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Portfolio Optimization using Artificial Intelligence: a systematic literature review

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Abstract

Artificial intelligence (AI) models can help investors find portfolios in which the focus is to optimize the risk-return relationship. There are several algorithms and techniques in the literature that allow the application of tests to a set of historical data for the selection and validation of investment portfolios. Based on this, this research intends to examine the contribution of the main machine learning techniques used in portfolio management through a systematic literature review. By using the Methodi Ordinatio for selection and ranking of articles, we classified papers considering object of study, type of AI used, period of analysis, data frequency, balance and cardinality. In addition, we detail the main contributions and trends conceived until the year 2020. Therefore, our findings reveal gaps and suggest future works on the topic.

Keywords: artificial intelligence, portfolio management, literature review, reinforcement learning

Introduction

Despite Fama (1995) defending the efficient market hypothesis – in which asset prices would behave like a random walk and, thus, would be impossible to predict the direction and magnitude of market movements –, recent advances in the field of Artificial Intelligence (AI) – especially Machine Learning (ML) – allowed several studies to have been developed with the objective of applying these techniques to portfolio management.

Portfolio optimization involves the allocation of resources to a series of different asset classes to maximize yield and minimize risk in a given investment period (Skolpadungket, Dahal, & Harnpornchai, 2007). Proposed by Markowitz (1952), Modern Portfolio Theory proposes, in its most important aspect, the description of the impact on portfolio diversification by the number of securities within there and their covariance relationships (Mangram, 2013).

Numerous tools are used with the objective of improving the optimization and allocation process of portfolios, such as quadratic programming, which uses conventional mathematical techniques to circumvent the problem (Mencarelli & D'Ambrosio, 2019). On the other hand, ML algorithms can outperform humans and, therefore, be faster for taking decisions.

The ML framework comprises four types based on their ways of learning: supervised, unsupervised, semi-supervised, and reinforcement learning (Mammeri, 2019). Thus, this work intends, through from a systematic literature review, listing the main AI techniques used in portfolio management, in addition to detailing the main contributions and trends conceived up to the year 2020.

Many literature review works sought to detail the state of the art regarding the application of AI in various areas of finance. As an example, Bahrammirzaee (2010) conducts comparative research around credit assessment, portfolio management and financial predictions, evaluating three famous techniques: neural networks, expert systems and hybrid systems. Cavalcante et al.'s (2016) discuss general aspects of the main research involving AI and the financial market between the years 2009 and 2015, stating clustering techniques, prediction of market movements, mining of financial data, among others. Other works review the application of more specific algorithms, as in Inuiguchi and Ramík (2000) who show portfolio selection applications through fuzzy mathematical programming.

The methodology used for the ranking and selection of articles is the Methodi Ordinatio (Pagani, Kovaleski, & Resende, 2015). We apply an adaptation of the ProKnow-C (Afonso, Souza, Ensslin, & Ensslin, 2011) for the selection of publications and the InOrdinatio, which is an index to classify the selected works by relevance. This index crosses the three main factors evaluated in an article: impact factor, year of publication and number of citations. In this way, the 80 best classified articles were selected from a list of works prepared based on research carried out in the Web of Science and Scopus.

The analyzes of selected works show that there are many types of AI used for portfolio management. However, there are algorithms that predominate in the selected articles, such as evolutionary algorithms, fuzzy techniques, deep learning (DL) and reinforcement learning (RL). It is important to note that many articles present hybrid models, in which several AI models are used at the same time. It is concluded that techniques involving RL and neural networks have a greater tendency to be used in recent years, in addition to presenting greater space for new research and discussions on the subject.

This research contributes to the literature when presents the main contributions in AI applied to portfolio management through a systematic literature review. In addition, we state the main gaps that can guide future works on the subject.

This study is organized as follows. In addition to this introduction, a brief theoretical framework on the subject described in Section 2; Section 3 presents the protocol for collecting and organizing the literature; the results and discussion surrounding the research is available in Section 4; and, finally, the conclusions can be found in Section 5.

