ASSESSMENT 3 – CASE STUDY REPORT

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1. Introduction

Quantitative trading is a strategy that uses mathematical models in order to predict the value or direction of future security prices and/or returns (Sharma 2021). It is a strategy that is increasingly adopted by financial institutions, brokerages, trading firms and even individual traders/investors in order to inform their trading decisions. In this study, we will be exploring the explanatory and predictive power of supervised machine learning models in predicting the returns of Apple stock based on a number of technical indicators associated with two trading strategies, namely, momentum-based strategy and mean-reversion strategy. This is because the literature surrounding this topic observed the existence of both phenomena in explaining the movements of financial securities in the market (Klein 2010). The mean-reversion strategy assumes that price trends tend to revert back to their mean after a temporary deviation whereas a momentum-based strategy hypothesize that prices will generally move in the direction they were moving in before (Quantshare 2012). For a day/intra-day trader, knowing which strategy to adopt on a particular security informs their position on whether to buy and sell a security for a particular day. Accordingly, the following target questions will be addressed in this study:

1. Can supervised machine learning models predict the next day stock returns in order to generate profitable trading signals?
2. Can these models explain which technical indicators are best at predicting next day stock returns, and by extension, the trading strategy to adopt for a particular stock?

Our report is targeted towards day/intraday traders whose practice is to purchase and sell a security within a single trading day. By predicting next day stock returns, it enables them to manage their risk and execute profitable trades. Hence, the output of our model will be used to generate trading signals.

The process diagram below outlines the steps that will be undertaken in producing our models.

