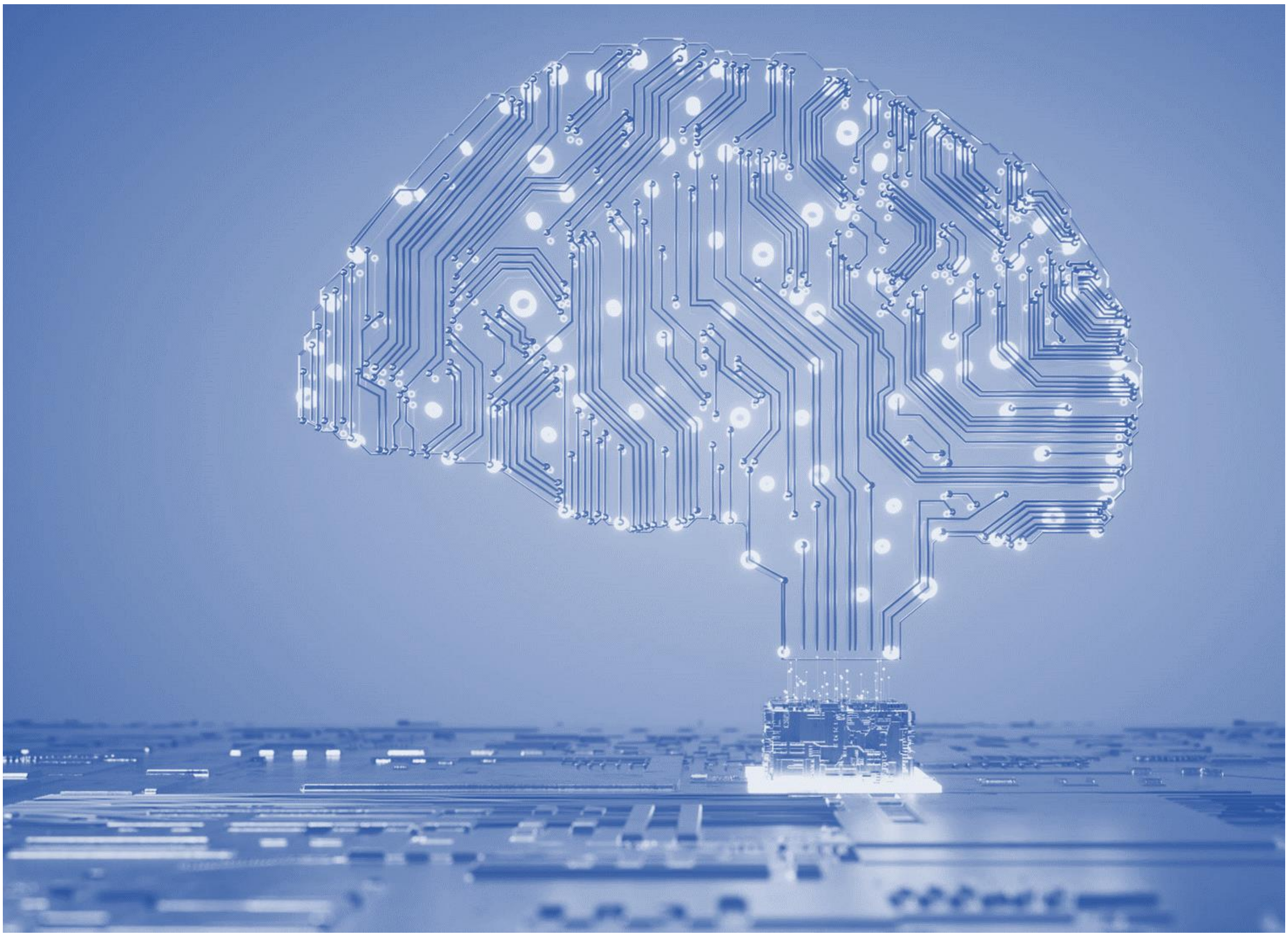


The New Age of Stock Screening:
Bridging the Gap between Traditional and Machine Learning Techniques
(with a Practical Case Study)

„I have not seen something like this since I would say 2007-2008, when
the cloud was just first coming out"
Satya Nadella, Microsoft CEO

Abstract: This paper dives into how AI and the subset ML[1] are reshaping the art of stock screening, a critical phase in the investment process. With a growing emphasis on data-driven decision-making, AI and ML not only offer a competitive edge but are increasingly becoming indispensable tools for investors. Central to the paper is the dynamic nature of ML algorithms, which adapt in real-time to shifting market conditions by continuously learning, thereby outperforming traditional methods in identifying investment opportunities. The efficiency gains, risk reduction and performance enhancement offered by these advanced techniques will be highlighted. The paper emphasizes the irreplaceable role of human expertise in the decision-making process, advocating for a collaborative approach where AI supports but does not replace human judgment. A real-world case study from 2021 of an Asset Management company illustrates the practical application and benefits of adopting AI-driven solutions. The case study reveals how the Asset Manager achieved superior performance by integrating ML-driven stock screening into their investment process, highlighting the role of data quality and the choice of algorithms in the success of these models.

December 2023

Beginnings: A Prelude

Incorporating Artificial Intelligence (AI) or the subset Machine Learning (ML)[1] into the field of investment is changing how we approach investments and the traditional methods used for screening stocks. This paper explains AI-enhanced stock screening, one part of the total investment process, focusing particularly on how ML can uncover new and promising investment opportunities to increase performance and save the investor or portfolio manager substantial time and costs. We aim to address commonly raised questions: How does ML-driven screening enhance traditional stock screening? Why should investors use it? Does the investor have to change the so far successful investment process?

