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Activation Function Sensitivity in LSTM-Based Peak Stock Price Forecasting for High-Volatility Financial Time Series

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Abstract

Stock price prediction remains an intriguing task due to the high volatility and complex temporal dependencies present in financial time-series data. Accurate prediction of the highest stock price is particularly important for investors seeking to identify market peaks and optimize trading strategies. This study investigates the effectiveness of Long Short-Term Memory (LSTM) networks in forecasting DELL's highest stock price by analyzing the impact of different activation functions. Historical stock price data from 2016 to 2024 were used, and several preprocessing techniques, including data normalization and chronological train-test splitting, were applied. The LSTM models were trained for 100 epochs and evaluated using Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE). The main contribution of this research is a comparative analysis of the sensitivity of LSTM prediction performance to different activation functions, namely ReLU, ELU, Sigmoid, and Tanh, in the context of high-volatility financial time-series data. The experimental results show that the LSTM model using the ReLU activation function achieved the best performance, with an RMSE of 0.557942, MSE of 0.311300, and MAE of 0.338773, outperforming the other activation functions. These findings demonstrate that activation function selection significantly influences LSTM forecasting performance. The results provide practical insights for financial analysts and investors in selecting appropriate deep learning configurations for more reliable stock price prediction.

Keywords: Long Short-Term Memory (LSTM), stock price prediction, activation functions, ReLU, financial forecasting

1 INTRODUCTION

The stock market plays a crucial role in the global economy, serving as a barometer of companies' financial health and influencing investment decisions. [1]. Among the numerous factors that drive stock market activity, stock price prediction remains a critical area of interest [2]. Investors rely on accurate stock price predictions to make informed decisions that maximize returns and minimize risk. [3]. However, predicting stock prices is inherently complex due to the volatility and unpredictability of financial markets, which are influenced by a myriad of factors such as economic conditions, company performance, and market sentiment. [4], [5].

In particular, predicting the highest price of a stock, such as DELL's, is challenging. [6]. The highest price often represents the peak value within a trading period, which is crucial for investors aiming to capitalize on short-term price fluctuations. [7]. Traditional forecasting methods often fail to account for the temporal dependencies and non-linear relationships inherent in stock price movements. [8], [9]. Thus, there is a need for more advanced methodologies capable of capturing these complex patterns to improve prediction accuracy. [10].

The primary challenge in predicting stock prices lies in the inherent complexity of financial data. [11]. Stock prices are influenced by numerous external factors, including market sentiment, economic indicators, and geopolitical events, making them highly volatile and complex to predict [12]. Furthermore, the stock price data itself often exhibits non-linear behavior and temporal dependencies, which traditional models such as linear regression or time-series forecasting methods struggle to capture effectively. [13].

Additionally, choosing the appropriate model and optimization techniques remains a significant hurdle. While machine learning models, such as Long Short-Term Memory (LSTM) networks, have shown promise in handling sequential data, such as time series, their performance can vary with configuration, including the selection of activation functions [14]. The challenge of selecting the optimal activation function to improve the model's predictive accuracy further complicates the application of LSTMs to stock price prediction [15].

Despite the growing adoption of Long Short Term Memory (LSTM) models in stock price forecasting, relatively limited attention has been given to the role of activation functions in influencing the predictive performance of these models. Most active studies chiefly focus on optimizing hyperparameters such as the number of layers, hidden units, learning rates, and dropout rates to improve forecasting accuracy. However, the selection of activation functions an essential component that determines how neural networks learn complex nonlinear relationships has not been systematically examined in the context of financial time series prediction. This limitation is peculiarly pertinent in extremely unstable markets, where the ability of the model to capture intense price fluctuations is critical. Consequently, there remains a research gap in understanding how different activation functions influence the learning dynamics and prediction accuracy of LSTM models for stock price forecasting, peculiarly for predicting peak stock prices in singular companies such as DELL.

This research aims to tackle these challenges by applying an LSTM model to predict DELL's highest stock price, using historical price data from 2016 to 2024. Specifically, the study aims to evaluate the performance of the LSTM model with various activation functions to determine which yields the highest prediction accuracy. The evaluation will be based on key metrics including Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE). Furthermore, the research will provide practical insights for investors on leveraging the optimized model to enhance decision-making in stock price predictions, ultimately helping them maximize returns and mitigate financial risks. This research not only advances deep learning techniques for financial forecasting but also provides valuable tools for investors to navigate the complexities of stock price prediction in a volatile market.