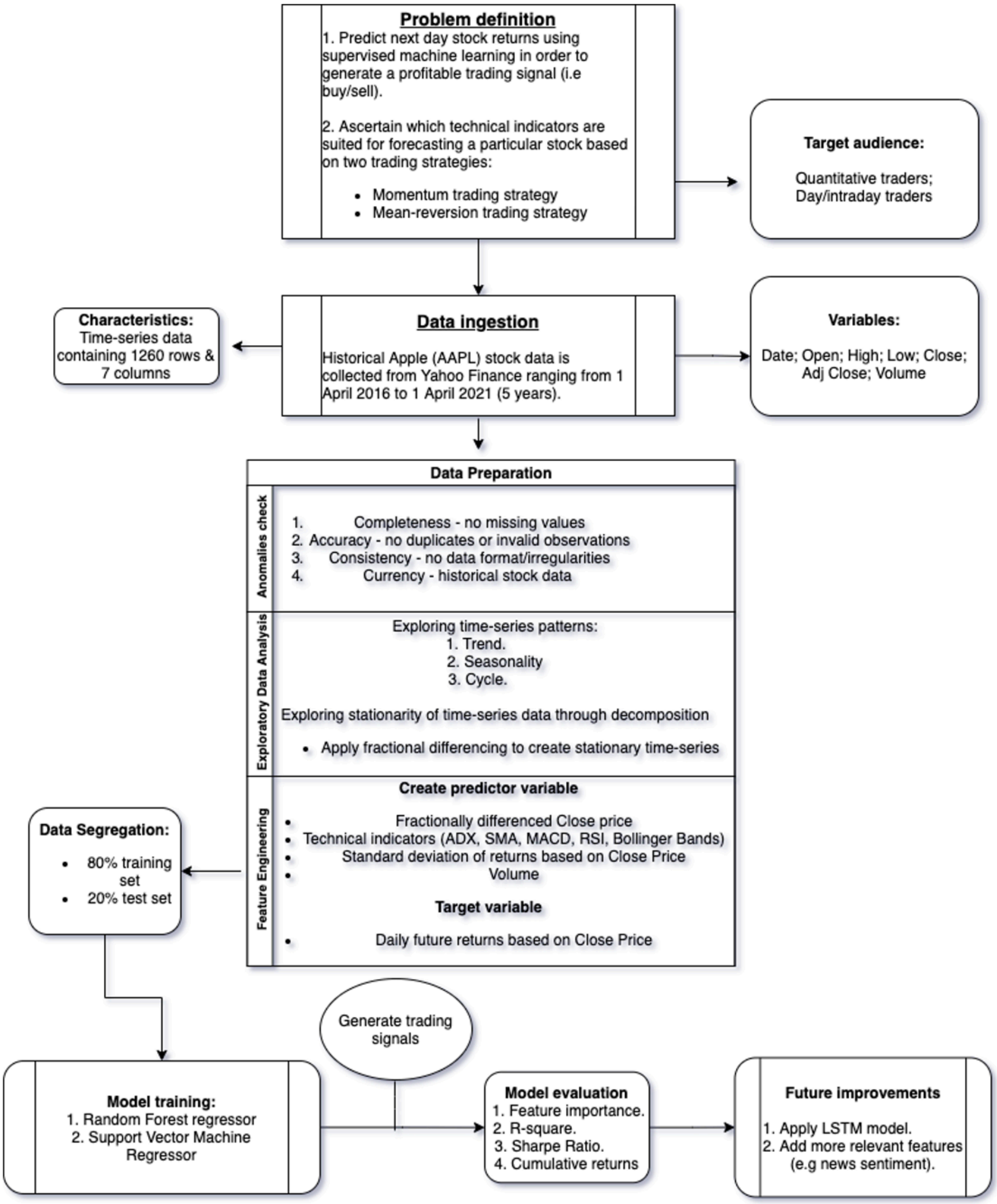


Figure 1. Supervised machine learning pipeline for predicting next day stock returns

2. Materials and Methods

We collected historical Apple stock data (AAPL) from Yahoo Finance for a period of 5 years ranging between 1st April 2016 to 1st April 2021. It is a time-series dataset containing 7 variables, namely, date, stock prices at different time periods within a trading day (i.e open, low, high, close, adjusted close), and volume representing the total amount of trading activity for a particular stock (Smigel n.d).

We then investigated the dataset for any anomalies to ensure that there are no duplicated/missing values, outliers, invalid observations and/or any other irregularities such as format errors. Since our dataset contain no irregularities, we performed exploratory data analysis in order to understand the underlying patterns in our time-series dataset.

Time-series data exhibits a variety of patterns. To understand our data, we split these underlying patterns into several components, namely, trend-cycle component, a seasonal component and a residual component (Hyndman & Athanasopoulos 2021). We do this using the adjusted close price because it is a more accurate view of the company's stock price since it has been adjusted for corporate actions such as dividends, stock splits, and new share issuance (Marwood 2018).

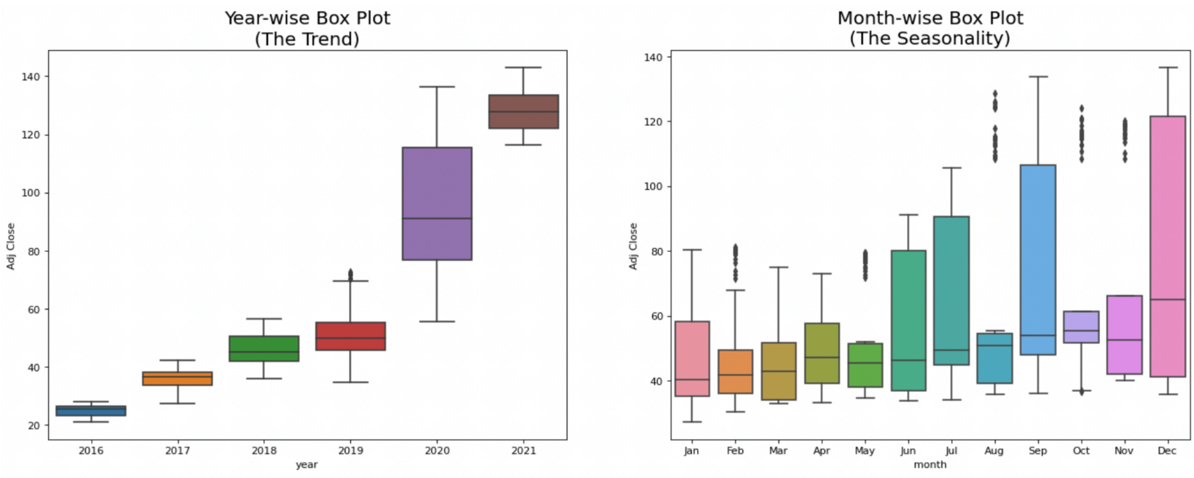


Figure 2. The trend and seasonality of Adjusted Close Price for Apple stock

Based on Figure 2 above, the year on year trend clearly shows that the adjusted closing price of AAPL have been increasing without fail. Furthermore, the variance and the mean value in September and December is much higher than the rest of the months indicating a strong seasonal effect. This is likely due to the fact that since 2011, AAPL tend to launch their iPhone products in September and majority of their sales are likely due to Christmas holidays in December (Infonewt 2020).

