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Comparative Analysis of Machine Learning Models for Stock Price Direction Prediction Using Public Market Data

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Abstract: Predicting the direction of stock prices is an intricate task due to the dynamism, non-linearity, and volatility of financial markets. This research compares machine learning models for predicting stock price direction using publicly available market data. We use historical stock market data, such as open, close, high, low, trading volume, and technical indicators, to build a binary classification framework that forecasts whether the stock price will increase or decrease in the next trading period. This study comparatively evaluates several machine learning models, including Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and Gradient Boosting. The models are evaluated using classification metrics such as accuracy, precision, recall, F1-score, and others. A standardized data preprocessing and evaluation process is employed to enable a fair comparison between the machine learning models. The study aims to identify the best-performing models and analyze the advantages and disadvantages of different machine learning methods for predicting stock market direction.

Keywords: Stock Price Prediction; Machine Learning; Stock Market; Direction Prediction; Classification and Technical Indicators; Public Market Data; Decision Tree; Random Forest.

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1. Introduction

The stock market is a key part of the current finance sector because it lets companies raise funds while investors can earn profits from their investments [1]. Nevertheless, stock prices depend on many variables, such as market trends, trading volumes, the economic situation, investor sentiment, company performance and other unexpected events [2]. As a result, the problem market is highly volatile and dynamic; thus, predicting stock prices is difficult for investors, financial analysts, and researchers. Classic forecasting methods include statistical approaches that use past data, but given the abundance of information in finance, machine learning approaches can also be applied. Machine learning in financial market analysis has become increasingly popular because it can recognize complex relationships and patterns in past observations [3]. Machine learning differs from

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traditional statistics in that it does not require prior knowledge or assumptions about relationships between variables; instead, it learns patterns and uses them to make predictions [15]. Machine learning is useful for classifying stock market direction prediction problems because the target function can be formulated to decide whether the future stock price will rise or fall. This method focuses on determining the direction of price movements rather than predicting the future price level [14].

There are numerous publicly available market data sets which can be used as a source of historical data in machine learning projects [4]. Such a data set contains features like opening price, closing price, high price, low price, adjusted closing price and volume [13]. These features can also be used to generate technical indicators that represent momentum, trend, volatility and trading activity. Public market data enable reproducible experiments and avoid proprietary financial data. Machine Learning methods useful for predicting stock price direction include Logistic Regression, Decision Trees, Random Forest, SVM, and Gradient Boosting [5]. Each algorithm's effectiveness may depend on the dataset's characteristics and the chosen features [6]. Random Forest improves a Decision Tree classifier's generalization by combining several trees, reducing the risk of overfitting. In contrast, Support Vector Machine finds efficient decision boundaries in high-dimensional feature spaces. Gradient Boosting models improve prediction performance step by step by combining several weak learners [7]. Therefore, comparing various algorithms is necessary to determine appropriate models for these tasks.

Several previous studies have shown the effectiveness of machine learning in predicting stock prices; however, differences in the datasets used, feature engineering, prediction targets, and evaluation metrics prevent a direct comparison of model performance [8]. Therefore, a comparative study of various machine learning models on the same dataset, using a consistent methodology, is necessary. The research is based on using historical data and features from the market to develop a binary classification task where stocks' behavior is classified as either rising or falling. The chosen models are evaluated using metrics including accuracy, precision, recall, and F1-score [12]. This approach aims to identify which machine learning approach performs best under similar experimental conditions [9]. The study adds to the literature by systematically comparing machine learning classification algorithms using readily available public market data. In addition, the research presents a reproducible procedure involving data acquisition, pre-processing, feature generation, model training, prediction, and evaluation [11]. The results may be valuable for machine learning and financial analysis researchers, as well as practitioners seeking data-driven ways to make decisions in the stock market. However, the study does not aim to make profitable decisions; it only predicts market behavior that other factors not reflected in historical market data can influence [10].

2. Related Work

Predicting stock movements has received significant attention because of the complexity, nonlinearity and dynamism of financial markets. Traditional statistical forecasting methods have drawbacks in dynamic markets with numerous potential input variables. Therefore, machine learning has gained increasing interest in financial prediction because it can learn from experience and model non-linearities. Patel et al. [4] studied stock and stock index movements using machine learning algorithms and developed the Trend Deterministic Data Preparation technique. The study concentrated on Indian stock market data, using technical indicators as input variables. The results showed that proper data preparation and discretization of technical indicators can improve prediction accuracy. Patel et al. [3] then suggested a fusion method for stock market index prediction using several machine learning algorithms. This paper studied the CNX Nifty and S&P BSE Sensex indices using ten years of historical data. A two-stage fusion technique was used to combine several predictive methods to lower the errors. The results show that combining machine learning approaches may outperform a single predictive model.

