Model Comparison for the Prediction of Stock Prices in the National Stock Exchange by Data Science Techniques

Sumbul S.K¹, Hemanth Kumar Molapata², G. Madhu Sudan^{3*}, Nagendra Kumar Kalaparthi⁴, Sreesaketh Karri⁵

 ¹Department of Statistics, University of Allahabad, Prayagraj, U.P.-211002 India.
 ²Asst Professor, Department of Statistics, Hindu College, UoD, New Delhi India.
 ³Asst Professor, Department of Statistics, University of Allahabad, Prayagraj-211002 India, Email: gmadhusudan7@gmail.com
 ⁴Asst Professor, Department of Statistics, S.V.College, UoD, New Delhi India.
 ⁵Asst Professor, Department of Statistics, Delhi Public School, Bangalore East India.
 *Corresponding Author

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ABSTRACT

One of the most intricate machine learning techniques is the share value prediction. It depends on a variety of factors that affect supply and demand. This paper analyses different strategies for forecasting future stock price and provides an example using a pre-built model that is adapted to the Indian stock market. This research work explains the systematics of machine learning-based approaches for stock market prediction based on the deployment of a generic framework. The aim of this work is to explore and identify the models and compare them for five National Stock Exchange (NSE) Index, 50 listed Indian companies and also analysed the best prediction model for each company accordingly.

Keywords: Machine Learning, Deep Learning, Regression Techniques, Evaluation Metrics.

INTRODUCTION

Predicting stock prices is a critical task in financial markets, and it has garnered significant attention from researchers and practitioners alike. In the context of the National Stock Exchange (NSE), which is one of the largest and most liquid stock exchanges globally, accurate stock price prediction can offer substantial advantages for investors and traders. This introduction outlines the importance of model comparison in stock price prediction and the methodologies typically employed to evaluate and compare these predictive models.

The NSE holds the fourteenth (14th) position in the top forty (40) future exchanges in the world. The stock market index of NSE was launched in 1996 by the name of S&P CNX Nifty (Nifty= national 50) which represents 50 stocks of 25 different economic sectors and is largely a diversified index. The NSE set the standards for many other exchanges by bringing innovative changes in products, trading, clearing, settlement, and regulations. All these made the NSE a market leader which helped set international standards for the Indian stock markets. A majority of the developments in Indian stock markets like the 19 corporatized, demutualized and fully automated Indian stock exchanges owe their origin to NSE. Thus the establishment of the NSE was a landmark in the Indian stock market scenario. Another feather to its cap is that NSE was the first stock exchange in the world to use satellite communication technology for trading. All these collectively resulted in better transparency and efficiency of Indian stock markets. Here in this report, we are going to use.

Objectives

- 1. To investigate the best prediction model for stocks of five companies in the National Stock Exchange Index 50 through machine learning techniques
- 2. To analyse the efficiency of each model evaluation metrics and features.
- 3. To model comparison of stock prices of five companies like TATA Steels, TCS, TATA Motors, SUN Pharma.

Motivation

Financial gain is the most fundamental motivation for predicting stock market prices. The ability to uncover a mathematical model that can consistently predict the direction of future stock prices would

make the owner of the model very wealthy. Thus, researchers, investors, and investment professionals always attempt to find a stock market model that would yield higher returns than their counterparts. Stock market prediction using modelling is done for the purpose of turning a profit by analysing and extracting information from historical stock market data to predict the future value of stocks. The goal is to understand the deep learning models and adapt them to the Indian market. The stock market has always seemed to people outside the domain of finance and statistics as a dangerous playground. Some, failing to grasp its inherent complexity, even consider it to be similar to gambling. This is obviously not a pure game of chance, and the importance of this capstone lies in giving your average trader normal citizen an informed insight into the stock market to at least make better choices than random decisions.

METHODOLOGY

The proposed model built different machine and deep learning algorithms to predict the stock returns of the NIFTY 50 for 5 companies. Our goal is to forecast the stock price of the NIFTY 50 index through time series prediction models by using following methods.

