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Review Article

Mapping the Knowledge Landscape of Machine Learning in Portfolio Optimization: A Bibliometric Analysis of Asset Allocation Research

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ABSTRACT

This study investigates the bibliometric analysis on asset allocation for portfolio optimization using machine learning algorithms. The primary objective is to identify and analyze the scientific literature through bibliometric analysis to uncover key themes, authors, sources, highly-cited articles, and countries involved in portfolio management research. To achieve this, 304 articles indexed in Scopus and Web of Science from 1990 to 2023 were analyzed. Using RStudio software, the study highlights various models employed in this field, along with tables, graphs, maps, and key performance metrics related to article production and citation impact.The findings reveal an upward trend in the use of machine learning for optimal portfolio management, asset allocation, and risk management since 2016. Additionally, the United States and China emerged as leading contributors to this literature. The results provide practical insights for market participants, especially those in fintech and finance sectors, to identify optimal machine learning solutions for decision-making processes. These findings also guide students in focusing their research efforts on underexplored areas within this domain.

1 Introduction

In financial markets, risk management and portfolio optimization are among the primary objectives and intellectual challenges faced by finance professionals and academics. Achieving an efficient model for financial asset allocation has become a major issue, as decisions related to asset allocation are often made under uncertainty and with incomplete information [1]. Other findings research, through a regular and logical process based on the judgment method in a survey of 14 experts in the field of capital market investment and a quantitative and multivariate model of fuzzy network analysis, to assess the level of

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importance, ranking and refining the effective factors. Portfolio optimization was undertaken. Based on the analysis, the variables of profit volatility, return on capital, company value, market risk, stock profitability, financial structure, liquidity and survival index can be introduced as the most important factors affecting the optimization of the stock portfolio [2]. Machine learning methodologies have been meticulously developed to effectively handle and analyze extensive datasets, and they have consistently exhibited remarkably high levels of predictive accuracy, particularly within the domains of investment strategies and various branches of computer science. Recent studies in finance explore how machine learning models can enhance the performance of traditional asset allocation models [3]. These applications simplify the resolution of linear and nonlinear problems, which traditional models often struggle with. As a result, deep learning and machine learning techniques, as subsets of artificial intelligence, have found extensive applications in finance [4].Given the importance of this subject, the current research reviews the literature on the application of machine learning in asset allocation, risk management, and portfolio optimization. The primary objective is to introduce and evaluate recent developments in computational methods. The study highlights key findings that enhance understanding of machine learning applications in asset allocation and risk management. The reviewed literature shows minimal overlap with recent books and review articles. This research utilizes a quantitative, objective, and transparent bibliometric analysis, combining data from Scopus and Web of Science to differentiate it from previous studies. Additionally, it complements earlier work in the field by highlighting similar findings in related areas of finance. Accordingly, the main research question of this study is: To what extent have machine learning algorithms gained importance and played a significant role in optimizing asset allocation and managing risk in investment portfolios?

2 Research Background

2.1. Theoretical Foundations of the Research

Traditionally, investors adopt an active approach to analyzing financial reports in search of the best stocks, focusing on investment returns [5]. By prioritizing assets based on expected returns and risk tolerance, they aim to construct an optimal portfolio. Moreover, by periodically revisiting their strategies and rebalancing their portfolio mix, they work towards achieving both long-term and short-term financial objectives [6, 7]. Markowitz (1952) developed the mean-variance (MV) portfolio model to outperform the market index in terms of asset returns [8]. Portfolio construction incorporates the average historical returns of stocks, the expected return, and the standard deviation of those returns as a measure of risk. Notably, many investors continue to rely on the MV strategy today [6]. Researchers such as Lopez de Prado [9], Schwendner et al. [10], Chen et al. [11], and Wang et al. [12] have successfully integrated machine learning algorithms with traditional asset allocation strategies, yielding results that surpass models like the minimum variance portfolio, equal risk contribution portfolio [13], maximum diversification portfolio [14], inverse variance portfolio [15], and equal weight portfolio [16] with the increasing complexity of methods and the growing need for computational efficiency, machine learning techniques have been developed to enhance the process.

Figure 1 illustrates various machine learning paradigms that have been designed to address different challenges within machine learning. The various methodologies associated with machine learning can be systematically classified into three distinct categories, which are clearly illustrated in the subsequent figure presented below: the first category is referred to as supervised learning, the second category is identified as unsupervised learning, and the third and final category is known as reinforcement learning

[17].

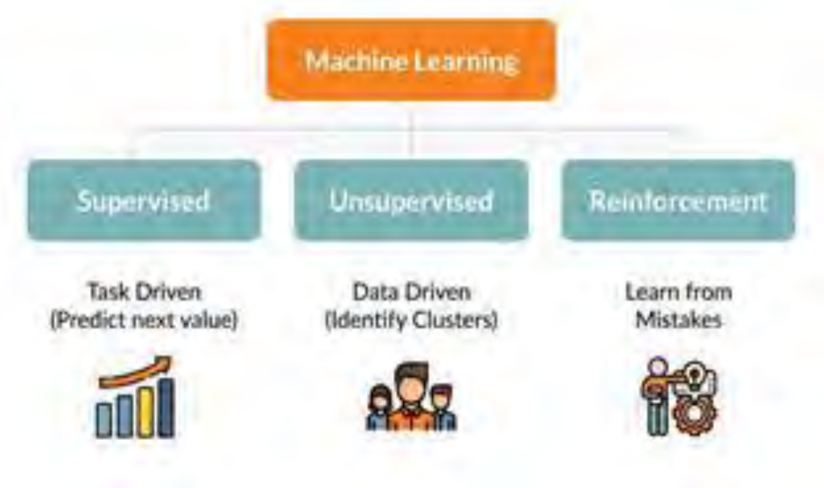


Fig. 1: Classification of Machine Learning Models [17]

All of the aforementioned methodologies can indeed be utilized effectively within the realm of portfolio management, which is a critical area of study in finance and investment; however, based on the findings from recent empirical research and scholarly studies conducted in this field, it has been determined that unsupervised learning algorithms are currently regarded as the most pragmatic and efficient approach available in contemporary practice [17].This investigation offers an extensive examination of machine learning methodologies, with a particular emphasis on unsupervised learning, within the context of portfolio optimization, thereby delivering enhanced understandings for scholars and participants in the financial markets. Through an analysis of the merits and limitations inherent in these methodologies, it aids asset managers and investors in making more enlightened choices.

The research presents a systematic framework for the comparative evaluation of machine learning models, delineates existing research deficiencies, and suggests novel trajectories for forthcoming inquiries. It assesses the efficacy of these methodologies when juxtaposed with traditional asset allocation paradigms in relation to risk and return profiles. Notable research deficiencies encompass the absence of comprehensive investigations into unsupervised learning applications in portfolio optimization, restricted exploration of its amalgamation with clustering-centric strategies, and inadequate comparative analyses of various machine learning techniques. The inquiry holds significant relevance for academics, institutional investors, financial analysts, fintech developers, and regulatory authorities. As an exhaustive review, it elucidates prospective research pathways and furnishes pragmatic insights for the integration of machine learning within portfolio management.