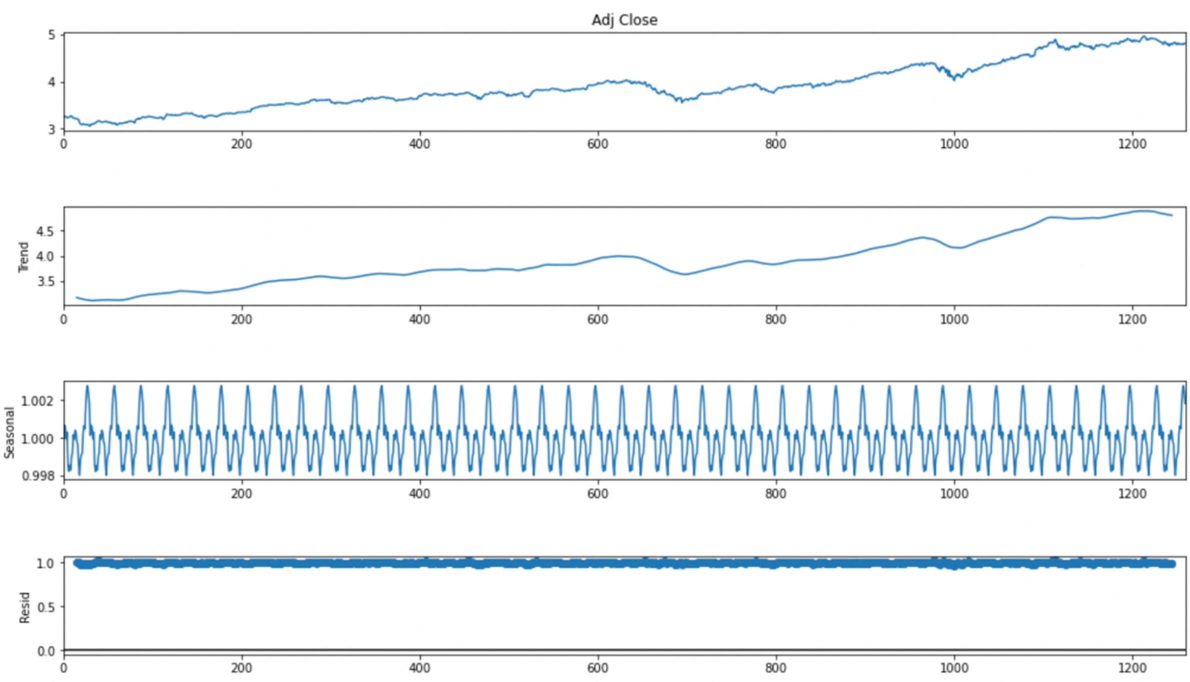
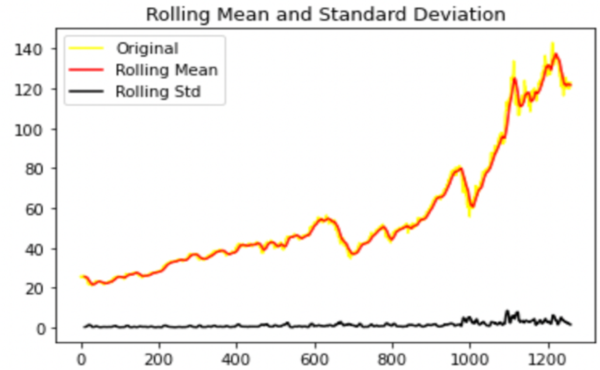


Figure 3. Decomposition of adjusted close price for AAPL stock

Furthermore, figure 3 revealed that the AAPL is very much dominated by the trend and seasonal components of the time series, with the residual component generally playing a minor role. The analysis above reveals that our data is not stationary as it exhibits a strong trend and seasonality (Hyndman & Athanasopoulos 2021). This is further confirmed by applying the Augmented Dickey Fuller (ADF) test for stationarity.

