volatility measurement methods with different formulas, which are simple volatility (S), log volatility (L), high-low volatility (HL) and high-low-closed volatility (HLC). These

https://doi.org/10.24191/mij.v6i2.5794

methods have been explored in studies conducted by Abidin and Jaffar (2014), Estember et al. (2016), Alhagyan et al. (2017), Hamzah et al. (2021), Badriah et al. (2018), Azizah et al. (2020), Fitria et al. (2021), and Muda and Ibrahim (2023).

Mathematically, GBM can be denoted by a stochastic differential equation where the GBM model refers to a stochastic process used to model the movement of stock prices over time by assuming that the logarithm of the stock price follows a random walk with a constant drift and volatility. Hence, the volatility parameter in the GBM model is crucial as it quantifies the level of uncertainty and the magnitude of price fluctuations (Nafi'a et al., 2024).

Table 1. Past research on volatility measurement

Authors	Simple S	Log L	High-Low HL	High-Low-Close HLC
Abidin and Jaffar (2014)	/	/	/	/
Estember et al., (2016)	/			
Alhagyan et al., (2017)	/	/		/
Hamzah et al., (2021)	/			
Badriah et al., (2018)	/			
Azizah et al., (2020)	/			
Fitria et al., (2021)	/			
Muda and Ibrahim (2023)	/	/		

Table 1 illustrates that previous research has predominantly utilized simple volatility to measure volatility. This study, however, will employ all four volatility measurements to determine the optimal volatility for forecasting within the GBM model. The volatility measurement that yields the lowest errors of MSE, MAPE and MAD when the GBM model is evaluated will be considered the most suitable volatility measurement.

As discussed in the introduction section, methods like decision trees, ARIMA and ANN have been used for stock price forecasting. However, the GBM model offers several advantages, particularly for short-term investment periods (Nafi'a et al., 2024; Ramadhan et al., 2024; Maulana et al., 2025). For instance, research by Fitria et al. (2021), concluded that the GBM model is a highly accurate tool for forecasting stock prices in both short- and long-term investments. These findings were nearly identical to those in research by Prasad et al. (2022), which examined the effectiveness of the GBM Monte Carlo simulation approach in forecasting Indian stock market prices. Based on historical data of stock prices from the previous year, their findings indicate that the GBM Monte Carlo simulation accurately predicts future stock values for a duration of three months.

Additionally, a study from Hamzah et al. (2021) evaluated the effectiveness of the GBM model in predicting Nestle stock prices by analyzing the performance assessment indicators. The week with the lowest Mean Square Error (MSE) value during the COVID-19 pandemic demonstrates that the short-term predictions using the GBM model are more effective than long-term predictions. Furthermore, the GBM approach can be employed to forecast Nestle's stock price during an economic downturn since the Mean Absolute Percentage Error (MAPE) values from all GBM simulations reveal that MAPE values are less than 10%. This result is almost like another research study by Menash et al. (2023), with aimed to forecast the movement of stock prices using both conventional and complex distributional assumptions. According to the study, all MAPE and MSE values for the normal and convoluted distributions supporting the GBM were approximately 10% or lower, demonstrating high forecast accuracy. All these recent researchers have started to shed light on this project's objective of determining the best volatility measurement for the GBM model for stock price forecasting through the calculation of MAPE and MSE values.

A study by Kowerski and Haniewska (2022) demonstrates that the likelihood of future stock prices may be accurately predicted using MAD and MAPE, enabling the company to utilize budget forecasting as a guide to plan the right investment in the future.

https://doi.org/10.24191/mij.v6i2.5794

In conclusion, while past research has established the utility of the GBM model for stock price forecasting and explored various volatility measures individually, a gap remains in systematically comparing different volatility measurements within the GBM model specifically for short-term forecasting in the Malaysian stock market. This gap has motivated this study to evaluate four distinct volatility models to identify the optimal one for enhancing the accuracy of short-term forecasting methods, aiming to provide a more robust tool for investors in making investment decisions.