2.2. A Review of the Theoretical Literature on Knowledge Mapping

This research endeavor meticulously utilizes the methodology known as bibliometric analysis, a concept that was originally introduced into the academic discourse by the scholar Pritchard in the year nineteen sixty-nine, who astutely observed that this analytical approach is especially relevant and beneficial in scholarly investigations that seek to systematically quantify and elucidate the intricate processes underlying the phenomena of written communication. [18]. Bibliometric analysis uses quantitative methods to assess, monitor, and analyze scientific information [19]. This approach highlights authors' publications, prominent journals, methodologies employed, and main findings [20], thus offering a comprehensive view of any research field [21]. Bibliometric methods encompass extensive bibliographic data and are applied in examining diverse topics [22], journals [23], countries [24], and other research aspects. Today, the popularity of knowledge mapping analysis in research reflects its application for managing large volumes of bibliographic data, enhancing effectiveness in scientific studies, and identifying gaps across various fields of science.

The table below briefly presents an example of suitable metrics for comparing and analyzing the main methods related to review studies [25]. Other findings suggest that cost stickiness has a positive impact on the relationship between institutional investors and passive institutional investors with conservatism [64]. The findings of some researchers showed that there is a significant relation between the stock market uncertainty changes in an economic boom and the investment risk in general, which is not significant in terms of the economic turndown. The Investment risk during both economic boom and recession is decreased by the unexpected increase in profit of each share and propagation of positive news. Although the risk is increased by the spread of negative forecasts in relation to shares [65]. The researchers' findings show that risk preimum was a determining factor in explaining changes in investors' expected rate of return, and that there was a conditional relationship between the Downside Beta and expected return. Therefore, to explain the relationship between risk and return, one must pay attention to the market direction[66].

Table 1: Comparison of Different Pertinent Review Methods [25]

Analysis Method	Objective	Application
Bibliometric Analysis	To uncover the status of emerging trends and provide the intellectual structure of a specific topic by summarizing large amounts of scientific data for both quantitative and qualitative analysis.	When datasets are large and the scope of the review is too extensive for manual analysis.
Meta-Analysis	To furnish a comprehensive synthesis of empirical data regarding the correlation between variables that have yet to be scrutinized in extant research pertaining to quantitative assessment.	When homogeneous studies are sufficiently extensive to summarize results without delving into content.
Systematic Literature Review	To summarize findings and results from the existing literature in a specific field for quantitative analysis.	If the content of all scientific data is small and manageable, and manual review is feasible.

3 Methodology

This research conducts a quantitative investigation using Bibliometric Analysis to identify and examine literature on asset allocation in investment portfolios, offering a comprehensive mapping of the knowledge structure in this field. A scientific roadmap and performance analysis of the study were subsequently conducted. The scientific roadmap, or Bibliometric Analysis, represents how trends, specialties, individual and collective articles, and authors interconnect [26].

To achieve a comprehensive quantitative analysis in the area of portfolio optimization, the following questions were initially posed:

Table 2: Research Questions

Question	Research Question	Objective	Motivation
Question 1	Which scholars and academic journals are leading the discourse on the utilization of machine learning for portfolio optimization, and which scholarly articles have received the highest number of citations?	To identify the most prolific sources and authors	In order to enhance comprehension of the principles of scientific leadership pertaining to the utilization of machine learning within the realm of portfolio optimization.
Question 2	Which countries have the largest share in scientific production on the topic of this study, and which keywords are most frequently used in the relevant literature?	To show which topics receive the most attention from researchers in different countries	To identify the key topics that scientific research is currently focusing on within the field of portfolio optimization using machine learning.
Question 3	Do bibliometric maps, charts, and data tables, along with the analysis of conceptual, intellectual, and social structures, demonstrate the widespread application of different asset allocation methods in portfolio optimization?	To conduct a thorough analysis and summarize it visually	To facilitate a better understanding of the current state of research in portfolio optimization by analyzing trends, themes, and influential contributions.
Question 4	What are the main contributions of studies related to asset allocation for portfolio optimization using machine learning from an inductive analysis perspective?	To become familiar with key works, methods used, applications, and results obtained	To assist the scientific community in enhancing productivity in this field

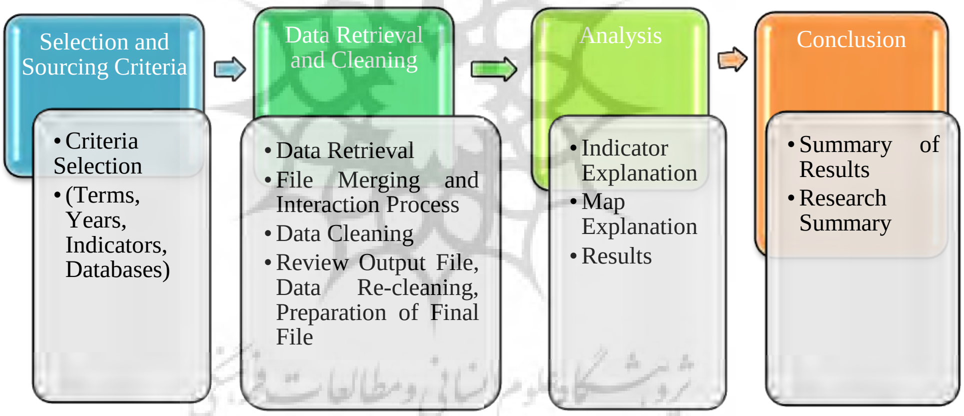


Fig. 2: Methodology Used [29]

3.1 Source Identification

Data was meticulously collected from an extensive array of scholarly articles that are indexed within the prestigious and widely recognized databases of Scopus and Web of Science, which were judiciously selected due to their remarkable compatibility with the advanced biblioshiny software, a powerful tool that significantly aids in the detailed analysis and interpretation of bibliometric data. The comprehensive search was conducted exclusively in the English language to ensure the acquisition of the most exhaustive and representative set of documents pertaining to the crucial subject of asset allocation for the optimization of investment portfolios. The selection of these two eminent databases was predicated on three principal criteria that are of paramount importance:

- These databases facilitate the bulk downloading of a substantial number of sources, thereby allowing for an efficient and effective collection of relevant literature.

- They possess an extensive historical time span that encompasses a wide range of relevant publications over numerous years.

- They also provide the capability for the simultaneous downloading of considerable amounts of stored information, thus enhancing the research process and data collection efficiency [30].

The comprehensive search, which was conducted on the date of May 10, 2023, employed the specific search terms illustrated in Figure 3 and encompassed all documents that had been published from the year 1990 through to April 2023. The data that was collected during this thorough investigation included a wealth of bibliometric information, and subsequent to a meticulous review facilitated by R software, non-relevant documents such as duplicates, conference papers, editorials, books, book chapters, news articles, and items that fell outside the realm of financial journals (including those from the fields of medical or environmental sciences) were systematically filtered out. R, being a powerful software for data analysis, played a crucial role in streamlining this review process. This rigorous process culminated in the establishment of a final set comprising 304 qualified articles, derived from an initial pool of 595 relevant documents, thereby capturing a representative sample of international scientific activity that was published within esteemed academic journals.

Data analysis was diligently performed utilizing Biblioshiny, which is an innovative web interface that is part of the Bibliometrix package (version 5.0) developed by the esteemed scholars Aria and Cuccurullo [31]. The Biblioshiny tool allows for the graphical representation of statistical data, thereby significantly enhancing the visualization of key themes and trends within the dataset. In the context of this study, the resulting charts vividly depict various topics that are intricately related to investment portfolios and the applications of machine learning within the defined timeframe, thus providing a comprehensive overview of the research landscape in this domain.

