

Big Data Driven Approach for Stock Price Forecasting Using Machine Learning

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Big data is becoming a major factor that changes or influences various things in real world. One of such is the financial market where the use of advanced analytical techniques, which leads to the changes in investment decisions, can be really of huge effect. Simply put, the main point of implementing the most modern tools and methods to analyze the data inflow basing on the idea of data exploitation is clear and obvious. Thus, the impact of big data on the financial markets is massive enough since it can lead to the improvement of the stock price predictions as well as making the decision process of investors more transparent, easier and quicker. This report is a comprehensive review of the Apple Inc. stock trading data from 2020 to 2025. Big data tools will be necessary to load and process a vast amount of financial data, thus, laying a solid foundation for the analysis in order to uncover phenomena and market trends caused by various events. In addition, machine learning algorithms will be deployed to construct accurate forecasting models that can recognize complex data patterns. The objective of this study is to apply big data and machine learning techniques to forecast Apple Inc. stock price which would be an example of how such technological innovations can lead to a significant increase in the accuracy of financial forecasting. In addition, this paper will also compare the predicted data with the real ones so as to figure out the models' performance.

Keywords: Big data, Spark framework, Prediction, Machine learning, XGBoost



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1. INTRODUCTION

Throughout the digital revolution, data has become one of the most valuable assets in various sectors, among which finance is the most affected area. Since new technologies are continuously emerging, daily data generation is also increasing; thus, businesses and investors can always be up-to-date with the market. Big data, which refers to very large and complex data sets that cannot be easily managed by standard methods, has been in the center of the business world's attention [1]. The combination of big data and advanced analytics has been the main reason of the radical change of financial markets, as it can reveal the new behavioral patterns and trends of the markets that were previously unknown. The main source of these market performance patterns over time is the use of the data, and thus the investment decisions become more informed [1].

Apache Spark is an ideal big data tool. Spark is a rather quick and effective tool for handling a very large volume of data and it provides very modern features, for example, in-memory data processing, thus the analysis is significantly sped up. Besides that, Spark has a number of libraries that are very easy to use machine learning techniques such as MLlib, thus it is very simple for researchers and professionals to develop advanced forecasting and data analysis models [2]. When combined with big data, machine learning techniques can dramatically improve the accuracy of financial forecasts. By employing sophisticated algorithms, learning models are able to analyze the historical data and then predict the future price changes [3] [4]. This is a completely new territory for investors, who can thus decide to use data as a support for their strategies, and have confidence that the analytics they provide are reliable [3]. Machine learning techniques share a considerable overlap with this framework, and one of their contributions is to raise the level of accuracy in predicting and recognizing patterns. Among them, XGBoost is one of the most influential algorithms because of its very high data processing efficiency and greatly improved performance by the use of such methods as tree boosting. The Support Vector Regression (SVR) method can very well deal with non-linear data, and thus, as a matter of fact, it is the best choice for price prediction. Gradient Boosting is yet another very strong tool, which, operations-wise, are quite opposite, as it, instead, improves models by pointing to higher errors in the previous estimates hence the overall model performance is enhanced further [5] [6].

These methods enable markets to efficiently identify the sources of their performance, thus investors gaining the advantage of spotting opportunities and risks quickly and accurately. Still, the continuously increasing reliance on big data and machine learning necessitates a deep understanding of the mode of usage of these tools in various sectors before leading to the next innovations in finance [6].

The financial markets are notorious for their complexity and changing nature which makes the task of predicting stock prices accurately very challenging. The idea of using big data analytics combined with machine

learning techniques as a solution to improve the predictive accuracy has been the focus of research in the last few years.