Theoretical reference

After Markowitz (1952) established the Modern Portfolio Theory (MPT), several works emerged with the objective of studying efficient portfolios, in which the risk-return relationship tried to be optimized as possible. According to the MPT, through diversification, risk can be reduced without changing the expected return on the portfolio. In other words, an investor can maximize the expected return of the portfolio while minimizing its variance of the return (Rubinstein, 2002).

Regarding the application of AI for portfolio optimization, it is possible to find several works in the literature. In the work of Chang, Meade, Beasley and Sharaiha (2000), the problem of finding the efficient frontier is considered through three heuristic models: genetic (evolutionary) algorithms, tabu search and simulated annealing. Li, Qin, and Kar (2010) uses an asymmetric mean-variance model with fuzzy returns and an integration of genetic algorithms. According to the author, the methodology used can be extended to problems of portfolio selection in hybrid and uncertain environments.

Huang (2012) also employs genetic algorithms in conjunction with SVR (support vector regressor). According to the work, the hybrid model performs better than the tested benchmarks.

Some works use newer AI techniques, such as the work by Almahdi and Yang (2017), in which RL models and recurrent neural networks are used to build an adaptive portfolio.

There are examples of works that combine conventional techniques with machine learning: Nobre and Neves (2019) uses the discrete wavelet transform together with unsupervised learning, XGboost and genetic algorithms to build a portfolio with better returns and low risk.

Based on the cited examples, considering the numerous existing works in the area, this research intends to highlight the main differences in the methods developed in the selected works. The idea is to identify the algorithms, data (stocks, simulated data or others), frequency of observations (intra-daily, daily, monthly and annual), transaction costs, portfolio balance, cardinality and the number of assets used. In this way, it is possible to detect possible improvements and propose future contributions to the theme.

Methodology

The systematic review is an important tool to bring together the main studies already carried out on a topic, and it is particularly relevant to map the topics studied and identify possible gaps and opportunities for future studies (Henriques, Sobreiro, Kimura, & Mariano, 2020).

We apply the Methodi Ordinatio to select the main studies, as it is a multi-criteria methodology that facilitates the process of building a portfolio, since the classification task is performed before the systematic analysis. In this way, relevant works can be identified in the early stages of the process, saving greater wear and tear when analyzing articles of low scientific relevance (Pagani et al., 2015). This methodology uses the InOrdinatio formula to classify articles according to their scientific relevance (Equation 1).

$$InOrdinatio = (IF/1000) + \alpha * [10 - (Research.Year - Publish.Year + (\sum Ci) \quad (1)$$

where: *IF* is the impact factor, α is a weighting factor ranging from 1 to 10, to be assigned by the researcher; Research.Year is the year of the research execution; Publish.Year is the year of the publication of the article; and $\sum Ci$ is the citation amount of the article.

Papers Selection

The first step of the Methodi Ordinatio refers to the establishment of the research intent, which in the present case is to review scientific articles related to the application of AI for portfolio optimization. A preliminary search carried out with the keywords in the databases and then we defined a combination of the keywords and the databases to be used.

From the problem definition, the key terms on which the descriptor assembly was based were defined, divided into two columns separated by areas of research interest. Thus, joining the two groups through Boolean terms, the search descriptor was established, as shown in Table 1. This descriptor was applied to the "keywords" field of the selected databases, Scopus and Web of Science, chosen for their scientific importance and scope. After filtering by the "Article" category, we found 714 articles in Web of Science and 348 articles in Scopus. After removing the duplicate articles, 806 articles remained in our database.

The metric chosen to measure the impact factor was the SJR (SCImago Journal Rank indicator). For the number of citations, the value informed by the databases was considered, and in case of divergence (in duplicate articles), the number of citations indicated by the Web of science prevailed.