This scholarly investigation employs the methodological framework that has been meticulously advocated by Cobo et al. [27], with the explicit aim of visually elucidating the various research topics along with their intricate structures that exist within the dataset, utilizing sophisticated mapping techniques that facilitate a deeper understanding of these relationships. In the subsequent phase of the analytical process, the scholarly articles are systematically organized in a manner that reflects a descending order based on the total citation counts as well as the average citations that are attributed to each publication, thereby allowing for a more nuanced comparison of their impact. For the execution of this particular section, the comprehensive guidelines that have been meticulously delineated by Heradio et al. [28] were scrupulously adhered to, ensuring that the analysis aligns with established academic standards. Figure 2 serves as a visual representation that effectively illustrates the sequential steps that are integral to this methodological process, thereby providing clarity to the reader regarding the procedural framework employed in this study.

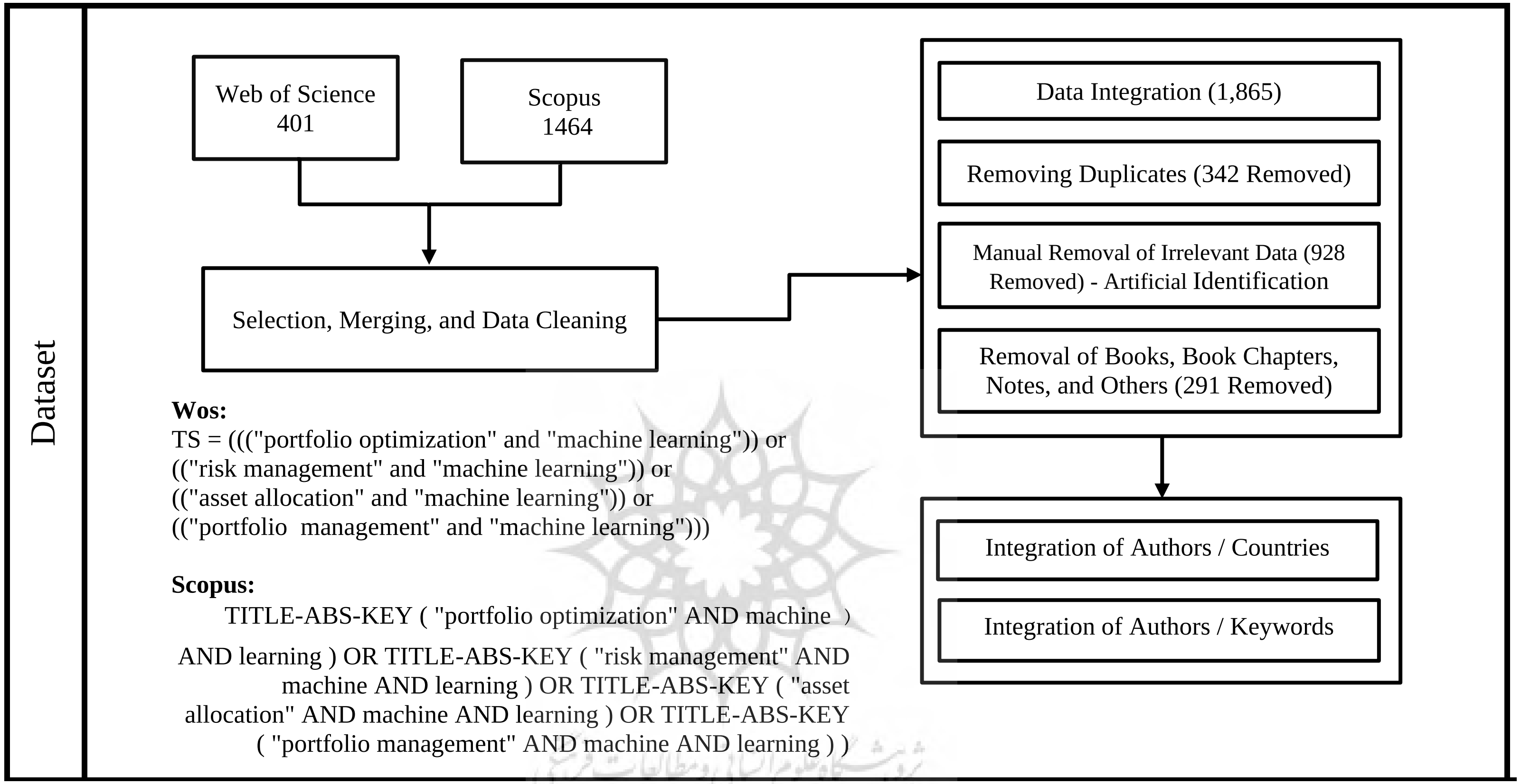


Fig. 3: Data Extraction and Cleaning Process
Source: Researcher's Findings

Note: The number of documents before removing conference papers, books, book chapters, notes, and other types of documents was 595, and after the removal, it was reduced to 304.

4 Findings

The principal methodology for evaluating research performance in this investigation is citation analysis, wherein an elevated citation frequency signifies a more substantial impact within the discipline. The h-index functions as a robust metric, encompassing both the volume and the influence of a researcher's scientific contributions. The outcomes of the data analysis are encapsulated in the descriptive statistics presented in Table 3. Findings indicate that the application of machine learning in portfolio optimization is a significant academic interest, as refelected by the 304 articles analyzed and an average of over 10 citations per article.

Table 3: Primary Data

Description	Results
Main Data Information	
Duration	1990:2023
Sources (Journals, Books, etc.)	373
Documents	595
Annual Growth Rate(%)	12.81%
Average Document Age	3.83 years
Average Citationsper Document	10.82
Sources	21,596
Documented Topics	
Keywords (ID)	2,763
Author Keywords (DE)	1,443
Authors	
Total Authors	1,532
Single-Author Documents	84
Author Collaboration	
Single-Author Documents	98
Collaborators per Document	3.07
International Collaborators(%)	1.18%
Document Types	
Article	304
Book	19
Book Chapter	24
Conference Paper	215
Review	23
Other	10

Source: Researcher's Findings

In addressing the first research question, Figure 4 highlights the most prolific authors over the past five years: Wang Y, Chen Y, Creamer G, Wu X, and Al J M. Wang Y has concentrated on topics such as financial risk assessment using neural networks [32], stock index prediction via the SVR model enhanced with the Bat optimization algorithm [33], and applying an interpretable reinforcement learning model for portfolio optimization [34]. Conversely, Chen Y has proposed a hybrid portfolio selection method based on empirical data from the Shanghai Stock Exchange [35]. Other authors have investigated various optimization algorithms to assess, enhance, and analyze investment portfolios according to specific economic indicators.