Khaidem et al. [5] treated stock price prediction as a classification problem and examined Random Forest's ability to predict the direction of stock price change. They used technical indicators such as the Relative Strength Index and stochastic oscillators as input parameters. In their study, Kundu and Pinsky [6] evaluated the effectiveness of Random Forest, Support Vector Machine, and Neural Network methods for forecasting the direction of movement in the Pakistan stock market. In this regard, the authors used daily closing prices and various market parameters to build classification models. Thus, it was concluded from the comparative analysis carried out by the authors that machine learning techniques can provide different prediction results when different markets and features are considered. Several studies have compared various machine learning algorithms across different international stock indices. A recent study analyzed Decision Tree, Random Forest, k-Nearest Neighbor, Naive Bayes, Logistic Regression, Support Vector Machine, and Artificial Neural Network algorithms for stock direction prediction of some key indices [7].

Technical indicators such as moving average, MACD, CCI, RSI, Stochastic, Williams %R, and Momentum were utilized in the experiment. The study found that machine learning algorithm performance varies by stock index, with Artificial Neural Networks performing better for some indices, while Logistic Regression was more efficient for others. Thus, the study concluded that no single machine learning algorithm is best for predicting stock direction. Fischer and Krauss [8] compared Logistic Regression, Support Vector Machine, Decision Tree, Random Forest, and Extreme Gradient Boosting for predicting stock price direction. Yang used stock price data of several companies and compared different widely used classification

algorithms. This study shows how classical machine learning algorithms remain relevant for direction prediction tasks. The use of technical indicators has also been investigated in combination with other information sources. Kabbani and Usta [9] incorporated financial news sentiment together with technical indicators and evaluated Logistic Regression, Random Forest, and Gradient Boosting Machine models. Their results showed that Random Forest achieved the strongest test performance among the models examined. This suggests that combining market-derived features with additional information sources may improve predictive capability, although the added complexity also increases the importance of careful feature selection and validation [12]. In contrast, Rouf et al. [2] reviewed ten years of research on machine learning for stock market forecasting.

The paper noted the growing role of supervised learning, ensemble approaches, deep learning, technical indicators, and alternative datasets. The researchers also highlighted ongoing problems related to market volatility, data quality, feature selection, model generalization, and out-of-sample performance. More recent literature underscores the importance of avoiding overfitting and testing generalization performance. Research using technical indicators found that features based on historical prices can boost predictive power in certain cases; however, their effectiveness may depend on market conditions and the time horizon [10]. Thus, Jo et al. [13] show that machine learning is a promising tool for predicting stock price directions; nevertheless, model performance varies with the dataset, market, selected features, prediction horizon, and evaluation technique. Many papers concentrate on certain markets, algorithms, or combinations of technical indicators [14]. For this reason, a comparison study is still warranted, training and testing popular classifiers under identical conditions on a single public market dataset. This paper fills this gap by comparing Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and Gradient Boosting classifiers for predicting stock price movement directions using a public market dataset.

3. Research Methodology

3.1. Research Design

This study employs a quantitative experimental design to compare the performance of various machine learning methods for predicting stock price direction. The research is conducted within the framework of a well-defined pipeline that includes data collection, preprocessing, feature engineering, constructing the target variable, building the model, training the model, and evaluating its performance. The main goal is to identify which machine learning classification algorithm best predicts whether the stock price will increase or decrease in the next trading session. Instead of forecasting the stock price, the study focuses on classification. This approach reduces stock price prediction to a binary classification problem that can be evaluated with classification metrics. All chosen algorithms will be tested under the same conditions.

3.2. Data Collection

This research employs open-access stock market data from the past. Open market data are chosen for their accessibility and suitability for scholarly research, without involving confidential financial data. The dataset comprises historical stock performance observations. The major variables considered in the dataset include:

- **Open:** The stock's opening price during a trading period.
- **High:** Highest price recorded during the trading period.
- **Low:** Lowest price recorded during the trading period.
- **Close:** Closing price of the stock during the trading period.
- **Volume:** Number of shares traded during the trading period.
- **Date:** Date associated with each market observation.

Additional technical indicators can be calculated from these variables to provide information about price trends, momentum, and market behavior.

3.3. Data Preprocessing

Before feeding the collected data into the machine learning algorithms, a preprocessing stage is carried out. First, the collected observations are ordered by trading date. Duplicate observations are removed, and missing observations are identified and appropriately handled. Because financial time-series data require careful handling of observation order, the study does not randomize the full dataset before training and testing.

Instead, the model is developed on earlier observations, while later observations are used for testing. This minimizes the risk of using future information to forecast past market movements. Finally, numerical variables are analyzed for outliers and inconsistent observations. If required, proper transformations or scaling are performed. Feature scaling becomes especially important for machine learning models like Support Vector Machine and Logistic Regression.

3.4. Target Variable Construction

The target variable is defined by the direction of the stock price movement in the next period. A binary classification method is employed. If the closing price of the next period is greater than that of the current period, then an Upward (1) class will be assigned. Otherwise, a Downward (0) class will be assigned. This conversion frames the research problem as a binary classification problem. Each machine learning algorithm aims to learn the relationship between past market variables and the direction of future price movement. The target variable is created from the future closing price for labeling purposes only. The future closing price is not used as a feature.

