Predicting Stock Market Trends Using LSTM
An Analysis

Shubhayu Shrestha
The University of Texas at Austin

CS395T: Case Studies in Machine Learning

Dr. Junfeng Jiao

December 4th, 2023

Table of Contents

1. Introduction and Research Background

The stock market has captivated the attention of investors, traders, and financial analysts; many of whom have a goal to decipher its intricate patterns and predict trends with precision to lead to substantial gains. It is "one of the most important and active financial markets" (Wang et al., 2016). Although the complexity makes the stock market fascinating, it also renders predicting its future movements a formidable challenge "as the nature of the stock market has always been vague for investors because predicting the performance of a stock market" (Khan et al., 2023).

There are many factors that can facilitate change in market value in a day such as country's economic change, product value, and the "sentiment of customers or buyers that is their opinion on a particular product or service provided by the company" (Pawar et al., 2019). Considering the many factors that can affect the market value of stock, the direction of them can be predicted by analyzing market indicators, which can be obtained by analyzing market breadth. Market breadth "indicates the number of companies that have obtained new high valuations, in comparison to the number that have obtained poor valuations" (Shetty et al., 2019). These market indicators can be utilized to signal a bullish or bearish market, where bullish signals will indicate when a stock is going to increase in value, and a bearish meaning that the value will decrease in value.

In recent years, the ascendancy of machine learning (ML) has introduced another entity in market analysis "since it enables many opportunities such as forecasting the future stock movements, making optimal investment decisions, and algorithmic trading" (Cipiloglu et al., 2022). This technology, armed with the capacity to sift through vast datasets, presents a compelling approach on forecasting stock market trends.

The advent of neural networks, notably recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, marked a significant leap in the quest for accurate stock market predictions. RNNs, tailored for processing sequential data and can exhibit a capacity to grasp temporal dependencies and unearth long-range patterns. LSTMs, a specialized variant of RNNs, "can be used for handling time-series problems since they have the ability to identify long-term patterns in sequential data" (Cipiloglu et al., 2022), in which "time-series forecasting models are the models that are capable to predict future values based on previously observed values" (Loukas, 2020), which would make them perfectly adept at forecasting in the volatile domain of stock markets. In this paper, we will discuss the different machine learning implementations towards stock market analysis and support the utilization of LSTM to predict stock market trends as using machine learning can aid investors and traders in making informed decisions based on prior market trends, utilizing historical stock market data to develop predictive models.

2. Research and Methods

2.1 Literature Review

Among the diverse algorithmic approaches, decision trees, recurrent neural networks (RNNs), long short-term memory (LSTM) networks, linear regression, and support vector machines (SVMs) have emerged as prominent tools for stock market prediction. This section will delve into the application of these algorithms, examining their underlying principles and effectiveness in capturing market trends and will discuss why we believe.

Decision trees are another powerful machine learning algorithm that can be used for stock market prediction. They are a type of supervised learning algorithm that works by building a tree-like structure that partitions the data into smaller subsets based on specific criteria and proven to be effective for stock market prediction, particularly for short-term predictions. The purpose of using decision trees to track the stock market is to “track useful information from huge volume of data” (Liu & Li, 2022).

Support Vector Machines (SVMs) is another machine learning algorithm that has “been implemented in classification, recognition, regression and time series” (Kara et al., 2011). SVMs operate by “mapping data to a high-dimensional feature space so that data points can be categorized, even when the data are not otherwise linearly separable” (IBM, n.d.). While SVMs offer promising capabilities for stock market prediction, they also have some limitations, such as it being “not suitable for large data sets … [and] not perform[ing] very well when the data set has more noise” (Raj, 2022).

Linear regression a “category of supervised machine learning algorithm where the expected yield is tenacious and highlights a consistent incline” (Titarmare, 2022) that can be used to predict future stock prices by assuming a linear relationship between the stock price and other information boundaries, such as company earnings, interest rates, or economic indicators. It also has limitations, such as assuming a linear relationship between variables and not being able to capture complex nonlinear relationships. Despite these limitations, linear regression can still be a useful tool for stock market prediction, especially when used in conjunction with other techniques, such as neural networks or SVMs.

