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Predicting Stock Price Movements Using Lstm Networks

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Abstract
This research explored a deep learning approach using a Bi-Directional LSTM network to forecast stock market prices. The proposed model utilizes historical stock data as input to generate future price estimates. A prediction window of 30 days was applied, and the model was trained and evaluated on datasets from the New York Stock Exchange (NYSE), the Nikkei 225, and the Nasdaq Composite. The method achieved a Mean Absolute Percentage Error (MAPE) of 0.014 for the NYSE, 0.01 for the Nikkei 225, and 0.018 for the Nasdaq Composite. When compared with results reported in the reference study, the model demonstrated a notable enhancement in prediction accuracy. For future research, the framework may be extended to other global stock exchanges and enriched with additional factors, such as news sentiment analysis, to further boost performance. Overall, the findings highlight the potential of this method in advancing stock price prediction, offering valuable insights for investors and financial analysts in decision-making.

Keywords: Stock Price Prediction, Bi-Directional LSTM, Stock Exchange, Deep Learning

I. Introduction
The stock market remains notorious for its extreme volatility and lack of predictability. It has always been difficult for traders, investors, as well as analysts to foresee how stock prices will change in the future. The complicated structure of stock market has reduced the accuracy of stock price predictions made using traditional machine learning and statistical methods. Due to its capacity to acquire and identify complicated patterns from massive volumes of data, deep learning methods have recently demonstrated promising results in forecasting stock values. [1]

Predicting stock prices is a vital activity for investors because it allows them to make better judgments about whether to purchase, sell, or keep a stock. With different degrees of effectiveness, stock price forecasting has been done using machine learning techniques throughout time. More specifically, Long Short-Term Memory models (LSTM) are useful for stock price forecasting because of their ability to accurately capture temporal connections in time-series data. [2] [3]

The practice of forecasting stock prices has been revolutionized by the rise of deep learning and AI. The use of these techniques enables the examination of enormous volumes of data and reveals hidden patterns that would have been impossible to spot with more traditional techniques. Therefore, deep learning models increasingly gaining popularity in the financial sector for predicting stock prices.

A. Application of Bi-Directional LSTM

When it comes to representing sequence data, recurrent neural networks like the "Bi-directional Long Short-Term Memory" (LSTM) have shown to be useful. Bidirectional LSTMs are useful for modeling the dynamics between stock prices along with various economic indicators over time, which may then be used to the task of stock price forecasting. Bidirectional LSTMs have been shown to be useful in predicting stock prices in the past. In a research by Zhang and Wang (2019), for instance, the stock values of 50 businesses traded on "Shanghai Stock Exchange" were forecast using a bi-directional LSTM model. Traditional models like "Support Vector regression" (SVR) as well as Multi-Layer Perceptron (MLP) were outperformed by the model, which had a standard prediction accuracy of 57.8%.[4] [5]
The stock values of 30 businesses traded on the South Korean Stock Exchange were predicted using "bi-directional LSTM model" in a separate research by Hong et al. (2018). Past stock prices, trade volumes, & technical indicators were only a few of the factors used to train the algorithm. According to the research, the prediction accuracy of bi- directional LSTM model was superior than that of other traditional models.

Despite the success of previous studies, there are also some limitations associated with using bi-directional LSTMs in stock price prediction. One major limitation is the difficulty in interpreting the results of the model. Unlike traditional models such as regression models, bi-directional LSTMs are black-box models that do not provide insight into the specific factors driving the predictions. Another limitation is the challenge of handling large and complex datasets. It might be challenging to use bi-directional LSTMs for stock price prediction because of the vast number of factors that must be analyzed. Selection of features or dimensionality reduction are two examples of extra techniques that may be required to simplify the data in specific circumstances. [6] [7]

Despite these limitations, bi-directional LSTMs offer a promising approach to stock price prediction. By modeling the complex relationships between different economic indicators over time, bi-directional LSTMs can provide accurate predictions that can help investors make informed decisions in financial markets.