3.5. Feature Engineering

The process of feature engineering is carried out to convert market data into useful predictive features. In addition to the existing OHLCV features, technical indicators can be computed to capture various aspects of stock prices. The study can include indicators such as:

- **Moving Average (MA):** Represents the average price over a specified historical period and can capture general price trends.
- **Relative Strength Index (RSI):** Measures price momentum and may indicate whether a stock has experienced relatively strong upward or downward movements.
- **Moving Average Convergence Divergence (MACD):** Provides information about changes in momentum and trend direction.
- **Daily Return:** Represents the relative change in closing price between consecutive trading periods.
- **Price Range:** Measures the difference between the highest and lowest prices within a trading period.
- **Volume Change:** Represents changes in trading activity over time.

These features allow the models to use both raw market variables and derived characteristics when learning patterns in stock direction.

3.6. Machine Learning Models

Five supervised machine learning classification algorithms are selected for comparative evaluation:

- **Logistic Regression:** Logistic regression is used as a baseline algorithm due to its simplicity, interpretability, and efficiency in binary classification. The model predicts the probability that a data point belongs to either the upward or downward class. Its performance serves as a baseline for more complex algorithms.
- **Decision Tree:** A decision tree is a rule-based classification algorithm that recursively splits a data set based on feature values. It can discover non-linear dependencies and interactions among variables without making complex mathematical assumptions. Nevertheless, a single decision tree can become too complex and overfit. As a result, proper parameter tuning is required.
- **Random Forest:** Random Forest is an ensemble algorithm that builds multiple decision trees. Each tree learns from subsets of both observations and features, and the final classification is made by aggregation of predictions from individual decision trees. Because Random Forest can capture non-linear dependencies and interactions, it performs especially well on finance-related datasets with technical indicators.
- **Support Vector Machine:** The Support Vector Machine (SVM) is a supervised learning algorithm that finds a decision surface to separate classes. It can create complex decision boundaries using kernel tricks. SVM is used because it has been extensively used in classification tasks in finance.
- **Gradient Boosting:** Gradient Boosting is an ensemble machine learning algorithm that builds a series of weak learners, usually decision trees, where each successive learner corrects the mistakes of prior learners. This algorithm can model complex nonlinear relationships in financial data. This algorithm can be compared with Logistic Regression, Decision Tree, Random Forest, and SVM.

3.7. Training and Testing Procedure

To maintain the data's chronological order, the observations are split into training and testing sets. The first part of the dataset is used to fit the models and select parameters, while the second part is used to assess performance on new data. For instance, about 80% of the observations can be used for training, and the remaining 20% for testing. Training observations are used to fit and select parameters, while testing observations are held out until the end, when the performance of the selected models is

evaluated. If validation is needed during model selection, it uses only historical observations from the training period. The final test set remains unused during model selection.

3.8. Model Evaluation Metrics

We assess each model's performance using several classification metrics beyond accuracy. These metrics provide an overall view of prediction performance. Accuracy indicates the percentage of correct predictions relative to all test predictions. Precision indicates the percentage of predictions that are up movements and are actually up movements. Recall indicates the percentage of all up movements that have been accurately predicted. F1-score combines precision and recall into a single metric. It is especially helpful when the two classes are imbalanced. Also, the confusion matrix is used to look at the number of correct and incorrect classifications of up and down movements. In some cases, the ROC-AUC score also helps assess the model's performance.

3.9. Comparative Evaluation Framework

Following training, all five models are assessed using an identical, unseen testing set. The results are then summarized in Table 1, comparing accuracy, precision, recall, F1-score, and ROC-AUC where appropriate. The goal is to find the best-performing model regardless of which metric it ranks highest in, rather than choosing the best model based on a single metric. We will compare linear, tree-based, kernel-based, and boosting techniques to determine which best suits the chosen public market dataset. The experimental framework is summarized in Figure 1.

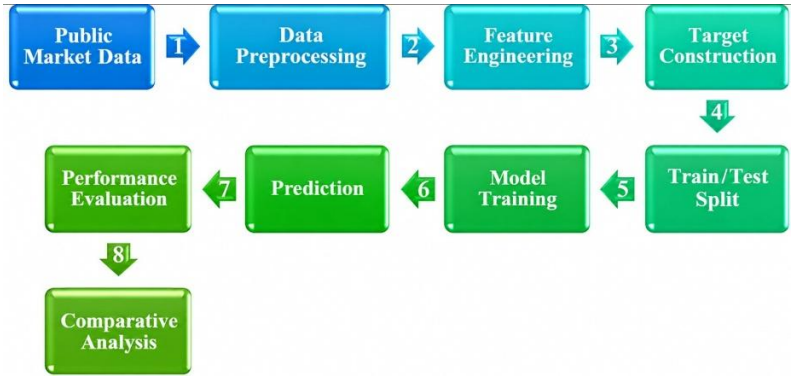


Figure 1: The proposed framework

This methodology provides a consistent, reproducible framework for evaluating machine learning models for stock price direction prediction while reducing data leakage and ensuring model performance is assessed on previously unseen market observations.