Table 1

Key search terms

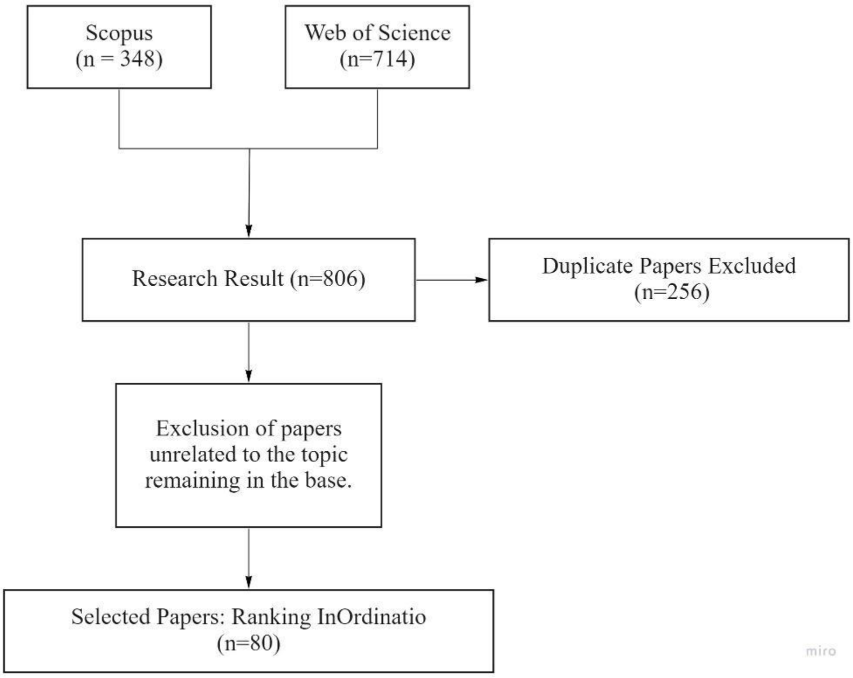
First Group	Second group
portfolio optimization	machine learning deep learning fuzzy genetic algorithm reinforcement learning

Descritor: (Portfolio optimization AND artificial intelligence) OR (portfolio optimization AND machine learning) OR (portfolio optimization AND deep learning) OR (portfolio optimization AND fuzzy) OR (portfolio optimization AND genetic algorithm) OR (portfolio optimization AND reinforcement learning)

The InOrdinatio formula was applied to rank the articles with the greatest impact, assigning α = 10 to give the greatest weight to the relevance of the articles. The titles and abstracts of the first ranked were read to exclude reviews or articles out of scope (portfolio management). Finally, the first 80 articles were selected for systematic reading and analysis. The entire selection process is illustrated in Figure 1.

Figure 1

Flow of the selection process of articles used in the systematic review.



Systematic Analysis of Literature

The categories described in Table 2 were considered for the research. Category 1 concerns the Study Object, that is, on which focus is AI applied to the portfolio optimization.

Table 2

Investigated categories, divided into sub-categories (coded for simplicity in visualization)

Categories 3 to 7 have an additional sub-category called "Not Informed"

Category	Meaning	Subcategory
1	Study object	A - Stocks
		B - Simulated data
		C - Cryptocurrency
2	Type of IA	A- Fuzzy
		B - Reinforcement
		C - Evolutionary Algorithms
		D - Deep Learning
		E - Others
3	Analysis period	A - Less than 2 years
		B - Between 2 and 5 Years
		C - Between 6 and 10 years
		D- More than 10 years
		E - Not found
4	Data frequency	A - Intra-day
		B - Daily
		C - Weekly
		D - Monthly
		E - Not found
5	Balancing	A - Yes
		B - No
		C - Not found
6	Transaction cost	A - Yes
		B - No
		C - Not found
7	Cardinality	A – Yes
		B – No
		C - Not found

