Influence of machine learning on stock pricing: a meta-analysis

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ABSTRACT,
Determining the performance of a stock, the growth of a stock and the risk of a stock are vital parts of the stock market and global market. Machine learning is a promising way to do this. Stock prices are used to determine the risk and securities linked to the stock. With the rise of cryptocurrency and better computers, the eyes of people in the investment market are looking for new opportunities to improve their returns. This thesis explains what machine learning is, how prices for stocks are determined and how machine learning has helped the investment market to become more accurate with the pricing. The findings of research papers are compiled and a conclusion will be drawn from it.

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Keywords
Machine learning, Stock market, Investment performance

1. INTRODUCTION

The face of investing is changing. In the 80's and 90's only big companies and very rich individuals involved themselves with investments and the stock market but recently advertisements on the television to invest occur daily, mostly from pension funds and banks. Investors used the CAPM model and Fama French Three Factors model as indicators for the performance of a stock (Ndikum, 2020). These two approaches are elaborated on later in the thesis. Nowadays mankind generates and captures over 2.5 quintillion bytes of data on a single day (Ndikum, 2020). In this thesis, techniques of machine learning to predict stock prices and techniques to determine the influence of machine learning on today's stock market are discussed. A stock price is set by determining the risk of losing the investment against the possible return on the investment. According to the efficient market hypothesis, stock prices should not be predictable (Jaydip Sen, 2018). However, later work has shown that with the right models and network indicators we can improve prediction accuracy about stock prices movements (Lee et al., 2019). There is evidence of the possibility to predict stock prices by rate of return on investment according to empirical analyses on the stock market in the United States (Song et al., 2018). Many different disciplines within the financial world like economics, mathematics, physics, and computer science have tried to come up with a way to reliably predict stock prices (Song et al., 2018). In today's fast moving high tech world, a lot depends on data processing. Technology has come a long way in terms of data processing power. Today we not only have self-driving cars but also self-learning computers. Developers and technological advancement made it possible to develop a programme that can read and understand algorithms in a way that was not possible before. Machine learning can include a lot of data in a data set and find correlations where a human would be lost already. Ndikum states in his paper from 2020 that machine learning can determine cross platform correlations. Meaning it can see and understand social media trend effects on stock prices and predict price fluctuations accordingly (Ndikum, 2020). This thesis tries to answer the main research question which states: To what extent does machine learning add value to existing stock pricing strategies? Since machine learning is able to predict trends better and account for abnormalities, the prediction is that machine learning has added value to stock pricing. The hypothesis is therefore that machine learning adds value to already existing stock pricing strategies.

2. MACHINE LEARNING

2.1 What is Machine Learning

Machine learning is part of Artificial intelligence. Ndikum defines Artificial Intelligence as "isolation of a particular information processing problem, the formulation of a computational theory for it, the construction of an algorithm that implements it, and a practical demonstration that the algorithm is successful ''(Ndikum 2020, page 4). If we turn to the explanation of machine learning in the dictionary, the Oxford dictionary reads: "the use and development of computer systems that are able to learn and adapt without following explicit instructions, by using algorithms and statistical models to analyse and draw inferences from patterns in data." Ndikum adds to this that machine learning algorithms are designed to deal with immense amounts of data which can be high dimensional and unstructured (Ndikum, 2020). Machine learning is letting a computer try time after time to solve a problem using a punish reward system. Machine learning is used in a lot of sectors, including urban traffic allocation or the gaming industry. Technology has made it possible for a computer or program to learn by trying, failing and doing it again with the just learned information, just like a toddler learns to walk, but there are more applications of machine learning. Since machine learning goes through data by itself it can find patterns that humans would not see since they are not linear nor one dimensional. This means if investors apply machine learning to the financial world, it can look into the past of the investment markets and recognize correlations between multiple stocks with which it can predict the future stock price. Not only does it look into the past fluctuations of the stock. It can also see social media activity and trends to match with the stock's fluctuations and draw predictions from it. Since machine learning can take many forms, it is hard to find a single definition in the literature. Gu et al. describes machine learning by a diverse collection of high-dimensional models for statistical prediction, combined with regularisation methods for model selection and mitigation of overfit and efficient algorithms for searching among a vast number of potential model specifications (Gu, 2020). The thing all definitions share is that machine learning consists of algorithms learning from data while implementing learned data in an automated data analysis.

