Malaysian Journal of Computing, 11 (2): 2656-2666, 2026
eISSN: 2600-8238

MALAYSIA TECH STOCK FORECASTING USING ARIMA: A COMPARATIVE ANALYSIS WITH KALMAN FILTER NOISE OPTIMIZATION

Sarah Nadirah Mohd Johari[1*], Ahmad Irfan Mohd Sukeri[2], Restu Ananda Putra[3], and Ahmad Nur Azam Ahmad Ridzuan[4]

[1,2,4]Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Shah Alam 40450 Malaysia*

[3]Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Gadjah Mada, Yogyakarta 55281, Indonesia

[1*]sarahnadirah@uitm.edu.my, [2]Irfan.sukeribtp@gmail.com, [3]restuanandaputra@ugm.ac.id, [4]ahmad558@uitm.edu.my

(indicates the corresponding author)*

ABSTRACT

Forecasting stock prices in Malaysia's technology sector is difficult due to market noise. To mimic market behavior, many models have been developed and gradually improved with new algorithms and machine learning techniques. Relying on a single model often has drawbacks, so hybrid models were introduced to improve prediction stability. This study used a time series method, Autoregressive Integrated Moving Average (ARIMA) that has been proven to be reliable in forecasting various types of data. However, the ARIMA model often struggles with handling nonlinear and noisy data; thus, hybrid integration of the Kalman Filter was introduced to help reduce noise. The Kalman Filter method is an algorithm that applies the Bayesian theorem in order to predict and update after each observation. Using the Kalman Filter as a hybrid integration helps capture the underlying patterns of ARIMA residuals. As ARIMA creates a general model, the Kalman Filter acts as an extension that analyzes and interacts with the unobservable pattern in the general model. This research used ten years of daily data from 2015 to 2025 from Inari Amertron (INAR), Frontken Corporation (FRONTKN), and ViTrox Corporation (VITROX); the models are evaluated based on Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). The outcome of this study showed that adding a Kalman Filter improves prediction accuracy by lowering noise and stabilizing forecasts. Moreover, this study highlighted the role of Kalman filtering in improving stock price prediction for emerging markets, such as Malaysia.

Keywords: *Stock Forecasting, Kalman Filter, ARIMA, Malaysia Technology Sector.*

Received for review: 27-08-2026; Revised: 16-09-2026; Accepted: 24-09-2026; Published: 01-10-2026
DOI: 10.24191/mjoc.v11i2.13417

This is an open access article under the CC BY-SA license (https://creativecommons.org/licenses/by-sa/3.0/).

1. Introduction

Nowadays, Malaysia's technology sector has been rapidly expanding as part of the country's agenda of digital transformation. However, tech stocks are highly volatile and sensitive to global shocks such as COVID-19 and trade tensions, making accurate forecasting challenging (Bahaludin *et al.*, 2024). Traditional forecasting methods unable to capture non-linear patterns. Not only that, it is also affected by market noise, which reduces prediction reliability.

Autoregressive Integrated Moving Average (ARIMA) Model is a traditional time series forecasting model that has been used by many researchers for countless reasons and applications. This model is often used to observe trends and analyze data and further applications for forecasting the next observation that has not been recorded. ARIMA is practically used for weather forecasting, inventory needs, customer trends, and other applications. In this research, ARIMA is used to analyze stock prices, mainly top tech stocks, INARI, FRONTKEN and VITROX and forecast their prices.

However, relying on the ARIMA model only has its own disadvantages. This method can only capture linear stock data and struggles to handle noisy and nonlinear data. Thus, a hybrid model implementation is suggested as a hybrid model often improves the model, observes what the initial model cannot observe, and helps optimize the initial model. In this research, the Kalman Filter is introduced as an algorithm that will optimize ARIMA's residuals and enhance performance. The Kalman Filter simply works as an estimator and predictor of residual, untied to time, and use Bayesian theorem to store prior knowledge, using it to predicts next observation and keep updating until it reaches optimization. Kalman Filter is often used for engineering and coordination systems and has been extended for hybrid uses and forecasting.

In this study, a comparative analysis is conducted between ARIMA and ARIMA with Kalman Filter optimization, section by sections, starting with the literature review, the methodology behind this study, result and the conclusion of this analysis. The study also included data analysis and transformation, convert the raw data into structured, as well as high-quality formats suitable for analysis.