Category 2 refers to the type of artificial intelligence used. A - Fuzzy is an AI technique that tries to imitate the logic of human reasoning using if-then rules, with categorical premises instead of exact values, and has been shown to be useful for making predictions (Bustos & Pomares-Quimbaya, 2020). B – RL is a type of machine learning in which a system learns from its previous interactions with the environment to efficiently select its future actions, and is considered suitable for solving optimization problems (Mammeri, 2019). C - Evolutionary Algorithms is an approach based on the Darwinian principle that the fittest survives in nature, so that an initial population is generated randomly and has its suitability evaluated by an evaluation function that defines how good is the solution that each chromosome represents (in the case of portfolio optimization, the weight of each individual asset in the portfolio) (Lwin, Qu, & Kendall, 2014). D - Deep Learning allows computational models, which are composed of multiple processing layers (neurons), to learn information using data representations with a high degree of abstraction (LeCun, Bengio, & Hinton, 2015).

Category 3 identifies the Analysis Period used (for studies with non-simulated data), that is, which considers the time horizon for the learning/application of the methods. Category 4 brings the Frequency of the data used.

Category 5 verifies the application of the techniques of continuous or periodic rebalancing of the portfolios. Category 6 sought to identify whether the research considered the transaction costs embedded in portfolio movements and adjustments, which may be particularly relevant in cases where portfolio rebalancing is used, as it can significantly increase the volume of transactions. and, consequently, their costs.

Category 7 - Cardinality is a constraint that limits the number of assets that make up the portfolio, replicating the practice in which investors often prefer to have a limited number of assets in their portfolio, due to the difficulty of monitoring many assets (Lwin et al., 2014).

After that, we analysed the classification to: (i) reveal relevant insights, (ii) find potential gaps for investigation, and point out interesting opportunities for future works.

Results and discussion

The articles were selected using the criterion α = 10 of the InOrdinatio equation, which prioritizes the most recent works. Figure 2 illustrates the distribution of selected articles by year. It was found that 48 of the selected articles were published in 2020, which reinforces the relevance of the research carried out. Thus, it is possible to better observe the trends conceived up to the researched cut-off year.

In order to visualize the main topics discussed in the selection made, a word cloud was constructed, a graph in which it is possible to verify the most frequent expressions through their relative sizes, based on the titles of the analyzed articles. Figure 3 illustrates this process.

When analyzing the word cloud, it can be noticed that the terms "Fuzzy", "Deep Learning" and "Genetic" stand out, reinforcing the numerous presence of these algorithms in the selected articles. Other terms like "hybrid", "multi-objective", "rysk" and "return" appear in larger size as well, demonstrating the main topics discussed. It is important to note that "portfolio selection", "approach", "portfolio", "optimization", "selection", "based", "model", "using", "stock", "trading", "algorithm" and "problem" were dropped as being redundant for the topic, in addition to allowing a better understanding of the other terms present.