Recurrent Neural Networks (RNNs) are a "class of deep learning models that possess internal memory, enabling them to capture sequential dependencies" (Shiri, 2023). RNNs can capture temporal dependencies in data, which is essential for predicting future trends based on past observations (Satria, 2023). In the context of stock market prediction, RNNs can be trained on historical stock price data and other financial indicators to determine future market movements. By analyzing these patterns, RNNs can make predictions about future stock prices, providing valuable insights for investors and traders.

While RNNs have demonstrated their effectiveness in stock market trend prediction, long short-term memory (LSTM) networks have emerged as a more powerful and refined approach. "Long Short-Term Memory (LSTM) is one of many types of Recurrent Neural Network RNN, it's also capable of catching data from past stages and use it for future predictions" (Moghar, 2020) and addresses the vanishing and exploding gradient problems often encountered in traditional RNNs. LSTMs overcome these limitations by incorporating a gating mechanism that controls the flow of data. This allows LSTMs to effectively capture both short-term and long-term dependencies, which can make them optimal for stock market prediction. Compared to other algorithms, "LSTM superiorities include the constant backpropagation of errors in memory cells resulting in the ability of LSTM to bridge long-time lags… [and] LSTM can handle noise, distributed representation, and continuity" (Satria, 2023) in which allows it to perform well in stock market prediction tasks, particularly for long-term trend analysis, hence, the focus of this paper will be to analyze LSTM on predicting future trends as it solves for "time-series problems since they have the ability to identify long-term patterns in sequential data" (Cipiloglu et al., 2022.)

2.2 Data Collection and Preprocessing:

For this project we will utilize the Kaggle dataset 'Huge Stock Market Dataset' created by Boris Marjanovic. This dataset includes High-quality financial data with historical daily price and volume data for all US-based stocks and ETFs trading on the NYSE, NASDAQ, and NYSE MKT. The prices of the stocks have been adjusted for dividends and splits. The dataset includes data for each stock from the company’s beginning up until the date 11/10/2017. For this paper, we will analyze two companies: Apple (AAPL) and Tesla (TSLA).

The dataset is in a comma separated text file following the format: Date, Open, High, Low, Close, Volume, OpenInt. The ‘Date’ column represents the date of the stock market transaction, the ‘Open’ column represents the opening price of the stock on that date, ‘High’ represents the highest price that the stock reached that day, ‘Low’ represents the lowest price reached that day, ‘Close’ represents the closing price of the stock at the end of trading hours on that date, ‘Volume’ represents the number of shares of the stock that were traded that day, and finally, ‘OpenInt’ represents the number of open positions in the stock at the end of the trading day.

Before proceeding with model development, we will prepare the data, a crucial step in ensuring the quality and reliability of the model's predictions. This involves cleaning the data to remove any inconsistencies or outliers, carefully handling missing values to maintain data integrity, and selecting the most relevant features to enhance the model's performance. Additionally, we will set the Date column as the index to establish a temporal sequence for the data, enabling the model to effectively capture the time-dependent patterns inherent in stock price movements.

Prior to model development, we will visualize the historical closing stock price data provided from the Kaggle dataset for TSLA and AAPL stocks. This visual exploration will enable me to identify any patterns, trends, and potential anomalies in the data, providing valuable insights for subsequent modeling steps. Furthermore, we will employ MinMaxScaler to normalize the data, ensuring that all features are scaled within a common range. This normalization is particularly important for Long Short-Term Memory (LSTM) networks, as they are sensitive to the scale of the input data.

Figure 1: Tesla closing price chart.

Figure 2: Apple closing price chart.

2.3 Model Development

To begin, we split the data into training, validation, and test sets. Splitting the dataset into training, validation, and test sets is a "crucial step in building a machine learning model, as it allows for the model to be trained on one set, tuned on another, and evaluated on a final set" (Or, 2023). We will split it into these three categories so that we can use the training set to train the model, the validation set to tune the parameters, and the test set to evaluate the performance. Given that our dataset is quite large, this can benefit from having a higher portion of training data hence, we will split the data to use 80% for training, 20% for validation.

