Application of New Discriminant Ratio to Improve Algorithmic Predictions of Financial Asset Prices

Saad Ahmed

MSc in Computer Science
The University of Bath
2021/22

Application of New Discriminant Ratio to Improve Algorithmic Predictions of Financial Asset Prices

Application of New Discriminant Ratio to Improve Algorithmic Predictions of Financial Asset Prices

Submitted by: Saad Ahmed

Copyright

Declaration

This dissertation is submitted to the University of Bath in accordance with the requirements of the degree of the MSc in Computer Science in the Department of Computer Science. No portion of the work in this dissertation has been submitted in support of an application for any other degree or qualification of this or any other university or institution of learning. Except where specifically acknowledged, it is the work of the author.

Abstract

This dissertation involves using a newly created ratio known as the D-ratio from another author (Dessain, 2022a) and applying it to the context of financial asset price prediction which was a future work suggestion by that author. This new ratio replaces the limitations faced by using the Sharpe Ratio for hedge funds which employ algorithmic trading strategies and improves the effectiveness of algorithms to predict future financial asset prices. Three machine learning algorithms are analysed to produce their D-ratios to determine the added value they bring over the Sharpe Ratio and whether they are applicable in practice. This study finds that the ratio is inadequate for use in reality by hedge funds, but does have advantages that make it more favourable than the Sharpe ratio. It suggests areas to improve the ratio further and greatly aids the value of the existing literature by being one of the first pieces of research to adopt the new ratio in this context.

Contents

CONTENTS ..... **I**

LIST OF FIGURES ..... **II**

ACKNOWLEDGEMENTS ..... **III**

CHAPTER 1 : **1**

INTRODUCTION **1**

1.1 MOTIVATION 1
1.2 OBJECTIVES AND DELIVERABLES 2

CHAPTER 2 : **3**

LITERATURE AND TECHNOLOGY SURVEY **3**

2.1 BACKGROUND OF QUANTITATIVE INVESTING INVOLVING MACHINE LEARNING TECHNIQUES: 3
2.2 RATIOS AND THE ISSUES OF WHETHER FINANCIAL INSTRUMENTS ARE NORMALLY DISTRIBUTED. 5
2.3 REVIEW OF MACHINE LEARNING TECHNIQUES 6
2.3.1 Support vector machine 6
2.3.2 Naïve Bayes: 6
2.3.3 Random Forest 7
2.3.4 K-nearest neighbors 7
2.3.5 Artificial Neural Networks and Deep Neural Networks 7
2.3.6 Genetic Algorithms 8
2.4 CONSIDERATIONS: 9

CHAPTER 3 : **10**

DESIGN OF THE EXPERIMENTS **10**

3.1 DESIGN OF THE EXPERIMENT 10
3.2 THE FORMULAS .....

Contents

CHAPTER 4 : **12**

ANALYSIS OF THE EXPERIMENTAL RESULTS **12**

4.1 2018 RESULTS: 12
4.2 2019 RESULTS: 15
4.3 ANALYSIS OF 2018 RESULTS: 17
4.3.1 The Sharpe Ratios: *17*
4.3.2 The D-Ratios: *17*
4.4 ANALYSIS OF 2019 RESULTS: 18
4.4.1 The Sharpe Ratios: *18*
4.4.2 The D-Ratios: *19*

CHAPTER 5 : **20**

CRITICAL EVALUATION AND CONCLUSION **20**

5.1 EVALUATION OF STUDY: 20
5.2 CONCLUSION: 21

BIBLIOGRAPHY **22**

APPENDIX A **30**

CODE **30**

List of Figures

FIGURE 1: 2018 ANNUAL AVERAGE PROFIT PER DAY AND SHAPE RATIO FOR EACH MODEL 12
FIGURE 2: D-RETURN, D-VAR AND D-RATIO FOR SUPPORT VECTOR CLASSIFIER ALGORITHM 13
FIGURE 3: D-RETURN, D-VAR AND D-RATIO FOR RANDOM FOREST ALGORITHM 13
FIGURE 4: D-RETURN, D-VAR AND D-RATIO FOR K-NEAREST NEIGHBOUR ALGORITHM 13
FIGURE 5: PREDICTION OF CLOSING PRICE FOR SUPPORT VECTOR CLASSIFIER ALGORITHM (BLUE: PREDICTED, YELLOW: ACTUAL) 13
FIGURE 6: PREDICTION OF CLOSING PRICE FOR RANDOM FOREST ALGORITHM (BLUE: PREDICTED, YELLOW: ACTUAL) 14
FIGURE 7: PREDICTION OF CLOSING PRICE FOR K-NEAREST NEIGHBOUR ALGORITHM (BLUE: PREDICTED, YELLOW: ACTUAL) 14
FIGURE 8: ANNUAL AVERAGE PROFIT PER DAY AND SHAPE RATIO FOR EACH MODEL.......................... 15
FIGURE 9: D-RETURN, D-VAR AND D-RATIO FOR SUPPORT VECTOR CLASSIFIER ALGORITHM 15
FIGURE 10: D-RETURN, D-VAR AND D-RATIO FOR RANDOM FOREST ALGORITHM 15
FIGURE 11: D-RETURN, D-VAR AND D-RATIO FOR K-NEAREST NEIGHBOUR ALGORITHM 15
FIGURE 12: PREDICTION OF CLOSING PRICE FOR SUPPORT VECTOR CLASSIFIER ALGORITHM (BLUE: PREDICTED, YELLOW: ACTUAL) 16
FIGURE 13: PREDICTION OF CLOSING PRICE FOR RANDOM FOREST ALGORITHM (BLUE: PREDICTED, YELLOW: ACTUAL) 16
FIGURE 14: PREDICTION OF CLOSING PRICE FOR K-NEAREST NEIGHBOUR ALGORITHM (BLUE: PREDICTED, YELLOW: ACTUAL) 16
FIGURE 15: CODE TO CLASSIFY PROBLEM INTO TWO CHOICES, 'UP' OR 'DOWN' FOR THE ALGORITHM PREDICTION AND CALCULATE THE GAIN OR LOSS FOR EACH DAY 30
FIGURE 16: FORMULAS TO CALCULATE CF-VAR VALUES FOR EACH D-RATIO AS SEEN ON: HTTPS://GITHUB.COM/JDE65/D-RATIO/BLOB/MAIN/D_RATIO.PY 31
FIGURE 17: CALCULATION CODE OF EACH D-RATIO, THAT HAS BEEN APPLIED TO EACH ALGORITHM ... 32

Acknowledgements

I would like to thank my project supervisor, Cherry Zhao, for her advice and my parents for financially supporting me through my degree, because without them, I would not have had the opportunity to study at the University of Bath and work towards my goals in life.

Chapter 1 :

Introduction

1.1 Motivation

The major goal of any algorithmic hedge fund that employs quantitative investment trading strategies looking to make incredible profits has always been to attempt to predict the future price or returns of assets so that several highly profitable algorithmic trading strategies can be developed to create consistent yearly abnormal returns for investors. The problem of how to accurately predict future prices and returns must be approached by researching what the best performance metrics, technical analysis methods, trading strategies, and trading optimisation tools are the most effective for providing even the slightest competitive advantage which is the goal of any hedge fund in the industry. Hundreds of thousands of teams of quantitative developers, researchers, traders, and portfolio managers work around the clock all across the world to gain any information advantage which helps their investment philosophies and attracts more capital, and returns than their competition. It is for this reason that hedge funds make millions of dollars of investments into research to develop any information advantage that competitors do not possess, which is why using machine learning methods to predict financial market prices has become the new goal of the industry.

Throughout the history of the field, what really provides insight into the added value of that competitive advantage gained are the performance metrics of the trading strategy. These are metrics are classified into many types such as measuring error in prediction, the accuracy of predictions, results of predictions, and risk-adjusted prediction metrics, of which the most common is known as the Sharpe ratio. This ratio defined as the mean of returns divided by the standard deviation of returns has been the golden standard for measuring performance in the hedge fund industry.

Despite being the golden standard, the ratio suffers from several issues in the algorithmic trading context which inhibits its validity and makes it less useful as a performance metric. Firstly, as seen in 2763 hedge funds, the ratio made no improvement to help rank performance, because it assumes that output is normally distributed (Eling and Schuhmacher, 2007) and as the prices and returns of assets do not follow the Gaussian distribution, the metric loses its significance without assumptions (Farinelli et al., 2008). It also has a high-ranking correlation with other return metrics such as the Omega, Sharpe-Omega, Sortino, and Kappa ratio (Guo and Xiao, 2016), all of which do not explain how the choice of the algorithm itself impacts the prediction result and in addition, the Sharpe ratio varies depending on the asset being measured which makes it an inadequate tool for comparing different assets. Despite it providing some usefulness in determining risk-adjusted returns, it does not take into account the true value that using a certain type of machine learning algorithm brings.

