

RESEARCH ARTICLE

Systematic Comparison, Evaluation and Identification of Robust Model to Forecast the Closing Price of S&P 500 Financial Sector through Classical and AI-Based Approaches

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Abstract

S&P 500 is the largest and state-of-the-art stock market index in North America, which attracted a wide range of audience. The primary objective of this study is to compare the widely used four stock forecasting approaches: Long Term- Short Term Memory (LSTM), Gated Recurrent Unit, (GRU), Convolutional Neural Network, (CNN) and traditional forecasting approach: Auto- Regressive Integrated Moving Average (ARIMA) to identify the best and more robust forecasting model for daily and weekly closing price on the S&P 500 financial sector. Thus, we developed and compared the performance and quality of these AI-based approaches with baseline traditional ARIMA model using well- defined two statistical metrics, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) as the evaluation criterion. In the scope of our study, we have found that the LSTM outperforms (with more than 15% improvement in RMSE and with more than 30% improvement in MAE compared to ARIMA) 2 out of 3 train/test data splits compared to other proposed deep learning approaches including GRU and traditional ARIMA models with respect to two widely used RMSE and MAE evaluation metrics for daily closing price forecasting in the S&P 500 Financial Sector. Additionally, in the weekly closing price forecasting models, the traditional ARIMA model outperforms all deep learning models on 2 out of 3 train/test data splits with respect to the statistical metric RMSE.

Key Words: LSTM; GRU; CNN; ARIMA; S&P 500; Prediction; Time series forecasting; Deep learning

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1. Introduction

Financial markets are one of the greatest innovations in the modern world which plays a significant role in the economy of a country. The main objective of the financial markets is to facilitate smooth operations by allocating resources and converting financial assets into cash for businesses and entrepreneurs. Thus, financial markets behave as an interface for the interaction between people who have money to buy financial assets and people who need money to support and improve or maintain their financial assets for a better future [1,2]. The following Figure 1 illustrates the four major financial markets around the globe among others.

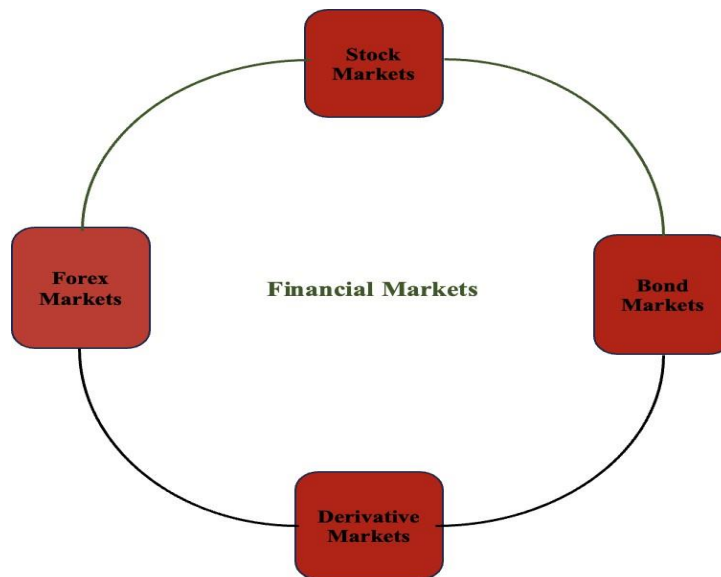


Figure 1: Major financial markets around the globe.

Stock market indexes are state of art in financial markets and most of the people around the world have been influenced. Also, it has been used to gauge the economy of the country [3]. However, there are two primary objectives of the stock market indexes that help companies to raise their capital by publicly offering shares for sale which leads to the expansion of the business and secondly, financial markets allow investors an opportunity to have a share from the profit of the company, earn income through dividends, earn profit through capital gains, etc. Nasdaq, Standard and Poor's 500 (or S&P 500 or Fortune 500), and Dow Jones are the major stock market indexes which are based in the U.S. For instance, the S&P 500 index is a market capitalization-weighted index that tracks down the movements of the stock prices and key performing factors of the 500 largest publicly traded companies in the United States. As of September 2023, the S&P. 500 indexes have traded 503 individual stocks within the index and each of these individual stocks belongs to one of the eleven business segments of the S&P 500. The following Figure 2 graphically illustrates the sector breakdown of the S&P 500 index concerning their representative weights on the S&P 500 index.

Financial market practitioners, researchers, and investors have been working on stock market indexes to get a better understanding of the underlying behavior of their stock of interest. Some of the technical analysis, forecasting of the stock prices, and related works can be found in the literature [4-6]. However, in real-world situations, it is very difficult to analyze the behavior of the stock market because of its inherited uncertainty behavior, sensitivity towards political and economic decisions, and company- specific variables [7,8].

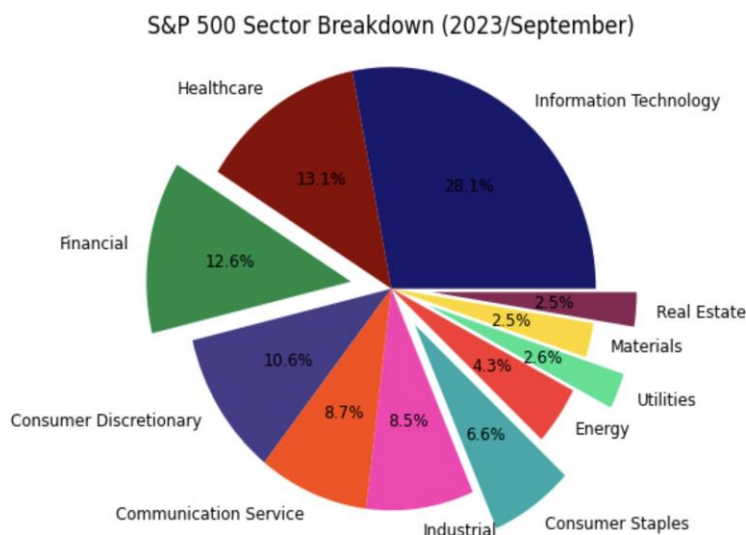


Figure 2: Sector breakdown of S&P 500 index concerning their representative weights on S&P 500 index.

