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Stock market prediction employing ensemble methods: the Nifty50 index

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ABSTRACT

Accurately forecasting stock fluctuations can yield high investment returns while minimizing risk. However, market volatility makes these projections unlikely. As a result, stock market data analysis is significant for research. Analysts and researchers have developed various stock price prediction systems to help investors make informed judgments. Extensive studies show that machine learning can anticipate markets by examining stock data. This article proposed and evaluated different ensemble learning techniques such as max voting, bagging, boosting, and stacking to forecast the Nifty50 index efficiently. In addition, an embedded feature selection is performed to choose an optimal set of fundamental indicators as input to the model, and extensive hyperparameter tuning is applied using grid search to each base regressor to enhance performance. Our findings suggest the bagging and stacking ensemble models with random forest (RF) feature selection offer lower error rates. The bagging and stacking regressor model 2 outperformed all other models with the lowest root mean square error (RMSE) of 0.0084 and 0.0085, respectively, showing a better fit of ensemble regressors. Finally, the findings show that machine learning algorithms can help fundamental analyses make stock investment decisions.

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1. INTRODUCTION

In the field of financial economics, a crucial topic is the connection that exists between the performance of markets and the risk that is associated with the economy. According to the broadly recognized random walk theory (RWT), the markets operate randomly and unexpectedly [1], [2]. The prompt and precise reflection of all available information in the prices of securities characterizes an efficient market hypothesis (EMH). Market efficiency is categorized into three distinct forms: weak, semi-strong, and strong forms. They claim that technical or fundamental analysis cannot forecast stock prices [3]. Fundamental and technical stock investment analyses increase investor decision-making and profitability. Many astute investors employ diverse approaches, such as fundamental and technical analysis, forecasting algorithms, and functions to forecast equity prices and their performance [4]. The first supports long-term forecasting and requires a detailed review of a firm’s economic status, monetary environment, liabilities, leadership, assets, goods, and competition [5], [6], while the latter forecasts stock price trends based on past changes and used for short-term forecasting [7]. However, the fractal market hypothesis (FMH)-proposes that financial markets exhibit fractal patterns and self-similarity across different timeframes. FMH considers the daily randomness of the market, and prices can be predicted with market characteristics such as non-linearity and long-term dependence [8]. Empirical evidence shows stock prices do not follow random walks [9]. According to modern behavioral finance experts, investors are emotional, and their cognitive biases driven by external market sentiments affect firm value and stock price [10]–[12]. Stock values have been evaluated since the market's creation, and retail participation in Indian stock markets has increased significantly. As India's economy rises, it is stock market will improve, attracting capital and investors. There are many kinds of research works in forecasting using time series analysis. The fundamental analysis benefits long-term investors, but day traders ignore it. Thus, fundamental analysis is vital to making long-term stock investment selections. Some of the most significant tasks based on this are listed here.

The stock market's performance affects other macroeconomic parameters and determines an economy's direction. For instance, Tripathi and Seth [13] used macro variables, such as currency, interest, and inflation rates, affecting the Nifty50 market. A country's stock market maturity, currency value, and interest rate reveal its traits [14]. Mishra and Dhole [15] examined the national stock exchange (NSE) stock co-movement. Synchronization is negatively connected with business group association and leverage and is positively correlated with growth and profit volatility. To assess the long-term relationship between Indian equities market value and macroeconomic variables (exchange rate, foreign reserve, and consumer price index (CPI)), Yadav *et al.* [16] used vector error correction model (VECM) and Johansen's co-integration tests. Currency exchange rates have long intrigued economists, policymakers, and investors [17]. Economic dynamics and market performance are strongly correlated, as shown by several research. The connection between the stock market and its stock market returns in Pakistan, India, China, South Korea, and Hong Kong is examined. This analysis yields two key conclusions. First, there are options for investor diversification; second, domestic factors (macroeconomic variables) impact stock markets [18]. Autoregressive moving average (ARMA) and macroeconomic factors were used to analyze bombay stock exchange (BSE) returns. The analysis found that foreign institutional investments (FIIN), risk in standard and poor's (RS&P), standard and poor's (S&P) 500 return, and United States treasury bill rate (USTBR) had large and positive regression coefficient values, showing that these four factors positively impact the Indian stock market [19]. An event study approach was analyzed on samples of Russian and Indian businesses. Berezinets *et al.* [20] conclude that both good and poor dividend surprises cause the Russian market to react negatively; good dividend surprises cause optimistic irregular earnings on Indian equities, while wicked and no astonishments cause undesirable reactions in the Indian market. In addition, Misra [21] examined the association between macroeconomic factors and the BSE SENSEX. All the variables exhibit long-run causation, while only inflation and the money supply exhibit short-run causality. Patel [22] found the BSE and S&P CNX Nifty were affected by the exchange rate, index of industrial production (IIP), inflation, money supply, silver, oil, and gold prices. The unit root was found using the augmented dickey-fuller test (ADF), Johansen co-integration test, VECM, and Granger causality tests.

