

Evaluation of the machine learning and deep learning models for forecasting the Indian stock market

Jitendrakumar Rameshbhai Patel^{1*}, Dr. Jigar Ashokkumar Soni²

^{1*}Ph.D. Scholar, Sankalchand Patel University, Visnagar.

Email: jrpatel591987@gmail.com

²Assistant Professor Sankalchand Patel University, Visnagar.

Email: jasoniict_spc@spu.ac.in

Abstract

Stock market trading is one of the most integral financial transactions as it affects the economy. The stock market is extremely volatile and unpredictable, and using precise forecasting models seems to be the only way for investors to mitigate risk and maximise profits. Attaining complete accuracy in forecasting market trends is still a challenge, in spite of continuous efforts. However, in the past few years, the research on the development of data-driven models to enhance the accuracy of stock price forecasting has become a critical development, which has led to the development of Machine Learning (ML) and Deep Learning (DL) techniques.

In this research, we have trained six different algorithms to predict the share prices of 11 highly successful companies in India, such as Support Vector Regression (SVR), Random Forest (RF), XGBoost, Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) [4]. This study, it is based on the literature data for 5 years, which includes all the data of the stock market. The paper gives a brief summary of the technique, which includes the data pretreatment technique, the model development, as well as performance evaluation metrics.

In this study, the two standard and data-driven methods to predict the stock market have been examined, and they have gained popularity in recent years' stock market prediction studies. The implementation and the training of the model procedure are explained in detail and in a step-by-step fashion, and a comprehensive comparison of the selected algorithms is provided. The outcome of such techniques as the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) [16] outperform ordinary machine learning techniques in terms of accuracy and predictive performance. The number of acceptances is described in tabular form and graphically.

Index Terms: Stock market prediction, Time series forecasting, Recurrent neural networks (RNN), Long short-term memory (LSTM), Gated recurrent unit (GRU), machine learning techniques, and deep learning models.

1. Introduction

Recognising the ever-growing significance of machine learning (ML) in analytical evaluation, we have studied a few research projects on machine learning in forecasting analytics. In this work, applying 6 algorithms in the emergence and decision-making models of the field, especially in predicting stock market trends, was highlighted and extended the previous ones. As such, the work connects the dots between the classical applications of machine learning and its real-world applications in financial prediction.

In this paper, six different algorithms (Support Vector Re-gression (SVR), Random Forest (RF), XGBoost, Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU)) are investigated and tested for predicting a stock market trend. The explanation of each model is intentionally assessed using key assessment measures like R-squared (R^2), Root Mean Square Error (RMSE) and Symmetric Mean Absolute Percentage Error (SMAPE). The aim of this comparison is to provide the closest model to a real model to make accurate forecasts of the stock price.

In this one, the foundation is the use of high-quality real information to train the machine

learning models, which will then be able to identify important connections and trends in stock market movements. This portion of data-set is known as a 'training dataset'. The models gradually enhance their forecasting accuracy based on their learning from real trading scenarios, leading to more accurate future predictions. In financial applications, ML models are becoming more popular for their capability to learn continuously and for discrimination based on data, and investors are increasingly turning to these tools to help them make investment decisions.

In addition to implementing strategies, this paper thoroughly investigates the working principles and the performance of the five selected algorithms as well as their relative abilities in stock market trend prediction. The set of data analysed is the stock price records of eleven leading companies in India, which are active companies in the stock market, trading actively and with fluctuating stock prices. The companies that have been picked up are Adani Ports, Asian Paints, Axis Bank, HDFC Bank, ICICI Bank, Kotak Bank, Hindustan Unilever, Maruti, NTPC, Tata Steel, TCS and Titan. Historical data from Yahoo Finance was used for the stock data to ensure consistency and accuracy from 2020 to 2024.

II. About Stock Market

Corporate equity, or stock or shares, is a financial asset that represents ownership in a company, and they give the shareholder a proportionate share of the company's profits and assets. The percentage of shares in a corporation that are owned by the shareholders relative to the number of shares that were issued is the level of ownership.

The stock market of India has experienced a remarkable rise in growth and influence over the last few years, and in the current times is the 3rd largest in the world. A stock is a share in a business, which is a part of the business's resources and profits. When a company has 100 shares of equal size, a shareholder will own 100th of the company when he or she buys a single share. The stock exchanges are linked by computerised systems for matching orders. Supply and demand of a stock in the market can vary with time [18].