Financial Sector is the 3rd largest sector in the S&P 500 index which is accountable for 12.6% out of the total weight of the entire S&P 500 index as shown in Figure 2. The Financial sector of the S&P 500 consists of major financial institutions such as Banks, Credit Unions, Insurance Companies, Credit Card Companies, etc. Moreover, it plays a major role in the economy as well as day-to-day life. So, the Financial Sector of the S&P 500 provides a significant impact on society. Thus, in our recent developments on the S&P 500, we have selected the Financial Sector of the S&P 500 and developed a real data-driven analytical model [9]. Then we utilized surface response analysis along with the desirability function to optimize the Financial and Economic indicators that we found in the literature [10]. After a systematic review of the literature on the subject area, we strongly believe that it is significantly important to analyze the behavior of the S&P 500 Financial Sector. After analyzing the S&P 500 Financial Sector, we believe that this will have a significant impact on the stock market practitioners and for the community to make their next move strategically.

Forecasting S&P Financial Sector has significant importance to the stock market practitioners and researchers have adopted various existing methodologies to forecast stock prices of the S&P 500 Financial Sector [11,12]. Thus, identifying the best-performing forecasting model for a specific time window (daily or weekly) has a significant importance to financial market practitioners. Hence, within the context of this paper, we develop forecasting models using AI-based models along with traditional ARIMA models for weekly closing prices and daily closing prices. Then, we would compare the performance of the proposed models using well-defined statistical metrics to identify the best model to forecast daily closing prices as well as weekly closing prices. To fulfill the primary objective of this study we used the standard ARIMA method and AI-based deep learning methods such as Long Term-Short Term Memory (LSTM), Recurrent Gated Unit (GRU) and Convolutional Neural Network (CNN) which were trained on the same training set and test set of the same data set of the S&P 500 Financial sector Daily Closing Price. Then, we compared the performance of the proposed models to identify the most suitable forecasting model for the S&P 500 Financial Sector Daily Closing Price and Weekly Closing Price using well-defined statistical metrics RMSE and MAE. The rest of our study has been organized in the following way, Section 2 discusses the data and its characteristics through exploratory data analysis. Then Section 3 briefly introduces the

traditional and artificial intelligence-based methodologies that were utilized for time series forecasting in this study. Section 4 illustrates and compares the results of the proposed forecasting models based on well-defined statistical metrics. Finally, Section 5 discusses and presents the summary along with concluding remarks.

2. Explanatory Data Analysis

The main objective of this paper is to identify the robust model that forecasts the S&P 500 financial sector's daily closing price with a high degree of accuracy. Thus, we obtained the daily closing price and weekly closing price of the S&P 500 Financial sector from January 4th 2010 to November 11th 2023 and January 1st 2000 to July 22nd 2024 respectively from Yahoo Finance [13]. So, our daily data consists of 3483 observations in total for the daily closing price and 1282 observations for the weekly closing price. The behavior of the daily and weekly closing price with respect to time are graphically illustrated in the following Figure 3 and Figure 4 respectively.

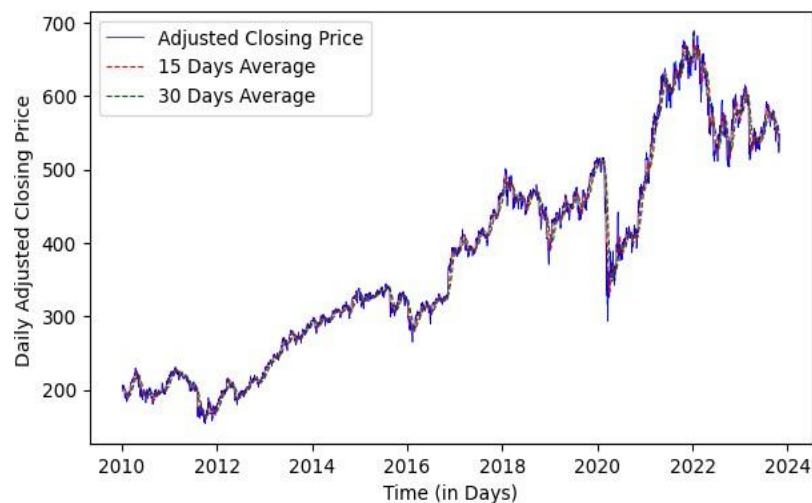


Figure 3: Behavior of daily closing price of S&P 500 financial sector.

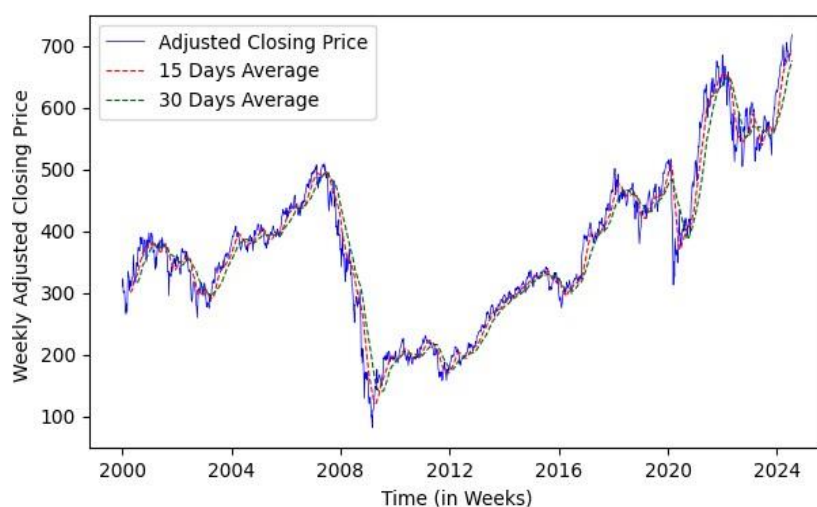


Figure 4: Behavior of weekly closing price of S&P 500 financial sector.