As a gap existed in the current literature to determine a performance metric for algorithmic trading that overcomes the limitations of the Sharpe ratio, a new ratio known as the Determinant or D-ratio was created to measure the added value gained by choosing a specific algorithm that did not suffer the limitations of the Sharpe ratio (Dessain, 2022a). It does this by instead observing the daily log returns to remove the assumption of the normal distribution of returns and uses Corniche-Fisher expansion as a substitute for the standard deviation to provide more insight into the risk of using a specific algorithm. This dissertation is based upon this research and is an extension of the author’s study, as suggested by the author for future research, to apply the ratio in a price prediction context. Using the ratio in this way, which has rarely been seen to be used in the existing literature will add immense value to the field and provide much-needed insight into whether the ratio is more or less effective for hedge funds in providing value as compared to the Shape ratio.

1.2 Objectives and Deliverables

Therefore, the proposed project objectives and deliverables are shown as follows:

1. Compare the prediction power for the most widely used machine learning algorithms to predict future financial security prices by building a classification problem of whether each algorithm decides to buy or sell based on the prediction of the asset’s next day’s closing price.

2. For each machine learning algorithm, compare and contrast the differences observed and value added when evaluating performance using both the Sharpe ratio and the D-ratio.

Chapter 2 :

Literature and Technology Survey

2.1 Background of Quantitative Investing involving Machine Learning Techniques:

To understand the roots of true quantitative investing using artificial intelligence (AI) techniques, it is necessary to first understand how investing in financial markets developed. In 1934, the book Security Analysis was released following the crash of Wall Street in 1929 which became the first to define a systematic framework for analysing the fundamental details of company stocks and distinguishing speculation from analysis-based investing (Graham et al., 2008). This was the beginning of analysing data to reach investment decisions.

Decades later in 1952, the first proposal for the mathematical representation of risk was made and defined as the standard deviation of returns within a portfolio of market securities, as seen in the book Portfolio Selection (Markowitz, 1952). Ideas to quantify risk began as a way of understanding the connection between humans' behaviour, risks, and returns, from the perspective of a mutual, asset, or hedge fund manager (Kahn, 2018). Now, new mathematical approaches to making investment decisions were being developed.

With the rise of technology and evolving computational power, larger volumes of market data could be analysed and more data-focused methods for making investment decisions became popular. One such model was the Capital Asset Pricing Model (CAPM) (Sharpe, 1964) which explored how the expected return of an asset can be calculated while diversifying a portfolio by reducing its standard deviation as a measure of risk, as well as the first discussion of market risk premiums (Mossin, 1966) which proves that a graph exists between expected yield and standard deviation of an asset where the price of risk known as the market premium acts as the slope. This supports the known idea today that more risk equals more reward, assuming a market equilibrium. The discussion of heuristics in the valuation of risky assets also became a talking point (Lintner, 1965) and later on, the application of human behavioural research gave rise to the study of behavioural finance (Tversky and Kahneman, 1974), which explores the reasons for various investment trends seen in markets and finance.

Another key theory emerged known as the efficient market hypothesis (EMH) (Fama, 1970) which built up the perspective that well-developed capital markets are efficient and fully reflect all available public information, so the market return cannot be beaten by seeking to trade in different ways. Two key foundational papers challenged and debunked this idea. One introduced the idea of a conventional asset beta value, which takes into account significant extra market components, like accounting ratios, that over time may give a higher return than the market (Rosenberg, 1974) while the other proves that by using the CAPM, a well-diversified portfolio can be built that outperforms the return given by the market (Ross, 1976). Both academics argued that inefficiencies that create the differences in prices can not only be exploited to generate profitable strategies, but also can be used to deliver better risk-adjusted return models as well.

New advances in machine learning and the rise of quantitative investing grew within both hedge funds and investment banks before the financial crisis as a means to outperform competitors in the wider investment industry, as the idea that machine learning does provide a powerful and principle framework for trading optimisation via historical data was solidified (Kearns and Nevmyvaka, 2013). Since this understanding has been in place, techniques have developed from simply using AI to replicate simple human thinking patterns (Tsaih, Hsu, and Lai, 1998) to using evolutionary algorithms from the field of genetics to build option trading strategies that adapt and procreate in a survival of the fittest context. All of that is a trading idea based on Darwin’s theory of Evolution (Ucar, Ozbayoglu, and Ucar, 2015).

Many strategies employed by hedge funds are broken down into a wide range of sub-categories and can focus on using leverage, advanced financial asset price and risk prediction, hedging against downfall market prices, and optimising portfolios for profit maximisation. AI has become fundamental in many respects such as employing Monte-Carlo simulations to deliver better than expected results during model testing (López de Prado, 2016), using deep learning techniques to optimally select stocks (Heaton, Polson and Witte, 2016), building transparent prediction models (Nakagawa, Uchida and Aoshima, 2019), speeding up the buy and sell order process for live trading strategies (De Spiegeleer et al., 2018) and optimising the expected utility of the final wealth obtained from investment decisions (Ritter, 2017). It is truly no surprise then, that so many hedge funds exist today and hire the best quantitative researchers and developers to build and test models in strategies to achieve the highest return possible for their investors, in the safest way possible.

2.2 Ratios and the issues of whether financial instruments are normally distributed.

The most well-known ratio for measuring the risk-adjusted return in the hedge fund industry has been the Sharpe ratio which is calculated as the mean of excess returns divided by their standard deviation as a measure of risk. This works well by taking into account the effect of leverage and assuming that the mean and standard deviation fully describe the return profile and distribution generated by the strategy. However, since its inception, its validity as a performance measure for hedge funds has always been in question because returns are not normally distributed in reality and have heavy and fat-tailed distributions which tend to be skewed (Samunderu and Murahwa, 2021). In addition, three different asset returns could have the same Shape ratio, but have their standard deviations describe different levels of risks (Cascon and Shadwick, 2006) and this can lead to sub-optimal decision making, ratios which can be either misleading or gamed by selecting certain assets over others (Auer and Schuhmacher, 2013).

Since it is very common to observe asset distributions with fat-tailed distribution returns caused by highly volatile events, many practitioners of the industry have sought to replace the standard deviation with a proxy known as the value at risk (var). Var has been used to measure risk partly due to capturing price information during volatile events in which the standard deviation misses but also because it is required by the Basel Committee on Banking Supervision for banks to prevent them from taking on too much risk (Singh, 2003). The var is the probability of which a trading strategy will lose a defined amount, based on historical asset price information which avoids assuming the normality of returns or using a variance-covariance calculation which does assume the normality of returns. Where the use of this proxy fails however is in assuming that future periods of volatility can be predicted from historical price information (Baker and Filbeck, 2015). Therefore, despite being a commonly used measure, it also fails to address non-normal returns and describe the volatility or risk of a trading strategy. Where the var ratio is useful, however, is to take into account the skewness and kurtosis of the return distributions which capture more of the risks involved in trading strategies. As hedge funds employ a wide variety of trading strategies that are often event-driven or take advantage of risks between assets in emerging markets, they may often experience returns with high negative skewness but also large excess kurtosis (Brooks and Kat, 2002).

For these reasons, this study will utilise a modified var ratio, known as the Cornish Fisher (CF) value at risk ratio (CF-var) (Dessain, 2022b). This ratio uses CF expansion to remove normal distribution properties of the original var, thus allowing it to be an effective measure for risk taking into account the mean, standard deviation, skewness, and kurtosis of a return generated in non-normal conditions which would be more appropriate for return analysis (Maillard, 2012).

As previously discussed, there are many techniques in the literature for this area of research and the advantages and disadvantages of the most common methods are discussed below.

2.3 Review of Machine Learning Techniques

2.3.1 Support vector machine

The support vector machine (SVM) technique seeks to understand and determine the margin of error that can be experienced by a model when trying to predict the price (Huang, Nakamori, and Wang, 2005). This makes the technique one of the most commonly used types because models can be turned to increase or decrease error margins, in line with market dynamics and portfolio manager preferences. This is done by classifying data variables and converting them from one dimension to another according to kernel functions that define the hyperplanes between each dimension (Pai and Lin, 2005), which allows lesser diversions between forecasted and observed prices (Sedighi et al., 2019), especially due to the high generalisation ability for two-group classification problems (Cortes and Vapnik, 1995) such as the type this study is presenting. However, the SVM algorithm also assumes that all features give the same contribution to the target value which is not always the case (Nti, Adekoya, and Weyori, 2020). Despite this, given the advantages, this is one of the techniques that will be selected and this observation will be taken into account.

2.3.2 Naïve Bayes:

The Naïve Bayes classification algorithm has also been used to classify data based on the Bayesian Theory of Probability. Researchers argue that found that they produce the lowest accuracy in stock price predictions as compared to other methods because they cannot pay attention to features in the data with large information game values which reduces the error of classifications (Xianya, Mo, and Haifeng, 2019). However, the limited sample size in this paper is not strong enough to draw this conclusion. A more fitting conclusion that has been identified is that they tend to have higher stock prediction accuracy when focused on news sentiment data as compared to numeric data (Mohan et al., 2019)., as it is easier for the algorithm to assign a probability based on the type of news article. Given that this study will only consider financial price data, it would be unwise to use this technique.