The stock exchange is a location where investors trade shares of a company that is listed on the exchange. The trading is a secondary market as business promoters have already sold a significant portion of their stake in the business through initial offerings. The two main exchanges in India are the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE), which have about 5,000 and 1,600 listed businesses, respectively. Though the exchange is smaller in size, both of these exchanges use the same trading platform and also have their demat account and trading account to make trades.

Stock markets provide the facility for people to exchange securities, which helps them to invest their funds and provides businesses with increased inflows of funds. The stock market of India has reworked investment behaviour throughout time, especially for middle-class investors seeking greater returns in the face of falling interest rates and inflation. This consistent rise may be attributed to the rising importance of the equities market as well as the critical position of the stock exchanges in India's economic progress.

III. Different Methods for Stock Price Prediction

There are several techniques for forecasting stock prices, which are used in technical research.

There are many applications of statistical methods in advanced, especially in developing machine learning-based strategies, like Statistical Methods [9]. Popularly used methods in this area are the Echo State Networks (ESN), ARIMA and regression models. The basic characteristics of statistical methods are the assumptions of linearity and stationarity of the data [13]. Several approaches were tested in such as Re-regression algorithms, Quadratic Discriminant Analysis (QDA) and Linear Discriminant Analysis (LDA) methods. Similarly, explored the popular ARIMA model and highlighted its applicability to time series data. Another closely related method of modelling stationary time series that contain autoregressive and moving average models is called Auto-Regressive Moving Average (ARMA) [17]. An extension of ARMA, the ARIMA model transforms non-stationary time series into stationary time series, which improves the improvement of accuracy and reliability in forecasting [2].

The main idea behind the pattern recognition techniques is to find patterns and structures in the past data. This means that a thorough analysis of the stock market data is required to identify trends that can indicate future market changes. Always, traders are going to use OHLC (open-high-low-close) candlestick charts to make instant trading decisions based on the candlestick patterns. Previous studies have investigated the regular trend and volatility in stock prices to gain insight into the direction of stock price changes. Analysis of charts involves looking at the price movement in the past to see how it relates to what is known about the market and predicting how the price of a stock will move in the future [22].

Financial prediction heavily relies on machine learning (ML), particularly for predicting stock prices. The ML algorithms are of two types: supervised and unsupervised. Supervised learning is a subset of machine learning where the models are trained with labelled data to make predictions (classification or regression). In contrast, unsupervised learning infers patterns, correlations or clusters in the financial data from unlabelled data. Without regulation, unsupervised machine learning techniques play a key role in the dynamics of bargaining.

Public sentiment evaluation is based on data from news outlets and social media to gain insight into public opinion on financial events. This has turned into a crucial method to forecast stock market movements. We can collect sentiment data from written content, such as articles and tweets, to enhance how well predictive models work. These sentiment-related features have been seen to significantly enhance the performance of models and the accuracy of trend prediction, according to studies [11].

IV. MACHINE LEARNING ALGORITHMS APPLIED:

Support Vector Regression

The method of Support Vector Regression (SVR) is a supervised learning technique that is applied to classification and regression tasks. In this technique, it utilises support vectors to establish the structure of an ideal hyperplane with the maximum margin, which is the best fit for the data. Similar to SVM [14], SVR successfully models complex relationships, and it is especially suited for time-series forecasting, financial market analysis, etc.

Random Forest

For the sake of increasing prediction accuracy and stability, the Random Forest supervised learning technique constructs several decision trees and combines their output. This flexible model can be used to solve classification and regression problems. It does this to make it harder to overfit the model and to increase the noise added by only splitting nodes with a subset of features. There are a number of hyperparameters that are provided by decision trees and the algorithm. Random Forest is highly resistant to noise, is versatile in dealing with various types of data sources and works well in large data sets. However, it has one major drawback due to its computational cost, as it involves having a large number of trees; this can slow down training and prediction.