In today's world, where data is king and nearly half of all existing data has been generated in the past two years alone[2], the application of AI is not just a short-term competitive advantage, but a necessity in the long-term. AI-driven approaches in stock screening adjust dynamically to different market environments and have the potential to discover a wider array of investment opportunities compared to traditional techniques.

Stock screening has evolved from manual analyses in the pre-1970s to sophisticated ML technologies today. Initially, investors relied on printed financial statements, but with the arrival of computers and the internet, they shifted to using spreadsheets, online platforms and real-time data. The 2000s introduced algorithmic and quantitative analyses, allowing for more complex mathematical modelling. Nowadays, stock screening incorporates big data and ML, enabling the processing of vast, diverse data sets and the identification of complex market patterns. This evolution reflects a consistent aim to identify investment opportunities using increasingly advanced technologies more efficiently.

We explore the synergy between the analytical power of AI and the experience and instincts of the human investor, highlighting that while AI provides a robust analytical framework, the human element in decision-making remains central. Let's be clear, AI is like a sophisticated toolbox, supporting the decision process. It's not there to take over the job of the human investor.

The paper begins with a short overview of the entire investment process, setting the foundation for a deeper understanding of stock screening's role within this framework. We then delve into the traditional techniques of stock screening, providing insights into their methodologies and limitations. This sets the stage for an exploration of advanced AI and ML methods in stock screening, highlighting how these new approaches overcome traditional constraints. A particular emphasis is placed on the critical importance of data quality in these advanced methods. A significant addition to this version of the paper is an in-depth case study of an Asset Manager who has successfully integrated ML-based stock screening, demonstrating the positive impact on investment performance.

The author brings expertise to the table by drawing upon extensive time as an equity fund manager and a recognized expert in integrating AI into investment strategies.

Integrating AI and ML into investment strategies is an industry disruptor, offering novel ways to find new stock ideas and save substantial cost and time.

In our data-rich world, using AI isn't just a competitive advantage - it will be essential.

The paper emphasizes that while AI is a powerful tool, the human expertise in decision-making still counts.

A real-world case study demonstrates the practical benefits of ML in stock screening.

Essential Steps in the Investment Process for Equity Investors

This paper examines the role of stock screening in the investment process where the focus is on generating investment ideas.

We introduce the "Investment Circle", the investment process for fundamental, long-only equity investors.

Let's explore where stock screening fits into the overall investment process. This varies based on whether the investor focuses on a bottom-up or top-down investment approach. Interestingly, despite investors often identifying with one method or the other, many actually combine elements of both in practice.

What we outline here primarily applies to the fundamental, long-only equity investors or portfolio manager. It's important to note that for other investment categories such as fixed income, multi-asset or alternative assets, the strategies and processes employed can be quite different.

We will delve into the process step of generating investment ideas, screening for stocks. We plan to discuss the other steps of the investment process in subsequent papers over the following weeks.

During each phase of the investment process shown in Figure 1, we can integrate advanced technologies like AI and ML to enhance the outcome.

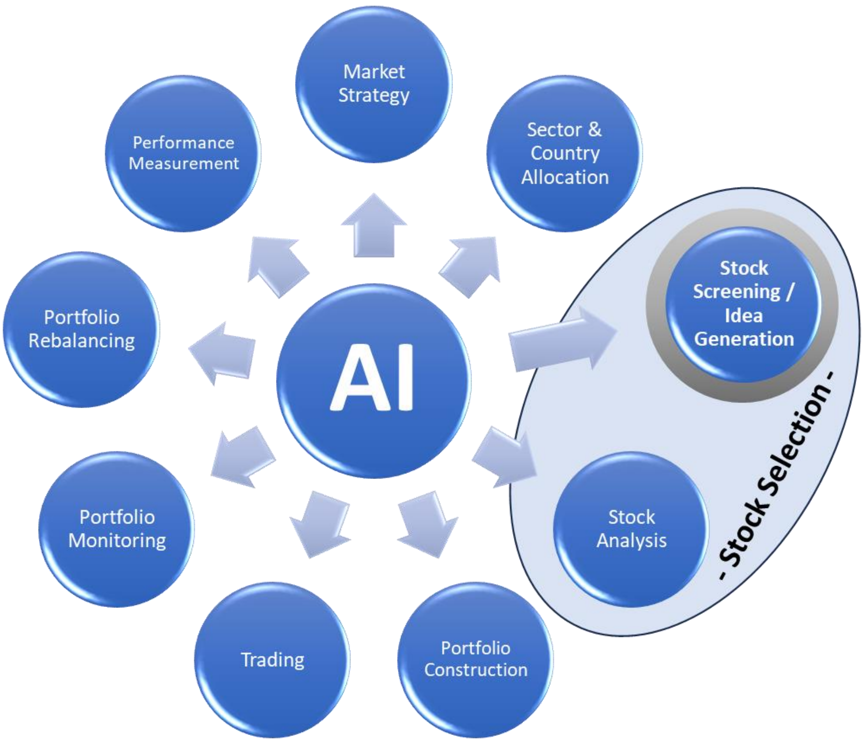


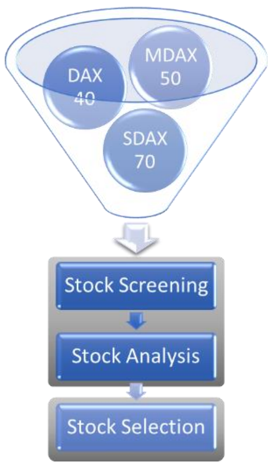
Figure 1: Investment Circle

The typical investment process begins with establishing a broad market strategy by gaining insight into the overall market trends. This crucial groundwork is typically laid out during regular investment committee meetings, which might occur monthly or quarterly.