2.3.3 Random Forest

The random forest (RF) technique creates many unique decision trees that work together as an ensemble where the trees take a majority vote to effectively classify a problem which is the model's prediction. It is highly effective in the context of financial market prediction because it can be used for continuous data and follows the Law of Large Numbers which prevents overfitting (Breiman, 2001) and is quite successful due to its ability to model non-linear dynamics in data (Ciner, 2019) which is the case in the context of financial asset prices. Furthermore, they have been found previously to be better at stock market price predictions than both support vector machines and artificial neural networks, (Basak et al., 2019) and are consistently ranked as one of the best methods for price prediction in a financial market context (Basher and Sadorsky, 2022). It was for these reasons, that this algorithm was also chosen for this study.

2.3.4 K-nearest neighbors

The K-nearest neighbor (KNN) machine learning algorithm utilises a method of data classification which assumes that one data point in one group of points is related to another group based on some method of calculating the distance between them by using their distance, closeness, or pre-defined similarity. This distance ensures a good generalisation of the estimation of values (Bermejo and Cabestany, 2000) and is highly effective for the cluster of analysis of financial stock market data such as for the stocks of the S&P 500 index (Nie and Song, 2018). This would make it ideal for this study. In addition, it has been found to have better prediction power when combined with other methods such as the SVM (Nayak, Mishra, and Rath, 2015) and provides insight in a stock market context because it depends on the representativeness and extensiveness of data (Lin, Lin, and Cao, 2021).

2.3.5 Artificial Neural Networks and Deep Neural Networks

Artificial neural networks (ANNs) utilise a large number of neurons that artificially replicate biological mind techniques to solve complex problems, by focusing on creating different transformations to the feature space, within a given context. In the context of determining asset prices, they are one of the most common methods used as they do not contain standard formulas, which make them easily adapt to changes in the market (Guresen, Kayakutlu, and Daim, 2011) and as a soft computing technique, are more efficient than complex models used for short term forecasting (Adebiyi, Adewumi, and Ayo, 2014).

However, they have been found to be the best for forecasting the prices for Bitcoin (Seo and Kim, 2020), which is one of the world's most volatile assets, which may be aided by their ability to optimise weighted parameters of transfer functions between the layers of the model to significantly minimise the errors in future predictions (Lahmiri, 2014). Since this study is focusing on a less volatile asset and given that this technique is one of the best methods of modelling human thinking patterns (Adya and Collopy, 1998), which this paper is not taking into account, this technique, although highly effective in other contexts, was not ideal for this study.

Deep neural networks (DNNs) are improvements over ANNs, however, they have more secret layers for the processing of raw data by the use of feature extraction and transformation of the layers within the model. Researchers used long short-term memory (LSTM) which utilises feedback connections between layers in the algorithm and found that two models were almost 60% accurate when predicting stock prices (Pang et al., 2018). Another paper examines the use of LSTM methods and found that their results trump other techniques for prediction power that apply classification without storing memory (Fischer and Krauss, 2018). However, since the SVM, RF, and KNN algorithms were optimal for this study, DNNs were not considered.

2.3.6 Genetic Algorithms

As discussed previously genetic algorithms are a technique used to mimic the evolution process of humans using a context concerning the survival of the fittest trading strategies. This is often looked at favourably by quantitative researchers as it is seen as a novel method that takes one branch of science and uses it in the field of quantitative investing. Researchers herald these techniques when used in hybrid trading systems based on the Korean Stock market (Kim et al., 2017), however, their research is incredibly complex to reproduce and compare with other literature as the authors have to build 50 sets of decision rules for making a prediction and model simplicity is not the goal as the idea is to increase the complexity of structures undergoing adaptation (Koza, 1994). This added complexity in addition to the ability to modify solutions within each iterative generation of the objective function (Strader et al, 2020), makes them a much less favourable choice because as observed in these research articles, the reasons why one strategy is stronger or weaker fail to be explained and as the complexity of the models cannot always be explained, the validity of the results obtained is questionable.

2.4 Considerations:

As this dissertation is an attempt to make predictions using financial market data, it is necessary to understand elements of the literature that may lead to sub-optimal research quality.

Firstly, if one algorithm chosen claims to have a higher prediction power (Ballings et al., 2015), that conclusion can only be true for the geographical origins of the dataset. Secondly, claiming that techniques work for a long period, such as for a one-year investment horizon (Patel et al., 2015) should be avoided, as the primary aim in this field of research is to understand and emulate a short-term trading strategy. Thirdly, some researchers (Moghaddam, Moghaddam, and Esfandyari, 2016) and (Malagrino, Roman, and Monteiro, 2018) use smaller time frames of data that create artificial results for headline figures and statements, which can be misleading and need to be avoided. This would make the validity of results questionable because for significant results it is vital that data covering a long period of time needs to be used (Pehlivanlı, Aşıkgil, and Gülay, 2016). Finally, research that claims very high prediction accuracies such as a 98.3% forecast of a monthly index (Boyacioglu and Avci, 2010) need to be avoided as well. If the results were truly that accurate, the researchers would treat them as proprietary like hedge funds and keep that high prediction method for their profit-making purposes (Théate and Ernst, 2021).

Chapter 3 :

Design of the Experiments

3.1 Design of the experiment

As noted in the previous chapter the 3 machine learning algorithms chosen were the k-nearest neighbors (KNN), random forest (RF), and support vector machine techniques (SVM), as these would test both the prediction power and validity of the D-ratio.

To effectively design the experiment, firstly the problem of predicting the next day's closing or opening price so that it can effectively work in this manner is transformed into a machine learning classification problem. That is rather than directly focusing on the price, each algorithm will seek to understand whether the next day's predicted closing price is higher or lower than the day's opening price. If it is higher the algorithm will classify that day as being 'up', because if it buys the opening price and sells the closing price, it will create a profit. While if the next day's predicted closing price is less than its opening price, the algorithm will sell and classify the day as 'down', because if it were to buy instead, it would create a loss.

In addition, each algorithm also employs an additional strategy which is known as the 'buy and hold' which assumes that each future day is consistently seen as 'up' and its opening price is always bought regardless of its predicted closing price. This means that whether the machine learning algorithmic strategy will see it as either an 'up' day to buy or a 'down' day to sell, the buy and hold strategy will continue to buy regardless of whether the model makes a profit or a loss that day.

This added buy and hold trading strategy created for all the machine learning algorithms serves as a benchmark to test the performance of their original model's trading strategy, and seek to analyse the effectiveness of the original algorithms in predicting the price. This 'buy and hold' trading strategy is effective in testing performance because it allows a method to compare the results obtained with that of the original strategy and seek to understand whether the original is worth employing.

In theory, the original trading strategy which seeks to predict both ‘up’ and ‘down’ days should be more accurate, and have a higher Sharpe ratio and D-ratio than the buy and hold model which seeks to only buy regardless, even if a loss is made.

For each machine learning algorithm, a Sharpe ratio will be created which is calculated as the mean of the returns over the year divided by the return’s standard deviation which acts as a measure of risk. This ratio will describe whether the algorithm will produce a better return for each unit of risk taken which means that a higher Sharpe ratio indicates better prediction power and a more profitable strategy to choose for trading the asset. While a negative ratio indicates that the algorithm will make a loss regardless of the level of the risk taken. It is at this stage in the previous literature that an algorithmic trading strategy has been disregarded and disused because it is not profitable to employ.

In addition to computing a Sharpe ratio, each algorithm will have its own Discriminant ratio or D-ratio which is comprised of a D-return and a D-variance (d-var) which are laid out in the next section (Dessain, 2022c). These additional metrics, the D-ratio being the most important will be the key to unlocking the algorithm’s potential prediction power and provide more insight than the Sharpe ratio on the choice of one algorithm relative to others. This is because the formulas are based on the log of returns which are obtained from predicting the closing price, to avoid assuming that asset prices are normally distributed. These components of the study are defined below.

3.2 The formulas

D-return = 1 + (Return $_{\text{algorithm}}$ – Return $_{\text{Buy/hold model}}$) / Absolute (Return $_{\text{Buy/hold model}}$)

D-var = Var $_{\text{Buy/hold model}}$ / var $_{\text{algorithm}}$

D-ratio = D-return * D-var

Firstly, the D-return measures the relative return generated by the machine learning algorithm relative to its buy and hold model’s return. If it is higher than 1, it exceeds the return of the buy and hold model and this means that the algorithm is worth utilising. The D-var ratio uses the Corniche-Fisher variance as described in the literature review to provide a level of risk, where if the value of D-var is higher than 1, the risk of using the algorithm is lower than the risk contained in the buy and hold model. Therefore, it would be desirable to have a higher d-var ratio. Finally, the Discriminant or the D-ratio determines the added value given by the choice of the algorithm in determining the risk-adjusted returns. Compared to other algorithms, the higher the D-ratio, the more prediction power the algorithm possesses.

The asset selected is the S&P 500 index, known as ‘SPY’ in the freely available Yahoo Finance database. Results are obtained for both 2018 and 2019, a loss-making year, and a profitable year respectively to make effective comparisons.