XG-Boost

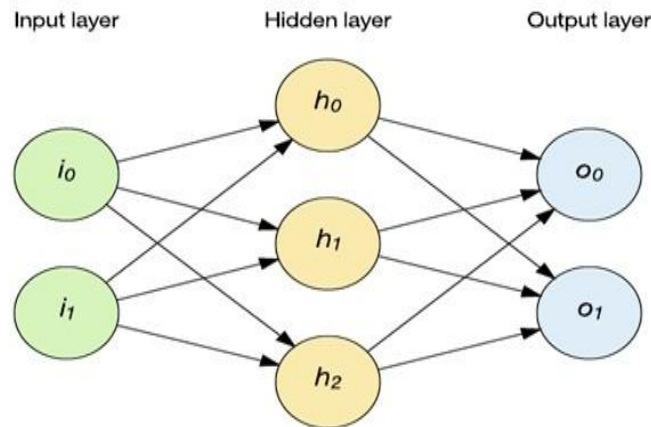


Fig. 1. RNN Layer

By enhancing the objective function using a second-order Taylor series approximation, XG-Boost (Extreme Gradient Boosting) improves computational complexity and accuracy. It also includes a normalisation term that encourages avoiding overfitting and regulates tree complexity. At each node, XG-Boost automatically selects a default direction (left or right), based on the fact that it could perform better by allocating missing values to either the left or right subtree. Owing to this mechanism, the approach can effectively manage parts of the datasets so that it retains high prediction capabilities [12]. An additive tree model serves as the foundation for XG-

Boost's fundamental algorithmic idea.

1. Each tree added by the algorithm learns a new function $f(x)$ that fits the residuals (errors) of the preceding forecast.
2. A total of k tree is produced following training. Each sample's data point passes through each tree and lands in a leaf node that corresponds to a certain score.

3. A predicted value for that sample is then measured by adding the scores from each tree.

By reducing residual errors, preserving computational efficiency, and preventing overfitting, this iterative procedure enables XG-Boost to slowly increase model accuracy [24].

RNN

Recurrent neural networks (RNNs) is a particular family of neural networks designed to handle sequential or time-dependent data by combining data from earlier time steps. If this network can take the results of the previous estimation and use them as inputs for the next, it's called "recurrent" [20].

In a normal Feedforward network, nodes have no links between each other from one time step to another; only links between the input layer and the hidden layer and from the hidden layer to the output layer. These types of designs can accommodate the sequential dependencies defined above. RNNs, at the same time, create recurrent connections inside the hidden layer, allowing previous outputs to have a direct impact on present estimation.

The hidden layer of an RNN systemically learns temporal dependencies of sequential data by taking in the current data and the previous hidden layer's output. RNNs can be used to model complex sequences like speech recognition, time series prediction and NLP [25].

Long Short-Term Memory (LSTM)

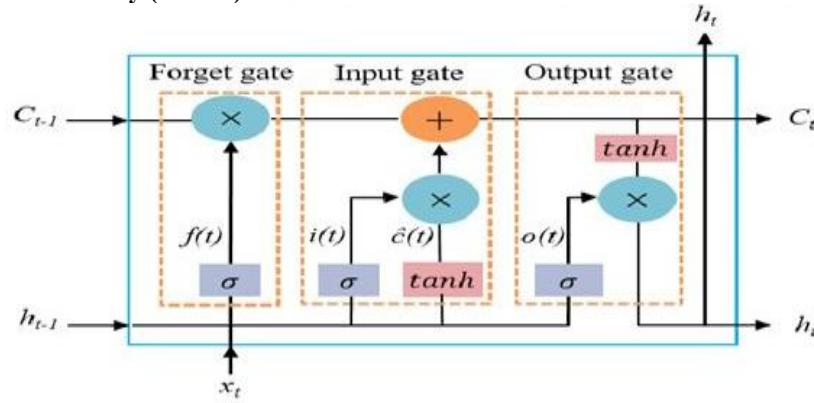


Fig. 2. LSTM Layer

The Long Short-Term Memory (LSTM) is a very successful type of Recurrent Neural Network (RNN) used to create time series data and to capture long-term dependencies. It can make very accurate predictions of future values and can detect temporal patterns in long sequences.

The three primal parts of an LSTM memory cell are the forget gate, input gate and output gate, as shown in Figure 2. The output of the LSTM unit at the previous time step is h_{t-1} , and the cell state at the previous time step is C_{t-1} . The current input is represented by x_t , and the activation function is r . The output of the candidate cell, C_t , is used as the input in the forget gate; the output of the forget gate at the present time step is called $f(t)$, the output of the output gate is called O_t , and the output of the LSTM unit at the present time step is called h_t .