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Results of dickey fuller test
Test Statistics                   0.273960
p-value                           0.976118
No. of lags used                 20.000000
Number of observations used    1239.000000
critical value (1%)              -3.435639
critical value (5%)              -2.863876
critical value (10%)             -2.568013
dtype: float64
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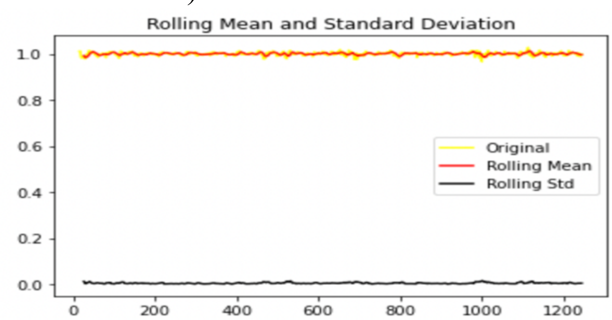
Figure 4. ADF test for stationary on adj close price of AAPL

Here, we can see that both the mean and standard deviation are not flat lines indicating that these statistical properties are not constant. Furthermore, the test statistics is greater than the critical value thus pointing to the conclusion that the time-series is not stationary (Jain 2016).

To ensure that our models do not produce unreliable and spurious results, we must transform our time series data so that it becomes stationary (Iordanova 2020). This is because the stock price and size of the company has changed over time. Hence, the raw stock price 10 years ago will perform poorly when used to predict price movements today unless the statistical properties like the mean and variance of the adjusted close price is made constant (Hyndman & Athanasopoulos 2021).

The two common methods for making our time-series data stationary are decomposition and differencing. The decomposition method requires that we model the trend and seasonality components in our time-series, remove them from the observations, and then train our models based on the residuals (Brownlee 2017).

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Results of dickey fuller test
Test Statistics                -9.907222e+00
p-value                         3.239387e-17
No. of lags used                2.100000e+01
Number of observations used     1.208000e+03
critical value (1%)            -3.435775e+00
critical value (5%)            -2.863936e+00
critical value (10%)           -2.568045e+00
dtype: float64
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Figure 5. ADF test for stationarity on the residuals of adj close price of AAPL

When comparing Figure 5 from Figure 4, we can clearly see that the data is stationary. Since the value of the ADF test statistics is lower, we can assume stationarity (Jain 2016). However, we can clearly see that this method also eliminates the series-specific memory in the data such as trends thus inadvertently affecting the predictive power of our models (Kuttruf 2019).

To resolve this trade-off between memory and stationarity, we have applied the fractional differencing method as it is able to make the data stationary while still preserving some of the memory (De Prado 2018).

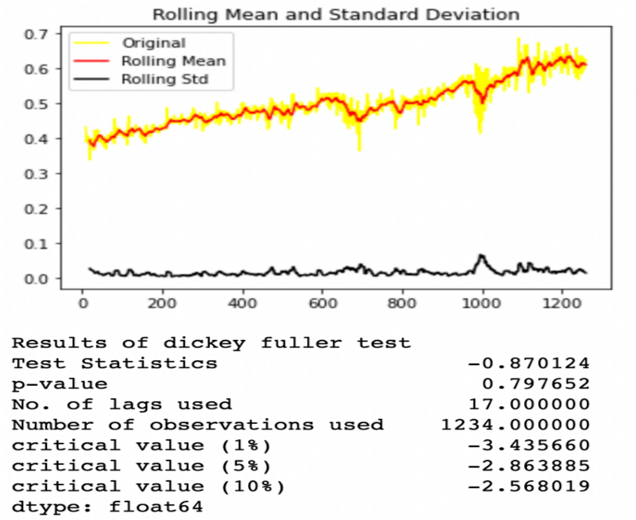

Figure 6. ADF test for stationarity on fractionally differenced adj close price of AAPL

Here, we can see that the ADF test statistics is lower than in Figure 4 but still retains some memory when compared against Figure 5. From the fractionally differenced adjusted close price, we then create our predictor and target variables.

Our predictor variables consist of technical indicators typically used by quantitative traders when adopting either a mean-reversion strategy or momentum-based strategy as seen in Figure 7 below (Marwood 2018; CMC Markets 2021).