Machine Learning Models

1.Simple Linear regression, 2.Polynomial Regression, 3.Support Vector Regression, 4.Random Forest Regressor, 5.Decision Tree Regressor, 6.XG Boost Regressor, 7.Gaussian Naive Bayes, 8.Lazy Predict Regressor

Evaluation Metrics

Evaluation metrics are attached to the tasks of machine learning and since we are trying to predict future stock prices using deep learning approaches we need to use multiple evaluation metrics to examine and determine our model's performance. We established a set of the most commonly used metrics which are (1) Accuracy, (2) the root mean square error (RMSE), (3) mean absolute error (MAE), (4) the mean square error (MSE) and (5) coefficient of determination (R²) for comparing and optimizing our prediction models. These criteria are preferred to be smaller since they indicate the prediction error of the models.

Empirical Investigation





Table(1a). Here, in this table 1(a) we get Random Forest Regressor with the lowest RMSE so it's the bestmodel for Tata Steels.

| Tata - Steel Stocks | | | | | | |
|-------------------------|----------------------|----------|---------|---------|--|--|
| Model Name | R ² Score | MAE | MSE | RMSE | | |
| Linear Regression | 0.01533 | 121.2278 | 22976.7 | 151.581 | | |
| Polynomial Regression | 0.07529 | 117.1852 | 21534.9 | 146.748 | | |
| SVR | 0.2027 | 0.6216 | 0.8192 | 0.9051 | | |
| Random Forest Regressor | 0.9942 | 0.05258 | 0.00591 | 0.07688 | | |
| Decision Tree Regressor | 0.9902 | 0.06287 | 0.00916 | 0.09569 | | |
| XG Boost Regressor | 0.9921 | 0.06189 | 0.00787 | 0.08871 | | |
| Naive Bayes | 0.3955 | 80.2863 | 14289.4 | 119.538 | | |

 Table 1(b).
 Here, in Table 1(b) through lazy predict we have ranked the model's according to their accuracy, R-Square and MSE. Among models, we can see here also Random Forest is among the best-fitted model after Extra Tree Regressor

| Lazy Predict - Regressors - Tata Steel | | | | | | |
|--|-------------|---------|--------|----------|--|--|
| Model | Adjusted R- | R- | RMSE | Time | | |
| | Squared | Squared | | Taken | | |
| Extra Trees Regressor | 0.9948 | 0.9948 | 0.0707 | 0.3587 | | |
| Random Forest Regressor | 0.9932 | 0.9932 | 0.0806 | 0.5006 | | |
| Bagging Regressor | 0.9927 | 0.9927 | 0.0834 | 0.0603 | | |
| K Neighbours Regressor | 0.9916 | 0.9916 | 0.0894 | 0.0257 | | |
| XGB Regressor | 0.9916 | 0.9916 | 0.0895 | 0.1613 | | |
| Decision Tree Regressor | 0.9913 | 0.9913 | 0.0910 | 0.0139 | | |
| Hist Gradient boosting Regressor | 0.9752 | 0.9752 | 0.1537 | 0.3603 | | |
| LGBM Regressor | 0.9749 | 0.9749 | 0.1547 | 0.0769 | | |
| Gradient Boosting Regressor | 0.9584 | 0.9584 | 0.1991 | 0.2246 | | |
| Gaussian Process Regressor | 0.6923 | 0.6926 | 0.5415 | 1.6192 | | |
| Ada Boost Regressor | 0.5408 | 0.5412 | 0.6616 | 0.0617 | | |
| MLP Regressor | 0.3195 | 0.3201 | 0.8053 | 3.8624 | | |
| Nu SVR | 0.2620 | 0.2626 | 0.8387 | 0.8394 | | |
| SVR | 0.2315 | 0.2322 | 0.8558 | 0.4735 | | |
| Huber Regressor | 0.0235 | 0.0243 | 0.9647 | 0.0159 | | |
| Kernel Ridge | 0.0227 | 0.0235 | 0.9651 | 0.5132 | | |
| Lars CV | 0.0222 | 0.0231 | 0.9653 | 0.0200 | | |
| Lasso Lars CV | 0.0222 | 0.0231 | 0.9653 | 0.0138 | | |
| Lasso Lars IC | 0.0222 | 0.0231 | 0.9653 | 0.0106 | | |
| Linear Regression | 0.0222 | 0.0231 | 0.9653 | 0.0091 | | |
| Lars | 0.0222 | 0.0231 | 0.9653 | 0.0277 | | |
| Orthogonal Matching Pursuit | 0.0222 | 0.0231 | 0.9653 | 0.0131 | | |
| Transformed Target Regressor | 0.0222 | 0.0231 | 0.9653 | 0.0139 | | |
| Ridge | 0.0222 | 0.0231 | 0.9653 | 0.0121 | | |
| Lasso CV | 0.0222 | 0.0231 | 0.9654 | 0.0801 | | |
| Elastic Net CV | 0.0222 | 0.0230 | 0.9654 | 0.0896 | | |
| Ridge CV | 0.0222 | 0.0230 | 0.9654 | 0.0095 | | |
| Bayesian Ridge | 0.0220 | 0.0228 | 0.9655 | 0.0144 | | |
| SGD Regressor | 0.0215 | 0.0223 | 0.9657 | 0.0105 | | |
| Linear SVR | 0.0191 | 0.0200 | 0.9669 | 0.0146 | | |
| Tweedie Regressor | 0.0139 | 0.0148 | 0.9694 | 0.0106 | | |
| Lasso Lars | -0.0018 | -0.0009 | 0.9771 | 0.0134 | | |
| Dummy Regressor | -0.0018 | -0.0009 | 0.9771 | 0.0088 | | |
| Lasso | -0.0018 | -0.0009 | 0.9771 | 0.0127 | | |
| Elastic Net | -0.0018 | -0.0009 | 0.9771 | 0.0097 | | |
| Quantile Regressor | -0.0026 | -0.0018 | 0.9775 | 506.3521 | | |
| RANSAC Regressor | -0.0211 | -0.0203 | 0.9865 | 0.0432 | | |
| Passive Aggressive Regressor | -0.1181 | -0.1171 | 1.0323 | 0.0165 | | |

