COMPARATIVE ANALYSIS OF REGRESSION MODELS FOR STOCK PRICE PREDICTION: LINEAR, SUPPORT VECTOR, POLYNOMIAL, AND LASSO

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Abstract
This paper investigates the performance of various regression-based machine learning techniques for short-term stock price prediction. Four regression algorithms – linear regression, support vector regression (SVR), polynomial regression and LASSO regression – were applied to Apple Inc's historical price data for two-years ending on October 1st, 2024, to predict the next day's closing stock price. Technical indicators such as moving average, relative strength index (RSI) and lag features were included in the regressions to improve prediction performance. Evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R^2) were employed to assess the models' performance. Results show that linear regression and LASSO regression were the most performant models, reaching R^2 values of more than 0.95, with minimal error values. While SVR yielded the poorest results when accounting for all metrics. Overall, the study highlights the predictive power of simpler regression models over more complex ones in stock price predictions and offers recommendations for model selection.

Keywords
Stock market, machine learning, predictions, regressions, linear regression, LASSO regression, polynomial regression, support vector regression

JEL Classification
C32; C52; C53; G10

Introduction
The exponential increase in computational power, coupled with the decrease in compute prices and rise in data availability have brought artificial intelligence and machine learning back into the public's attention. Several aspects of the financial markets and

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investing process have been influenced by artificial intelligence and machine learning. Algorithmic trading strategies use machine learning techniques to analyze vast amounts of data and swiftly identify patterns and trends to predict stock prices and execute trades based on those inputs (Talreja and Thavi, 2024) (Kumar, 2024) (S. Sahu, 2024). Machine learning algorithms can also be used to analyze historical data and patterns to identify potential risks or predict future market volatility, crucial aspects in portfolio risk management (Hajj and Hammoud, 2023).
Being a component in a more complex trading and investing system, stock price predictions can help investors make the right decisions in terms of maximizing their returns and minimizing their losses. But this has long been a challenging task, given the inherent volatility and complexity of financial markets. Although econometric methodologies were used for decades, with the rise of machine learning, regression techniques are increasingly being applied in this domain.
Regression analysis in the context of stock market predictions involves predicting the future stock prices (the dependent variable) based on historical prices or technical indicators (the independent variables). Several studies in recent times have reported effectiveness on this task by using techniques ranging from simple linear regression models to advanced methods such as Support Vector Regression, Polynomial Regression, or LASSO (Least Absolute Shrinkage and Selection Operator) Regression. These models offer distinct advantages depending on the dataset's linearity (or lack thereof), as well as their ability to counteract overfitting or to handle complex market dynamics.
Linear regression is a simple and highly interpretable technique. This model has been shown to effectively capture stock price movements and trends based on historical data, thus making it a strong baseline model for benchmarking other techniques. SVR is intended for modelling nonlinear relationships, often promising good performance in complex, volatile market situations. While polynomial regression can model more complex relationships, its added complexity adds the risk of overfitting. Lastly, LASSO regression incorporates regularization as a means of balancing model complexity and predictive power in generally noisy financial environments.
While machine learning techniques can be used to try and predict long term price trends (Seca, 2019), researchers have explored the use of machine learning to predict the long-term value of financial stocks as well (Dhilipan, 2021), this study aims to compare the performance of these four regression models in predicting the future stock closing price of the largest publicly traded company Apple Inc. Technical indicators, such as 10-day moving average, the relative strength index, and lag features, are added to improve the predictive accuracy. The performance of all models is then assessed based on mean average error, mean squared errors and R^2 to find which one provides the best solution for short-term stock price forecasting.

1. Review of scientific literature

Regression based machine learning techniques are increasingly popular in the stock market prediction domain. This review aims to synthesize findings from various research papers on regression methods and their use in predicting stock prices across various methodologies and datasets.

Regression analysis refers to the statistical methods used to model the relationship between a dependent variable and one or more independent variables. In the stock market prediction context, the dependent variable is usually the future price of a stock, while the independent variables can include historical prices or trading volumes, and various technical indicators derived from the price action of the stock. The most used regression methods, and the ones tackled in this paper, are linear regression, support vector regression, polynomial regression and LASSO regression.

