Past, present, and future of the application of machine learning in cryptocurrency research

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Abstract: Cryptocurrency has captured the interest of financial scholars and become a major research topic in blockchain. In cryptocurrency research, the use of machine learning algorithms is enabled by the presence of many types of data and abundant resources. However, there is currently no comprehensive review on cryptocurrencies using machine learning. Therefore, we collect papers on cryptocurrency-related using machine learning in the web of science database, and summarise these papers according to the algorithm, and draw the following conclusions: (1) The application of machine learning for cryptocurrencies research is increasing year over year; (2) Predicting cryptocurrency price trends and income fluctuations is the most relevant research topic; (3) The machine learning algorithm utilised in cryptocurrency research is not unique, and the practise of combining multiple machine learning approaches has emerged; (4) Concerns such as overfitting and interpretability still persist with machine learning methods.. Finally, we suggest future research directions.

Keywords: Cryptocurrency; Machine learning; Blockchain; Bibliometric analysis

1. Introduction

Cryptocurrency is a rapidly expanding global market. (Delfabbro et al., 2021; Derbentsev et al., 2021). Cryptocurrencies are used for cross-border payments and financial investments, making them a valuable digital and safe-haven asset (Kim et al., 2021; Kamal and Hassan, 2022). There are over 9,000 cryptocurrencies with a total market capitalization of $1.01T as of August 2022 [1]. The bottom layer of cryptocurrencies is a distributed ledger known as blockchain (Nakamoto, 2008). The data types and accessibility of cryptocurrencies provide a foundation for research in this area. However, big data pose severe challenges to data-processing systems. Machine Learning (ML) algorithm is suitable for large-scale data processing and has achieved remarkable success (Jordan and Mitchell, 2015). Specifically, as processing power and analytical tools develop, ML algorithms are increasingly utilised to design cryptocurrency investment strategies, trade fraud identification, illegal transaction identification, sentiment analysis, and predict cryptocurrency price and volatility (Goodell et al., 2021). On the one hand, ML algorithms can assist investors in obtaining larger profits. On the other hand, ML algorithms might cause a heightened sensitivity to the price of cryptocurrencies, resulting in significant price fluctuation. As the financial market pays more attention to cryptocurrencies, ML algorithms have gradually attracted the interest of academics (Alhenawi et al., 2022; Ahmed et al., 2022; Shahbazi and Byun, 2022). Bitcoin (BTC), the most well-known cryptocurrency, is the first widely used decentralised digital currency (Ferdous et al., 2021). Bitcoin accounts for the majority of cryptocurrency research, and price and volatility forecasts have become popular topics (Jia et al.,2022). Therefore, ML algorithms should be given specific consideration in cryptocurrency research and summarised as required.

A few literature papers on cryptocurrencies have compared the performance of various ML algorithms in cryptocurrencies analysis and prediction. For example, Anghel (2021) compared the differences in the application of ML algorithms and technical analysis algorithms in cryptocurrency trading rules and found that both

[1] data source: https://cn.investing.com/crypto/currencies

algorithms could effectively predict the price of cryptocurrency; however, the prediction effect was greatly reduced after controlling for some factors, indicating that the cryptocurrency market is effective. In addition, ML algorithms outperformed technical analysis in predicting the performance of small and illiquid cryptocurrencies. Khedr et al. (2021) summarised the research of ML algorithms in cryptocurrency price prediction from 2010 to 2020. Researchers believe cryptocurrency research is still in its infancy, and the prediction performance of the neural network (NN) model is better than that of the time series model. Models that rely on training tend to predict cryptocurrency price and volatility better. Al-hashedi and Magalingam (2021) focused on the application status of machine-learning algorithms for financial fraud detection. They found that the support vector machines (SVM) is the most widely used detection technology, followed by naive Bayes and random forest (RF). The aforementioned works have offered a complete description and comparison of the application of ML algorithms in various study domains, which can assist future researchers in gaining a thorough grasp of the current state of the subject. However, these studies focus on a specific aspect of cryptocurrencies and lack a comprehensive examination and analysis of their condition as a whole.

To this end, we retrieve and classify the literature using ML algorithms in cryptocurrency analysis from 2000 to 2022[2], conduct a systematic literature review, and propose future directions based on the collected 431 papers (from the Web of Science (WOS) database) that used or reviewed various ML algorithms, such as deep learning, reinforcement learning, and random forest.

The contributions of our study are as follows. First, this study is the first systematic review of the literature on ML algorithms in the cryptocurrency region. This

[2] Note: the purpose of this paper is to collect as much literature as possible related to the research objectives of this paper.

study has compiled a set of frontier methods for cryptocurrency research, including supervised algorithms and unsupervised learning algorithms. Second, the literature analysis method adopted in this study is objective and advanced. In our work, the knowledge graph method is used to explore the relationship and structure in these papers. In addition, this study also uses manual collection and sorting to determine the application status of different types of algorithms in cryptocurrency research. Third, our work reviews the essential topics of cryptocurrency research, including the price prediction of cryptocurrency, identification of illegal cryptocurrency transactions, and design of cryptocurrency investment portfolios, which provide a reference for future research. Finally, we propose future research directions and discuss important research topics in this field, which is a summary of cryptocurrency research.

The remaining sections of this work are structured as follows. This study's literature review methodology and data are introduced in Section 2. Section 3 provides a comprehensive overview of the literature we gathered and the corresponding findings. In Section 4, the ML algorithm for cryptocurrency research is discussed. Section 5 presents the outlook for future research in this topic, while Section 6 provides the conclusion.

2. Data and methodology

2.1 Background on Machine learning and Cryptocurrency

2.1.1 Machine learning

Researchers generally believe that ML algorithms are used to determine rules by analysing massive data samples and conducting mathematical modelling on the samples to complete tasks such as classification, clustering, and prediction. According to Jordan and Mitchell (2015), "Machine learning addresses the question of how to build computers that improve automatically through experience". Table 1 lists the four definitions of ML algorithms. The differences in the algorithms are mainly reflected in the representation of candidate programs and how the search is performed in the program space.

Insert Table 1 here

ML algorithms are designed to accomplish two main tasks: supervised and unsupervised learning. Supervised learning means that a sample includes both input and output indicators. ML algorithms build a rule, and the input indicator is mapped to the output using this rule. In unsupervised learning, the samples do not have the original labels. In other words, there are no output indicators. ML algorithms can be used in financial modelling, molecular and materials science (Suzuki et al., 2020), cancer prognosis and prediction (Kourou et al., 2015), genetics, and genomics (Libbrecht and Noble, 2015). Among them, supervised learning is the most commonly used.

Moreover, ML algorithms can be divided into four categories, as shown in Figure 1. The first type is a supervised learning algorithm, such as linear regression, decision tree, and SVM. The second type is an unsupervised learning algorithm, including a dimensionality reduction algorithm, density estimation, clustering algorithm, etc. The third type is a semi-supervised learning algorithm, which is between a supervised learning algorithm and an unsupervised learning algorithm, such as a generation or co-training model. The last type is other algorithms not covered by the above three categories, such as reinforcement learning, combinatorial modelling, and text analysis.

Insert Figure 1 here

2.1.2 Cryptocurrency

According to Merriam Webster's definition, "cryptocurrency" refers to any form of currency that only exists digitally[3], that usually has no central issuing or regulating authority, but instead uses a decentralised system to record transactions and manage the issuance of new units, and that relies on cryptography to prevent counterfeiting and fraudulent transactions.

Corbet et al. (2019) defined cryptocurrency as a peer-to-peer electronic cash system that allows online payments to be sent directly from one party to another without going through a financial institution. The other definition given by Delfabbro et al. (2021) is "digital 'coins' or assets based on blockchain technology".

2.2 Data collection

2.2.1 The source of data collection

WOS and Scopus are the primary sources of citation data (Mongeon and Paul-Hus, 2016), of which Thomson Reuters founded WOS, and Elsevier owns Scopus. For quite a long time, WOS has been the only database of publications and citations covering all scientific fields, thus becoming a valuable tool for bibliometric analysis (Vieira and Gomes, 2009). Compared with Scopus, WOS has a much longer history, and users can access earlier research records. In addition, WOS can carry out detailed citation analysis of the literature (Falagas et al., 2008), and the literature records can be downloaded and directly analysed using the Citespace software. Therefore, we selected the WOS database for this study.