Additionally, he found a connection between the exchange rate, oil prices, IIP, and stock market indices. Finally, Gopinathan and Durai [23] found long-term correlations between fundamental factors. VECM tests, Johansen co-integration, and summary statistics examine fluctuations. Additional macroeconomic issues that may affect the stock market would expand the study. AI incorporates machine learning. Some stock prediction studies included fundamental analysis and machine learning. Quah [24] compared three basic stock selection machine learning algorithms. Graham's book encouraged this author to forecast 11 popular financial ratios [25]. Macro and microeconomic factors affect investment outcomes. Random forest (RF) outperformed support vector machine (SVM) and naive Bayes (NB) with 0.751 F-score to predict stocks using eleven fundamental metrics [26]. The research examines whether fractal patterns are present in the behavior of the EURIBOR panel banks across multiple Eurozone nations [27].

From the literature, fundamental analysis predicts, performs, and analyzes market price movements using micro and macroeconomic data. A few aspects must be considered to develop a more useful predictive model utilizing this approach: i) the earlier study featured multi-collinearity and correlated input factors; ii) endogeneity can bias the estimates and mislead; iii) financial time series are non-stationary, non-linear, high-noise, and may not reflect complicated dynamics, making traditional statistical models challenging to predict; and iv) the literature review showed various feature selection methodologies essential for constructing reliable prediction algorithms. This study adds the following to scientific understanding to fill the research gaps in previous studies: i) this study uses state-of-the-art ensemble learning algorithms to capture the financial market's complex non-linear patterns, and dynamics by employing a fundamental analysis-based approach; ii) this work contributes by selecting highly perceptive features from an existing collection of fundamental characteristics using an embedded feature selection strategy to improve model performance with fewer features; iii) the GridSearchCV technique has been utilized to determine the optimal hyperparameter to enhance the model's performance; and iv) the results showed that bagging and stacking ensemble models using RF feature selection had the lowest error rates.

2. METHOD

2.1. Data preparation and pre-processing

The prediction in this work is based on a fundamental analysis approach. In this experiment, fundamental indicators for the period Jan 2011 to Dec 2019 were obtained from the Reserve Bank of India and NSE databases. Table 1 depicts the fundamental indicators and its description. All these fundamental indicators forming feature set of the proposed ensemble regressors and analysis of the Indian stock market on the Nifty50 index. Prior to further processing, these characteristics were normalized to the interval [0, 1]. However certain traits may be unnecessary and provide information that is already known for the learning task, while others may be useful and provide false information that impairs learning outcomes. In this work, a feature selection strategy based on embedded systems is adopted to eliminate features that are unnecessary or redundant. Feature selection is integrated into the classifier via an embedded approach. The advantages of both filter and wrapper methods are combined in embedded methods, which represent a hybrid approach [28], [29].

Table 1. Fundamental indicators used

Feature name	Description of the feature
Price-to-earnings (P/E) ratio	The P/E ratio quantifies the relative valuation of a company’s shares in relation to it is earnings per share (EPS).
Price-to-book (P/B) ratio	How much an investor is willing to pay for a firm compared to its book value is what the P/B ratio reveals.
Dividend yield	Dividend yield measures annual dividend payout as a percentage of stock price and is a standard financial indicator of a company’s financial health.
Exchange rate	The term “exchange rate” refers to the agreed-upon percentage by which one currency can be traded for another in the financial market. This study considers the US Dollar, Pound Sterling, Euro, and Japanese Yen exchange rates.
Inflation (CPI and WPI)	The rate at which inflation causes prices across the board to rise is known as the inflation rate.
Gross domestic product (GDP)	It estimates a country’s GDP and growth rate by providing an economic snapshot.
Index of industrial production (IIP)	The IIP measures the health of India’s manufacturing sector. There are three main categories within IIP: industry, mining, and energy production.