Chapter 4 :

Analysis of the Experimental Results

4.1 2018 Results:

Figure 1: 2018 Annual average profit per day and Shape Ratio for each model

```
Annual profit for svc: -0.968
Sharp ratio for svc: -0.49721924420447533
Buy and hold model  profit for svc: 1.476923076923077
Buy and hold model Sharp ratio for svc: 0.762337799466492
-----------------------------------------------------------------------
Annual profit for Random Forest: -0.1929734386724358
Sharp ratio for Random Forest: -0.10353117448195666
Buy and hold model  profit for Random Forest: 1.0358186050607319
Buy and hold model Sharp ratio for Random Forest: 1.0114053208409988
-----------------------------------------------------------------------
Annual profit for knn: -0.1826666666666672
Sharp ratio for knn: -0.11405772987401949
Buy and hold model  profit for knn: 0.6604166666666652
Buy and hold model Sharp ratio for knn: 0.784955753675575
```

Figure 2: D-return, D-Var and D-ratio for support vector classifier algorithm

```
SVC D-return =  2.3027484687404978
SVC D-var =  -0.08340115613235509
SVC D-Ratio =  -0.19205188457496786
```

Figure 3: D-return, D-Var and D-ratio for random forest algorithm

```
RF-Regressor D-return =  5.967255130108931
RF- Regressor D-var =  -46.749289597442264
RF- Regressor D-Ratio =  -278.96493817928547
```

Figure 4: D-return, D-Var and D-ratio for k-nearest neighbour algorithm

```
knn D-return =  0.40184988087182O9
knn D-var =  4.097750041803664
knn D-Ratio =  1.6466803661413014
```

Figure 5: Prediction of closing price for support vector classifier algorithm (blue: predicted, yellow: actual)

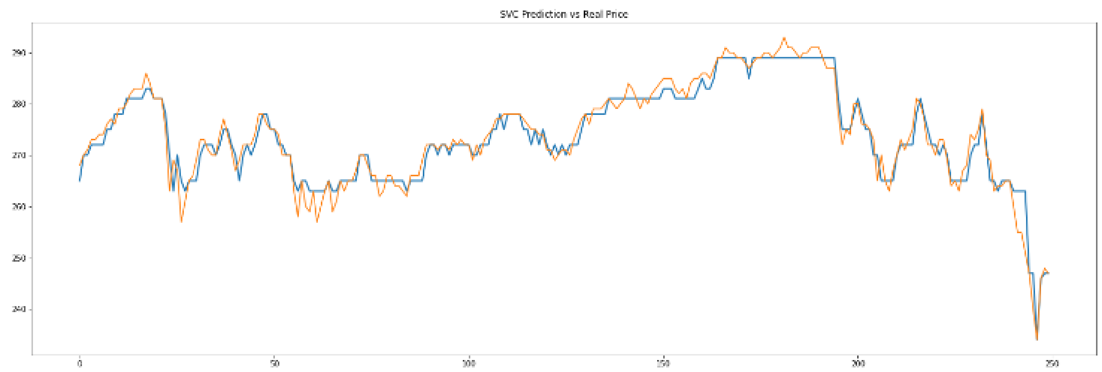


Figure 6: Prediction of closing price for random forest algorithm (blue: predicted, yellow: actual)

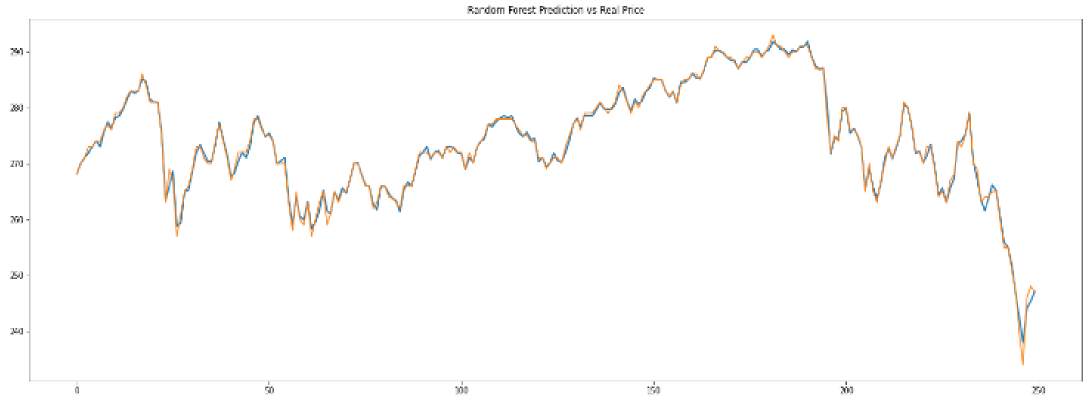
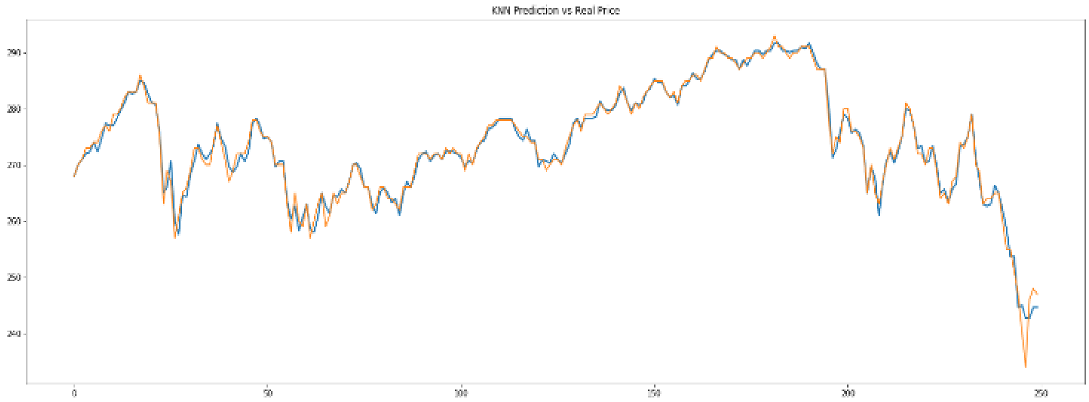


Figure 7: Prediction of closing price for k-nearest neighbour algorithm (blue: predicted, yellow: actual)



4.2 2019 Results:

Figure 8: Annual average profit per day and Shape Ratio for each model

```
Annual profit for svc: 0.055776892430278883
Sharp ratio for svc: 0.025445629522109863
Buy and hold model  profit for svc: 1.7666666666666666
Buy and hold model Sharp ratio for svc: 0.9432291055379428
----------------------------------------------------------------------
Annual profit for Random Forest: 0.18575691174695302
Sharp ratio for Random Forest: 0.15915657113369944
Buy and hold model  profit for Random Forest: 0.8087335613631906
Buy and hold model Sharp ratio for Random Forest: 1.080397663300118
----------------------------------------------------------------------
Annual profit for knn: 0.22974767596281367
Sharp ratio for knn: 0.21308032938654434
Buy and hold model  profit for knn: 0.692307692307692
Buy and hold model Sharp ratio for knn: 0.917778441561165
```

Figure 9: D-return, D-Var and D-ratio for support vector classifier algorithm

```
SVC D-return =  0.9506009892051424
SVC D-var =  -5.071908879410223
SVC D-Ratio =  -4.821361597925703
```

Figure 10: D-return, D-Var and D-ratio for random forest algorithm

```
RF-Regressor D-return =  2.2105957032079253
RF- Regressor D-var =  7.9294833118065595
RF- Regressor D-Ratio =  17.52888173773853
```

Figure 11: D-return, D-Var and D-ratio for k-nearest neighbour algorithm

```
knn D-return =  2.0858281869085973
knn D-var =  3.9996587469598697
knn D-Ratio =  8.342600952424418
```

Figure 12: Prediction of closing price for support vector classifier algorithm (blue: predicted, yellow: actual)

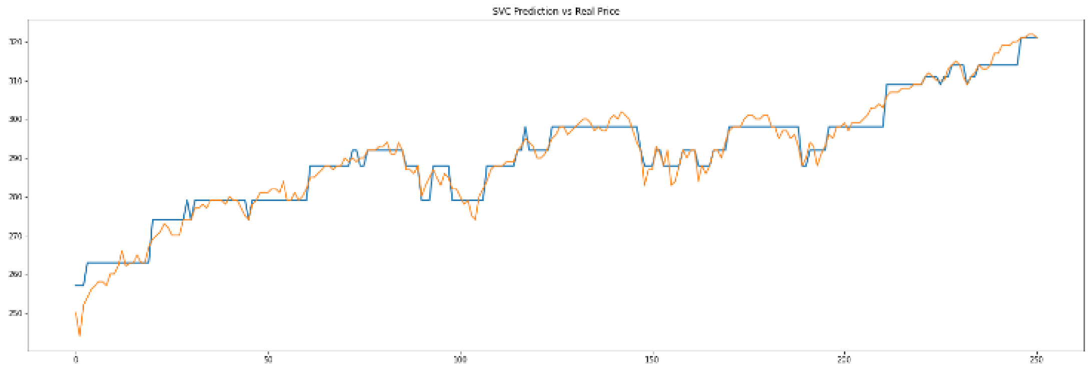


Figure 13: Prediction of closing price for random forest algorithm (blue: predicted, yellow: actual)