3. METHODOLOGY

3.1 Volatility Measurement

The study begins by identifying the most effective volatility measurement model. As previously mentioned, four different volatility formulas have been employed in prior research which are simple volatility (S), log volatility (L), high-low volatility (HL), and high-low-closed volatility (HLC). The formulas are designated as equation (1), equation (2), equation (3), and equation (4), respectively.

$$\text{Simple Volatility (S), } \sigma = \sqrt{\frac{1}{(n-1)\Delta t}\sum_{i=1}^{n}\left(R_i - \overline{R}\right)^2} \tag{1}$$

$$\text{Log Volatility (L), } \sigma = \sqrt{\frac{1}{(n-1)\Delta t}\sum_{i=1}^{n}\left(\log(S_i) - \log(S_{i-1})\right)^{2}} \tag{2}$$

$$\text{High-Low Volatiltiy (HL), } \sigma = \sqrt{\frac{1}{(n-1)\Delta t 4\log 2}\sum_{i=1}^{n}\left(\log(H_1) - \log(H_1)\right)^2} \tag{3}$$

High-Low-Closed Volatility (HLC),

$$\sigma = \sqrt{\frac{1}{(n-1)\Delta t}\left\{\sum_{i=1}^{n}0.5\left(\log(H_i) - \log(L_i)\right)^2 - \sum_{i=1}^{n}0.3\left(\log(S_i) - \log(S_{i-1})\right)^2\right\}} \tag{4}$$

where σ represents the volatility value, R_i is the stock return at time $i, \overline{R}$ is the mean of stock return, n is the amount of stock return, Δt denotes the time steps, S_i is the stock price at time i and S_{i-1} is the stock price at time $i-1$.

This study will analyze the 30 top companies that have been listed on the Kuala Lumpur Composite Index (KLCI) of Bursa Malaysia. Data on the chosen companies will be collected from Yahoo Finance website and will be based on daily data. This study will utilize four months of data (March 20, 2023, to July 13, 2023). This study assumes that during this time, the Malaysian economy remained relatively stable, without significant impacts from seasonal changes, political events, natural disasters, or war. This four-months daily data is considered sufficient to capture short-term fluctuations and trends in stock prices (Abidin & Jaffar, 2014; Nafi'a et al., 2024; Ramadhan et al., 2024; Maulana et al., 2025).

Furthermore, focusing on the top 30 companies listed in the KLCI represents a significant portion of the Malaysian stock market's total value and trading activity. Hence, the sample is relevant for understanding the overall market dynamics and provides insights for investors primarily interested in major Malaysian stocks.

https://doi.org/10.24191/mij.v6i2.5794

3.2 Geometric Brownian Motion (GBM)

The collected data will be used to forecast future stock prices using the GBM model. This process involves a four-step approach:

First, stock returns are calculated from the training dataset using equation (5):

$$R_i = \frac{S_i - S_{i-1}}{S_{i-1}} \tag{5}$$

where R_i represents the stock return at time i, S_i is the stock price at time i, and S_{i-1} is the stock price at time $i-1$.

Next, the drift (μ) and volatility (σ) values are generated (Hamzah et al., 2021). These values serve as constant stock parameters used to forecast future stock prices (Farida et al., 2018). The drift value, also known as the drift coefficient, represents the mean of the return rate, indicating the average price increase over time. It is calculated using equation (6):

$$\mu = \frac{1}{Mdt}\sum_{i=1}^{n} R_i \tag{6}$$

where μ represents the drift value, R_i is the stock return at time i, M is the amount of stock return, and dt represents the time steps.

Then, the volatility value, also known as the diffusion coefficient, represents the fluctuation of stock prices over time. It is the sample standard deviation of stock returns over the specified time step. The volatility is calculated using the formulas presented in equation (1–4).

Finally, the forecasted stock prices are computed based on the GBM model (Estember et al., 2016) using equation (7):

$$S(t) = S(0)e^{\left(\mu - \frac{\sigma^2}{2}\right)t + \sigma W_i} \tag{7}$$

where $S(t)$ represents the future stock value, $S(0)$ is the initial stock value, μ is the daily drift calculated using equation (6), σ is the volatility value derived from equation (1), t is the time step, and W_i is a value sampled from the standard normal distribution.

3.3 Validated the Accuracy of GBM Model

To evaluate the accuracy of the best GBM model, the Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Deviation (MAD) values are employed.

$$\text{MSE} = \frac{1}{N}\sum_{t=1}^{n}\left(A_t - F_t\right)^2 \tag{8}$$

https://doi.org/10.24191/mij.v6i2.5794

$$\text{MAPE} = \frac{1}{N}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{9}$$

$$\text{MAD} = \frac{1}{N}\sum_{t=1}^{n}\left|A_t - F_t\right| \tag{10}$$

where A_t represents the actual stock price at time t, F_t is the forecasted stock price at time t, and N is the number of stock price data. Table 2 presents the accuracy classification based on MAPE values (Zach, 2020).