2.2. Base model: support vector regressor

Supervised machine learning reduces error and increases geometric margins with the SVM. It is a regression and pattern categorization algorithm. SVM mapped non-linear samples to a large-dimensional space using a kernel function, making them linearly separable. Different kernel functions greatly affected SVM classification performance. The radial basis function (RBF) was frequently employed in practical applications due to it is fewer parameters and superior performance [30], [31]. The RBF kernel formula is:

$$K(\, x, x_i) = \exp\,(-\, \frac{||x - x_i\,||^2|}{\sigma^2})$$

where x and x_i are ample vectors, δ is the RBF kernel function and a free parameter.

2.3. Ensemble techniques

Meta-algorithms called “ensemble approaches” blend multiple machine learning methods into one forecasting model to either reduce variance (bagging) or bias (boosting) or to improve forecasts. It also enhances robustness and provides a generalized model [32]. This article discusses the fundamental analysis of stock market forecasting utilizing ensemble approaches, including max-voting, bagging, boosting, and stacking. Max voting is typically applied to classification or regression problems. Each model predicts and votes for each sample. The prediction class contains only the sample class’s highest-voted class. Bootstrap aggregation, often known as bagging classifier/regressor, is an early ensemble method intended to reduce variance. They aggregate predictions from each regressor model trained on a random subset of the training data. The RF method is efficient at feature selection. RF is a reliable strategy for dealing with imbalanced, missing, and multicollinear data. Algorithm 1 shows the bagging steps. Boosting is an ensemble learning method that strengthens weak learners to reduce training errors. AdaBoost is an ensemble learning method that stands for adaptive boosting, and in this method, weak learners are helped by increasing their weights and allowing them to vote on the final model. AdaBoost regressor fits the dataset and adjusts weights based on the error rate. Algorithm 1 is an illustration of the method. Algorithm 2 shows the AdaBoost technique.

```
Algorithm 1: Bagging
Input:
Dataset $S = \{x_i y_i\}_{i=1}^{n}$; Base learning algorithm $L$; Several base learners $m$.
Process:
$for\, j = 1\ to\ m$:
    $S_j = bootstrap(S)$; // Generate a bootstrap sample from S
    $h_j = L(S_j)$     // From the bootstrap sample, train a base learner $h_j$
end.
Output:$H(x) = model(\ h_1(x), \ldots., h_m(x))$
```

```
Algorithm 2: AdaBoost technique
Input:    Dataset $= \{x_i y_i\}_{i=1}^{m}$. A weight vector $Z_t$ is created based on the weight of each training set sample; The number of learning rounds is given by T, while L stands for the fundamental learning algorithm.
Process:
 Step 1: Initializing the weight distribution
            $D_1(i) = {}^1\!/_m$
 Step 2:  for $t = 1,2, \ldots., T$:
            $h_t = L\,\{D, D_t\}$;        //Using distribution, $D_t$ train a base learner $h_t$ from $D$.
        $\epsilon_t = Pr_{i\sim D_1}[h_t(x_i\ +\ y_i\ )]$;  // Calculate the error of $h_t$
            $\alpha_t = \frac{1}{2}\ ln \frac{1-\epsilon_t}{\epsilon_t}$
 // The distribution update using  $z_t$ a normalization factor that enables $D_{t+1}$to be a distribution
            $D_{t+1}(i) = \frac{D_t(i)}{sum(Z_t)} \times \begin{cases} \exp\,(-\alpha_t) & if\ h_t(x_i) = y_i \\ \exp\,(\alpha_t) & if\ h_t(x_i)\ \neq y_i \end{cases}$
            end
Output:  $F_{(x)} = sign \sum_{t=1}^{T} a_t\, h_t(x)$
```