Mean-reversion strategy	**Momentum-based strategy**
Bollinger Bands (BBANDS)	Average Directional Index (ADX)
Standard deviation	Simple Moving Average (SMA)
	Moving Average Convergence/Divergence (MACD)
Relative Strength Index (RSI)	

Figure 7. Technical indicators used for the two strategies (Marwood 2018; CMC Markets 2021)

These indicators are calculated based on the fractionally differenced high, low and close prices. We also included the fractionally differenced close price as well as volume as our predictor variables. Our target variable is the daily future returns and is computed based on the fractionally differenced close price whereby the value of the computed returns is shifted backwards by one day to reflect the actual value of future returns.

We then split the dataset into two parts. The first 80% of the dataset will be used to train the model and perform hyperparameter tuning. The remaining 20% will be used to evaluate our models.

In order to examine the explanatory and predictive powers of our models, we fitted our dataset using a random forest regressor (RFR) and support vector machine regressor (SVR). Since SVR is affected by the range in the variables, we applied the min-max normalization to prevent the magnitude of certain variables from overwhelming the others (Bhandari 2020). Consequently, we tuned the hyperparameters through an iterative process whereby we define a range of possible values for all the hyperparameters, evaluate the performance of each model and select the hyperparameters that produces the result that overcame our baseline (Jordan 2017). The goal is for the R-squared value of our models to be higher than the baseline thus indicating a better fit (Martin 2013).

Depending on the predictions, we will buy the stock at open price and sell the stock at close price in the same day where the returns is positive. Conversely, we will short-sell the stock at open price and complete the short-sell at the close price where the returns is negative. Finally, we will calculate the Sharpe ratio as well as plotting the cumulative returns. Our best model will be the model that generates the most profitable trading signals.

3. Results and discussion

Model type	R-squared (without tuning)	R-squared (with tuning)
Naïve baseline	-5.179179043635074e-06	
Support Vector Machine Regressor (SVR)	-0.5528578527870651	0.2064410995261221
Random Forest Regressor (RFR)	-2.0544670355820602	0.2834282136980948

Figure 8. Comparison of model performance on test set against baseline based on R-squared

Based on the table above, both our models performed better than the baseline especially after hyperparameter tuning. However, while the R-squared value for both our models is not high, it is able to indicate that there is a reliable relationship between the respective technical indicators for each strategy and stock returns (Martin 2013). We are not expecting a high R-squared value because these technical indicators cannot possibly explain a high percentage of the variation in stock returns, as they are affected by many other factors such as news/market sentiment, industry performance, company performance and so on (Harper 2019).

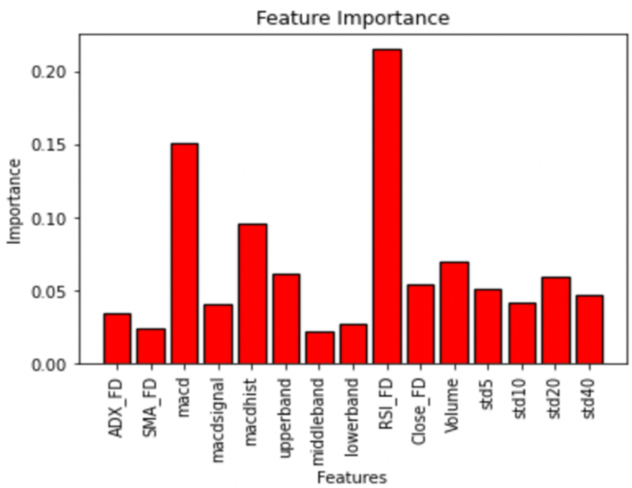

Figure 9. Feature importance for predicting stock returns

Consequently, figure 9 revealed that the most important technical indicators for predicting stock returns is RSI and MACD indicating that the AAPL stock is following a momentum-based strategy. This insight may inform day/intra-day traders on the strategy to adopt when trading AAPL stock such as applying the same technical indicators but with different time granularities in order to gain better insight and decision-making.