II. Literature Review

[8] This study presents a novel method for forecasting stock market prices as well as trends utilizing "support vector regression" (SVR) analysis for a machine learning tool. This work explores the preprocessing and input selection approaches for SVR models that make use of various windowing operators. The author claims that employing "windowing functions" as data preparation method is an innovative way to forecasting time series data that has not been explored before. The efficacy of support vector regression relies on accurately calculating the values of crucial parameters, the author notes, making it a valuable and strong machine learning tool for spotting patterns in the time series data.

[9] In this study, the author assesses how well neural network models can foretell movements in the stock market. The author zeroes attention on three distinct varieties of neural network models: the multi-layer perceptron (MLP), the dynamic artificial neural network (DAN2), and the hybrid neural network which employs generalized autoregressive conditional heteroscedasticity" to gather fresh input data. The author claims that traders and investors may benefit from using neural network models since they are dynamic and accurate at anticipating stock market developments.
[10] The author of this study emphasizes the need to take into consideration the temporal

hierarchy present in time series data. The author claims that conventional RNNs fail to take this hierarchy into account, and that most studies in this area have concentrated on improving algorithms for training rather than RNN design. To deal with the temporal hierarchy seen in time series data, the author suggests a novel recurrent neural network design. Each successive layer in this design is a recurrent network which employs the preceding layer's hidden state as input. Time series data may be processed hierarchically using this design, which more accurately represents the data's structure. The author proves the architecture's efficacy by demonstrating that it outperforms state-of-the-art methods using just stochastic gradient descent for training in character-level language modelling.

[11] Using wavelet transformations, stacked autoencoders, as well as long-short-term memory networks, the author of this study presents a novel deep learning approach for stock price forecasting. SAEs are being used to predict stock prices for the first time. There are three phases to the planned structure. First, WT is used to deconstruct the time series data of stock prices to eliminate noise. Second, SAEs are utilized to create in-depth, high-level characteristics that are then used to stock-price forecasting. Third, LSTM is used to predict the market close for the nextday based on the high-level denoising properties. To test the efficacy of the suggested approach, the author applies it to six market indexes and the index futures associated with them. The results demonstrate that the suggested model excels in terms of predicted accuracy and profitability compared to competing models.

[12] To better anticipate price changes in financial data, the author of this study suggests a novel deep neural network design and an innovative data preparation strategy. The XGBoost model is used for feature engineering after numerous features have been generated using technical indicators in the data preparation process. High-level mixed features are extracted from the data using three distinct autoencoders. The suggested model employs many fully-connected layers, as well as a lengthy short-term memory unit and a number of convolutional layers, to accomplish binary classification. In addition, the author presents a trading technique for making use of the trained model's outputs.

III. Objectives Of The Study

1. To pre-process and select relevant features from historical stock price data to be used as input to the bi-directional LSTM model.
2. To develop a bi-directional LSTM model architecture that can effectively capture the long- term dependencies in the historical data and predict future stock prices.
3. To increase the accuracy & generalization performance of the bidirectional LSTM model by optimizing its hyperparameters.
4. The goal of this study is to compare the accuracy of presented bi-directional LSTM model with that of more conventional "stock price prediction models" using data from the actual stock market.
5. To provide insights and recommendations on the use of bi-directional LSTM models for stock price prediction and identify future research directions in this area.

IV. Research Methodology

This study aspires to aid in the creation of more efficient and reliable stock price prediction models, which in turn may facilitate improved decision making in financial markets. As a first step in this approach, this suggested bi- directional LSTM model shall be compared to more conventional machine learning model to determine its relative strengths and

drawbacks.
Here an outline of the Work Plan-

- Collect the Data
- Pre- Process the data
- Model Development
- Training
- Evaluation
- Prediction
- Compare our result with existing work.