Stacking is an ensemble learning approach aggregating results from many classifications or regression models using a meta-classifier or meta-regressor. A series of learning algorithms form the stacking ensemble's base, making it very diversified. The stacking ensemble technique considered the primary classifier and meta classifier's learning capabilities, improving the final classification's performance [33]. In this proposed stacking, the outputs of the models are combined to obtain the final prediction for any instance x_i. Stacking introduces a level-1 approach called meta-learner to learn the weights β_j of the level-0 predictors. That is, for the meta learner (level-1), the prediction $y(x_i)$ of each training instance x_i is training data, which can be described as follows:

$$y(x_i) = \sum_{j=1}^{4} \beta_j\, h_j(\, x_i)$$

where x_i is the samples, β_j is the optimal weight of level-0 predictors, and h_j is the base model. The stacking algorithm is discussed briefly in Algorithm 3.

```
Algorithm 3: Stacking ensemble
Input: Dataset   $D = \{x_i y_i\}_{i=1}^{m}$
Process:
Step 1: learning regressors at the first level
for $t = 1\ to\ T$ do
    Learn a $r_t$ base learning algorithm based on D
end for
Step 2: Build a novel dataset of forecasts from D
for $i = 1\ to\ m$ do
    $D_h = \{\ x_i'\ y_i\}$, where $x_i' = \{\ h_1(x_i), \ldots., h_T(x_i)\}$
end for
Step 3: A meta-learning regressor: Learn $R$ based on $D_h$
return R
Output: R: An ensemble regressor.
```

3. RESULTS AND DISCUSSION

3.1. Experimental procedure, feature selection, and model evaluation

The entire experiment is coded with Python 3.9 on Anaconda Navigator 2.1.2 and Jupyter Notebook, using an AMD Ryzen 5 5600H with Nvidia Geoforce GTX, Radeon Graphics 3.00 GHz, 1 Core CPU, 8 GB RAM, and Windows 10 64-bit OS. Figure 1 depicts the Nifty50 index closing values from 2011 to 2019 and Figure 2 shows the proposed method's experimental process. Stock market forecasting systems use feature vectors as input, hence feature selection is crucial. Mining a set of perceptive traits is vital for stock market system model improvement. The literature has suggested several features, but few have ranked highly discriminating features. In this article, we employed a feature selection strategy, namely an embedded method using RF to select highly discriminating features and input these features to the proposed model to forecast the stock market efficiently.

