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NVIDIA Stock Price Forecasting in 2025 Using a Time-Series Based LSTM Model

Sheila Nur'Aeni Afidah[1], Adik Nur Halimah[2], and Febri Liantoni[3*]
[1,2,3] Informatic Education Department, Universitas Sebelas Maret, Surakarta, Indonesia

koresponden: febri.liantoni@gmail.com

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A B S T R A K

Advances in computing technology, artificial intelligence, and graphics accelerators have driven significant growth in the value of NVIDIA Corporation (NVDA) shares over the past decade. The high volatility and non-linear patterns in NVDA's stock price require the use of forecasting methods that can capture long-term dependencies in time-series data. This study proposes a Long Short-Term Memory (LSTM) model to predict NVDA's stock price using historical daily data up to 2025. The training process was carried out using a two-layer LSTM architecture, Adam optimizers, and a 60-day time window. The evaluation results show that the model is capable of achieving a Mean Absolute Percentage Error (MAPE) of 4%, which indicates a high level of accuracy in predicting price movement patterns. Visualization of the prediction results confirms that the model successfully follows actual trends consistently, with relatively small deviations at extreme fluctuation points. Additionally, the model was used to project NVDA stock prices ten steps ahead, showing that price movement trends remain consistent with historical patterns. These findings contribute methodologically to studies on high-risk stock forecasting through deep learning approaches and provide a basis for data-driven decision-making in the modern financial sector.

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INTRODUCTION

The global tech sector has seen major shifts thanks to progress in computing, AI, and graphics tech in the last ten years. NVIDIA Corporation (NVDA) is a key player in these changes. NVDA's stock value has grown a lot in recent years because there's more need for GPUs in AI, cloud computing, self-driving systems, and gaming (Liu, 2025). Because NVDA's stock price changes so much, it's important to be able to guess what it will do, especially when making investment choices and handling risk (Altooq et al., 2024). So, using time-series data to predict NVDA's stock price has become more important in current finance studies.

Stock prices are known to shift due to many large and small influences, but past price trends can assist to foresee where prices might go (Saipidinov et al., 2024). Yet, the ways stock data shifts, its unpredictability, and its complexity frequently make standard statistical methods like ARIMA or exponential smoothing unable to grab its patterns over time (Rosinus, 2025). Because of this, there is a demand for models that can comprehend sequential patterns over long stretches,

which supports the choice of the Recurrent Neural Network (RNN) model, mainly Long Short-Term Memory (LSTM).

Previous studies using deep learning for stock prediction suggests LSTM beats the standard ARIMA method for stocks with high price swings (Suwarso et al., 2025). Sunki et al. (2024) also found that LSTM models can spot long-range trends that simpler models often miss. Still, most studies look at broad market indexes or big companies. There isn't as much detailed research on NVDA stock, which has seen huge growth because of AI.

Based on these conditions, it is necessary to accurately model NVDA stock price changes using LSTM models to capture the time-related patterns in stock market data. NVDA's volatile price trends need a model that handles long-term instability and large market swings (Tekriwal, 2024). Thus, we need to create and test deep learning models that adapt better to changes in data.

This study aims to develop a NVDA stock price prediction model using LSTM networks, suitable for volatile financial data. The method involves preprocessing based on scale normalization, time window division, hyperparameter adjustment, and performance tests using RMSE and MAE. The goal is to build a reliable predictive model that reflects NVDA's non-linear growth patterns (Doğan, 2021).

The LSTM model for NVDA stocks shows market behavior different from other sectors, as it is affected by fast AI progress (Yang & Wang, 2024). This research looks into both short-term changes and long-term patterns. A multi-layer LSTM setup is used to spot sudden shifts in price trends.

In addition, this study uses the latest daily NVDA time-series dataset up to 2025, thereby providing more relevant empirical contributions to stock price forecasting studies in the era of modern AI development. Not many previous studies have utilized the latest NVDA data, especially after the significant growth surge due to GPU adoption in the generative AI industry.