2.Tata Motors

| Table 2(a). Here, in this table 2(a) we get Random Forest Regressor with the lowest RMSE so it's the best |
|---|
| model for Tata Motor |
| |

| Tata – Motor's Stocks | | | | | | |
|-------------------------|----------------------|----------|------------|----------|--|--|
| Model Name | R ² Score | MAE | MSE | RMSE | | |
| Linear Regression | 0.2756 | 176.7341 | 51000.0537 | 225.8319 | | |
| Polynomial Regression | 0.3240 | 158.3552 | 44493.7503 | 210.9354 | | |
| SVR | 0.3036 | 0.4910 | 0.6683 | 0.8175 | | |
| Random Forest Regressor | 0.9977 | 0.0315 | 0.0021 | 0.0467 | | |
| Decision Tree Regressor | 0.9973 | 0.0363 | 0.0027 | 0.0523 | | |
| XG Boost Regressor | 0.9974 | 0.0353 | 0.0026 | 0.0510 | | |
| Naive Bayes | 0.7673 | 76.4671 | 16886.2892 | 129.9472 | | |

| Table 2(b). Here, in Table 2(b) through lazy predict we have ranked the model's according to their |
|--|
| accuracy, R-Square, and MSE. Among models, we can see here also Random Forest is among the best- |
| Gette diverse distance Transport of Transport |