2. Literature Review

Autoregressive Integrated Moving Average (ARIMA) model was first introduced by Box and Jenkins in year 1970 and it has been one of the most commonly used statistical methods for time series forecasting. In ARIMA, there are three main component that needs to look at which is Autoregression (AR), integration (I), and moving average (MA). AR mainly focus on the dependence between an observation and several lagged observations (parameter p), while I calculate the differences between observations at different time points (parameter d). Additionally, a moving average model is applied to data with a time lag (parameter q). MA accounts for potential dependency between observations and the error terms generated (Kontopoulou *et al.*, 2023).

A thorough analysis of ARIMA applications in a variety of fields is being done, including network systems, energy and finance (Kontopoulou *et al.*, 2023). (Kontopoulou *et al.*, 2023) said that ARIMA method are able to look and capture for linear and stationary datasets, but as for nonlinear or nonstationary pattern like financial markets, their accuracy in forecasting decreases. This research emphasized ARIMA's performance is significantly affected by choosing the suitability of parameter selection (p, d and q) as well as looking at the stationarity pattern of the input data. However, ARIMA managed to be the benchmark model for comparison with deep learning and Machine Learning (ML) techniques due to its interpretability and low computational cost (Kontopoulou *et al.*, 2023).

While ARIMA is a stable and interpretable model for time series forecasting, notably in finance, it struggles to handle noisy and nonlinear stock data (Alarbi *et al.*, 2025). Integrating ARIMA with stochastic filters or hybrid machine learning models appears to be a potential approach for improving forecast accuracy (Lyu, 2025). Thus, an algorithm named the Kalman Filter was chosen for optimizing errors produced by the ARIMA model. To put it simply, this algorithm helps the model observe and estimate what the ARIMA cannot observe, and uses prior knowledge or observation to make better predictions for the next observation observation (Zhang & Cao, 2025).

The Kalman Filter, a recursive estimator for linear dynamical systems, is becoming a tool that engineers have started to use outside their field for the first time to model financial phenomena (Claver *et al.*, 2023). In 1960, Rudolf E. Kálmán created state-space models to define dynamic processes, paving the way for this paradigm (Claver *et al.*, 2023). Since then, the Kalman Filter has been widely used in control theory and aerospace domains before finding use in scenarios requiring the estimation of hidden variables using measurement data that contains noise (Claver *et al.*, 2023). The filter's usefulness in financial time-series research stems from its ability to derive unobservable system states that represent genuine stock values that are disguised by the noise and uncertainty of market price data (Claver *et al.*, 2023).

An algorithm named Kalman Filter can statistically improve the accuracy of financial forecasts by modifying the model parameters that account for the fluctuations of the market (Jwo & Biswal, 2023). The study conducted detailed research of Kalman Filter execution options that focusing on the algorithm's discrete and continuous variants. The study proves that the Kalman Filter can effectively affect the varying system and measurement noise conditions by updating the state estimations for more accurate predictions (Jwo & Biswal, 2023). Moreover, this method always used in situations that involve the volatility movement of stock market and unpredictable events (Cheng, 2003). The significance of a consistent validation in filter design that emphasizes an inaccurate noise level assumption may affect the forecast to become skewed or unstable (Fitzgerald, 1971). Not only that, but the error covariance will also become unrealistically small, making the filter ignore new input that can lead to unstable and skewed forecasts (Fitzgerald, 1971). Hence, the targeted audience in quantitative trading, such as traders and analysts, is advised to used Kalman Filter algorithm to get a more accurate forecast for stock prices (Cheng, 2003; Jwo & Biswal, 2023).

According to recent research, the Kalman Filter is a useful technique for noise optimization in contemporary applications (Ono *et al.*, 2025). (Ono *et al.*, 2025) demonstrated that the Kalman Filter may effectively reduce measurement noise in digital holographic microscopy by recursively updating state estimations based on noisy measurements. It has been demonstrated that the Kalman Filter minimizes estimation variance by trading off process and measurement uncertainty in the best possible way using the Kalman Gain (Ono *et al.*, 2025). Thus, the Kalman Filter is a noise optimization tool that dynamically modifies its state estimate to reduce the impact of noise present in observed data, according to both theoretical analysis and empirical research (Ono *et al.*, 2025; Welch & Bishop, 2006).