2.2 Machine Learning in Finance

Dixon (2019) states that finance is the ideal circumstance for machine learning to take place since it has all the ingredients "vast amounts of data, the computational and human resources, direct profit and loss implications, and a highly competitive environment where every advantage is needed if one is to succeed". (Dixon, 2019, page 2). Machine learning is mostly used for detecting fraud, automating trading activities and providing advice and recommendations to investors. Machine Learning has three subcategories in finance which are unsupervised machine learning, supervised machine learning and reinforcement learning (Dixon, 2019). The last two decades the focus was on developing new and reliable ways of determining stock prices. What investors are trying to achieve is an algorithm that can consistently predict further stock values. Critics in the investment world have said that Machine Learning is just a black box and we do not understand how the algorithm comes up with its values (Ndikum, 2020). Ndikum gives the global crisis of 2007 till 2009 as an example of why we should be careful with algorithms and predictions we do not fully understand. Humans have a low tolerance to failures of machines as shown by Dietvorst in 1275, known as the algorithm aversion. This can be seen in the strict regulation of the EU in response to development in the IT world. However, the supervised learning approach of machine learning has shown to be much more precise compared to the traditional models in a study done by Ndikum in 2020. When tested on the US equities market the machine learning approach had a far better performance than the traditional CAPM method. Ndikum predicts that as the world moves into an age of big data, science data and machine learning, algorithms will become more and more important and will dominate the world of economics and finance.

2.2.1 Unsupervised Machine Learning

Unsupervised machine learning is a technique to partition and reduce the dimensions of data by using algorithms to cluster unlabelled data with which hidden patterns or data groupings can be discovered without the need of human intervention or as Dixon (2019) states it, without a teacher. There is no feedback loop or as Dixon calls it feedback from a teacher (Dixon, 2019). An example of this form of machine learning is K-means clustering for portfolio selection in finance. (Dixon, 2019)

2.2.2 Supervised Machine Learning

Another version of machine learning is supervised machine learning (SML). The name already suggests that supervised machine learning needs the help of a human. Contrary to unsupervised machine learning, it uses labelled data. Supervised machine learning can produce general patterns and hypotheses from examples it has been given in the form of a training dataset. This data is not changed anymore after the parameters are set; therefore it is also called offline learning (Dixon, 2019). A human or so called teacher writes an algorithm in which is stated what to look for or an exact right output for each data point from a training dataset. This training set can be called feedback according to Dixon (Dixon, 2019). SML then tries to categorise the data, making it easier for a human to understand. Examples of SML are rule-based techniques, logic-based techniques, instance-based techniques and stochastic techniques (Singh et al., 2016).

2.2.3 Reinforcement Learning

There is also a form of machine learning called reinforcement learning. Dixon states that because reinforcement learning is so difficult to understand it is the most under-exploited method of machine learning in finance, even though it is the most useful (Dixon, 2019). RL (reinforcement learning) means that the algorithm evolves according to what it learns. It starts off with a data set which it needs to look for. We can compare it with a car on a simulated race track. The AI is told to finish the race with the car and give it a certain number of rules. For example, the car can drive only forward, it is not allowed to go off the track and the goal is to finish the race. The AI is then told every time it goes off the track that it is wrong about doing that but gets positive feedback when it passes a certain checkpoint. This way we let the AI know the desired behaviour and if we let the AI try enough times, it will learn how to drive the car within the boundaries set by us over the finish line in the quickest time. We can also apply this to other problems the AI needs to solve. RL is based on stochastic control. Stochastic control is a subfield of control theory which focuses on the existence of uncertainty either in observations or in the noise that drives the evolution of the system (Kappen, 2006). This feedback is added and the original parameters and policies are changed. RL is a generalisation of stochastic dynamic programming (Dixon, 2019). Some people call this form of Machine Learning deep learning. Dixon stated that reinforcement learning is the perfect fit for a trade execution algorithm because RL is the most suitable paradigm when there is a need to both optimise a utility function and the decisions to change the state. This is the case with trading because it should maximise the risk adjusted return and reduce the effect of price impact by making smaller orders out of large block orders (Dixon, 2019).