2 LITERATURE REVIEW

Stock price prediction has been a significant area of research due to its complexity and importance in financial decision-making. Numerous studies have applied Long Short-Term Memory (LSTM) networks to forecast stock prices, demonstrating the model's ability to capture temporal dependencies in financial data. However, the effect of different activation functions on the performance of LSTM models in predicting stock prices, particularly for individual stocks such as DELL, has not been widely explored.

M. Kumaresan et al. (2023) explored the use of LSTM for stock price prediction. However, they focused primarily on hyperparameters such as batch size, learning rate, and the number of hidden layers, without delving into the impact of activation functions [16]. Their research found that the LSTM performed well overall. However, they did not assess how different activation functions might affect the model's ability to predict the highest stock prices of companies like DELL. Further studies are required to understand how activation functions influence model performance in such contexts.

Similarly, Zian Wang (2024) compared LSTM with ARIMA for stock price forecasting and highlighted LSTM's advantages, including a 92% reduction in error rates. [17]. However, like the previous study, it did not consider the effects of activation functions on model performance. Instead, the research focused on the general applicability of LSTMs across multiple stocks, such as the S&P 500. However, it did not provide insights into how activation functions specifically impact the accuracy of DELL stock price predictions.

Jaya Bharathi M et al. (2024) proposed an advanced LSTM model for stock price forecasting, which achieved a high accuracy rate of 92% [18]. However, this research focused more on optimizing the overall architecture of the LSTM model and integrating Explainable AI (XAI) techniques, rather than examining the role of different activation functions in the LSTM model. The study did not explore how activation functions such as ReLU, ELU, Sigmoid, or Tanh could affect the model's predictive accuracy for specific stocks, including DELL.

Haoran Li (2024) emphasized the importance of LSTM architecture, particularly the number of neurons and dropout rates, in achieving accurate stock price predictions. [19]. However, the study did not consider the effect of activation functions on model performance, which could play a pivotal role in how well the model generalizes to unseen data and how it handles volatile market conditions, such as those seen in DELL's stock history.

Barathi Subramanian et al. (2024) investigated the limitations of traditional activation functions, such as sigmoid and tanh, when applied to small datasets. [20]. They proposed an alternative activation function, Sigmoid Tanh Squared (SST), to enhance learning and gradient flow, which could potentially improve stock price prediction accuracy when data is limited. However, their research did not specifically analyze the impact of these functions on DELL's stock, leaving room for further exploration into how these activation functions influence LSTM performance in predicting individual stock prices.

Jongjin Jung and Ji Yeon Kim (2024) examined the importance of model optimization for stock price forecasting, but did not discuss the effects of activation functions on model accuracy. [21]. Their study compared various parameter settings and highlighted the need for further research into how different activation functions can be fine-tuned to optimize LSTM performance, particularly for high-volatility stocks such as DELL.

In contrast, several other studies [22], [23], [24] explored LSTM applications for predicting stock prices but did not delve into activation function optimization. Their work emphasized LSTM's ability to handle sequential data and capture temporal dependencies in stock price movements, but the choice of activation function was not a primary focus.

While previous studies have demonstrated the effectiveness of LSTM for stock price prediction, a noticeable gap remains in the literature regarding the impact of activation function selection on model performance. Most studies focus on optimizing hyperparameters, such as the number of layers, the number of neurons, and dropout rates. However, few have systematically investigated how different activation functions, including ReLU, ELU, Sigmoid, and tanh, influence LSTM models' ability to predict stock prices, particularly for individual stocks such as DELL.

The lack of studies specifically addressing the role of activation functions in financial forecasting models represents a significant gap in the existing literature. Understanding how these functions impact prediction accuracy is crucial, as activation functions are integral to the learning dynamics of neural networks. Different activation functions can significantly alter the model's ability to capture complex, non-linear patterns in stock price movements, and their effect might vary depending on the volatility and behavior of the specific stock being predicted.

This research aims to fill this gap by focusing specifically on the impact of activation functions, including ReLU, ELU, Sigmoid, and Tanh, in predicting the highest stock price of DELL. By comparing the performance of these activation functions in stock price forecasting, this study will provide valuable insights into how the choice of activation function can influence the accuracy and reliability of LSTM models in the financial domain.