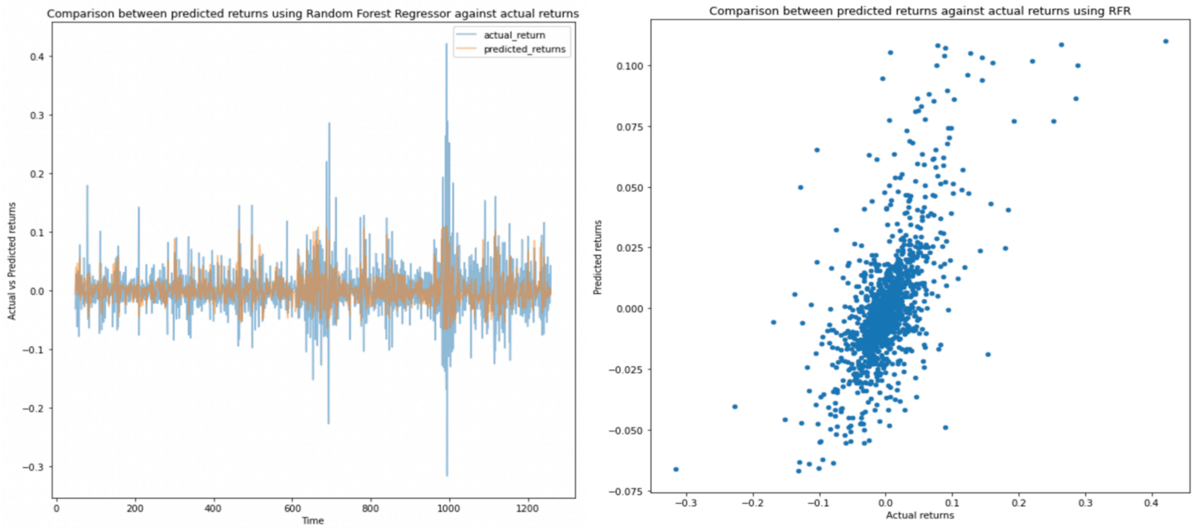

Figure 10. Comparing the predicted returns against actual returns for our RFR model

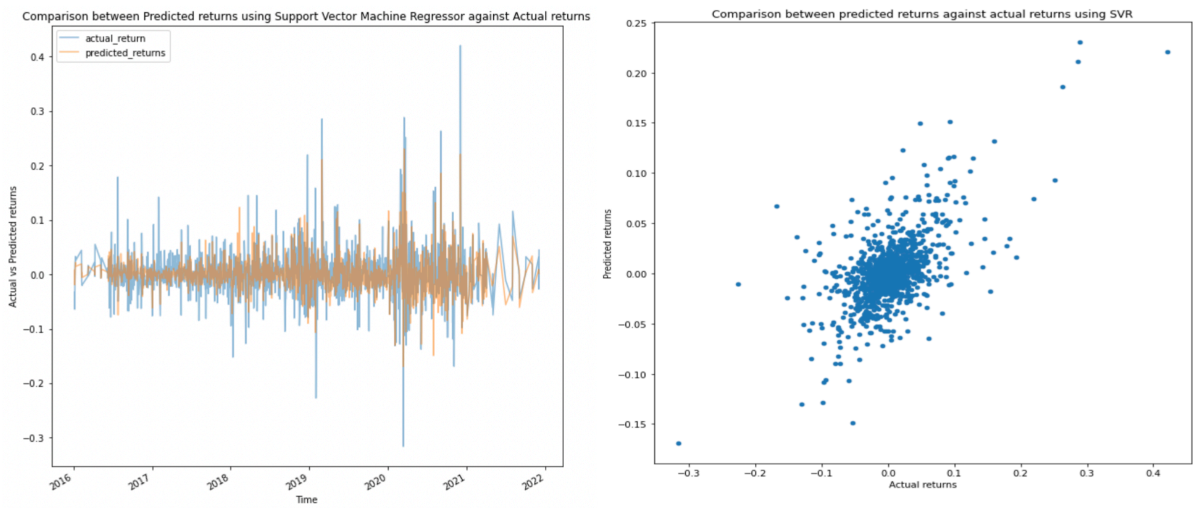

Figure 11. Comparing the predicted returns against actual returns for our SVR model

A deeper inspection on our RFR and SVR model revealed that they can predict with relatively good accuracy where the returns are between -0.025 and 0.025 as well as -0.05 and 0.05 respectively. For values falling out of these thresholds, we assigned a signal of 0 indicating that a trading signal is not generated by our model whereas a signal of 1 is given where the return is positive and -1 where the return is negative. Accordingly, we are able to generate trading signals based on these thresholds as illustrated in Figure 12 below.