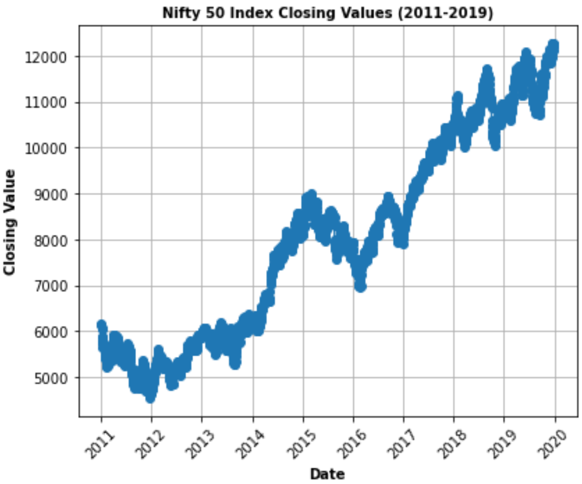


Figure 1. The Nifty50 index's closing values

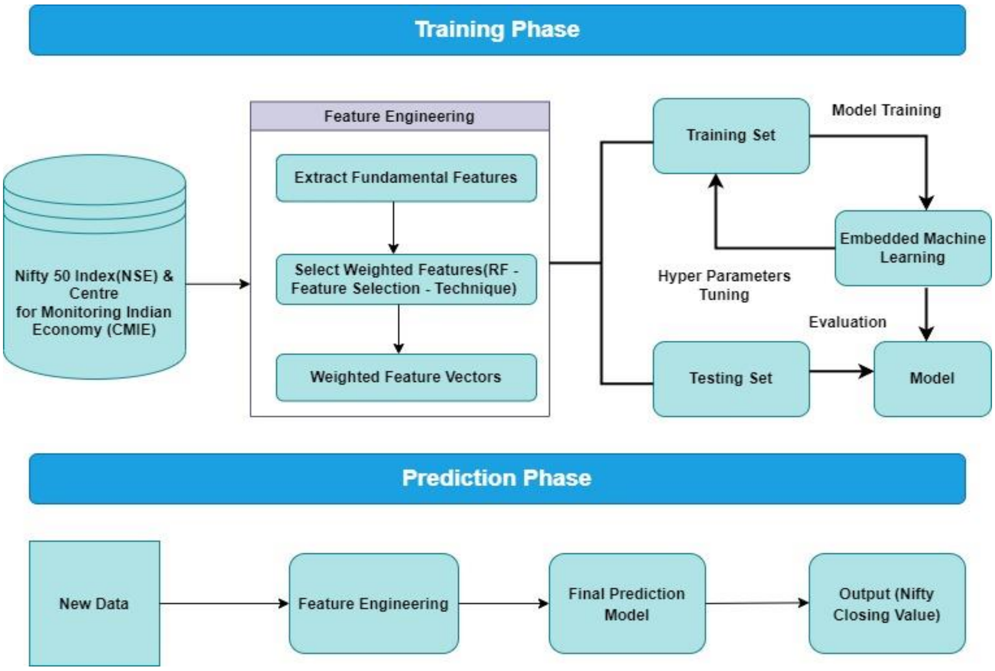

Training Phase
Feature Engineering
Extract Fundamental Features
Select Weighted Features(RF - Feature Selection - Technique)
Weighted Feature Vectors
Nifty 50 Index(NSE) & Centre for Monitoring Indian Economy (CMIE)
Training Set
Model Training
Embedded Machine Learning
Hyper Parameters Tuning
Evaluation
Testing Set
Model
Prediction Phase
New Data
Feature Engineering
Final Prediction Model
Output (Nifty Closing Value)

Figure 2. The proposed method's experimental process

Table 2 provides information on different feature selection techniques, the corresponding feature selection algorithms used, the selected feature sets, and the number of features used for each method. These were then chosen for model development and conducting experiment results. Table 3 provides an overview of the base and ensemble models used in the proposed work. These models leverage different techniques to enhance prediction accuracy and capture the relationships between the features and the target variable.

Table 2. Feature selection type and its algorithm

Feature selection type	Feature selection algorithm	Feature set	Number of features used
Embedded	Random forest	{Euro, US_Dollar, Pound_Sterling, P_E, Japanese_Yen, P_B, Div_Yield}	7

Table 3. Proposed work’s base and ensemble models

Models	Base and ensemble techniques
Support vector regression (SVR)	Base regressor
MAX Voting	Ensemble voting regressor
Bagging with RF	Ensemble bagging regressor
Boosting with AdaBoost	Ensemble boosting regressor
Stacked regressor model 1	Base learners-RF, gradient boosting regression (GBR), and SVR. Final estimator-linear regression (LR).
Stacked regressor model 2	Base learners-decision tree regressor (DTR), GBR, and SVR. Final estimator-RF

Machine learning tasks are associated with evaluation metrics, and because we are attempting to forecast future stock values using machine learning methodologies, we must employ many evaluation metrics to assess and determine our model’s performance and behavior. As demonstrated in (1)-(4), mean square error (MSE), root mean square error (RMSE), mean absolute percentage (MAP), and coefficient of multiple determinations for multiple regressions (R^2) were utilized to evaluate the efficacy of our suggested approaches. These criteria are preferred to be smaller because they represent the models’ prediction error.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{1=1}^{n}(y_i - \bar{y})^2} \tag{1}$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{4}$$

The performance of any classifier or regressor highly depends on its hyperparameter setting. Researchers have previously used hyperparameter tuning to improve model performance. Because there were few combinations, grid search was used to find the finest set of hyperparameters. The optimal hyperparameter combinations were determined by computing performance metrics based on parameter default values from training and test data. Table 4 shows the tuned hyperparameters and their optimal values for the single machine learning algorithms, and these hyperparameters are employed in the experimental work.

Table 4. Hyperparameter selection using gridsearchCV()

Bagging-RF		AdaBoostRegressor	
n_estimators	50	n_estimators	50
max_features	auto	learning_rate	0.01
max_depth	3	SVR	
min_samples_leaf	5	kernel='rbf', gamma=‘auto'	

