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A Comparative Analysis of the Accuracy of the ARIMA, LSTM, and Holt-Winters Methods in Forecasting SSD Prices Based on Historical Marketplace Data

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ABSTRACT

The fluctuation of Solid-State Drive (SSD) prices, influenced by market demand, NAND Flash availability, technological developments, and the increasing need for storage in Artificial Intelligence (AI) and data centers, has become a challenge in determining purchasing timing and sales strategies. Accurate price prediction is required to assist consumers and business actors in making better decisions. This study aims to compare the performance of three time series forecasting models, namely ARIMA, Long Short-Term Memory (LSTM), and Holt-Winters Exponential Smoothing, in predicting the daily prices of 512 GB NVMe SSDs. The data used in this study consist of historical SSD price data collected from Shopee, Tokopedia, and eBay during the period of December 2025 to May 2026, which were converted into USD for consistency. The research process includes data collection, preprocessing, implementation of the three models, and performance evaluation using RMSE, MAE, and MAPE metrics. The results show that the LSTM model achieved the best performance with a MAPE value of 8.10%, compared to ARIMA at 10.88% and Holt-Winters at 11.87%. These findings indicate that LSTM is more effective in capturing complex and fluctuating data patterns, making it more optimal for SSD price prediction.

INTRODUCTION

The development of information technology and the increasing need for data storage have caused the use of Solid-State Drive (SSD)-based storage media to increase (Pallivalappil & Jagadeesha, 2023; Ren et al., 2025; Serajeh Hassani et al., 2026; Sun, 2024; Zhou, 2024; 하진용, 2025). SSDs are widely used in personal computers, laptops, workstations, and servers because they have higher data read and write speeds than conventional storage media such as Hard Disk Drives (HDDs) (Bhushan, 2023; Kasenda et al., 2024; Spiteri & Klenk, 2025; Wilson, 2024). In addition to having faster performance, SSDs are also considered more stable, power-saving, and able to improve the work efficiency of computer systems.

As the use of digital technology increases, the need for data storage capacity also continues to increase (Hendrawan et al., 2024; Kamyab et al., 2023; Li & Wang, 2022; Mumtaz et al., 2023; Niaz, 2022; Vărzaru & Bocean, 2024). The development of technologies such as cloud computing, big data, Artificial Intelligence (AI), and data centers has driven the high demand for NAND Flash-based storage devices which are the main components of SSDs. This condition has caused the demand for memory chips to increase globally.

Based on a report from TrendForce, the price of NAND Flash and DRAM will increase in early 2026 due to the high demand for AI-based servers and limited memory production capacity. In addition, Mobile Europe mentioned that the price of memory is expected to

experience a significant surge due to the increasing need for global AI infrastructure (Abdullayev, 2023; Lee, 2022; Matsuoka, 2026; Sankar et al., 2023; Van Der Vlist et al., 2024).

The increasing use of AI technology has caused the need for servers and data centers to increase. This condition has an impact on the high demand for memory chips such as DRAM and NAND Flash used in AI servers and SSDs. Memory manufacturers are starting to prioritize production for server AI needs over the consumer market, so that the supply of SSDs becomes more limited and affects price changes in the market.

In addition to market demand factors, supply chain and production conditions also affect changes in memory and SSD prices. An article from TechTimes explains that the almost doubled increase in AI server spending has contributed to the increase in DRAM prices. In addition, potential production disruptions due to Samsung's worker actions are also expected to affect the stability of global memory chip supply.

Changes in NAND Flash prices directly impact the price of SSDs in the consumer market. Based on a report from GamersNexus, the price of SSDs has changed significantly due to fluctuations in the price of NAND Flash, the manufacturer's production strategy, and global market conditions. This causes the price of SSDs to increase or decrease in a certain period.

Periodic changes in the price of SSDs indicate a pattern of fluctuations that can be analyzed using the time series approach. By utilizing historical price data, price rise and fall patterns can be used to predict prices in the coming period. Analysis of SSD price movements is important because it can provide an overview of future price trends for both consumers and computer hardware business players.

The methods used in this study are the ARIMA, LSTM, and Holt-Winters Exponential Smoothing methods. These three methods were chosen because each has complementary advantages in analyzing and predicting time series data based on historical data patterns.

The Autoregressive Integrated Moving Average (ARIMA) method was chosen because it is able to model trends and fluctuations of data statistically so that it is suitable for predicting non-stationary price movements. This method has been widely used in forecasting research in various fields due to its ability to capture autoregressive patterns and moving averages in historical data. However, ARIMA has limitations in capturing complex non-linear patterns in data.