Being a simple and interpretable method, linear regression is one of the foundational techniques used in both traditional econometrics and machine learning. Oladapo et al. have found that trading volume and stock prices exhibit a statistically significant correlation, leading to a regression equation that is able to predict a large portion of the price variance based on volume (Oladapo et al., 2023). Thus, indicating that linear regression can effectively capture some of the underlying dynamics of stock price movements.

Moreover, Khandare and Patil highlighted that linear regression exhibits a higher accuracy when compared to other forecasting methods, despite the method's simplicity and stock market's complex behaviour (Khandare and Patil, 2021). In another paper, Bouzgarne et al. featured linear regression alongside more complex algorithms such as Long Short-Term Memory (LSTM) and Random Forest to demonstrate its utility as a prediction benchmark (Bouzgarne et al., 2024).

Another popular regression method which found applications in stock price prediction is support vector regression. SVR, through its kernel function, has an advantage when modelling nonlinear relationships. In Huang's work, SVR, by allowing for more granular modelling of more complex stock price movements, has shown promising results in stock price prediction and has outperformed simpler models such as linear regression (Huang, 2024).

Furthermore, SVR has been shown to yield higher accuracy in predictions even in volatile market conditions, making it a valuable tool for investors seeking to optimize their trading strategies in these kinds of environments (Sagar et al., 2023). The discussion of basic linear regression principles is further enhanced with advanced regression techniques such as SVR, thus helping investors in better understanding the market dynamics.

Going further, the polynomial regression extends the simple linear regression model by fitting a polynomial equation to the data, which enables the modelling of more complex relationships. Although less mentioned in the academic literature in the context of stock price prediction, polynomial regression is one of the better ways to model nonlinear trends in stock prices. Research by Zeng et al. indicates that polynomial regression enhances predictions where the relationship between the predictors and target variable is inherently nonlinear (Zeng et al., 2023).

Lastly, LASSO regression is a technique that performs both variable selection and regularization to improve prediction accuracy and enhance the interpretability of statistical models. Being able to shrink coefficients to zero, LASSO is effective at selecting a simpler version of the model to avoid overfitting, a crucial aspect in the volatile environment of stock markets.

Using historical stock prices and transforming them into new variables for model inputs, Divya et al. revealed that LASSO regression outperformed traditional methods in terms of accuracy metrics such as Mean Absolute Error and Root Mean Squared Error (Dhivya et al., 2023). Further expanding on the application of LASSO regression, Rastogi et al. used technical indicators such as moving averages and the Relative Strength Index to predict stock prices of the NIFTY 50 index. The results showed increased prediction accuracy by using calculated features based on time lag with the LASSO regression (Akshar et al., 2021).

A comparative analysis among different regression methods confirms that traditional linear regression is a good starting point for stock price prediction, but advanced techniques like SVR, and hybrid models further improve the performance. For instance, linear regression may display good performance in capturing the linear pattern, but struggles with capturing the intricate dynamics of financial markets characterized by a strong nonlinear pattern and external influences such as economic indicators and market sentiment (Yenkikar and Babu, 2023). The SVR's efficiency in handling nonlinear relationships, thus improving predictive performance under volatile market conditions has been highlighted by Wang as well (Wang, 2020).

Despite the strengths of regression-based methods, several challenges persist in the field of stock price prediction. The inherent volatility and unpredictable nature of financial markets add significant obstacles on the road towards accurate forecasting. According to Vancsura and Bareith, market behaviour can be severely influenced by external factors such as economic crises, further complicating the modelling process (Vancsura and Bareith, 2023). Stock prices and market movements are influenced by a plethora of factors such as economic indicators, investor sentiment, company announcements or geopolitical events. These events are often unpredictable and unexpected, thus making it harder for machine learning models that are being trained on historical data to accurately predict and account for them (Yadav, 2024). Additionally, the overfitting of models, especially in machine learning applications, remains a concern that introduces the need for models to be carefully validated and tested on unseen data. As the performance of machine learning models relies heavily on the quality of data (Guennioui et al., 2024), especially in volatile markets (Kapinus et al., 2024), one should pay increased attention to data incosistencies and inaccuracies such as missing values or erroneous data can negatively impact the models' predictive capabilities leading to false predictions that could have serious financial repercussions.

Feature selection is also a facet that plays a crucial role in improving the predictive accuracy of regression models. Research has shown that performance increases significantly when relevant predictors are included in the model, emphasizing the importance of proper feature engineering in predicting stock prices (Wong et al., 2023).