3. HOW IS STOCK PRICE DETERMINED

3.1 What is Stock

Movies like the Wolf of Wall Street and the Big short have put a certain image on Wall Street and the stock market. The image of it being a big bunch of big spenders who do not care about any rules and who can do whatever they want. However, the reality is different. There is a lot of control on the stock market and not everyone can be successful on it. The market works in a way that when one makes money, someone else loses it , making the end result equal. Therefore, the reality of the stock market is less colourful and optimistic than the movies paints it to be (Wang, 2003). The stock market has always been popular for economic and psychological studies since there is a lot of money to be made, with the right approach. However, the stock market is very dynamic, non-linear, complicated, nonparametric and if the market is functioning correctly, it is chaotic in nature (Tan et al., 2005). But first the question following question needs to be answered: what is the stock market? First let's take a look at what a stock is. A stock is a financial product that belongs to a company which is lent to investors to raise capital. When an investor buys shares or stocks from a company, the investor becomes a shareholder of that company. In exchange for buying the stock from the company, stockholders get a return on the stock, which is called dividend and they get a vote on the company's future plans (fundamentals of Corporate finance, David Hillier, 2017). The amount of dividend received and how heavy the vote counts, depends on the percentage of stocks owned by the investor. (Brealy at el., 2001) When a company is a start-up, it needs investors to start a revenue stream but when the company outgrows the start-up phase and is in need of more capital it can turn to the stock market. The company will then go public and offer shares to consumers. When this happens for the first time it is called an IPO (initial public offering). The IPO price is set by an investment bank but most of the time this does not raise all the capital the company wants, or the company has further need of capital. In this case the company can choose to add more shares to the public market. When the company does this, it is called seasoned shares. Both the IPO and the seasoned shares are traded on the primary market. This means it is bought from the company or investment bank directly. People in the investment world call it the secondary market when these shares are then resold or traded among investors themselves. This research will focus on pricing in the primary market. So how does an investment bank set the stock price? There are numerous ways to do this but in this research the capital asset pricing model and the Fama-French multi-factor models are discussed later on. This is because these are the two primary ways taught in business schools and both have actively been used in the stock market to predict stock movements by traders. The selected studies also use these approaches to benchmark the performance of machine learning too. After discussing the CAPM and the Fama-French multi-factor models, the sharp-ratio will be introduced since this is a basic and well known way to express risk linked to a stock which is taught in most business studies. When evaluating if machine learning has added value to the investment sector, it's performance will be compared with traditional approaches giving the possibility to determine if machine learning can outperform the traditional approaches. As will be explained below the CAPM, Fama-French multi-factor models and sharp-ratio are used to find or evaluate the expected performance of a stock, the risk the stock has and the expected growth of the stock. These will therefore be our focus point of evaluating the performance of machine learning in investments.