To overcome these limitations, this study also uses the Long Short-Term Memory (LSTM) method, which is a deep learning architecture based on the Recurrent Neural Network that is specifically designed to process sequential and time series data. LSTM is able to capture long-term detentions in historical data as well as model non-linear relationships that cannot be captured by conventional statistical methods such as ARIMA, thus potentially producing more accurate predictions on volatile price data.

In addition, the Holt-Winters Exponential Smoothing method is also used because of its ability to model time series data that contains elements of trends and seasonal patterns at the same time. This method works by giving greater weight to the latest data through three parameters, namely level, trend, and seasonality, so that it is suitable for use in price data that shows gradual but patterned changes.

A significant gap exists in applying these methods specifically to computer hardware price forecasting. While time series models have been extensively studied for stock prices, sales forecasting, and energy prediction, limited research has applied and compared these methods for technology product price prediction, particularly SSDs. Market dynamics for computer hardware involve unique factors such as semiconductor supply chain constraints, technological innovation cycles, and AI-driven demand surges that differ from typical consumer goods or financial instruments. This study fills this gap by comparing the performance of ARIMA, LSTM, and Holt-Winters in forecasting SSD prices based on historical marketplace data.

This study aims to compare the performance of the Autoregressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), and Holt-Winters Exponential Smoothing methods in predicting the price movement of the 512 GB NVMe SSD based on historical data obtained from the Shopee, Tokopedia, and eBay marketplaces. This research is motivated by fluctuations in SSD prices influenced by the increasing demand for memory chips for Artificial Intelligence (AI) and data center needs, changes in NAND Flash and DRAM prices, and the absence of a comparative study comparing the three methods for predicting the price of computer hardware. The scope of the study was limited to the time series data analysis of the price of NVMe SSDs with a capacity of 512 GB with a focus on the analysis of data characteristics, the implementation of the three forecasting methods, and the comparison of the accuracy level of the model using historical data. The results of the research are expected to make a theoretical contribution in enriching the literature on the application of forecasting methods to the price of technology products, as well as providing practical benefits for consumers in determining purchase time, for business actors in supporting stock planning and sales strategies, and for academics as a reference for the development of research in the field of time series-based price prediction.

METHOD

This study used a quantitative approach with a time series analysis method to compare the accuracy of the Autoregressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), and Holt-Winters Exponential Smoothing methods in predicting the price of a 512 GB NVMe SSD. The object of the research is in the form of historical data on SSD prices collected from the eBay, Shopee, and Tokopedia marketplaces during the period from December 2025 to May 2026. The data collected includes product name, capacity, interface type, price, data collection date, and product link. Furthermore, the data is processed through the preprocessing stage which includes data type transformation, data cleaning, data filtering according to the research criteria, and data division into 80% training data and 20% test data based on time sequence to maintain time series characteristics.

The analysis stage was carried out by building the ARIMA, LSTM, and Holt-Winters models using Python on the Google Colab platform with the help of the Pandas, Statsmodels, TensorFlow, Scikit-learn, NumPy, and Matplotlib libraries. In the ARIMA method, stationary testing was carried out using Augmented Dickey-Fuller (ADF), Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analysis, as well as the selection of the best model based on the Akaike Information Criterion (AIC) value. Meanwhile, the LSTM model is built using a layered neural network architecture to study nonlinear patterns in the

data, while the Holt-Winters model is used to model the level, trend, and seasonal components. The performance of the three models was evaluated using the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) metrics. The model with the lowest prediction error value is set as the best model to forecast the price of a 512 GB NVMe SSD in the next period.

RESULTS AND DISCUSSION

Modeling using the LSTM Method

Modeling using the LSTM method was carried out using the same dataset as the AREMA method. Data sharing also uses the same proportion, namely 80% for training data and 20% for data testing.

Preprocessing Data LSTM

Before being included in the LSTM model, the SSD price data is first normalized using Min-Max Scaling into the range [0,1]. Normalization is carried out to maintain the stability of the model training process and accelerate the convergence of optimization algorithms.