2.2.2 Keyword selection strategy and refinement process

According to the definition of important concepts, we set up retrieval statements in the WOS (Core Collection). The retrieval statement defines the publication type and retrieval subject. As shown in Table 2, the retrieval statement consists of three parts: the retrieval statement related to ML algorithms and cryptocurrency and the two

[3] Merriam-Webster. (n.d.). Cryptocurrency. In Merriam-Webster.com dictionary. Retrieved November 22, 2020, from https://www.merriam-webster.com/dictionary/cryptocurrency

document types, including articles and reviews. The paper we collected should simultaneously meet these three conditions at the same time.

Insert Table 2 here

We searched the WOS (Core Collection) literature and obtained samples (see Appendix 1). Within the full-time frame of the database, 431 pieces of paper met the search criteria. Among them, the first article appeared in 2014. Figure 2 shows the number of articles published from 2014-2021. One article was published from 2014 to 2022, and the number of relevant studies increased rapidly after 2018, reaching 179 in 2021.

Insert Figure 2 here

2.3 Study methodology and tools

In the bibliometric analysis of this study, co-citation networks, keyword bursting, and performance analyses are selected. Co-citation analysis is a literature coupling analysis method that can present a clear knowledge structure in a field (Small, 1973). Burst analysis measures the sudden change in keyword frequency over time and duration (Kleinberg, 2002), which can find potentially interesting works and attract significant attention in a short time (Chen et al., 2009).

3. Findings

3.1 Performance analysis of ML research in cryptocurrency

3.1.1 Top cited article

Some studies have had an important academic status in researching this topic because of their high citation counts. Therefore, a different explanation is required. As shown in Table 3, the most cited article among the sample is Urquhart's (2017) study on the BTC's inefficiency. This paper concludes that the cryptocurrency market, like other financial markets, also has price clustering and that cryptocurrencies' price and trading volume are closely related to this phenomenon. In addition, the first four papers were published in short articles before 2017, the earliest influential exploration in the cryptocurrency field.

Insert Table 3 Here

3.1.2 Important journal

As listed in Table 4, 43 articles were published on IEEE Access, and the specific gravity was 9.885%. Journals' JCR classification is based on computer science, theory, and methods. The journal names *Applied Soft Computing and Neural Computing Applications*, which belongs to this field, also include many articles. In addition to journals in the computing field, business-related journals (including business, finance, and operations research and management science) have also published related papers. For example, 20 articles in our sample were published in Finance Research Letters. Ten articles were published in *Expert Systems with Applications*, and seven were published in *Research in International Business and Finance.*

Insert Table 4 Here

3.2 Structure analysis of ML algorithms in cryptocurrency

3.2.1 Co-citation network

As shown in Figure 3, the co-citation network consists of 395 nodes and 730 edges. The network was trimmed using the Pathfinder algorithm. The network modularity value was 0.8623 (larger than 0.3), indicating that the network's community structure is significant. The silhouette coefficient reflects network homogeneity. The higher the silhouette coefficient, the better the result of network clustering. In this network, the value of this indicator is 0.9359, indicating that the clustering results are credible.

In the co-citation network, nodes represent the corresponding articles, and the connection between nodes indicates that the two connected articles are cited by one article simultaneously. The denser the connection, the closer the relationship between the literature in the group and the corresponding research topics. The colours of the nodes in Figure 3 are also different, representing the different clusters to which the literature belongs. According to the clustering algorithm provided by CiteSpace, cluster labels were obtained, and the colours of the different clusters were also different. In addition, CiteSpace also numbered the tags according to the size of each cluster. The largest category is Bitcoin prediction, followed by liquidity connectivity and technical trading.

Insert Figure 3 Here

3.2.2 Evolution of research topics

Figure 4 plots the burst emergence of keywords, and 15 keywords have been hot topics for some time. This Figure shows the top 15 keywords and sorts them according to the start and end time of emergence. Among them, the word expression appeared the earliest, with the corresponding intensity of 2.52, and the period was from 2015 to 2018. The following keywords are price clustering and economic policy uncertainty. Keywords can be divided into two categories: model keywords and topic keywords. Model keywords include region, time series, prediction, predict predictive model, Spillover etc.; topic keywords include price clustering, economic policy uncertainty, inefficiency, return, smart contract, stock, Internet, etc. This indicates that since 2019, researchers in this field have generally focused on the price prediction of cryptocurrency. The research object has also transitioned from price accumulation to economic policy uncertainty, smart contract and the Internet.

Insert Figure 4 Here

3.2.3 Application of machine learning in cryptocurrency

From the analysis of keyword emergence, we can see that regression, time-series, and prediction-related models have become the corresponding research hotspots. Researchers have also received special attention for cryptocurrency price prediction in co-citation analysis. Therefore, this section introduces several algorithms commonly used in cryptocurrency research, such as neural networks, deep learning, and reinforcement learning. They play an essential role in the price characteristics of cryptocurrencies, identifying illicit transactions, etc.

(1) Linear model

Researchers often use linear models to characterise the linear correlation between variables. The advantages of linear models are their simplicity of operation and interpretability. Table 5 presents the application of linear models in cryptocurrencies, and we found that linear models are often used to predict the prices of cryptocurrencies (Chen et al., 2020; Cohen, 2020; Poongodi et al., 2020; Saad et al., 2020; Uras et al., 2020; Akyildirim et al., 2021; Mohamed et al., 2022; Sebastiao and Godinho, 2021).

Insert Table 5 Here

Linear models have also become important for analysing cryptocurrency adoption behaviour (Nikic, 2018; Gagarina et al., 2019). In these studies, linear models can be used alone or compared with other models. In addition, linear models can also be used to build combinatorial models for price forecasting research.

For example, Chen et al. (2020) used linear model and ML algorithms to predict Bitcoin price. They found that linear models were better than other ML models. Poongodi et al. (2020) compared linear models and the SVM model in Ethereum price prediction and found that linear models are better than the SVM model. Akyildirim et al. (2021) compared the effects of linear models, SVM, neural networks, and ensemble models on cryptocurrency prediction. They believed that ML algorithms could make short-term predictions of cryptocurrencies. Researchers also have constructed ensemble models based on linear models (Saad et al., 2020). In addition, media sentiment is used to make cryptocurrency price predictions (Yasir et al., 2020). Scholars have sought to improve model prediction accuracy by constructing linear models. Borges and Neves (2020) also supported this conclusion. They found that ML-based investment selection was better than random selection.

There are a few cases where the linear model is used alone for the analysis. In their exploration, scholars mainly used a variety of algorithms, including linear models, for comparison or integration. Researchers have generally used linear models to study cryptocurrencies since 2018 and have achieved certain results. There are few cases in which the linear model is used alone for analysis in their exploration. Therefore, it can be said that linear models are a fundamental algorithm for conducting cryptocurrency research, especially in cryptocurrency price forecasting.

(2) Decision tree

The decision tree model is a supervised learning algorithm that can deal with classification tasks. Decision tree algorithms include ID3(Quinlan, 1979; Quinlan, 1986), C4.5(Quinlan, 2014) and CART (Breiman et al., 1984). The key to building a decision tree is the selection of the optimal partition index, and the primary selection bases are information gain and the Gini index. The tree must be pruned to avoid overfitting. Recently, the random forest algorithm based on the decision tree has attracted many researchers' attention.

The decision tree algorithm is primarily used for illegal transaction identification and price prediction in cryptocurrencies. Relatively few studies on cryptocurrency use the decision tree algorithm alone. As seen in Table 6, Most studies have combined decision trees and optimisation algorithms to improve the efficiency and accuracy of judgment. In our sample, at least nine articles used a decision tree.

Insert Table 6 Here

For example, Zhou et al. (2020) used a decision tree to classify commodities in an ideal market to identify illegal trades involving cryptocurrencies. Al-Haija and Alsulami (2021) used two supervised learning algorithms, including a decision tree, to identify ransomware payments. Their research showed that the two-classification algorithm based on the decision tree had an accuracy of 99.9%, and the multi-classification algorithm had an accuracy of 99.4%. Nerurkar et al. (2021) proposed an ensemble decision tree algorithm to identify illegal transactions and users in the BTC exchange market, outperforming SVM and logistic regression with an accuracy rate of 91%.

In the identification of illegal transactions, researchers not only need to design ensemble algorithms, including the decision tree model, but also need to compare the partition accuracy of different algorithms. Among them, the decision tree algorithm has high division accuracy. In addition to identifying illegal transactions, decision tree algorithms are used for prediction. For example, Chen et al. (2021b) used the GARCH model and decision tree algorithm to predict BTC's price and found decision tree has higher accuracy. Sun et al. (2020) use a light gradient boosting machine (Light GBM) to predict the prices of 42 currencies. Their research found that the comprehensive strength of cryptocurrencies affects the prediction performance and that the Light GBM algorithm is better than the other algorithms.