Table 2. MAPE value accuracy classification

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

4. RESULT AND DISCUSSION

The top 30 stocks under the KLCI were analyzed. Table 3 illustrates four forecasted prices using different volatility measurements, from equation (1–4), in comparison with the actual prices of Hong Leong Bank Berhad.

Based on Table 3, the comparison between the one-month forecasted prices and the actual prices indicated that the simple volatility produced the closest forecasted prices to the actual prices; hence, S is better than L, HL, and HLC volatility measurements.

Table 3. Forecasted price versus actual prices of Hong Leong Bank Berhad

Date	Forecast (S)	Forecast (L)	Forecast (HL)	Forecast (HLC)	Actual Price
7/13/2023	18.90	18.90	18.90	18.90	18.90
7/14/2023	19.05	18.92	18.92	18.92	19.00
7/17/2023	19.03	18.94	18.94	18.94	19.00
7/18/2023	18.96	18.96	18.96	18.96	18.92
7/20/2023	19.26	18.98	18.98	18.98	18.92
7/21/2023	19.38	19.00	19.00	19.00	18.94
7/24/2023	19.27	19.02	19.02	19.02	18.94
7/25/2023	19.17	19.04	19.04	19.04	19.18
7/26/2023	19.51	19.06	19.06	19.06	19.56
7/27/2023	19.58	19.08	19.08	19.08	19.60
7/28/2023	19.56	19.10	19.10	19.10	19.54
7/31/2023	19.49	19.12	19.12	19.12	19.58
8/1/2023	19.70	19.14	19.14	19.14	19.50
8/2/2023	19.76	19.16	19.16	19.16	19.40
8/3/2023	19.46	19.18	19.18	19.18	19.44
8/4/2023	19.79	19.20	19.20	19.20	19.58
8/7/2023	19.82	19.22	19.22	19.22	19.66
8/8/2023	19.24	19.23	19.23	19.23	19.70
8/9/2023	19.37	19.25	19.25	19.25	20.10
8/10/2023	19.74	19.28	19.28	19.28	19.86
8/11/2023	19.50	19.29	19.30	19.29	19.80

https://doi.org/10.24191/mij.v6i2.5794

Fig. 1 displays a sample of the graphs, illustrating the use of different volatility measurements in the GBM model.

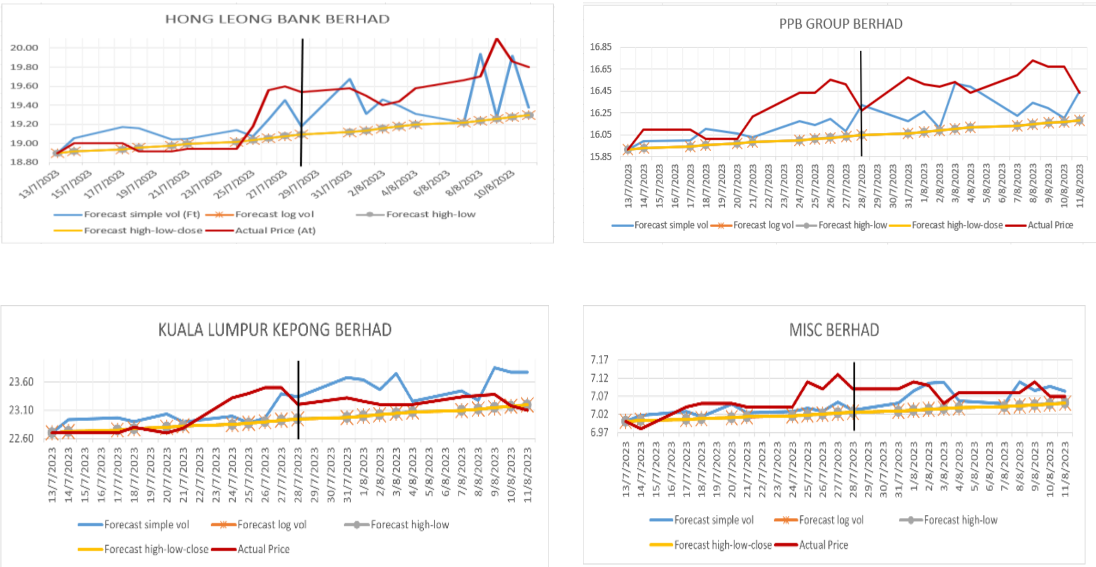

Fig. 1. A sample of graphs of different volatility measurements applied in the GBM model