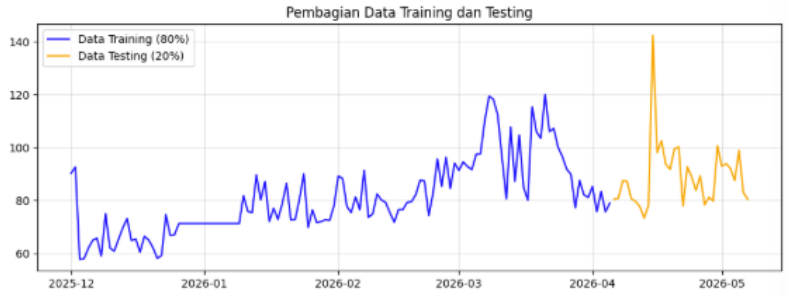


Figure 1. Data Visualization After Min-Max Scaling Normalization

After the training process is complete, the prediction results are returned to the original price scale using the inverse transform process so that they can be compared directly with the actual data in USD units.

LSTM Model Architecture Development

The LSTM model is built using the TensorFlow/Keras framework with the following architecture:

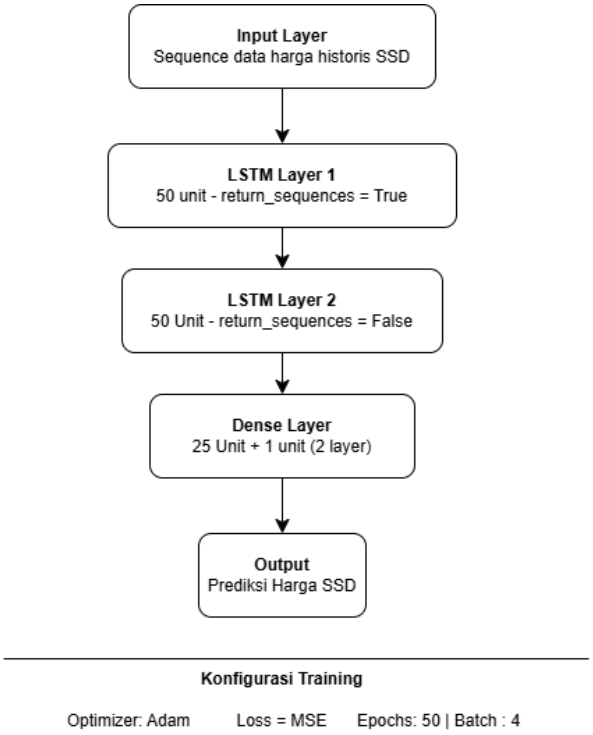


Figure 2. LSTM Model Architecture

Table 1. LSTM Model Architecture Configuration

Components	Remarks
Input Layer	SSD historical price data sequence
LSTM Layer 1	50 unit, return_sequences=True
LSTM Layer 2	50 unit, Return sequences=False
Dense Layer	25 Unit + 1 unit (2 layer)
Batch Size	4

LSTM Model Training

The LSTM model training process is carried out using training data. During the training process, the loss value is monitored to ensure the model has a good convergence.

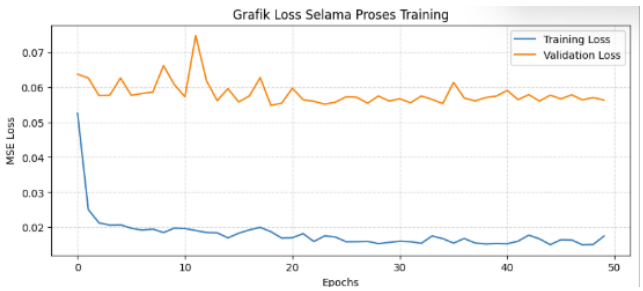


Figure 3. LSTM Model Training Loss and Validation Loss Chart

Based on figure 3, the development of Training Loss and Validation Loss values during the 50 epoch of the LSTM model training process. The loss used in this study is Mean Squared Error (MSE) which functions to measure the level of model prediction error on actual data.

At the beginning of the training process, the training loss value was in the range of 0.053 and experienced a significant decrease to reach around 0.020 in the first few epochs. This

decrease shows that the model managed to learn the basic pattern from the historical data of the price of the 512 GB NVMe SSD. After the 10th epoch, the value of training loss tends to be stable in the range of 0.015–0.020, which indicates that the learning process has approached a convergent condition.

Meanwhile, the validation loss value is in the range **of 0.055–0.075** throughout the training process. Despite some fluctuations, the validation loss was relatively stable and did not show a significant increase as the number of epochs increased. This shows that the model is still able to generalize the validation data and does not experience extreme overfitting.

However, there is a fairly consistent distance between the training loss curve and validation loss. Training loss is in a much lower range than validation loss, which indicates that the model has a better ability to predict training data than data never seen before. This condition shows an indication of mild overfitting, although it does not cause a drastic decrease in validation performance.