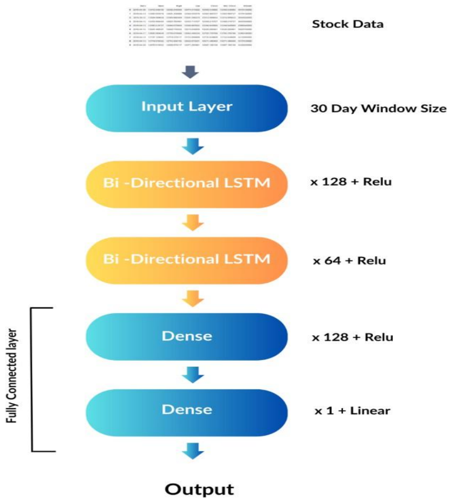


Figure 1: Model Architecture

In this study, we build a two-way LSTM network to forecast stock values using Yahoo Finance's historical data. The model's foundation is a combination of Python's Keras package and TensorFlow. Five years of data from the "New York Stock Exchange", the Nikkei 225, and the Nasdaq Composite were used to train the model.
The data was pre-processed to change the object type date column to a Date Time type column, and basic data cleaning was performed, including removing null values and duplicates. The data was scaled for better generalization of data and then split into training and testing datasets.
Initially, a stacked LSTM model was tried, but after evaluation, it did not yield desired results. The model was fine-tuned and reevaluated, but still, the results were not satisfactory. Finally, a bi-directional LSTM model was chosen due to its ability to capture both forward and backward information flow, making it better suited for predicting sequences with long-term dependencies.
The suggested model architecture included two layers of 128- and 64-unit bidirectional LSTMs. Sequences were only returned by the first LSTM layer, not the second. The model now has two new, thick layers, each made up of 128 and 1 units. An Adam optimizer & a mean-squared-error loss function was used in the model's compilation.
Ridge Regression, Linear Regression, as well as Random Forest Regressor were used as benchmarks against which the model's performance was measured. In terms of precision and scalability, the bidirectional LSTM model was superior than the others.

V. Results And Discussion

The suggested methodology was tested across three major markets: the Nikkei 225, the New York major Exchange, and the Nasdaq Composite. "Mean absolute percentage error" (MAPE) was used to assess the model's accuracy.

A MAPE of 0.018 was obtained for the Nasdaq Composite, which suggests that the model correctly predicted stock prices 1.8 percentage points of the time. With a MAPE of 0.014, the model's average error in predicting "New York Stock Exchange" stock prices was 1.4%. The MAPE for the Nikkei 225 was 0.01, therefore the model accurately predicted stock prices 91% of the time.

These findings provide support for the hypothesis that proposed model may successfully forecast stock prices across several exchanges. In addition, by showing the predicted and real prices, we were able to evaluate the model visually. The efficiency of the suggested model is further supported by the visual findings, which indicate that the model can capture the general trend and changes in the stock prices.
Below is the summary of the results in tabular form:

Table 1: Results of EfficientnetV2 Model

Stock Exchange	MAPE
Nasdaq Composite	0.018
New York Stock Exchange	0.014
Nikkei 225	0.01