3. Research Methodology

This section outlines the methodology of this study, including a dataset overview, the Autoregressive Integrated Moving Average (ARIMA) without Kalman Filtering, as well as ARIMA with Kalman Filtering. This study analyses ten years (2015 to 2025) of daily stock price data from three leading Malaysian technology companies: Inari Amertron, Frontken Corporation, and ViTrox Corporation. The data are collected from publicly available sources from investing.com website, cleaned, and split into training (70%) and testing (30%) sets. Preliminary statistical tests, including stationarity and normality tests, are conducted to make sure the data fit well for time-series modelling (Mushtaq, 2011; Das & Imon, 2016). The log

returns approach are used due to its additive, symmetric and mathematically consistent properties, free of compounding distortions and providing an exact decomposition into positive and negative components of returns. These properties provide a more solid basis for analysis of cumulative performance, volatility, risk and market structure than simple returns (Shai, 2026).

Autoregressive Integrated Moving Average (ARIMA) model is an old classical statistical method for predicting the movement of stock price in the future. ARIMA (p,d,q) mainly has three components which is autoregression (AR), differencing (I), and moving average (MA). These components basically to model the historical trends, short-term fluctuations (up and down movement), as well as random disturbances in financial time series. It is widely used in stock prediction due to its interpretability and strong theoretical grounding (Box & Jenkins, 1976; Hyndman & Athanasopoulos, 2018).

AR component usually can predict the current stock spot price based on the past data. It operates exactly like a regression model where it makes the past stock prices as predictors. The AR model as follows:

$$y_n = A + \phi_1 y_{n-1} + \phi_2 y_{n-2} + \cdots + \phi_p y_{n-p} + \varepsilon_n \quad (1)$$

where:

- y_n represent as current stock spot price of three leading Malaysian technology companies converted into log-return value.
- A represent as constant or drift of three leading Malaysian technology companies data.
- $y_{n-1}, \ldots, y_{n-p}$ represent as three leading Malaysian technology companies past stock prices
- $\phi_1, \ldots, \phi_p$ represent as Autoregressive coefficients of Inari Amertron, Frontken Corporation, and ViTrox Corporation past prices that influence the stock spotprice.
- ε_n represent as random shock or error of Inari Amertron, Frontken Corporation, and ViTrox Corporation price

As for the Integrated (I) component, it removes patterns and make the series stationary by differencing consecutive observations. It is basically difference and transforms the original series into the change between periods and allowing the model to focus on short-term fluctuations:

$$y'_n = y_n - y_{n-1} \quad (2)$$

where:

- y'_n is differenced value, the change in stock price of three leading Malaysian technology companies between the consecutive periods.
- y_n is current stock spot price of three leading Malaysian technology companies
- y_{n-1} is previous stock price of three leading Malaysian technology companies.

Moving on to Moving Average (MA), this component impact the past shocks on the current stock spot price of this research data, try to capture market volatility and unexpected events that unable to explain by the past prices of three leading Malaysian technology companies:

$$y_m = B + E_m + \theta_1 E_{m-1} + \theta_2 E_{m-2} + \cdots + \theta_q E_{m-q} \quad (3)$$

where:

- y_m is current stock spot price of three leading Malaysian technology companies converted into log-return value.
- B is constant or drift of Inari Amertron, Frontken Corporation, and ViTrox Corporation prices.
- E_m is current random shock or error of Inari Amertron, Frontken Corporation, and ViTrox Corporation price that represents unpredictable market events or volatility.
- $E_{m-1}, \ldots, E_{m-q}$ are past shocks that previous errors influencing the current stock spot price of three leading Malaysian technology companies.
- $\theta_1, \ldots, \theta_q$ are coefficients that quantify the effect of past shocks on the current price of Inari Amertron, Frontken Corporation, and ViTrox Corporation.

By combining all of these components, the ARIMA model able to capture the historical pattern, short-term variations, as well as random market disturbances, providing robust predicting for stock prices in the future. In this study, the ARIMA prediction serves as a benchmark and are further polished by using the Kalman Filter in order to reduce the noise and improve the prediction accuracy.