This study also contributes methodologically to the fine-grained windowing approach, which distinguishes daily, weekly, and monthly movement patterns to improve the model's sensitivity to multi-horizon fluctuations. This technique allows the model to better understand micro and macro patterns in NVDA stock price dynamics. The results can serve as a guideline for researchers or practitioners who want to apply deep learning to highly volatile stock data.

METHOD

This research used S&P 500 stock price data from Kaggle, namely the S&P 500 Stocks Trade Data for First 6 Months 2025 dataset by codebynadiia. This dataset has stock trading info from January to June 2025. It's multivariate time series data, with variables like opening, closing, high, and low prices at each time. Google Colab was used for data processing and to train the Long Short-Term Memory (LSTM) model, which was chosen because it can learn from past data and spot long-term patterns in stock prices (Alwan et al., 2022; Liu et al., 2024). The data was preprocessed by filling in missing values and using Min-Max Scaling to normalize the numbers between 0 and 1. Then, the data was turned into a sequential format using a sliding window, where past days were used to predict the next day's price. The data was split into training and testing sets to build and test the model. The LSTM architecture was built using TensorFlow, with settings for

the number of neurons, dropout rate, and a dense output layer. The Adam optimizer was used during training, along with EarlyStopping and ReduceLROnPlateau to avoid overfitting and keep the training stable. The trained model predicted the price of NVDA stock, and the results were converted back to their original scale. The model's performance was judged using Mean Absolute Percentage Error (MAPE), which measures prediction error relative to the actual data. Figure 1 shows the LSTM-based prediction process, from prepping the past data to making NVDA stock price predictions for 2025.