2. Research methodology

The section describes the methodology for predicting stock prices based on the four machine learning regression approaches described. Accordingly, the approach encompasses the steps related to data collection, feature engineering, training the models on various regression algorithms, and stock price forecasting with the help of historical data.

Yahoo Finance was used to obtain historical data for the past two years ending on the first of October 2024 of Apple's stock price. This company was selected due to it being the highest market capitalization in the entire stock market and being one of the most followed stocks by investors, thus making it a prime candidate for our comparison. Moreover, Apple's stock high trading volume means that several trading strategies could be used in real-world trading with a lower impact on overall stock prices. Being known for its relatively stable long-term performance, as well as stock price fluctuations, this stock provides us with a prime candidate for evaluating regression techniques, while its prominent position in indexes and status of blue-chip company could imply that insights drawn from Apple's stock prediction could have broader implications for similar blue-chip companies. The two-year period ending on October 1st, 2024, was selected to capture the recent trends as well as ensuring we have enough data to reliably train and evaluate the models. The two-year window provides a balance between capturing the recent state of the market as well as capturing trend changes and drawdowns in the stock price. The data was downloaded from Yahoo Finance through the publicly available yfinance Python library. For simplicity and relevance to the stock price prediction task, only the Close price was used in training and testing the models.

The selected regression techniques were chosen to provide a comprehensive comparison of both linear and non-linear techniques in stock price prediction. Linear regression, due to its interpretability, simplicity and use in several studies serves as the baseline comparison model for our comparison. Support vector regression, due to its ability to model complex relationships, was chosen to account for potential nonlinearities. Polynomial regression serves as the middle ground between the two, allowing for some nonlinearity without over-complicating the model. Lastly, LASSO regression, due to its L1 regularization parameter, was chosen for its capability of dealing with cases of overfitting by penalizing irrelevant features in the dataset. This mix of models allows for an evaluation of strengths and weaknesses of different approaches in stock price prediction, a task known for its unpredictability.

To enhance the dataset and improve the prediction accuracy, three features were created based on stock price history. Encompassing the last two weeks of trading data, the 10-day moving average (MA) was calculated to capture the short-term trends and smooth the daily fluctuations. The 10-day window of the moving average provides a good trade-off between short-term changes in price and determination of the overall trend. The 14-day (RSI) was used as a measure of the speed and change of price movements. With values between 0 and 100, this RSI shows whether the stock is overbought (when displaying values above 70) or oversold (when displaying values below 30). As a standard practice in technical analysis, the 14-day value of this momentum oscillator has been chosen. Lastly, lag features were added to capture the historical movement of the analyzed stock. The lag features are important because, in many cases, stock prices have autocorrelation - that is, the prices for previous days can be useful in predicting future values. In this case, the closing prices of the last five days were chosen. These features are selected based on their broad application in financial analysis and technical trading strategies, where they often help identify stock price momentum, support, and resistance levels.

After these features were generated, the dataset was cleaned to remove rows with missing values, which is commonly the case after computing moving averages or the RSI. Then, the data was split into a training set comprised of the first 80% of the observations, and a testing set comprised of the remaining 20% observations. Before feeding the data into the models, the features were normalized using the StandardScaler method of the scikit learn Python library. Scaling is crucial in machine learning to ensure the results are not skewed. For the stock price prediction, four regression algorithms were used, selected based their various strengths in handling different relationships between the features and the target variable.

Linear regression looks at the linear relationship between the input features and the target variable as expressed by the closing price. It can also be said that linear regression serves as the baseline comparison model due to its simplicity and interpretability.

For the SVR, a radial basis function (RBF) kernel was used to model the nonlinear relationship between feature values and stock prices. The RBF kernel makes it possible for the SVR to model even more intricate patterns in data. The hyperparameters were chosen as C = 100, gamma = 0.001, and epsilon = 0.001. These hyperparameters were chosen by trial-and-error strategy to balance model flexibility and generalization. Controlling the trade-off between maximizing the margin and minimizing the classification error, the higher value of 100 for the C parameter allows the model to better fit the training data, an essential aspect to maximize the accuracy of the prediction task. A relatively small value of 0.001 was chosen for the gamma parameter to ensure control over the influence of individual data points, allowing the model to better generalize across the dataset. Lastly, the small value of 0.001 chosen for the epsilon parameter ensures precise fitting and reduces the margin of error in the predicted stock prices.