Overall, the graph in figure 4.8 shows that the LSTM model has managed to study historical data patterns well and achieve stable conditions before the 50th epoch. The stability of the validation loss value indicates that the model has good enough generalization capabilities to be used in the process of forecasting the price of the 512 GB NVMe SSD in the following period.

Proses Forecasting LSTM

After the training process is completed, the LSTM model is used to predict testing data and forecasting the price of SSDs in the coming period.



Figure 4. Comparison of Actual Data and LSTM Prediction Results

Based on Figure 4, the predictive results of the LSTM model show a better ability to follow actual price fluctuations than the ARRIMA method. This is due to LSTM's ability to capture the non-linear patterns and long-term specificity contained in historical SSD price data.

Models LSTM is able to respond better to gradual price changes, although in some periods of very sudden price spikes, the model still shows a discrepancy between the predicted value and the actual value.

date	Harga Aktual	Hasil Prediksi LSTM	Selisih (Error)
2026-04-13	73.316458	80.491333	-7.174875
2026-04-14	78.229143	78.171989	0.057153
2026-04-15	142.369574	77.904816	64.464759
2026-04-16	98.017363	102.096634	-4.079271
2026-04-17	102.560594	102.737427	-0.176833
2026-04-18	93.675806	100.271492	-6.595686
2026-04-19	91.714348	94.542633	-2.828285
2026-04-20	99.361136	90.871979	8.489158
2026-04-21	100.197000	92.230873	7.966127
2026-04-22	77.885841	94.214645	-16.328805
2026-04-23	92.724656	87.678017	5.046640
2026-04-24	88.947083	87.961037	0.986047
2026-04-25	83.731121	87.855797	-4.124676
2026-04-26	89.303386	86.049194	3.254191
2026-04-27	78.293688	86.644104	-8.350417
2026-04-28	81.181271	83.764305	-2.583034
2026-04-29	79.776512	82.389786	-2.613274
2026-04-30	100.617376	81.349808	19.267568
2026-05-01	92.866475	87.617157	5.249318
2026-05-02	93.884921	90.372322	3.512599
2026-05-03	92.046514	91.626572	0.419942
2026-05-04	87.537364	91.219940	-3.682577
2026-05-05	98.898165	89.014778	9.883387
2026-05-06	83.000894	91.666512	-8.665617
2026-05-07	80.488649	88.112915	-7.624266

Figure 5. LSTM Method SSD Price Prediction Results on Test Data

Figure 4.10 shows the price prediction results of a 512 GB NVMe SSD using the LSTM method in the test data. The table shows a comparison between the actual price, the model's prediction, and the resulting error in each observation period.

Based on the predictive results obtained, the LSTM model was able to produce predictive values that were relatively close to the actual price in most of the test period. This can be seen from several dates that have a small error value, such as on April 14, 2026 with an actual price of 78.229143 and a prediction result of 78.171989 resulting in an error of 0.057153. In addition, on April 24, 2026, an error of 0.986047 was also obtained which showed that the model was able to predict prices with a fairly good level of accuracy.

However, there are some periods where the model produces considerable errors. The largest error occurred on April 15, 2026 with a value of 64.464759. In that period the actual price reached 142.369574, while the model only predicted 77.904816. This significant difference shows that the LSTM model has not been able to capture the sudden price spike. Similar conditions were also seen on April 30, 2026 with an error of 19.267568 and on April 22, 2026 with an error of -16.328805.

In general, the prediction results show that the LSTM model tends to produce more stable values than the actual data. Most of them are in the range of 80 to 100, while actual data fluctuates higher. This characteristic indicates that the model has successfully studied general patterns of historical price movements, but it has difficulty in anticipating extreme or irregular price changes.

From these results, it can be concluded that the LSTM method has a fairly good ability to model the price trend of the 512 GB NVMe SSD and produce a prediction that is relatively close to the actual value under normal conditions. However, the model performance can still be affected by a drastic spike or decrease in price, so further evaluation using MAE, RMSE, and MAPE metrics is needed to determine the overall accuracy level of the model.

LSTM Model Evaluation

The results of the LSTM model evaluation are shown in Table 4.5. The evaluation was carried out using three measurement metrics, namely Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). These three metrics were used to measure the model's level of accuracy in predicting the price of a 512 GB NVMe SSD based on historical data that had been used during the training process.