Critical components of the investment process are the third and fourth steps, which collectively form the heart of stock selection. It's essential to understand that the process begins with 'Idea Generation' which is the focus of this paper. However, this is merely the first step in the sophisticated stock selection journey. Following this, we move to the second phase, 'Stock Analysis'. We refer to this also as 'Investment Research', a broad term that encompasses the art and science of choosing stocks. Here, investors undertake a deep dive, a more nuanced examination of the potential investment and constructs an overall investment case. This analysis phase can span up to many weeks, though the exact duration may vary based on the specific practices and methodologies of the investment team.

Why is idea generation or stock screening essential for investors? With approximately 440 listed companies in Germany alone[3] and about 58,000 worldwide[4], it's impossible for an investor to conduct in-depth research on each stock. To efficiently manage these vast options, stock screening is a crucial first step. It helps in filtering and identifying stocks with the potential to outperform the market over a given time frame, thus enhancing the chances of generating outperformance or 'alpha' to the overall market.

Consider a German investor monitoring stocks from the DAX, MDAX, and SDAX, totalling 160 listed companies. If this investor holds 30 stocks in the portfolio, the goal is to determine which of the 160 stocks are outperforming the market. It's not possible to continuously look at all 160 stocks in detail. This is where stock screening comes into play, narrowing down the choices for more focused analysis and research.



What do the results from such a screening look like? Often, they present a group of stocks marked as 'Buy'. For instance, from the 160 stocks, a list of 10 high-potential stocks might be identified. More commonly, the screening process ranks these stocks, making it easier to spot the top choices and those that might not be as promising. This ranking is typically based on specific criteria or input factors which are talked in more detail below. As mentioned, identifying the 10 high-potential stocks is just the first step of stock selection.

The frequency of stock screening varies – it could be daily, weekly, or monthly, with no set rule on timing.

The typical investment process includes one essential step, 'Stock Selection'. This step can be divided into 'Idea Generation' and 'Stock Analysis/Research'.

Stock screening is vital in this process, especially given the vast number of listed companies. It helps investors filter and identify potential high-performing stocks, thereby enhancing their chances of outperforming the market.

The stock screening, which can be conducted at varying frequencies, narrows down choices and is often resulting in a ranked list of stocks with high potential from a larger pool.

More detailed analysis and research will be done after the result of the stock screening.

In summary, stock screening is an invaluable tool for investors, helping them to manage large pools of stocks and focus on the most promising investments, thus making the stock selection more manageable and strategic.

Before we delve into the world of Machine Learning for stock screening, let's first understand the traditional methods in how we have done screening stocks for years.

Understanding the Foundations: Traditional Stock Screening Techniques

What exactly is the process behind traditional stock screening? Let's start by identifying the necessary input factors. In the world of stock screening, a wide variety of factors come into play, such as revenue growth, dividend yield or P/E ratios. The choice and number of these factors varies widely among investors, largely influenced by their personal investing style, preferences and investment horizon. For instance, value investors prioritize different factors compared to growth investors, and similarly, those focusing on large-cap stocks often consider different factors than those targeting small-cap stocks, and so forth.

A common line among these diverse investing approaches is the reliance on quantitative factors. Quantitative factors or hard facts are essentially objective, measurable data. Stock screening primarily centres on these fundamental financial metrics. Moreover, technical factors such as trading volume or stock price volatility can also be integrated into the screening process.

A key limitation of focusing primarily on quantitative factors is the exclusion of unstructured data. Sources such as news articles, social media sentiment, and economic reports, although highly relevant in our interconnected world, often remain untapped due to their unstructured nature.

Next to quantitative factors are qualitative factors or soft facts like the track record of a company's management team or its competitive edge in the market, aren't typically the main focus during the initial screening phase. However, they play a crucial role in the subsequent stage, stock analysis, where they form a significant component of extensive research.

While we have primarily discussed the positive screening factors, it's essential to note that there are negative screening elements as well, such as the debt ratio. Basically, these factors serve as exclusionary parameters.

A further and important limitation to consider is the sensitivity to emotional bias. Traditional stock screening conducted by human investors can often be influenced by personal biases or emotional reactions, resulting in a less objective stock screening results.

In brief, traditional stock screening is a multifaceted process, deeply rooted in quantitative analysis but has some limitations.

Traditional stock screening involves analysing a range of factors which vary according to the investor's styles, such as value or growth investing.

This method heavily relies on quantitative, measurable data to create a scorecard that guides investment decisions. While qualitative aspects can also be considered, they are more prominent in in-depth stock analysis rather than in the initial screening.

Traditional stock screening has some limitations, such as overlooking unstructured data like news articles and being highly sensitive to emotional biases.

As a side note, there are also instances where valuable stock ideas may emerge outside of the intended stock screening. Many investors keep a watchlist with stocks they like. These stock ideas could be triggered by strong company reporting, good management discussions, positive earnings calls or analyst recommendations.

When screening for stocks, a common approach is to use linear models. Think of a linear model as a recipe that helps to pick stocks based on a mix of ingredients, the input factors. The linear model tells how much of each ingredient to put in. In the investment world, linear models are a good starting point, but they often oversimplify things. Take, for example, dividend yield and the resulting stock performance. A higher dividend yield may be attractive to income-focused investors but doesn't always correlate linearly with total returns. In fact, a very high dividend yield can sometimes be a red flag, indicating potential problems ahead for the stock, including the sustainability of the dividend payment.