After the comparison of various machine learning methods like linear regression, neural networks, and decision trees for stock price prediction, Karthikeyan et. al., in single-author research, [7] conveyed, from their experiment with historical market data, that neural networks are the most accurate in predicting stock movements. In his paper, Modi et. al. [8] works on the application of big data in stock market analysis. It elaborates on the tools used in the process of gathering financial data and news and the adoption of the analytical techniques such as sentiment analysis. The paper concludes that the integration of big data has been a major facilitator of a great prediction of the future, hence, it has become very instrumental in the decision-making process of investors. Argade et. al., [9] paper is an investigation of various academic works that focus on the application of machine learning in stock price prediction. The paper discusses methods such as logistic regression and support vector machines and also points out that data and model selection can considerably affect prediction accuracy. Deepa and Murugesakumar's research, 2023, presents big data as a medium of increasing the accuracy of financial market predictions [10]. The paper insists on the implementation of both quantitative and qualitative data and, furthermore, it introduces big data analytics together with sentiment analysis. Their research findings reveal that the combined use of these datasets offers a more comprehensive view of market behavior. Gupta and Jaiswal's [11] article is a debate about the relative performance of deep learning models versus statistical methods in stock price forecasting. The work is grounded on the complete execution of various algorithms such as Auto Regressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), and Convolutional Neural Network (CNN) to analyze the Standard and Poor's 500 index data. The desire of the models to predict the future is the reason for the models' evaluation where, for instance, the Mean Absolute Error (MAE) is a measure that is employed. In other words, LSTM is called the best model since it gives the lowest MAE value of the research. Moreover, the paper highlights an essential role for Data Preprocessing and a condition that the time series should be stationary if the output is to be correct. Furthermore, the paper also hints at the potential of employing machine learning methods in the financial markets to devise more efficient investment strategies.

The stock price prediction with big data analytics and machine learning still remains a critical issue despite the innovative solutions that have been proposed in recent years. The market for stocks is always dynamic and highly influenced by economic, political, and social factors, which means that these changes bring new challenges for the models used in predicting the market trends. Though the use of these technologies has improved prediction accuracy to a certain extent, one should be aware of the limitations and possible mishaps of relying on these approaches only for making investment decisions. Research and innovation should always be there to improve the performance of prediction models in the financial markets that change daily. However, there have always been different factors that affect the cost of a stock, such as the assumptions of the financial specialist, general sentiment on the organization, news from various sources, and even events that cause the whole stock market to vary. The accuracy of the stock cost prediction model can be increased by using the financial ratio together with a model that can sufficiently analyze estimations.

Table 1. Literature Review Comparison

Research	Year of Publication	Use of Big Data Framework	Framework Type	Use of Machine Learning Techniques	AI Technique Type	Results	Limitations
A Study on Stock Forecasting [11]	2023	Yes	Apache Hadoop	Yes	LSTM, RNN, CNN	Improved prediction accuracy	Requires extensive data preprocessing
Role of Big Data Analysis [10]	2023	Yes	Apache Spark	Yes	SVM, Linear Regression	Enhanced decision-making in financial markets	Complexity in data integration
Machine Learning in Stock Market [9]	2021	Yes	Not specified	Yes	Random Forest, SVM	Effective for stock price prediction	Data quality issues can affect results
Predicting Stock Prices [7]	2021	Yes	Not specified	Yes	Moving Average, Linear Regression	Reduced forecasting errors	Limited by historical data used
Big Data Analysis in Stock Market [8]	2019	Yes	Cloudera Hadoop	Yes	Regression, Neural Networks	High accuracy in predictions	High computational resources required

2. METHOD

This research proposes a feasible structure and framework for using online big data and computing to perform regressions that predict stock market trends. It focuses on the collection and cleaning of data and the use of different models for prediction. Combining big data and machine learning turned out to be a great way of forecasting stock prices, according to the experiments. Our central point is to set up a reliable prediction system. In order to create and evaluate our model, we made use of data from Apple Inc. Source of data is Apple Inc. The dataset is made up of the date, opening and closing value, the highest and lowest price of a stock or a stock index, and stock volume. In this research, we have taken into account the closing price for each of the stock. The data was split into the training set that covers the period from October 2020 to October 2024 and the test set, which includes the data from October 2024 to October 2025. We have created a model that can forecast the closing price of the Apple index on a daily basis using that data. The figure 1 is the structure of the work. The study aims to obtain future trading prices in the stock market by predicting the value of these values. This is done through:

1. Data collection: A sample of data was taken in the form of a data set for trading Apple shares for the period from 2020 to 2025 through the fields (Open, High, Low, Volume).
2. Data processing: The data set collected in the previous stage is converted to the Spark Big Data framework for processing. This stage consists of several steps (removing missing and incorrect values and converting data to appropriate formats).
3. Data analysis: The data obtained after the processing process in the Big Data framework is transferred to the next stage. At this stage, the data set is entered into four machine learning techniques (Linear Regression, XG Boost, SVR and Gradient Boosting) to train the model.
4. Prediction: The trained model is used to predict future results based on new data.
5. Results: A future date of several days is chosen and stock prices and trading value are predicted. The figure 2 shows the system steps.