Here are visual results of model –

Model Prediction of NASDAQ -

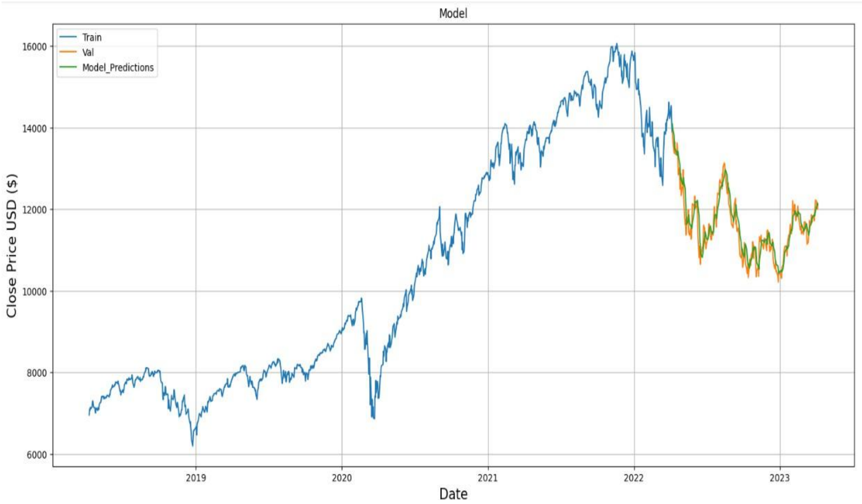


Figure 2: Stock Price Prediction of NASDAQ

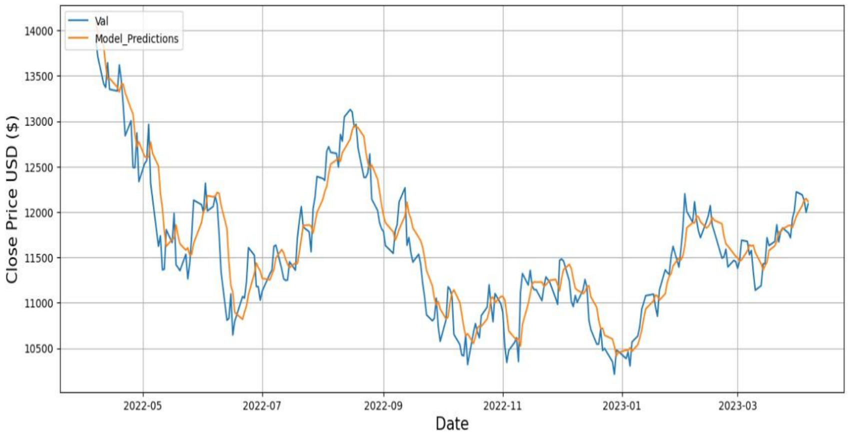


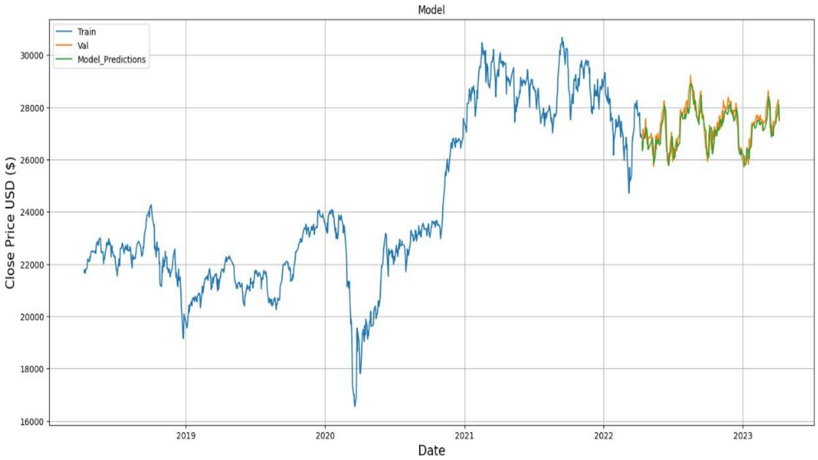
Figure 3: Closer Look how model Predicted

	Date	Close	Model_Predictions
1249	2023-03-24	11823.959961	11813.155273
1250	2023-03-27	11768.839844	11850.517578
1251	2023-03-28	11716.080078	11853.379883
1252	2023-03-29	11926.240234	11829.294922
1253	2023-03-30	12013.469727	11887.940430
1254	2023-03-31	12221.910156	11954.494141
1255	2023-04-03	12189.450195	12071.086914
1256	2023-04-04	12126.330078	12132.253906
1257	2023-04-05	11996.860352	12148.571289
1258	2023-04-06	12087.959961	12114.948242