At this point, it is very important to identify systematic and unsystematic components of our time series data. Decomposition can be used to identify the systematic, unsystematic components, and hidden components of the time series, and that will help us to get an understanding of the complexity of our data and do better analysis of the data utilizing different best-fitted approaches to the problem of interest [14,15]. Thus, we have decomposed our time series data into three major components: Trend, Seasonality, and Noise (or random) and Figure 5 is showing the decomposition of daily closing price as a reference. According to the decomposition, it is evident that the data that we are interested in is consistent with only the systematic component which is the upward trend over time.

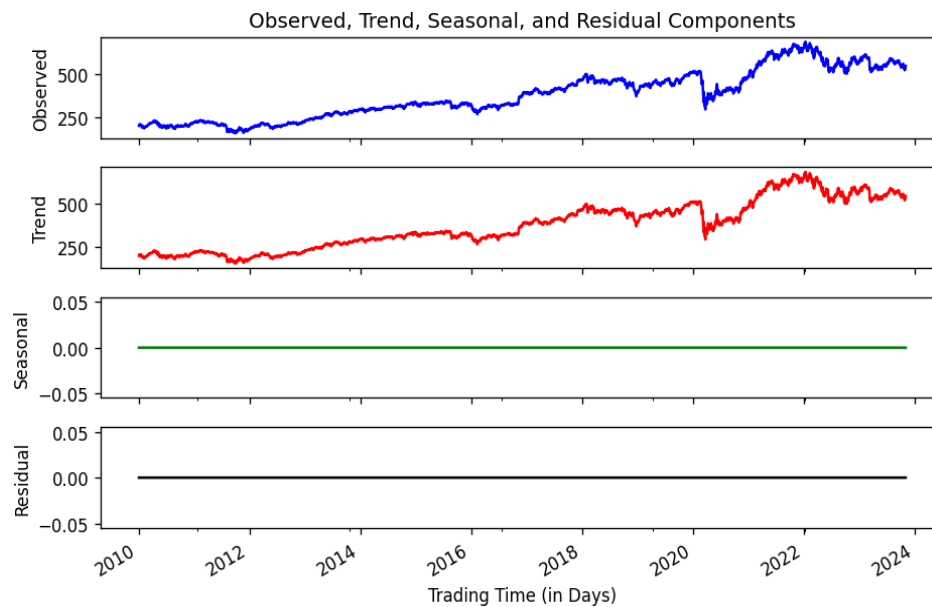


Figure 5: *Decomposition of the daily closing price of S&P 500 financial sector.*

Next, we further dug and checked the behavior of the statistical properties of the data over time because traditional time series approaches like Auto-Regressive Integrated Moving Average (ARIMA) models need stationary data to perform well. The above Figure 5 shows an upward trend over time which is evident in the nonstationary behavior of the daily closing price of the S&P 500 Financial sector. Also, the non-stationary behavior of the data is confirmed by utilizing a well-defined Augmented Dickey-Fuller Test (ADF) results given in Table 1.

Table 1: *Results of the ADF test.*

Number of Observation	Test-parameter	P-value
3483	-1.7826	0.3891

Furthermore, the non-stationary behavior of the daily closing price of the S&P 500 Financial sector is examined using the Partial Auto Correlation Plot (PACF), and Auto Correlation Plot (ACF) given by Figure 6 below.

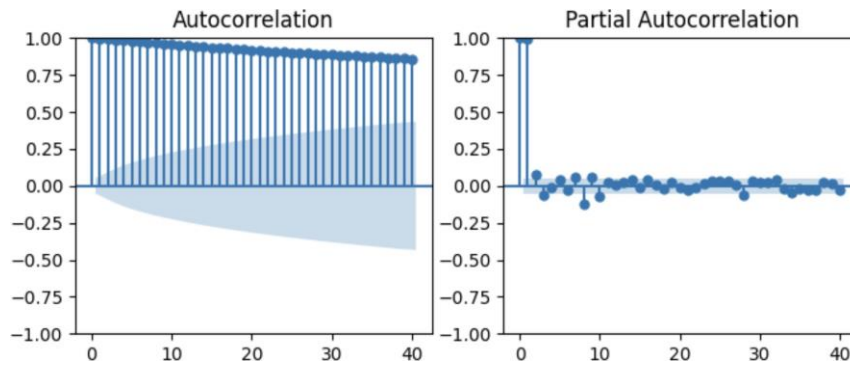


Figure 6: ACF and PACF of observed daily closing price of S&P 500 financial sector.

However, we can perform the first-order differencing on the time series observations to make our observations stationary. The following Figure 7 graphically illustrates the behavior of the time series before and after performing the first-order differencing for the weekly closing price from 2009 as a reference.

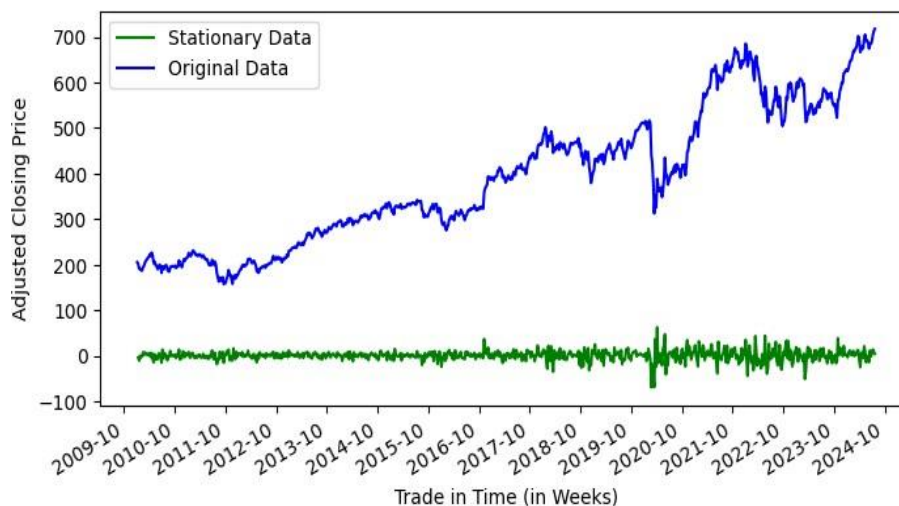


Figure 7: Stationary weekly closing prices vs weekly observed closing price of S&P 500 financial sector.