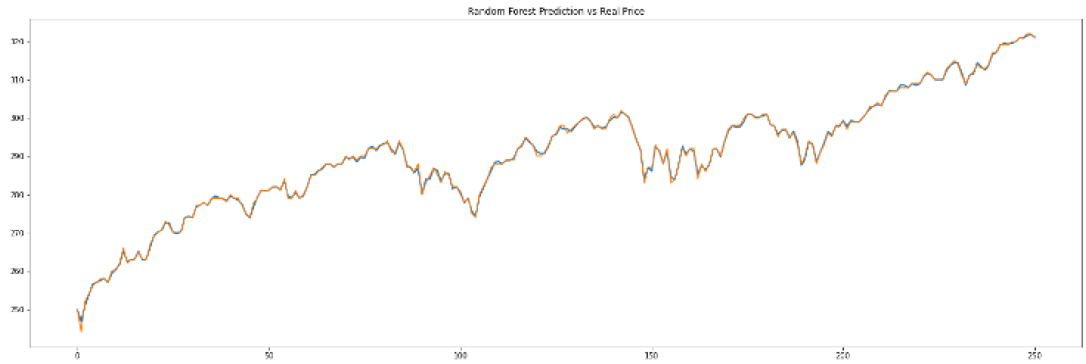
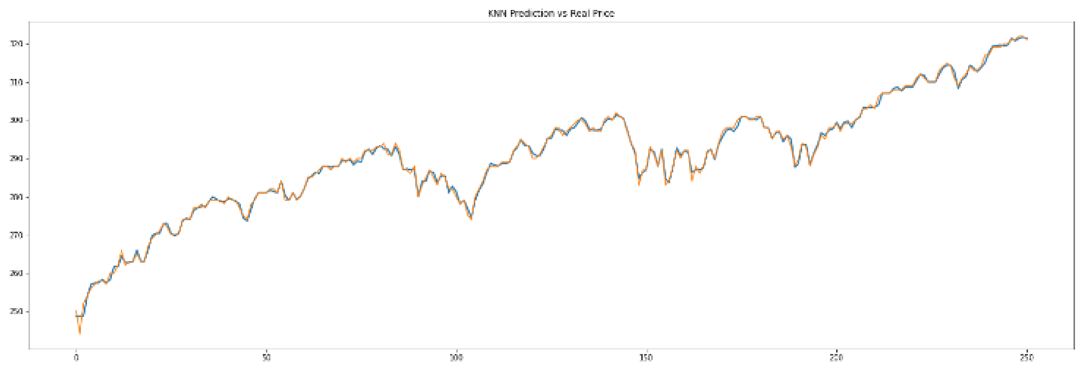


Figure 14: Prediction of closing price for k-nearest neighbour algorithm (blue: predicted, yellow: actual)



4.3 Analysis of 2018 Results:

4.3.1 The Sharpe Ratios:

As seen in figure 1, the daily average profits are all negative, however, this isn't so surprising, given that in 2018 the return of the S&P 500 index itself was also negative, i.e., it was a loss-making year. The annual Sharpe ratios are therefore all negative as well with the RF having the lowest value of -0.10 followed closely by the KNN technique being -0.11. The lowest Sharpe ratio is -0.50 for the SVC technique which shows in comparison, that the SVC delivers the worst risk-adjusted return as compared to the KNN and RF techniques, whilst the predicted risk-adjusted return for the RF is the best.

The buy and hold models Sharpe Ratios, however, are all much higher for their relative algorithms, suggesting that it would be better to avoid the use of an algorithmic trading strategy altogether as they would deliver the best risk-adjusted returns than using the machine learning techniques.

Given that all three machine learning models deliver a negative return for the risk they take of making a prediction and that the buy and hold models all have a positive Sharpe Ratio, it can be argued that a conclusion can be made to disregard them and focus on other machine learning techniques which seek to obtain positive results instead. This is the basis of how previous studies have been conducted in the literature and ultimately, this ends any further analysis being conducted within those studies, as the trading strategies are seen to be inadequate for use. However, given that results are not normally distributed in reality, this is where the computation of the D-ratios really provides added value as the potential for the prediction power of the algorithm can be explored before the trading strategy is disregarded, even for loss-making strategies.

4.3.2 The D-Ratios:

As seen in figures 2, 3, and 4, the D-return is the highest for the RF, 2nd best for the SVC and below 1 for the KNN technique. This means that compared to the Sharpe ratios, both the SVC and the RF techniques are more profitable than their buy and hold models, which goes against the conclusion of the results that would have been given had the Sharpe ratio been used on its own. This is interesting because now it can be seen how these ratios add more value and insight to the study and they are more applicable than the Sharpe Ratio in the context of the non-normal reality of asset prices.

Focusing on the D-var results in figures 2, 3, and 4, it can be seen that the KNN has the highest value of 4.1 and therefore has the lowest risk compared to its buy and hold model, while both the SVC and RF values are negative, which imply that these techniques are riskier than compared to their buy and hold models. This is also a unique insight presented by computing the D-var because the assumption behind the buy and hold model was that it is much less risky than attempting to make a strategy based on an algorithm prediction which is also confirmed by the Sharpe Ratio. Rather then, the D-var explains that making a prediction using machine learning may deliver less volatile results than compared to a simple buy and hold strategy which is useful to know, for conducting further analysis beyond this study. It is worth noting that for the RF model, the D-var and also its D-ratio are far lower than 1 which was a surprising result, and will be treated as an anomaly so that the other two methods can be better compared.

Comparing the D-ratios of the SVC and KNN provide the most useful insights since this computation takes into account both the previous D-return and D-var calculations. As seen in figures 2 and 4, the D-ratio for the SVC is lower than 1, implying that the risk-adjusted return delivered by this model is lower than its corresponding risk-adjusted return given by its buy and hold model, while the D-ratio of 1.6 is greater than 1 for the KNN model. This is incredibly useful insight as well because it means that the KNN is both better at producing greater returns and less volatile returns than relying on the buy and hold model alone despite the KNN's Sharpe Ratio being negative. In addition, rather than disregarding the three models based on their Sharpe Ratios, the KNN can be specifically selected for further analysis going forward to understand more about its prediction capabilities.

For the three models, the prediction of the closing price was very accurate as seen in figures 5, 6, and 7, which was also a surprising result, given how the predicted and actual prices were not expected to be so closely aligned. This could be a cause of concern because it would imply an incorrect level of accuracy of predictions, however, this can be explained by the relatively short daily prediction period and despite this, it would not deter the results of the ratios obtained by the study, so the study is not affected in any way. It is worth noting that this is the same for the 2019 results as well, as seen in figures 12, 13, and 14.

Overall, these results provide useful insight in this period of time, however, to gain an even more comprehensive understanding, it was worth conducting the same analysis in an overall profitable year, which is why the calculations were also computed for 2019 as well.

4.4 Analysis of 2019 Results:

4.4.1 The Sharpe Ratios:

As seen in figure 8, all the Sharpe Ratios for the 3 machine learning models are below 1 which is another surprising result given that the buy and hold model's Sharpe Ratios for the SVC and KNN are close to 1 and are above 1 for the RF model. This would imply that for all the techniques, it would be better to rely upon a buy and hold trading strategy. While the Shape ratios are low, this may be explained by the fact that 2019 was a highly profitable year for the S&P 500 and during this year it would have made more sense to buy and hold, rather than make predictions.

However, this could only have been known in hindsight now that the results for the year are known, so despite the ratios being close to 0, the D-ratios are still calculated as they would have been done during 2019 as well.

4.4.2 The D-Ratios:

As seen in figures 9, 10, and 11, the D-return are above 1 for the RF and KNN models which means they would deliver better returns than their buy and hold models as compared to the SVC model, which almost equals the return of its buy and hold model, as its almost equal to 1. This also opposes the conclusion seen in 2018 which is that the Sharpe ratio would have suggested that all three models would have delivered less profitable results. To illiterate again, the D-ratios are seen to be more accurate given that they don’t assume a normal distribution of returns which does not exist in reality and hinders the Sharpe ratio. The D-return, therefore, provides a useful insight, to continue exploring the other results obtained during this year.

Within the same figures, it can be seen that the D-var is negative for the SVC while it’s above 1 for both the KNN and especially for the RF model which has a value of 7.9. This is a surprising result because it would indicate that the RF model is far safer than the buy and hold model, but given what we know about 2019 now, it goes against the truth that in 2019, it was safer to employ a buy and hold strategy than to algorithmically predict prices.

When comparing the D-ratios it can be seen that the SVC is below 1 which means it is not a reliable strategy to use while the KNN model produces a D-ratio of 8.3 and the RF model produces a result of 17.5. These results produced by the RF and KNN are especially surprising because they are far higher than 1 and are seen as to be too good to be true, and given the levels of both their high D-return and D-var values, the final results generated seem too unrealistic to be relied upon. Therefore, no technique can be selected as optimal using the D-ratios in this case. In this case, then, it may make more sense to stick with the Sharpe Ratios as they seem more realistic.