Figure 2

Distribution of selected articles by year and by type of Artificial Intelligence

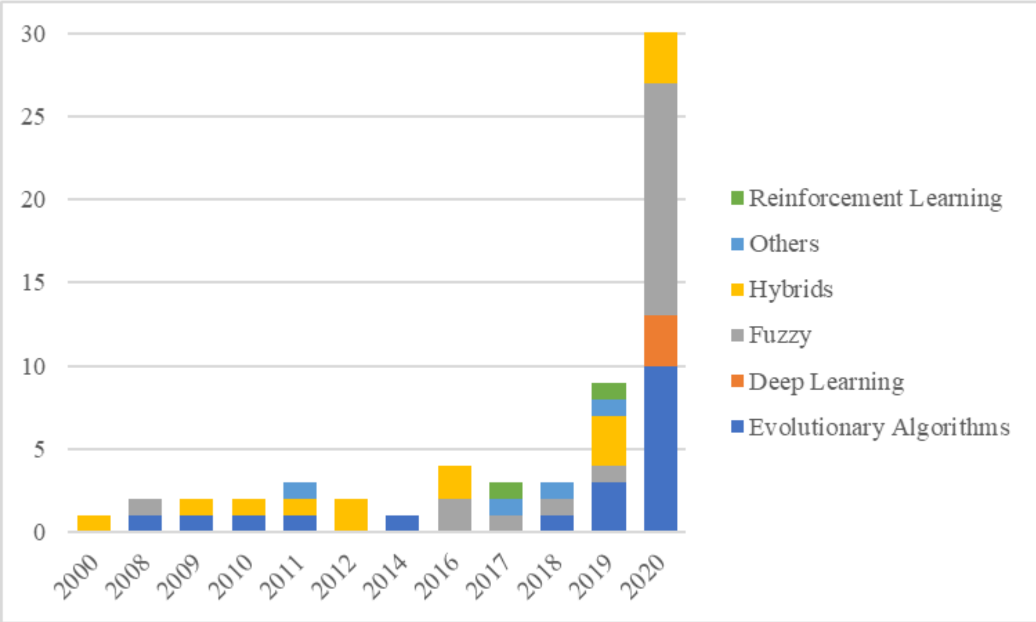
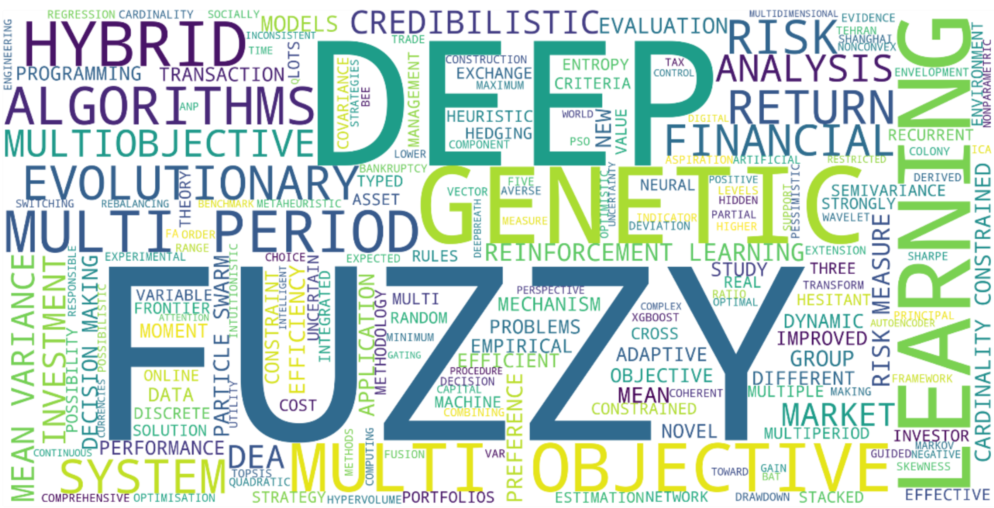