3. Problem Definition and Methodologies

The main objective of this study is to forecast the S&P 500 Financial Sector's daily and weekly closing prices with high accuracy (i.e., with minimum possible deviation from the actual closing price). Thus, we have utilized the well-known time series forecasting methodologies through traditional and deep learning approaches. So, the Auto-Regressive Integrated Moving Average (ARIMA) from the traditional method is selected and used as the baseline for our forecasting. Then we evaluated the performance of the modern AI-based methodologies compared to the baseline. Thus, the Long Term-Short short-term memory (LSTM) from recurrent neural networks, Gated Recurrent Unit (GRU), and finally, Convolutional Neural Network (CNN) are utilized as state of art AI-based methodologies. The following section briefly discusses the basic underlying concepts of the above-mentioned traditional and artificial intelligence-based approaches.

3.1. Long Term-Short Term Memory (LSTM)

Long Short-Term Memory (LSTM) Recurrent Neural Network was first introduced by Sepp Hochreiter in 1997 [16]. This novel method addressed the weakness of exploding or vanishing gradient of the traditional Recurrent Neural Networks concerning long sequence data [17,18]. Thus, LSTM is successfully applied in subject areas such as handwriting recognition [19], speech recognition [20], machine translation [21], time series forecasting on social media activities [22], Health Sciences [23], etc. with the long sequential data since the LSTM is capable of learning long sequential data. When it comes to the structure of the LSTM unit it consists of three gates namely, an input gate, an output gate, a forget gate, and two recurrent features, the hidden state (denoted by h) and the cell state (denoted by C). The information flow in and out of these recurrent features is controlled by those three gates and a graphical illustration of the LSTM unit is given by Figure 8. Further details on how to train the LSTM and identify the optimal parameters for the LSTM and applications on finance can be found in the literature, [24-27].

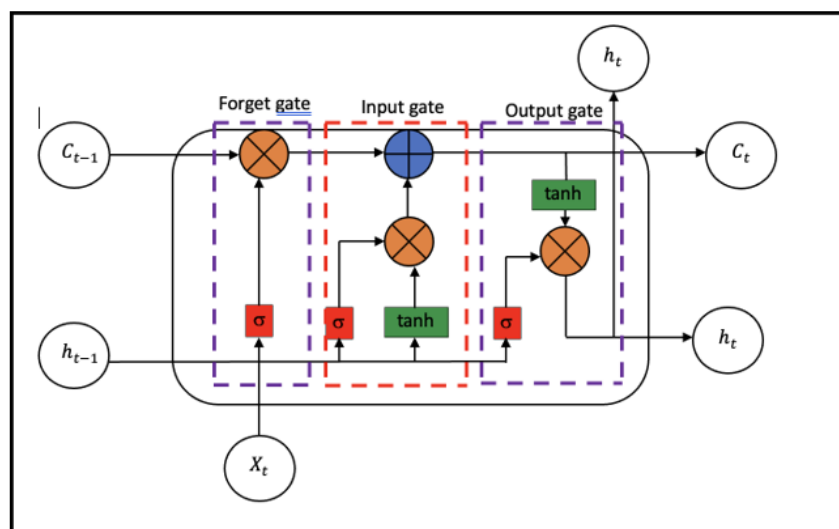


Figure 8: Graphical visualization of the LSTM unit.

3.2. Gated Recurrent Unit (GRU)

The Gated Recurrent Unit (GRU) can be identified as the youngest sibling of the LSTM which was proposed by Kyunghyun Cho et al in 2014. However, GRU consists of only two gates, one is called the update gate which is a combination of the input gate and forget gate of the LSTM unit and the second one is the reset gate [28,29]. Researchers are more into GRU over LSTM because it requires less memory and is computationally faster compared to LSTM, but LSTM outperforms GRU for the data with longer sequences [30]. The following Figure graphically illustrates the underlying idea of the GRU unit and related information on how to train and how the computation part works for the GRU and its real-world application can be found in the literature [31-33]. Figure 9 graphically illustrates the mechanism of the GRU unit.

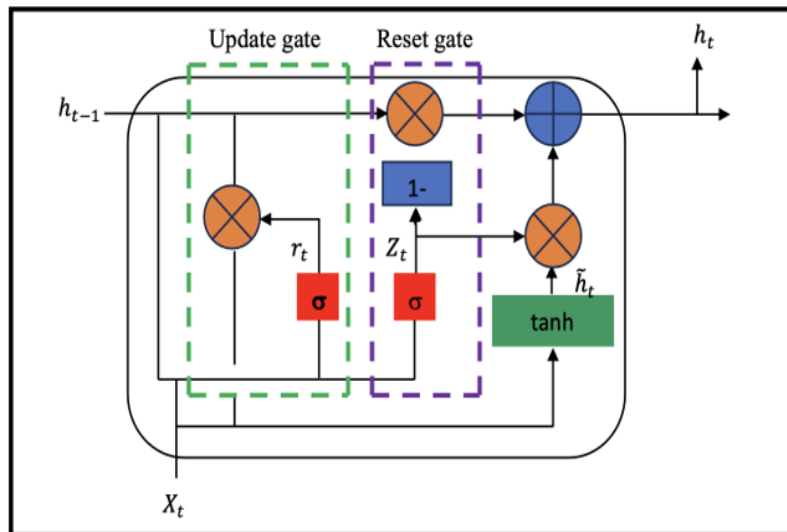


Figure 9: Graphical visualization of GRU unit.

3.3. Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) model is a widely adopted feed-forward neural network type that is used to achieve high performance on modeling tasks related to image processing. For the first time, the CNN model was successfully proposed by Lucan, et al. [34]. In CNN every convolutional layer is consistent with two major layers; a convolutional layer followed by a pooling layer. The convolutional layer has the responsibility to identify the most important features from the data while the pooling layer is responsible for summarizing and gathering the most prominent features in the same neighborhood before feeding them to the dense layer. The broader illustration of how CNN works and the computations that are performed by each of the layers can be found in the literature [35,36]. The following Figure 10 graphically illustrates the architecture of the basic CNN with only one convolutional layer. The CNN has been successfully implemented in time series forecasting and some of the significant works can be found in the literature [37-40].