(3) Neural Network

An Artificial Neural Network (ANN) refers to a series of mathematical models inspired by biology and neuroscience. These models simulate biological neural networks by abstracting the human brain's artificial intelligence (A. I.) neural network.

ANN is also referred to as neural networks or neural models. According to different network structures, neural network models can be divided into feedforward networks (multilayer perceptron (MLP)), feedback networks (memory networks), and graph networks. Feedforward networks include fully connected feedforward networks and convolutional neural networks (CNN); memory networks include recurrent neural networks (RNN), Hopfield networks, Boltzmann machines, and restricted Boltzmann machines, which mainly include graph convolutional networks, graph attention networks, and message-passing neural networks.

According to the universal approximation theorem (Cybenko, 1989; Hornik et al., 1989), neural networks can approximate any given continuous function and, thus, have powerful fitting capabilities. Therefore, neural network models have extensive applications in cryptocurrency risk management. Among the articles we collected, 37 papers used neural network models (see Table 7), most of which were used in prediction, and a few were used in investment strategy.

Insert Table 7 Here

Neural networks are primarily used to predict cryptocurrency prices or returns. The algorithms they used include long short-term memory (LSTM) (Alonso-Monsalve et al., 2020; Patel et al., 2020; Saad et al., 2020; Alkhodhairi et al., 2021), CNN, Bayesian neural networks (Jang and Lee, 2018; Cocco et al., 2021), and deep neural networks (Sattarov et al., 2020; Wei et al., 2021). The LSTM model is a time RNN that can solve the disappearing and exploding gradient problems in a simple RNN. By constructing LSTM models or constructing more complex models based on LSTM models, researchers have found that LSTM models are highly accurate and robust.

In addition to the prediction problem, the investment strategy problem is important for applying neural network models. Researchers use neural network models alone when solving cryptocurrency investment strategy problems, such as LSTM, RNN, CNN, and ANN. However, they use deep reinforcement learning (DRL) models for portfolio management and trading system design (Lucarelli and Borrotti, 2020; Weng et al., 2020). In addition, neural network models have been used to solve Bitcoin address classification and blockchain node feature recognition (Michalski et al., 2020).

(4) Support Vector Machine

SVM (Cortes and Vapnik, 1995) is a critical classification model used in text analysis (Table 8). SVM are typically used to predict cryptocurrency prices. Regression models based on SVM have also been adopted to make more accurate predictions. Furthermore, the SVM is used to design an automatic cryptocurrency trading model for the investment strategy problem. Unfortunately, the SVM is more sensitive to the choice of the kernel function, and thus, it is not suitable for large-scale datasets. This has led researchers to combine SVM with other models in cryptocurrency risk management research (Valencia et al., 2019; Akyildirim et al., 2020; Sun et al., 2020; Sun et al., 2021).

Insert Table 8 Here

Additionally, SVM was also used as a benchmark model. Researchers have compared it with other models to judge the prediction performance, but they have obtained different conclusions (Chen et al., 2020; Sun et al., 2020). For example, Chen et al. (2020) predicted the Bitcoin price and found that SVM performed best among ML models. However, Sun et al. (2020) found that the light gradient boosting machine (Light GBM) was better than the SVM in predicting cryptocurrency prices.

In addition, SVM and its extended form are also used in cryptocurrency portfolio management (Madan et al., 2015; Żbikowski, 2016). For example, Żbikowski (2016) compared the performance of simple technical indicators, the box SVM, and the volume weight SVM in automatic Bitcoin trading. The authors found that using ML models can improve overall trading performance. Madan et al. (2015) used an SVM to design a Bitcoin automatic trading algorithm and found that the error rate of the SVM was higher. SVM also has applications in other cryptocurrency areas (Michalski et al., 2020; Akba et al., 2021).

(5) Clustering methods

Clustering algorithms are classic unsupervised ML algorithms. When a training sample is unlabelled, and the researcher hopes to obtain the inherent law of the training sample through data analysis, a clustering algorithm is often selected. There are two main types of clustering algorithms: hierarchical clustering and k-means clustering.

Table 9 reports the application of clustering algorithms in cryptocurrency research. In our sample, at least 18 papers use clustering algorithms to study cryptocurrency-related problems. Such as the price characteristics of cryptocurrencies, market structure, herd behaviour, etc. Clustering algorithms can be used in research in many cryptocurrency fields. Researchers can work with clustering algorithms alone or in combination with complex networks, decision trees, and Neural Networks. For example, when a clustering algorithm is used to analyse the price characteristics of cryptocurrencies, Papadamou et al. (2021) used the club-cluster algorithm to divide cryptocurrencies into two groups, and their study found that out of 216 cryptocurrencies studied, 207 exhibited herding behaviour.

Insert Table 9 Here

Manavi et al. (2020) used a hierarchical clustering algorithm to analyse the correlation between cryptocurrencies and other assets and showed that most assets and cryptocurrencies had no significant correlations; the cryptocurrency and foreign exchange markets belong to different clusters. Kondor et al. (2014) conducted a cluster analysis of the Bitcoin transaction network when clustering algorithms were used in related research on blockchain transactions. They found that the clustering coefficient of the Bitcoin transaction stage is higher.

(6) Reinforcement learning

Reinforcement learning is an approach that continuously learns from interactions to solve such problems. As shown in Table 10, reinforcement learning and deep learning are often used in cryptocurrency research, called deep reinforcement learning (DRL). DRL is performed by defining the problem using reinforcement learning and optimising the objective function using deep learning. DRL algorithms can be divided into policy gradient and Q-value learning methods.

Insert Table 10 Here

Reinforcement learning algorithm is mainly used to formulate and execute cryptocurrency investment strategies. For example, Lucarelli and Borrotti (2020) proposed a deep Q-learning portfolio-management framework. The framework consists of a local agent that understands asset behaviour and a global agent that understands global rewards. The framework was applied to a portfolio of encrypted assets composed of four cryptocurrencies and achieved the expected results. Weng et al. (2020) proposed a cryptocurrency portfolio management system based on a deep neural network. The system used a deep CNN to update the reward signal for reinforcement learning. The proposed method has a lower short-term risk index than the traditional method. Sattarov et al. (2020) designed a cryptocurrency trading algorithm based on DRL. Using this algorithm, researchers can find suitable trading points, increasing Bitcoin's original return by 14%. Li et al. (2021a) proposed a novel ensemble portfolio optimisation (NEPO) framework that combines LSTM models and reinforcement learning algorithms. Empirical analysis shows that the NEPO framework can improve prediction accuracy.

Reinforcement learning algorithms are used in blockchain transaction design and identifying illicit transactions. For example, Lim et al. (2021) used the DRL algorithm to identify criminal networks using cryptocurrencies. Reinforcement learning has also been used to study Bitcoin mining mechanisms. For example, Rakkini and Geetha (2021) used reinforcement learning algorithms to design an incentive mechanism to motivate miners to continue linking new blocks after honest blocks.

(7) Other algorithms

This study cannot exhaust all ML algorithms. In addition to the above methods, some algorithms, such as the ensemble model, are used in cryptocurrency research. The combined model proposed by the authors can predict real-time data under a non-stationary background. For example, Fang et al. (2021) constructed a neural network model and added the LSTM model as a neuron into the framework of the combined model to predict cryptocurrency prices.

4. Discussion on machine learning used in cryptocurrency research

Above, we provide a systematic review of ML in cryptocurrency research. Although cryptocurrency market research using ML has been around for eight years (2014-2022), this is just the beginning of cryptocurrency research (Goodell et al., 2021; Ahmed et al., 2022). It is necessary to think dialectically about the breakthroughs and problems faced after applying ML algorithms to cryptocurrency research to provide theoretical guidance for research in this field.