Figure 3

Word cloud

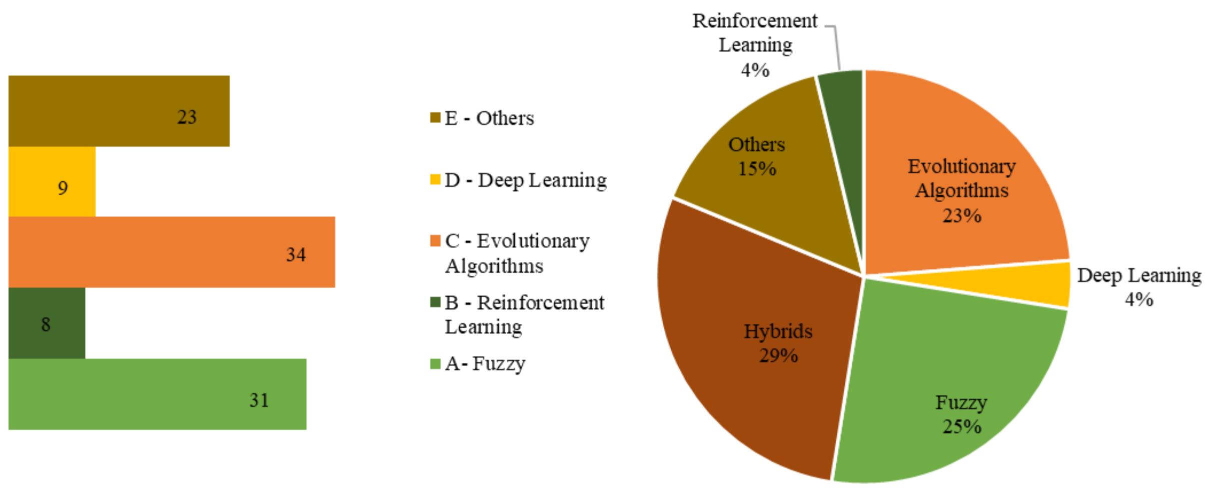


Category 2, the most important observed during the review, was the type of AI algorithm used in the works. We observed that most of the research used hybrid models, in which two or more algorithms have been applied to the portfolio management. However, some models stood out due to the number of appearances.

Figure 4 shows the main types of AI found. It is important to note that the total number of algorithms is greater than the number of articles selected due to the presence of the hybrid models.

Figure 4

Main AI Models found by the absolute count of the algorithms used and considering the intersections between them



As mentioned before, some techniques stand out due to the number of times they were found. Models using fuzzy logic, reinforcement learning, evolutionary algorithms, and deep learning were found 31, 8, 34, 9 times, respectively. However, an expressive number (23) of techniques that appeared three times or less were classified within the "Other" class.

To examine the categorization of articles, Table 6 (at the end of the article) illustrates the results obtained by this literature review, remembering that the categories follow the coding provided in Table 2.

It is interesting to note that the works using Deep Learning or Reinforcement Learning are relatively more recent, being between the years 2017 and 2020. The other techniques, in general, have been used for a longer period. Regarding the object of study, it is possible to verify that most of the research uses only stocks to compose the portfolios. However, there are essays that use simulated data (artificially produced), and only one work uses cryptocurrencies (virtual currencies). Table 3 illustrates this information.

Table 3

Object of Study

Object of Study	Quantity
A – Stocks	71
B – Simulated data	8
C - Cryptocurrencies	1

Tables 4 and 5 summarize the results found in relation to the remaining categories presented in the review.

Table 4

Categories related to data (analysis period and data frequency)

Classification	Analysis period		Data frequency	
	Meaning	Quantity	Meaning	Quantity
A	Less than 2 years	8	Intraday	2
B	Between 2 and 5 Years	19	Daily	23
C	Between 6 and 10 years	18	Weekly	18
D	More than 10 years	12	Monthly	9
E	Not found	23	Not found	27

Analyzing the "Analysis period" category, it can be stated that most works apply portfolio optimization in databases between 2 and 5 years or between 6 and 10 years (categories B and C). It is important to point out that more reliable results in the area of machine learning require a large volume of data to validate the strategies. In the "Frequency" category, it is observed that few works, only 2, use the selection of portfolios for intraday periods. This may be related to the lack of available data for this period. However, jobs using hourly (or minute) frequencies could more reliably represent real-time trading.

As shown in Figure 5, many works have considered issues such as balancing, transaction costs and cardinality in their research. However, it is worth mentioning that many articles did not bring information about the use of these tools, which can make replication and validation of the results present in these works difficult.

Figure 5

Binary categories of procedures adopted (balance of portfolios, cardinality, and transaction costs in the model)