| Model | Adjusted R- | R- | RMSE | Time |
|----------------------------------|-------------|---------|--------|--------|
| | Squared | Squared | _ | Taken |
| Extra Trees Regressor | 0.9984 | 0.9984 | 0.0393 | 0.4031 |
| Random Forest Regressor | 0.9977 | 0.9977 | 0.0466 | 0.8320 |
| Bagging Regressor | 0.9975 | 0.9975 | 0.0489 | 0.1034 |
| K Neighbours Regressor | 0.9973 | 0.9973 | 0.0508 | 0.0166 |
| XG B Regressor | 0.9973 | 0.9973 | 0.0510 | 0.8657 |
| Decision Tree Regressor | 0.9969 | 0.9969 | 0.0545 | 0.0146 |
| Extra Tree Regressor | 0.9968 | 0.9968 | 0.0553 | 0.0200 |
| LGBM Regressor | 0.9916 | 0.9916 | 0.0897 | 0.1321 |
| Gradient Boosting Regressor | 0.9893 | 0.9893 | 0.1013 | 0.2804 |
| Hist Gradient Boosting Regressor | 0.9881 | 0.9881 | 0.1071 | 0.3629 |
| Ada Boost Regressor | 0.7853 | 0.7855 | 0.4544 | 0.1071 |
| Gaussian Process Regressor | 0.7715 | 0.7717 | 0.4687 | 2.2282 |
| MLP Regressor | 0.5559 | 0.5562 | 0.6535 | 3.5471 |
| Nu SVR | 0.3892 | 0.3897 | 0.7664 | 0.6670 |
| SVR | 0.3575 | 0.3580 | 0.7860 | 0.9787 |
| Huber Regressor | 0.2442 | 0.2448 | 0.8525 | 0.0212 |
| Kernel Ridge | 0.2438 | 0.2443 | 0.8528 | 0.6910 |
| Elastic Net CV | 0.2432 | 0.2438 | 0.8531 | 0.0690 |
| Lasso CV | 0.2432 | 0.2438 | 0.8531 | 0.1008 |
| Bayesian Ridge | 0.2432 | 0.2438 | 0.8531 | 0.0209 |
| Ridge CV | 0.2432 | 0.2438 | 0.8531 | 0.0169 |
| Ridge | 0.2432 | 0.2438 | 0.8531 | 0.0178 |
| Lars | 0.2432 | 0.2437 | 0.8531 | 0.0163 |
| Orthogonal Matching Pursuit | 0.2432 | 0.2437 | 0.8531 | 0.0123 |
| Lasso Lars IC | 0.2432 | 0.2437 | 0.8531 | 0.0103 |
| Lasso Lars CV | 0.2432 | 0.2437 | 0.8531 | 0.0140 |
| Lars CV | 0.2432 | 0.2437 | 0.8531 | 0.0234 |
| Linear Regression | 0.2432 | 0.2437 | 0.8531 | 0.0086 |
| Transformed Target Regressor | 0.2432 | 0.2437 | 0.8531 | 0.0148 |
| Linear SVR | 0.2426 | 0.2432 | 0.8534 | 0.0120 |
| SGD Regressor | 0.2417 | 0.2423 | 0.8539 | 0.0153 |
| Tweedie Regressor | 0.1888 | 0.1894 | 0.8832 | 0.0176 |
| RANSAC Regressor | 0.1187 | 0.1194 | 0.9206 | 0.0801 |
| Elastic Net | 0.0036 | 0.0043 | 0.9789 | 0.0111 |
| Dummy Regressor | -0.0011 | -0.0003 | 0.9812 | 0.0094 |
| Lasso | -0.0011 | -0.0003 | 0.9812 | 0.0124 |

| Lasso Lars | -0.0011 | -0.0003 | 0.9812 | 0.0128 |
|------------------------------|---------|---------|--------|----------|
| Quantile Regressor | -0.0281 | -0.0273 | 0.9943 | 881.4672 |
| Passive Aggressive Regressor | -0.1531 | -0.1522 | 1.0530 | 0.0129 |

3.Tata Consultancy Services (TCS)

Table 3(a). Here, in this table 3(a) we get Decision Tree Regressor with the lowest RMSE so it's the bestmodel for TCS.

| TCS STOCKS | | | | |
|-------------------------|----------------------|----------|-------------|----------|
| Model Name | R ² Score | MAE | MSE | RMSE |
| Linear Regression | 0.5498 | 424.9136 | 230796.8076 | 480.4131 |
| Polynomial Regression | 0.5823 | 404.7083 | 214688.6935 | 463.3451 |
| SVR | 0.8923 | 0.2291 | 0.1107 | 0.3327 |
| Random Forest Regressor | 0.9907 | 0.0315 | 0.0092 | 0.0962 |
| Decision Tree Regressor | 0.9979 | 0.0317 | 0.0020 | 0.0454 |
| XG Boost Regressor | 0.9964 | 0.0329 | 0.0034 | 0.0591 |
| Naive Bayes | 0.8907 | 115.5789 | 57099.6642 | 238.9553 |

Table 3(b). Here, in Table 3(b) through lazy predict we have ranked the model's according to theiraccuracy, R-Square, and MSE. Among models, we can see here also Decision Tree Regressor is the best-
fitted model for TCS.