3.2 Capital Asset Pricing Model

The Capital Asset Pricing Model is a fundamental contribution to our understanding of the determinants of asset prices (Perold, 2004). It was developed by Sharpe et al. in in the 1960's and is an expansion on the model made by Harry Markowitz in 1959. Sharpe ended up winning a Nobel prize for it in the 1990's (Fama & French, 2004). The CAPM is used to relate the risk and the expected performance of a certain stock. Even though the CAPM is one of the most important models taught in business studies and sometimes the only one, it has its flaws (Fama & French, 2004). There are a lot of empirical studies and records showing that the model is often faulty (Fama & French, 2004). The CAPM has the assumption that investors are risk averse, meaning that they want to have the least amount of risk possible, and that investors will only care about the mean and the variance of a one-period investment return (Fama & French, 2004). The CAPM also assumes that there is complete agreement in the market and that investors can borrow risk-free assets unrestricted and sell risky assets unrestricted, which is unfortunately not true (Fama & French, 2004). The CAPM also assumes that the only influence on the assets return is its risk in regard to the market. However, Fama and French state that all models have unrealistic simplification and should therefore always be tested against data (Fama & French, 2004). In the CAPM model, the risk premium of a certain asset will move in proportion to that asset's beta (Fama & French, 2004). This means that we can define the $E(r\text{x})$ defined as the expected return on asset x, rf is the risk-free rate of return, βx is the beta of the asset, and $(E(rM) - rf)$ is the market risk premium (Ndikum, 2020). When we take a closer look at the equation we see two things that need further explanation. These are the risk-free rate of return and the Beta. A risk-free rate of return means that the market considers this investment safe and with a very low risk, resulting in the idea that you will get the return from the asset. An example of this is a government bond, since the prospect of a government going bankrupt and not being able to pay back the dividend is close to zero (Brealy et al., 2017). In general, a government bond is considered to be the least risky investment a person can make (Brealy et al., 2017). Therefore, we can use the value of a government bond in the CAPM model as our risk-free rate of return. We now look at the Beta of an asset. The Beta shows how sensitive the value of the asset is regarding the market. To clarify, when an asset has a Beta of 1.0, we can say that the asset follows the market. So if the market increases by 0.2, the asset increases by 0.2 times the Beta. The asset can also have a lower or negative beta, for example a beta of -1.0. This would mean that the asset's value reacts opposite to that of the market.

3.3 Fama-French Multi-Factor Models

Fama and French introduced a multi-factor model with multiple risk factors in 1993. The developers of the models aimed at creating a more accurate model than the CAPM. Both models rely on the Beta of a stock. However, the biggest characteristic of the Fama-French models is that they use more than one beta. There are two versions of the Fama-French model, the three-factor model and the five-factor model. First, the three-factor model will be illustrated which consists of the following equation (Brealy et al., 2017), (Kohlscheen & Takáts, 2021):

$$r\text{x} - rf = \beta M(rM - rf) + \beta size(SMB) + \beta book{-}to{-}market\ (HML) + \alpha$$

In this equation, $r\text{x}$ is defined as the return on asset, or portfolio, x, rf is the risk-free rate of return, $(rM - rf)$ is defined as the market risk premium, Small Minus Big (SMB) is the return on small-firm stocks minus return on CAPM model as follows:

$$E(r\text{x}) = rf + \beta\text{x}(E(rM) - rf)$$

Here, large-firm stocks and High Minus Low (HML) is the return on high book-to-market-ratio stocks minus return on low book-to-market ratio stocks (Brealy et al., 2017). Just as in the CAPM model the betas serve the need to show the reaction and sensitivity of the underlying stock making the value of the asset to the market. Fama and French added the factors profitability patterns and investment patterns later after more research resulting in the five factor Fama-French model (Fama & French, 2015). The equation for the five-factor Fama-French model is (Wang et al., 2021):

$$ri - rf = \beta M(rM - rf) + \beta size(SMB) + \beta book{-}to{-}market\ (HML) + \beta profitability(RMW) + \beta investment\ (CMA) + \alpha$$

Here, the first part of the equitation is the same as the three factor equation but with the addition of the RMW (Robust Minus Weak) factor which is defined as the returns on stocks with robust profitability minus returns on stocks with weak profitability and the CMA (Conservatively Minus Aggressively) factor which is defined as the returns on stocks of low investment firms minus the returns on stocks of high investment firms (Wang et al., 2021). According to Fama & French, the five factor model is an improvement and more accurate than the three factor model (Fama & French, 2015).

3.4 Sharpe Ratio

When investors asses a stock, the risk the stock carries with it is a big factor. One of the most common ways of measuring the risk of a stock is via the Sharpe ratio. The Sharpe ratio is the calculation of the risk premium, the expected return of the asset above the risk free rate, divided by the standard deviation. The equation is as follows;

$$sharpe\ ratio = \frac{Risk\ Premium}{Standard\ Deviation} \quad \text{or } SR = \frac{r - rf}{\sigma}$$

Brealey says in his book principles of corporate finance that the Sharpe ratio is used by investors to measure the risk-adjusted performance of investment managers (Brealey et al., 2014). Next to the sharp ratio there is a risk for human investors to make mistakes based on biases of the human. Since machine learning does not have emotions, it can also not have biases. Machine learning is therefore better capable of dealing with risk then humans are (Nabipour et al., 2020).