4.1 The benefits of machine learning

ML algorithms can improve the accuracy of cryptocurrency price prediction. The connotation of price prediction includes two aspects: the prediction of price trends and the prediction of absolute prices. Traditional econometric models face challenges in flexibly handling high-dimensional and high-frequency data. In addition, traditional methods require more computational time. Therefore, ML has certain advantages in processing cryptocurrency data. In the literature we have collected, deep learning algorithms, such as neural networks, predict the price movements of cryptocurrencies. The LSTM model introduces the concept of control gates, which the model can filter. The most valuable information for forecasting activities is extracted, thereby improving the accuracy of forecasting (Ji et al., 2019; Lahmiri and Bekiros, 2019)

ML algorithms can process different types of large-scale data to maximise the value of the information. As the complexity of encrypted currency data, such as transaction data, blockchain network data, transaction fees, and other block data, increases, researchers must use different models to capture more complex data forms (Jay et al., 2020). ML algorithms can process price-return data for cryptocurrencies, such as Bitcoin (Sebastiao and Godinho, 2021) and data on blockchain node addresses (Zheng et al., 2020). Chen et al. (2020) showed that machine-learning models outperform traditional statistical methods in handling high-frequency data. The RMSE comparison of different ML models showed that the mixed model had a lower error level and better prediction accuracy (Nosratabadi et al., 2020). Kamisalic et al. (2021) compared various algorithms in fraud detection, which need to deal with encrypted data in the blockchain. They found that the best algorithms in the field of fraud detection are random forest and gradient boosting.

4.2 The challenges of machine learning

ML algorithms still have the following shortcomings: first, this algorithm has the problem of overfitting; second, the algorithm also has the problem of difficulty in explaining and black box; third, the analysis through ML easily causes data security problems.

Overfitting is an important problem in ML, and it also exists in cryptocurrency research, especially when using multiparameter neural network models. This is a severe problem in the generalisation of the model (Srivastava et al., 2014). According to Hawkins (2004), overfitting has the following disadvantages. For example, an overfitted model may incorporate irrelevant components into the model analysis, and an overfitted model may also integrate invalid predictors in the analysis, resulting in wasted computing resources. Worse of all, overfitting makes the model less portable or completely non-portable.

Many machine-learning models fall into the black box and cannot be interpreted in a human-comprehensible manner. Models that lack transparency can have serious consequences (Rudin, 2019). If a model cannot make interpretable decisions, it is challenging to achieve real-world reliability (Benítez et al., 1997). In addition, unexplainable machine-learning models also face difficulties in practical operations (Lundberg et al., 2018).

5. Suggestions for future research

ML is one of the most critical tools in cryptocurrency research. This study proposes several possible future research topics in this field based on existing literature.

First, cryptocurrency-related research should not be limited to Bitcoin. Currently, more than 9,000 cryptocurrencies exist worldwide, and the diversified cryptocurrency landscape should attract the attention of researchers (Dastgir et al., 2019; Bouri and Gupta, 2021; Li et al., 2021b). In addition, cryptocurrencies are often traded in U.S. dollars, and future research should consider other currencies (Bouri et al., 2017). What are the differences between cryptocurrencies and traditional assets as new assets? The relationship between its value and traditional assets deserves further analysis (Urquhart and Zhang, 2018; Qin et al., 2021; Su et al., 2020)

Second, cryptocurrencies are often used in underground transactions and money laundering as private financial assets. Applying advanced ML algorithms to effectively supervise the cryptocurrency market is an important direction for future research in this field. (Foley et al., 2019). Countries worldwide have different regulatory attitudes and practices towards cryptocurrencies, and the uncertainty of future regulatory policies is an important research direction in this field (Guesmi et al., 2019; Hasan et al., 2021; Lucey et al., 2022). In future research, new tools for measuring policy uncertainty should be considered for a more in-depth analysis.

Third, since the end of 2019, COVID-19 has ravaged the world and has profoundly impacted real industries and financial markets. Shocks to the cryptocurrency market are becoming a new research hotspot (Aysan et al., 2019; Goodell and Goutte, 2021a, 2021b; Jalal et al., 2021; Akhtaruzzaman et al., 2022). The network analysis method can measure the spillover risk caused by COVID-19. Prediction algorithms used in previous studies, such as regression models, neural network models, and SVM models, can still be used to predict the price and return of cryptocurrency; however, the epidemic impact needs to be included in the influencing factors. The text analysis algorithm can also be used to measure public sentiment fluctuations caused by the covid-19 outbreak. On this basis, researchers can analyse the impact of sentiment fluctuations on the cryptocurrency market. In addition to COVID-19, other influencing factors can also be valued in future research, such as the search volume of Bitcoin on the Internet (Balcilar et al., 2017).

In addition, future research directions are also pointed out in the cryptocurrency literature reviews. García-Corral et al. (2022) argued that cryptocurrency inefficiencies and mining costs are concerning. Yue et al. (2021) believed that the macroeconomic effects, influence mechanisms, and legal digital currency of cryptocurrencies would become a research hotspot in the future. In research on Bitcoin transaction networks, compatible transaction network modelling, network-based information supplementation, dynamic analysis and online modelling of transaction networks, and transaction auditing and tracking will become future research directions.

6. Conclusions

This article reviews the use of machine-learning algorithms in cryptocurrency research since 2014. To systematically and comprehensively analyse the research situation in this field, we adopted two methods: bibliometrics and thematic review. Bibliometrics provides an overall picture of research in this field and the evolution of research topics. A survey based on metrology described the application status of neural networks, linear models, and discriminative models in cryptocurrencies. Finally, based on the existing research, we propose possible future research directions in the field of cryptocurrency. Machine-learning algorithms play a key role in the study of these issues.

The findings of bibliometrics and thematic reviews are as follows. First, the use of ML to conduct cryptocurrency research shows an upward trend yearly. Most of the research objects are mainstream cryptocurrencies such as Bitcoin. Second, when selecting research questions, predicting cryptocurrency price trends and income fluctuations is a topic of interest to researchers. Research on cryptocurrency investment strategies using reinforcement learning algorithms has also attracted attention. Third, the ML algorithms used in cryptocurrency research are not single. Researchers are more likely to have useful ensemble models to improve the accuracy of the model, but this may lead to overfitting.

Our work has important management implications for both cryptocurrency investors and cryptocurrency regulators. For investors in cryptocurrencies, price fluctuations and earnings forecasts are hot topics, and ML algorithms are often used to make predictions. To improve the accuracy of predictions, investors should collect extensive, reliable, and timely data information, compare the prediction impacts of various algorithms, enhance the model's interpretability and fitting effect, and prevent over-fitting issues. For cryptocurrency regulators, illegal transactions based on cryptocurrencies should be of particular concern. ML algorithms can also identify illegal transactions in addition to traditional regulatory methods.

Due to the limitation of space, this paper cannot introduce the application of all ML algorithms in detail, so the author only selects some widely used ML algorithms. Such as neural network models and decision tree algorithms. It can not be ignored that some new algorithms keep emerging, can better deal with high-dimensional and high-frequency data, and have equal processing capacity for unstructured data.

Ethical approval

This article does not contain any studies with animals performed by any of the authors.

Informed consent

Informed consent was obtained from all the individual participants included in the study.

Declaration of Competing Interest

The authors declare no competing interests.

Reference

Abu Al-Haija, Q., Alsulami, A.A., 2021. High performance classification model to identify ransomware payments for heterogeneous Bitcoin networks. *Electronics*, 10(17), 2113. https://doi.org/10.3390/electronics10172113.

Aggarwal, D., Chandrasekaran, S., Annamalai, B., 2020. A complete empirical ensemble mode decomposition and support vector machine-based approach to predict Bitcoin prices. *J Behav Exp Finance* 27, 100335. https://doi.org/10.1016/j.jbef.2020.100335.

Ahmed, S., Alshater, M. M., El Ammari, A., Hammami, H., 2022. Artificial intelligence and machine learning in finance: A bibliometric review. *Res Int Bus Finance* 61, 101646. https://doi.org/10.1016/j.ribaf.2022.101646.

Akba, F., Medeni, I.T., Guzel, M.S., Askerzade, I., 2021. Manipulator detection in cryptocurrency markets based on forecasting anomalies. *IEEE Access* 9, 108819-https://doi.org/108831. 10.1109/ACCESS.2021.3101528.

Akhtaruzzaman, M., Boubaker, S., Nguyen, D. K., Rahman, M. R., 2022. Systemic risk-sharing framework of cryptocurrencies in the COVID–19 crisis. *Financ. Res. Lett.* 2022, 102787. https://doi.org/10.1016/j.frl.2022.102787.

Akyildirim, E., Cepni, O., Corbet, S., Uddin, G. S., 2021a. Forecasting mid-price movement of Bitcoin futures using machine learning. *Ann Oper Res*.2021, 1-32. https://doi.org/10.1007/s10479-021-04205-x.(文中未出现）

Akyildirim, E., Goncu, A., Sensoy, A., 2021. Prediction of cryptocurrency returns using machine learning. *Ann Oper Res.* 297(1), 3-36. https://doi.org/10.1007/s10479-020-03575-y.