| Lazy Predict - Tcs Stocks | | | | | | |
|----------------------------------|--------------------|---------------|--------|---------------|--|--|
| Model | Adjusted R-Squared | R- Squared | RMSE | Time Taken | | |
| Decision Tree Regressor | 0.9980 | 0.9980 | 0.0444 | 0.1379 | | |
| Extra Tree Regressor | 0.9974 | 0.9974 | 0.0504 | 0.0104 | | |
| Extra Trees Regressor | 0.9971 | 0.9971 | 0.0532 | 0.2417 | | |
| K Neighbours Regressor | 0.9971 | 0.9971 | 0.0535 | 0.0277 | | |
| Bagging Regressor | 0.9965 | 0.9965 | 0.0589 | 0.0435 | | |
| Random Forest Regressor | 0.9963 | 0.9963 | 0.0602 | 0.3229 | | |
| Hist Gradient Boosting Regressor | 0.9934 | 0.9934 | 0.0806 | 4.7159 | | |
| XGB Regressor | 0.9929 | 0.9929 | 0.0834 | 0.0086 | | |
| Gradient Boosting Regressor | 0.9885 | 0.9885 | 0.1063 | 0.2548 | | |
| LGBM Regressor | 0.9873 | 0.9873 | 0.1113 | 0.0615 | | |
| Ada Boost Regressor | 0.9426 | 0.9426 | 0.2370 | 0.1249 | | |
| Gaussian Process Regressor | 0.9316 | 0.9317 | 0.2586 | 1.3541 | | |
| SVR | 0.9014 | 0.9015 | 0.3105 | 0.2660 | | |
| Nu SVR | 0.9002 | 0.9003 | 0.3125 | 0.7260 | | |
| MLP Regressor | 0.8772 | 0.8773 | 0.3465 | 4.8935 | | |
| SGD Regressor | 0.5804 | 0.5808 | 0.6406 | 0.0068 | | |
| Huber Regressor | 0.5804 | 0.5808 | 0.6406 | 0.0244 | | |
| Orthogonal Matching Pursuit | 0.5803 | 0.5806 | 0.6407 | 0.0300 | | |
| Lars CV | 0.5803 | 0.5806 | 0.6407 | 0.0430 | | |
| Transformed Target Regressor | 0.5803 | 0.5806 | 0.6407 | 0.0103 | | |
| Lasso Lars CV | 0.5803 | 0.5806 | 0.6407 | 0.0208 | | |
| Lasso Lars IC | 0.5803 | 0.5806 | 0.6407 | 0.0165 | | |
| Linear Regression | 0.5803 | 0.5806 | 0.6407 | 0.0106 | | |
| Lars | 0.5803 | 0.5806 | 0.6407 | 0.0344 | | |
| Bayesian Ridge | 0.5803 | 0.5806 | 0.6407 | 0.0080 | | |

| Ridge | 0.5803 | 0.5806 | 0.6407 | 0.0091 |
|------------------------------|---------|---------|--------|----------|
| Ridge CV | 0.5803 | 0.5806 | 0.6407 | 0.0061 |
| Lasso CV | 0.5803 | 0.5806 | 0.6407 | 0.1337 |
| Elastic Net CV | 0.5803 | 0.5806 | 0.6407 | 0.0437 |
| Kernel Ridge | 0.5798 | 0.5801 | 0.6411 | 0.7406 |
| Linear SVR | 0.5773 | 0.5776 | 0.6430 | 0.0200 |
| RANSAC Regressor | 0.5733 | 0.5736 | 0.6460 | 0.0351 |
| Tweedie Regressor | 0.4321 | 0.4325 | 0.7453 | 0.0071 |
| Passive Aggressive Regressor | 0.3118 | 0.3124 | 0.8204 | 0.0173 |
| Elastic Net | 0.2240 | 0.2246 | 0.8712 | 0.0057 |
| Dummy Regressor | -0.0024 | -0.0016 | 0.9901 | 0.0051 |
| Lasso | -0.0024 | -0.0016 | 0.9901 | 0.0327 |
| Lasso Lars | -0.0024 | -0.0016 | 0.9901 | 0.0129 |
| Quantile Regressor | -0.0163 | -0.0155 | 0.9970 | 261.3351 |