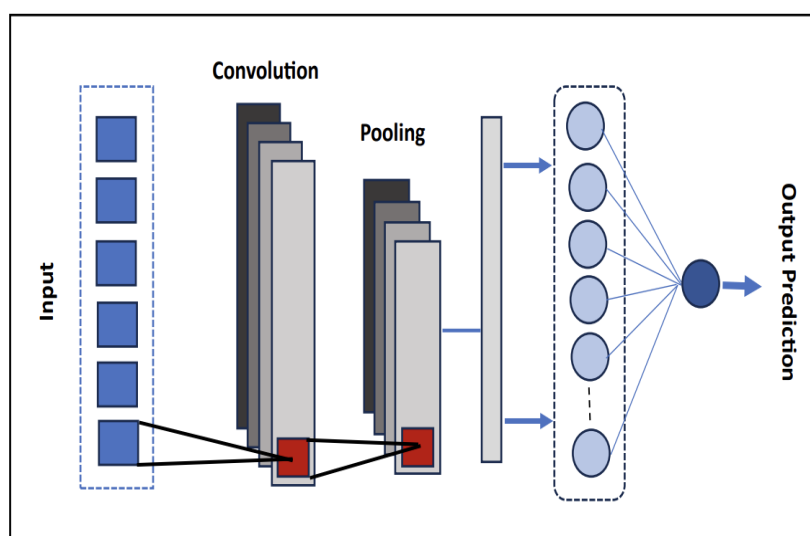


Figure 10: Graphical visualization of CNN.

4. Results, Comparison, and Evaluation

In this study, we have trained 3 well-known deep learning-based models, LSTM, GRU, and CNN to forecast the S&P 500 Financial Sector's closing price (Daily and Weekly). Then the performance of the proposed deep learning models is compared with the baseline time series forecasting model, ARIMA.

4.1. Experimental setup

In the process of developing proposed deep learning models, it is crucial to partition data into training/ validation/ testing. Thus, primarily we consider three cases for Training, Validation, and Test data splitting which are the most widely adopted data split standards in the field. Split 1: 80%/10%/10%, Split 2: 70%/20%/10%, and Split 3: 60%/20%/20%. The following Figure 11 graphically illustrates the data splitting approaches that we have utilized to develop the proposed models with daily closing prices.

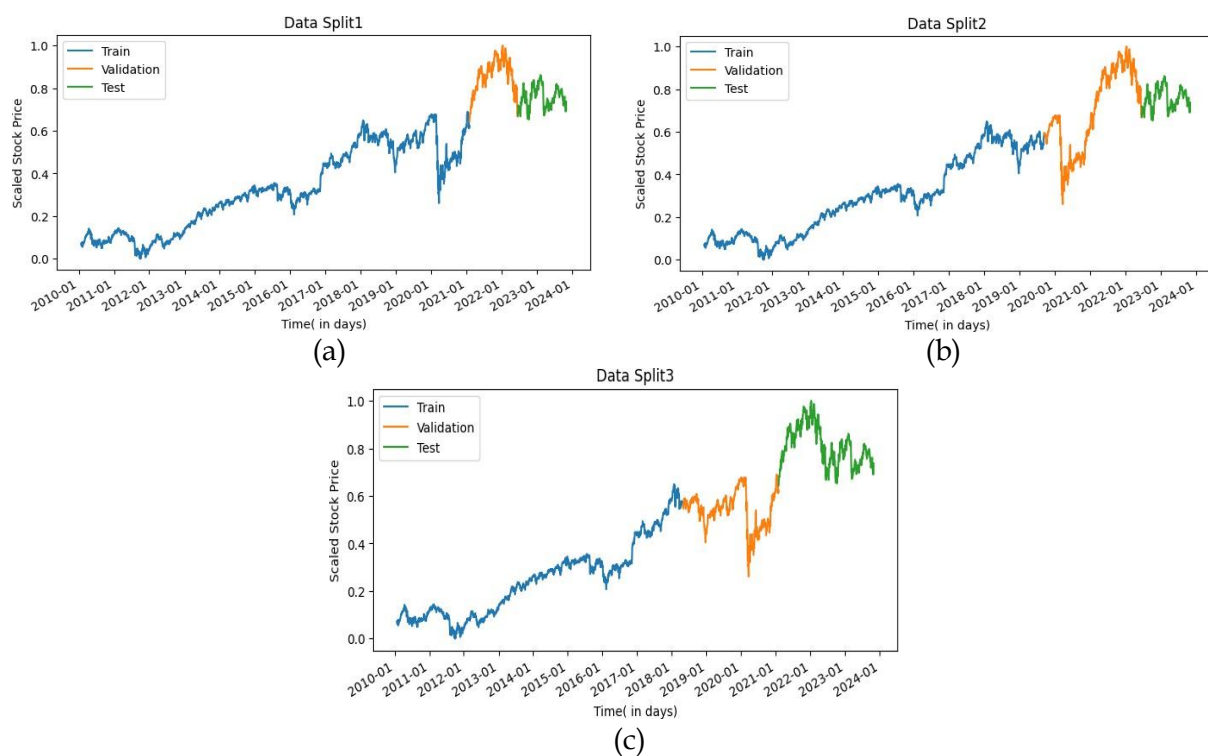


Figure 11 (a), (b) and (c): Data split for daily closing prices (Train/ Validation/ Test).