Going further, a second-degree polynomial regression was used to ensure the model captures the nonlinear relationship between the input features and the stock price. The degree was limited to two in order not to overfit and at the same time to keep the potential nonlinear structure of data.

Lastly, the LASSO regression used applies an L1 regularization which penalizes large coefficients, thus preventing overfitting. An alpha coefficient value of 0.01 was chosen as a trade-off between model complexity and generalization, allowing the model to exclude the irrelevant features while also avoiding overfitting and retaining predictive power. A lower value was chosen for the alpha parameter after testing higher values and observing that too much regularization led to underfitting and thus, significant features were excluded from the prediction, reducing the predictive power of the model.

Each model was trained on the training set and had its performance evaluated on the test set. For the polynomial regression, the features were transformed using second-degree polynomials before applying linear regression, while the SVR, LASSO and linear regression models were trained directly on the scaled features. Predictions on both training and test sets were performed for every model. After training, each model was used to make a prediction for the next day's closing price using input features from previous days.

To assess the accuracy of each model's predictions, Mean Absolute Error, Mean Squared Error and R^2 were used. Measuring the average magnitude of errors in predictions, MAE is useful for understanding the model's average prediction error in dollar terms without considering the direction of the error. Squaring the errors before averaging them, MSE gives more weight to larger errors, thus helping in assessing the model’s sensitivity to large deviations between actual and predicted values. Lastly, the R^2 score quantifies the proportion of variance in the stock price explained by the model, a R^2 closer to 1 indicates a strong predictive ability.

The actual stock prices and predictions from each model were visualized using the matplotlib Python library. For each model, the actual price and the predicted was plotted on a separate graph, while a final plot displays the actual price and the predicted values for linear regression, SVR, polynomial regression and LASSO regression. The x-axis displays the stock price in US dollars, while the y-axis displays the dates on which the predictions were made.

3. Results and discussion

The results of the stock price prediction task using the four different regression models, linear, support vector, polynomial and LASSO, as evaluated using the MAE, MSE and R^2 are presented in the table below.

Table no. 1. Evaluation metrics of the regression models for the stock price prediction task

Model	MAE	MSE	R^2
Linear Regression	2.157542	7.905652	0.957859
Support Vector Regression	4.812588	33.992182	0.818803
Polynomial Regression	2.577798	11.435999	0.93904
LASSO Regression	2.194596	8.009757	0.957304

Source: Author's own work

The best performing model was the linear regression, achieving the lowest MAE (2.16), MSE (7.91) values and the highest R^2 (0.958). These results highlight the model's strong prediction power, accounting for approximately 95.8% of the variance in stock price. While the small errors suggest that linear regression accurately captures the stock price trends. It could be worth exploring this technique's performance and ability to capture non-linear patterns, as Mo's research suggest it might have difficulties in accurately predicting during volatile market conditions (Mo, 2023). The predicted values of the linear regression model (the blue line) can be observed plotted against the actual price (the black line) in the graph below.

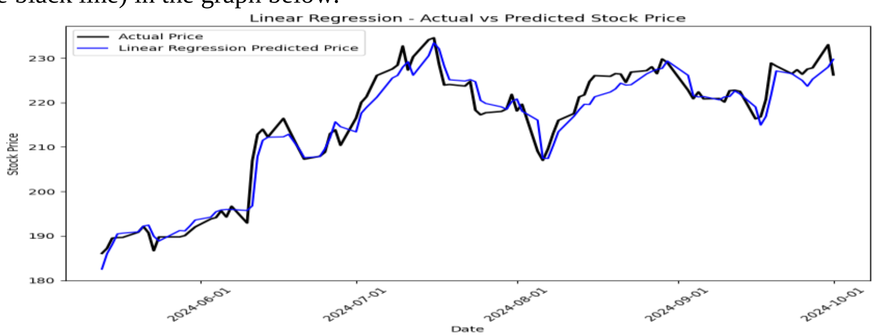

Figure no. 1: Linear regression predicted price against the actual price

Source: Author's own work

With a MAE of 2.19 (0.03 higher than the linear regression), a MSE of 8.01 (0.1 higher than the linear regression) and a R^2 of 0.957 (0.01 lower than the linear regression) the LASSO regression stands in the not too distant second place. This indicates that LASSO regression's regularization parameter which was meant to penalize large coefficients didn't drastically affect its performance. LASSO's ability to counteract overfitting through coefficient regularization has likely contributed to its strong performance. Although not overtaking linear regression in terms of absolute results, LASSO could be a better option when there's a need to prevent overfitting, or when dealing with noisy data. Using its regularization capabilities, LASSO could also be the better option when dealing with high-dimensionality datasets (Yang et al., 2022). The predicted values of the LASSO regression model (the blue line) can be observed and plotted against the actual price (the black line) in the graph below.