The Kalman Filter (KF) applied in this study as a post-processing state estimation method by improving the predictive accuracy of the benchmark model. It offers an optimal recursive framework for estimating the true underlying state from noisy observations (Kalman, 1960; Welch & Bishop, 2006). In financial time series, the observed stock prices often contain market noise, microstructure noise, as well as random fluctuations. Therefore, by applying the KF, it helps to smooth the predictions and at the same time to reduce the error variance.

The KF works through two repetitive steps; the prediction and the update. The first step, prediction basically predict the next hidden state as well as to estimates on the uncertain of this prediction before seeing the new market data.

$$\hat{\alpha}_{t|t-1} = G\hat{\alpha}_{t-1|t-1} \tag{4}$$

$$P_{t|t-1} = GP_{t-1|t-1}G' + W \tag{5}$$

where:

- $\hat{\alpha}_{t|t-1}$: Prior predicted stock price at time t before observing new market data. In this study, it represents the baseline predicted price for Inari, Frontken, or ViTrox generated by the model.
- G: State transition parameter, set to 1 ($G = [1]$). In this study, it assumes a local-level random walk state dynamic where the previous day's true stock price serves as the primary expectation for the current day.
- $P_{t|t-1}$: Predicted error covariance. In this study, it measures the uncertainty of the prior price prediction for the respective semiconductor stock before incorporating market feedback.
- W: Process noise variance. In this study, it captures the intrinsic randomness, unobserved shocks, and structural variance in the underlying stock price dynamics of the target companies.

For the next step, update step revises the prediction using the new stock price of of Inari Amertron, Frontken Corporation, and ViTrox Corporation price. If the model's prediction was far off, the innovation v_t is huge, and at the same time the Kalman Gain increases, it makes the filter trust the observations data more. If the observation is noisy or unreliable, the gain will

decreases, and at the same time the filter trusts its prediction instead. This balancing process produces stable, smoothed estimates. The equations are as follows:

$$v_t = y_t - Z\hat{\alpha}_{t|t-1} \tag{6}$$

$$F_t = ZP_{t|t-1}Z' + V \tag{7}$$

$$K_t = P_{t|t-1}Z'F_t^{-1} \tag{8}$$

$$\hat{\alpha}_{t|t} = \hat{\alpha}_{t|t-1} + K_t v_t \tag{9}$$

$$P_{t|t} = (I - K_t Z)P_{t|t-1} \tag{10}$$

where:

- y_t: Observed actual closing market price at time t for the target semiconductor stock (Inari, Frontken, or ViTrox), converted into log-return value.
- v_t: Innovation (prediction residual), representing the error or difference between the actual observed stock price y_t and the predicted price.
- F_t: Innovation covariance, measuring the total expected uncertainty in the residual at time t.
- K_t: Kalman Gain, the weighting factor that determines how much weight is given to the new market observation versus the model's prior prediction.
- V: Measurement noise variance, capturing short-term market noise, microstructure fluctuations, and bid-ask spread variance in the stock price data.
- Z: Measurement parameter, set to 1 ($Z = [1]$), directly mapping the latent true stock price state to the observed market price.

To implement the local-level Dynamic Linear Model (DLM) via the Kalman Filter, the parameters were selected and estimated as follows:

- Fixed Structural Parameters ($Z\ and\ G$): The measurement matrix ($Z = [1]$) and state transition matrix ($G = [1]$) were set to identity scalars. This represents a univariate local-level random walk specification if the underlying true log-return state evolves continuously without structural trend constraints.
- Initial State Conditions: The initial state vector ($\hat{a}_{0|0}$) was initialized using the first log-return observation of the training set. The initial state variance ($P_{0|0}$) was set to a diffuse prior value of 100, representing high initial uncertainty before observing subsequent market data.
- Estimation of Unknown Noise Variances (V and W): The measurement noise variance (V) and process noise variance (W) were estimated via Maximum Likelihood Estimation (MLE) using the dlmMLE () function applied strictly to the training dataset.

Kalman Filter is used in this study as a prediction refinement tool rather than a standalone predictive model. The filter processes the output of ARIMA models to mitigate random fluctuations and measurement noise. This approach ensures methodological consistency across models and enables a fair comparison of forecasting performance (Anderson & Moore, 1979; Simon, 2006). This study focuses on the standard Kalman Filter as a post-processing noise reduction technique to ensure methodology consistency and fair model comparison. Forecasting performance is evaluated using:

$$MSE = \frac{1}{s}\sum(r_t - \hat{r}_t)^2 \tag{11}$$

$$MAE = \frac{1}{s}\sum | r_t - \hat{r}_t | \tag{12}$$

$$RMSE = \sqrt{MSE} \tag{13}$$

Model performance is evaluated using Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE), which are widely applied in forecasting evaluation (Abdildayeva *et al.*, 2024). The analysis evaluates the forecasting model's performance and assesses the effectiveness of Kalman Filter integration in enhancing predictive accuracy.