4. METHODOLOGY

This thesis is a literature and meta-analysis review with the aim to answer the question: To what extent does machine learning add value to existing stock pricing strategies? A meta-analysis is conducted by integrating past findings of empirical research. Since there have been multiple empirical studies that question the value of machine learning in investment it is valuable to compile a meta-analysis of previous findings. The papers will be found using the Utwente library and online library. The University of

Twente has access to several databases otherwise not accessible and also articles that are accessible through google scholar. After this conclusions can be drawn regarding the research questions and the hypothesis can be accepted or rejected. This thesis will look if machine learning can improve on the prediction of the performance, the growth and the risk of a stock. These used to be determined with the CAPM, Fama-French multi-factor models and sharp-ratio. This study therefore looks at articles discussing the performance of machine learning compared to these three traditional approaches or the areas these traditional approaches are used for. The findings will be summarised in table 2 so it get an overview of the bigger picture. After the summary in the table, the findings will be more clearly explained in the findings section. For the meta-analysis eleven papers are used. Of these articles ten discuss Machine Learning performance and influence in the performance of a stock, one about growth and four about risk. This makes the nature of this study quantitative.

5. FINDINGS

5.1 Added Value of Machine Learning With Performance

Performance of a stock is important to every investor. It indicates if a stock is profitable or not. It is therefore no surprise a lot of researchers focus their attention on the performance part of added value of machine learning in stock pricing. Chia-Cheng et al. found in a study in 2020 that the three Machine Learning methods used which were ANN, SVM and random forest yielded a higher return ratio than the benchmark index of the stocks.

indicators	ANN	SVM	RAN FOR	GSPC
MAX	4.0979	4.9593	4.9593	4.9593
MIN	−4.9593	−4.0979	−4.0979	−4.0979
STD	0.832	0.8306	0.8304	0.8328
MEAN	0.0469	0.0672	0.0694	0.0285
Median	0.0352	0.0695	0.0621	0.0381

Table 1: Mean Returns Generated By the Machine Learning Models (Chia-Chen et al., 2020)

Table 1 shows the findings of Chia-Cheng et al. It shows the mean returns generated by the machine learning models which are ANN, an artificial neural network, SVM which is the support vector machines and the RAN FOR is the random forest. The GSPC stock index is the benchmark used in the study. We can conclude from these findings that the proposed Machine Learning models have a significantly higher mean return compared to the GSPC stock benchmark (Chia-Chen et al., 2020).

Dixon et al. states that with the use of Machine Learning we can provide a more general framework for financial modelling than the linear parametric have been able to do before. With this we can generalise archetypal modelling approaches, such as factor modelling, derivative pricing, portfolio construction and consumption, optimal hedging with model-free, data-driven approaches. Dixon et al. state that supervised learning and reinforcement in investment and trading would be the best practices for machine learning to be successfully adopted in the investment industry. Dixon et al. does warn that machine learning can only add value if we respect the interpretability and robustness that machine learning needs. Therefore Dixon et al. stated that we have to match the traditional ways of financial modelling and econometrics frameworks with machine learning (Dixon et al., 2019).

Emerson et al. found that the use of machine learning improves the return forecast. He found that researchers use ANN like Deep neural networks, CNNs (Convolutional neural network) and LSTMs (Long short-term memory) to improve return forecasts made with traditional inputs like fundamental accounting data or technical indicators. Emerson et al. sum up success researchers have made using machine learning like; Emerson states that researchers use a CNN strategy to analyse and detect price movement patterns in high-frequency limit order book data. Emerson also states that machine learning was able to create a model that forecasts future fundamental data based on a trailing five-years window. When the forecasting fundamental data was used compared to the traditional value model the researchers were able to increase their compounded annual return from 14.4% to 17.1%. With the help of machine learning researchers could improve their buy-hold-sell strategy for 43 CME listed commodities with an accuracy of 42% (Emerson at all, 2019).