Overfitting and underfitting are prevalent issues in machine learning, and it is crucial to address them to ensure the model's generalizability and performance. Overfitting occurs when the model gets trained with so much data that it ends up starting to "it starts learning from the noise and inaccurate data entries in our data set" (GeeksforGeeks, 2023). Underfitting, on the other hand, occurs when the "model is too simple to capture data complexities… [which will] result in poor performance both on the training and testing data." (GeeksforGeeks, 2023).

To combat overfitting, we have implemented early stopping, a technique that dynamically monitors the model's performance on a validation set during training. If the validation loss ceases to improve over a specified number of epochs, the training process is halted, preventing the model from overfitting. This approach allows the model to learn effectively without becoming too specific to the training data.

To implement early stopping in this context, we have utilized the EarlyStopping callback from the TensorFlow library. This callback takes three main parameters: monitor (the metric to monitor for improvement), patience (the number of epochs to wait for improvement before stopping) and restore_best_weights (whether to restore the model's weights to the best ones obtained during training).

The metric to monitor for improvement to use 'val_loss' to track the validation loss. Patience is set this to 10, indicating that if the validation loss doesn't improve for 10 consecutive epochs, training will cease. Finally, restore_best_weights field is set to True to ensure the model uses the best parameters it encountered during training.

Given the implementation of early stopping, I have set the number of epochs to 500. The early stopping callback will “stop training when a monitored metric has stopped improving” (Keras, n.d.). we have also set the batch size to 64, a common choice for LSTM and it was considered that “network with too large or too low batch size shows a negative effect on the precision of the learning during training as it decreases the stochasticity of the gradient descent” (Kumar et al., 2021). I have also enabled verbose mode, which provides progress updates during training. This allows me to monitor the model's progress and identify any potential issues.

Finally, by enabling early stopping, we ensure that the model doesn't overfit and generalizes well to unseen data. This technique is crucial for building robust and reliable machine learning models.

3. Materials and Data Sources Results

3.1 LSTM Model Analysis - TSLA

After successfully training the LSTM model, we began an analysis of its performance on the TSLA dataset. The initial iteration focused on predicting the stock market based on the closing price. This approach demonstrated the model's ability to capture the overall trend of the stock price movement, evident from the similarity between the original graph and the LSTM-generated forecasts.

```
Root Mean Squared Error (RMSE): 6.662950012883671
Mean Absolute Error (MAE): 5.064947520294601
MAE Percentage: 1.8941639123803904
```

Date	Close	Predictions
2016-05-25	219.58	219.397003
2016-05-26	225.12	220.912888
2016-05-27	223.04	225.915756
2016-05-31	223.23	226.099930
2016-06-01	219.56	225.813934
...	...	...
2017-11-06	302.78	301.955383
2017-11-07	306.05	302.435211
2017-11-08	304.31	305.434601
2017-11-09	302.99	304.074951
2017-11-10	302.99	301.987305

Figure 3: Tesla close price history with predictions and training data.

A closer examination of the generated forecasts revealed minimal outliers, indicating the model's robustness and ability to handle variations in the data. This observation is crucial for real-world applications, where outliers can significantly impact decision-making.

The LSTM model's success in replicating the overall wave pattern of the original graph highlights its capability to learn and adapt to long-term trends in the data. This ability is particularly valuable for long-term financial forecasting, where identifying and understanding long-term trends is paramount.

To further assess the model's performance, we analyzed the error metrics such as mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE). These metrics provide valuable insights into the accuracy of the model's predictions.