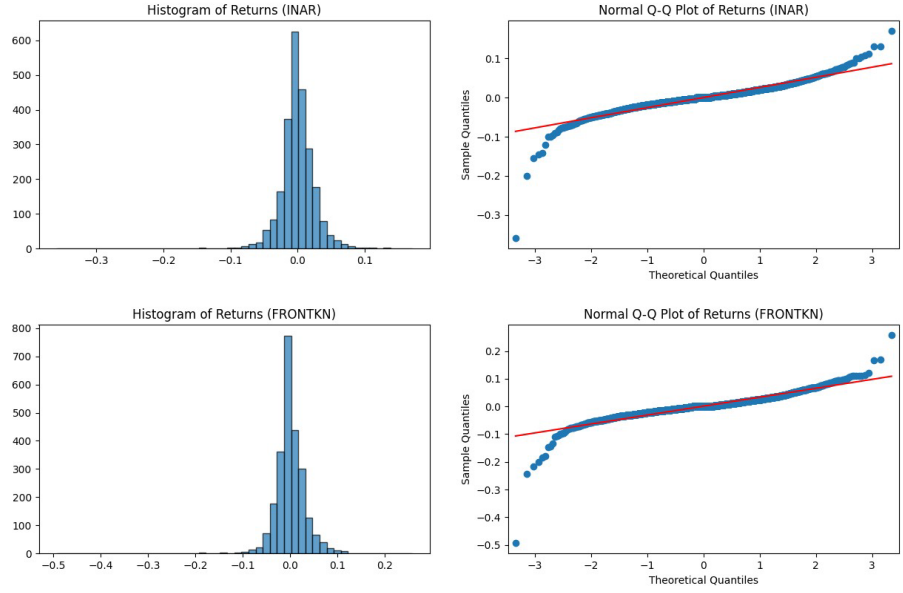
4. Results and Discussions

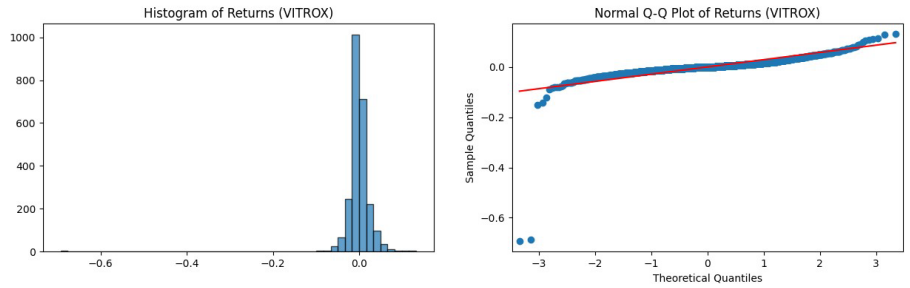
The study analysed three major Malaysian technology stocks with the biggest capital; Inari Amertron Berhad (INAR), Frontken Corporation Berhad (FRONTKN), and ViTrox Corporation Berhad (VITROX). As for the first objective, Augmented Dickey-Fuller (ADF) test revealed that the original stock prices were not stable. To achieve stationarity, the data was transformed into logarithm returns, which helped improve the accuracy of the predictive modeling. Normality tests indicated that the stock return series displayed fat-tailed behavior and were not normally distributed due to market shocks and volatility clustering.

Table 1: ADF Test for three companies stock prices in log return

	INAR	**FRONTKN**	**VITROX**
ADF Statistics	-26.8416	-14.9254	-33.6922
P - value	0.0000e+00 (<0.05)	1.3915e-27 (<0.05)	0.0000e+00 (<0.05)

Figure 1: Histogram & QQ Plot visual for three companies stock prices in log return





As result, the hypothesis of Kalman Filter helps optimizing noise proven to be true. Integrating the Kalman Filter acted as a noise optimizer, improving the accuracy of all models by 0.7% to 0.87% (compared using MSE). Table 2 shows all baseline and hybrid models' performance.