Simple linear techniques are often used in traditional stock screening since they are easy to understand. However, they oversimplify scenarios, are inflexible and not always correlate linearly with total returns.

Linear Regression is simple. It creates a straight-line equation to fit the data, minimizing the difference between the predicted and actual values. But its straightforward nature can be a drawback, making it less flexible and often more disposed to errors compared to more complex models. Despite these limitations, linear models, and their variations, are popular because they are easy to understand.[5]

As mentioned above, our primary aim of screening is to get stock ideas. Here's a breakdown of the process:

1. **Selection of Input Factors:** This is our starting point where we decide which input factors are essential in our assessment.
2. **Data Gathering**: Once we've outlined our factors, the next move is to collect the relevant data.
3. **Assigning Weights to Factors (often done by using linear models):** Every factor isn't equally significant. While often we might give them equal importance, sometimes based on historical evidence or a strong rationale, certain factors might weigh more than others.
4. **Ranking Stocks:** With all the data in place and weights assigned, we rank the stocks. This helps in identifying which stocks seem more promising than others based on our chosen factors.

At the end of this procedure, we have a list of stocks. They will be ranked starting from the most attractive to those that might not seem as appealing, all determined by our set factors.

To conclude, traditional stock screening methods present many limitations, particularly when compared with the advanced capabilities of modern AI and ML techniques. These advanced methodologies, which we will delve into in the following chapter, offer a clear contrast in efficiency and effectiveness. In the dynamic world of investing, the capacity to adopt and leverage such methods can provide a substantial competitive edge – at least in the short-term.

Advanced AI Strategies in the Stock Screening Processes

Exploring the World of Machine Learning Models:

As previously discussed, the goal of stock screening is to identify promising investment opportunities. The advantage of using Machine Learning for this task lies in its dynamic adaptability to changing market conditions by continuously learning, highlighting stocks that traditional screening might overlook by recognizing patterns and correlations, and save time and cost due to its ability to analyse large data volume in short time.

ML dynamically adapts to market changes, identifying stocks traditional methods might miss by recognizing patterns and correlations, saving time and substantial expenses/costs through its ability to analyse large volumes of data quickly.

ML models learn continuously with new data and get better over time.

The ability to produce neutral, unbiased results is also very important. This objectivity is essential to spot potential buying opportunities in out-of-favour stocks and to provide timely sell signals for existing portfolio holdings. It helps prevent investors from holding on to favoured stocks for too long.

Dynamic adaptability of ML models is quite similar to how an experienced portfolio manager adapts to new market data. Initially, the model is trained on a vast amount of data, the training or in-sample data. After it is released, the model further learns with new or out-of-sample data to adapt and improve. For some ML models, this adaptive learning happens through periodic retraining where the model is updated with new data. For other models, there might be a more continuous learning process, where the model frequently updates itself. In essence, the ML models learn and improve their performance over time.

While investors are able of conducting part of the stock screening to those performed by ML, it's important to acknowledge the hugely superior speed at which machines can work with giant data sets and process these calculations. A strong advantage of employing ML here is the significant reduction in the time required to complete these analyses. This automation of the stock screening process is also more cost-efficient by reducing the need for extensive human analysis.

Traditional stock screening primarily relies on historical financial data from recent reporting. Though projections and analyst expectations can be incorporated for a more forward-looking perspective, traditional methods often fail to adjust to new market conditions like the change in investment regime end of 2021.

ML models identify correlations between different variables (e.g. changes in interest rates, inflation and other macroeconomic data) and determine patterns to predict the current investment regime. Based on these insights, ML can adjust its recommended investment strategies. For example, if it anticipates a shift towards a value regime, it might recommend stocks with lower PE-ratios.

Therefore, there is a growing demand for stock screening techniques that are continuously evolving, dynamically updating and adapting based on new data.

In a nutshell, Table 1 outlines the benefits of ML-based stock screening. All of the advantages can be summarized in three generic terms: performance enhancement, efficiency gain and risk reduction.

1	**Dynamic adjustment** to changing markets: due to adaptive learning with new data
2	**Additional investment opportunities**: due to pattern recognition, use of structured and unstructured data
3	**Unbiased**: objective results and more rational investment decisions
4	**Risk Management**: by integrating a wider range of data sources and signals
5	**Time saving**: due to efficient data processing
6	**Cost saving**: due to automating the stock screening process

Table 1: Advantages of ML-based stock screening

In ML the choice of input factors can also be influenced by the investor's preference. Nevertheless, in contrast to traditional techniques ML possesses the unique ability to identify and clarify which combination of these factors is crucial across varying times and investment styles. Techniques such as Recursive Feature Elimination and Principal Component Analysis play a crucial role in determining the key input factors and single out less important factors.

When exploring ML techniques to generate stock ideas, several algorithms are commonly used. To grasp the more complex, non-linear relationships in financial markets, advanced statistical methods might be needed. In the investment field, being aware of these complex dynamics can be a significant advantage. A stock price can for example be influenced by competitive technologies, short squeeze or regulatory changes, all interplaying in complex ways that don't follow a straight line.

ML can identify crucial input factors, adapting to investor preferences and varying market conditions. They are particularly good at understanding complex, non-linear financial data.

Selecting algorithms involves balancing performance and accuracy, with complex models often yielding superior results despite their challenges in comprehension.

Diversifying the screening approach by employing different algorithms and combining their insights through ensemble methods enhances the effectiveness of the screening process.