Gu et al. found in his performed research that the machine learning method with neural networks performed best in accurately predicting the asset price. Regression trees were also affective but less effective than ANN. Gu et al. states that ANN is more effective because it can accommodate nonlinear interactions which are not noticed by other methods. Gu et al. found that in contrast to other fields, in investments the use of shallow Machine Learning is more useful then deep Machine Learning. Gu et al. suggests that this is because of comparative dearth of data and low signal-to-noise ratio in asset pricing problems. Gu et al. also states that Machine Learning is more useful when it has more data to work with, so it is better in forecasting large and liquid stock returns and portfolios. The Machine Learning methods use the return reversal and momentum the most to predict the asset price. Other powerful predictors to the Machine Learning methods are stock liquidity, stock volatility, and valuation ratios. Gu et al. states that now we have Machine Learning methods that can more accurately predict returns the landscape of investment will change. Since Machine Learning is more accurate the risk premiums are less shrouded in approximation and estimation error and will therefore decrease, thus a better view on the stock's performance over all (Gu at all, 2020). Leung proves in his research that data mining and machine learning can and should be used by businesses and investors. By letting a Machine Learning model, structural support vector machine (SSVM), learn how to use the catting plane algorithm by teaching it minimum graph cuts, it could solve the optimization problem found in a prediction model with a complex graph with multiple edges per node. Which in this study represents complex relationships between companies that affect the stock price. After this the model was used on the problem of stock price prediction. Here the accuracy of the SSVM model was higher than 78%, which confirms that the model has successfully been learned without it overfitting. Leung has therefor shown the effectiveness of SSVM in stock price prediction (leung et al., 2014).

Nabipour et al. found that after testing the capability to predict the movement of stocks of nine different Machine Learning models

paper	performance	growth	risk
Cheriyan et al	x	After testing three different algorithms of machine learning, it was found that the gradient boost algorithm was very good at predicting growth with an accuracy of 98%	x
Chia-Cheng et al	The three methods used, ANN, SVM and random forest all exceeded the benchmarks index in their performance. ANN scored a mean of 0.0469, SVM scored 0.0672 and random forest scored 0.0694, compared to the benchmark GSPC which scored 0.0285	x	The three methods used, ANN, SVM and random forest all exceeded risk-adjusted performance measures compared to the benchmark index. ANN scored a mean of 0.0523, SVM scored 0.0768 and random forest scored 0.0795, compared to the benchmark GSPC which scored 0.0301
Dixon et al	Neural network proposed by Dixon generates higher information ratios then the linear factor model which means that the ML approaches were better performing then the traditional ones.	x	x
Emerson et al	ML is used to extract new inputs from alternative data as well as being used for traditional inputs making the prediction more reliable. The forecasting fundamental data performed better, increasing the compounded annual return from 14.4% to 17.1%	x	ML can find companies that are in danger of bankruptcy next to being able to predict risk well from the traditional measures
Gu et al	Shallow machine learning instead of deep machine learning performed well in forecasting large and more liquid stock returns and portfolio's and has a better R^2 when combining all data.	x	ML doubles the performance of leading regression-based strategy with neural network forecast
Leung et al	ML had learned a model without over-fitting with a success rate of over 78% proving it can be used in stock price prediction. Therefor being capable of predicting stock more accurately then tradition approaches.	x	x
Nabipour et al	Deep learning methods with binary data was the best to predict stock market movement with an average F- score of 83% compared to continuous data algorithms which had an average F-score of 63%. This shows ML outperformed traditional approaches.	x	Machine learning greatly reduces the risk of trend prediction
Ndikum	ML was capable of having far lower mean squared error then the CAPM, with ML having the highest MSE at 0.3628 and CAPM at 1.6001. This shows that ML out-performans traditional approaches	x	x
Usmani et al	ML was able to predict the market performance 77% correct using the Multi-Layer Perceptron algorithm showing the usefulness of machine learning in investment strategies.	x	x
Vijh et al	Machine learning techniques like ANN models improve efficiencies by 60-86% compared to past methods, showing that ML outperformed traditional approaches.	x	x
Zhong et al	PCA-DNN classifiers outperform the benchmark index with the proper number of hidden layers showing ML outperformans traditional approaches.	x	x