The individual Recurrent Neural Network (RNN), LSTM, and GRU models consist of only one RNN layer followed by a dense layer to produce prediction observations. An individual CNN model includes a convolution layer, a max pooling layer, and a flattened layer followed by a fully connected layer. Adam was used as an optimizer for all the above- proposed models because of its significant performance enhancements [41]. Furthermore, each model has been trained for 200 epochs considering Mean Squared Error (MSE) as the loss function. Finally, we have identified the best-performed hyperparameters throughout the process of hyperparameter tuning using kerastuner [42]. More specifically we have tuned three hyperparameters, called, the number of units per layer from 1 to 30 for recurrent networks and choice of (32, 64, 128) for CNN, learning rate starting from 1×10^{-4} for all models, batch

size choices from (16, 32, 64, 128). Furthermore, L2 regularization and an early stopping criterion have been implemented to prevent overfitting of the proposed deep learning models and choices for the L2 regularization parameter are from the interval between 1×10^{-4} and 1×10^{-1} [43,44]. Forecasting models for daily closing prices were trained using a 15-day look-back window and for weekly closing prices, we used a 12-week look-back window. Note that all of our proposed model architectures have the number of parameters that are less than the number of training examples. ARIMA model was used as the baseline model to compare with the proposed deep learning models. In the process of building the ARIMA model, we utilized the same data split that was used for the Deep learning models. However, we have converted it into a stationary time series by using first-order differencing as shown in Figure 7 and used the ARIMA (p,1, q) model. For the values of p and q, we have selected the values between 1 to 3. Then the best values for two parameters: p and q have been identified based on the minimum values of AIC and BIC.

4.2. Evaluation Metric

Finally, to evaluate the proposed models we have employed two well-defined statistical methods: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

4.2.1. Root Mean Squared Error (RMSE)

Root Mean Squared Error (RMSE) is a widely used statistical metric to assess the quality of a model. It identifies the square root of the mean of the squared deviation of the predicted values from its original state and its analytical form is given by the following Equation 1,

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Y_{true} - Y_{pred})^2}{n}} \quad (1)$$

where n is the total number of observations, Y_{true} is true value of the i^{th} observation while \hat{Y}_{pred} is the predicted/forecasted value of the i^{th} observation.

4.2.2. Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is one of the most widely adopted statistical metrics in the field of machine learning and other fields to ensure the quality of a model. The following Equation 2 gives the analytical form of the MAE,

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left[\frac{|Y_{true} - \hat{Y}_{pred}|}{|Y_{true}|} \right] \quad (2)$$

where Y_{true} is the i^{th} observation value, \hat{Y}_{pred} is the i^{th} estimated value using the proposed model, and n is the sample size.

4.3. Results and Model Comparison

We have trained RNN-based models (LSTM, GRU) and CNN, to identify the best-performing hyperparameters giving the minimum possible errors (RMSE and MAE) for each AI model and ARIMA by utilizing the mentioned train data splits and calculated proposed evaluation statistical metrics for test data of each data split for both daily closing price and weekly closing price. For instance, the following Figure 12 (a.LSTM, b.GRU, c.CNN) graphically illustrates

the behavior of the training and validation error for all three AI-based models for train/test split 1.

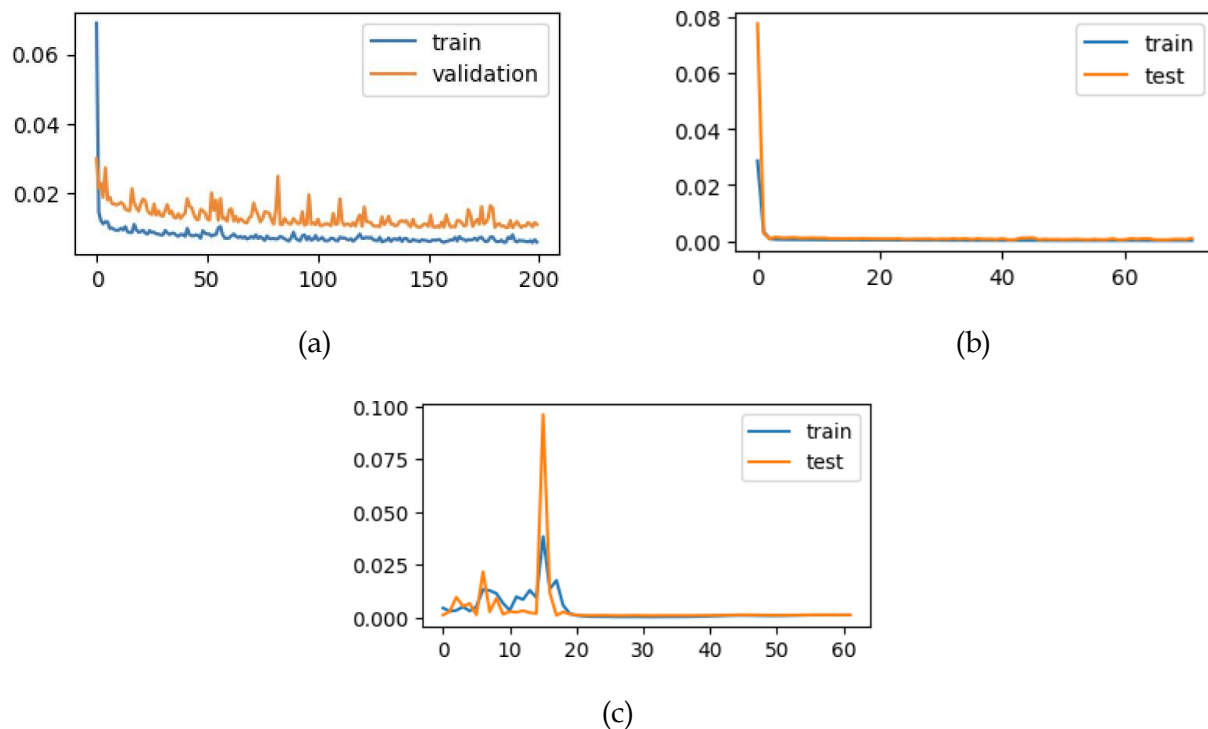


Figure 12 (a), (b) and (c): Behavior of Training vs Validation for train/test split 1.

In the above Figure 12 all three models did not indicate any overfitting or under-fitting of the training and validation data. Thus, it illustrates the high quality of our training process and it has identified the hyperparameters for each of the models for the train/ test split 1 (for LSTM, number of units 7, regularization parameter 0.00695, batch size 64, learning rate 0.0117, for GRU number of units 16, regularization parameter 0.000515, batch size 128, learning rate 0.00583, for CNN filters 32, regularization parameter 0.000172, batch size 128, learning rate 0.00132). The computed evaluation metric values for test data of each split are reported in the following Table 2 and Table 3 for daily and weekly data, respectively. According to the daily closing price forecast evaluation metrics, given by Table 2, we observe that RNN-based models outperform the CNN model and baseline ARIMA for all three data splitting cases concerning statistical metrics RMSE and MAE. For instance, in

Table 2: Results of the model performance on the test data of daily losing price (15-day window).