ML provides a fast, unbiased way for stock screening, continually adapting to market changes, with the key being the right algorithm choice and approach diversification.

In Figure 2 we show various ML algorithms that are commonly used, focusing primarily on the distinction between supervised and unsupervised learning. Supervised learning algorithms build predictive models using both input and output data (e.g. for stock price prediction), while unsupervised learning algorithms categorize and analyse data based solely on input data (e.g. sentiment analysis).

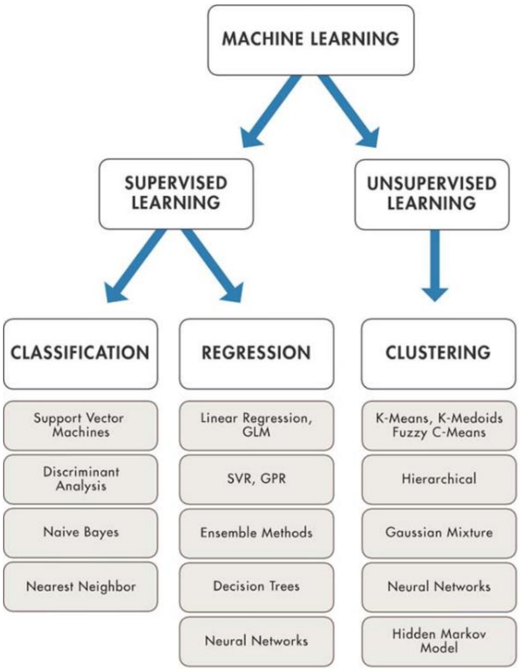


Figure 2: Breakdown of ML algorithms

More complex algorithms that are popular choices for stock screening are the random forest approach (which combines the insights of multiple decision trees), gradient boosting (similar to random forest, but masters more complexity), deep learning with neural networks or a combination. Deep learning with neural networks is especially well suited at handling complex, non-linear relationships between a multitude of input factors[6] and can be applied in both supervised and unsupervised learning contexts.

Each of these algorithms has its unique set of advantages and limitations, much like various investment strategies. The choice of a particular algorithm depends on a range of considerations, including its performance, processing speed and accuracy. The crucial strategy is to tailor the choice of algorithm to the specific requirements and to ensure a diverse approach. Just as putting all funds in a single stock is risky, depending entirely on one algorithm for screening is not advisable. Generally, more complex models tend to yield superior outcomes, though they might be more challenging to understand.

To enhance the screening outcome, it's beneficial to merge insights from different algorithms through ensemble methods such as stacking or voting.

In summary, stock screening aims to find the best investment opportunities and ML offers a fast and unbiased way to do this. Unlike traditional methods, which often lag in adapting to new market conditions, ML continuously updates and adapts. The key is to choose the right algorithm for stock screening and diversify the approach, much like diversifying a portfolio. Combining insights from various algorithms can further refine investment choices.

In the next chapter we shortly discuss Natural Language Processing as a powerful tool for extracting valuable insights from unstructured textual data.

Natural Language Processing in Stock Screening:

Natural Language Processing (NLP) is not an established way of screening for stocks, but it is becoming increasingly popular as an additional tool. Primarily, NLP serves in Sentiment Analysis, where it processes large volumes of news articles or social media posts to determine the public opinion about a company. Similarly, it plays a significant role in analysing earnings calls, where it interprets the transcripts of companies' earnings discussions and to pick up on the tone and content of what company executives are saying. Some of the more sophisticated NLP systems are even capable of forecasting market responses to certain news items or events, drawing on historical data.

NLP is increasingly used as an additional tool for idea generation. It is especially employed for sentiment analysis of news and social media and interpreting earnings calls. It can also forecast market reactions to news by analysing historical data.

Nevertheless, NLP is not without its challenges. Much like how one wouldn't rely solely on rumour for investment choices, the reliability and quality of the textual data are crucial for effective NLP analysis. Additionally, understanding context remains difficult. The complexities and nuances of human language, such as irony or sarcasm, are sometimes lost on NLP algorithms, potentially leading to misinterpretations[7].

However, NLP faces challenges in data reliability and understanding context, as it may struggle with nuances.

Despite these challenges, NLP is becoming an important complement to ML in stock screening and analysis, providing an additional layer of insight.

Developing and implementing NLP models involves a series of critical steps. The process starts with acquiring text data, often scraped from various web sources. This data, ranging from earnings announcements to social media content, is typically unstructured and lacks a systematic format, making it inappropriate for direct processing by computers. Such unstructured data, which is a significant portion of available data today, can appear as text, images, videos, or audio files. To make this data usable for training models, it must first be converted into a structured format.

This conversion involves pre-processing, which includes cleaning the data and performing data wrangling to structure it properly. Subsequent step in developing an NLP model is data exploration. This includes exploratory data analysis, selecting and engineering relevant features.

Finally, before obtaining results from the NLP model, the focus shifts to model training. This contains choosing the appropriate model, training the model with the processed data, evaluating its performance and fine-tuning the model to optimize its accuracy and effectiveness.

While NLP is unlikely to completely replace ML methods of stock screening, it is steadily gaining recognition as a significant asset in an investor's toolkit. It's like adding a new analytical tool to the stock screening process; it gives another perspective that could help to get better results.

The Critical Role of Data in Screening Stocks

Data is the key component that drives the achievement of targeted outcomes. The quality and reliability of data directly shape the result of any analytical model. Essentially, data stands as the cornerstone for an effective screening process - a machine is only as intelligent as the data it learns from.