3.2. Prediction results of the models

Selecting a dataset is the initial step in most machine learning predictive analytics initiatives. This research used fundamental analysis-based machine learning models from Table 3 to predict the Nifty50 index closing value. The study evaluated ensemble stock market forecasting methods using fundamental analysis of the Nifty50 index. The study found that fundamental variables such as the P/E ratio, P/B ratio, dividend yield, exchange rate, inflation (CPI and WPI), GDP, and IIP can predict the Nifty50 index closing value. This study trains and tests all Table 3 machine learning models using 80% and 20% of samples. The study also discovered that employing embedding feature selection procedures made it possible to choose highly discriminating features from a set of fundamental indicators from Table 1. Table 2 shows that the embedding feature selection technique using RF picked essential feature sets for model development and experiment results. The regression metrics such as R-squared value, MSE, RMSE, and MAE were used to compare models. As in (1)-(4) describe related formulas. Machine learning regression tasks use MSE, RMSE, and MAE to compare a model's predicted and actual values. Thus, the smaller the MSE, RMSE, and MAE, the smaller the models predicted and actual values, and the greater the prediction accuracy and the higher the prediction accuracy and the higher R-squared values indicate fewer discrepancies between the observed and fitted data.

To evaluate the performance and demonstrate the usefulness of the proposed model, a comparative analysis was conducted with the SVR base model and various ensemble techniques such as max voting, bagging, boosting, and stacking. Table 5 presents the analysis of the base model and proposed ensemble techniques to test performance in terms of various regression metrics. It contains the evaluation results of different regression models for two scenarios: one with all the features and another with feature selection using the RF-embedded method for modeling. In the first scenario with all the features, SVR performs with error values MSE of 0.0026, RMSE of 0.0511, MAE of 0.0427, and R-squared value of 0.9670 indicates it explains approximately 96.70% of the variance in the data. The max voting shows higher errors (MSE=0.0088, RMSE=0.0941, MAE=0.0804), and R-squared value of 0.8885 suggests it explains about 88.85% of the variance compared to SVR and other models. Next, bagging with RF: performs well with low MSE of 0.0012, RMSE of 0.0352, MAE of 0.0272, and R-squared value of 0.9843 indicates it explains approximately 98.43% of the variance, making it one of the best models. Following, boosting with AdaBoost: performs well with relatively low errors and an R-squared value of 0.9807. Finally, stacking regressor Model1 and Model2: both models perform exceptionally well with extremely low MSE, RMSE, and MAE. R-squared values of 0.9940 and 0.9950 suggest they explain approximately 99.40% and 99.50% of the variance in the data, respectively. These models are the best performers.

Table 5. Performance analysis of the proposed model

	SVR	Max voting	Bagging with RF	Boosting with AdaBoost	Stacking regressor Model1	Stacking regressor Model2
			Testing phase (all the features)			
MSE	0.0026	0.0088	0.0012	0.0015	0.0004	0.0003
RMSE	0.0511	0.0941	0.0352	0.0391	0.0217	0.0198
MAE	0.0427	0.0804	0.0272	0.0307	0.0168	0.0144
R-squared	0.9670	0.8885	0.9843	0.9807	0.9940	0.9950
			Testing phase (feature selection using RF-embedded method)			
MSE	0.0036	0.0090	7.214e-05	0.0009	9.993e-05	7.235e-05
RMSE	0.0607	0.0949	0.0084	0.0305	0.0099	0.0085
MAE	0.0559	0.0808	0.0047	0.0251	0.0070	0.0057
R-squared	0.9535	0.8865	0.9990	0.9882	0.9987	0.9999

In the second scenario from Table 5, the feature selection method used is RF-embedded, which means that the RF algorithm was used to select the most essential features for modeling. The feature selection using the RF-embedded method improved specific models’ performance. The SVR model shows higher errors (MSE=0.0036, RMSE=0.00607, MAE=0.0559), and R-squared value of 0.9535, which explains about 95.35% of the variance compared to Scenario 1. The max voting model errors have increased slightly compared to Scenario 1. Next, bagging with RF shows significantly low errors (MSE=7.214e-05, RMSE=0.0084, and MAE=0.0047), and the R-squared value of 0.9990 indicates it explains almost all of the variance in the data. It performs exceptionally well in this scenario. Following, boosting with AdaBoost model errors have increased compared to Scenario 1, but it still performs well with an R-squared value of 0.9882. Finally, both stacking regressor Model1 and Model2 models have extremely low errors, even lower than in Scenario 1, and R-squared values are very close to 1 (0.9987 and 0.9999, respectively), indicating they almost perfectly explain the variance in the data. These models continue to be the best performers.