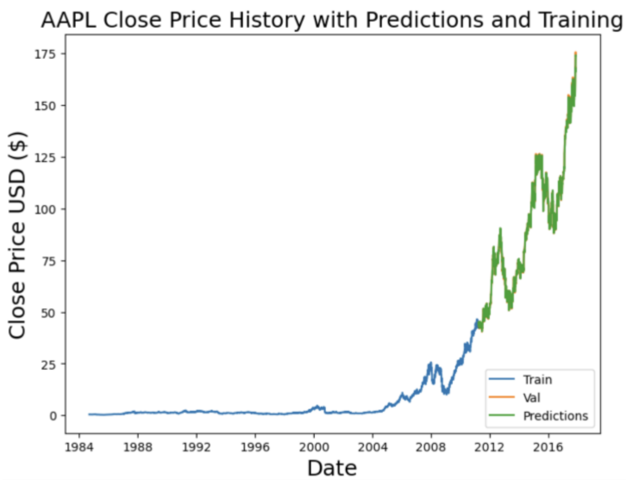
The RMSE and MAE values came in at a relatively low at 6.663 and 5.065, respectively considering that this is for financial predictions. These values indicate that the model's predictions are like the actual values, suggesting its effectiveness in capturing the underlying trends in the data.

MAE Percentage value of 1.89% further reinforces the model's accuracy. This metric implies that, on average, the model's predictions deviate from the actual values by 1.89%. This level of accuracy is generally considered good for financial forecasting, where even small deviations can have significant financial implications.

3.2 LSTM Model Analysis – AAPL

The positive results observed for TSLA were replicated when analyzing the model's performance on AAPL stock data. Analyzing the mean absolute error (MAE), root mean squared error (RMSE), and the mean absolute error (MAE) percentage for AAPL stocks, the RMSE and MAE values seem low at 1.4631 and 1.019 respectively, again indicating that the model is making predictions close to the actual values. The MAE Percentage of 1.17% suggests that, on average, the model's predictions are within 1.17% of the actual values. This consistency across different stock datasets highlights the model's generalizability and its ability to capture the dynamics of stock price movements.

```
Root Mean Squared Error (RMSE): 1.4631446842022033
Mean Absolute Error (MAE): 1.0193831191542044
MAE Percentage: 1.1698628730708927
```



Date	Close	Predictions
2011-03-24	44.179	43.806961
2011-03-25	45.019	44.269783
2011-03-28	44.877	45.067787
2011-03-29	44.945	45.119480
2011-03-30	44.646	45.080814
...	...	...
2017-11-06	173.630	169.765457
2017-11-07	174.180	172.256119
2017-11-08	175.610	173.027084
2017-11-09	175.250	174.108170
2017-11-10	174.670	173.929947

Figure 4: Apple close price history with predictions and training data.

3.3 Predicting Future 30 Day Trends – TSLA

Having established the model's effectiveness in making accurate predictions, the next step in this analysis involves leveraging its capabilities to forecast future stock trends. The model will be tasked with predicting the stock trends for TSLA and AAPL over the next 30 days.

By implementing the models.predict() function, we can generate predictions from the trained machine learning model. For TSLA, the visual representation of the predicted stock prices illustrates the anticipation of a downward movement in the stock price, followed by a gradual recovery.

Figure 5: Tesla close price history with future 30-day trend predictions with table with 3 head and 3 tail of the data points.

3.4 Predicting Future 30 Day Trends – AAPL

Following the same approach employed for TSLA, we now turn our attention to predicting the next 30-day stock trend for AAPL. Utilizing the trained machine learning model and the models.predict() function, we generate predictions for AAPL's stock prices. The model suggests a sharp decline in AAPL's stock price over the next 30 days.