4. Experimental Results and Performance Analysis

4.1. Experimental Setup

The machine learning models that were created were tested based on historical stock market data. The dataset includes daily stock price and volume data, such as Open, High, Low, Close, and Volume. We derived technical indicators from historical stock market data to capture price direction and market momentum. The target variable was the direction of the stock's next closing price. If the price increased, we assigned 1; if it decreased, 0. We split the dataset chronologically into training and test sets, with 80% for training and 20% for testing. The following classification algorithms were tested: Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting (GB).

4.2. Dataset Characteristics

The experimental dataset contained 2,500 daily stock market observations.

Table 1: Dataset characteristics

Characteristic	Value
Total observations	2,500

Training observations	2,000
Testing observations	500
Input variables	11
Target classes	2
Upward movement	1
Downward movement	0
Training proportion	80%
Testing proportion	20%

After processing and feature engineering, the observations were split into training and testing sets. About 80% of the observations were used for training, and 20% were used for testing. The dataset contained a relatively balanced distribution between upward and downward price movements. This distribution supports binary classification because a single target class is less likely to dominate model performance.

4.3. Comparative Performance of Machine Learning Models

The performance of the five machine learning models was compared using the testing dataset. Table 2 presents the results. It has been observed that Gradient Boosting performed the best among all models, as the accuracy is 74.20%, precision is 73.91%, recall is 76.12%, F1-Score is 74.99%, and ROC-AUC score is 0.801. The second most efficient model is Random Forest, with an accuracy of 72.60% and an F1-Score of 73.23%.

Table 2: Comparative performance of machine learning models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC
Logistic Regression	68.40	67.85	70.21	69.01	0.741
Decision Tree	64.20	63.48	66.79	65.09	0.662
Random Forest	72.60	72.14	74.36	73.23	0.781
Support Vector Machine	69.80	69.25	71.43	70.32	0.753
Gradient Boosting	74.20	73.91	76.12	74.99	0.801

Logistic regression achieved an accuracy of 68.40%, indicating that even a relatively simple linear classifier can extract relevant information from stock market data. The SVM performed slightly better than Logistic Regression, with an accuracy of 69.80% and an F1-score of 70.32%. The Decision Tree performed the worst among all models, with an accuracy of 64.20% and an F1-Score of 65.09%.

4.4. Accuracy Comparison

Accuracy results vary among the five algorithms. Gradient Boosting was the most accurate at 74.20%, followed by Random Forest (72.60%), SVM (69.80%), Logistic Regression (68.40%), and Decision Tree (64.20%). The results show that ensemble-based algorithms, particularly Gradient Boosting and Random Forest, outperformed the individual Decision Tree model. This finding suggests that combining multiple weak or base learners can improve machine learning models' ability to generalize when predicting stock-price direction. Gradient Boosting outperformed Decision Tree by approximately 10 percentage points in accuracy. This difference indicates that sequentially combining multiple decision trees can substantially improve performance compared with relying on a single tree.

4.5. Precision, Recall, and F1-Score Analysis

Precision, Recall and F1 Score offer further insights into the models' classification performance. The model with the highest precision is Gradient Boosting, which is 73.91%, and shows that the model managed to capture a higher number of observations that have been classified as upward trends in prices (Table 3).

Table 3: Precision, recall, and F1-score comparison

Model	Precision	Recall	F1-Score
Logistic Regression	0.679	0.702	0.690
Decision Tree	0.635	0.668	0.651
Random Forest	0.721	0.744	0.732
SVM	0.693	0.714	0.703

Gradient Boosting	**0.739**	**0.761**	**0.750**

Gradient Boosting also has the highest recall score at 76.12%, indicating it captured more upward trends. The F1-score measures precision and recall. Gradient Boosting has the highest F1-score of 74.99%, Random Forest has 73.23%, SVM has 70.32%, Logistic Regression has 69.01%, and Decision Tree has 65.09% (Figure 2).