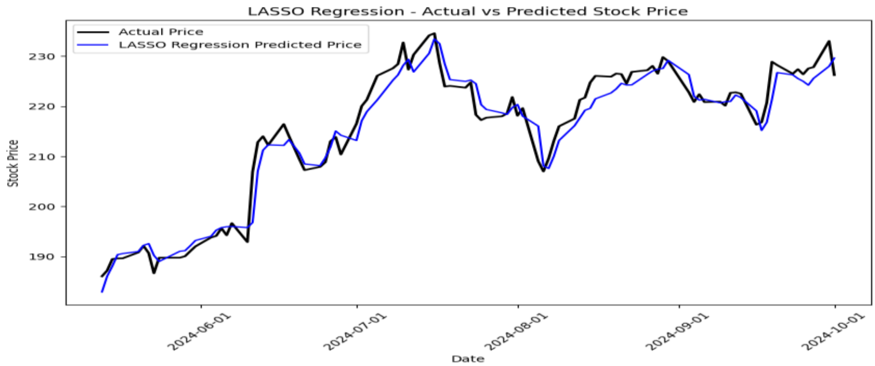

Figure no. 2: LASSO regression predicted price against the actual price
Source: Author's own work

Achieving decent results, the polynomial regression sits in the third place. With an MAE of 2.58 (0.42 higher than the linear regression), a MSE of 11.44 (3.53 higher than the linear regression), and an R^2 value of 0.939 (0.019 lower than the linear regression) the model has performed reasonably well but was not as effective as the simpler linear regression or LASSO regression models. By accounting for the nonlinear interactions between the features, polynomial regression was able to capture more complex patterns, this however came with the downside of higher errors when compared to the previous models. The model's higher complexity introduced by the polynomial terms, having potentially led to overfitting, could be one of the explanations for these scores. To counteract this drawback, more careful validation could be carried out as per Mo's recommendations (Mo, 2023). The predicted values of the polynomial regression model (the blue line) can be observed plotted against the actual price (the black line) in the graph below.

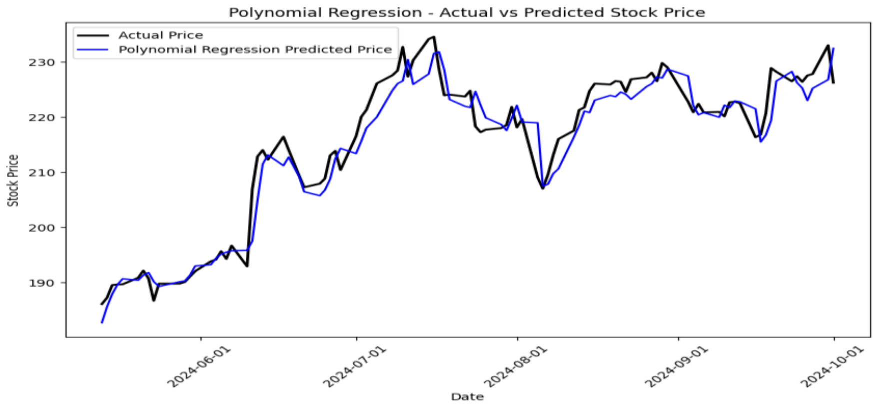

Figure no. 3: Polynomial regression predicted price against the actual price

Source: Author's own work

Lastly, SVR has been shown to have the poorest performance among the four models for this exercise. The MAE of 4.81 (2.65 higher than the linear regression), and MSE of 33.99 (26.08 higher than the linear regression) values are considerably higher than the other models, and the R^2 value of 0.819 (0.139 lower than the linear regression) indicates that this SVR model explains only 81.9% of the variance. These figures suggest that SVR struggles with capturing the trend in the stock price. This could be attributed to poor tuning of hyperparameters or to the model's increased sensitivity to certain features. Even after adjusting the kernel and regularization strength parameters, SVR has still failed to deliver results comparable to the other regression models, making it the least effective option for this exercise. However, as per Fang's findings, SVR might be more suited for capturing more complex relationships (Fang, 2020), as opposed to the simpler ones tackled in this study. The predicted values of the SVR model (the blue line) can be observed plotted against the actual price (the black line) in the graph below.