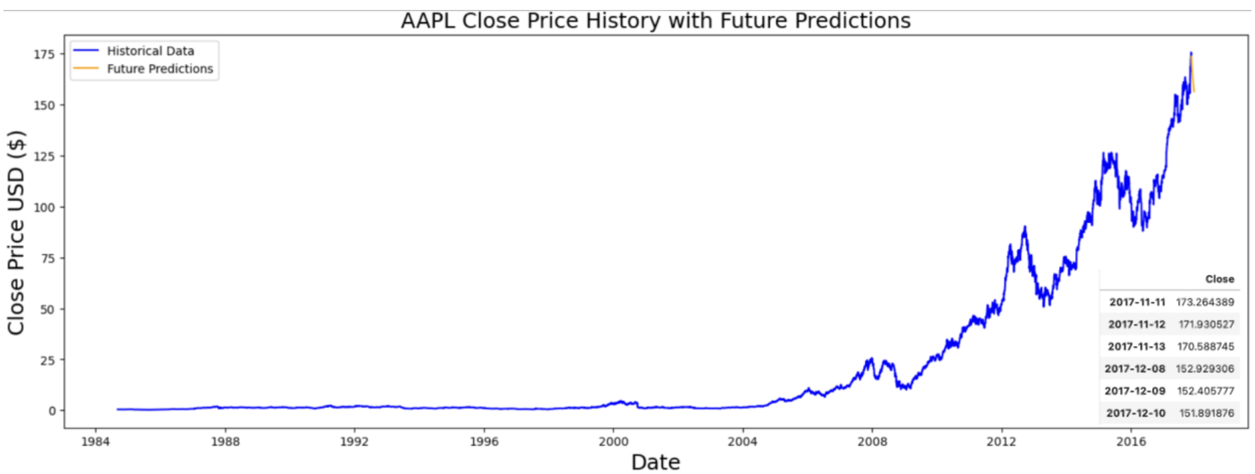


Figure 6: Apple close price history with 30-day trend predictions with table with 3 head and 3 tail of the data points.

These predictions provide valuable insights into the potential future trajectory for TSLA and AAPL stock prices. While the model's predictions cannot guarantee absolute certainty, they can serve as a valuable tool for informed decision-making in the financial realm.

4. Discussions and Conclusion

This paper has demonstrated the effectiveness of using a Long Short-Term Memory (LSTM) model to predict stock prices. By analyzing historical data for TSLA and AAPL stocks, the LSTM model was able to make accurate predictions for both stocks. The model was also able to forecast future trends with a reasonable degree of accuracy.

The results of this study suggest that LSTM models can be a valuable tool for stock market analysis. The ability of LSTM models to capture complex patterns and trends in historical data makes them a powerful resource for investors and financial analysts seeking to make informed decisions. However, of course, it is important to note that stock market forecasting is a complex task and there is no guarantee of accuracy. However, it is evident that LSTM models offer a promising approach that can be used to improve the accuracy of stock market forecasts.

Future research could focus on improving the accuracy of LSTM models by using larger datasets, incorporating additional features, and developing new training algorithms. Additionally, research could be conducted to investigate the use of LSTM models for other financial forecasting tasks, such as forecasting currency exchange. Furthermore, we could further analyze speed as well as "that is an important aspect of the online forecasting" (Wang, 2016). Especially if this model is to be used on live market data, speed would be of essence, some points to consider is that "for intra-day high frequency trading (HFT), the speed of incoming real-time market data is at millisecond level for most stock markets" (Wang, 2016) and that "the model's training or tuning time, on the other hand, is not critical, since those phases can be arranged as an overnight job and finish before the market opens" (Wang, 2016). Extreme learning machine (ELM) has been a new technique and has "reported to have high accuracy and fast prediction speed while solving various real-life problems" (Wang, 2016) and in a future iteration could be implemented to further enhance this study.

In conclusion, this study has shown that LSTM models are a promising tool for stock market analysis. Further research is needed to improve the accuracy of LSTM models and to investigate their use for other financial forecasting tasks. Overall, in this analysis of LSTM's ability on predicting future stock market trends, we discovered that LSTM models can be used to make accurate predictions of stock prices and can be used to forecast future stock trends, making them a promising tool for stock market analysis.

References

Bhandari, H. N., Rimal, B., Pokhrel, N. R., Rimal, R., Dahal, K. R., & Khatri, R. K. C. (2022, May 13). *Predicting stock market index using LSTM*. Machine Learning with Applications. https://www.sciencedirect.com/science/article/pii/S2666827022000378

Brownlee, J. (2019, August 6). *A gentle introduction to early stopping to avoid overtraining neural networks*. MachineLearningMastery.com. https://machinelearningmastery.com/early-stopping-to-avoid-overtraining-neural-network-models/

Cipiloglu Yildiz, Z., & Yildiz, S. B. (2022). A portfolio construction framework using LSTM-based stock markets forecasting. *International Journal of Finance and Economics*, *27*(2), 2356–2366. https://doi.org/10.1002/ijfe.2277