Model	RMSE			MAE		
	Split1	Split2	Split3	Split1	Split2	Split3
LSTM	7.27	7.28	9.08	5.68	5.63	7.39
GRU	7.54	6.91	9.43	5.82	5.26	7.68
CNN	12.66	11.66	14.89	9.75	9.14	10.99
ARIMA	10.29	8.64	16.54	10.29	8.64	14.19

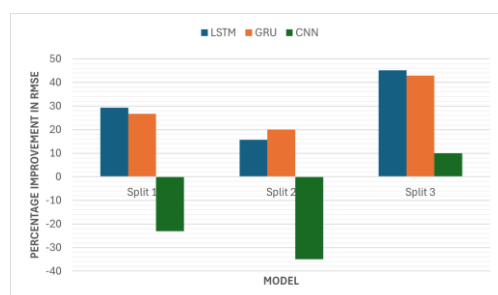
Table 3: Results of the model performance on the test data of weekly closing price (12-week window).

Model	RMSE			MAE		
	Split1	Split2	Split3	Split1	Split2	Split3
LSTM	17.26	22.89	22.94	13.03	19.28	17.59
GRU	20.52	19.22	18.68	17.25	14.44	14.49
CNN	46.04	31.68	32.23	39.46	27.12	23.98
ARIMA	16.90	13.23	21.70	16.90	13.23	17.18

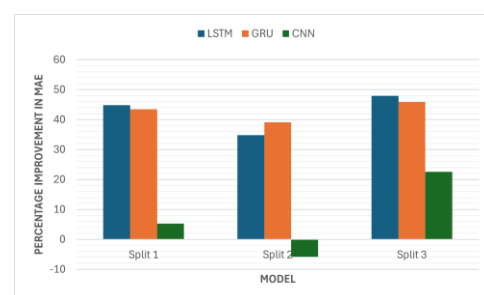
Split 3, the LSTM model achieved more than 47% improvement over the MAE statistical metric compared to the baseline model and it keeps performing at a very high level of improvement compared to the baseline model assessment. Also, according to Table 2 it is evident that the performance of LSTM and GRU are close to each other concerning statistical metrics RMSE and MAE. However, the CNN model showed poor performance compared to RNN-based models. Additionally, we observe that the weekly closing price forecasting evaluation metric, given by Table 3, behaved in contrast to the model behavior of daily closing price forecasting. The RNN-based models: LSTM and GRU outperform the CNN model drastically. However, they fail to outperform the baseline ARIMA model most of the time. All data splits show that the ARIMA model has the highest performance for most of the data splits concerning statistical metrics RMSE and MAE, except MAE in data split 1. Furthermore, the baseline ARIMA model outperforms the CNN-based forecasting model in all three data splits.

5. Summary and Discussion

We have developed and trained widely adopted RNN-based models: LSTM GRU and CNN-based model along with the traditional ARIMA model considering it as the baseline performance model in section 4. From Table 2 we were able to extract very important information as given by the following Figure 13, which reports the percentage improvements of the proposed deep learning models for forecasting the daily closing price of the S&P 500 Financial Sector. It is evident that RNN-based models perform with nearly 50% improvements on both RMSE and MAE evaluation metrics for Split 3, nearly 30% for Split 1, and nearly 20% for Split 2 when forecasting the daily closing price of the S&P 500 Financial Sector compared to its baseline model ARIMA. Also, with the MAE evaluation metric RNN-based models perform with over 30% improvements for all three data splitting procedures of daily closing price as shown in Figure 13 b.



(a)



(b)

Figure 13 (a) and (b): Comparison of percentage improvements of RMSE and MAE metrics on daily closing prices.

In Figure 14 it is evident that most of the models fail to outperform the baseline ARIMA model with respect to RMSE and MAE evaluation metrics. For instance, compared to the baseline ARIMA model, the performance of the CNN-based models shows poor performance in the context of three types of data splits.



Figure 14 (a) and (b): Comparison of percentage improvements of RMSE and MAE metrics on weekly closing prices.

According to the performance reported in Table 2 and Table 3 given in the previous section, the CNN models illustrate poor performance based on the RMSE and MAE while the LSTM and ARIMA models always outperform the CNN model. Thus, according to our study, it is wise to stay away from the CNN models when forecasting the closing price of the S&P 500 Financial Sector because of its poor performance, complexity, and time-consuming training procedure.

6. Conclusion

Our experimental evaluation illustrates the following very useful and important facts when forecasting the closing price of the S&P 500 Financial Sector weekly or daily basis. The RNN-based models: LSTM and GRU are highly driven by the number of observations in the study. Thus, it is wise to use recurrent neural networks specifically LSTM to forecast the daily closing price of the S&P 500 Financial Sector because according to our study, LSTM outperforms all three data Splits with respect to two evaluation metrics compared to the baseline ARIMA. However, when it comes to forecasting the weekly closing price of the S&P 500 the traditional ARIMA model performs well in 2 out of 3 data splits concerning the RMSE evaluation metric. We plan to develop a methodology to identify a forecasting model to forecast the closing price of the S&P 500 with as much as minimizing the uncertainty of the forecasting price in our future work.

References

1. Shah D, Isah H, Zulkernine F. Stock market analysis: a review and taxonomy of prediction techniques. *Int J Financ Stud*. 2019;7:1-22.
2. <https://www.wallstreetmojo.com/financial-market>.
3. Swensen J. Investigating use of beta coefficients for stock predictions. Honors Research Projects, Ohio, USA. 2015;1-15.