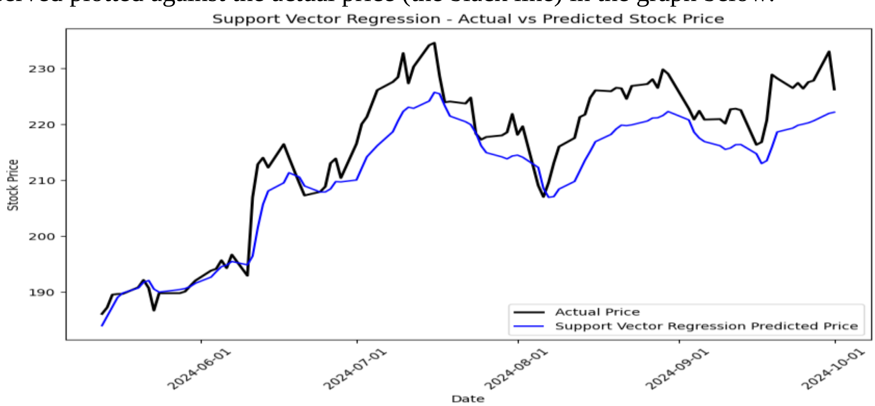

Figure no. 4: Support vector regression predicted price against the actual price

Source: Author's own work

Based on the evaluation metrics used, since both give similar MAE, MSE, and R^2 values, linear regression and LASSO regression are the best for predicting the next day prices. Their simplicity combined with high predictive accuracy makes them highly suitable in this context of short-term stock price prediction. The worst-performing model was the Support Vector regression. It had the highest level of errors and explained far less variation in the data when compared to other models. Even after tuning its parameters, SVR's stock price forecast continued to deviate from actual stock prices, suggesting that this model was not suitable for this dataset. Meanwhile, polynomial regression achieved only mediocre performance. For its added complexity, its benefits are limited compared to linear and LASSO regressions. In fact, the higher error rates could signal a slight risk of overfitting, making this model less practical than its simpler counterparts.

In conclusion, linear regression and LASSO regression are the most reliable regression models for predicting the next day's closing price based on previous closing prices, moving average and RSI, while SVR is not preferred due to its poor performance.

Nonetheless, further exploration can be done, and several other factors can influence the model selection decision. Depending on the data used, including its linearity, stationarity or presence of noise, some models may be more performant than others. More complex models such as polynomial regression or SVR can prove to be more performant than their counterparties in those cases (Mo, 2023). It falls upon every trader and investor to experiment and choose the right models for their data, context and use-cases.

The plot containing the actual stock price (using the colour black), and the predicted values of the linear regression (using the colour blue), support vector regression (using the colour orange), polynomial regression (using the colour green), and LASSO regression (using the colour red) can be observed below.

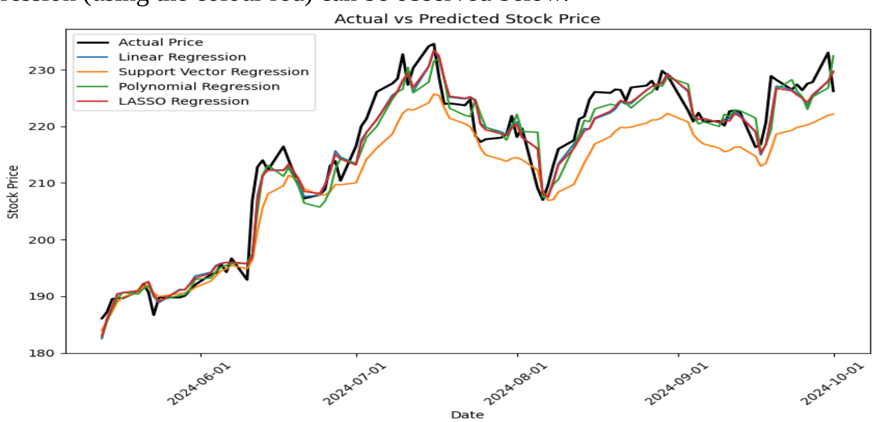

Figure no. 5: Linear regression, support vector regression, polynomial regression and LASSO regression predicted price against the actual price