Costa, T. F., & da Cruz, A. R. (n.d.). Stock-Pred: The LSTM Prophet of the Stock Market. In *Optimization, Learning Algorithms and Applications* (pp. 293–308). Springer International Publishing. https://doi.org/10.1007/978-3-031-23236-7_21https://search.lib.utexas.edu/discovery/fulldisplay?docid=cdi_proquest_miscellaneous_29417066&context=PC&vid=01UTAU_INST:SEARCH&lang=en&search_scope=MyInst_and_CI&adaptor=Primo%20Central&tab=Everything&query=any,contains,Decision%20Trees%20stock&offset=0

GeeksforGeeks. (2023, August 31). *ML: Underfitting and overfitting*. GeeksforGeeks. https://www.geeksforgeeks.org/underfitting-and-overfitting-in-machine-learning/

IBM. (n.d.). How SVM works. https://www.ibm.com/docs/en/spss-modeler/saas?topic=models-how-svmworks#:~:text=SVM%20works%20by%20mapping%20data,be%20drawn%20as%20a%20hyperplane.

Ihlayyel, H. A. K., Sharef, N. M., Nazri, M. Z. A., & bakar, A. A. (2018). An enhanced feature representation based on linear regression model for stock market prediction. *Intelligent Data Analysis*, *22*(1), 45–76. https://doi.org/10.3233/IDA-163316

Kara, Y., Acar Boyacioglu, M., & Baykan, Ö. K. (2011). Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul Stock Exchange. *Expert Systems with Applications*, *38*(5), 5311–5319. https://doi.org/10.1016/j.eswa.2010.10.027

Keras. (n.d.). *Keras Documentation: Earlystopping*. https://keras.io/api/callbacks/early_stopping/

Khan, A. H., Shah, A., Ali, A., Shahid, R., Zahid, Z. U., Sharif, M. U., Jan, T., & Zafar, M. H. (2023). A performance comparison of machine learning models for stock market prediction with novel investment strategy. *PloS One*, *18*(9), e0286362–e0286362. https://doi.org/10.1371/journal.pone.0286362

Kumar, K., & Haider, Md. T. U. (2021). Enhanced Prediction of Intra-day Stock Market Using Metaheuristic Optimization on RNN–LSTM Network. *New Generation Computing*, *39*(1), 231–272. https://doi.org/10.1007/s00354-020-00104-0

Lean Yu, L. Y., Huanhuan Chen, H. C., Shouyang Wang, S. W., & Kin Keung Lai, K. K. L. (2009). Evolving Least Squares Support Vector Machines for Stock Market Trend Mining. *IEEE Transactions on Evolutionary Computation*, *13*(1), 87–102. https://doi.org/10.1109/TEVC.2008.928176

Liu, G. S., & Li, T. (2011). Stock Price's Prediction with Decision Tree. *Applied Mechanics and Materials*, *48–49*, 1116–1121. https://doi.org/10.4028/www.scientific.net/AMM.48-49.1116

Loukas, S. (2023, September 18). *LSTM time-series forecasting: Predicting stock prices using an LSTM model*. Medium. https://towardsdatascience.com/lstm-time-series-forecasting-predicting-stock-prices-using-an-lstm-model-6223e9644a2f

Madeeh, O. D., & Abdullah, H. S. (2021). An Efficient Prediction Model based on Machine Learning Techniques for Prediction of the Stock Market. *Journal of Physics. Conference Series*, *1804*(1), 12008-. https://doi.org/10.1088/1742-6596/1804/1/012008

Moghar, A., & Hamiche, M. (2020, April 14). *Stock market prediction using LSTM recurrent neural network*. Procedia Computer Science. https://www.sciencedirect.com/science/article/pii/S1877050920304865

NepTechGuy. (2022). *Stock Market Prediction Using Stacked LSTM*. *YouTube*. Retrieved November 29, 2023, from https://www.youtube.com/watch?v=ozQz_r9yk84&t=86s.