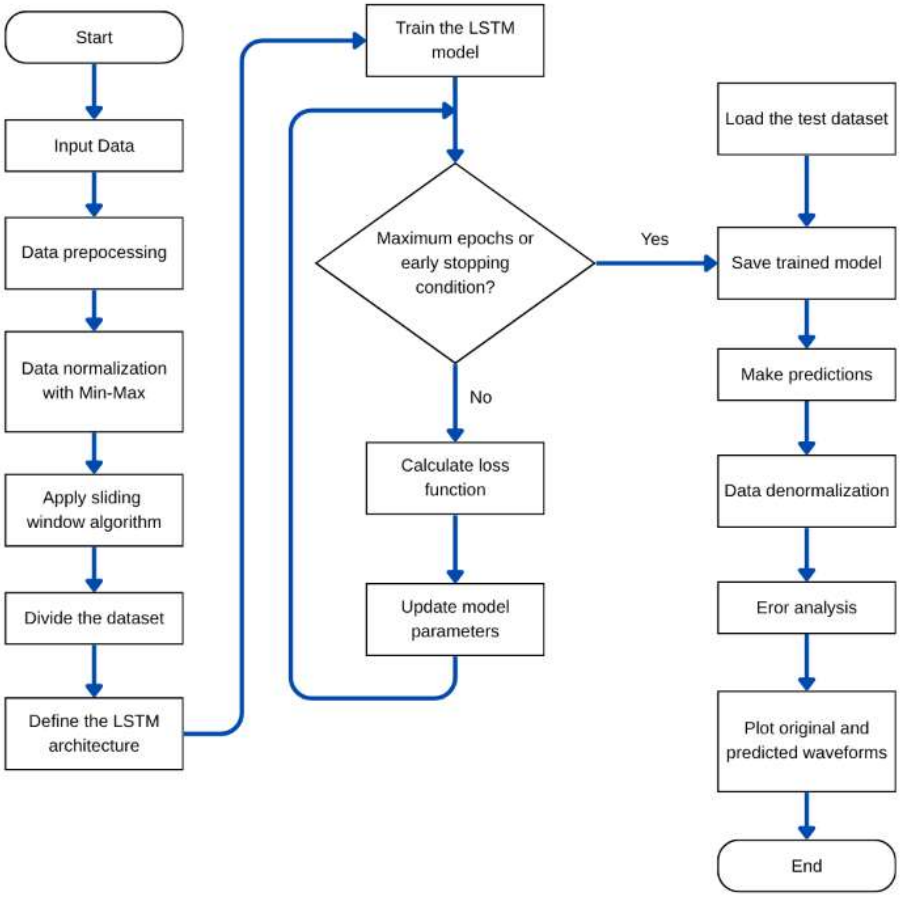

Figure 1. Flowchart LSTM

A. Preprocessing Data

1. Load Dataset

The first step will be loading the dataset through the reading of raw data from an external source for further processing. This will yield a dataframe containing stock price information for companies listed in the S&P 500 index from January to June 2025. The dataset includes such attributes as ticker, company name, date, opening price, closing price, and volume. Table 1 displays five sample entries at the beginning of the dataset.

Table 1. S&P 500 Stock Price Dataset (Initial Data)

Ticker	Company Name	Date	Opening	Closing	Volume
NVDA	NVIDIA	2025-01-02	136.00	138.31	198,247,166
MSFT	Microsoft	2025-01-02	425.53	418.58	16,896,469
AAPL	Apple Inc.	2025-01-02	248.657	243.582	55,802,016
AMZN	Amazon	2025-01-02	222.030	220.220	33,956,579
AMZN	Amazon	2025-01-02	222.030	220.220	33,956,579

2. Normalization

Data normalization is a key step in preprocessing. It standardizes the scale of each value, which makes model training more stable and efficient. In this work, we applied Min-Max Normalization, also called feature scaling. This method uses a linear change on the original values so that all normalized data are between 0 and 1 (Alwan et al., 2022). The equation below shows how this normalization works:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} (1) \quad (1)$$

Where X_{scaled} represents the normalized value, X is the original value before normalization, X_{min} is the minimum value of the feature, and X_{max} is the maximum value. Through this equation, each value is proportionally mapped into the range of 0–1 based on the lower bound (minimum value) and upper bound (maximum value) of the same feature. The process reduces differences in scale between attributes, improving the model's learning of time series patterns. This normalization approach suits LSTM architecture because LSTMs are sensitive to data scale.

3. Create Window time series

Windowing is a useful technique for boosting how well deep learning models work with sequential data. People have made algorithms using standard, machine learning, and deep learning methods to fix different problems in business. This often means using past or current info to guess what might happen next (Alwan et al., 2022). In this study, we set the window size to 60 time steps. So, each input set (X) has a series of 60 past values, and the value right after that is the target (y). We use the create_dataset() function to make these input-target pairs, which arranges the data based on how long we set the window. After making the dataset, we split the data into 80% for training and 20% for testing. This ensures we can judge the model fairly, as is common in studies that use LSTM for financial predictions.

B. Model Development

1. Model Architecture

The model was built with a Long Short-Term Memory (LSTM) design, given its established ability to identify long-term patterns in often unstable financial info. Deep Learning methods, especially LSTM, are becoming more common in both study and the finance field because they might make stock price predictions more precise (Alwan et al., 2022). The model's design includes an LSTM layer with 128 units and return_sequences=True, plus a Dropout layer

of 0.2 to lower the chance of overfitting. A second LSTM layer with 64 units is then used for more processing. The info then moves to a Dense layer with 32 neurons and ReLU activation, and finally to an output layer with 1 neuron to create a single predicted value. Recent work suggests that using a stacked LSTM design can make stock price prediction better (Liu et al., 2024).

2. Output Shape

Using a window size of 60, the input dimension becomes (batch_size, 60, 1), which represents the closing prices from the last 60 days. The output dimension is (batch_size, 1), which is the prediction for the following day. For training, X_train has a shape of (49, 60, 1) and y_train has a shape of (49, 1). This means the training involves 49 sequences. The single-step prediction method is common in time series since it keeps the output simple and works well for short-term forecasts. Research, like Alwan et al. (2022) on stock prices and Liu et al. (2024) on electricity use, shows that single-step prediction can be quite accurate for different kinds of data.