4. Fama EF. Random walks in stock market prices. *Financ Anal J.* 1995;51:75-80.
5. Arevalo R, Garcia J, Guijarro F, et al. A dynamic trading rule based on filtered flag pattern recognition for stock market price forecasting. *Expert Systems with Applications.* 2017;81:177-92.
6. Bini BS, Mathew T. Clustering and regression techniques for stock prediction. *Procedia Technology.* 2016;24:1248-55.
7. Abu-Mostafa YS, Atiya AF. Introduction to financial forecasting. *Applied Intelligence.* 1996;6:205-213.
8. Zhong X, Enke D. Forecasting daily stock market return using dimensionality reduction. *Expert Systems with Applications.* 2017;67:126-39.
9. Iluppangama M, Tsokos CP, Abeywardana GD. A real data-driven stochastic analytical model that predicts weekly closing price of the financial sector of the S&P 500. under review.
10. Iluppangama M, Abeywardana GD, Tsokos CP. Identifying the values of the indicators that will maximize the weekly closing price of the financial sector of the S&P 500. under review.
11. Shah D, Isah H, Zulkernine F. Stock market analysis: a review and taxonomy of prediction techniques. *Int J Financial Stud.* 2019;7:1-22.
12. Siami-Namini S, Tavakoli N, Namin AS. A comparison of arima and LSTM in forecasting time series. 17th IEEE International Conference on Machine Learning and Applications, USA. 2018.
13. <https://finance.yahoo.com/quote/%5ESP500-40/history/>
14. Dudek G. Std: a seasonal-trend-dispersion decomposition of time series. *IEEE Trans on Knowl and Data Eng.* 2023;35:10339-50.
15. Dokumentov A, Hyndman RJ. STR: Seasonal-trend decomposition using regression. 2022;1:50-62.
16. Hochreiter S, Schmidhuber J. Long Short-Term Memory. *Neural Computation.* 1997;9:1735-80.
17. Staudemeyer RC, Morris ER. Understanding LSTM - a tutorial into long short-term memory recurrent neural networks. *ArXiv Prepr.* 2019:1-42.
18. Sherstinsky A. Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. *Physica D: Nonlinear Phenomena.* 2020;404:132306
19. Paul IJL, Sasirekha S, Vishnu DR, et al. Recognition of handwritten text using long short-term memory (LSTM) recurrent neural network (RNN). *AIP Conf Proc.* 2019;2095:030011.

20. Oruh J, Viriri S, Adegun A. Long short-term memory recurrent neural network for automatic speech recognition. *IEEE Access*. 2022;10:30069-79.
21. Ren B. The use of machine translation algorithm based on residual and LSTM neural network in translation teaching. *PLOS ONE*. 2020;15:1-16.
22. NGK Wai, Horawalavithana S, Iamitchi A. Forecasting topic activity with exogenous and endogenous information signals in twitter. *Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, USA*. 2022.
23. Pham TD. Time-frequency time-space LSTM for robust classification of physiological signals. *Scientific Reports*. 2021;11:6936.
24. H Dhake, Y Kashyap, P Kosmopoulos. Algorithms for hyperparameter tuning of LSTMs for time series forecasting. *Remote Sensing*. 2023;15:2076.
25. Bala R, Singh RP. Financial and non-stationary time series forecasting using LSTM recurrent neural network for short and long horizon. *10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), India*. 2019.
26. Li S, Luo R, Zhang W, et al. Preprocessing method for industrial data based on LSTM model prediction. *10th International Conference on Information Systems and Computing Technology, China*. 2022.
27. Yao S, Luo L, Peng H. High-frequency stock trend forecast using LSTM model. *13th International Conference on Computer Science & Education, Sri Lanka*. 2018.
28. <https://www.analyticsvidhya.com/blog/2021/03/introduction-to-gated-recurrent-unit-gru/>
29. Cho K, Van Merriënboer B, Gulcehre C, et al. Learning phrase representations using RNN encoder-decoder for statistical machine translation. *ArXiv Prepr*. 2014;1-15.
30. Cahuantzi R, Chen X, Guttel S. A comparison of LSTM and GRU networks for learning symbolic sequences. *ArXiv Prepr*. 2023:771-85.
31. Darmawan H, Yuliana M, Hadi MZS. GRU and XGBOOST performance with hyperparameter tuning using GridSearchCV and Bayesian optimization on an IOT-based weather prediction system. *Int J Adv Sci Eng Inf Techno*. 2023;13:851-62.
32. Liu Y, Wang Z, Zheng B. Application of regularized GRU-LSTM model in stock price prediction. *IEEE 5th International Conference on Computer and Communications, China*. 2019.
33. Zhao R, Wang D, Yan R, et al. Machine health monitoring using local feature-based gated recurrent unit networks. *IEEE Transactions on Industrial Electronics*. 2018;65:1539-48.
34. Lecun Y, Bottou L, Bengio Y, et al. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*. 1998;86:2278-2324.

35. Alzubaidi L, Zhang J, Humaidi A, et al. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *J Big Data*. 2021;8:1-74.
36. <https://www.analyticsvidhya.com/convolutional-neural-networks-cnn/>
37. Mehtab S, Sen J, Dasgupta S. Robust analysis of stock price time series using CNN and LSTM-based deep learning models. 4th International Conference on Electronics, Communication and Aerospace Technology, India. 2020.
38. Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. *Communication of the ACM*. 2017;60:84-90.
39. Deng J, Dong W, Socher R, et al. ImageNet: a large-scale hierarchical image database. *IEEE Conference on Computer Vision and Pattern Recognition, USA*. 2009.
40. Wibawa AP, Utama ABP, Elmunsyah H, et al. Time-series analysis with smoothed convolutional neural network. *J Big Data*. 2022;9:44.
41. Kingma DP, Ba J. Adam: a method for stochastic optimization. *ArXiv*. 2017;6980:1-15.
42. Joshi S, Owens JA, Shah S, et al. Analysis of preprocessing techniques, keras tuner, and transfer learning on cloud street image data. *IEEE International Conference on Big Data, USA*. 2021.
43. Kandel I, Castelli M. The effect of batch size on the generalizability of the convolutional neural networks on a histopathology dataset. *ICT Express*. 2020;6:312-15.
44. Pienaar SW, Malekian R. Human activity recognition using LSTM-RNN deep neural network architecture. *IEEE 2nd wireless Africa conference, South Africa*. 2019.