Alessandretti, L., ElBahrawy, A., Aiello, L.M., Baronchelli, A., 2018. Anticipating cryptocurrency prices using machine learning. *Complexity* 2018, 8983590:1-8983590:16. https://doi.org/10.1155/2018/8983590.

Al-Hashedi, K. G., Magalingam, P., 2021. Financial fraud detection applying data mining techniques: A comprehensive review from 2009 to 2019. *Comput Sci Rev* 40, 100402. https://doi.org/10.1016/j.cosrev.2021.100402.

Alhenawi, Y., Hassan, M. K., Hasan, R., 2022. Evolution of research in finance over the last two decades–a topographical view. *Res. Int. Bus. Finance* 59, 101550. https://doi.org/10.1016/j.ribaf.2021.101550.

Alkhodhairi, R.K., Aljalhami, S.R., Rusayni, N.K., Alshobaili, J.F., Al-Shargabi, A.A., Alabdulatif, A., 2021. Bitcoin candlestick prediction with deep Neural Networks based on real time data. *CMC-Comput. Mat. Contin.* 68(3), 3215-3233. https://doi.org/10.1016/j.ribaf.2021.101550.

Alonso, S.L.N., Jorge-Vazquez, J., Fernandez, M.A.E., Forradellas, R.F.R., 2021. Cryptocurrency mining from an economic and environmental perspective. Analysis of the most and least sustainable countries. *Energies* 14 (14), 4254. https://doi.org/10.3390/en14144254.

Alonso-Monsalve, S., Suarez-Cetrulo, A.L., Cervantes, A., Quintana, D., 2020. Convolution on Neural Networks for high-frequency trend prediction of cryptocurrency exchange rates using technical indicators. *Expert Syst Appl* 149, 113250. https://doi.org/10.1016/j.eswa.2020.113250.

Anghel, D. G., 2021. A reality check on trading rule performance in the cryptocurrency market: Machine learning vs. technical analysis. Finance. Res. Lett. 39, 101655.

https://doi.org/10.1016/j.frl.2020.101655.

Atsalakis, G.S., Atsalaki, L.G., Pasiouras, F., Zopounidis, C., 2019. Bitcoin price forecasting with neuro-fuzzy techniques. *Eur J Oper Res* 276(2), 770-780. https://doi.org/10.1016/j.ejor.2019.01.040.

Aysan, A.F., Demir, E., Gozgor, G., Lau, C.K.M., 2019. Effects of the geopolitical risks on Bitcoin returns and volatility. *Res Int Bus Financ* 47, 511-518. https://doi.org/10.1016/j.ribaf.2018.09.011.

Balcilar, M., Bouri, E., Gupta, R., Roubaud, D., 2017. Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Econ Model* 64, 74-81. https://doi.org/10.1016/j.econmod.2017.03.019.

Baur, D. G., Hoang, L., 2021. The Bitcoin gold correlation puzzle. *J Behav Exp Financ* 32, 100561 文中未出现.

Bayhan, S., Zubow, A., Gawlowicz, P., Wolisz, A., 2019. Smart contracts for spectrum sensing as a service. *IEEE Trans Cogn Commun Netw* 5(3), 648-660. https://doi.org/10.1109/TCCN.2019.2936190.

Benítez, J.M., Castro, J.L., Requena, I., 1997. Are artificial Neural Networks black boxes? *IEEE Trans Neural Netw* 8, 1156-1164. https://doi.org/10.1109/72.623216.

Bishop, C. M., 2006. Pattern recognition and machine learning (Information science and statistics). Springer-Verlag New York, Inc. https://doi.org/10.1109/TAC.1974.1100578.删除

Borges, T.A., Neves, R.F., 2020. Ensemble of machine learning algorithms for cryptocurrency investment with different data resampling methods. *Appl Soft Comput* 90 , 106187. https://doi.org/10.1016/j.asoc.2020.106187.

Bouri, E., Gupta, R., 2021. Predicting Bitcoin returns: Comparing the roles of newspaper-and internet search-based measures of uncertainty. *Financ. Res. Lett.*

38, 101398. https://doi.org/10.1016/j.frl.2019.101398.

Bouri, E., Gupta, R., Tiwari, A. K., Roubaud, D., 2017. Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Financ. Res. Lett.* 23, 87-95. https://doi.org/10.1016/j.frl.2017.02.009.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L. I., 2017. On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?. *Financ. Res. Lett.* 20, 192-198. https://doi.org/10.1016/j.frl.2016.09.025.

Breiman, L., Friedman, J., Stone, C.J., Olshen, R.A., 1984. Classification and regression trees. *CRC press*.

Chang, T.H., Svetinovic, D., 2020. Improving Bitcoin ownership identification using transaction patterns analysis. *IEEE Trans Syst Man Cybern Syst* 50(1), 9-20. https://doi.org/10.1109/TSMC.2018.2867497.

Chen, C., Chen, Y., Horowitz, M., Hou, H., Liu, Z., Pellegrino, D . ,2009. Towards an explanatory and computational theory of scientific discovery. *J. Informetr.* 3(3), 191-209. https://doi.org/10.1016/j.joi.2009.03.004.

Chen, H.L., Chen, Z.Y., Lin, F.T., Zhuang, P.F., 2021a. Effective management for blockchain-based agri-food supply chains using deep reinforcement learning. *IEEE Access* 9, 36008-36018. https://doi.org/10.1109/ACCESS.2021.3062410.

Chen, S.,2022. Cryptocurrency financial risk analysis based on deep machine learning. Complexity, 2022, 2611063. https://doi.org/10.1155/2022/2611063.

Chen, T.H., Chen, M.Y., Du, G.T., 2021b. The determinants of Bitcoin's price: utilization of GARCH and machine learning approaches. *Comput Econ* 57(1), 267-280. https://doi.org/10.1007/s10614-020-10057-7.

Chen, Z.S., Li, C.H., Sun, W.J., 2020. Bitcoin price prediction using machine learning:

An approach to sample dimension engineering. *J Comput Methods Appl Math* 365, 112395. https://doi.org/10.1016/j.cam.2019.112395.

Chowdhury, R., Rahman, M.A., Rahman, M.S., Mahdy, M.R.C., 2020. An approach to predict and forecast the price of constituents and index of cryptocurrency using machine learning. *Phys A: Stat Mech Appl* 551, 124569. https://doi.org/10.1016/j.physa.2020.124569.

Ciaian, P., Rajcaniova, M., Kancs, D. A., 2016. The economics of Bitcoin price formation. *Appl Econ* 48(19), 1799-1815. https://doi.org/10.1080/00036846.2015.1109038.

Cocco, L., Tonelli, R., Marchesi, M., 2021. Predictions of Bitcoin prices through machine learning based frameworks. *PeerJ Comput. Sci.* 7, e413. https://doi.org/10.7717/peerj-cs.413.

Cohen, G., 2020. Forecasting Bitcoin trends using algorithmic learning systems. *Entropy* 22 (8), 83. https://doi.org/10.3390/e22080838.

Corbet, S., Lucey, B., Urquhart, A., Yarovaya, L., 2019. Cryptocurrencies as a financial asset: A systematic analysis. *Int Rev Financial Anal* 62, 182-199. https://doi.org/10.1016/j.irfa.2018.09.003.

Cortes, C., Vapnik, V., 1995. Support-vector networks. *Mach Learn* 20, 25. https://doi.org/10.1023/A:1022627411411.

Crowcroft, J., Maesa, D.D., Magrini, A., Marino, A., Ricci, L., 2021. Leveraging the users graph and trustful transactions for the analysis of Bitcoin price. *IEEE Trans Netw Sci Eng* 8(2), 1338-1352. https://doi.org/10.1109/TNSE.2020.3008600.

Cybenko, G., 1989. Approximation by superpositions of a sigmoidal function. Math *Control Signal Syst* 5(4), 455. https://doi.org/10.1007/BF02134016.

Dastgir, S., Demir, E., Downing, G., Gozgor, G., Lau, C.K.M., 2019. The causal relationship between Bitcoin attention and Bitcoin returns: Evidence from the Copula-based Granger causality test. *Financ. Res. Lett.* 28, 160-164. https://doi.org/10.1016/j.frl.2018.04.019.

Delfabbro, P., King, D.L., Williams, J., 2021. The psychology of cryptocurrency trading: Risk and protective factors. *J Behav Addict* 10(2), 201-207. https://doi.org/10.1556/2006.2021.00037.