Data quality and reliability are fundamental in achieving effective outcomes in stock screening, particularly when using ML techniques. In stock screenings, quantitative data from various sources like financial statements, technical data and economic indicators are used.

In the space of stock screenings, quantitative data sources are predominantly used. These are data types that can be expressed numerically, such as financial information from balance sheets and income statements, technical data like stock prices and trading volumes and various economic indicators including inflation rates or interest rates. Governmental data, which might cover aspects like trade balances or fiscal deficits, also play a role. Renowned data providers in this field include Bloomberg, FactSet, Refinitiv, MSCI and S&P Global among others. Additionally, sell-side analyst data like ratings and forecasts are also used.

High-quality data is crucial, requiring careful preparation and processing to enhance its efficacy and avoid misleading results. With the principle that better data quality leads to more reliable and better results.

The importance of high-quality data is vital, not just in traditional stock screening, but it becomes even more crucial when using ML-based screening techniques, which rely on a larger set of data. It demands careful preparation and processing. During data preparation, the focus is on enhancing the data's quality and ensuring its volume is appropriate for the intended screening. This stage is critical for refining the data to its most useful form. Skipping this step can lead to time wasted on analysing inaccurate or misleading results. The rule of thumb is simple: the higher the quality of the data, the better and more reliable the outcomes of the screening are.

In the following chapter, we delve into a real-world application, presenting an in-depth analysis of an asset manager who has successfully integrated AI into their investment strategy. This practical case study offers insights into the practicalities and benefits of adopting AI in for stock screening.

Case Study – Italian Asset Manager

The Challenge:

In 2021, an Italian Banking Group with a separate Asset Management (AM) division and more than 60bn AuM in various investment strategies wanted to start implementing AI-driven solutions. The objective was twofold: to enhance the performance of its diverse investment strategies and to lower costs by reducing reliance on expensive internal and external analysts. Additionally, the group planned to advance the investment approach through automation to save valuable time, without compromising their existing fundamental investment process. Important for the AM was to maintain their core approach, ensuring portfolio managers continued to play a key role in investment decisions, using their expertise and judgement. The intention was to minimally disrupt the existing investment workflow.

An Italian Asset Manager wanted to boost performance, lower cost and time expenditure by implementing AI in the investment process but still providing the portfolio manager full flexibility.

AI was recognized as the future in asset management, but in-house development was hindered by high costs, shortage in IT expertise, urgent deployment needs and inflexibility in internal projects.

So far, traditional stock screening was done by using fundamental analysis and leveraging sell-side research which were very time-consuming procedures, often biased and therefore didn’t result into the best outcomes.

While they saw the use of AI as the way forward, they couldn't build the AI solutions in-house due to the substantial investment required, a lack of IT expertise, the urgency for a quick deployment and the inflexibility associated with internal development projects.

Faced with the evolving landscape of asset management, the AM recognized the potential and need of using advanced technology to enhance its investment strategies. Therefore, they planned to initiate a pilot program to integrate external AI solutions, specifically at first for their European Large Cap strategy.

Solution Overview:

Due to the decision against internal developments the AM decided to use the expertise of a well-recognized third-party software provider. This decision was supported by the backing of notable investors and the provider's proven track record. The software provider's offering is a sophisticated stock screening tool and AI-powered investment strategies, utilizing diverse machine learning algorithms and a user-friendly web interface, tailored for portfolio managers.

The AM decided against internal development and for an external AI solution which is state-o-the-art, more flexible and cheaper

The AM experienced a swift and efficient implementation phase. Key steps included defining the investment universe and outlining the process methodology. Within a matter of weeks, the AM seamlessly included the AI-driven stock screening tool into their investment process.

The external solution included a stock screening tool with ML algorithms and a user-friendly interface, tailored for portfolio managers. Within weeks, the AI-driven stock screening tool was seamlessly integrated into the investment process.

The software provider delivered a fine-tuned version of its European equities predictive model, which ranks a universe of 50 European large cap stocks (based on the EURO STOXX 50) in terms of their expected performance, measured by 1-month forward return. It incorporates a broad array of data: daily and intraday market statistics, fundamental and macroeconomic indicators, linked indices and securities (such as commodities, VIX, FX), as well as sentiment indicators from news and social media, options data, and analyst predictions.

The software provider delivered a fine-tuned version of its European equities predictive model, which ranks a universe of 50 European large cap stocks in terms of their expected performance, measured by 1-month forward return.

In partnership with the AM, a long-only investment model was set up, incorporating weekly rebalancing. This model is communicated to the AM through SFTP, email and a web application.

The ranking of the 50 European stocks serves for idea generation and stock screening. It is the first step of the total stock selection process. The second step involves the portfolio managers and analysts applying their expertise in fundamental analysis to these shortlisted stocks.

Good data quality is extremely important. Data preparation is a significant first step for getting good results. The Data Engineers of the software provider cleanse the data, ensuring accuracy and reliability. They tackle issues like data inconsistencies, outliers, structural shifts, and gaps. Post-cleansing, the data undergoes transformation and feature engineering, making it ready for input into the models.

The algorithms it uses are a mix of supervised neural networks, tree-based models, and boosting-based models. This combination, selected for its robustness and adaptability, has been trained on a decade's worth of data (2010-2020). In simpler terms, they combine different types of AI models that are good at learning from new data and making predictions. They chose this blend because apparently it works the best and remains effective over time across various datasets. It's like having a team of expert analysts, each with their own specialty, working together to analyse market trends and make investment decisions.