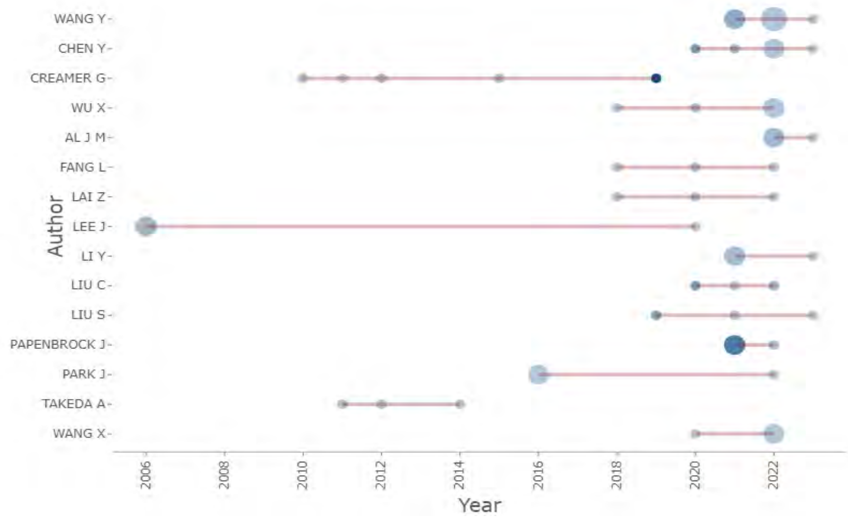


Fig. 4: Most Cited Authors
Source: Researcher's Findings

The main institutional affiliations can be seen in Figure (5). This figure shows that Islamic Azad University, with 9 published papers in the analyzed dataset, is the most productive institution in the field of applying machine learning in portfolio optimization. In second to fourth place, the Spanish university Complutense University of Madrid, Malaysia's Jinan University, and China's Nanjing University of Information Science and Technology are each ranked with 5 papers.

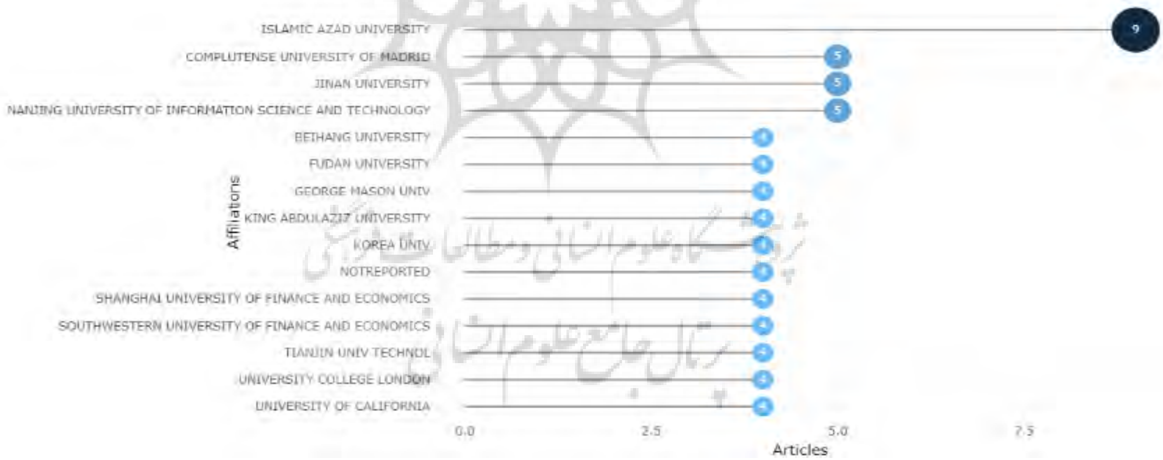


Fig. 5: Most Related Affiliated Institutions
Source: Researcher's Findings

In this research, a similarity criterion called connectivity strength was used to create knowledge mapping maps. It is worth mentioning that this criterion provides significant assistance in preparing various scientific maps and better displaying the dynamic and structural aspects of the obtained data [36].

Table 4 presents information about influential and effective journals in the fields of expert systems and finance. By examining the number of articles and the h-index, it is evident that the journal "Expert Systems with Applications" has the greatest impact in this area, with 28 articles and an h-index of 17. Other journals, such as "Quantitative Finance" and "Journal of Financial Data Science," also contribute significantly to the scientific literature, with dozens of articles published and appropriate h-index values.

Table 4: Most Influential and Efficient Journals

Source	Number of Articles	h_index
Expert Systems with Applications	28	17
Quantitative Finance	10	6
European Journal of Operational Research	7	5
Journal of Financial Data Science	16	4
Journal of Risk and Financial Management	7	4
Annals of Operations Research	6	3
Applied Soft Computing	3	3
Decision Support Systems	3	3
IEEE Access	9	3
Cognitive Computation	3	2
Computational Economics	4	2
Computational Intelligence and Neuroscience	5	2
Frontiers in Artificial Intelligence	3	2
Journal of Fuzzy Systems and Intelligent Systems	2	2
Journal of Risk Management in Financial Institutions	4	2

Source: Researcher's Findings

4.1 Key Documents and Frequently Used Terms in The Dataset

A comprehensive research study that is characterized by an exceptional citation count undeniably exerts a profound influence on the progression of researchers who are diligently working to advance the specific field of investigation that is being examined in the scholarly literature [36]. In this context, Table 5 meticulously delineates the documents that have achieved the highest citation counts, thereby providing invaluable insights into the most impactful works within the realm of academic research. The document that has garnered the most citations, which is meticulously authored by Barboza et al. [37], boasts an impressive total of 336 citations, while the subsequent document authored by Huang [38] follows closely with a citation count of 171, both of which were published in distinguished journals, namely Expert Systems with Applications and Applied Soft Computing, respectively. Occupying the third position in this hierarchy of citation counts is the work of Ghoddusi et al. [39], which has accumulated a noteworthy total of 158 citations and was published in the reputable journal Energy Economics. Figure 6 serves as a visual representation that illustrates the most frequently occurring terms within the dataset, thereby providing a comprehensive overview of the thematic focus of the literature. The foremost four terms identified correspond directly to phrases extracted from the search strings utilized in the research, with "risk assessment" emerging as the most prevalent term among them. Other terms that are frequently encountered within the dataset include "trade", "financial markets", "forecasting,", "financial data processing" and "deep learning" all of which collectively underscore the significant role that machine learning plays in the domain of portfolio management. Furthermore, the co-occurrence of these keywords not only highlights their individual significance but also serves to illustrate the intricate knowledge structure that exists within the body of literature pertaining to this field of study.