At the same time, such accessing mechanisms help regulate the flow of information, enabling the LSTM to overcome the vanishing gradient problem that is common to standard RNNs, by remembering relevant information for longer and discarding irrelevant information [5].

Gated Recurrent Unit (GRU)

One of the variants of the RNN that is well connected with Long Short-Term Memory (LSTM) is the Gated Re-current Unit (GRU). Both systems can learn the long-term dependencies in sequential data; however, the GRU has two gates (update and reset), and it has fewer parameters and is structurally simpler. Unlike LSTM, which has a dedicated memory cell to control information flow, the GRU employs gating techniques to control information flowing through the hidden state.

The reset gate determines the amount of data to be discarded, while the update gate determines the amount of data to be preserved when computing the new candidate activation [6]. GRUs can be compact and still be as accurate as LSTMs in terms of accuracy, and are more efficient in terms of number. The first GRU layer in the implemented model has 32 units, input shape is (15, 1), and return sequences is True. A second layer of GRUs with 32 units is used for return sequences, where the true sequences are those that are executed in reverse order. The output of the last recurrent layer (an LSTM layer of 32 units) is passed to a dense layer. The model was trained for 200 epochs with Mean Squared

Error (MSE) as the loss function, and the Adam optimiser was used for training the model [3].

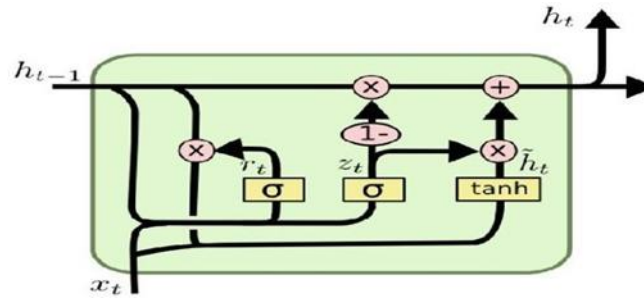


Fig. 3. GRU Layer

Methodology

The method adopted in a research study is how it is set up and ensures that it is reliable, valid and precise. The methodology adopted in this study has been well planned and scientifically organized to get reliable and comprehensive results from the implementation procedure.

The subsequent steps make up the sequential framework that the research technique follows. Initially, there were many open-source sites that could be used to get raw stock information. Post-processing the data involved data cleaning, data scaling, data normalization, etc., to prepare the data for evaluation. The data set is then split into a training set and a testing set for the convenience of model estimation.

In the next step, six predictive models were called: Random Forest, Support Vector Regression, XGBoost, Simple RNN, Long Short-Term Memory and GRU using different machine learning methods. Each model was trained on the training data set and tested on the testing data set to estimate the accuracy of prediction and also to find out the fluctuations from the actual values.

Finally, the performance of these six models was assessed using 11 firm datasets, mainly by using accurate statistical criteria, namely Symmetric Mean Absolute Percentage Error (SMAPE), R2 (Coefficient of Determination) and Root Mean Square Error (RMSE). The above estimation metrics were used to study the accuracy of the models, understand the behavior of the algorithms and provide a reliable evaluation of the prediction accuracy [10].

Data Description

Machine Learning is the first step towards a predictive study, which is to get a proper dataset. The time period for the current study is from January 2020 to December 2024, and the historical stock prices were gathered from Yahoo Finance [1] for the period. Eleven major Indian companies that have a big impact on the country's market and economy are included in the dataset. The data includes all the most important financial indicators, such as opening price, closing price, high price, low price of the day, last traded price and the closing price. Some of the companies selected are Adani Ports, Asian Paints, Axis Bank, ICICI Bank, Kotak Bank, Hindustan Unilever Limited, Maruti, NTPC, Tata Steel, Tata Consultancy Services (TCS) and Titan. The stock data were from representative samples from Yahoo Finance, and the data were from the stocks' daily prices.

Data pre-processing

Preprocessing is an integral component of any data-driven project, especially one dealing with large volumes of data, and is crucial for ensuring the reliability and effectiveness of the data. Cleaning, scaling and normalizing the data involves cleaning up raw and unshaped data and normalizing the data to improve the quality of the data and to allow meaningful assessment. The amount of data is not the key factor in predicting the efficiency of the results, but rather the quality of the data. The data was pre-processed using Min-Max scaling, and great care was taken when handling missing, null and unknown data for consistency [7]. The NumPy and Pandas libraries were heavily relied upon in Python for data manipulation and mathematical predictions. Python data processing modules NumPy and Pandas were much utilized for mathematical estimation. Besides, the data was also presented graphically with Matplotlib, which helped to clarify patterns and trends in the data.