Figures 3 and 4 visually compare the base and proposed ensemble learning models and various regression metrics. It is observed that the proposed ensemble learning models exhibited higher performance except for the max voting ensemble regressor compared to the SVR model. Also, it is observed that using the embedded RF feature selection technique gives promising results (i.e, low errors with high accuracy) compared to the non-feature selection technique (i.e., using all the features). The ensemble technique, max voting, had higher errors compared to other models in both scenarios. The stacking ensemble was grouped into two models: stacking regressor Model1 (where base learners-RF, GBR, and SVR. Final estimator-LR) and stacking regressor Model1 (where base learners-DTR, GBR, and SVR. Final estimator-RF). Across both scenarios, i.e., using all the features and embedded feature selection using RF, the stacking regressor models (Model1 and Model2) consistently outperformed all other models in terms of predictive accuracy and ability to explain the variance in the data.

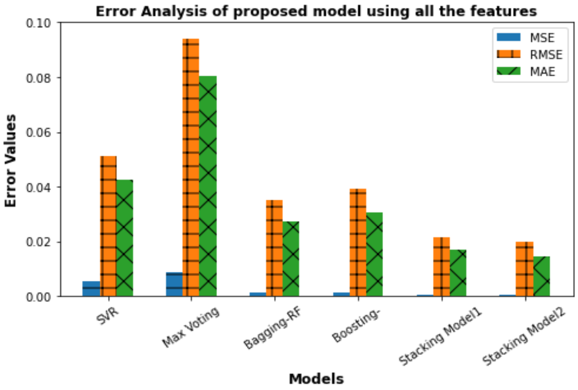


Figure 3. Comparison of MSE, RMSE, and MAE using all the features

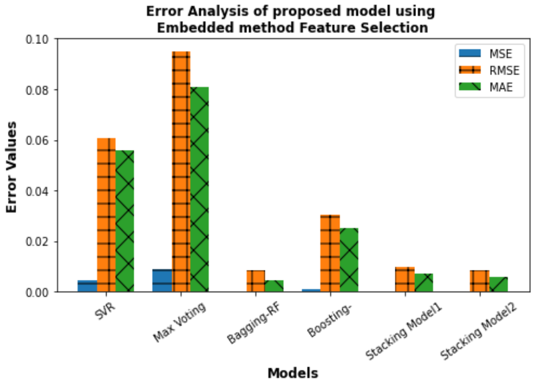


Figure 4. Comparison of MSE, RMSE, and MAE using embedded method-RF feature selection

Table 6 evaluates the existing and proposed ensemble model on the fundamental dataset using the embedded method-RF feature selection. The stacking regressor models (Model1 and Model2) have higher performance in terms of R-squared metric and lower RMSE values compared to the existing model in the fundamental analysis. These stacking models leverage the strengths of multiple base models and combine their predictions, leading to superior performance.

Table 6. Comparative analysis for the proposed and the existing methods using fundamental analysis

Dataset	Author	Model	MSE	RMSE	MAE	R-squared
BSE-inflation, IIP, gold price, rate of interest, exchange rate, FII, and supply of money	[21]	VECM	NA	NA	NA	0.6490
Nifty50 index-Exchange rate, Gross domestic product of USA, Foreign institutional investor of India, Fiscal deficit, Gold price/10 g, S and P, Interest rate of USA, Inflation, Industrial production index of India	[34]	Ordinary linear square (OLS)	NA	NA	NA	0.836
Bucharest stock exchange-The research data set has 39 variables, 35 of which are technical analysis variables and four macroeconomic factors.	[35]	SVM-ICA	NA	0.022593	NA	NA
Refer to Table 2.	Proposed method	Ensemble model (stacking regressor model 1)	9.993e-05	0.0099	0.0070	0.9987
		Ensemble model (stacking regressor model 2)	7.235e-05	0.0085	0.0057	0.9999

The R-squared value on existing methods and proposed ensemble techniques using the embedded method-RF feature selection is shown in Figure 5. The bagging with RF model offers significantly higher performance with R-squared value of 0.9990, which indicates it explains almost all of the variance in the data. It performs exceptionally well in this scenario. The stacking regressor models (Model1 and Model2) have higher R-squared values and are very close to 1 (0.9987 and 0.9999, respectively), indicating they almost perfectly explain the variance in the data. These models continue to be the best performers. Figure 5 shows the proposed ensemble technique's higher performance in terms of the R-squared metric compared to existing methods. The plot in Figures 6(a) and (b) shows the actual and forecast values of the Nifty50 index using stacking regressor Model1 and Model2, proposed in Table 3. The green data points signify the actual Nifty50 index values, while the red data points denote the forecast Nifty50 index values. Also, we can notice an autocorrelation between actual and forecast values.