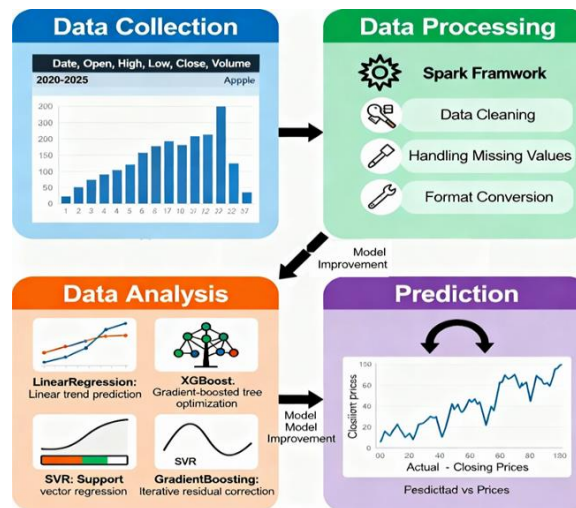


Figure 1. System Structure

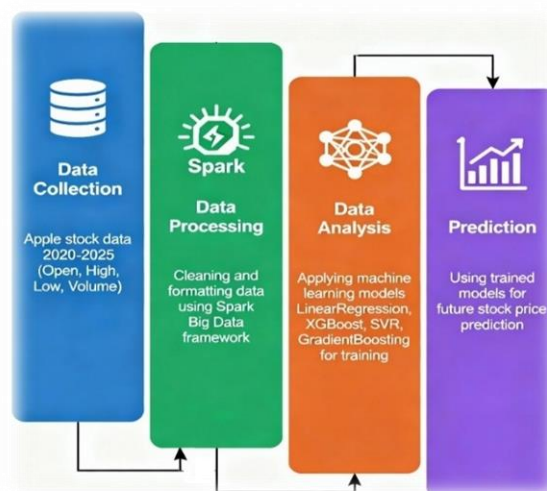


Figure 2. System Stapes

2.1. Raw Data Collection Phase

Raw data collection is a fundamental step in any research study, as it provides the foundation upon which analysis and results are built. Any financial analysis or research is built upon raw data. It is the basic source of information for decision-making. When one gathers precise and trustworthy data, powerful analytical models that forecast market movements and explain investor behavior can be put into use. The period for data gathering was decided to be between October 2020 and October 2025. It offers a complete view of the stock's performance over a particular time period and thus makes trend and price change analysis easier. The finance library, which is known for its user friendliness and dependability, was the source from which the financial data was retrieved. This library offers a straightforward interface for communication with financial market data. The data that was needed was taken from the internet. The data that has been collected comprises the opening price, the high price, the low price, the closing price, and the trading volume. The information is very necessary for the performance of the stock to be understood and the market trends to be analyzed.

2.2. Data Processing Phase

The step of organizing data is crucial for maintaining the accuracy and trustworthiness of the analyses that will follow. By enhancing the quality of the data, error occurrences are lowered, while, at the same time, the performance of analytical models is made better. This, in turn, leads to the improvement of data quality as well as getting data ready for analytical models. In this case, the Apache Spark framework was adopted, which is a leading-edge solution for big data processing and analytics, thus, it was the most feasible option for complex analytical projects. Once the raw data is gathered, the data is taken to the Apache Spark framework to carry out the data cleaning process, which is the most important step to result accuracy. Basically, this step is about dealing with missing or incorrect values by eliminating rows with missing data or substituting missing values with suitable ones. All these changes contribute to upgrading data quality and making it a guarantee that the analyses to be followed will be trustworthy.