4.Adani Ports

 Table 4 (a). Here, in this table 4(a) we get XG Boost Regressor with the lowest RMSE so it's the best model for Adani Ports.

| Adani Port - Stocks | | | | | | |
|-------------------------|----------------------|---------|-----------|---------|--|--|
| Model Name | R ² Score | MAE | MSE | RMSE | | |
| Linear Regression | 0.685 | 47.6460 | 4154.8293 | 64.4579 | | |
| Polynomial Regression | 0.6871 | 47.7759 | 4601.8127 | 67.8366 | | |
| SVR | 0.8406 | 0.2753 | 0.1460 | 0.3821 | | |
| Random Forest Regressor | 0.9970 | 0.0381 | 0.0032 | 0.0571 | | |
| Decision Tree Regressor | 0.9963 | 0.0398 | 0.0033 | 0.0580 | | |
| XG Boost Regressor | 0.9969 | 0.0396 | 0.0032 | 0.0567 | | |
| Naive Bayes | 0.9230 | 19.9492 | 1047.4420 | 32.3642 | | |

Table 4(b). Here, in Table 4(b) through lazy predict we have ranked the model's according to theiraccuracy, R-Square, and MSE. Among models, we can see here X G Boost Regressor is among the best-
fitted model after Extra Tree Regressor.

| Lazy Predict - Adani Ports Stock | | | | |
|----------------------------------|-------------|---------|--------|--------|
| Model | Adjusted R- | R- | RMSE | Time |
| | Squared | Squared | | Taken |
| Extra Trees Regressor | 0.9974 | 0.9974 | 0.0509 | 0.1698 |
| XG B Regressor | 0.9969 | 0.9969 | 0.0557 | 0.2495 |
| K Neighbours Regressor | 0.9967 | 0.9967 | 0.0580 | 0.0081 |
| Bagging Regressor | 0.9966 | 0.9966 | 0.0581 | 0.0288 |
| Random Forest Regressor | 0.9965 | 0.9965 | 0.0591 | 0.0859 |
| Decision Tree Regressor | 0.9957 | 0.9957 | 0.0660 | 0.0071 |
| Extra Tree Regressor | 0.9951 | 0.9951 | 0.0700 | 0.0083 |
| LGBM Regressor | 0.9928 | 0.9928 | 0.0853 | 0.0456 |
| Hist Gradient Boosting Regressor | 0.9926 | 0.9926 | 0.0861 | 2.4305 |
| Gradient Boosting Regressor | 0.9914 | 0.9914 | 0.0930 | 0.1814 |
| Gaussian Process Regressor | 0.9662 | 0.9663 | 0.1843 | 0.4332 |
| Ada Boost Regressor | 0.9408 | 0.9408 | 0.2440 | 0.0343 |
| SVR | 0.8265 | 0.8268 | 0.4176 | 0.0949 |
| Nu SVR | 0.8264 | 0.8267 | 0.4177 | 0.1662 |
| MLP Regressor | 0.7233 | 0.7237 | 0.5273 | 0.9946 |
| SGD Regressor | 0.6546 | 0.6551 | 0.5892 | 0.0065 |
| Elastic Net CV | 0.6544 | 0.6549 | 0.5894 | 0.0485 |