Derbentsev, V., Babenko, V., Khrustalev, K. I. R. I. L. L., Obruch, H., Khrustalova, S. O. F. I. I. A., 2021. Comparative performance of machine learning ensemble algorithms for forecasting cryptocurrency prices. *Int. J. Integr. Eng.* 34(1), 140-148. https://doi.org/ 10.5829/IJE.2021.34.01A.16.

Dyhrberg, A. H.,2016. Bitcoin, gold and the dollar–A GARCH volatility analysis. *Financ. Res. Lett.* 16, 85-92. https://doi.org/10.1016/j.frl.2015.10.008.

El Naqa, I., Murphy, M. J., 2015. What is machine learning?. In machine learning in radiation oncology. Springer, Cham. 3-11. https://doi.org/10.1136/archdischild-2020-319415.

Falagas, M. E., Pitsouni, E. I., Malietzis, G. A., Pappas, G., 2008. Comparison of PubMed, Scopus, web of science, and Google scholar: strengths and weaknesses. *FASEB J.* 22(2), 338-342. https://doi.org/10.1096/fj.07-9492LSF.

Fang, F., Chung, W., Ventre, C., Basios, M., Kanthan, L., Li, L., Wu, F., 2021. Ascertaining price formation in cryptocurrency markets with machine learning. *Eur. J. Finance* 1-23. https://doi.org/10.1080/1351847X.2021.1908390.

Ferdiansyah, F., Othman, S.H., Radzi, R.Z.R.M., Stiawan, D., Sazaki, Y., Ependi, U., 2019. A LSTM-method for Bitcoin price prediction: A case study yahoo finance stock market, 2019 International Conference on Electrical Engineering and Computer Science (ICECOS). *IEEE* 206-210.

https://doi.org/10.1109/ICECOS47637.2019.8984499.

Ferdous, M.S., Chowdhury, M.J.M., Hoque, M.A., 2021. A survey of consensus algorithms in public blockchain systems for crypto-currencies. *J Netw Comput Appl* 182. https://doi.org/10.1016/j.jnca.2021.103035.

Foley, S., Karlsen, J.R., Putniņš, T.J., 2019. Sex, drugs, and Bitcoin: How much illegal activity is financed through cryptocurrencies? *Rev Financ Stud* 32(5), 1798-1853. https://doi.org/10.1093/rfs/hhz015.

Gagarina, M., Nestik, T., Drobysheva, T., 2019. Social and Psychological Predictors of Youths' Attitudes to Cryptocurrency. *Behav Sci* 9 (12), 118. https://doi.org/10.3390/bs9120118.

García-Corral, F.J., Cordero-García, J.A., de Pablo-Valenciano, J., Uribe-Toril, J., 2022. A bibliometric review of cryptocurrencies: how have they grown? *Financ. Innov.* 8(1), 1-31. https://doi.org/10.1186/s40854-021-00306-5.

Gerlach, J.C., Demos, G., Sornette, D., 2019. Dissection of Bitcoin's multiscale bubble history from January 2012 to February 2018. *R Soc Open Sci* 6(7), 180643. https://doi.org/10.1098/rsos.180643.

Gidea, M., Goldsmith, D., Katz, Y., Roldan, P., Shmalo, Y., 2020. Topological recognition of critical transitions in time series of cryptocurrencies. *Phys A: Stat Mech Appl* 548, 123843. https://doi.org/10.1016/j.physa.2019.123843.

Giron, A.A., Martina, J.E., Custodio, R., 2021. Steganographic analysis of blockchains. *Sensors* 21(12), 4078. https://doi.org/10.3390/s21124078.

Goodell, J. W., Goutte, S., 2021a. Co-movement of COVID-19 and Bitcoin: Evidence from wavelet coherence analysis. *Financ. Res. Lett.* 38, 101625. https://doi.org/10.1016/j.frl.2020.101625.

Goodell, J. W., Goutte, S., 2021b. Diversifying equity with cryptocurrencies during

COVID-19. *Int. Rev. Financ. Anal.* 76, 101781. https://doi.org/10.1016/j.irfa.2021.101781.

Jalal, R.N.U.D., Alon, I., Paltrinieri, A., 2021. A bibliometric review of cryptocurrencies as a financial asset. *Technol Anal Strateg Manag* 1-16. https://doi.org/10.1080/09537325.2021.1939001.

Jana, R. K., Ghosh, I., Wallin, M. W., 2022. Taming energy and electronic waste generation in bitcoin mining: Insights from Facebook prophet and deep neural network. *Technol Forecast Soc Change* 178, 121584. https://doi.org/10.1016/j.techfore.2022.121584.

Jang, H., Lee, J., 2017. An empirical study on modeling and prediction of Bitcoin prices with bayesian Neural Networks based on blockchain information. *IEEE Access* 6, 5427-5437.

Jay, P., Kalariya, V., Parmar, P., Tanwar, S., Kumar, N., Alazab, M., 2020. Stochastic Neural Networks for cryptocurrency price prediction. *IEEE Access* 8, 82804-82818. https://doi.org/10.1109/ACCESS.2020.2990659

Ji, S.W., Kim, O.M., Im, H., 2019. A comparative study of Bitcoin price prediction using deep learning. *Mathematics* 7(10), 898. https://doi.org/10.3390/math7100898.

Jia, B., Goodell, J. W., Shen, D., 2022. Momentum or reversal: Which is the appropriate third factor for cryptocurrencies?. *Financ. Res. Lett.* 45, 102139. https://doi.org/10.1016/j.frl.2021.102139.

Jordan, M.I., Mitchell, T.M., 2015. Machine learning: Trends, perspectives, and prospects. *Science* 349, 255-260. https://doi.org/10.1126/science.aaa8415.

Kamal, J. B., Hassan, M. K., 2022. Asymmetric connectedness between cryptocurrency environment attention index and green assets. *J Econ Asymmetries*

25, e00240. https://doi.org/10.1016/j.jeca.2022.e00240.

Kamisalic, A., Kramberger, R., Fister, I., 2021. Synergy of blockchain technology and data mining techniques for anomaly detection. *Appl. Sci.-Basel* 11(17), 7987. https://doi.org/10.3390/app11177987.

Katsiampa, P. 2017. Volatility estimation for Bitcoin: A comparison of GARCH models. *Econ. Lett.* 158, 3-6. https://doi.org/10.1016/j.econlet.2017.06.023.

Khedr, A. M., Arif, I., El-Bannany, M., Alhashmi, S. M., Sreedharan, M., 2021. Cryptocurrency price prediction using traditional statistical and machine-learning techniques: A survey. *Intell. Syst. Account. Finance Manag.* 28(1), 3-34. https://doi.org/10.1002/isaf.1488.

Kim, H. M., Bock, G. W., Lee, G., 2021. Predicting Ethereum prices with machine learning based on Blockchain information. *Expert Syst. Appl.* 184, 115480. https://doi.org/10.1016/j.eswa.2021.115480.

Kleinberg, J., 2002. Bursty and hierarchical structure in streams. In Proceedings of the eighth ACM SIGKDD international conference on knowledge discovery and data mining (pp. 91–101). NewYork, NY: ACM Press. https://doi.org/10.1023/A:1024940629314.

Kondor, D., Posfai, M., Csabai, I., Vattay, G., 2014. Do the rich get richer? An empirical analysis of the Bitcoin transaction network. *PLoS ONE* 9 (2), e86197. https://doi.org/10.1371/journal.pone.0086197.

Kourou, K., Exarchos, T.P., Exarchos, K.P., Karamouzis, M.V., Fotiadis, D.I., 2015. Machine learning applications in cancer prognosis and prediction. *Comput Struct Biotechnol J* 13, 8-17. https://doi.org/10.1016/j.csbj.2014.11.005.

Kumari, A., Tanwar, S., 2021. A reinforcement-learning-based secure demand response scheme for smart grid system. *IEEE Internet Things J* 9(3), 2180-2191.

https://doi.org/10.1109/JIOT.2021.3090305.

Kumari, A., Tanwar, S., 2021. Multiagent-based secure energy management for multimedia grid communication using Q-learning. *Multimed Tools Appl* 1-21. https://doi.org/10.1007/s11042-021-11491-x.

Kurbucz, M.T., 2019. Predicting the price of Bitcoin by the most frequent edges of its transaction network. *Econ. Lett.* 184, 108655. https://doi.org/10.1016/j.econlet.2019.108655.