Splitting of data into train and test dataset

The data was then split into the training set and the test set as mentioned above and preprocessed.

In this study, the split ratio of 99:1 was preferred since the data of the stock market is volatile, and it requires a large amount of historical information to run the model correctly. All 2312 data points were included as trading days, and the last eight data points were reserved as test data, and the remaining 2304 were used as training data. The research is aimed at forecasting time series, so this requires a higher training part to include temporal dependencies in the data. Some data was withheld for cross-validation to further enhance the power of the model. The module Scikit-learn was used for data splitting.

The ratio of the number of trains to tests is important, as an incorrect ratio may cause overfitting or underfitting. That is why the importance of controlling the ratio balance is to ensure that the model is assessed correctly and results in reliable predictions.

Training of models

The procedure by which machine learning and deep learning algorithms learn from data to provide precise predictions is known as model training. To train six machine learning and deep learning algorithms, 11 different companies' datasets were used. Training was done to ensure maximum model consideration with minimum overfitting and underfitting. This is a supervised learning problem, and the data was utilized to develop the target attribute to make predictions. The Random Forest, Support Vector Regression, XG-Boost, Simple RNN and Long Short-Term Memory models explored relevant factors to estimate the effectiveness of the model, such as training time and time-lag error. To make the learning more flexible, the weights were randomized during the iterative model fitting.

Testing the models

The last stage was performed using classical assessment measures to test the model's performance. The six models trained - Random Forest, Support Vector Regression, XG-Boost, Simple RNN, Long Short-Term Memory and GRU -



Fig. 4.

were evaluated on an 8-point test set that mimics the real-time fluctuations. The three-performance metrics that we use here are SMAPE, RMSE and R2 [8].

The SMAPE is used to determine the accuracy of prediction. The lower the SMAPE value, the more accurate the prediction. The RMSE is the average of the magnitude of the errors between the predicted value and the actual value. The lower the RMSE is the better the performance of the model. The higher the number, the more explanatory power it has, e.g. +1. R2 is an approximation of the level of correlation between the actual and expected results.

After testing, a relative performance analysis was carried out, and the results are presented in the next section. The equations for SMAPE, RMSE and R² are given in equations (1), (2), and (3).

Symmetric Mean Absolute Percentage Error (SMAPE) Result

The results of the project's effective implementation are presented in tables and graphs in this part. For this study, six algorithms (Random Forest, Support Vector Regression, XGBoost, Simple RNN, Long Short-Term Memory and GRU) were chosen to predict the stock prices of twelve different companies. The data set was very large, covering four years of data (2020-2024). The models would be tested for 8 trading days, as the ratio of train to test was 99:1. The data were used for training purposes for 2304 days, and the remaining 8 days were used for testing the trained models. The KPIs used to evaluate the models are: Root Mean Square Error (RMSE), R-squared value (R2), and Symmetric Mean Absolute Percentage Error (SMAPE) [19]. These are the salient and commonly used criteria of evaluation that help the user draw inferences on the different models under consideration [21].

V. Future Scope

In the future, the introduction of other architectures such as attention-based LSTM, external economic affairs and sentiment-based data may enhance the accuracy of stock prediction [15], and hybrid ensemble architectures are possible with GRU/LSTM and other models. Furthermore, the real-time application of the model, irregularity forecasting, and hyperparameter tuning can improve the robustness and usability of predictions for analysts and investors [23].



Fig. 5.



Fig. 6.



Fig. 7.



Fig. 8.