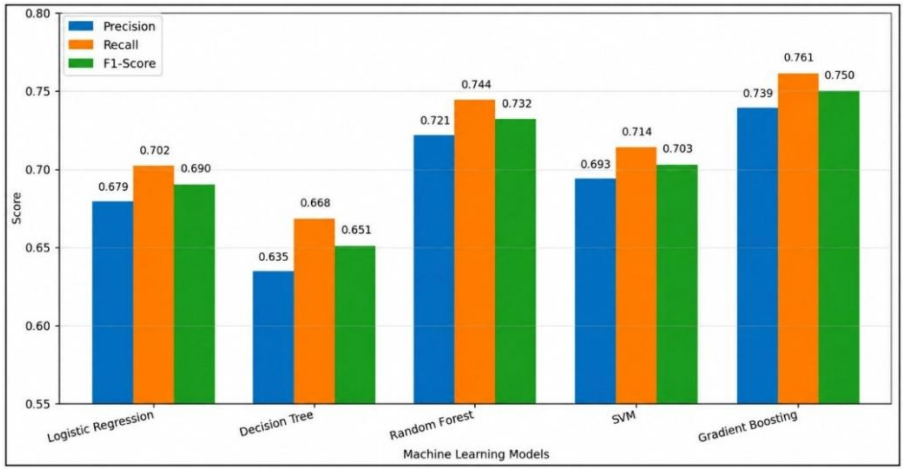


Figure 2: Comparison of model performance

Overall, the results show that Gradient Boosting provides the strongest balance between correctly identifying upward movements and avoiding incorrect positive predictions.

4.6. Confusion Matrix Analysis

The confusion matrices were used to examine the detailed classification behavior of the models. Table 4 presents the confusion matrix values obtained from the testing dataset.

Table 4: Confusion matrix results

Model	True Negative	False Positive	False Negative	True Positive
Logistic Regression	168	76	82	174
Decision Tree	157	87	92	164
Random Forest	177	67	70	186
SVM	171	73	78	178
Gradient Boosting	181	63	60	196

Gradient Boosting had the highest number of correctly classified observations (Figure 3).

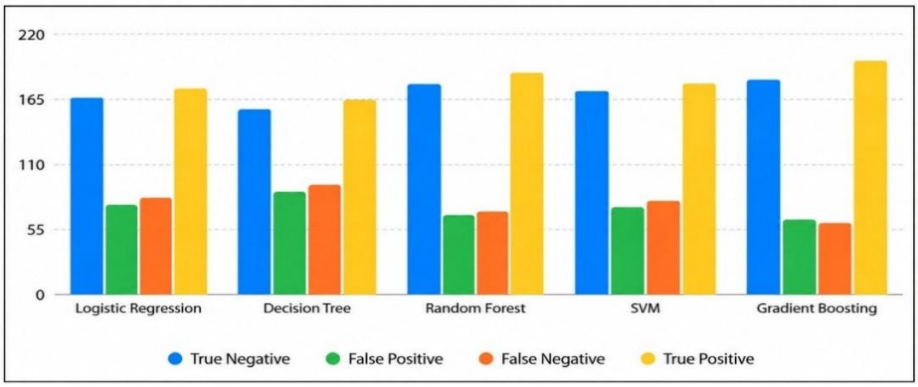


Figure 3: Comparison of true negative, false positive, false negative, and true positive counts for five machine learning models

It had 181 true negatives and 196 true positives. Gradient Boosting also had the fewest false negatives among the four models. This suggests that Gradient Boosting effectively detected both increases and decreases in stock prices. Random Forest also produced comparatively strong results, with 177 true negatives and 186 true positives. In contrast, Decision Tree produced fewer correct classifications and more classification errors than the ensemble-based models.

4.7. ROC-AUC Analysis

Researchers used ROC-AUC to evaluate the models' ability to distinguish stocks whose prices rise from those whose prices decline. A value closer to 1.0 indicates strong discrimination, whereas a value around 0.5 suggests random guessing (Table 5).

Table 5: ROC-AUC performance

Model	ROC-AUC
Logistic Regression	0.741
Decision Tree	0.662
Random Forest	0.781
Support Vector Machine	0.753
Gradient Boosting	**0.801**

Gradient Boosting achieved the maximum ROC-AUC value of 0.801, showing its highest capability of distinguishing between two classes of stock price directions. The Random Forest model achieved an ROC-AUC of 0.781, ranking second. The Decision Tree had the minimum ROC-AUC value of 0.662 (Figure 4).