Based on Fig. 1, the graph illustrates that in the first two weeks, the values between the actual price and simple volatility were consistently close, but after two weeks, the MSE, MAPE and MAD error values changed due to the increased data fluctuation. Considering these observations, it could be inferred that simple volatility stands out as one of the most accurate measurements of volatility.

The finding that the GBM model, utilizing simple volatility, provided the most reliable forecasts for a period of up to two weeks is consistent with the work of Abidin and Jaffar (2014). The decreasing accuracy observed after this timeframe can be attributed to the fundamental assumptions of the GBM model. GBM simplifies market dynamics by assuming constant drift and volatility. While these assumptions may hold reasonably well over shorter periods, the longer the forecast extends, the more likely it is that actual market drift and volatility will change due to unforeseen events, evolving investor sentiment, and other market forces. This deviation from the model's core assumptions directly contributes to the reduced predictive power beyond the two-week investment.

Therefore, using S in GBM was able to forecast prices for a two-week investment. Hence, MSE, MAPE and MAD values will be calculated to determine the error for each company by using equation (8–10).

https://doi.org/10.24191/mij.v6i2.5794

Table 4. Forecast versus actual prices and the MSE, MAPE and MAD values for a two-week investment period

Companies	Actual (RM)	Forecasted (RM)	MSE (%)	MAPE (%)	MAD (%)
TELEKOM	4.99	4.77	1.94	2.20	10.91
MAXIS BERHAD	3.99	4.02	0.06	0.46	1.77
SIME DARBY BERHAD	2.05	2.04	0.13	1.45	2.96
PPB GROUP BERHAD	16.27	16.13	3.97	0.91	17.53
MR DIY GROUP (M) BERHAD	1.49	1.48	0.11	1.85	2.60
HONG LEONG FINANCIAL	18.2	17.72	4.94	0.85	16.83
QL RESOURCES BERHAD	5.39	5.33	0.21	0.61	3.03
SIME DARBY PLANTATION	4.55	4.42	1.81	2.33	10.45
IOI CORPORATION BERHAD	4.08	3.87	2.54	3.45	13.99
TENAGA NASIONAL BERHAD	9.4	9.08	7.35	2.30	20.52
GENTING MALAYSIA BERHAD	2.52	2.46	0.24	1.73	4.22
PETRONAS CHEMICALS	6.77	6.27	10.46	3.79	26.54
KUALA LUMPUR KEPONG	23.20	23.39	10.07	1.23	22.93
AMMB HOLDINGS BERHAD	3.82	3.65	0.12	2.02	7.83
MISC BERHAD	7.09	7.06	0.10	0.41	3.30
GENTING BERHAD	4.26	4.12	0.77	1.76	7.40
MALAYAN BANKING BERHAD	8.70	8.49	1.45	1.18	10.53
AXIATA GROUP BERHAD	2.60	2.52	0.24	1.70	4.35
RHB BANK BERHAD	5.51	5.36	1.06	1.53	8.47
CELCOMDIGI BERHAD	4.37	4.18	2.73	3.52	14.98
HONG LEONG BANK BERHAD	19.54	19.24	7.78	1.20	18.77
PRESS METAL ALUMINIUM	4.98	4.88	0.55	1.36	6.22
PETRONAS DAGANGAN	22.78	22.52	6.13	0.87	25.48
PETRONAS GAS BERHAD	16.92	17.18	4.55	1.14	19.67
PUBLIC BANK BERHAD	4.05	3.85	1.19	2.36	9.55
IHH HEALTHCARE BERHAD	5.86	5.79	0.46	1.06	6.12
CIMB GROUP HOLDINGS	5.33	5.09	2.79	2.59	13.40
DIALOG GROUP BERHAD	2.25	2.19	0.28	1.96	4.38
WETSPORTS HOLDINGS	3.43	3.48	0.39	1.64	5.47
NESTLE MALAYSIA BERHAD	131.29	152.52	13207.14	7.76	1265.46