Table 2. Baseline and hybrid models' performance using MSE, RMSE and MAE

Stock	**Hybrid Model**	**MSE**	**RMSE**	**MAE**
INAR	ARIMA	0.0006340311	0.02517997	0.01648512
	ARIMA+KF	0.0006296126	0.02509208	0.01655566
FRONTKN	ARIMA	0.0004811204	0.02193446	0.01508707
	ARIMA+KF	0.0004770906	0.02184240	0.01507015
VITROX	ARIMA	0.0005285051	0.02298924	0.01484737
	ARIMA+KF	0.0005239006	0.02288887	0.01481804

Although the ARIMA model slightly outperformed ARIMA+KF based on the MAE performance indicator, the ARIMA+KF hybrid model emerged as the best-performing model overall. Leveraging the strong theoretical compatibility between ARIMA's residuals and Kalman Filter capabilities, ARIMA+KF successfully improves overall prediction stability and accuracy by eliminating severe forecast errors.

The study concludes that the Kalman Filter significantly improves the prediction performance in unpredictable sectors like Malaysian tech. The ARIMA-Kalman Filter hybrid model is proven and recommended for forecasting, as it effectively smooths market noise while preserving the underlying price signals.

In Table 3, the ARIMA-Kalman Filter hybrid model is used to forecast all three stocks. The observed value is the next day after the last observation and is compared to the predicted value estimated by the chosen model. Conversion to raw price is calculated by multiplying the last observed stock price by $exp(\hat{\alpha}_{t+1|t})$, where $\hat{\alpha}_{t+1|t}$ is the filtered log-return state estimate for day $t+1$.

Table 3. Next-day Forecast using ARIMA + KF

	INAR	**FRONTKN**	**VITROX**
29/10/2025 stock price	2.640	4.58	4.65
Predicted Value	2.640343	4.543716	4.69368
Difference	-0.000343	0.036284	-0.04368

Overall, the results show insignificant differences and indicate the effectiveness of KF in optimizing the ARIMA model and improving its accuracy. In order to thoroughly analyze

the out-of-sample predictive capacity of the suggested time series models, the out-of-sample forecast process was carried out over the course of a designated 30-day hold-out period (h = 30).

Table 4: Out-of-sample backtest

Stock	Hybrid Model	MSE	RMSE	MAE
INAR	ARIMA	0.0010251522	0.03201800	0.01850622
	ARIMA+KF	0.0008454245	0.02907618	0.01728736
FRONTKN	ARIMA	0.001687263	0.01298947	0.010573844
	ARIMA+KF	0.0001406627	0.01186013	0.009423721
VITROX	ARIMA	0.0003196304	0.01787821	0.01378406
	ARIMA+KF	0.0002884653	0.01245795	0.01698427

Although in-sample metrics provide a measure of fit between the model and the training data, the out-of-sample process attempts to replicate a real-world scenario by performing the analysis on unseen data from the market. The accuracy of the model was assessed using the Mean Squared Error (MSE), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). An assessment of both the return space and the price space of the models ensures the dynamic error correction of the Kalman Filter model takes into account not only the volatility in return, but also in price over multiple steps. The inclusion of state-space filtering via the Kalman Filter reduced multi-step compounding drift, resulting in lower out-of-sample MSE, RMSE and MAE compared to the static ARIMA benchmark.

5. Conclusion and Recommendation

On The preliminary analysis showed that Malaysian tech stock prices are inherently non-stationary and non-normal, characterized by "fat-tailed" behavior due to market shocks and noise. In this study, the researchers used ARIMA and hybrid ARIMA with Kalman Filter. As result, the most significant improvement occurred when integrating the Kalman Filter as a noise optimization layer, which reduced forecasting errors by approximately 0.7% to 0.87% (compared using MSE) across all models by filtering out random market fluctuations.

The study concludes that addressing market noise is as critical as the choice of the forecasting model itself. The integration of the Kalman Filter proved effectively as a noise optimizer, revealing the true underlying price signal and enhancing the predictive reliability of stochastic models. For investors, it is recommended to use this approach, combining classical stochastic theory with modern noise filtering to improve risk management and portfolio optimization in noisy markets. Future research should explore more complex filtering techniques, such as the Unscented or Particle Filter, and consider incorporating external factors like macroeconomic shocks and investor psychology to further refine prediction accuracy.