3 RESEARCH METHODS

In this study, we applied a systematic approach to develop and evaluate a predictive model for forecasting DELL's highest stock price using Long Short-Term Memory (LSTM) networks. Figure 1 shows that the methodology is designed to address the challenges of time-series prediction, where capturing the temporal dependencies and non-linear patterns in financial data is crucial. The methods outlined below detail the steps for preprocessing the dataset, building the LSTM model, and evaluating its performance across various activation functions. By focusing on key stages such as data cleaning, normalization, and splitting, we ensure the model's robustness and accuracy, ultimately providing valuable insights for investors and analysts into stock price prediction.

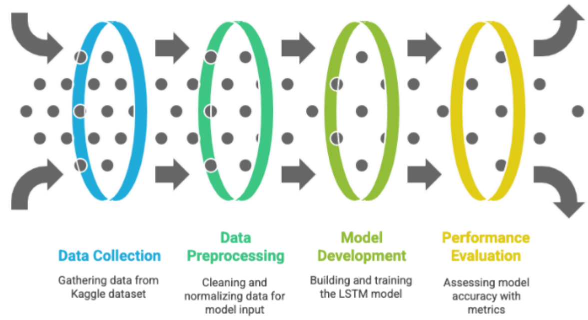

Figure 1. Proposed Method

3.1 Data Collection and Dataset Description

This research utilizes historical stock price data of DELL, obtained from Kaggle's "Microsoft Stock Data and Key Affiliated Companies" dataset. The dataset spans from August 17, 2016, to October 30, 2024, and contains 2,042 data points. The data includes key financial indicators: date, opening price, highest price, lowest price, closing price, adjusted closing price, and trading volume. For this study, the focus is on the "High" column, which records the highest stock price for DELL on each trading day. This column serves as the target variable for prediction, specifically predicting the highest price of DELL stock within the given time series.

3.2 Data Preprocessing

Data preprocessing in this study involved several critical steps to prepare the dataset for the LSTM model. First, data cleaning was performed to handle missing values by removing rows with null entries, ensuring data integrity. The dataset was then reduced to relevant features, specifically the "Date" and "High" columns, with the "Date" column formatted as datetime to maintain chronological order. Next, normalization was applied using Min-Max scaling, which scaled the "High" prices to the range [0,1], ensuring consistency for model input. The data was split into training and testing sets with a 70:30 ratio, maintaining chronological ordering to prevent future data leakage. The training dataset contained 1,429 data points, while the testing set contained 613.

The mathematical model used in this research is the Long Short-Term Memory (LSTM) network, which can be represented as follows:

$$h_t = \text{LSTM}(x_t, h_{t-1}, C_{t-1}) \tag{1}$$

where:

- h_t is the hidden state at time t
- x_t is the input at time t
- h_{t-1} is the previous hidden state
- c_{t-1} is the previous cell state.

The model's prediction for the highest stock price at time t, denoted as $\hat{y}$, is calculated as in (2):

$$\hat{y}_t = W_{\text{output}} h_t + b_{\text{output}} \tag{2}$$

where W_{output} is the weight matrix and b_{output} is the bias term. The model is trained using the Adam optimizer, and the loss is calculated in (3) using Mean Squared Error (MSE), which is minimized during training:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

where y_i represents the actual stock price and $\hat{y}_i$ is the predicted value.

3.3 Model Development

The model developed in this study is an LSTM network, specifically designed for time-series prediction tasks due to its capability to capture long-term dependencies. The model architecture consists of a single LSTM layer with seven units, followed by a Dense layer to output the predicted highest stock price. The choice of activation functions includes ReLU, ELU, Sigmoid, and Tanh, each selected for their unique characteristics in influencing the model's learning behavior. The model was trained for 100 epochs using the Adam optimizer with a batch size of 32, employing early stopping to prevent overfitting. Performance evaluation was done using three metrics: Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE), to assess the model's prediction accuracy and robustness

.

3.4 Performance Comparison

To determine the most effective activation function for predicting DELL's highest stock price, the LSTM model's performance with each activation function was compared using RMSE, MSE, and MAE. The results of these evaluations provide insights into which activation function yields the most accurate predictions.

3.5 Experimental Setup

The experiments were conducted using Python, leveraging libraries such as Keras to build and train the LSTM model, Pandas for data manipulation, NumPy for numerical calculations, and Matplotlib for data visualization. The models were trained and evaluated on a local machine with sufficient computational power, including access to high-performance hardware for faster training using a Graphics Processing Unit (GPU).