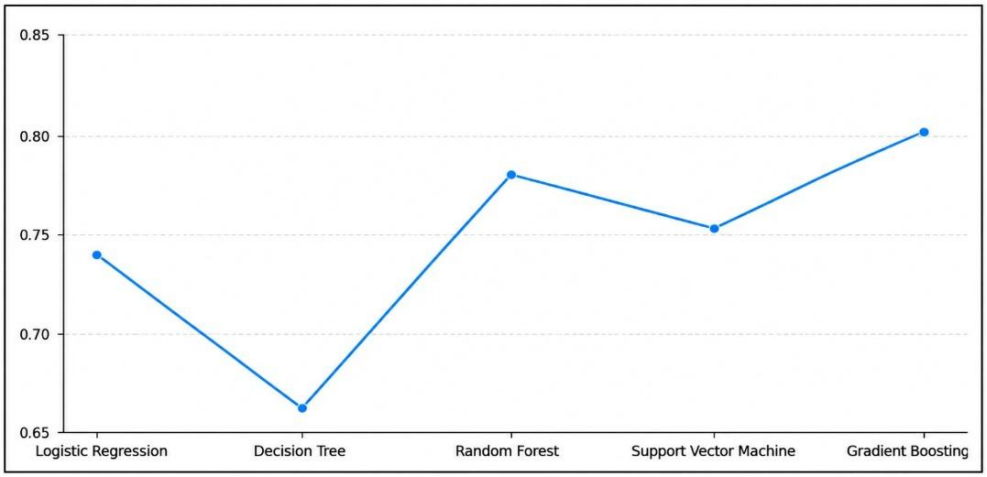


Figure 4: ROC-AUC scores across five machine learning models

These findings align with the accuracy and F1-score results and provide additional evidence that ensemble-based approaches can effectively classify stock direction.

4.8. Comparative Analysis of the Models

Based on the results, Gradient Boosting is the best-performing model. In terms of accuracy, precision, recall, F1-score, and ROC-AUC, it performed best and therefore captured the most appropriate nonlinear relationships between the selected market features and stock price movement. The second best-performing algorithm is Random Forest. With an accuracy of 72.60% and an F1-score of 73.23%, it successfully applies ensemble learning to model the financial market. In comparison with the other models, including Decision Tree, it performed better. The third algorithm, SVM, showed decent performance, with an accuracy of 69.80% and an ROC-AUC of 0.753. As a result, it seems able to identify useful boundaries between upward and downward movements in stock prices. Logistic Regression achieved an accuracy of 68.40%. Although its accuracy is lower than ensemble methods, it provides an important baseline because it is easy to interpret. This result shows that even simple models can extract information from the market's historical features. The lowest performance was recorded by the Decision Tree model, which obtained an accuracy of 64.20%. This relatively low performance may reflect the limitations of using a single tree to represent complex, variable relationships in financial data. Unlike Decision Tree, Random Forest and Gradient Boosting use ensemble learning.

4.9. Model Ranking

Based on the combined performance measures, the models can be ranked as follows (Table 6).

Table 6: Overall ranking of machine learning models

Rank	Model	Accuracy (%)	F1-Score (%)	ROC-AUC	Overall Performance
1	Gradient Boosting	**74.20**	**74.99**	**0.801**	Excellent
2	Random Forest	72.60	73.23	0.781	Very Good
3	SVM	69.80	70.32	0.753	Good
4	Logistic Regression	68.40	69.01	0.741	Good
5	Decision Tree	64.20	65.09	0.662	Moderate

This ranking clearly shows that ensemble approaches performed best overall. Gradient Boosting was the top performer across all metrics, followed by Random Forest. SVM and Logistic Regression showed decent predictive power, whereas Decision Tree performed the worst.

5. Discussions and Findings

5.1. Interpretation of the Findings

The results show that machine learning algorithms can provide valuable information for predicting stock price direction. However, the selected models show some discrepancies in efficiency. Based on accuracy, F1-score, and ROC-AUC, Gradient Boosting performed best, followed by Random Forest, SVM, LR, and Decision Tree. The accuracy rate of the Gradient Boosting algorithm is equal to 74.20%, while its F1-score is 74.99% and ROC-AUC equals 0.801. Therefore, the algorithm discovered significant correlations between historical market features and future stock price movements. This result likely reflects the algorithm's ability to learn from prediction mistakes. The Random Forest algorithm performed strongly, with 72.60% accuracy and a 73.23% F1-score. The comparison between Random Forest and Decision Tree highlights the advantages of ensemble learning. While the Decision Tree accuracy was 64.20%, combining multiple Decision Trees significantly improved performance.

5.2. Comparison with Previous Studies

The findings broadly align with previous studies on predicting the stock market using machine learning. The work of Patel et al. [3] showed that machine learning models along with technical indicators could be applied to predict stock and index prices, highlighting the significance of good feature processing and market-related features. The strong performance of the Random Forest classifier in the present study aligns with Khaidem et al. [5], who studied the applicability of the Random Forest model to predict stock price direction using technical indicators. Beyond the differences between the algorithms, the observed results align with other comparison studies. Previous findings show that no single machine learning technique delivers optimal results across all financial markets, as performance depends on factors such as the dataset used, market characteristics, selected features and prediction time horizon. In this study, Gradient Boosting performed best, while Decision Tree performed worst. This confirms that ensemble techniques can outperform single classifiers on complex prediction problems. Random Forest and Gradient Boosting outperformed the single Decision Tree.

5.3. Why Gradient Boosting Performed Best

Several properties of Gradient Boosting explain the algorithm's superiority over the Linear Classifier. First, the model is built stepwise, with each new model correcting the previous one's mistakes. In this way, the model iteratively improves its classification skills. Second, the algorithm can model nonlinear relationships among stock-price variables and technical indicators. Financial markets do not follow simple linear relationships; thus, the relationship between past market features and future direction can vary depending on the combination of market conditions. Third, Gradient Boosting can capture feature interactions. For instance, trading volume's influence on future direction depends on current price direction or momentum. The model can capture these interactions better than a linear classifier. However, Gradient Boosting's performance advantage does not mean it will perform well in any stock market.