They focus less on fine-tuning each individual model (like tweaking settings to get the best performance from each one) and more on improving the overall model. So, the specific types of ML algorithms used might change going forward as they find better ways to build this ensemble. Think of it as continuously upgrading their team of analysts with newer, more efficient members to stay ahead in the financial markets.

Result:

The AM was very pleased with the result of the ML-driven portfolio screening. The screening portfolio outperformed the underlying index almost every quarter.

The ML-driven portfolio screening outperformed the underlying index almost every quarter since inception.

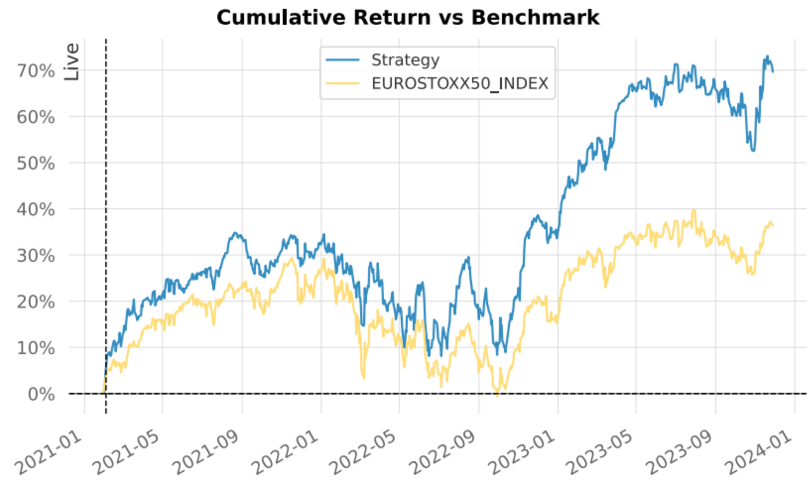
The graph below illustrates the performance comparison between the live "Strategy" portfolio and the EURO STOXX 50 index. This live portfolio is composed of the top 10 stocks selected from the EURO STOXX 50 and determined by the AI algorithms, equally weighted and rebalanced weekly. Since its inception in February 2021, the portfolio has achieved a remarkable outperformance over the EURO STOXX 50 of 33.2% (end of Nov. 2023). This outperformance can be largely attributed to the strong influence of Value and Quality factors during this period.

The portfolio demonstrated robust performance even when the market environment shifted, such as after the FED policy change in late 2021.

Furthermore, even during a significant market change, started by the US Federal Reserve's shift from quantitative easing to tapering in the fourth quarter of 2021, the portfolio maintained its robust performance. In the 12 months following this regime change, it continued to outperform the benchmark by 3.0%.

The composition of the portfolio has evolved significantly over time, with minimal overlap between the initial and latest portfolios. This reflects the adaptability of the ML algorithm in response to changing market conditions.

The success of this ML-driven approach has led to a significant increase in the AuM of the European Large Cap strategy.



	Benchmark	Strategy
Cumulative Return	36.45%	69.65%
CAGR﹪	11.21%	20.05%
Sharpe	0.68	1.07
Sortino	0.97	1.63
Volatility (ann.)	18.09%	18.72%
Calmar	0.48	1.01
Skew	0.01	0.36
Kurtosis	3.98	2.71
Max Drawdown	-23.17%	-19.81%

Table 2 presents an interesting view of the strategy portfolio, which comprises the top 10 stocks, equally weighted. What stands out in this analysis is the dynamic nature of the portfolio composition over time. The contrast is particularly evident when comparing the initial portfolio as of February 3, 2021, with the latest portfolio on October 31, 2023. The two compositions show minimal overlap, highlighting the portfolio's evolution.

Table 2: Top10 Portfolio Holdings

03.02.2021	29.10.2021	30.09.2022	31.10.2023
AIRBUS	ADIDAS	ADIDAS	ADYEN
AMADEUS IT GROUP	AIR LIQUIDE	ADYEN	AIRBUS
AXA	DANONE	AIR LIQUIDE	ASML HOLDING
BAYER	DEUTSCHE BOERSE	MERCEDES-BENZ	BMW
BNP PARIBAS	IBERDROLA	DHL GROUP	MERCEDES-BENZ
ING GROEP	KONE	INFINEON	DHL GROUP
INTESA SANPAOLO	LINDE	L'OREAL	FLUTTER ENTERTAINMENT
SAFRAN	L'OREAL	SCHNEIDER ELECTRIC	KERING
VINCI	SANOFI	SIEMENS	LVMH
VOLKSWAGEN	VONOVIA	VONOVIA	SAINT GOBAIN

This dynamic shift in the portfolio composition is largely influenced by the adaptive factor weighting employed by the ML algorithm. The algorithm's ability to adjust factor weightings in response to changing market parameters ensures that the portfolio remains agile and responsive to changing market trends, as reflected in the evolving composition of its holdings.

Table 3 shows that most crucial input categories for the algorithms adapt to changing market conditions. In Q4-2021 the fundamental category was strongest with input factors like EPS or Price/Book ratio. However, as of Q4-2023, this focus has shifted, with Volatility and Technical Indicators emerging as the predominant category.

Table 3: Categories ranked according to importance for the algorithms

Rank	Q4 2021	Q4 2022	Q4 2023
1	fundamentals	price_momentum	volatility
2	volatility	technical_indicators	technical_indicators
3	technical_indicators	fundamentals	price_momentum
4	price_momentum	volatility	sector
5	macro_sentiment	sector	macro_sentiment
6	sector	market_dispersion	market_dispersion
7	market_dispersion	macro	fundamentals
8	macro	macro_sentiment	macro

To illustrate some factor examples within each input category: EPS, DPS and PE-ratio are key factors under Fundamentals, the Relative Strength Index and Percentage Price Oscillator are significant within Technical Indicators, and 1-Month Return, 1-Week Ranking are essential in the Price Momentum category. Each of these categories is comprised of numerous factors which dynamically change in importance.