This analysis opens up the need for the critical evaluation of the results and D-ratio calculations in the following chapter.

Chapter 5 :

Critical evaluation and conclusion

5.1 Evaluation of study:

To start with, it is worth mentioning that because the D-ratio was recently created, there are no cases in the existing literature that adopt the use of this measure for analysis. This means that it makes this study worthwhile because it adds its own value to what is already known, but also makes it more difficult to make effective comparisons because there of no professional academic sources citing the use of the original paper. Therefore, the evaluation can only be obtained from what has been observed in this study and the original paper.

Firstly, in hindsight, there are two key elements of this study that could have been altered to produce better analysis and results. These are the choice of the prediction period for the trading strategy and the length of the time frame of data chosen. As the strategy focused on the next day's closing price, it was observed that there were very few differences observed day to day at different times throughout 2018 and 2019, which is why the graphs of the predicted versus the actual price appear to look so accurate. If for example, the next week's closing price was being predicted, this may have given a better understanding of the specific algorithm's prediction power visually over the time period. Furthermore, had the prediction period and the time frame been longer than 1 year, there would have been an opportunity to first train the algorithms on one dataset before testing their ability to predict prices in another dataset. Not doing this has not hindered this study in any way, but if it were done, it's certainly possible that the results obtained would have been more realistic.

Secondly, it is worth noting the downsides to using the D-ratio in practice. Its first major flaw is that by only considering the log of returns to avoid the issue of assuming the normality of returns generated by predicting the closing price, each loss generated by either the algorithm or the buy and hold model must be first converted to its absolute value, for the D-ratio to work. This is because the log of a negative number, such as a loss, is undefined. It could be argued then, that the D-ratio is only really applicable in times when the return generated is profitable. This means that despite obtaining the results seen for the D-ratios for 2018, it's possible that selecting one algorithm to be optimal over another may be misleading because in any case, a loss was made and questions may be raised by other academics on the validity of results obtained by converting loss values to positive numbers to provide insight. Still, at this stage when there are no comparisons to be made in the literature, the results of the D-ratio do provide insight. This is just one element to keep in mind for future studies by other researchers.

Its second major flaw is that the D-ratio is that for certain values CF-var values that make up the D-var, there exists a domain of validity of results for which the CF-var can be effectively calculated. This domain excludes certain values of extreme kurtosis or skewness observed by the returns generated by either the algorithm or the buy and hold strategy and this can lead to misleading results (Amédée-Manesme, Barthélémy, and Maillard, 2018). This very well may be the reason why the D-ratios for the RF and KNN models were observed as anomalies and abnormally large in 2019. Since 2019 was such a highly profitable year for the S&P 500 index, it could have easily been the case that the returns existed outside this domain of validity which is why the results were so large. This may hinder the D-ratios application in practice because there are many years when the returns generated can be highly profitable. It also, therefore, hinders itself as a prediction metric for hedge funds, because those funds are constantly seeking abnormally large returns so this ratio may not even work for them, which is concerning.

Therefore, there needs to be more research into how much the D-ratio is affected by the extreme values of skewness and kurtosis of returns generated. Had this study been conducted again, this topic of the domain of validity would have been the main focus, as it is clear now that this would add the most value to the existing literature and determine whether this new ratio could replace the Sharpe Ratio in practice.

5.2 Conclusion:

This study sought to compare the prediction power of some of the most widely used machine learning algorithms and this was attempted by comparing and contrasting the differences observed and value added by using both the Sharpe Ratios and D-ratios together to analyse the ability to predict the next day's closing price. Through the analysis, it was easy to see why the D-ratio added more value than the Sharpe ratio, because it gave more insight into the profitability that was generated because of the algorithm to predict prices and was more favourable in the non-normal context of asset prices. However, the D-ratio has flaws such as only being viable in years where returns are positive and needing its returns to exist within the domain of validity of the CF-var to produce a valid D-var result. Until these issues are resolved, the D-ratio cannot be used to aid the price prediction power by hedge funds.

(6,627: Words)

Bibliography

1. Eling, M. and Schuhmacher, F., (2007), ‘Does the choice of performance measure influence the evaluation of hedge funds?’, *Journal of Banking & Finance*, 31(9), pp. 2632-2647. Available at: https://doi.org/10.1016/j.jbankfin.2006.09.015 (Accessed 8 May 2022)
2. Farinelli, S., Ferreira, M., Rossello, D., Thoeny, M. and Tibiletti, L., (2008), ‘Beyond Sharpe ratio: Optimal asset allocation using different performance ratios’, *Journal of Banking & Finance*, 32(10), pp. 2057-2063. Available at: https://doi.org/10.1016/j.jbankfin.2007.12.026 (Accessed 8 May 2022)
3. Guo, B. and Xiao, Y., (2016), ‘A note on why doesn't the choice of performance measure matter?’, *Finance Research Letters*, 16(1), pp. 248-254. Available at: https://doi.org/10.1016/j.frl.2015.12.001 (Accessed 8 May 2022)
4. Dessain, J., (2022a), ‘Machine learning models predicting returns: Why most popular performance metrics are misleading and proposal for an efficient metric’, *Expert Systems with Applications*, 199(1), pp. 116970. Available at: https://doi.org/10.1016/j.eswa.2022.116970 (Accessed 8 May 2022)
5. Borch, C., (2022) ‘Machine learning, knowledge risk, and principal-agent problems in automated trading’, Technology in Society, 68. Available at: https://doi.org/10.1016/j.techsoc.2021.101852 (Accessed 1 Apr 2022)
6. Graham, B., Dodd, D., Buffett, W. and Klarman, S., (2008) *Security Analysis: Foreword by Warren Buffett*, New York: McGraw-Hill.
7. Markowitz, H., (1952), ‘Portfolio Selection’, *The Journal of Finance*, 7(1), pp. 77-91. Available at: https://doi.org/10.2307/2975974 (Accessed 1 May 2022)
8. Kahn, R., (2018), ‘The Future of Investment Management’, *CFA Institute Research Foundation*, pp 1. Available at: https://dx.doi.org/10.2139/ssrn.3474545 (Accessed 1 May 2022)
9. Sharpe, W., (1964), ‘Capital Asset Prices: A Theory of Market Equillibrium Under Conditions of Risk’, *The Journal of Finance*, 19(3), pp. 425-442. Available at: https://doi.org/10.1111/j.1540-6261.1964.tb02865.x (Accessed 1 May 2022)
10. Mossin, J., (1966), ‘Equilibrium in a Capital Asset Market’, *Econometrica*, 34(4), pp. 768. Available at: https://doi.org/10.2307/1910098 (Accessed 1 May 2022)

11. Lintner, J., (1965), ‘The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets’, *The Review of Economics and Statistics*, 47(1), pp. 13. Available at: https://doi.org/10.2307/1924119 (Accessed 1 May 2022)

12. Tversky, A. and Kahneman, D., (1974) ‘Judgment under Uncertainty: Heuristics and Biases’, *Science*, 185(4157), pp. 1124-1131. Available at: http://10.1126/science.185.4157.1124 (Accessed 1 May 2022)

13. Fama, E., (1970), ‘Efficient Capital Markets: A Review of Theory and Empirical Work’, *The Journal of Finance*, 25(2), pp. 383. Available at: https://doi.org/10.2307/2325486 (Accessed 1 May 2022)

14. Rosenberg, B., (1974), ‘Extra-Market Components of Covariance in Security Returns’, *The Journal of Financial and Quantitative Analysis*, 9(2), pp. 263, Available at: https://doi.org/10.2307/2330104 (Accessed 1 May 2022)

15. Ross, S., (1976), ‘The Arbitrage Theory of Capital Asset Pricing’, *Journal of Economic Theory*, 13(3), pp. 341-360. Available at: https://doi.org/10.1016/0022-0531(76)90046-6 (Accessed 1 May 2022)

16. Kearns, M. and Nevmyvaka, Y., (2013), ‘High Frequency Trading - New Realities for Traders, Markets and Regulators’. London: Incisive Media, pp. 91-125.