4 RESULTS AND DISCUSSION

4.1 Results

To ensure the robustness and originality of the implementation, the LSTM model in this study was configured with a single LSTM layer consisting of seven hidden units followed by a dense output layer for regression prediction. The model was trained using the Adam optimizer with a batch size of 32 for 100 epochs , while the loss function was defined using Mean Squared Error (MSE). Early stopping was applied to reduce the risk of overfitting during training. In addition to the training and testing split (70:30), model validation was performed by monitoring the training loss and testing performance across epochs to ensure steady convergence of the model.

Although the dataset was obtained from Kaggle, the implementation in this research was independently developed developed by designing a customized LSTM configuration and consistently evaluating four activation functions (ReLU, ELU, Sigmoid, and Tanh) within the comparable experimental framework . The experimental results indicate that the ReLU activation function achieves superior predictive performance compared with the different functions . This can be explained by the ability of ReLU to mitigate the vanishing gradient problem and maintain efficient gradient propagation during backpropagation , enabling the model to learn nonlinear patterns and sharp fluctuations further efficaciously in unstable financial time series data. In contrast, Sigmoid and Tanh tend to suffer from gradient saturation , which slows the learning process and limits the model's ability to capture explosive changes in stock prices.

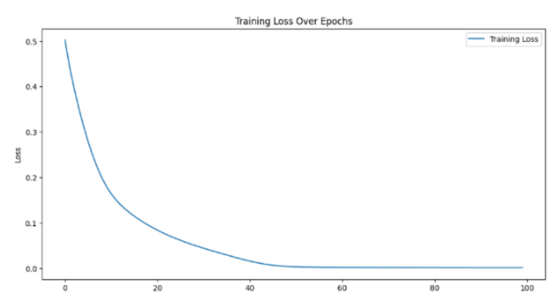

Figure 2. Training Loss ReLU Activation Function

The ReLU activation function demonstrated the best performance across all metrics. As shown in Figure 2, the model's training loss significantly decreased over the epochs, indicating effective learning. The RMSE, MSE, and MAE for the ReLU model were the lowest among the activation functions, indicating higher prediction accuracy and a better fit to historical data. This result suggests that ReLU is the most effective activation function for capturing the patterns in DELL's stock price.

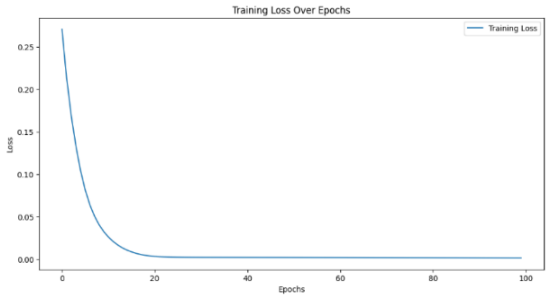

Figure 3. Training Loss ELU Activation Function

The ELU activation function showed a consistent decrease in training loss over the epochs, as illustrated in Figure 3. However, the performance on the test data was not as robust as ReLU. While the model performed well on the training data, it exhibited signs of overfitting, as evidenced by higher error metrics on the testing dataset. This suggests that ELU may struggle to generalize effectively to unseen data, rendering it less suitable for this stock price prediction task.

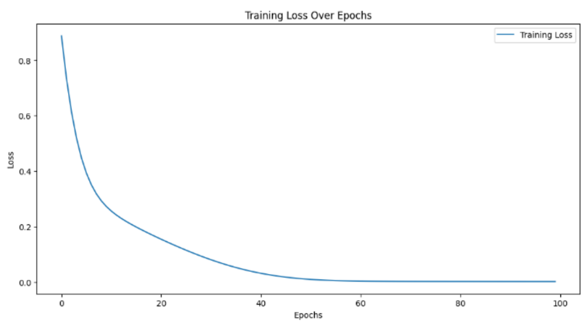

Figure 4. Training Loss Sigmoid Activation Function

The Sigmoid activation function, shown in Figure 4, exhibited slower convergence than ReLU and ELU, with a less pronounced reduction in loss over the epochs. The model trained with the Sigmoid function exhibited significant overfitting, leading to poorer performance on the test data. The prediction errors, as measured by RMSE, MSE, and MAE, were higher than those of the ReLU model, suggesting that Sigmoid is less suited for this particular prediction task.