| Lasso (V | 0.6543 | 0.6548 | 0 5894 | 0.0957 |
|------------------------------|---------|---------|--------|--------|
| Ridge | 0.6543 | 0.6548 | 0 5894 | 0.0102 |
| Ruge Bayesian Ridge | 0.6543 | 0.6548 | 0.5091 | 0.0162 |
| Dayesian Muge | 0.0343 | 0.0340 | 0.3074 | 0.0002 |
| Ridge CV | 0.6543 | 0.6548 | 0.5895 | 0.0086 |
| Lasso Lars IC | 0.6543 | 0.6548 | 0.5895 | 0.0114 |
| Linear Regression | 0.6543 | 0.6548 | 0.5895 | 0.0094 |
| Transformed Target Regressor | 0.6543 | 0.6548 | 0.5895 | 0.0108 |
| Lars CV | 0.6543 | 0.6548 | 0.5895 | 0.0141 |
| Lars | 0.6543 | 0.6548 | 0.5895 | 0.0091 |
| Orthogonal Matching Pursuit | 0.6543 | 0.6548 | 0.5895 | 0.0059 |
| Lasso Lars CV | 0.6543 | 0.6548 | 0.5895 | 0.0157 |
| Kernel Ridge | 0.6539 | 0.6544 | 0.5898 | 0.0828 |
| Huber Regressor | 0.6536 | 0.6541 | 0.5901 | 0.0115 |
| Linear SVR | 0.6456 | 0.6461 | 0.5968 | 0.0148 |
| RANSAC Regressor | 0.6344 | 0.6349 | 0.6062 | 0.0287 |
| Passive Aggressive Regressor | 0.5822 | 0.5828 | 0.6480 | 0.0076 |
| Tweedie Regressor | 0.5000 | 0.5007 | 0.7089 | 0.0083 |
| Elastic Net | 0.3083 | 0.3093 | 0.8338 | 0.0085 |
| Dummy Regressor | -0.0036 | -0.0021 | 1.0043 | 0.0067 |
| Lasso | -0.0036 | -0.0021 | 1.0043 | 0.0451 |
| Lasso Lars | -0.0036 | -0.0021 | 1.0043 | 0.0110 |

5.Sun Pharma

 Table 5 (a). Here, in this table 5(a) we get Random Forest Regressor with the lowest RMSE so it's the best model for Sun Pharma.

 Sum Pharma

| Sun Pharma - Stocks | | | | |
|-------------------------|----------------------|----------|-------------|----------|
| Model Name | R ² Score | MAE | MSE | RMSE |
| Linear Regression | 0.0088 | 278.6273 | 144506.5291 | 380.1401 |
| Polynomial Regression | 0.2054 | 204.7373 | 93975.2800 | 306.5539 |
| SVR | 0.5135 | 0.3710 | 0.4460 | 0.6678 |
| Random Forest Regressor | 0.9952 | 0.0344 | 0.0051 | 0.0712 |
| Decision Tree Regressor | 0.9796 | 0.0394 | 0.0209 | 0.1447 |
| XG Boost Regressor | 0.9490 | 0.0455 | 0.0510 | 0.2258 |
| Naive Bayes | 0.6012 | 112.7557 | 55604.6150 | 235.8063 |

Table 5(b). Here, in Table 5(b) through lazy predict we have ranked the model's according to their accuracy, R-Square, and MSE. Among models, we can see here also Random Forest Regressor is among the

| 1 | | best-fitted model after Extra Trees Regressor and KNN Regressor. | - |
|---|------------------|--|---|
| | Lazy Predict - 9 | Sun Pharma | |

| Lazy Predict - Sun Pharma | | | | |
|----------------------------------|--------------------|---------|--------|--------|
| Model | Adjusted R-Squared | R- | RMSE | Time |
| | | Squared | | Taken |
| K Neighbours Regressor | 0.9838 | 0.9839 | 0.1304 | 0.0124 |
| Extra Trees Regressor | 0.9817 | 0.9817 | 0.1390 | 0.4961 |
| Random Forest Regressor | 0.9745 | 0.9745 | 0.1639 | 0.4002 |
| Bagging Regressor | 0.9715 | 0.9715 | 0.1733 | 0.0577 |
| XG B Regressor | 0.9669 | 0.9669 | 0.1866 | 0.1426 |
| Extra Tree Regressor | 0.9638 | 0.9638 | 0.1952 | 0.0105 |
| Decision Tree Regressor | 0.9578 | 0.9578 | 0.2107 | 0.0096 |
| LGB M Regressor | 0.9505 | 0.9505 | 0.2283 | 0.0583 |
| Gradient Boosting Regressor | 0.9498 | 0.9498 | 0.2299 | 0.2176 |
| Hist Gradient Boosting Regressor | 0.9023 | 0.9024 | 0.3207 | 0.4084 |
| Ada Boost Regressor | 0.8542 | 0.8543 | 0.3918 | 0.1347 |