Or, B. (2023, October 14). *On Common Split for Training, Validation, and Test Sets in Machine Learning*. Medium. https://pub.towardsai.net/breaking-the-mold-challenging-the-common-split-for-training-validation-and-test-sets-in-machine-271fd405493d

Pawar, K., Jalem, R.S., Tiwari, V. (2019). Stock Market Price Prediction Using LSTM RNN. In: Rathore, V., Worring, M., Mishra, D., Joshi, A., Maheshwari, S. (eds) Emerging Trends in Expert Applications and Security. Advances in Intelligent Systems and Computing, vol 841. Springer, Singapore. https://doi.org/10.1007/978-981-13-2285-3_58

Raj, A. (2022, August 6). *Everything about support vector classification - above and beyond*. Medium. https://towardsdatascience.com/everything-about-svm-classification-above-and-beyond-cc665bfd993e

Satria, Dias. (2023). PREDICTING BANKING STOCK PRICES USING RNN, LSTM, AND GRU APPROACH. *Applied Computer Science (Lublin)*, *19*(1), 82–94. https://doi.org/10.35784/acs-2023-06

Sharma, P. (2023, September 23). *Stock market prediction using machine learning*. Analytics Vidhya. https://www.analyticsvidhya.com/blog/2021/10/machine-learning-for-stock-market-prediction-with-step-by-step-implementation/

Shetty, N. R., Patnaik, L. M., Nagaraj, H. C., Hamsavath, P. N., & Nalini, N. (2019). Practical Market Indicators for Algorithmic Stock Market Trading: Machine Learning Techniques and Grid Strategy. In *Emerging Research in Computing, Information, Communication and Applications* (Vol. 906, pp. 121–132). Springer Singapore Pte. Limited. https://doi.org/10.1007/978-981-13-6001-5_10

Shiri, Farhad Mortezapour, Perumal, T., Norwati Mustapha, & Raihani Mohamed. (2023). A Comprehensive Overview and Comparative Analysis on Deep Learning Models: CNN, RNN, LSTM, GRU. *ArXiv.Org*. https://doi.org/10.48550/arxiv.2305.17473

Shukla, A., Murthy, B. K., Hasteer, N., & Van Belle, J.-P. (2023). Comparative Analysis of LSTM, Encoder-Decoder and GRU Models for Stock Price Prediction. In *Computational Intelligence* (Vol. 968, pp. 399–410). Springer. https://doi.org/10.1007/978-981-19-7346-8_34

Singh, M., Tyagi, V., Gupta, P. K., Flusser, J., Ören, T., & Sonawane, V. R. (2021). Prediction of Stock Price for Indian Stock Market: A Comparative Study Using LSTM and GRU. In *Advances in Computing and Data Sciences* (Vol. 1441, pp. 292–302). Springer International Publishing AG. https://doi.org/10.1007/978-3-030-88244-0_28’

Titarmare, N., Wazarkar, M., Palkar, P., Alwaria, R., Shetye, A., & Khodiyar, R. (2022). Stock market predictions using linear regression. *AIP Conference Proceedings*, *2424*(1). https://doi.org/10.1063/5.0076964

Vishwas, B. V., & Patel, Ashish. (2020). *Hands-on Time Series Analysis with Python From Basics to Bleeding Edge Techniques / by B V Vishwas, ASHISH PATEL.* (1st ed. 2020.). Apress. https://doi.org/10.1007/978-1-4842-5992-4

Wang, R., Cai, Y., Cao, J., Wang, F., Min, H., & Deng, X. (2016). Empirical analysis: stock market prediction via extreme learning machine. *Neural Computing & Applications*, *27*(1), 67–78. https://doi.org/10.1007/s00521-014-1550-z

Wu, M.-C., Lin, S.-Y., & Lin, C.-H. (2006). An effective application of decision tree to stock trading. *Expert Systems with Applications*, *31*(2), 270–274. https://doi.org/10.1016/j.eswa.2005.09.026

Zhou, F., Zhang, Q., Sornette, D., & Jiang, L. (2019). Cascading logistic regression onto gradient boosted decision trees for forecasting and trading stock indices. *Applied Soft Computing*, *84*, 105747-. https://doi.org/10.1016/j.asoc.2019.105747