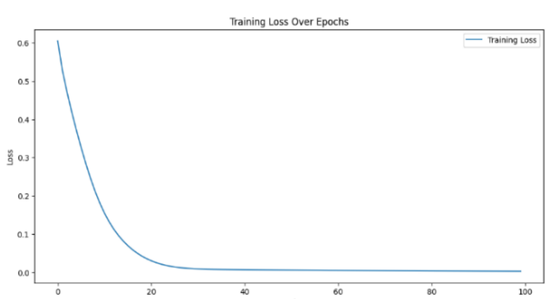

Figure 5. Training Loss Tanh Activation Function

The Tanh activation function, as seen in Figure 5, demonstrated the slowest improvement in training loss. Despite a steady reduction in loss during training, the model exhibited significant overfitting, with a substantial discrepancy between its training and testing performance. The error metrics for the Tanh model were the highest, indicating that this activation function does not effectively capture the complex patterns in stock price movements.

To further quantify each activation function's performance, the models were evaluated using three commonly used metrics: Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE). These metrics provide insight into the overall prediction accuracy and the magnitude of errors for each model. The results are summarized in Table 1.

Table 1. Comparison of Evaluation Metrics

Activation Function	R2 Score	RMSE	MSE	MAE
ReLU	0.843773	0.557942	0.3113	0.338773
ELU	0.2873	1.191694	1.420135	0.680826
Sigmoid	0.328764	1.156508	1.337512	0.654547
Tanh	-0.023218	1.427892	2.038876	0.843087

The table clearly shows that the ReLU activation function outperforms the other activation functions, achieving the lowest RMSE, MSE, and MAE values and the highest R^2 score. This indicates that the ReLU-based model is the most accurate at predicting DELL's highest stock price. In contrast, Tanh performed the worst, with the highest errors across all metrics, suggesting it is not an ideal choice for this type of financial prediction task.

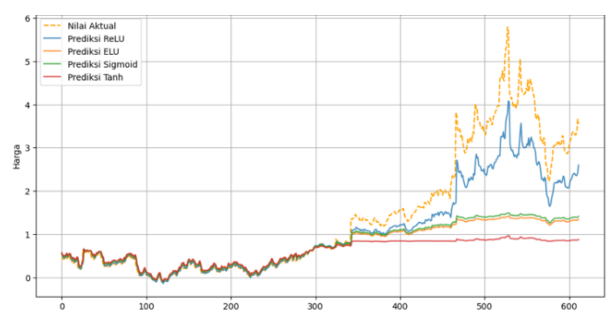

Figure 6. Comparison of Prediction Results for The Highest Stock Price Of DELL Using Four Different Activation Functions In The LSTM Model

Figure 6 compares prediction results for DELL's highest stock price across four activation functions in the LSTM model: ReLU, ELU, Sigmoid, and Tanh. The graph clearly illustrates how each activation function impacts the model's ability to predict stock prices at various time points, with the predicted values compared against the actual values, represented by the yellow dashed line.

The ReLU activation function provided the most accurate predictions, aligning closely with the actual stock prices, especially during price surges. This indicates that the ReLU model effectively captures the fluctuations and key patterns in the stock price, making it the best-performing activation function in this study. On the other hand, the ELU model showed predictions that were generally close to the actual prices but lacked precision, particularly during sharp increases in stock prices. Although it followed the overall trend, it lagged behind actual prices during volatile periods, making it less effective than ReLU.

The Sigmoid activation function exhibited noticeable deviations from the actual stock prices, particularly during high-volatility periods. The Sigmoid model struggled to capture sharp rises and falls in stock prices, resulting in less accurate predictions than ReLU and ELU. Finally, the Tanh activation function showed the least accurate predictions, with significant discrepancies from the actual values. The Tanh model consistently underperformed during price surges, indicating it was unable to capture the complexity of stock price fluctuations.

In conclusion, Figure 6 demonstrates that ReLU offers the most accurate and reliable predictions for DELL's highest stock price, successfully tracking both trends and sharp price fluctuations. The findings from the model evaluation have significant implications for business and investment decision-making. Accurate prediction of stock prices, remarkably the highest price, plays a crucial role in informing trading strategies and investment decisions. By employing an LSTM model with the ReLU activation function, investors can potentially achieve better forecasting performance, enabling more informed decisions about buying and selling DELL stock. Accurate predictions of the highest stock price enable investors to identify peak market conditions and capitalize on price surges, thereby improving the timing of their trades.