Table 2. LTSM Model Results

Evaluation Metrics	Value
MAE	$8.14
MAPE(%)	8.10%
RMSE	14.79

Based on **Table 2**, the LSTM model produces **an MAE value of 8.14**. This value shows that the average absolute difference between the actual price and the prediction results produced by the model is 8.14 units of price. The smaller the MAE value, the closer the prediction results are to the actual value, so the MAE value obtained shows that the model has a relatively low prediction error rate.

The MAPE value of 8.10% shows that the average presentation of model prediction errors is only 8.10% against the actual data. Based on the MAPE interpretation criteria, values below 10% are included in the category of highly accurate forecasting and are smaller than using the ARRIMA method. These results indicate that the LSTM model has an excellent ability to perform the price of a 512 GB NVMe SSD.

In addition, the model produces an RMSE value of 14.79. The RMSE value is used to measure the magnitude of prediction errors by giving greater weight to high errors. The RMSE value that is larger than MAE shows that there are still some data that have a considerable prediction difference, especially when there is a significant price spike. However, the RMSE values obtained still show that the model is able to maintain good predictive performance overall.

Based on the results of the evaluation in table 4.5, it can be concluded that the LSTM method is able to produce a fairly accurate prediction of the price of a 512 GB NVMe SSD. This shows that the low MAE score, the RMSE score is still acceptable, and the MAPE score of 8.10% which is included in the very good category.

Modeling Using the Holt-Winters Method

Modeling using the Holt-Winters Exponential Smoothing method was performed using the same historical dataset of 512 GB NVMe SSD prices. Data sharing uses the same proportion as the previous method, namely 80% data training and 20% data testing.

Identify Trend and Seasonal Patterns

Before building the Holt-Winters model, the trend and seasonal components contained in the data were identified.

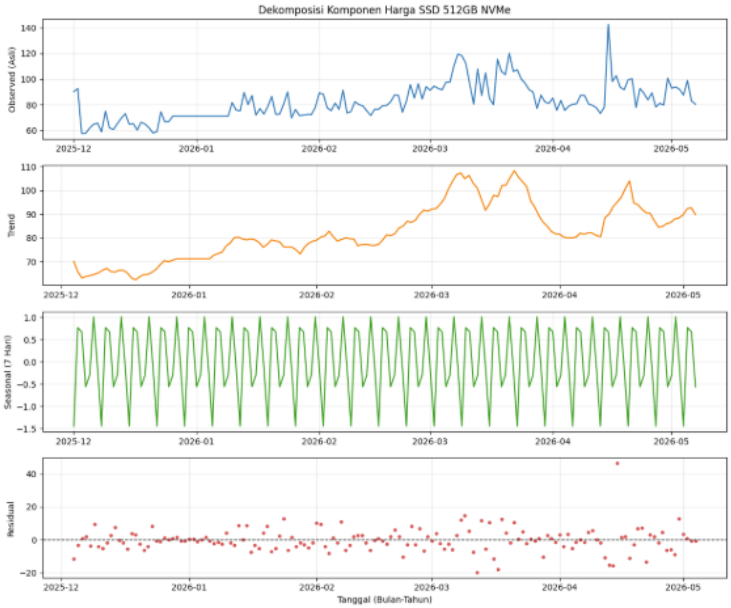


Figure 6. Decomposition of Components Price 512GB NVMe SSD

Based on Figure 4.11, the trend component shows the price movement pattern of the 512 GB NVMe SSD in the Long term after seasonal influences and random components are separated from the original data. It can be seen that the price of SSDs experienced a fairly dynamic trend change during the observation period from December 2025 to May 2026.

At the beginning of the observation period, which is around December 2025 to January 2026, the trend component shows a gradual upward trend from the price range of around 65 USD to 80 USD. This increase indicates a relatively stable price increase at the beginning of the observation period.

Entering February to mid-March 2026, the price trend has increased more significantly to reach a high value in the range of 105-108 USD. This condition shows that in that period there was a fairly strong price increase compared to the previous period. This increase can be caused by various market factors, such as changes in demand, stock availability, and economic conditions that affect the price of computer components.

After peaking in mid-2026, the trend component experienced a sharp decline to close to the range of 80 USD in early April 2026. The decline indicates a price correction after a period of fairly high increases. Furthermore, in mid-April 2026, there was a return to an increasing trend to reach the range of 100 USD before it declined again and stabilized in the range of 85 – 95 USD towards the end of the observation period.