Table 5: Most Globally Cited Documents

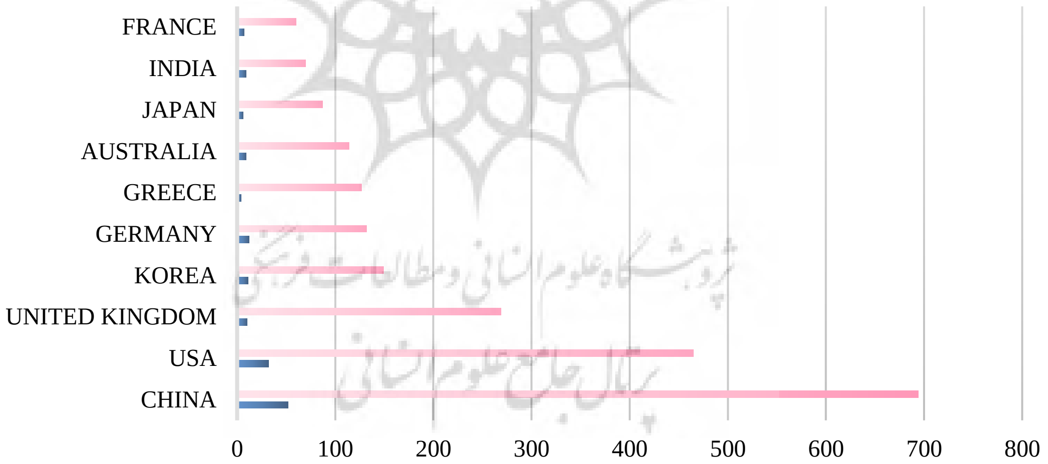
Authors	Title	Source	Total Citations	Highlights
Barboza et al [37]	Machine learning models and bankruptcy prediction	Expert Systems with Applications	336	Examination and testing of machine learning models for bankruptcy prediction.
Huang [38]	A hybrid stock selection model using genetic algorithms and support vector regression	Applied Soft Computing	171	Development of an effective stock selection method using Genetic Algorithms (GAs) and Support Vector Regression) SVR).
Ghoddusi et al [39]	Machine learning in energy economics and finance: A review	Energy Economics	158	A review of the growth dedicated to machine learning applications in the fields of energy economics and finance.
Briand et al [40]	Property-based software engineering measurement	IEEE Transactions on Software Engineering	149	Introduction of a mathematical framework to provide definitions for several important measurement concepts such as size, length, complexity, continuity, and coupling.
Henrique [41]	Stock price prediction using support vector regression on daily and up to the minute prices	The Journal of Finance and Data Science	136	Introduction and use of Support Vector Regression (SVR) aimed at predicting stock prices.
Groth and Muntermann [42]	An intraday market risk management approach based on textual analysis	Decision Support Systems	115	Utilization of four different learners: Naïve Bayes, k-Nearest Neighbors, Neural Networks, and Support Vector Machines to identify patterns in news data related to company disclosures that affect stock prices.
Ban et al [43]	Machine learning and portfolio optimization	Management Science	103	Use of two machine learning methods: Performance-Based Regularization (PBR) for estimating models with lower error and cross-validation for portfolio optimization.
Paiva et al [44]	Decision-making for financial trading: A fusion approach of machine learning and portfolio selection	Expert Systems with Applications	99	Development of a model using a fusion approach of machine learning classifiers based on Support Vector Machines (SVM) and Mean-Variance (MV) method for portfolio selection, compared to SVM/1 + N and Random + MV methods.

Source: Researcher's Findings

Fig. 6: Most Frequent Keywords
Source: Researcher's Findings

4.2 Generating Countries/Regions

In response to the secondary question of this research, Figure 7 presents the publications and citations from six leading countries/regions. According to the data, the People's Republic of China ranks first in terms of publication volume with 52 documents, followed by the United States (32), Germany (12), and South Korea (11). In terms of citations, China also leads with 694 citations, followed by the United States (465), the United Kingdom (269), and South Korea (149). China has established itself as a global leader in machine learning technology, and Chinese universities are increasingly focused on research in this area to tackle challenges in financial portfolio risk management. This focus is largely driven by the high receptivity of the Chinese population to emerging technologies, making China a crucial market for machine learning advancements worldwide.



	CHINA	USA	UNITED KINGDOM	KOREA	GERMANY	GREECE	AUSTRALIA	JAPAN	INDIA	FRANCE
C	694	465	269	149	132	127	114	87	70	60
P	52	32	10	11	12	4	9	6	9	7

Fig. 7: Trend of Scientific Publications per Country (1990-2023)
Source: Researcher's Findings

The financial utilizations of machine learning are extensive and diverse. Figure 8 highlights the connections between key keywords—investment, learning systems, risk assessment, and portfolio optimization—and countries like China and the United States, as well as leading universities, indicating their higher academic prominence. The topics related to risk assessment in financial markets, forecasting, trading, deep learning, financial data processing, electronic trading, and learning algorithms are part of the broader research landscape.

As shown in Figure 9, the evolution of these topics is illustrated using a Sankey diagram, a specialized flow chart. This diagram visualizes the thematic progression over time in the field of portfolio management and machine learning. It helps to understand how different topics have evolved and been applied within the context of portfolio management. Furthermore, Figure 9 provides quantitative insights into the flow of topics, their directional movement, and the relationships between transformations in these topics [45].

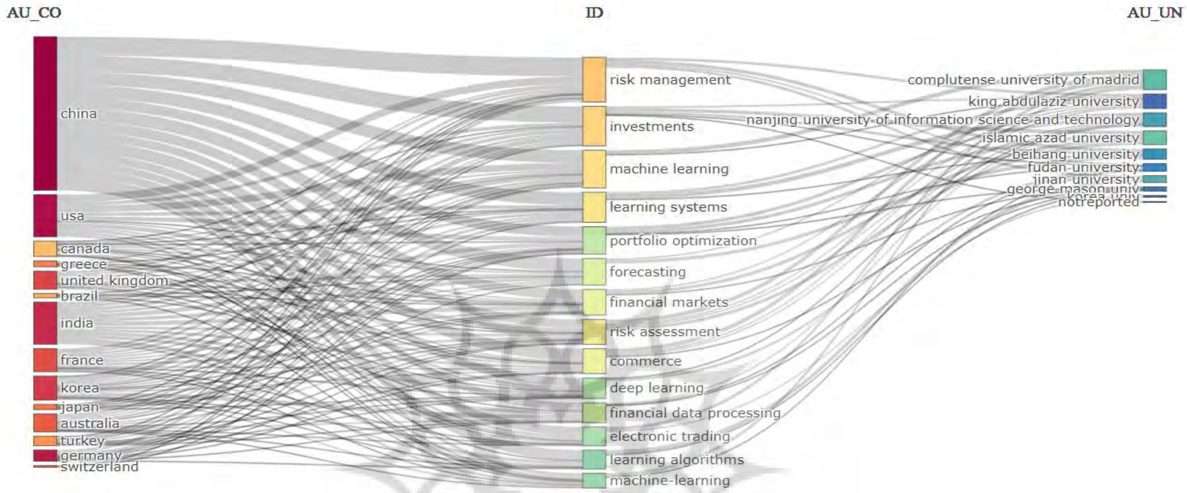


Fig. 8: Network of Connections Between Countries, Keywords, and Authoring Universities
Source: Researcher's Findings

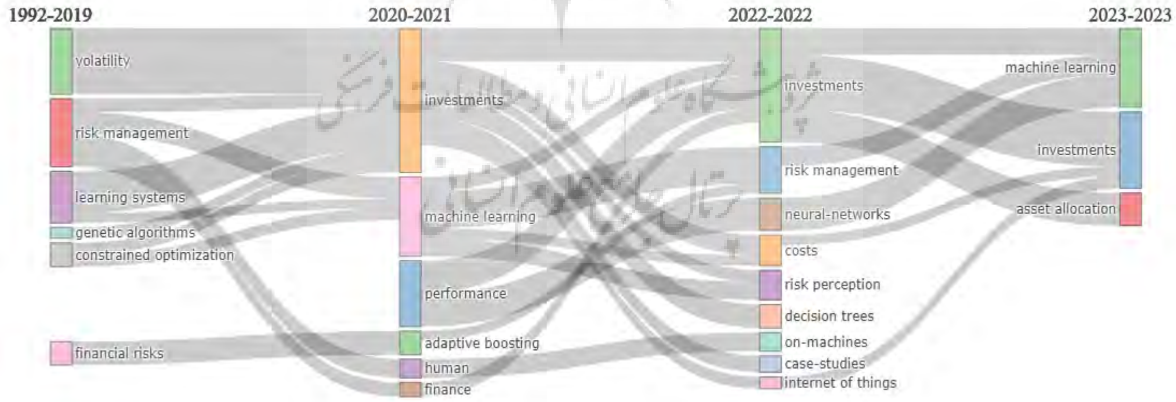


Fig. 9: Thematic Evolution
Source: Researcher's Findings

4.3 Main Topics in Keywords Based on Factor Analysis

In response to the third question, Figure 10 presents a two-dimensional map created from the keywords in “Keywords Plus”. Factor analysis, a powerful tool for summarizing data with multiple variables, is employed to facilitate the reduction of the dataset into a lower-dimensional framework. This method enables the visualization of hidden patterns within the data. Within the representation, keywords situated in proximity to the center of the cluster signify subjects that have attracted considerable scholarly interest in recent years, while keywords at the edges of the clusters indicate topics that have been less explored in the research [46].