Data undergoes different kinds of transformations in order to make the work of the analyst easier. For instance, one may be required to change the data type of a few columns such as trade date to date/time type for the historical data. Such operations enable the models to perform more precise calculations on the time-series data. Once data cleaning and transformation are done; preliminary descriptive analyses are implemented. These analyses are the basis for the subsequent detailed investigations and they provide a number of benefits by exposing the basic statistics (aggregates) that facilitate understanding the trends and patterns existing. After data have been neatly arranged, the final data are saved in a suitable format (CSV). Hence, the data can be available for the next stages of the analysis.

2.3. Data Analysis Phase

Data analysis is the next step after data organization and preparation, and it includes machine learning techniques as well. At this point, the function of data analysis is a turning one in finding the data trends and obtaining the data that should be the basis of the decision-making. This step is crucial for getting the valuable business insights from the data and broadening the general understanding of the stock. As a result of implementing these techniques on the data, trends become visible and stock prices for the future can be estimated thus, investment decisions to a great extent, being informed. The application of machine learning techniques, therefore, is one of the major factors leading to the great effectiveness and precision of the analysis, which is a crucial step in the financial markets. A set of popular methods is employed in this case, namely linear regression, XGBoost, supported vector regression (SVR), and gradient boosting.

Linear regression is one of the simplest and most popular machine learning models used to predict continuous values. This model relies on establishing a linear relationship between input variables (features) and the target variable. The model is trained on data using the least squares method to minimize the difference between predicted and actual values. Linear regression is expressed by equation 1.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \epsilon \quad (1)$$

- y : The dependent variable (the value we want to predict).
- β_0 : The intercept (constant term).
- $\beta_1, \beta_2, \dots, \beta_n$: The regression coefficients for the features x_1, x_2, \dots, x_n
- ϵ : The error term (noise in the model).

XGBoost is a sophisticated tree-boosting model. It is regarded as one of the most powerful machine learning models that has won numerous competitions and has been applied widely with great success. The main idea of XGBoost is to build a forest of trees and use voting to make a decision, thus allowing the prediction accuracy to be increased. Besides, it is capable of handling big data very fast and in a few steps as well. XGBoost is represented by the following equation 2.

$$f(x) = \sum_{k=1}^K h_k(x) \tag{2}$$

- $f(x)$: The final model.
- K : The number of trees.
- $h_k(x)$: The k^{th} tree used in the model.

Supported regression is a regression support technique used to predict continuous values by building a model based on high-dimensional spaces. It is pretty an approach where non-linear data scenarios are used in most cases. SVR is a margin-based concept; thus, it tries to get the best line dividing the data keeping the largest number of points within a certain margin. SVR is represented by equation 3.

$$f(x) = \langle w, \phi(x) \rangle + b \tag{3}$$

- $f(x)$: The predicted value.
- w : The weights in the high-dimensional space.
- $\phi(x)$: The kernel function that changes the data into a higher-dimensional space.
- b : The bias term.

Boosted regression is another method that also utilizes tree boosting but differs slightly from XGBoost in how it does this. The model is created one after another, hence each tree is trained on the parts of data (errors) where the previous trees made mistakes. Such a way is very effective to increase the prediction power of the model as the model gets more and more it learns from its previous errors. Gradient Boosting is shown with an equation 4.

$$f(x) = f_0(x) + \sum_{m=1}^M \gamma_m h_m(x) \tag{4}$$

- $f(x)$: The model after the combination of all parts of the works (trees).
- $f_0(x)$: The first model (usually the mean value).
- γ_m : The coefficient for the m^{th} tree.
- $h_m(x)$: The m^{th} tree added to make the model better.

2.4. Prediction Phase

The prediction process for stock analysis starts by fetching Apple stock trading data from the period of 2020 to 2025. The data set includes opening, high, low prices, and volume of trade. After the data is gathered, it is changed over to Spark framework for execution, where the missing and incorrect value issues are fixed, and the data is presented in the new formats. The cleaned data is then used to train the model with four machine learning techniques: Linear Regression, XG Boost, Support Vector Regression (SVR), and Gradient Boosting. The trained model is then used to estimate the results with new data. Hence, a date in the future is drawn to anticipate stock prices and trade values, thus, helping the investors to see into the future of the market and decide accordingly. Table 2 illustrates the model training process and the training ratios used.