Overall, the trend component in Figure 4.11 shows that the price of a 512 GB NVMe SSD has a fairly clear and non-stationary long-term change pattern. The existence of this strong trend pattern indicates that the price of SSDs is affected by factors that cause gradual price changes over time.

Selection of Holt-Winters Model Variations

There are two variations of the Holt-Winters model tested in this study, namely the additive model and the multiplicative model. The selection of the best variation is made based on the AIC value and the error value generated.

Table 3. Comparison of the Holt-Winters Model

Variasi Model	AIC	IT IS	MAPE (%)	RMSE
Additive	549.09	11.76	11.87%	11.87%
Multiplicative	548.39	13.22	13.50%	18.27

Based on the comparison results in Table 3, the Holt-Winters Additive model produces an MAE value of 11.76, MAPE of 11.87%, and an RMSE of 17.05. Meanwhile, the Holt-Winters Multiplicative model produced an MAE value of 13.22, MAPE of 13.50%, and RMSE of 18.27. Although the Multiplicative model has a slightly lower AIC value, the difference is relatively small and is not followed by an increase in prediction accuracy. In contrast, the Additive model produces lower MAE, MAPE, and RMSE values, indicating a smaller rate of prediction error. In addition, the results of time series decomposition show that the seasonal components in the 512 GB NVMe SSD price data have a relatively constant amplitude, making it more suitable to be modeled using the Additive approach. Therefore, the Holt-Winters Additive model was chosen as the best model for the forecasting process in this study.

Estimasi Parameter Holt-Winters

The optimal parameter estimation is carried out through an optimization process to minimize the value of prediction errors. The results of the best Holt-Winters model parameter estimation are shown in table 4.

Table 4. Parameter model Holt-Winters

Parameter	Symbol	Value
Level	A (alpha)	0.4702
Trend	B (beta)	0.0000
Seasonal	Γ (gamma)	0.0000

Based on the results of the optimal parameter estimation of the Holt-Winters Additive model, a α value of 0.4702 was obtained, while the values of β and γ were close to 0. The α value indicates that the level component has a considerable influence on the forecasting process. Meanwhile, β and γ values that are close to zero indicate that the trend and seasonal components do not make a significant contribution to updating the model. These findings are in line with the results of time series decomposition which show that the seasonal pattern in the price data of the 512 GB NVMe SSD is relatively weak and the trend change occurs gradually. Thus, the price movement of SSDs in the observation period was more influenced by the level component than the trend and seasonal component.

Proses Forecasting Holt-Winters

After the Holt-Winters model is formed with optimal parameters, a prediction process is carried out on data testing and forecasting the price of SSDs in the future period.



Figure 7. Comparison of Actual Data and Holt-Winters Prediction Results

Figure 7 shows a comparison between the actual price of a 512 GB NVMe SSD and the predicted results generated by the Holt-Winters Additive method in the test data. Based on the graph, it can be seen that the Holt-Winters model is able to follow the general pattern of price movements, but produces predictions that are relatively more stable than actual data. The predicted value tends to be in the range of 76 to 80 USD, while the actual price shows higher fluctuations with a range of around 73 to 142 USD.

The relatively flat prediction pattern suggests that the model captures more level components than extreme price changes. As a result, when there is a significant price spike, the model is unable to adjust the prediction quickly, resulting in a sizable prediction difference over several observation periods.

date	Harga Aktual	Hasil Prediksi Holt-Winters	Selisih (Error)
2026-04-06	80.457158	78.563728	1.893430
2026-04-07	80.825316	80.981838	-0.156522
2026-04-08	87.337475	76.550519	10.786955
2026-04-09	87.256774	76.464606	10.792168
2026-04-10	80.641759	77.520792	3.120967
2026-04-11	79.599712	79.953558	-0.353847
2026-04-12	77.606634	78.773929	-1.167296
2026-04-13	73.316458	78.373612	-5.057154
2026-04-14	78.229143	80.791723	-2.562580
2026-04-15	142.369574	76.360404	66.009171
2026-04-16	98.017363	76.274491	21.742872
2026-04-17	102.560594	77.330676	25.229918
2026-04-18	93.675806	79.763443	13.912364
2026-04-19	91.714348	78.583814	13.130534
2026-04-20	99.361136	78.183497	21.177639
2026-04-21	100.197000	80.601607	19.595393
2026-04-22	77.885841	76.170288	1.715552
2026-04-23	92.724656	76.084375	16.640281
2026-04-24	88.947083	77.140561	11.806522
2026-04-25	83.731121	79.573327	4.157793
2026-04-26	89.303386	78.393699	10.909687
2026-04-27	78.293688	77.993381	0.300306
2026-04-28	81.181271	80.411492	0.769779
2026-04-29	79.776512	75.980173	3.796339
2026-04-30	100.617376	75.894260	24.723116
2026-05-01	92.866475	76.950445	15.916030
2026-05-02	93.884921	79.383212	14.501709
2026-05-03	92.046514	78.203583	13.842931
2026-05-04	87.537364	77.803266	9.734098
2026-05-05	98.898165	80.221376	18.676789