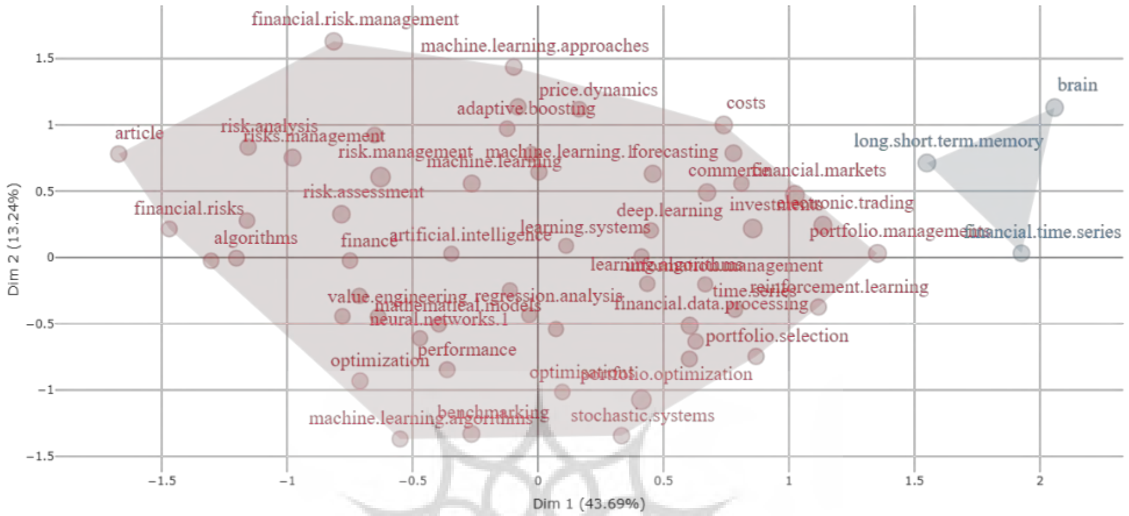


Fig. 10: Cluster Analysis Factor Map

Source: Researcher's Findings

The larger cluster encompasses practical terms related to portfolio optimization and various types of machine learning algorithms used by investors, analysts, and asset managers. The second cluster also highlights the importance of the topic of time intervals in the statistical data of this research.

4.4 Simultaneous Network Representation

In order to achieve a thorough comprehension of the conceptual framework, an exhaustive mapping of the terminology employed by authors was undertaken. The concurrent analysis illustrated in Figure 11 elucidates not only the predominant keywords, such as asset allocation and portfolio management, but also associated subjects including risk management, investment, and learning systems. Concurrent keyword analysis constitutes an efficacious approach for investigating knowledge frameworks and discerning research trajectories. It facilitates the differentiation between primary and secondary scholarly publications [47]. The analysis starts by identifying nodes, where their size reflects the number of documents, and the lines connecting them represent relationships between two groups. A short line indicates a strong connection between the keywords, while a longer line suggests a weaker link [48]. In this analysis, the primary keywords identified in the first cluster are "risk management", "investment", and "machine learning". Each cluster represents a keyword and shows the frequency and number of connections between them in publications. These clusters are color-coded, with the blue cluster highlighting "risk management", "investment" and "machine learning" , while the red cluster emphasizes "risk assessment", "finance" , "risk prediction", "algorithms", "risk analysis" and "value engineering".

Since this research mapped a quantitative knowledge structure, the number of simultaneous keyword links was moderate. As depicted in Figure 11, two groups show a stronger relationship: "investment in financial markets utilizing machine learning" and "application of machine learning in risk assessment".

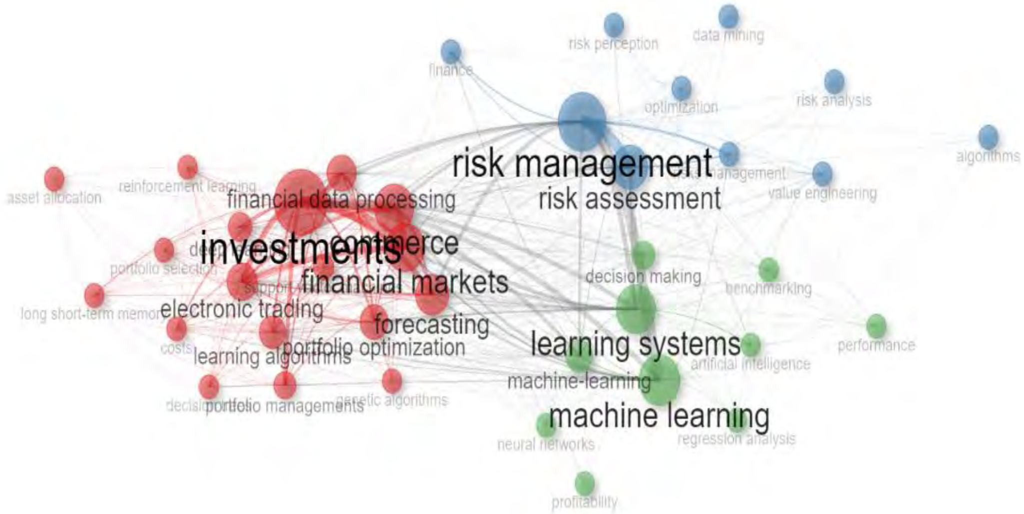


Fig. 11: Cluster Analysis Keyword Network
Source: Researcher's Findings

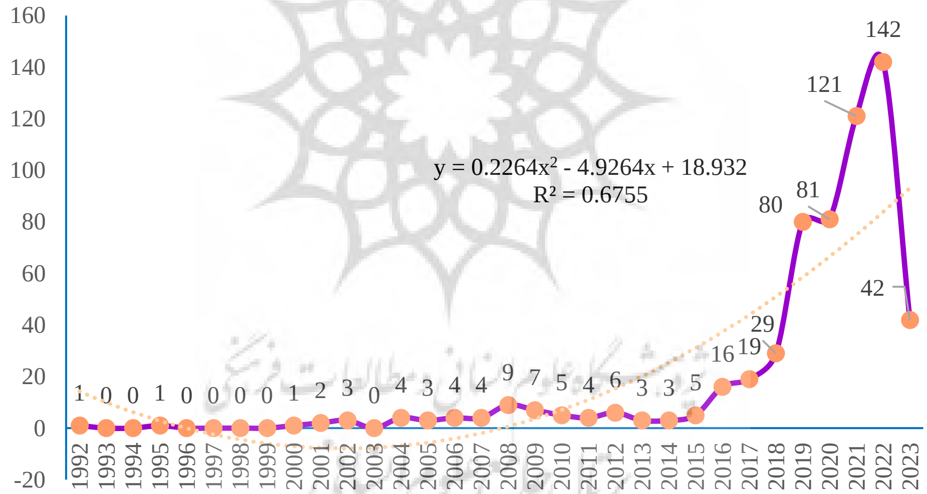


Fig. 12: Annual Scientific Production
Source: Researcher's Findings

Note: The annual productivity of the scientific output of machine learning applications in portfolio optimization. The trend line calculations are exponential.