For businesses, especially those in the financial sector, adopting machine learning models such as LSTMs with optimized activation functions can enhance risk management and more effectively allocate resources. By reducing prediction errors, the model enhances the accuracy of stock price forecasts, which in turn enables businesses to plan more effectively, minimize financial risks, and capitalize on market opportunities. The superior performance of the ReLU-based model underscores the importance of selecting the optimal configuration to improve financial predictions, ultimately leading to improved profitability in the long run. Moreover, such predictive models can be integrated into trading systems, providing real-time insights into market trends and helping businesses stay competitive in dynamic market environments.

4.2 Discussions

The results of this study highlight the significant influence of the choice of activation function on the performance of LSTM models in predicting DELL's highest stock price. The ReLU activation function consistently outperformed the other functions in terms of prediction accuracy. This aligns with previous research. [19] that emphasized the importance of optimizing the LSTM architecture to improve stock price prediction accuracy. ReLU effectively captured both general trends and sharp price surges, making it the most suitable activation function for predicting volatile stock prices, such as DELL's.

In contrast, the ELU, Sigmoid, and Tanh functions performed less effectively. Although ELU showed potential, it was prone to overfitting, especially during periods of high volatility. Both Sigmoid and tanh struggled to capture sudden price fluctuations, resulting in higher error rates compared to ReLU. This finding supports the limitations noted by [20], who found that traditional activation functions, such as Sigmoid and Tanh, were less effective for complex, non-linear stock price patterns.

While the LSTM model demonstrated strong performance with ReLU, its interpretability remains a challenge, as LSTM models are often considered "black-box" models. Future work could integrate Explainable AI (XAI) techniques, such as LIME (Local Interpretable Model-agnostic Explanations), to enhance model transparency, particularly in financial decision-making contexts. This would help investors better understand the factors influencing stock price predictions, thereby enhancing confidence in decision-making.

From a business perspective, accurately predicting stock prices is crucial for making informed investment decisions. The superior performance of the ReLU-based LSTM model demonstrates its potential as a reliable tool for predicting DELL's highest stock price, helping investors determine optimal entry and exit points. However, as with any model, the study's findings suggest the need for ongoing research to optimize LSTM models, particularly in terms of activation functions, to improve forecasting accuracy, especially in volatile markets.

Looking ahead, future research could explore the integration of external factors, such as market sentiment and macroeconomic indicators, that also influence stock prices. Incorporating such factors, along with advanced machine learning techniques such as reinforcement learning and ensemble methods, could enhance the robustness and predictive power of the LSTM model, making it even more valuable for real-world financial applications.

5 CONCLUSION

This study has demonstrated the significant impact of activation function selection on the performance of LSTM models in predicting DELL's highest stock price. By applying and comparing four activation functions—ReLU, ELU, Sigmoid, and Tanh—we found that ReLU consistently outperformed the others in prediction accuracy. The best-performing model, using ReLU, achieved the following evaluation metrics: RMSE of 0.557942, MSE of 0.311300, and MAE of 0.338773. These results confirm that the ReLU activation function yields the most accurate forecasts for DELL's highest stock price, particularly in capturing both general trends and the sharp price fluctuations typically observed in stock markets.

The contribution of this research lies in its focus on the effect of activation functions on the performance of LSTM models for predicting individual stock prices, specifically for DELL. Previous studies have explored LSTM models for stock price prediction, but have often overlooked the impact of activation functions. By addressing this gap, this study provides valuable insights into how ReLU, in particular, can enhance the accuracy of stock price forecasts.

Furthermore, the findings from this study have practical implications for investors and financial analysts. By using LSTM models with an appropriate activation function, such as ReLU, stakeholders can make more informed investment decisions by optimizing buy, sell, or hold strategies based on more accurate stock price predictions. This research also underscores the importance of further investigating model interpretability and integrating external market factors to enhance the reliability and applicability of LSTM models in real-world financial forecasting.

In conclusion, this study makes a significant contribution to understanding how activation functions affect the performance of LSTM models for stock price prediction. It also lays the groundwork for future research that could explore the integration of explainable AI techniques and external factors, further refining the predictive power and interpretability of financial forecasting models.

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