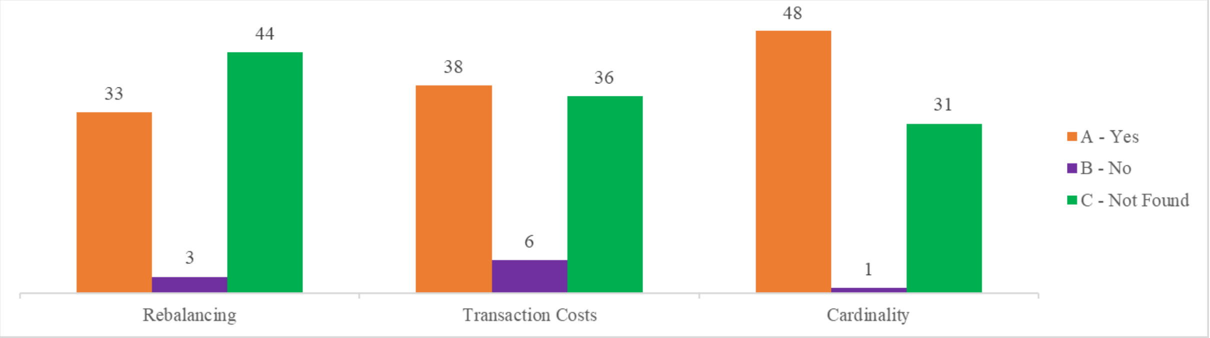


Table 5 illustrates the relationship between the object of study, type of AI and period of the databases used.

Table 5

Crossing of categories

Objeto do estudo/ Tipo de IA	Período de Estudo (anos)					
	<2	2-5	6-10	>10	NI	Total
A - Ações	8	18	18	12	15	71
A - Fuzzy	7	5	6	2	5	25
B - Reinforcement		2	2	3		7
C - Alg. Evoluc.	2	9	10	4	7	35
D - Deep Learning			3	2	3	8
E - Outros	2	5	5	7	3	22
B - Dados simulados					8	8
A					6	6
C					3	3
C - Criptomoedas		1				1
B, D, E		1				1

Through the analysis of Table 5, interesting gaps present in the researched topic can be extracted. It is reinforced that the use of RL algorithms is still low, and that this technique was not used for periods of less than two years. The same is true for deep learning models. However, it should be noted that these techniques require a extensive database for training and validating the algorithms, which may explain the lack of them in the aforementioned categories.

Another relevant point noted in the research is that the RL and DL models often appear together, called deep reinforcement learning. This technique can be found in selected works, as in Vo et al. (2019), Soleymani and Paquet (2020), Aboussalah and Lee (2020) and Weng et al. (2020). In these research, the objective is mainly to aid decision making by using RL techniques.

Table 5 also reinforces the lack of studies found using other types of assets in the composition of portfolios, only the work by Weng et al. (2020) uses digital currencies in conjunction with three AI algorithms.

Conclusion

This research was dedicated to reviewing the state of the art of AI applications in portfolio management. Information such as the type of algorithm used, characteristics of the databases, in addition to the presence of balance and cardinality, were examined.

The results show that there is a significant presence of evolutionary algorithms and fuzzy techniques - in addition to hybrid models that use two or more algorithms at the same time. However, there has been a trend in techniques involving deep learning and reinforcement learning in recent years. It is important to note that a large range of studies did not report data on the use of cardinality, balance and the type of data (frequency and period of the base) used in the surveys, which makes replication and analysis difficult of the results.

Despite the high number of hybrid models found in the research, there was a small use of RL algorithms in conjunction with other techniques.

In addition, a low presence of unconventional assets in the composition of the portfolios could be verified: only one work dedicated to the use of cryptocurrencies and we did not find studies using commodities or currencies and indices.

The article limited to analyzing the effectiveness of the researched models (return and risk achieved by the portfolios) due to the different types of data used: assets, frequency, period analyzed, among other categories. Thus, comparing the results would not provide relevant information, since the articles did not employ the same methods.

This work contributes to the literature as it describes the current state of the art, stating the main AI algorithms used and the notable trends developed in recent years. For future work, we suggest the use of deep learning algorithms in conjunction with RL techniques and other techniques, such as evolutionary algorithms.

It is also possible to add different assets to the composition of portfolios, such as commodities and virtual currencies.