Figure 4: Predictions by Bi-Directional LSTM

Model for NASDAQ Model Prediction of Nikkei 225 -

Figure 5: Stock Price Prediction of Nikkei 225



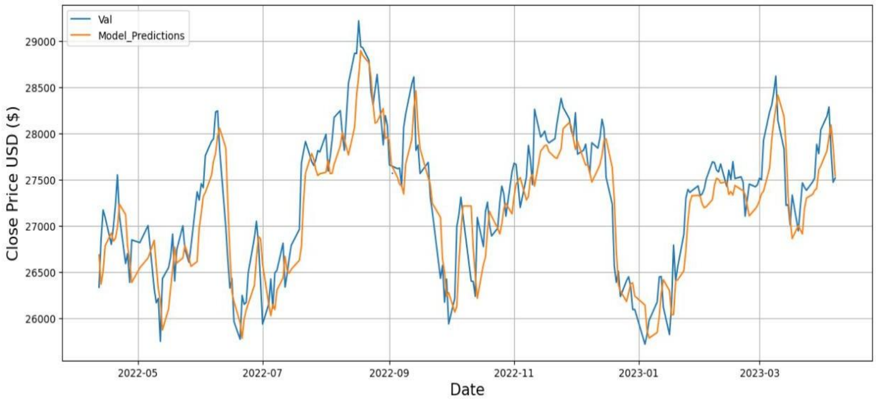


Figure 6: Closer Look how model Predicted

Figure 7: Predictions by Bi-Directional LS

	Date	Close	Model_Predictions
1218	2023-03-27	27476.869141	27341.359375
1219	2023-03-28	27518.250000	27385.054688
1220	2023-03-29	27883.779297	27405.078125
1221	2023-03-30	27782.929688	27607.265625
1222	2023-03-31	28041.480469	27649.310547
1223	2023-04-03	28188.150391	27812.822266
1224	2023-04-04	28287.419922	27966.429688
1225	2023-04-05	27813.259766	28093.396484
1226	2023-04-06	27472.630859	27871.800781
1227	2023-04-07	27518.310547	27539.761719