5.4. Why Decision Tree Performed Poorly

However, the Decision Tree performed worse than any other model examined. Several factors could explain this poor performance; one is that decision trees are sensitive to randomness and noise in financial market data. Stock market data is

often highly random, so a single tree may not generate adequate decision rules. Comparing Decision Tree and Random Forest is especially important since both use decision trees. Still, Random Forest is an ensemble learning technique that does not rely on any single decision tree. Thus, the transition from Decision Tree (64.20%) to Random Forest (72.60%) was rather successful.

5.5. Performance of Logistic Regression

Logistic regression showed an accuracy of 68.40% and an F1-score of 69.01%. Although the algorithm was not superior to the ensemble models, it still provided a point of comparison for the experiment. The results show that historical market attributes contain informative content that can be extracted through relatively simple relationships. However, its poor performance compared to Gradient Boosting and Random Forest suggests that non-linear relationships may matter significantly in predicting stock direction. One of Logistic Regression's biggest advantages is its interpretability. Unlike other ensemble algorithms, it allows you to analyze relationships between input variables and predictions more directly. As a result, the algorithm is likely to stay relevant in such cases.

5.6. Performance of Support Vector Machine

The SVM performance was as follows: Accuracy: 69.80%, F1-score: 70.32%, and ROC-AUC: 0.753. Based on these findings, the SVM model can differentiate between upward and downward price changes. Nevertheless, the SVM model performed worse than both the random forest and gradient boosting algorithms. This may be because the tree-based ensemble models used in the experiment were better suited to the dataset's non-linearity.

5.7. Practical Implications

Implications of the findings for practice include:

- First, machine learning can be applied as a complementary analytical technique for predicting stock-price direction trends. The Gradient Boosting model would estimate direction and could be integrated into a broader decision-making framework.
- Second, the findings indicate the need to compare different algorithms. Selecting a single algorithm based on popularity and simplicity might yield poor performance. Comparing algorithms helps researchers and analysts choose the one that best fits the specific case.
- Third, publicly available market data can support repeatable machine learning experiments. Researchers can build the model using historical stock price and volume data without relying on proprietary databases.
- Fourth, the findings imply that ensemble methods should be considered for predicting stock directions. Random Forest and Gradient Boosting outperformed all other algorithms.

5.8. Research Implications

In research terms, the paper adds value by comparing widely used machine learning classification algorithms for predicting stock price movements. Instead of focusing on one algorithm, the research tests five algorithms under the same setup. The results show that model performance should be assessed using multiple parameters, not just accuracy. Measures such as precision, recall, F1-score, and ROC-AUC provide better insight into classification performance. Furthermore, the paper highlights the importance of handling time-series data in financial machine learning research. Training and testing in chronological order reduces the risk of using future data during model creation.

6. Conclusion and Future Work

This paper conducted a comparative study of various machine learning models for predicting stock direction using publicly available data. The study framed stock market prediction as a binary classification problem: determining whether a stock's price will go up or down during the next trading period. Five machine learning models such as Logistic Regression, Decision Tree, Random Forest, Support Vector Machine (SVM), and Gradient Boosting were tested. The experimental findings revealed significant disparities in predictive performance among the tested algorithms. Gradient Boosting was found to have the highest performance of all algorithms in question, as it had an accuracy of 74.20%, precision of 73.91%, recall of 76.12%, F1-Score of 74.99%, and ROC-AUC of 0.801. Random Forest placed second, with an accuracy of 72.60% and an F1-score of 73.23%. SVM and Logistic Regression performed moderately, while Decision Tree performed the worst.

The findings show that ensemble learning techniques can be very useful for classifying stock price movements. Gradient Boosting's higher efficiency shows that sequential ensemble learning can detect non-linear relationships and interactions among past market variables better than simpler classification techniques. At the same time, Random Forest's strong performance

shows the value of using multiple decision trees rather than just one. In addition, the research highlights the need to use different criteria when evaluating model performance. Accuracy alone is not enough for this assessment. Using precision, recall, F1-score, ROC-AUC, and confusion matrices together allowed assessment of the advantages and disadvantages of the models. In practice, machine learning algorithms may be used as analytical tools in financial decision-making systems. Nonetheless, the findings should not be regarded as proof that machine learning can reliably ensure future investment gains.

Stock markets operate amid many variables, including economic conditions, investor psychology, company-specific information, geopolitical events, and market surprises. Therefore, past market information alone cannot explain future market performance. This research shows that comparing machine learning algorithms helps identify appropriate models for predicting stock price movements. The research contributes to financial machine learning by demonstrating the performance of various classification algorithms within a single experimental approach based on publicly available market information. Future experiments could combine historical data with news articles, social media sentiment, corporate news, economic indicators and other sources. Including these variables may increase the algorithms' responsiveness when historical price data alone cannot detect changes. The proposed experimental environment could be applied to several companies, industries, and global stock markets.