Based on the MAPE values in Table 4 and the accuracy classification in Table 2, 30 companies demonstrated highly accurate forecasts (MAPE < 10%). For MSE, 27 out of 30 companies showed high accuracy with values less than 10%. The three companies with MSE above 10% were Petronas Chemicals Group Berhad (10.46%), Kuala Lumpur Kepong Berhad (10.07%) and Nestle Malaysia Berhad (13207.14%). Regarding MAD values, the results were split with 50% of the companies showing high accuracy and the other 50% showing lower accuracy. The exceptionally high MSE and MAD values for Nestle Malaysia Berhad were likely due to significant daily fluctuations in its stock price, indicating higher volatility compared to the other 29 companies, which in turn led to larger forecasting errors. Excluding Nestle Malaysia Berhad, the results in Table 4 generally indicate that the GBM model using simple volatility provides highly accurate forecasts for a two-week investment. This suggests that investors and analysts can have reasonable confidence in applying this model for short-term investment strategies for most major Malaysian stocks.

This study aimed to address the gap in understanding the most effective volatility measurement for short-term stock price forecasting using GBM in the Malaysian market. Our findings indicate that the simple volatility model provides the most accurate short-term forecasts across the majority of the top 30 KLCI companies, thus offering a practical solution for the short-term forecasting needs of investors and analysts in this specific market, a need not fully addressed by longer-term forecasting methods or studies focusing on different markets.

https://doi.org/10.24191/mij.v6i2.5794

5. CONCLUSION

One effective method for forecasting short-term investment involves models like GBM. This study specifically applied GBM over a two-week period, focusing on the crucial aspect of volatility measurement. By examining four distinct volatility measurements, simple volatility (S), log volatility (L), high-low volatility (HL) and high-low-closed volatility (HLC), the findings indicate that simple volatility (S) yielded the closest forecast to actual stock prices, as evidenced in Table 3 and Figure 1.

Furthermore, the overall high accuracy of the forecasts generated by GBM, with most MSE, MAPE, and MAD values falling below 10% as shown in Table 4, confirms its potential as a valuable tool for short-term stock market forecasting. These results suggest that for investors and analysts focusing on short-term investment in the Malaysian stock market, utilizing GBM with a simple volatility measurement can provide a reasonably accurate basis for making timely trading decisions.

This method offers a more direct and easily implementable method compared to more complex forecasting methods, potentially aiding in navigating short-term price fluctuations and identifying potential profit opportunities within two weeks of investment. However, a limitation is that the model's accuracy may be affected by periods of high market turbulence or unforeseen economic events not captured in the historical data. Additionally, the assumption of constant drift and volatility in GBM may not hold perfectly over longer periods.

Future research could explore the application of GBM with dynamic volatility models to potentially improve forecasting accuracy beyond the two-week investment period. Investigating the model's performance across different market capitalizations or specific industry sectors within Malaysian market would also provide valuable insights. Finally, comparing the effectiveness of GBM with other short-term forecasting methods in the Malaysian context could further enrich the understanding of optimal forecasting strategies.

6. ACKNOWLEDGEMENT/FUNDING

This research was funded by Universiti Teknologi MARA, GDT2021/1-27.

7. CONFLICT OF INTEREST STATEMENT

The authors declare there is no conflict of interest in the subject matter or materials discussed in this manuscript.

8. AUTHORS' CONTRIBUTIONS

Individual contributions of authors are as follows: Conceptualization, Siti Nazifah Zainol Abidin, Farah Syahida Fauzi, Sabihah Maisarah Sharudin and Nur Asyikin Abdullah; Methodology, Siti Nazifah Zainol Abidin, Farah Syahida Fauzi, Sabihah Maisarah Sharudin and Nur Asyikin Abdullah; software, Farah Syahida Fauzi, Sabihah Maisarah Sharudin and Nur Asyikin Abdullah; data curation; Farah Syahida Fauzi, Sabihah Maisarah Sharudin and Nur Asyikin Abdullah; writing, Siti Nazifah Zainol Abidin, Siti Maisarah Md Zain, Farah Syahida Fauzi, Sabihah Maisarah Sharudin and Nur Asyikin Abdullah; supervision, Siti Nazifah Zainol Abidin and Siti Maisarah Md Zain. All authors have read and agreed to the published version of the manuscript.

https://doi.org/10.24191/mij.v6i2.5794

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