Table 2: Significant Findings

that when using binary data instead of continuous data the average F-score is significantly higher. Next to this they found that the Machine Learning method RNN and LSTM were the best from the nine Machine Learning methods (Nabipour, 2020). Ndikum compared supervised machine learning algorithms performances to the CAPM model, which is a fundamental analysis model taught in almost all business studies. By doing this he could determine if Machine Learning methods outperformed the CAPM model in financial asset price forecasting. His success indicator was the Mean squared error (MSE). Ndikum found that the CAPM was significantly outperformed by all six of his selected Machine Learning methods ((NGBoost, XGBoost, Catboost, LightGBM, Shallow FNN, Deep FNN). The CAPM had an MSE of 1.6001 while the worst performing Machine Learning method, which was shallow, FNN had a MSE of 0.3628 and the best performing Machine Learning method, Catboost, had an MSE of 0.3125. Ndikum therefore concludes that Machine Learning models are better in predicting asset prices then the CAPM (Ndikum, 2020).

Usmani et al. confirms in his research that machine learning techniques can predict stock performance. The machine learning techniques were able to predict the KSE-100 index accurately and SVM was the most accurate in the training set. However Usmani et al. states that Multi-Layer Perceptron (MLP) is the most efficient in predicting market performance since it was more effective on the test set. Results can be found in the table 3 and the table is directly copied from the paper.

Data set used for verification	Machine learning Algorithms			
	SLP	MLP	RBF	SVM
Training set	83%	67%	61%	100%
Training set	0%	77%	63%	60%
Average	71.50%	72%	62%	80%

Table 3: Findings Performance ML From Usmani et al. (2016)

This research has shown that Multi-Layer Perceptron (MLP) can accurately predict stock performance with lack of resources and little data about the market itself. The table above shows Usmani et al. findings on performance of machine learning. The table is directly copied from the paper, but I believe there is a mistake in the table. The second row should not again be training set but test set. This is also in line with what Usmani et al. writes in the conclusion of the paper. (Usmani et al., 2016).

Vijh et al. studied if the two Machine Learning models ANN (Artificial Neural Network) and RF (Random Forest) are efficient in predicting stock price at closing times. In this research they use ANN and RF to calculate the Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Bias Error (MBE). From the research we can conclude that ANN is a better model to use since it gives improved RMSE and MAPE values as seen in the table below. with ANN it was possible to calculate the best RMSE at 0.42, MAPE at 0.77 and MBE at 0.013 (Vijh et al., 2020). The full results are presented in table 4.

Company	ANN			RF		
	RMSE	MAPE	MBE	RMSE	MAPE	MBE
Nike	1.10	1.07%	-0.0522	1.29	1.14%	-0.0521
Goldman Sachs	3.30	1.09%	0.0762	3.40	1.01%	0.0761
JP Morgan and Co.	1.28	0.89%	-0.0310	1.41	0.93%	-0.0313
Johnson & Johnson	1.54	0.70%	-0.0138	1.53	0.75%	-0.0138
Pfizer Inc.	0.42	0.77%	-0.0156	0.43	0.8%	-0.0155

Table 4: Findings Performance of ANN and RF (Vijh et al., 2020)

Zhong et al. conducted research on what form of machine learning is most accurate in predicting the daily return of the stock market. Zhong et al. concludes that among the current machine learning models, the PCA-DNN classifiers are the best at achieving classification accuracy and therefore result in the best trading strategy performance. This however is dependent on the amount of hidden layers involved. Zhong discovered that this is where the problem is occurring since the hidden layers are a black box that is not theoretically confirmed. Therefore Zhong mentions in his conclusion that there needs to be more research into the hidden layers around DNN algorithms (Zhong et al., 2019).

5.2 Added Value of Machine Learning With Growth

Chariyan et al. researched intelligent sales prediction with Machine Learning methods since a lot of businesses depend on having a good knowledge of the upcoming demands and sales. Chariyan et al. test the effectiveness of three different models. These models are Gradient Boosted Trees (GBT), Decision Trees (DT) and the Generalized Linear Model (GLM). Chariyan et al. finds that GBT is the best model with the accuracy rate of 98 % and a minimum error rate. Chariyan et al. testing the three models their accuracy rate, error rate, precision, recall and kappa. The results of the study can be found in the table below. This table is directly copied out of the paper (Chariyan et al., 2022).