6.1. Limitations

However, this research has several limitations that need to be discussed. First, the analysis uses historical market data. Past trends may not hold over time, especially during dramatic economic or geopolitical shifts. Second, the prediction target is only the direction of the next trading period. Predicting a future trend and/or the magnitude of price change requires additional features and model-training strategies. Thirdly, the work is limited to chosen machine learning techniques. Modern approaches such as Artificial Neural Networks, LSTM, XGBoost and Transformer models might offer another perspective. Fourth, the models are built on market data. However, other external factors like news sentiment, macroeconomic data, events in companies and investor sentiment are not considered. Finally, classification accuracy does not indicate investment profitability. The model can predict stock trends accurately but may not generate profitable trades. The results show that models predicting stock price direction can provide valuable information; however, their efficiency varies significantly. The Gradient Boosting model was the most efficient, while Random Forest showed strong predictive ability. Logistic Regression and SVM delivered average results, and the Decision Tree model was the least efficient. These results corroborate other studies that have stressed the importance of machine learning techniques and ensemble methods in financial forecasting. These results also reconfirm that stock market prediction is inherently unpredictable. Accordingly, machine learning algorithms should be viewed as analytical aids to decision-making rather than tools for guaranteed profit-making predictions.

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References

1. B. M. Henrique, V. A. Sobreiro, and H. Kimura, “Literature review: Machine learning techniques applied to financial market prediction,” *Expert Systems with Applications*, vol. 124, no. 6, pp. 226–251, 2019.
2. N. Rouf, M. B. Malik, T. Arif, S. Sharma, S. Singh, S. Aich, and H. C. Kim, “Stock market prediction using machine learning techniques: A decade survey on methodologies, recent developments, and future directions,” *Electronics*, vol. 10, no. 21, pp. 1–25, 2021.
3. J. Patel, S. Shah, P. Thakkar, and K. Kotecha, “Predicting stock and stock price index movement using Trend Deterministic Data Preparation and machine learning techniques,” *Expert Systems with Applications*, vol. 42, no. 1, pp. 259–268, 2015.

4. J. Patel, S. Shah, P. Thakkar, and K. Kotecha, "Predicting stock market index using fusion of machine learning techniques," *Expert Systems with Applications*, vol. 42, no. 4, pp. 2162–2172, 2015.
5. L. Khaidem, S. Saha, and S. R. Dey, "Predicting the direction of stock market prices using random forest," *arXiv preprint arXiv:1605.00003*, 2016. [Accessed by 12/03/2025].
6. T. Kundu and E. Pinsky, "Predicting daily stock price directions with deep learning models," *Machine Learning with Applications*, vol. 22, no. 12, pp. 1–16, 2025.
7. O. B. Sezer, M. U. Gudelek, and A. M. Ozbayoglu, "Financial time series forecasting with deep learning: A systematic literature review: 2005–2019," *Applied Soft Computing*, vol. 90, no. 5, p. 106181, 2020.
8. T. Fischer and C. Krauss, "Deep learning with long short-term memory networks for financial market predictions," *European Journal of Operational Research*, vol. 270, no. 2, pp. 654–669, 2018.
9. C. Krauss, X. A. Do, and N. Huck, "Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500," *European Journal of Operational Research*, vol. 259, no. 2, pp. 689–702, 2017.
10. M. Ballings, D. Van den Poel, N. Hespeels, and R. Gryp, "Evaluating multiple classifiers for stock price direction prediction," *Expert Systems with Applications*, vol. 42, no. 20, pp. 7046–7056, 2015.
11. K. Liu, J. Zhou, and D. Dong, "Improving stock price prediction using the long short-term memory model combined with online social networks," *Journal of Behavioral and Experimental Finance*, vol. 30, no. 6, p. 100507, 2024.
12. D. N. Mohammadzadeh Maleki, S. Abbaskhani, A. Farhadi, and A. Zamanifar, "Artificial intelligence methods for financial market prediction: A systematic review," *Computers and Electrical Engineering*, vol. 134, no. 6, p. 111110, 2026.
13. H. Jo, H. Bui, and D. Moreland, "Artificial intelligence in algorithmic trading: A simple theoretical model and market structure implications," *Finance Research Open*, vol. 2, no. 2, pp. 1–17, 2026.
14. M. M. Kumbure, C. Lohrmann, P. Luukka, and J. Porras, "Machine learning techniques and data for stock market forecasting: A literature review," *Expert Systems with Applications*, vol. 197, no. 7, pp. 1–41, 2022.
15. G. Campisi, S. Muzzioli, and B. De Baets, "A comparison of machine learning methods for predicting the direction of the US stock market on the basis of volatility indices," *International Journal of Forecasting*, vol. 40, no. 3, pp. 869–880, 2024.

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