Figure 12 illustrates the scientific production in the field of machine learning applications for portfolio optimization from 1990 to April 2023, showing a significant increase in publications, especially from 2015 onwards, with a peak of 142 papers in 2021. This surge indicates a growing interest in machine learning techniques within capital management. Furthermore, the exponential trend equation and its coefficient of determination emphasize a notable yet variable growth pattern in this area.

5 Stage Two Analysis

This section provides a brief evaluation and categorization of the most cited articles. Unlike other studies [49], which focus exclusively on a quantitative approach, this research adopts a dual quantitative-qualitative methodology based on the research of NourAhmadi et al [20]. As a result, our analysis extends beyond merely counting articles, authors, or journals, and instead delves into the most relevant data related to the application of machine learning in portfolio optimization.

The simultaneous onset and stagnation of COVID-19 globally forced investors and fintech organizations to reconsider their traditional strategies for optimizing asset allocation. Additionally, there is a possibility of future occurrences of strong black swan events, as has been seen in the past [50]. Consequently, the authors of this research believe that fund managers and other active market investors can rely on news and leverage modern global technologies and tools to predict market movements and accurately value investments during times of high volatility, with a focus on investing in quality companies; thus enhancing potential returns and risk diversification.

The main focus of this section of the present research is on gathering and reviewing recent advancements in machine learning models for asset allocation in an optimized portfolio. Figure (13) illustrates the categorization of groups and the methods considered within each group.

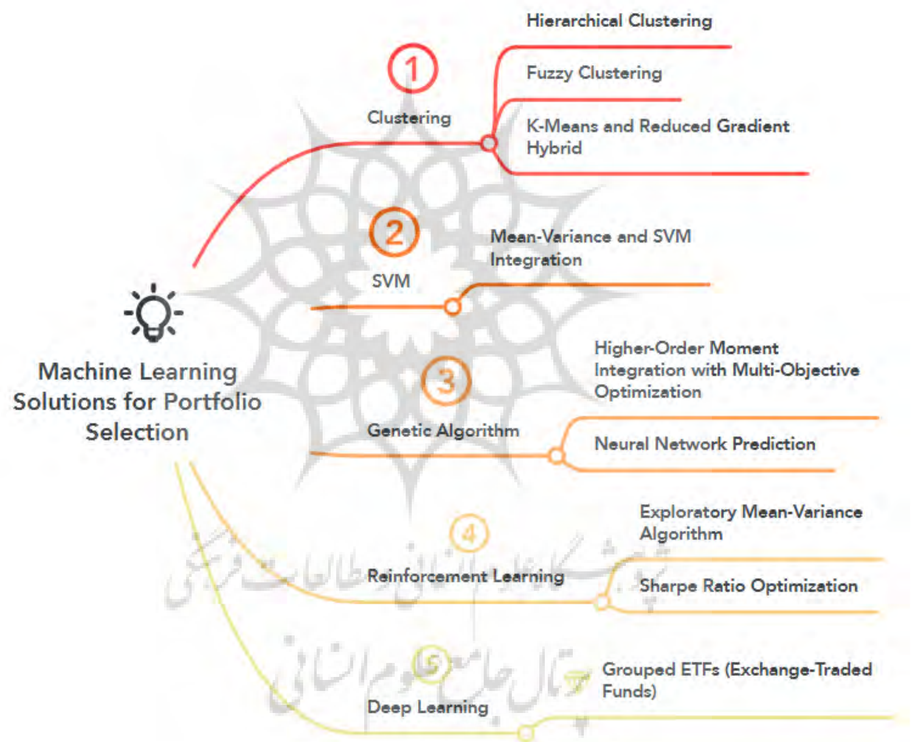


Fig. 13: Machine Learning Solutions in Portfolio Selection
Source: Researcher's Findings

Table (6) reviews the background of research conducted on the application of machine learning methods in investment portfolios.

Table 6: Research on Machine Learning Applications in Portfolio Management

Algorithm	Author	Index/Stocks	Models	Portfolio Strategy	Time Period	Number of Stocks in Portfolio	Performance Evaluation
Clustering	Ciciretti Bucci et al [51]	Top 100 stocks in SP 500	Bootstrapping operator	Comparison of the minimum cluster method, hierarchical risk parity (HRP), Markowitz minimum Sharpe portfolio (MSR), and minimum variance portfolio (MVP)	January 2010 to September 2021	30 stocks	Average return = 14.65%, Standard deviation = 13.31%, Skewness = -1.29, Kurtosis = 2.45, Sharpe = 0.8, Sortino = 1.42, Information ratio = 4.81, Treynor = 0.98
	Lim and Ong [52]	Top 82 stocks listed on SGX	Shape-based clustering	Hierarchical clustering, AHC-DTW	2015 to 2017	Varies from 3 to 6 stocks per portfolio	Average return = 9.24%, Average Sharpe = 33.98
	Duarte and de Castro [53]	Stocks traded on B3 (Brazilian Stock Exchange)	Fuzzy clustering	Markowitz mean-variance model and risk parity model	From December 30, 2009 to December 30, 2017	N/A	Return = 151.9%, Risk = 14.2%, Asset turnover = 31.4%, Maximum drawdown = -16.9%, Sharpe = 1.8
	Duarte and de Castro [54]	20 stocks from B3 (Brazilian Stock Exchange)	Partitional clustering	Markowitz mean-variance model and risk parity model	From December 2005 to April 2020	20 stocks	Return = 9.1%, Risk = 22.3%, Asset turnover = 22.5%, Maximum drawdown = -47.7%, Sharpe = -0.1%
	Koratamaddi et al [55]	30 companies in the Dow Jones Industrial Average	Deep Deterministic Policy Gradient (DDPG)	Comparison with mean-variance, minimum variance, DDPG, adaptive DDPG, and sentiment-aware adaptive DDPG trader agent	January 1, 2001 to February 10, 2018	Maximum of 5 stocks per day	Sharpe ratio = 2.07, Annual return % = 22.05, Annual std error = 0.096
SVM	Paiva et al [44]	53 to 73 stocks listed in Ibovespa, São Paulo Stock Exchange	SVM	Mean-variance portfolio compared to 1/N	June 2001 to December 2016	7 stocks	Accuracy = 54.97%, Feature = 70.29%
	Ma et al [56]	49 stocks from the China Securities Index (CSI) 100	Random Forest > SVR, LSTM, CNN, DMLP and ARIMA	Mean-variance and Omega portfolio	January 4, 2007 to December 31, 2015	N/A	Excess return = 121.53%, Standard deviation = 111.3980, Information ratio = 0.8693, Total return = 679.36%, Maximumdrawdown = -70.42% and Turnover rate = 149.72%
	Du [57]	20 stocks from CSI 300 and SP 500	Support Vector Machines (SVM), Random Forest algorithms, and Attention-driven Long Short-Term Memory networks (LSTM)	Mean-variance portfolio compared to 1/N	May 4, 2012 to August 4, 2020	Less than 20 stocks	Accuracy = 92.59% (CSI 300) and 88.52% (SP 500), Sharpe ratio = 9.31 (CSI 300) and 2.77 (SP 500)