TABLE I: Comparison About RMSE

RMSE	GRU	LSTM	Random Forest	SVR	Simple RNN	XG-Boost
ADANIPOINTS.NS	0.030629	0.040523	0.166887109	0.504498	0.331401067	0.148905
ASIANPAINT.NS	0.030064	0.051033	0.022858683	0.039371	0.028603204	0.026344
AXISBANK.NS	0.022675	0.035941	0.079160851	0.282186	0.02389458	0.073792
HINDUNILVR.NS	0.033088	0.048145	0.079828142	0.177473	0.044191026	0.101057
ICICIBANK.NS	0.019547	0.02955	0.179229452	0.40987	0.058298475	0.192722
KOTAKBANK.NS	0.030011	0.038421	0.026613175	0.04053	0.032286134	0.027185
MARUTI.NS	0.030334	0.038994	0.167135385	0.423388	0.040109037	0.177243
NTPC.NS	0.044202	0.063028	0.178327112	0.466816	0.077794975	0.18585
TATASTEEL.NS	0.023489	0.037627	0.142007802	0.330528	0.026532233	0.137223
TCS.NS	0.088256	0.042397	0.138701039	0.37711	0.036613377	0.152564
TITAN.NS	0.038089	0.04685	0.047269487	0.10292	0.031926665	0.050813
AVG	0.035489	0.042955	0.111638021	0.28679	0.066513707	0.115791

TABLE II: Comparison about R2

R2	GRU	LSTM	Random Forest	SVR	Simple RNN	XG-Boost
ADANIPOINTS.NS	0.847206	0.732541	-3.53624	-40.4543	-16.887873	-2.61135
ASIANPAINT.NS	0.934609	0.811578	0.962197	0.887856	0.940809	0.949788
AXISBANK.NS	0.885502	0.712329	-0.39551	-16.733	0.872852	-0.21264
HINDUNILVR.NS	0.957988	0.91105	0.75546	-0.20866	0.925061	0.6081
ICICIBANK.NS	0.956994	0.901712	-2.6158	-17.9095	0.617439	-3.1807
KOTAKBANK.NS	0.705722	0.517703	0.768592	0.4633	0.659421	0.758542
MARUTI.NS	0.869064	0.783631	-2.97497	-24.5079	0.771081	-3.47026
NTPC.NS	0.762879	0.517884	-2.85938	-25.4469	0.265511	-3.19186
TATASTEEL.NS	0.893383	0.726417	-2.89676	-20.1103	0.863972	-2.63857
TCS.NS	-0.34379	0.6899	-2.31894	-23.5344	0.768730	-3.01556
TITAN.NS	0.601874	0.39765	0.386813	-1.90689	0.720270	0.291445
AVG	0.86815	0.734983	-1.42138	-16.0021	-1.219081	-1.44322

TABLE IIICOMPARISION ABOUT SMAPE

SMAPE	GRU	LSTM	Random Forest	SVR	Simple RNN	XG-Boost
ADANIPOINTS.NS	10.85639	10.82567	19.06762	83.63173	47.11647	16.3344
ASIANPAINT.NS	18.03855	17.47529	18.8184	17.44479	18.32472	18.38735
AXISBANK.NS	8.813076	8.548197	8.222709	35.57201	8.406041	7.86499
HINDUNILVR.NS	28.68695	28.79334	26.65081	26.55757	28.81171	25.95395
ICICIBANK.NS	13.13131	12.74797	19.92315	57.40015	13.20154	21.76094
KOTAKBANK.NS	9.221998	9.050029	9.414771	10.2839	9.690942	9.584042
MARUTI.NS	11.51221	11.56205	19.74973	63.02043	11.44767	21.18876
NTPC.NS	13.51644	14.05942	20.5507	76.36582	12.94047	21.71237
TATASTEEL.NS	9.668552	9.759087	15.44469	44.69245	9.349405	14.87035
TCS.NS	12.45787	9.981748	14.36803	53.18977	9.298904	16.5147
TITAN.NS	8.22301	7.900245	6.96514	10.83574	7.363917	6.767855
AVG	13.71616	13.64678	17.53806	46.10765	17.69877	17.51746



Fig. 9.

VI. Conclusion

The experimental view shows that deep learning models, in particular GRU and LSTM, perform better in stock price prediction than ordinary machine learning methods. GRU achieved more accuracy and abilities in learning temporal connections in stock data with the best R^2 value of 0.868 and the lowest RMSE value of 0.035 among all tested models. Also, LSTM prompted competitive results with a slightly higher SMAPE value of 13.64%, considering its dependability in simulating sequential financial trends. On the other hand, a usual model such as Random Forest and SVR showed poor performance in terms of negative R^2 and higher RMSE values, indicating their limitations in handling time-series data..

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