Lahmiri, S., Bekiros, S., 2019. Cryptocurrency forecasting with deep learning chaotic Neural Networks. *Chaos Solit Fractals* 118, 35-40. https://doi.org/10.1016/j.chaos.2018.11.014

Lahmiri, S., Bekiros, S., 2020a. Intelligent forecasting with machine learning trading systems in chaotic intraday Bitcoin market. *Chaos Solit Fractals* 133, 109641. https://doi.org/10.1016/j.chaos.2020.109641.

Lahmiri, S., Bekiros, S., 2020b. Randomness, Informational entropy, and volatility interdependencies among the major world markets: The role of the COVID-19 pandemic. *Entropy* 22(8), 833. https://doi.org/10.3390/e22080833

Lamothe-Fernandez, P., Alaminos, D., Lamothe-Lopez, P., Fernandez-Gamez, M.A., 2020. Deep learning methods for modeling Bitcoin price. *Mathematics* 8(8), 1245. https://doi.org/10.3390/math8081245.

Lee, R.S.T., 2020. Chaotic type-2 transient-fuzzy deep neuro-oscillatory network (ct2tfdnn) for worldwide financial prediction. *IEEE Trans Fuzzy Syst* 28(4), 731-745. https://doi.org/10.1109/TFUZZ.2019.2914642.

Levulyte, L., Sapkauskiene, A., 2021. Cryptocurrency in context of fiat money functions. *Quart Rev Econ Financ* 82, 44-54. https://doi.org/10.1016/j.qref.2021.07.003.

Li, Y.Z., Jiang, S.R., Wei, Y.J., Wang, S.Y., 2021a. Take Bitcoin into your portfolio: a novel ensemble portfolio optimization framework for broad commodity assets. *Financ. Innov.* 7(1), 1-26. https://doi.org/10.1186/s40854-021-00281-x

Li, Z., Chen, L., Dong, H., 2021b. What are Bitcoin market reactions to its-related events? *Int Rev Econ Financ* 73, 1-10. https://doi.org/10.1016/j.iref.2020.12.020

Libbrecht, M.W., Noble, W.S., 2015. Machine learning applications in genetics and genomics. *Nat Rev Genet* 16(6), 321-332. https://doi.org/10.1038/nrg3920.

Lim, M., Abdullah, A., Jhanjhi, N.Z., 2021. Performance optimization of criminal network hidden link prediction model with deep reinforcement learning. *J King Saud Univ-Comput Inf Sci* 33(10), 1202-1210. https://doi.org/10.1016/j.jksuci.2019.07.010.

Livieris, I.E., Kiriakidou, N., Stavroyiannis, S., Pintelas, P., 2021. An Advanced CNN-LSTM Model for Cryptocurrency Forecasting. *Electronics* 10(3), 287. https://doi.org/10.3390/electronics10030287.

Livieris, I.E., Stavroyiannis, S., Pintelas, E., Kotsilieris, T., Pintelas, P., A dropout weight-constrained recurrent Neural Network model for forecasting the price of major cryptocurrencies and CCi30 index. *Evol Syst* 13(1), 85-100.https://doi.org/10.1007/s12530-020-09361-2.

Lorenzo, L., Arroyo, J., 2022. Analysis of the cryptocurrency market using different prototype-based clustering techniques. *Financial Innov.* 8(1), 1-46. https://doi.org/10.1186/s40854-021-00310-9.

Lucarelli, G., Borrotti, M., 2020. A deep Q-learning portfolio management framework for the cryptocurrency market. *Neural Comput Appl* 32(23), 17229-17244. https://doi.org/10.1007/s00521-020-05359-8.

Lucey, B. M., Vigne, S. A., Yarovaya, L., Wang, Y., 2022. The cryptocurrency uncertainty index. *Financ. Res. Lett.* 45, 102147. https://doi.org/10.1016/j.frl.2021.102147.

Lundberg, S.M., Nair, B., Vavilala, M.S., Horibe, M., Eisses, M.J., Adams, T., Liston, D.E., Low, D.K.-W., Newman, S.-F., Kim, J., 2018. Explainable machine-learning predictions for the prevention of hypoxaemia during surgery. *Nat Biomed Eng* 2(10), 749-760. https://doi.org/10.1038/s41551-018-0304-0

Ma, F.C., Ren, M., Fu, Y., Wang, M.Z., Li, H.Z., Song, H.B., Jiang, Y., 2021. Security reinforcement for Ethereum virtual machine. *Inf Process Manag* 58(4), 102565. https://doi.org/10.1016/j.ipm.2021.102565.

Madan, I., Saluja, S., Zhao, A., 2015. Automated bitcoin trading via machine learning algorithms. URL: http://cs229. stanford. edu/proj2014/Isaac% 20Madan, 20.

Mahesh, B., 2020. Machine learning algorithms-a review. *Int. J. Sci. Res.* 9, 381-386.

Mallqui, D.C.A., Fernandes, R.A.S., 2019. Predicting the direction, maximum, minimum and closing prices of daily Bitcoin exchange rate using machine learning techniques. *Appl Soft Comput* 75, 596-606. https://doi.org/10.1016/j.asoc.2018.11.038.

Manavi, S.A., Jafari, G., Rouhani, S., Ausloos, M., 2020. Demythifying the belief in cryptocurrencies decentralized aspects. A study of cryptocurrencies time cross-correlations with common currencies, commodities and financial indices. *Phys A: Stat Mech Appl* 556, 124759. https://doi.org/10.1016/j.physa.2020.124759.

Mao, D.H., Wang, F., Wang, Y.L., Hao, Z.H., 2019. Visual and user-defined smart contract designing system based on automatic coding. *IEEE Access* 7, 73131-73143. https://doi.org/10.1016/j.physa.2020.124759.

McNally, S., Roche, J., Caton, S., 2018, March. Predicting the price of Bitcoin using machine learning. *In 2018 26th Proc Euromicro Int Conf Parallel Distrib Netw*

Based Process 339-343. https://doi.org/10.1109/ACCESS.2019.2920776

Meiklejohn, S., Pomarole, M., Jordan, G., Levchenko, K., McCoy, D., Voelker, G.M., Savage, S., 2016. A fistful of Bitcoins: characterizing payments among men with no names. *Commun. ACM* 59(4), 86-93. https://doi.org/10.1145/2896384.

Michalski, R., Dziubaltowska, D., Macek, P., 2020. Revealing the character of nodes in a blockchain with supervised learning. *IEEE Access* 8, 109639-109647. https://doi.org/10.1109/ACCESS.2020.3001676.

Mills, D.J., Nower, L., 2019. Preliminary findings on cryptocurrency trading among regular gamblers: A new risk for problem gambling? *Addict Behav* 92, 136-140. https://doi.org/10.1016/j.addbeh.2019.01.005.

Mohamed, M.A., El-Henawy, I.M., Salah, A., 2022. Price prediction of seasonal items using machine learning and statistical methods. C*MC- Comput Mater Contin* 70(2), 3473-3489.

Mongeon, P., Paul-Hus, A.,2016. The journal coverage of Web of Science and Scopus: a comparative analysis. *Scientometrics.* 106(1), 213-228. https://doi.org/10.1007/s11192-015-1765-5.

Mudassir, M., Bennbaia, S., Unal, D., Hammoudeh, M., 2020. Time-series forecasting of Bitcoin prices using high-dimensional features: a machine learning approach. *Neural Comput Appl* 1-15. https://doi.org/10.1007/s00521-020-05129-6.

Nakamoto, S., 2008. Bitcoin: A peer-to-peer electronic cash system. *Decentralized Bus Rev* 21260.

Nakano, M., Takahashi, A., Takahashi, S., 2018. Bitcoin technical trading with artificial Neural Network. *Phys A: Stat Mech Appl* 510, 587-609. https://doi.org/10.1016/j.physa.2018.07.017.

Nerurkar, P., Bhirud, S., Patel, D., Ludinard, R., Busnel, Y., Kumari, S., 2021.

Supervised learning model for identifying illegal activities in Bitcoin. *Appl. Intell.* 51(6), 3824-3843. https://doi.org/10.1007/s10489-020-02048-w.

Nghiem, H., Muric, G., Morstatter, F., Ferrara, E., 2021. Detecting cryptocurrency pump-and-dump frauds using market and social signals. *Expert Syst Appl* 182, 115284. https://doi.org/10.1016/j.eswa.2021.115284.

Nikic, V., 2018. Perception of user interests for the development of Bitcoin, the new payment technology in the see countries. *Transform Bus Econ* 17 (3C), 106-115.