Figure 8. 512 GB NVMe SSD Price Forecast Results – Holt-Winters

To see the predicted results in more detail, the comparison between the actual price and the Holt-Winters prediction results is shown in **Figure 8**. The image shows the actual price value, prediction results, and error difference generated on each test date.

Based on Figure 4.13, there are several periods in which the model produces predictions that are quite close to the actual price. For example, on April 7, 2026 the actual price is 80.825316 USD and the prediction result is 80.981838 USD with an error of -0.156522. In addition, on April 27, 2026, an error of 0.300306 was obtained and on April 28, 2026 it was 0.769779. The relatively small error value shows that the model is able to provide fairly accurate predictions when the price moves under normal conditions.

However, there are some periods with considerable errors. The biggest error occurred on April 15, 2026, where the actual price reached 142.369574 USD while the model only predicted 76.360404 USD, resulting in an error of 66.009171. Fairly high errors were also seen on April 16, 2026, April 17, 2026, and April 30, 2026. This suggests that the Holt-Winters model has difficulty capturing sudden price spikes because the changes do not follow previously studied historical patterns.

Based on Figure 4.12, the results of the Holt-Winters model predictions show the ability to follow trend patterns and seasonal variations contained in the SSD price data. This method produces smoother predictions than LSTMs, but is still able to capture the overall direction of price movements.

Unlike ARIMA which produces predictions that tend to be constant, the Holt-Winters model is able to generate predictive values that vary according to the components of trends and seasonalities that have been learned from historical data.

Evaluation of the Holt-Winters Model

Table 5. Results of the Holt-Winters Model Evaluation

Evaluation Metrics	Value
MAE	11.76
MAPE (%)	11.87%
RMSE	17.05

The results of the evaluation of the Holt-Winters Additive model are shown in Table 5. The evaluation was carried out using three measurement metrics, namely Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). These three metrics are used to measure the level of prediction error and assess the model's ability to forecast the price of a 512 GB NVMe SSD.

Based on Table 5, the Holt-Winters model yields an MAE value of 11.76. This value shows that the average absolute difference between the actual price and the predicted results generated by the model is 11.76 USD. The smaller the MAE score obtained, the closer the prediction results are to the actual score.

The MAPE value of 11.87% indicates that the average percentage of model prediction error is 11.87% against the actual price. Based on the MAPE interpretation criteria, values in the range of 10%–20% are included in the good forecasting category. These results show that the Holt-Winters method has a fairly good ability to predict the price of a 512 GB NVMe SSD during the test period.

In addition, an RMSE value of 17.05 was obtained. The RMSE value is used to measure the magnitude of prediction errors by assigning a greater penalty for high errors. The RMSE value is greater than MAE shows that there are several test data that have a considerable prediction difference. This condition is in accordance with the results of the previous analysis which showed that the Holt-Winters model has difficulty in predicting sudden price spikes, resulting in relatively high errors in certain periods.

Overall, the results of the evaluation in Table 4.8 show that the Holt-Winters Additive method is able to produce a fairly good prediction in describing the general pattern of price movements of 512 GB NVMe SSDs. However, the model still has limitations in anticipating extreme price fluctuations, so its accuracy can still be improved through comparison with other methods used in this study.

Comparison of the Performance of the Three Methods

After the three methods were applied and evaluated, a performance comparison was carried out based on the MAE, MAPE, and RMSE values produced by each method.

Table 6. Comparison of the Accuracy of the Three Methods

Yes	Method	MAE	MAPE(%)	RMSE	Category: Akurasi
1.	ARIMA	$10.85	10.88%	16.16	Good
2.	LTSM	$8.14	8.10%	14.79	Excellent
3.	Holt-Winters	$11.76	11.87%	17.05	Good

Table 7. MAPE Interpretation

MAPE Values	Accuracy Rate
< 10 %	Excellent
10% - 20%	Good
20% - 50%	Enough
>50%	Not Good

Based on table 7, it can be identified that the method that produces the smallest MAE, MAPE, and RMSE values as the best method in predicting the price movement of the 512GB NVMe SSD. This comparison provides a comprehensive overview of the advantages and limitations of each approach in the context of computer hardware price data.