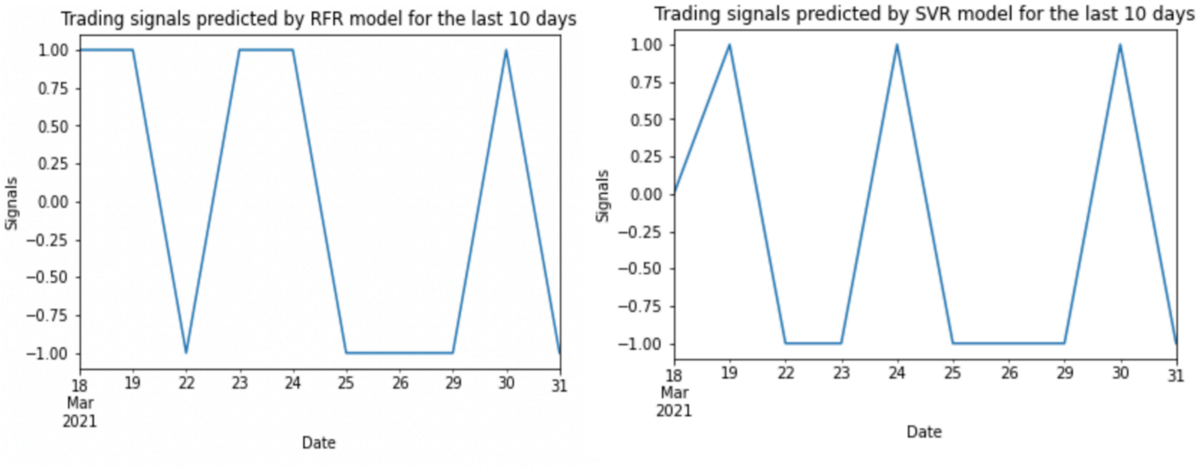

Figure 12. Trading signals generated by our models

From these signals, we calculated the Sharpe ratio as well as the cumulative returns for each model in order to assess their profitability. The Sharpe ratio helps us to understand the return of an investment compared to its risk thus allowing us to evaluate the performance of our models. A model with a ratio of 1 or better is good, 2 or better is very good, and 3 or better is excellent (Lioudis 2021).

Model type	Train set	Test set
Support Vector Machine Regressor (SVR)	4.40151	3.66644
Random Forest Regressor (RFR)	5.76938	3.17004

Figure 13. Sharpe Ratio for our SVR and RFR models

Although both our models performed well, we can see that our RFR model performed extremely well on the training set compared to the test set indicating that it was overfitting. On the other hand, our SVR model performed better on the test set than the RFR model despite not performing as well on the training set.

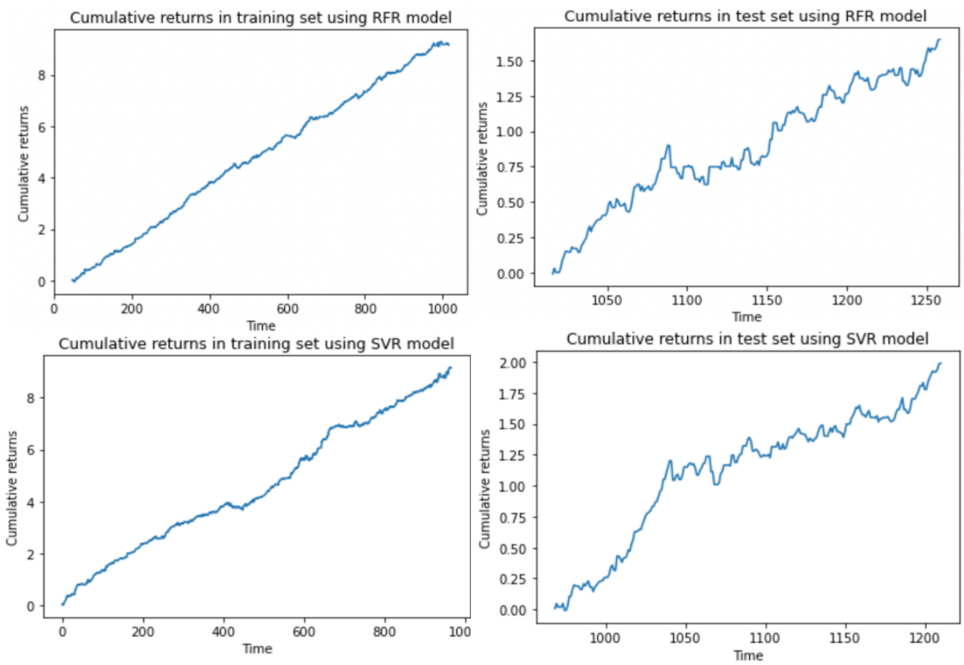

Figure 14. Comparing the cumulative returns of RFR and SVR model on training and test set

In real life trading, we are more interested in the model's performance in the test set as it represents unseen data. As seen in Figure 13 and 14, we can clearly deduce that the SVR model generates a more profitable trading signal than the RFR model in the test set. This is likely due to the fact that RFR performs better with categorical variables compared to numerical ones (Au 2018). Hence, our most profitable model is SVR.