Model name	Performance Summary of ML Algorithms				
	Accuracy Rate (%)	Error Rate	Precision	Recall	Kappa
GLM	64	36	5.36	0	0
DT	71	29	11.24	15.61	0.501
GBT	98	2	50	50	0.962

Table 5: Findings Chariyan et al. (2022)

5.3 Added Value of Machine Learning With Risk

Chia-Cheng et al. found that the three methods used in their research to find the best performance related machine learning model, ANN, SVM and random forest. All exceeded risk-adjusted performance measures compared to the benchmark index. This means that when using these models, the Sharp ratio is lower. Chia-Chang et al. were even able to get a positive Sharpe ratio with their Machine Learning models while the benchmark index gave a negative 1.

year	GSPC	ANN	SVM	TREE
2014	0.0629	−0.0444	0.1399	0.1366
2015	−0.0081	0.1136	0.0144	0.1266
2016	0.0556	0.0398	0.0807	0.0691
2017	0.1631	0.0144	0.21	0.2242
2018	−0.0239	0.0939	0.0489	−0.0368
5 years	0.0301	0.0523	0.0768	0.0795

Table 6: Findings Chia-Cheng et al. (2022)

The table above shows the findings of the Sharpe ratio by Chia-Cheng et al. In this table GSPC is the benchmark index, ANN, an artificial neural network, SVM the support vector machines and the ran for the random forest. As shown in the table the Machine Learning models perform significantly better (Chia-Cheng et al., 2022).

Emerson et al. found that Machine Learning is in general accurate with prediction risk in stocks, but it is also effective at finding companies that are on the brink of going into bankruptcy. The Machine Learning models can see and predict those risks better then human calculation can and has therefore significant added value for investors. Next to this, Emerson et al. found that when Machine Learning is used in a way where it k-means clusters to make a risk model by grouping stock returns paired with standard deviation squared and adjusted by mean absolute deviation, it outperformed any traditional statistical risk model used in quantitative trading (Emerson et al, 2019).

Gu et al. found that Machine Learning doubles the performance of leading regression-based strategy with neural network forecast. However Gu et al. mostly write about the risk premium and not general risk, but the two terms are connected. Gu et al. defines two kinds of risk. They use the Sharpe ratio and R^2. Both improve when Machine Learning models are used. Gu et al. also gives benchmarks for risk in prediction accuracy. Since Machine Learning is more accurate the risk premiums are less shrouded in approximation and estimation error and will therefore go down, thus allowing for a better view on the stock's performance over all (Gu at el., 2020).

Nabipour et al. states in the research that humans are likely to make decisions based on past experiences and see patterns themselves. However humans often do not see the right pattern and are therefore prone to the risk of trend prediction of the stock market. Machine Learning is not led by emotions and is therefore not able to make the same mistake. This wipes out the risk of trend prediction all together (Nabipour et al., 2020).

6. CONCLUSION

This thesis did a meta-analysis of eleven papers to answer the question; To what extent does machine learning add value to existing stock pricing strategies? The thesis uses ten papers to find out if machine learning adds value to the performance of stock pricing strategies, one paper to answer if machine learning adds value to growth prediction of a stock and four papers to answer if machine learning adds value to existing risk measurement in stock pricing. From the research, we can conclude that machine learning is better and more precise than existing traditional methods discussed in this thesis and therefore adds value to the investor in all these sectors since all the papers analysed are in favour of machine learning in investment. Only one paper suggested that traditional approaches are just as good if there were not enough hidden layers used. We can therefore accept the hypothesis and answer the research question in a one contained sentence; machine learning adds value to existing stock pricing strategies by being more precise than any other strategy and therefore having the best risk to reward ratio.

7. ACKNOWLEDGEMENT

I would like to thank my supervisor Dr..Robert Gutsche for remaining my supervisor even when he did not work at the University of Twente anymore. Further I want to thank everyone who proofread the thesis and checked it for spelling mistakes.

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