Source: Author's own work

Conclusions

This research evaluated the performance of four regression-based machine learning models, linear regression, support vector regression, polynomial regression, LASSO regression, for short-term stock price prediction. With R^2 values of more than 0.95, linear regression and LASSO regression performed the best in predicting Apple Inc's next closing price based on the previous five closing prices, alongside moving average and relative strength index indicators. Their simplicity, combined with high prediction accuracy and minimal errors, make linear regression and LASSO regression suitable for predicting future prices of stocks based on historical data and technical indicators. With very similar performance to linear regression, LASSO regression, with its regularization technique that applies a penalty to prevent overfitting, could be a very robust option for volatile or noisy market conditions. Polynomial regression, while able to capture even more complex patterns, has shown higher error rates, suggesting an increased overfitting risk. Lastly, SVR yielded the poorest result by any metric, with both a significantly lower R^2 value, as well as higher MAE and MSE values, thus implying that SVR is not as well suited as its peers to stock price prediction tasks based on historical data and technical indicators. In fact, regarding technical indicator-based short-term stock price prediction, simpler models like linear regression and LASSO regression are more reliable. Advanced models like SVR might be useful in certain cases, but given their underperformance in this study, further fine-tuning and preprocessing of data could be needed if one wants them to be as competitive as simpler and more interpretable models.

A key limitation of this study is given by the relatively small dataset. While it provides a representative picture for a major stock, the two-years timespan and focus on a single company could mean that the conclusions may not generalize well to more stocks, other than other blue-chip companies. Stocks with lower trading volumes or different volatility patterns may exhibit different results. Additionally, only a limited number of technical indicators were included. While these indicators provide a fast-running time and decent results on our dataset, including other relevant indicators could improve prediction accuracy. This should be done on a trial-and-error basis to avoid adding too many indicators, some of which could be unnecessary and slow down the algorithms' running time. Although the study's focus is to compare the regression methods prediction capabilities, the short-term price prediction task used in our methodology does not consider external factors such as macroeconomic indicators or market sentiment, both known to have significant influence on stock prices. Lastly, the trial-and-error method of choosing the hyperparameters could benefit from more extensive tunning that could lead to better results.

Although this study sheds some light on the use of regression techniques in short-term stock price predictions based on historical data and technical indicators, further research is still needed to obtain a complete picture. Future research could explore the use of larger datasets that span multiple years and cover a wider range of stocks across different sectors, thus being able to capture more diverse market conditions and allow for a more comprehensive evaluation of the regression techniques. Although some regressions have underperformed in this study, they could outperform in other market conditions. Testing these models across various economic cycles, such as bull or bear markets, crashes or economic instability could provide more in-depth insights on how each model can be used

in different situations and market regimes. Moreover, the inclusion of additional technical indicators such as Bollinger Bands, Moving Average Convergence/Divergence (MACD) or stochastic oscillators could improve the prediction accuracy of the models. Leaving the realm of regression-only prediction, investigating how combinations with other different machine learning models, such as random forests or gradient boosting, could improve predictions is another avenue of future research. Lastly, more rigorous hyperparameter optimization techniques, such as grid search or Bayesian optimization could be used to enhance the fine tuning of the models.
While short-term price prediction in the stock market using these regression techniques can hold important economic implications for traders and investors, one should not overlook their shortcomings. While providing investors with a fast and interpretable tool to make buy or sell decisions and aid in identifying short-term trends and momentum shifts, these short-term predictions can be susceptible to market noise and sharp changes in trend, which can lead to misleading signals and significant financial losses. Moreover, overreliance on short-term predictions, without considering broader market trends, events and fundamental analysis can lead to poor investment decisions and permanent loss of capital. Thus, traders and investors need to understand the weak and strong points of these techniques and use them merely as a tool in their diverse toolset, not as the only method used. Due to the ever-changing nature of stock markets, we do not believe that these decisions should be one hundred percent automated. Human oversight is essential to ensure that the appropriate decisions are made when necessary.

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