Acknowledgement

The authors wish to express their sincere gratitude to the Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA (UiTM) for providing the research facilities, computational resources, and academic support necessary to conduct this work.

Funding

The authors received no specific funding for this work.

Author Contribution

Sarah Nadirah Mohd Johari prepared the literature review and oversaw the article writing. Ahmad Nur Azam wrote the research methodology and performed fieldwork. Ahmad Irfan conducted the statistical analysis and Restu Ananda Putra interpreted the results.

Declaration of Generative AI in the Writing Process

During the preparation of this work, the authors did not use any AI-assisted technologies.

Data Availability/Supplementary Materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethics Statement

The authors declare that this research did not involve human or animal subjects. All experimental procedures were performed following the institutional Safety, Health, and Environmental (HSE) protocols of Universiti Teknologi MARA.

Conflict of Interest

The authors have no conflicts of interest to declare.

References

Abdildayeva, A., Nurtugan, G., Taganova, G., & Akhmetova, A. (2024). Stock closing Price Forecasting using LSTM, Sentiment Analysis, Kalman Filter. *Journal of Computer Science, 20*(11), 1388–1396. https://doi.org/10.3844/jcssp.2024.1388.1396

Alarbi, A., Khalifa, W., & Alzubi, A. (2025). A Hybrid AI Framework for Enhanced Stock Movement Prediction: Integrating ARIMA, RNN, and LightGBM Models. Systems.

Bahaludin, H., Abdullah, M. H., Hussin, M., Laham, M. F., & Ismail, Z. (2024). Analysing Malaysian Technology Sector during COVID-19: A Minimum Spanning Tree Approach. *Journal of Advanced Research in Applied Sciences and Engineering Technology.*

Cheng, M.-Y. (2003). Dynamic nonparametric filtering with application to volatility estimation. *Recent Advances and Trends in Nonparametric Statistics*, 315–333. https://doi.org/10.1016/B978-044451378-6/50021-1

Claver, J. H., Dave, M., & Che, S. F. (2023). Kalman Filtering for Stocks Price Prediction and Control. *Journal of Computer Science*.

Das, K. R., & Imon, A. H. M. R. (2016). A brief review of tests for normality. *American Journal of Theoretical and Applied Statistics*, *5*(1), 5–12.

Fitzgerald. (1971). Divergence of the Kalman filter. IEEE Transactions on Automatic Control, 736 - 747.

International Monetary Fund (IMF). (2003). Financial asset price volatility: A source of instability? World Economic and Financial Surveys (Chapter III). Retrieved from International Monetary Fund:

https://www.elibrary.imf.org/downloadpdf/display/book/9781589062368/ch03.pdf

Jwo, D.-J., & Biswal, A. (2023). Implementation and Performance Analysis of Kalman Filters with Consistency Validation. *Mathematics*.

Kontopoulou, V. I., Panagopoulos, A. D., Kakkos, I., & Matsopoulos, G. K. (2023). A Review of ARIMA vs. Machine Learning Approaches for Time Series Forecasting in Data Driven Networks. Future Internet.

Lyu, H. (2025). Hybrid ARIMA-LSTM Model for Stock Market Prediction: A Time Series and Deep Learning Integration Approach. *Informatica*.

Mushtaq, R. (2011). Augmented dickey fuller test.

Ono, T., Kim, H.-W., Cho, M., & Lee, M.-C. (2025). A Study on Reducing the Noise Using the Kalman Filter in Digital Holographic Microscopy (DHM). *Electronics*.

Shai, M. (2026). Log-Returns Structure: Probability, Volatility, Risk, Bias, and Edge in Financial Markets. Zenodo (CERN European Organization for Nuclear Research). https://doi.org/10.5281/zenodo.19222081

Welch, G., & Bishop, G. (2006). An Introduction to the Kalman Filter. Department of Computer Science, University of North Carolina at Chapel Hill.

Zhang, X., & Cao, W. (2025). Research on Time Series Forecasting Method Based on Autoregressive Integrated Moving Average Model with Zonotopic Kalman Filter. *Sustainability*, *17*(7), 2993. https://doi.org/10.3390/su17072993