4. Future improvements

The literature surrounding stock prediction using statistical models have concluded that deep learning models can predict the fluctuation of stock price with greater accuracy than classical machine learning models. In particular, it was consistently concluded that Long Short-Term Memory (LSTM) models tend to outperform SVR, RFR and many other machine learning models when it comes to making stock predictions (Hu, Zhao & Khushi 2021). This is due to the fact that the LSTM model excels at modelling and processing sequential data, such as time-series data. It does so by maintaining the memory and behaviour of past data and using it to learn selectively by remembering or forgetting the required historical data when making a prediction (Zou & Qu 2020).

Since our most profitable model is SVR, it would be beneficial to compare its performance with LSTM. A research performed by Lakshminarayan & McCrae comparing the performance of the two models revealed that LSTM outperformed SVR when it comes to making stock prediction due to its ability to remember or forget the data in an efficient manner unlike SVR (Lakshminarayan & McCrae 2019). This is seen in Figure 15 below.

Model	R-squared
SVR (our model)	0.21
SVR including moving average as features	0.36
SVR including oil and gold prices as well as moving average as features.	0.51
LSTM including moving average as features	0.81
LSTM including oil and gold prices as well as moving average as features	0.83

Figure 15. Comparing our SVR model with Lakshminarayan & McCrae's SVR and LSTM model (Lakshminarayan & McCrae 2019).

Nevertheless, it is important to note that there are some differences in terms of the objective, features, data pre-processing and model evaluation steps that was undertaken. While we included moving average as one of our features, we did not include external features such as crude oil and gold prices. Furthermore, they also included all the stock price data (i.e open, low, close, high) whereas we only included the close price data. This is because one of our objective was to explain the relationship between the different technical indicators for each strategy in predicting stock returns. By contrast, their objective is purely to compare the predictive power of SVR and LSTM adjusting for different features as inputs. Consequently, they did not calculate the Sharpe ratio in order to assess the profitability of their models. Lastly, we also performed fractional differencing in order to improve the stationarity of our data while still retaining memory. Since the difficulty of predicting stock market arises from its non-stationarity behaviour, given better features, this method is likely to assist with improving the predictive ability of our models (De Prado 2018).

It is evident from the discussion above that the features used as inputs for our models can affect the quality of our predictions. Accordingly, since stock price is affected by many factors, we should consult domain experts and perform further research on the types of features that can improve our model's performance. For example, some studies have found that news sentiment data can improve the predictive power of a model (Hu, Zhao & Khushi 2021).

Although predictive models cannot provide direct causal explanations, they can assist in the discovery of new potential variables and the types of relationships that can be further investigated in terms of causality (Shmueli 2010). Since there are many different types of trading strategies, we can use predictive modelling alongside explanatory models in order to test the relevance of existing trading strategies and potentially develop new and more profitable ones.

5. Conclusion

In this paper, we discussed the explanatory and predictive powers of supervised machine learning models in predicting stock price returns. In doing so, we created features based on two trading strategies, namely, mean-reversion strategy and momentum-based strategy. These features are then fed into our RFR and SVR models. Although our models did not have a high R-squared, we were able to ascertain the most predictive features within our dataset as well as the relevant threshold for generating trading signals whereby our models were able to predict with relatively good accuracy and profitability. Moreover, we discussed how our predictions could be improved with the use of deep learning models such as LSTM. By way of comparison, we have shown that LSTM outperforms classical machine learning models such as SVR and RFR when predicting time-series stock data. Lastly, we noted the importance of using predictive modelling alongside explanatory modelling in order to test and create novel trading strategies in order to discover new potential variables and relationships that can be further investigated. Evidently, this will enable us to discover the most relevant features or strategies that can further improve the performance and profitability of our models.

2490 words

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