Table. 2 Describing the Model Training Process and Training Ratios

Model	Data Used	Training Data Ratio	Testing Data Ratio	Description
Linear Regression	Apple stock trading data	80%	20%	The model is trained on 80% of the data to learn patterns.
XG Boost	Apple stock trading data	80%	20%	Utilizes boosting algorithms to improve prediction accuracy.
Support Vector Regression (SVR)	Apple stock trading data	80%	20%	Uses support vectors to estimate continuous values.
Gradient Boosting	Apple stock trading data	80%	20%	Combines learning techniques to minimize errors.

3. RESULTS AND DISCUSSION

The designed model was actually tested. After collecting, processing, and analyzing Apple trading data for the period from October 2020 to October 2025, the test results were able to predict Apple's stock price for October 15, 2025, based on the forecasting methods used. The Linear Regression model predicted the stock price with a value of (233.114423). The XG Boost model predicted (236.068696). The SVR model predicted (239.094655). The Gradient Boosting model predicted (246.207581). Table 3 indicates the expected closure of the models.

Table. 3 Models Predicted Close in USD

Seq.	Model	Predicted Close
1	Linear Regression	233.114423
2	Gradient Boosting	236.068696
3	SVR	239.094655
4	XG Boost	246.207581

Through the readings predicted by the four models, the results indicate that the XG Boost model gave the best prediction than the other models by arriving at the real stock price on 15 Oct 2025 (247.86).

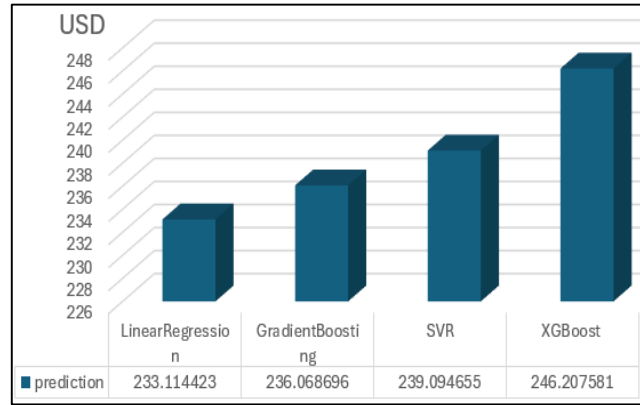


Figure 3. Models Predicted

According to the data recorded in table 4 and figure 5, the models for predicting Apple's closing stock price had a significant variation in terms of their forecast accuracy when compared to the actual stock value on October 15, 2025. For instance, the XG Boost model exhibited the minimum absolute difference vis-à-vis the actual value indicating its best performance in capturing complex data patterns as well as nonlinear market movements. Whereas, the Linear Regression model revealed the greatest difference which is ascribed to its incapacity to handle non-linear relationships in the data. The difference points to the importance of picking out the best model to increase the precision of financial predictions.

Table. 4 Models Predicted Close vs Actual Price and Absolute Error in USD

Model	Predicted Price	Actual Price	Absolute Error
Linear Regression	233.11	247.86	14.75
Gradient Boosting	236.07	247.86	11.79
SVR	239.09	247.86	8.77
XG Boost	246.21	247.86	1.65

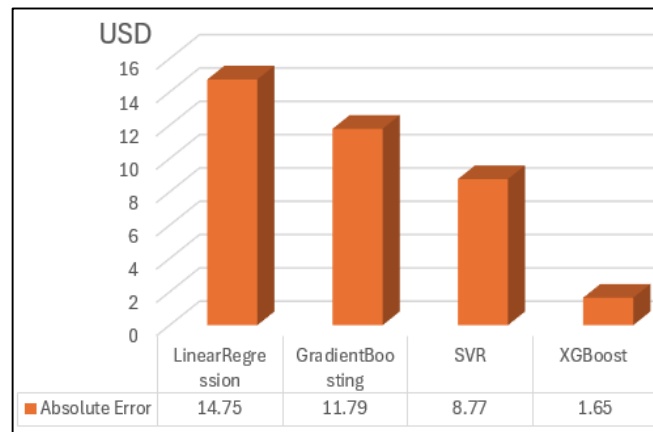


Figure 4. Difference between model predictions and actual price

The findings reveal the necessity of using different data sources and also considering the changes in the market that happens at the moment to be able to align models with financial reality which will then facilitate decision making at a higher level of confidence. The difference between forecasts and actual values illustrates the difficulties and fluctuations of the financial market and thus, a demonstration of the continuous requirement to advance and retrain predictive models so as to be at the same level as ongoing changes in the business environment.