17. Tsaih, R., Hsu, Y. and Lai, C., (1998), ‘Forecasting S&P 500 Stock Index Futures with a Hybrid AI System, *Decision Support Systems*, 23(2), pp. 161-174. Available at: https://doi.org/10.1016/S0167-9236(98)00028-1 (Accessed 1 May 2022)

18. Ucar, I., Ozbayoglu, A. and Ucar, M., (2015), ‘Developing a two-level options trading strategy based on option pair optimization of spread strategies with evolutionary algorithms’, *2015 IEEE Congress on Evolutionary Computation (CEC)*. Available at: http://10.1109/CEC.2015.7257199 (Accessed 1 May 2022)

19. López de Prado, M., (201), ‘Building Diversified Portfolios that Outperform Out of Sample’, *The Journal of Portfolio Management*, 42(4), pp. 59-69. Available at: https://doi.org/10.3905/jpm.2016.42.4.059 (Accessed 1 May 2022)

20. Heaton, J., Polson, N. and Witte, J., (2016), ‘Deep learning for finance: deep portfolios’, *Applied Stochastic Models in Business and Industry*, 33(1), pp. 3-12. Available at: http://10.1002/asmb.2209 (Accessed 1 May 2022)

21. Nakagawa, K., Uchida, T. and Aoshima, T., (2019), 'Deep Factor Model: Explaining Deep Learning Decisions for Forecasting Stock Returns with Layer-wise Relevance Propagation', *ECML PKDD 2018 Workshops*, pp. 37-50. Available at: https://doi.org/10.1007/978-3-030-13463-1_3 (Accessed 1 May 2022)

22. De Spiegeleer, J., Madan, D., Reyners, S. and Schoutens, W., (2018), 'Machine learning for quantitative finance: fast derivative pricing, hedging and fitting', *Quantitative Finance*, 18(10), pp. 1635-1643. Available at: https://doi.org/10.1080/14697688.2018.1495335 (Accessed 1 May 2022)

23. Ritter, G., (2017), 'Machine Learning for Trading', *Courant Institute of Mathematical Sciences*, pp. 1-19. Available from: https://dx.doi.org/10.2139/ssrn.3015609 (Accessed 1 May 2022)

24. Samunderu, E. and Murahwa, Y., (2021), 'Return Based Risk Measures for Non-Normally Distributed Returns: An Alternative Modelling Approach', *Journal of Risk and Financial Management*, 14(11), pp 540. Available at: https://www.mdpi.com/1911-8074/14/11/540 (Accessed 1 May 2022)

25. Cascon, A and Shadwick, F., (2010), 'The CS Character and Limitations of the Sharpe Ratio', *Journal of Investment Consulting*, 8(1), pp. 36-52, Summer 2006, Available at SSRN: https://ssrn.com/abstract=1687982 (Accessed 1 Jul 2022)

26. Auer, B. and Schuhmacher, F., (2013), 'Performance hypothesis testing with the Sharpe ratio: The case of hedge funds', *Finance Research Letters*, 10(4), pp.196-208. Available at: https://www.sciencedirect.com/science/article/pii/S1544612313000470 (Accessed 1 Jul 2022)

27. Singh, D., (2003), 'Basel Committee on Banking Supervision: The compliance function in banks', *Journal of Banking Regulation*, 5(2), pp.110-112. Available at: https://link.springer.com/article/10.1057/palgrave.jbr.2340160 (Accessed 1 July 2022)

28. Baker, H. and Filbeck, G., 2015. *Investment risk management*. Oxford: Oxford University Press, pp. 4-5.

29. Brooks, C. and Kat, H., (2002), 'The Statistical Properties of Hedge Fund Index Returns and Their Implications for Investors', *The Journal of Alternative Investments*, 5(2), pp. 26-44. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=289299 (Accessed 1 July 2022)

30. Dessain, J., (2022b), 'Machine learning models predicting returns: Why most popular performance metrics are misleading and proposal for an efficient metric', *Expert Systems with Applications*, 199, pp.116970. Available at:

https://www.sciencedirect.com/science/article/pii/S0957417422003967 (Accessed 1 July 2022)

31. Maillard, D., (2012), 'A User's Guide to the Cornish Fisher Expansion', *Conservatoire National des Arts et Métiers (CNAM); Amundi Asset Management*, pp. 1-20. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1997178 (Accessed 1 July 2022)

32. Huang, W., Nakamori, Y. and Wang, S., (2005), 'Forecasting stock market movement direction with support vector machine', *Computers & Operations Research*, 32(10), pp. 2513-2522. Available at: https://doi.org/10.1016/j.cor.2004.03.016 (Accessed 2 May 2022)

33. Pai, P. and Lin, C., (2005), 'A hybrid ARIMA and support vector machines model in stock price forecasting', *Omega*, 33(6), pp. 497-505. Available at: https://doi.org/10.1016/j.omega.2004.07.024 (Accessed 2 May 2022)

34. Sedighi, M., Jahangirnia, H., Gharakhani, M. and Farahani Fard, S., (2019), 'A Novel Hybrid Model for Stock Price Forecasting Based on Metaheuristics and Support Vector Machine', *Data*, 4(2), pp. 70-75. Available at: https://doi.org/10.3390/data4020075 (Accessed 5 May 2022)

35. Cortes, C. and Vapnik, V., (1995), 'Support-vector networks', *Machine Learning*, 20(3), pp. 273-297. Available at: https://doi.org/10.1007/BF00994018 (Accessed 5 May 2022)

36. Nti, I., Adekoya, A. and Weyori, B., (2020), 'A comprehensive evaluation of ensemble learning for stock-market prediction', *Journal of Big Data*, 7(1), pp. 1-7. Available at: https://doi.org/10.1186/s40537-020-00299-5 (Accessed 5 May 2022)

37. Xianya, J., Mo, H. and Haifeng, L., (2019), 'Stock Classification Prediction Based on Spark', *Procedia Computer Science*, 162(1), pp. 243-250. Available at: https://doi.org/10.1016/j.procs.2019.11.281 (Accessed 5 May 2022)

38. Mohan, S., Mullapudi, S., Sammeta, S., Vijayvergia, P. and Anastasiu, D., (2019), 'Stock Price Prediction Using News Sentiment Analysis', *2019 IEEE Fifth International Conference on Big Data Computing Service and Applications (BigDataService)*, 4(9), pp. 205-208. Available at: https://doi.org/10.1109/BigDataService.2019.00035 (Accessed 5 May 2022)

39. Breiman, L., (2001), 'Random Forests', *Machine Learning*, 45(1), pp. 5–32. Available at: https://link.springer.com/article/10.1023/A:1010933404324 (Accessed 1 Jul 2022)

40. Ciner, C., (2019), ‘Do industry returns predict the stock market? A reprise using the random forest’, *The Quarterly Review of Economics and Finance*, 72(1), pp. 152-158. Available at: https://www.sciencedirect.com/science/article/pii/S1062976918301066 (Accessed 1 Jul 2022)

41. Basak, S., Kar, S., Saha, S., Khaidem, L. and Dey, S., (2019), ‘Predicting the direction of stock market prices using tree-based classifiers’, *The North American Journal of Economics and Finance*, 47(1), pp. 552-567. Available at: https://www.sciencedirect.com/science/article/pii/S106294081730400X?via%3Dihub (Accessed 1 Jul 2022)

42. Basher, S. and Sadorsky, P., (2022), ‘Forecasting Bitcoin price direction with random forests: How important are interest rates, inflation, and market volatility?’, *Machine Learning with Applications*, 9(1), pp. 100355. Available from: https://www.sciencedirect.com/science/article/pii/S266682702200055X#b8 (Accessed 1 Jul 2022)

43. Bermejo, S. and Cabestany, J., (2000), ‘Adaptive soft k-nearest-neighbour classifiers’, *Pattern Recognition*, 33(12), pp. 1999-2005. Available at: https://www.sciencedirect.com/science/article/pii/S0031320399001867 (Accessed 1 Jul 2022)

44. Nie, C. and Song, F., (2018), ‘Analyzing the stock market based on the structure of kNN network’, *Chaos, Solitons & Fractals*, 113(1), pp. 148-159. Available at: https://www.sciencedirect.com/science/article/pii/S0960077918302753 (Accessed 1 Jul 2022)

45. Nayak, R., Mishra, D. and Rath, A., (2015), ‘A Naïve SVM-KNN based stock market trend reversal analysis for Indian benchmark indices’, *Applied Soft Computing*, 35(1), pp. 670-680. Available at: https://www.sciencedirect.com/science/article/pii/S1568494615003920 (Accessed 1 Jul 2022)

46. Lin, G., Lin, A. and Cao, J., (2021), ‘Multidimensional KNN algorithm based on EEMD and complexity measures in financial time series forecasting’, *Expert Systems with Applications*, 168, pp. 114443. Available at: https://www.sciencedirect.com/science/article/pii/S0957417420311015 (Accessed 1 Jul 2022)

47. Guresen, E., Kayakutlu, G. and Daim, T., (2011), ‘Using artificial neural network models in stock market index prediction’, *Expert Systems with Applications*, 38(8), pp. 10389-10397. Available from: https://doi.org/10.1016/j.eswa.2011.02.068 (Accessed 2 May 2022)

48. Adebiyi, A., Adewumi, A. and Ayo, C., (2014), 'Comparison of ARIMA and Artificial Neural Networks Models for Stock Price Prediction', *Journal of Applied Mathematics*, 2014(1), pp. 1-7. Available at: https://doi.org/10.1155/2014/614342 (Accessed 2 May 2022)

49. Seo, M. and Kim, G., (2020), 'Hybrid Forecasting Models Based on the Neural Networks for the Volatility of Bitcoin', *Applied Sciences*, 10(14), pp. 4760-4768. Available at: https://doi.org/10.3390/app10144768 (Accessed 2 May 2022)