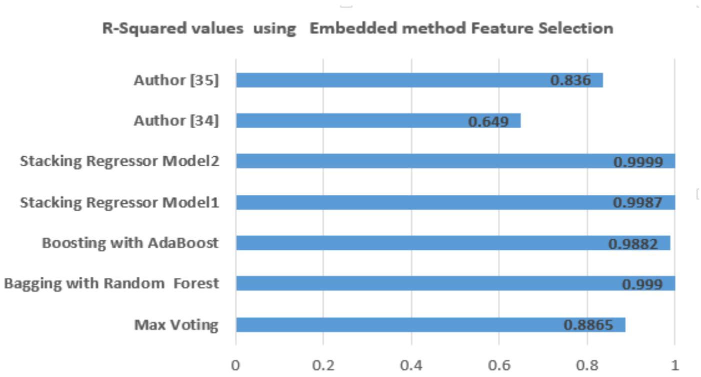
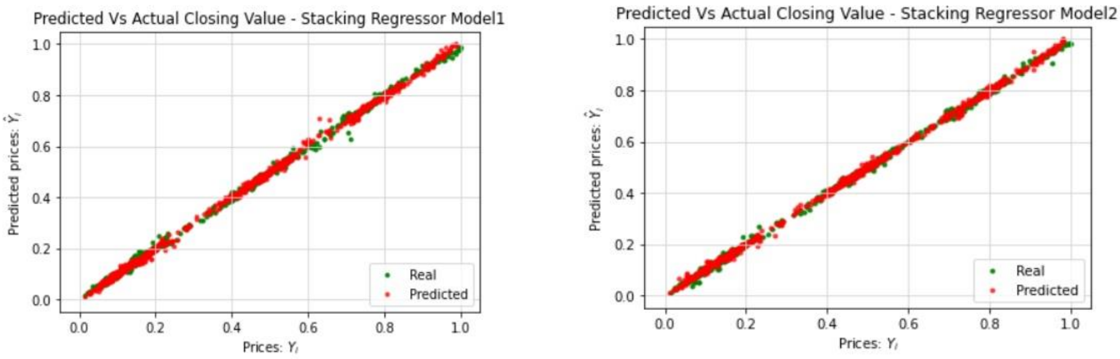


Figure 5. Comparison of R-squared value on existing methods and proposed ensemble techniques



(a) (b)

Figure 6. Stacking ensemble forecasting results (a) stacking regressor Model1 and (b) stacking regressor Model2

Based on the findings of this investigation, it can be concluded that the proposed ensemble machine learning approaches, except the max voting model, have demonstrated their efficacy in forecasting stock values inside financial markets. In this article, RF is used for its feature selection capability to identify the most relevant fundamental indicators and to capture time-dependent patterns in stock prices for stock market prediction, thus providing insights into market dynamics. Finally, our findings suggest the bagging and stacking ensemble models with RF feature selection offer lower error rates.

4. CONCLUSION AND RECOMMENDATION

The key objective of this manuscript was to forecast the closing value of the Nifty50 index using the fundamental indicators and state-of-the-art ensemble learning algorithms. The study showed that the embedded feature selection approach at the pre-processing step increased model performance by selecting relevant features and removing irrelevant ones from the core indicators. Next, ensemble learning methods were tested to capture complex non-linear data to forecast the Nifty50 index. The experimental results found that the bagging and stacking regressor Model2 with feature selection utilizing RF-embedded method has the lowest errors. Also, the stacking ensemble model performance depends on the metal learner. The stacking regressor Model2 has the best RMSE statistic, with a 0.004 error percentage and 0.9997 R-squared. The stacking regressor Model2 outperformed the stacking regressor Model1, albeit only slightly. Based on these discoveries, it can be concluded that the fundamental indicators considered in this study, along with the proposed feature selection techniques and ensemble learning models, offer an effective tool for forecasting the Nifty50 index in the stock market. The study provides valuable insights for financial investors, highlighting the advantages of employing ensemble machine-learning approaches for accurate and reliable stock market predictions. The system can be further enhanced in future work by incorporating deep learning and technical analysis techniques to create a more precise and reliable stock market forecasting system.

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