Genetic Algorithm	Kwak et al [58]	487 stocks in SP 500 and Hang Seng Index (HSI)	Neural Network	Equal-weight portfolio (1/N)	July 1, 2014 to December 31, 2019	Number of stocks in the portfolio includes: 50, 100, 200, and 487	RMSE = 0.0239, Average daily return = 0.09427, Daily return volatility = 0.00032
	Rubesam [59]	572 Brazilian stocks, Ibovespa index	The application of linear regression, including both regularization techniques such as LASSO and Ridge, Bayesian variable selection methodologies, Random Forest algorithms, Gradient Boosting frameworks, Neural Network architectures, and ensemble risk parity models demonstrates superior performance compared to short-term strategic approaches.	Equal risk contribution is better than short-term strategies	January 2003 to December 2018	Number of stocks per portfolio varies from 10 to 40	Average monthly return before costs = +2.06% and after costs = +1.23%, Monthly standard deviation = +2.94%, Annual Sharpe ratio before costs = +2.10 and after costs = +1.13, Maximum drawdown = -19.27%, Average monthly turnover = +117.12%, Average leverage = +1.66
Reinforcement Learning	Durall [60]	Selected 8 stocks from the U.S. market	Reinforcement learning	Tangent portfolio, minimum variance portfolio, risk parity, equal weight, A2C, PPO, DDPG, SAC and TD3	From January 1, 2010 to January 1, 2017	8 stocks	Statistics of best-performing indicators in a bear market: Annual return = +27.6%, Cumulative return = +0.42%, Annual volatility = +4.41%, Sharpe ratio = +0.79, Calmar ratio = +0.75, Maximum loss = -36.8%, Stability = +0.59
	Jang and Seong [61]	29 stocks from the Dow Jones Index	Deep reinforcement learning and neural network N/1 and Jiang et al.'s algorithms (2017) and Yang et al.'s algorithms (2020) and author's proposed method	N/1 and the algorithms of Jiang et al. (2017) and the algorithms of Yang et al. (2020) and the method proposed by the author	From January 1, 2008 to December 31, 2019	Portfolio includes: 29 stocks	cash value Final accumulated portfolio value = $12,970.29; Max drawdown ratio = -8.29; Sharpe ratio = +2.67
Deep learning	Yun et al [62]	32 selected ETFs from 28 countries	Deep learning N/1, Random Forest, Support Vector Regression, Multi-layer Perceptron, Long Short-Term Memory	N/1, random forest, support vector regression, multilayerperceptron, Short-term long-term memory	From May 20, 2002 to June 8, 2017	N/A	Return = 0.5659, Risk = 0.0330, Sharpe Ratio = 0.1411, Maximum Drawdown = -0.1843, Value at Risk = -0.0504, Expected Shortfall = -0.0629
	Chakravorty [63]	8 selected ETFs from the United States	Deep learning exploratory processes in machine learning, ETF clustering, risk parity approach	Machine learning exploratory processes, ETF grouping, risk parity approach	From 2014 to 2018	N/A	Maximum Drawdown = -9.33, Sharpe Ratio = 0.76, Sortino Ratio = 1.037

Source: Researcher's Findings

5.1. Analysis of Performance Evaluation Metrics

To compare the performance of different machine learning models or evaluate their effectiveness against other models, specific evaluation metrics are used. These are presented in Table 6 and Figure 14. However, ensuring the future performance of a model cannot be achieved by solely relying on these models in real-world scenarios. Therefore, it is essential to incorporate financial metrics to assess the effectiveness of both machine learning and traditional algorithms. Key metrics include the maximum drawdown ratio, the Sortino ratio, the Sharpe ratio, and the return-to-turnover ratio (both annual and average), all of which are commonly used in portfolio management today.

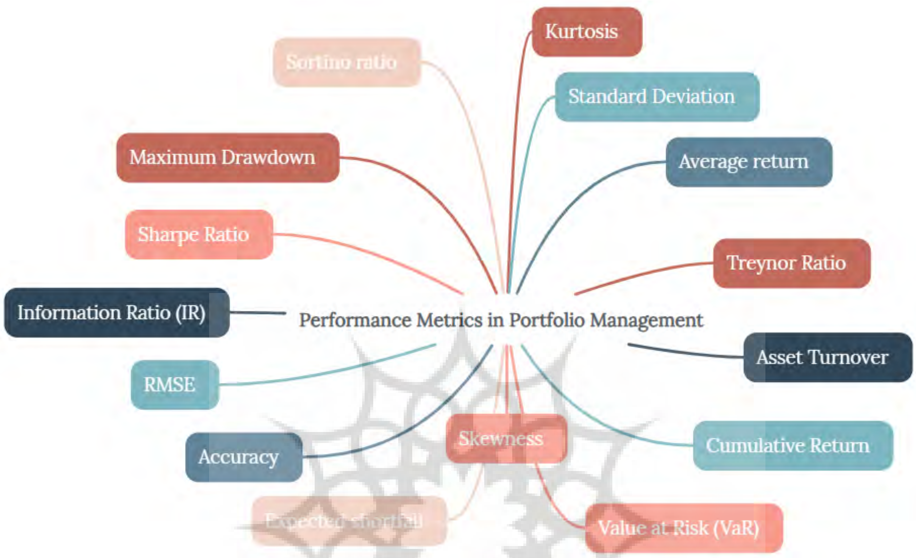


Fig. 14: Portfolio Performance Evaluation Criteria
Source: Researcher's Findings

6 Discussion and Conclusions

This research explores the literature on knowledge mapping related to the convergence of two fields: machine learning, a branch of computer science, and its application in optimizing investment portfolios. With the growing use of machine learning in portfolio management today, this study delves into the trends, accuracy, and capabilities of this technology. The first section reviews 304 articles published in reputable financial and computer science journals from Scopus and Web of Science since 1990, while the second section examines 12 articles selected by the authors. The study provides an overview of the types of models, datasets and performance metrics used in various algorithms, followed by an analysis of the results. The findings indicate that machine learning's application in the financial domain is expanding, and the effective performance of these algorithms challenges the efficient market hypothesis in the reviewed studies. The use of machine learning in wealth allocation and portfolio optimization has surpassed traditional models like minimum variance portfolios and 1/N strategies, even outperforming market index returns. From 2018 onwards, published studies in this field have significantly increased, reflecting growing interest and value in such research within financial markets. Chinese researchers have made notable contributions, ranking first, followed by scholars from the United States and the United Kingdom. Since this research focused exclusively on articles published in ScienceDirect and

Web of Science, it is possible that papers from other journals were not included in this study's data set. The use of various performance metrics, considering different conditions and characteristics in the financial data of the reviewed articles, makes direct comparisons across studies challenging. However, the evidence suggests that machine learning, compared to classical models, has significant potential to enhance investor satisfaction and profitability by processing large amounts of data more autonomously and accurately in investment decisions.

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