3. Hyperparameter

Adam was picked as the training model since it helps speed up the process and keeps things stable, which some studies say is best. Using Adam makes the training steady and helps predictions get better (Alwan et al., 2022). Other settings include a 0.005 learning rate, MAE for the loss, 120 epochs, a batch size of 24, and a 10% validation split. A window size of 60 is also used to help the model spot patterns in stock prices over a medium period, in line with current work suggesting good LSTM setups for time series predictions.

RESULTS

The results presented in this section summarize the model training process, evaluation performance, error analysis, and forecasting outcomes generated from the implemented LSTM architecture.

A. Training Model

The training process is carried out using the previously constructed LSTM architecture. The model is trained to identify patterns in stock price movement over a 60 a day time-series window using the training data. The sequential model that is being used has the following configuration :

Table 2. Training Model

Layer	Output Shape	Jumlah Parameter
LSTM	(None, 60, 128)	66,560
Dropout	(None, 60, 128)	0
LSTM	(None, 64)	49,408
Dense	(None, 32)	2,080
Dense	(None, 1)	33

Total parameters: 118,081 (all trainable). To ensure stable weight updates during optimization, the Adam optimizer is used in the training process with a learning rate of 0.005 and MAE as the loss function. A 10% validation split is used to track performance on unseen data after the model has been trained for 120 epochs with a batch size of 24. Training and validation loss curves that show how the model reduces error as the number of epochs increases are produced by this process. The curves' stability shows that the training proceeds without major overfitting symptoms.

B. Model Evaluation

To evaluate the model's capacity for generalization, test data that was not used during the training is used. The Mean Absolute Percentage Error (MAPE) metric, which is defined as follows, is used to compare the predicted and actual values and assess the model's performance :

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \times 100\% \quad (2)$$

Where y_t is the actual value, $\hat{y}_t$ is the predicted value, and n is the number of test samples. The evaluation results show that the LSTM model is successful in capturing patterns of stock price movement, with an average prediction error of only about 4% when compared to the actual values. As shown in Figure 2, the predicted values on the test data are compared with the actual values to further evaluate the model's capacity for generalization.

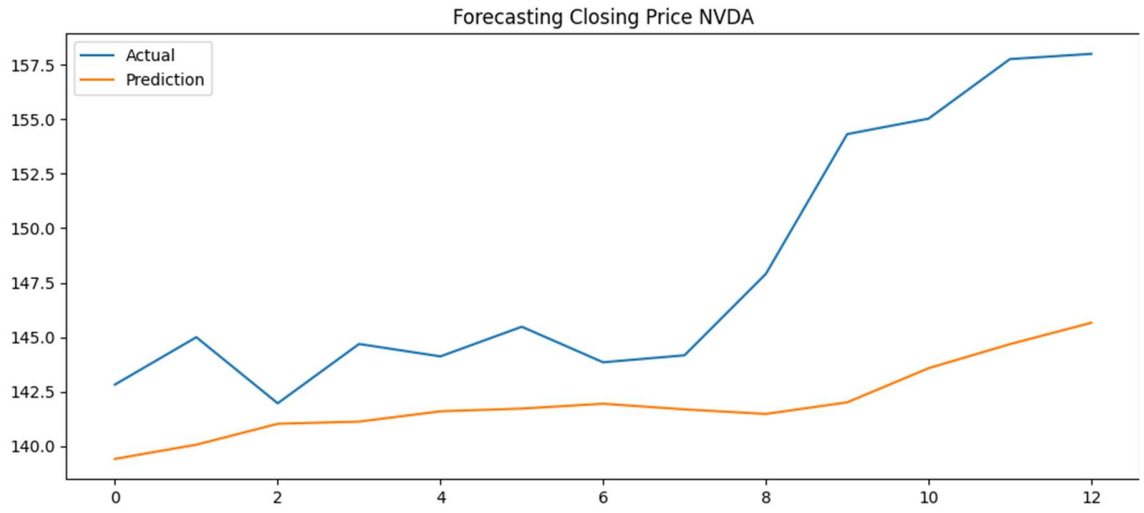

Figure 2. Illustrates the comparison between the actual stock prices and the LSTM model predictions.