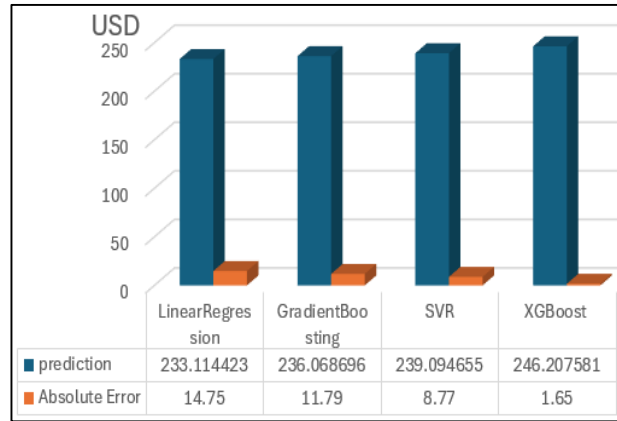


Figure 5. Apple Stock price: Models vs Actual

The proposed framework outperforms related works such as Gupta and Jaiswal [11], as LSTM achieved an average absolute error of 1.18 on Standard and Poor's 500 index data through time series preprocessing, by delivering superior prediction accuracy with an XGBoost absolute error of only 1.65\$ (versus actual 247.86\$ on October 15, 2025) on recent Apple stock data via scalable Apache Spark processing - reducing errors by up to 89% compared to linear regression in our tests (Tables 3-4).

Table. 5 Models Predicted Close vs Actual Price and Absolute Error in USD

Aspect	Gupta & Jaiswal	Sentiment + Big Data	Our Framework's Advantage
Best Error Metric	MAE=1.18 (LSTM)	Qualitative accuracy gains	Abs Error=1.65 USD (XGBoost); 78% lower than SVR
Data Handling	Stationarity checks	Hybrid quantitative/qualitative	Spark-based cleaning; handles 5-year OHLCV at scale
Scalability	Limited to ~7000 records	Real-time big data emphasis	80/20 split on 2020-2025 data; tree ensembles > RNNs
Innovation	DL vs. statistical debate	Market behavior integration	Big data efficiency + lowest error on volatile stock

Table 5 illustrates the advantage of our work in low-error practical forecasting of individual stocks, outperforming deep learning in unstable chains while enabling efficient big data pipelines - paving the way for hybrid extensions with sentiment analysis.

4. CONCLUSION

The experiment concluded with a range of forecast accuracies for the various predictive models on the closing price of Apple stock. Linear Regression, Gradient Boosting, SVR, and XGBoost models were run on Apple stock data that contained open, high, low, and volume from October 2020 to October 2025. In October 15, 2025, was the main point for evaluation. Thus, the results were basically showing how close the models' predictions are to the price actually recorded that day. Compared to classical linear models like linear regression, XGBoost showed a huge leap in accuracy which is mainly due to its ability to capture nonlinear interactions in the data. SVR was in the middle ground, thus indicating its capability to accommodate small errors within the error margin. The authors argue that the combination of several predictive methods with new big data not only tremendously increases the forecast quality but also makes buying and selling decisions more reliable to a great extent. It is worth noting that market movements are still random even after these model accuracies, and they are influenced by a multitude of economic and political factors that have not been taken into account in this analysis. Such results have a significant impact in demonstrating how different machine-learning methods can be successfully employed in stock market analysis. Besides, they point to the fact that it is absolutely imperative to supplement the data set with some economic and market news indicators not only to achieve a higher predictive accuracy but also to obtain a deeper insight into price changes.

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