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Table 6

Literature Review results coded into each of the 7 categories

#	Ano	1	2	3	4	5	6	7	#	Ano	1	2	3	4	5	6	7	#	Ano	1	2	3	4	5	6	7
1	2000	A	C, E	C	C	B	A	A	28	2019	B	C	E	E	A	A	A	55	2020	A	A	E	E	C	C	C
2	2010	B	A, C	E	E	C	C	C	29	2018	B	C	E	E	A	A	C	56	2020	A	C	B	D	C	C	A
3	2012	A	C, E	D	E	C	C	A	30	2020	B	A	E	E	C	C	C	57	2020	A	A, C	D	C	B	B	A
4	2017	A	A	A	E	C	C	C	31	2020	A	B	D	B	C	C	A	58	2020	A	D	E	B	A	C	A
5	2016	A	A	B	C	C	C	A	32	2020	A	A	C	C	A	A	A	59	2016	A	A, C	A	E	C	C	A
6	2014	A	C	C	C	C	B	A	33	2020	A	C	C	C	A	A	A	60	2020	A	A, C	D	B	A	A	A
7	2009	A	C	B	C	C	A	A	34	2020	A	C	B	C	A	A	C	61	2020	A	C	B	C	C	C	A
8	2011	A	E	A	E	C	C	A	35	2020	A	A	C	D	A	A	A	62	2020	A	E	B	B	C	C	A
9	2017	A	B	B	C	A	A	A	36	2011	A	C, E	C	C	A	A	A	63	2020	A	E	D	B	A	A	A
10	2008	B	A	E	E	C	C	A	37	2020	A	A, E	C	C	A	A	A	64	2020	A	C	E	B	A	A	A
11	2019	A	E	D	B	A	A	A	38	2020	A	A, C	B	C	A	B	A	65	2020	A	C	B	B	C	C	A
12	2020	A	E	B	B	A	A	A	39	2019	A	B, D	D	B	A	B	A	66	2020	A	E	E	B	C	C	C
13	2011	A	C	E	C	C	C	A	40	2020	A	A	E	E	C	C	C	67	2020	A	C	C	D	A	A	A
14	2018	A	E	D	D	C	C	C	41	2020	A	E	E	B	C	A	A	68	2019	A	C	C	E	C	C	C
15	2019	A	C, E	B	B	C	A	C	42	2019	A	A, C, E	E	E	B	A	A	69	2020	A	C	E	B	A	A	A
16	2016	A	A	C	C	A	A	A	43	2020	A	A	B	D	A	A	C	70	2010	A	C	E	E	C	C	A
17	2020	A	A	A	E	C	C	A	44	2020	A	A, C	A	E	A	A	A	71	2020	A	D	E	E	A	A	C
18	2017	A	E	B	B	C	B	A	45	2020	A	B, D, E	D	B	A	A	A	72	2020	A	A	C	D	A	A	C

#	Ano	1	2	3	4	5	6	7	#	Ano	1	2	3	4	5	6	7	#	Ano	1	2	3	4	5	6	7
19	2012	A	A, C	C	C	A	A	C	46	2020	A	B, D	C	A	A	A	A	73	2020	A	A	A	E	C	C	C
20	2020	A	C	E	E	C	C	C	47	2020	A	B, D	C	B	A	A	A	74	2020	A	C, D	E	E	C	C	C
21	2020	B	A	E	E	C	C	C	48	2020	A	A	B	E	C	A	C	75	2016	A	A, C	B	E	A	A	C
22	2019	A	B	B	B	A	A	C	49	2020	C	B, D, E	B	A	A	A	A	76	2020	A	C, E	C	D	C	C	C
23	2020	B	A	E	E	C	C	C	50	2019	A	C	D	C	C	C	A	77	2020	A	A	E	D	C	C	C
24	2008	A	C	B	D	C	A	C	51	2020	A	D	C	B	C	A	A	78	2020	A	E	D	B	A	A	A
25	2020	A	C	C	B	C	C	C	52	2020	A	A, E	A	B	C	C	A	79	2020	A	A	A	B	C	C	C
26	2009	A	C, E	C	C	C	C	A	53	2018	A	A	E	E	C	C	C	80	2020	A	E	D	E	C	C	C
27	2019	B	A	E	E	C	A	C	54	2020	A	E	B	B, C	A	B	B									