50. Lahmiri, S., (2014), 'Improving forecasting accuracy of the S&P 500 intra-day price direction using both wavelet low and high frequency coefficients', *Fluctuation and Noise Letters*, 13(01), pp. 13-19. Available at: http://10.1142/S0219477514500084 (Accessed 2 May 2022)

51. Adya, M. and Collopy, F., (1998), 'How effective are neural networks at forecasting and prediction? A review and evaluation', *Journal of Forecasting*, 17(5-6), pp. 481-495. Available at: https://doi.org/10.1002/%28SICI%291099-131X%281998090%2917%3A5%2F6%3C481%3A%3AAID-FOR709%3E3.0.CO%3B2-Q (Accessed 1 May 2022)

52. Pang, X., Zhou, Y., Wang, P., Lin, W. and Chang, V., (2018), 'An innovative neural network approach for stock market prediction', *The Journal of Supercomputing*, 76(3), pp. 2098-2118. Available at: https://doi.org/10.1007/s11227-017-2228-y (Accessed 7 May 2022)

53. Fischer, T. and Krauss, C., (2018), 'Deep learning with long short-term memory networks for financial market predictions', *European Journal of Operational Research*, 270(2), pp. 654-669. Available at: https://doi.org/10.1016/j.ejor.2017.11.054 (Accessed 7 May 2022)

54. Kim, Y., Ahn, W., Oh, K. and Enke, D., (2017), 'An intelligent hybrid trading system for discovering trading rules for the futures market using rough sets and genetic algorithms', *Applied Soft Computing*, 55(1), pp. 127-140. Available at: https://doi.org/10.1016/j.asoc.2017.02.006 (Accessed 5 May 2022)

55. Koza, J., (1994), 'Genetic programming as a means for programming computers by natural selection', *Statistics and Computing*, 4(2), pp. 87-112. Available at: https://doi.org/10.1007/BF00175355 (Accessed 5 May 2022)

56. Strader, Troy J.; Rozycki, John J.; Root, Thomas H.; and Huang, Yu-Hsiang (John), (2020), 'Machine Learning Stock Market Prediction Studies: Review and Research Directions', *Journal of International Technology and Information Management,* 28(4), article 3. Available at: https://scholarworks.lib.csusb.edu/jitim/vol28/iss4/3 (Accessed 5 May 2022)

57. Ballings, M., Van den Poel, D., Hespeels, N. and Gryp, R., (2015), ‘Evaluating multiple classifiers for stock price direction prediction’, *Expert Systems with Applications*, 42(20), pp. 7046-7056. Available at: https://doi.org/10.1016/j.eswa.2015.05.013 (Accessed 7 May 2022)

58. Patel, J., Shah, S., Thakkar, P. and Kotecha, K., (2015), ‘Predicting stock and stock price index movement using Trend Deterministic Data Preparation and machine learning techniques’, *Expert Systems with Applications*, 42(1), pp. 259-268. Available at: https://doi.org/10.1016/j.eswa.2014.07.040 (Accessed 7 May 2022)

59. Moghaddam, A., Moghaddam, M. and Esfandyari, M., (2016), ‘Stock market index prediction using artificial neural network’, *Journal of Economics, Finance and Administrative Science*, 21(41), pp. 89-93. Available at: https://doi.org/10.1016/j.jefas.2016.07.002 (Accessed 7 May 2022)

60. Malagrino, L., Roman, N. and Monteiro, A., (2018), ‘Forecasting stock market index daily direction: A Bayesian Network approach’, *Expert Systems with Applications*, 105(1), pp. 11-22. Available at: https://doi.org/10.1016/j.eswa.2018.03.039 (Accessed 7 May 2022)

61. Pehlivanlı, A., Aşıkgil, B. and Gülay, G., (2016), ‘Indicator selection with committee decision of filter methods for stock market price trend in ISE’, *Applied Soft Computing*, 49(1), pp. 792-800. Available at: https://doi.org/10.1016/j.asoc.2016.09.004 (Accessed 7 May 2022)

62. Boyacioglu, M. and Avci, D., (2010), ‘An Adaptive Network-Based Fuzzy Inference System (ANFIS) for the prediction of stock market return: The case of the Istanbul Stock Exchange’, *Expert Systems with Applications*, 37(12), pp. 7908-7912. Available at: https://doi.org/10.1016/j.eswa.2010.04.045 (Accessed 7 May 2022)

63. Théate, T. and Ernst, D., (2021), ‘An application of deep reinforcement learning to algorithmic trading’, *Expert Systems with Applications*, 173(1), pp. 114632. Available at: https://doi.org/10.1016/j.eswa.2021.114632 (Accessed 7 May 2022)

64. Dessain, J., (2022c), ‘Machine learning models predicting returns: Why most popular performance metrics are misleading and proposal for an efficient metric’, *Expert Systems with Applications*, 199(1), pp. 116970. Available at: https://doi.org/10.1016/j.eswa.2022.116970 (Accessed 8 May 2022)

65. Amédée-Manesme, C., Barthélémy, F. and Maillard, D., (2018), ‘Computation of the corrected Cornish–Fisher expansion using the response surface methodology: application to VaR and CvaR’ Annals of Operations Research, 281(1-2), pp. 423-453. Available at:

Application of New Discriminant Ratio to Improve Algorithmic Predictions of Financial Asset Prices

https://link.springer.com/article/10.1007/s10479-018-2792-4#article-info
(Accessed 1 Jul 2022)

Appendix A

Code

The following code snippets are the most useful to observe for this study. As the length of the code was too long, the full code was not presented here. Please refer to both Jupyter notebooks to view all of the code used.

Figure 15: Code to classify problem into two choices, ‘up’ or ‘down’ for the algorithm prediction and calculate the gain or loss for each day

```
def up_down(data_pred):
    for i in range(0,len(data_pred)):
      if (data_pred['predicted Close'][i] > data_pred['predicted Open'][i]):
        data_pred['action'][i] = 'Up'
        data_pred["Day"][i] = str(i)
      elif (data_pred['predicted Close'][i] == data_pred['predicted Open'][i]):
        data_pred['action'][i]= 'Up'
        data_pred["Day"][i] = str(i)
      elif (data_pred['predicted Close'][i] < data_pred['predicted Open'][i]):
        data_pred['action'][i]= 'Down'
        data_pred["Day"][i] = str(i)
    return data_pred

def gain_loss(data_pred):
    for i in range(0,len(data_pred)):
      data_pred['gain/loss'][i]= data_pred['predicted Close'][i] - data_pred['predicted Open'][i]
      data_pred['ratio'][i] = data_pred['gain/loss'][i] / data_pred['predicted Open'][i]
    return data_pred
```

Figure 16: Formulas to calculate cf-var values for each D-ratio as seen on: https://github.com/JDE65/D-ratio/blob/main/d_ratio.py

```
"""Reference: Dessain, J., (2022), ‘Machine learning models predicting returns:
Why most popular performance metrics are misleading and proposal for an efficient metric’,
Expert Systems with Applications, 199(1),
pp. 116970. Available at: https://doi.org/10.1016/j.eswa.2022.116970
https://github.com/JDE65/D-ratio/blob/main/d_ratio.py"""

def risk_skew_kurt(model_return):
    mean = np.mean(model_return)
    st_dev = np.std(model_return)
    skew = stats.skew(model_return)
    kurt = stats.kurtosis(model_return)
    return (mean, st_dev), (skew, kurt)

def risk_cf_exp_var(model_return, asset_value=100, confid=0.1):
        (mean, st_dev), (skew, kurt) = risk_skew_kurt(model_return)
        quantile = norm.ppf(confid)
        cf_exp = quantile + (quantile ** 2 - 1) * skew / 6
        + (quantile ** 3 - 3 * quantile) * kurt / 24
        - (2 * quantile ** 3 - 5 * quantile) * (skew ** 2) / 36
        cf_var = mean + st_dev * cf_exp
        cf_asset_value = asset_value * (1 + cf_var)
        return cf_exp, cf_var, cf_asset_value
```

Figure 17: Calculation code of each D-ratio, that has been applied to each algorithm

```
# Calculation of D-ratio. There are 252 trading days in the year

a = profit(data_pred_svc['gain/loss']) - profit(df_buy_and_hold_svc['gain/loss'])
a_ = math.log(abs(a)) * 252


b = (profit(df_buy_and_hold_svc['gain/loss']))
b_ = math.log(abs(b)) * 252


e = profit(data_pred_svc['gain/loss'])
e_ = math.log(abs(e)) * 252
cf_exp, cf_var, cf_asset_value = risk_cf_exp_var(e_)


f = profit(df_buy_and_hold_svc['gain/loss'])
f_ = math.log(abs(f)) * 252
cf_exp1, cf_var1, cf_asset_value1 = risk_cf_exp_var(f_)


d_return = ((1 + a_) / b_)
print("SVC D-return = ", d_return)

d_var = cf_var / cf_var1
print("SVC D-var = ", d_var)

d_ratio = (d_return * d_var)
print("SVC D-Ratio = ", d_ratio)
```