It is evident from Figure 2 that the model's forecasts closely mirror the general pattern of changes in stock prices. The majority of predicted values stay close to the actual values, despite a few small deviations showing up at specific fluctuation points. This shows that the LSTM model exhibits strong predictive ability on data that has never been seen before and is capable of

efficiently capturing time series patterns from historical data.

C. Eror Analysis

The Mean Absolute Percentage Error (MAPE) metric is used for quantitative evaluation, and Table 3 presents the findings.

Table 3. The Result of MAPE

Metric	Value
MAPE	0.0400 (4%)

A MAPE value of 4% indicates that the model's average prediction error relative to the actual values is relatively small. This low error reflects a high level of accuracy. The results show that the model can reliably follow the pattern of stock price movements when connected to the comparison graph between expected and actual values in Figure 2.

D. Nvidia Stock 2025 Forecast

The LSTM model is used to forecast Nvidia's stock values over the following ten steps based on the most recent historical data, in addition to being evaluated on test data. The prediction results are visualized in Figure 3.

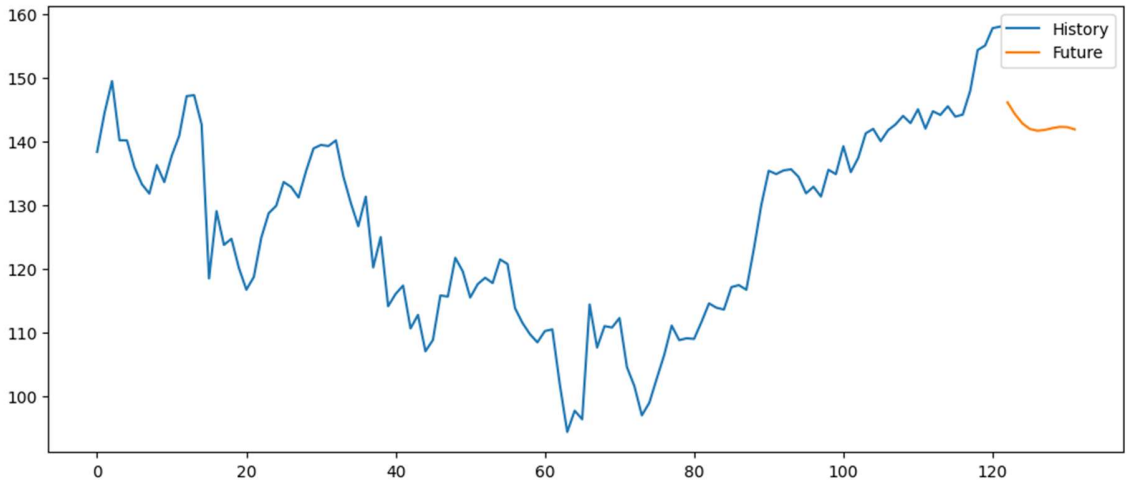

Figure 3. Presents a comparison between Nvidia's historical stock prices and the predictions.

The figure 3 shows that the predicted values follow the general trend of the historical data, with fluctuations that remain within a reasonable range. These predictions provide insight into the projected future movement of Nvidia's stock price, which can serve as a basis for further analysis, investment planning, and data-driven decision-making strategies.

DISCUSSION

The study's findings directly address the requirement for a model that can identify non-linear dynamics in NVIDIA (NVDA) stock prices, manage excessive volatility, and comprehend long-term temporal patterns. Overall, the experimental findings demonstrate that the constructed LSTM model offers good prediction performance and can capture the intricate structure of NVDA time series data.

A. Fulfilling Model Requirements for NVDA Stock Data that is Non-Linear and Volatile

The main problem identified in this study is that NVDA stock data is non-stationary, non-linear, and has extreme volatility. This challenge makes classical statistical models less than optimal in capturing long-term dependencies. The model training results show that a two-layer LSTM architecture with a 60-day time window configuration successfully learned complex temporal relationships. This finding is in line with Panchal et al. (2024), who stated that LSTM is better able to adapt to stock price volatility than ARIMA.