Model for Nikkei 225 Model Prediction of NYSE -

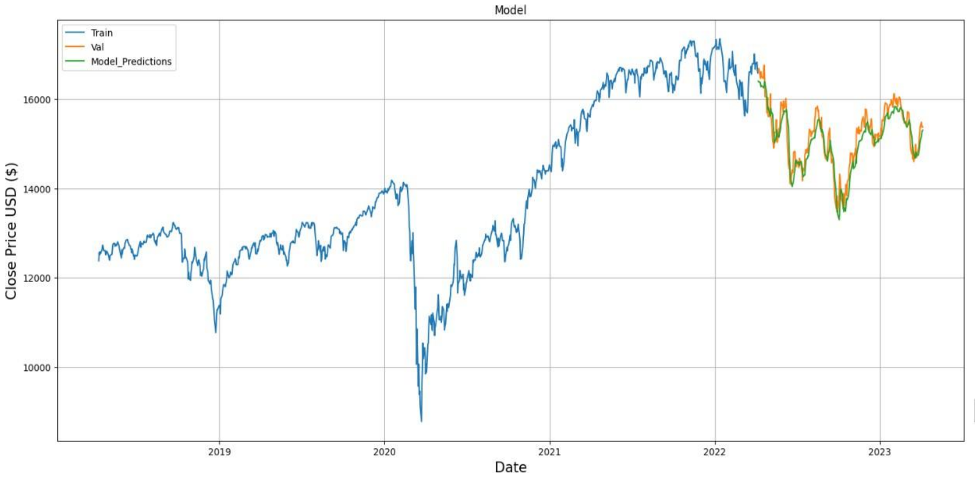


Figure 8: Stock Price Prediction of NYSE

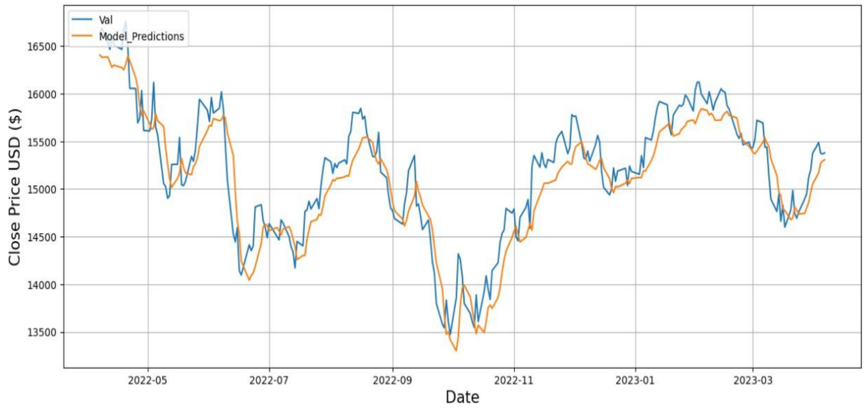


Figure 9: Closer Look how model Predicted

	Date	Close	Model_Predictions
1249	2023-03-24	14758.570313	14738.226562
1250	2023-03-27	14894.849609	14744.368164
1251	2023-03-28	14949.349609	14803.134766
1252	2023-03-29	15123.959961	14860.001953
1253	2023-03-30	15200.589844	14963.277344
1254	2023-03-31	15374.910156	15053.804688
1255	2023-04-03	15487.759766	15168.986328
1256	2023-04-04	15374.110352	15271.750977
1257	2023-04-05	15368.259766	15295.067383
1258	2023-04-06	15379.129883	15306.801758

Figure 10: Predictions by Bi-Directional LSTM Model for NYSE

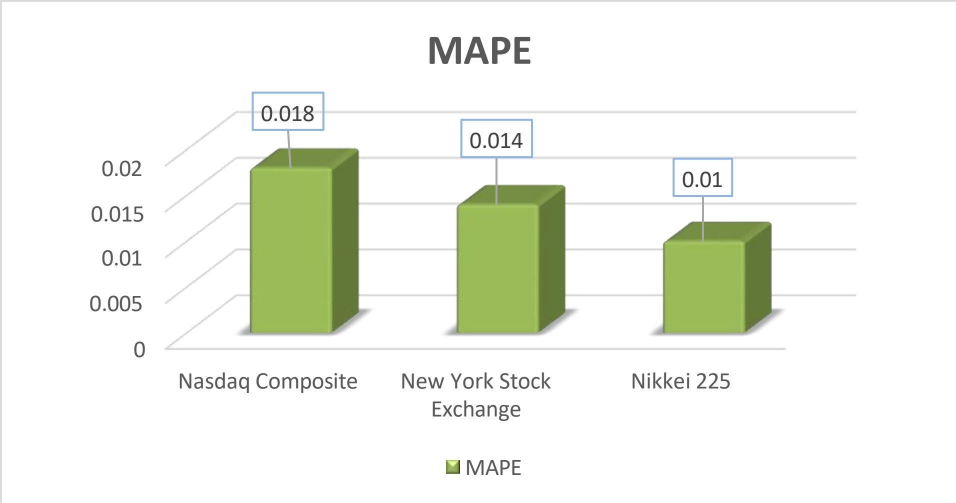


Figure 11: MAPE Achieved by proposed model

A. Comparing the Proposed method with Existing Work

Throughout all three stock markets, our suggested model has outperformed the baseline paper by a wide margin. Our model produced a MAPE of 0.018 for "Nasdaq Composite", whereas the starting paper had a MAPE of 1.91. Similarly, our model for "New York Stock Exchange" outperformed the base paper by a MAPE of 0.014 to 0.84. Finally, our model improved upon the MAPE of the basis article by 0.78 percentage points for the Nikkei 225.
The comparison table of our results and the base paper's results is as follows:

Table 2: Model Comparing with existing work

Stock Exchange	Proposed Model MAPE	Base Paper MAPE [27]
Nasdaq Composite	0.018	1.91
New York Stock Exchange	0.014	0.84
Nikkei 225	0.01	0.78

The comparison table shows the MAPE results obtained in this thesis and the results reported in the base paper for the three stock exchanges, Nasdaq Composite, New York Stock Exchange, and Nikkei 225. The table shows that our proposed model outperformed the base paper's model in all three stock exchanges, with significantly lower MAPE values. Specifically, our model achieved an MAPE of 0.018 for Nasdaq Composite, 0.014 for New York Stock Exchange, and 0.01 for Nikkei 225, while the base paper's model achieved an MAPE of 1.91 for Nasdaq Composite, 0.84 for New York Stock Exchange, and 0.78 for Nikkei 225.