| Gaussian Process Regressor | 0.6309 | 0.6311 | 0.6234 | 2.2539 |
|------------------------------|---------|---------|--------|----------|
| MLP Regressor | 0.5495 | 0.5498 | 0.6886 | 1.9807 |
| Nu SVR | 0.4601 | 0.4605 | 0.7539 | 1.0179 |
| SVR | 0.4520 | 0.4523 | 0.7595 | 0.4585 |
| Kernel Ridge | 0.0080 | 0.0086 | 1.0219 | 0.6401 |
| Lasso Lars IC | 0.0079 | 0.0086 | 1.0219 | 0.0068 |
| Transformed Target Regressor | 0.0079 | 0.0086 | 1.0219 | 0.0115 |
| Lars | 0.0079 | 0.0086 | 1.0219 | 0.0134 |
| Linear Regression | 0.0079 | 0.0086 | 1.0219 | 0.0063 |
| Orthogonal Matching Pursuit | 0.0079 | 0.0086 | 1.0219 | 0.0099 |
| Lasso Lars CV | 0.0079 | 0.0086 | 1.0219 | 0.0092 |
| Lars CV | 0.0079 | 0.0086 | 1.0219 | 0.0188 |
| Ridge | 0.0079 | 0.0086 | 1.0219 | 0.0085 |
| Ridge CV | 0.0079 | 0.0085 | 1.0219 | 0.0060 |
| Lasso CV | 0.0079 | 0.0085 | 1.0219 | 0.0749 |
| Elastic Net CV | 0.0079 | 0.0085 | 1.0220 | 0.0454 |
| Bayesian Ridge | 0.0079 | 0.0085 | 1.0220 | 0.0063 |
| SGD Regressor | 0.0077 | 0.0083 | 1.0221 | 0.0066 |
| Tweedie Regressor | 0.0056 | 0.0062 | 1.0232 | 0.0224 |
| Lasso | -0.0008 | -0.0001 | 1.0264 | 0.0080 |
| Dummy Regressor | -0.0008 | -0.0001 | 1.0264 | 0.0051 |
| Elastic Net | -0.0008 | -0.0001 | 1.0264 | 0.0055 |
| Lasso Lars | -0.0008 | -0.0001 | 1.0264 | 0.0078 |
| A Huber Regressor | -0.0534 | -0.0527 | 1.0530 | 0.0122 |
| Quantile Regressor | -0.1337 | -0.1330 | 1.0924 | 907.0397 |
| Linear SVR | -0.1351 | -0.1344 | 1.0931 | 0.0107 |
| RANSAC Regressor | -0.1556 | -0.1549 | 1.1030 | 0.0394 |
| Passive Aggressive Regressor | -0.2286 | -0.2278 | 1.1373 | 0.0189 |

Model Comparison of Stock Prices of Five Companies

Table 6: A low RMSE value indicates that the simulated and observed data are close to each other showing a better accuracy. Thus lower the RMSE better is the model performance. Hence, we can say on the basis of RMSE that the Random forest Regressor gives the best performance for 3 data sets of Nifty 50.

| Company Name | Best Model |
|--------------|-------------------------|
| Tata Steels | Random Forest Regressor |
| Tcs | Decision Tree Regressor |
| Tata Motors | Random Forest Regressor |
| Sun Pharma | Random Forest Regressor |

CONCLUSION

In the NSE, where market dynamics are fast-paced and complex, model comparison plays a pivotal role in identifying the most effective methods for stock price prediction. By leveraging various predictive models and employing rigorous comparison methodologies, investors and traders can enhance their decision-making processes and potentially gain a competitive edge in the financial markets.

Based on the comparison of stock prices prediction models for the five companies in Table (6) - Tata Steels, TCS, Tata Motors, Sun Pharma, and Adani Ports - the best model for each company was determined to be the Random Forest Regressor for Tata Steels, Tata Motors and Sun Pharma, the Decision Tree Regressor for TCS, and the XG Boost Regressor for Adani Ports.

The results of this comparison demonstrate the usefulness of machine learning models in predicting stock prices. However, it is important to note that these models are not fool proof and cannot predict future

market conditions with complete accuracy. Therefore, while machine learning models can be a valuable tool for predicting stock prices, investors should also consider other factors and consult with a financial advisor before making any investment decisions. It is important to note that the choice of the "best" model may vary depending on the specific dataset, features, and evaluation metrics used. The models mentioned above have been selected based on their performance in predicting stock prices for the respective companies. However, it is crucial to understand that stock price prediction is a challenging task, and various external factors can significantly influence stock prices, making accurate predictions difficult.

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