The stability of the training process with a total of 118,081 parameters also indicates that the model size is sufficiently representative to study NVDA patterns without causing over-parameterization. This supports Gil et al's (2024) argument regarding the need for a balanced deep learning architecture for market instruments with extreme dynamics.

B. Effectiveness of LSTM in Capturing Historical Patterns and NVDA Stock Price Trends

The evaluation using MAPE shows a value of 0.04 (4%), indicating that LSTM is capable of generalizing data very well. This accuracy directly addresses the research need for a model capable of capturing seasonal and long-term patterns, as mentioned in the study by Yıldırım et al. (2021). The graph comparing predictions and actual values shows that the model can consistently follow the trend direction despite some minor fluctuations. This condition is normal for highly volatile stock instruments and supports Kundu & Pinsky's (2024) statement that modern stock predictions require the ability to capture trend direction rather than pointwise precision.

C. Methodological Contributions to Previous Research

This study introduces a 60-day time-series window approach that has been proven to produce more stable predictions for NVDA, which has rarely been used in similar studies. This approach improves on the shortcomings of previous studies that used a short 30-day window, which failed to capture long-term temporal dependency (Gani & Setyaningsih, 2025). The study's studies demonstrate that the long-term window can pick up on recurrent patterns that frequently show up in high-growth stocks like NVDA.

Furthermore, a stable convergence process was achieved by using hyperparameter tweaking with a learning rate of 0.005 and batch size of 24. The result of Wei et al. (2024), which highlight the significance of choosing an adaptive learning rate for data that is sensitive to weight changes, are in line with this.

D. The Relevance of LSTM in Predicting the Movement of High-Growth Stocks such as NVDA

As mentioned in the introduction, one of the main problems is the lack of in-depth research on NVDA shares, especially after the wave of AI growth. The 10-step-ahead prediction of the developed model shows that it can follow historical trends and anticipate minor fluctuations. This confirms that LSTM not only learns local patterns, but also macro patterns in NVDA's share price.

These findings reinforce the arguments of Liu (2025) and Yang & Wang (2024) that AI-based technology stocks require prediction models that can accommodate multi-horizon fluctuations. The approach used in this study provides empirical evidence that LSTM is the appropriate approach for projecting stock prices in modern AI-driven market conditions.

CONCLUSION

This study aims to address the issue of how to build a model capable of capturing the complex temporal dynamics of NVDA stock prices, which are highly volatile due to the rapid development of AI and GPU technology. The results of the study provide several important conclusions. First, the developed LSTM architecture proved to be effective in understanding long-term sequential patterns in NVDA stock time-series data. This is evidenced by a stable training process over 120 epochs and no indication of overfitting in the training and validation loss curves. These results support previous research findings that LSTM excels at handling highly fluctuating non-linear data (Celik & Celik, 2025).

Second, the evaluation results using test data show that the model achieves a MAPE of 4%, which indicates an excellent level of accuracy for financial data with high volatility. This error value is also in line with recent studies that place MAPE < 5% as a strong performance indicator for deep learning models in modern stock markets (Cheng et al., 2022).

Third, despite minor discrepancies at times of abrupt shift, the comparison graph between real and forecasted values demonstrates that the model effectively tracks the primary pattern of price fluctuations. This consistency indicates that LSTM is capable of capturing long temporal dependencies that cannot be handled by linear statistical methods such as ARIMA (Rosinus, 2025).

Fourth, the 10-step forward prediction model shows projection results that are in line with historical trends and produce fluctuations that are still within a reasonable range. These forecasts offer useful information for additional research, investment plans, and data-driven decision-making.

Fifth, using a multi-horizon windowing technique and hyperparameter optimization created especially for NVDA's extreme growth characteristics in the wake of the generative AI revolution, this work adds something new. This approach has not been widely applied in previous studies, which generally use general stock datasets or market indices.

Overall, this study proves that the combination of modern time-series processing and layered LSTM models can provide superior prediction performance for high-risk stocks such as NVDA.

Thus, this model is relevant for adoption by researchers, financial analysts, and industry practitioners who need an adaptive, stable, and accurate deep learning-based forecasting system.

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