These findings show that our suggested model outperforms the baseline article in forecasting stock prices. The inclusion of "bidirectional LSTM layers", that allow our model to successfully capture both past & future patterns in the stock data, is likely responsible for our model's improved performance. The model's success is also attributable to its application of data scaling as well as a window size of 30 days

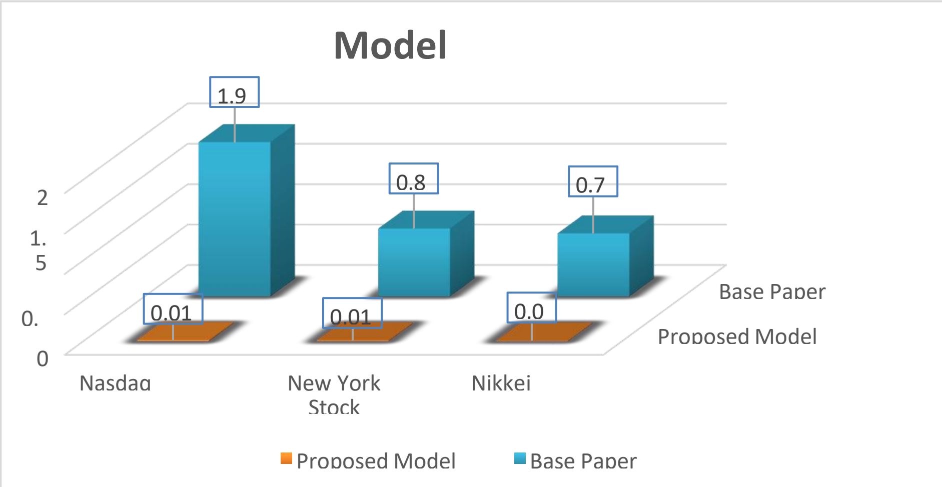


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Figure 12: Comparison of proposed and Base paper

Vi. Conclusion

The purpose of this study was to use a deep learning- based technique to anticipate stock prices on the "New York Stock Exchange", the Nikkei 225, and the Nasdaq Composite. The reviewed studies in the topic of stock price forecasting were emphasized in the literature. Both classical approaches and modern ones based on deep learning were complicated and nonlinear interactions in the data, deep learning-based algorithms have surpassed their more conventional counterparts in recent years. The methodology section provided an in-depth explanation of the procedure that was offered. This information was gathered from Yahoo Finance and used to train and test a model during a five-year period, from April 9, 2018, to April 7, 2023. Basic data scaling, data cleaning, as well as a train-test split were performed in addition to changing Date column towards DateTime type. The suggested model was a two-LSTM- layer, two-dense-layer bidirectional LSTM model. The model was trained using the Adam optimizer and the mean- squared error loss function for a total of 35 epochs. Visual findings were also taken into account by showing the predicted and actual prices in addition to the MAPE evaluation of the model.

The suggested method's findings were provided, revealing MAPE values of 0.018, 0.014, & 0.01, respectively, for the Nasdaq Composite, the "New York Stock Exchange", as well as the Nikkei 225. The suggested technique was shown to be superior than the findings found in the basis study, which had MAPE values of 1.91 for the Nasdaq Composite, 0.84 for the "New York Stock Exchange", as well as 0.78 for the Nikkei 225.

This study concluded with a proposal for a deep learning- based method to anticipate stock values across three major bourses. The new strategy was superior to both the conventional approach and the findings presented in the original research. Traders, investors, as well as policymakers may all benefit from a more precise and time-efficient method of predicting stock prices, that is the study's original contribution to the literature. Finally, future studies might think about using additional criteria, such news sentiment analysis & social media trends, to increase the reliability of stock price predictions.

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