The future performance of the ML-driven stock screening is of course unknown, as is the nature of financial markets. However, the software provider is committed to continuous improvement of the modelling techniques and the incorporation of new data sources. This dedication to advancement sets the external provider apart from an internal solution, benefiting from diverse feedback from various investors to refine algorithms.

It's important to emphasize that this ML-driven stock screening represents just the first step of the total stock selection process. Following this, the second step involves a critical and careful application of fundamental analysis by the portfolio managers and analysts. They delve into the stocks that have been shortlisted by the ML model, which already demonstrate robust performance. This additional layer of fundamental research provides an opportunity to further enhance the portfolio's performance.

In summary, the AM has consistently achieved superior results with the top 10 portfolio compared to the benchmark each year. The result has been a strong increase in AuM of the European Large Cap strategy. Therefore, the AM decided to extend the adoption of AI-driven stock screening to other investment strategies.

Takeaways

Integrating Artificial Intelligence and Machine Learning in stock screening offers dynamic adaptability to changing market conditions, the ability to identify overlooked patterns and correlations, and significant time and cost savings due to processing large data volumes. Overall, ML can increase total performance with reduced risk and improve efficiency.

ML provides unbiased, objective analysis, crucial for spotting investment opportunities and making timely decisions. ML's superior speed in handling extensive datasets and its constant learning make it highly responsive to market shifts, offering a clear advantage over traditional stock screening methods.

AI is especially strong in handling complex data. Its unique strength lies in its ability to understand non-linear relationships and dynamically adjust to shifts in market conditions.

The primary aim in stock screening is to identify promising investment ideas, which are further assessed through in-depth stock analysis. It's important to note that human expertise remains vital in this process. AI provides powerful tools for stock screening, but it cannot replace the nuanced decision-making of a human investor. Without AI, however, investors would face the time-consuming task of performing these analyses manually, which could span multiple days and still lead to poorer results.

Human analysts and machine-driven systems work best in tandem. While human analysts excel in closely researching a limited number of firms, robo-analysts or ML-systems can efficiently and objectively analyse thousands of companies simultaneously. Investment teams that effectively combine these strengths are likely to have a competitive edge in the demanding investment field.

We have shown that the accuracy and quality of the data used in stock screening are crucial. The reliability of the data directly influences the effectiveness of the AI model's outcomes.

AI and ML in stock screening can increase performance with reduced risk and improve efficiency by bringing dynamic adaptability to changing market conditions and processing large data volumes efficiently. This results in significant time and cost savings compared to traditional methods.

ML technologies provide an unbiased, objective analysis that is crucial for spotting investment opportunities. They excel at identifying patterns and correlations that might be overlooked by human analysts.

ML's speed and constant learning make it highly responsive to market changes, offering an advantage over traditional stock screening methods.

ML is particularly good at understanding complex, non-linear relationships and dynamically adjusting to shifts in market conditions.

While AI provides powerful tools in the investment process, human expertise remains vital. The best results come from a combination of human analysts and machine-driven systems, leveraging the strengths of both.

There are various approaches to implementing AI in the daily working routine of the investor and portfolio manager: For larger asset management firms, creating own AI-based tools is one option. This approach requires specialized in-house IT expertise. The upside is that these AI models can be tailored to fit specific needs and even include internal data. However, it's worth noting that developing own AI solutions can be costly, complicated and may not always have the latest technology. Staying up-to-date is crucial, especially considering how rapidly advancements in AI are happening. Alternatively, the investor can apply existing third-party software, which offers ready-to-use and often proven AI tools. They are cheap, flexible and state-of-the-art. Some asset managers also choose a hybrid approach, combining both methods.

As AI algorithms and computational capabilities continue to quickly advance, we expect these techniques to become even more sophisticated and integral to modern portfolio management.

Future developments in AI, particularly with the arrival of quantum computing, will significantly enhance stock screening. Quantum computing will offer unprecedented processing power, allowing for the analysis of vast datasets at speeds far beyond current capabilities. This will uncover complex market relationships and inefficiencies, leading to more sophisticated and efficient stock screening strategies. Alongside this, advancements in predictive analytics, natural language processing, and the integration of alternative data will provide even more accurate forecasts and investment insights, revolutionizing the way investors approach stock screening and portfolio management.

If you're considering the best approach to integrate AI into your investment process and need guidance, our team is here to assist you.

Implementing AI can be approached differently by asset management firms.

One option is to develop in-house AI-based tools, offering tailor-made solutions but requiring specialized IT expertise and potentially high costs, with the risk of becoming outdated quickly.

Alternatively, firms can use existing third-party software, which are cost-effective, flexible, and often incorporate the latest technology.

A hybrid approach, combining both methods, is also a choice for some asset managers, leveraging the benefits of both methods.

ML algorithms and computational capabilities are rapidly advancing, becoming increasingly sophisticated and integral to modern portfolio management.

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About SMC

SMC is an innovative consulting boutique specialized in Artificial Intelligence, Digital Transformation and Change Management processes. Initiated by a trio of industry-leading experts, SMC directs its expertise towards serving clients in Asset Management and the broader Industrial sector.

www.schopf-meta-consult.de

Sources and Comments

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