Based on the results of the comparison of the three methods, it was found that the LSTM method produced the highest level of accuracy with a MAPE value of 8.10%, followed by ARIMA of 10.88% and Holt-Winters of 11.87%. Thus, LSTM was declared the best method in this study because it was able to provide the lowest rate of prediction errors and produce forecasting performance that is included in the very good category.

Based on all stages of analysis and testing that have been carried out, the results of comparing the performance of three forecasting methods, namely ARIMA, LSTM, and Holt-Winters in predicting the price of a 512 GB NVMe SSD, were obtained. Comparisons were made using MAE, MAPE, and RMSE evaluation metrics to measure the level of prediction errors generated by each model.

The results of the study showed that the LSTM method provides the best performance compared to other methods. Based on Table 4.10, LSTM produces an MAE score of 8.14, MAPE of 8.10%, and RMSE of 14.79. This value was the lowest among all the methods tested,

indicating that the LSTM model had the least rate of prediction error. In addition, the MAPE value that is below 10% indicates that the LSTM model is included in the category of excellent (highly accurate forecasting). These results show that LSTM is able to capture non-linear patterns and long-term relationships in SSD price data more effectively than other methods.

The ARIMA method (0,1,1) occupies the second position with an MAE score of 10.85, MAPE of 10.88%, and an RMSE of 16.16. This value shows that ARIMA is still able to produce fairly good predictions and is included in the good forecasting category. However, compared to LSTMs, the error rate generated is still higher. This shows that the ARIMA model has limitations in modeling complex and fluctuating data patterns because it relies only on linear relationships from historical data.

Meanwhile, the Holt-Winters Additive method produced a MAE value of 11.76, MAPE of 11.87%, and RMSE of 17.05. This value is the highest compared to other methods. These results suggest that although Holt-Winters is able to capture trend patterns in the data, this method is less effective in predicting dynamically changing SSD price fluctuations. These findings are also supported by the results of estimating model parameters which show that trend and seasonal components have a relatively small contribution to the forecasting process.

Overall, the results show that deep learning-based methods, namely LSTM, have a better ability to predict the price of a 512 GB NVMe SSD than conventional statistical methods such as ARIMA and Holt-Winters. This is due to the ability of LSTMs to study non-linear patterns, long-term relationships, and complex data changes. Thus, LSTM can be recommended as the most optimal method to be used in forecasting the price of a 512 GB NVMe SSD based on the data used in this study.

Based on the results of the evaluation, the order of method performance from best to lowest is LSTM, ARIMA, and Holt-Winters. These results show that the more complex the characteristics of the time series data used, the methods capable of capturing non-linear relationships tend to produce higher levels of accuracy than traditional statistical methods.

CONCLUSION

Based on the results of analysis, modeling, and evaluation of historical data on the price of 512 GB NVMe SSDs, this study shows that the Long Short-Term Memory (LSTM) method provides the best performance compared to the ARIMA method and Holt-Winters Exponential Smoothing in conducting price forecasting. Historical data shows fluctuating patterns influenced by various factors, such as market demand, semiconductor supply chain conditions, storage technology developments, and the needs of the AI, cloud computing, and data center industries. The ARIMA model (0.1.1) produced an MAE value of 10.85, MAPE of 10.88%, and RMSE of 16.16, while the Holt-Winters model produced an MAE of 11.76, MAPE of 11.87%, and RMSE of 17.05. Meanwhile, the LSTM model obtained the best results with a MAE value of 8.14, MAPE of 8.10%, and RMSE of 14.79, which shows a very good level of accuracy in predicting the price of a 512 GB NVMe SSD. These findings indicate that the deep learning approach is more effective in modeling data that has non-linear and fluctuating patterns than conventional statistical methods. The results of the study also imply that historical data-based forecasting techniques can be used as a basis for decision-making for consumers, distributors, and business actors in determining purchase times, stock management, and planning hardware needs, and potentially being developed into an automatic

price forecasting system. For further research, it is recommended to use historical data with a longer period, add external variables that affect prices, develop more complex deep learning models such as GRUs, Bidirectional LSTMs, Transformers, or hybrid models, test different types and capacities of SSDs, and build a real-time price forecasting system that integrates with automated data retrieval from the marketplace.

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