Nosratabadi, S., Mosavi, A., Duan, P., Ghamisi, P., Filip, F., Band, S.S., Reuter, U., Gama, J., Gandomi, A.H., 2020. Data science in economics: comprehensive review of advanced machine learning and deep learning methods. *Mathematics* 8(10), 1799. https://doi.org/10.3390/math8101799.

Papadamou, S., Kyriazis, N.A., Tzeremes, P., Corbet, S., 2021. Herding behaviour and price convergence clubs in cryptocurrencies during bull and bear markets. *J Behav Exp Financ* 30, 100469. https://doi.org/10.1016/j.jbef.2021.100469.

Patel, M.M., Tanwar, S., Gupta, R., Kumar, N., 2020. A deep learning-based cryptocurrency price prediction scheme for financial institutions. *J Inf Secur Appl* 55, 102583. https://doi.org/10.1016/j.jisa.2020.102583.

Peng, Y.H., Albuquerque, P.H.M., de Sa, J.M.C., Padula, A.J.A., Montenegro, M.R., 2018. The best of two worlds: Forecasting high frequency volatility for cryptocurrencies and traditional currencies with Support Vector Regression. *Expert Syst Appl* 97, 177-192. https://doi.org/10.1016/j.eswa.2017.12.004.

Poongodi, M., Sharma, A., Vijayakumar, V., Bhardwaj, V., Sharma, A.P., Iqbal, R., Kumar, R., 2020. Prediction of the price of Ethereum blockchain cryptocurrency in an industrial finance system. *Comput Electr Eng* 81, 106527. https://doi.org/10.1016/j.compeleceng.2019.106527.

Qin, M., Su, C.-W., Tao, R., 2021. Bitcoin: A new basket for eggs? *Econ Model* 94, 896-907. https://doi.org/10.1016/j.econmod.2020.02.031.

Qiu, T., Zhang, M., Liu, X.Z., Liu, J., Chen, C., Zhao, W.B., 2021. A directed edge weight prediction model using decision tree ensembles in industrial Internet of things. *IEEE Trans Industr Inform* 17(3), 2160-2168. https://doi.org/10.1109/TII.2020.2995766.

Quinlan, J.R., 1979. Discovering rules by induction from large collections of examples. *Expert Syst Micro Electron Age. Edinburgh University Press.*

Quinlan, J.R., 1986. Induction of decision trees. *Mach. Learn.* 1(1), 81-106. https://doi.org/10.1023/A:1022643204877.

Quinlan, J.R., 2014. C4. 5: programs for machine learning. *Elsevier*.

Rakkini, M.J.J., Geetha, K., 2021. Deep learning classification of Bitcoin miners and exploration of upper confidence bound algorithm with less regret for the selection of honest mining. *J Ambient Intell Humaniz Comput* 1-17. https://doi.org/10.1007/s12652-021-03527-9.

Rudin, C., 2019. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nat. Mach. Intell.* 1(5), 206-215. https://doi.org/10.1038/s42256-019-0048-x.

Saad, M., Choi, J.C., Nyang, D., Kim, J., Mohaisen, A., 2020. Toward characterizing blockchain-based cryptocurrencies for highly accurate predictions. *IEEE Syst. J.* 14(1), 321-332. https://doi.org/10.1109/JSYST.2019.2927707

Sattarov, O., Muminov, A., Lee, C.W., Kang, H.K., Oh, R., Ahn, J., Oh, H.J., Jeon, H.S., 2020. Recommending cryptocurrency trading points with deep reinforcement learning approach. *Appl. Sci.-Basel* 10(4), 150. https://doi.org/10.3390/app10041506

Schnaubelt, M., 2022. Deep reinforcement learning for the optimal placement of cryptocurrency limit orders. *Eur. J. Oper. Res.* 296(3), 993-1006. https://doi.org/10.1016/j.ejor.2021.04.050.

Sebastiao, H., Godinho, P., 2021. Forecasting and trading cryptocurrencies with machine learning under changing market conditions. *Financ. Innov.* 7(1), 1-30. https://doi.org/10.1186/s40854-020-00217-x.

Seo, M., Kim, G., 2020. Hybrid forecasting models based on the Neural Networks for the volatility of Bitcoin. *Appl. Sci.-Basel* 10(14), 4768. https://doi.org/10.3390/app10144768.

Serrano, W., 2021. The random Neural Network in price predictions. *Neural. Comput. Appl.* 34(2), 855-873. https://doi.org/10.1007/s00521-021-05903-0.

Shahbazi, Z., Byun, Y. C., 2022. Knowledge Discovery on Cryptocurrency Exchange Rate Prediction Using Machine Learning Pipelines. Sensors 22(5), 1740. https://doi.org/10.3390/s22051740.

Shayegan, M. J., Sabor, H. R., Uddin, M., Chen, C. L., 2022. A Collective Anomaly Detection Technique to Detect Crypto Wallet Frauds on Bitcoin Network. Symmetry 14(2), 328. https://doi.org/10.3390/sym14020328.

Small, H., 1973. Co-citation in the scientific literature: A new measure of the relationship between two documents. *J Am Soc Inf Sci Technol* 24(4), 265-269. https://doi.org/10.1002/asi.4630240406.

Song, J.Y., Chang, W., Song, J.W., 2019. Cluster analysis on the structure of the cryptocurrency market via Bitcoin-Ethereum filtering. Physica A 527, 121339. https://doi.org/10.1016/j.physa.2019.121339.

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., Salakhutdinov, R., 2014. Dropout: a simple way to prevent Neural Networks from overfitting. *J Mach Learn*

Res 15, 1929-1958. http://dl.acm.org/citation.cfm?id=2670313.

Steinert, L., Herff, C., 2018. Predicting altcoin returns using social media. *PLoS ONE* 13(12), e0208119. https://doi.org/10.1371/journal.pone.0208119.

Su, C.-W., Qin, M., Tao, R., Umar, M., 2020. Financial implications of fourth industrial revolution: Can Bitcoin improve prospects of energy investment? *Technol Forecast Soc Change* 158(9), 120178. https://doi.org/10.1016/j.techfore.2020.120178.

Sun, X.L., Liu, M.X., Sima, Z.Q., 2020. A novel cryptocurrency price trend forecasting model based on LightGBM. *Financ. Res. Lett.* 32, 101084. https://doi.org/10.1016/j.frl.2018.12.032.

Sun, X.W., Yang, T., Hu, B., 2021. LSTM-TC: Bitcoin coin mixing detection method with a high recall. *Appl. Intell.* 52(1), 780-793. https://doi.org/10.1007/s10489-021-02453-9.

Suzuki, Y., Hino, H., Hawai, T., Saito, K., Kotsugi, M., Ono, K., 2020. Symmetry prediction and knowledge discovery from X-ray diffraction patterns using an interpretable machine learning approach. *Sci. Rep.* 10(1), 21790. https://doi.org/10.1038/s41598-020-77474-4.

Tanwar, S., Patel, N.P., Patel, S.N., Patel, J.R., Sharma, G., Davidson, I.E., 2021. Deep learning-based cryptocurrency price prediction scheme with inter-dependent relations. *IEEE Access* 9, 138633-138646. https://doi.org/10.1109/ACCESS.2021.3117848.

Tian, Z.Z., Tian, J., Wang, Z.M., Chen, Y.P., Xia, H., Chen, L.W., 2022. Landscape estimation of solidity version usage on Ethereum via version identification. *Int. J. Intell. Syst.* 37(1), 450-477. https://doi.org/10.1002/int.22633.

Tsimpourlas, F., Rooijackers, G., Rajan, A., Allamanis, M., 2021. Embedding and classifying test execution traces using Neural Networks. *IET Softw.* 16(3), 301-316.https://doi.org/10.1049/sfw2.12038.

Uras, N., Marchesi, L., Marchesi, M., Tonelli, R., 2020. Forecasting Bitcoin closing price series using linear regression and Neural Networks models. *PeerJ Comput. Sci.* 6, e279. https://doi.org/10.7717/peerj-cs.279.

Urquhart, A., 2017. Price clustering in Bitcoin. *Econ. Lett.* 159, 145-148. https://doi.org/10.1016/j.econlet.2017.07.035.

Urquhart, A., Zhang, H., 2018. Is Bitcoin a hedge or safe-haven for currencies. An intraday analysis. *Int. Rev. Financial Anal.* 63, 49-57. https://doi.org/10.1016/j.irfa.2019.02.009.

Valencia, F., Gomez-Espinosa, A., Valdes-Aguirre, B., 2019. Price movement prediction of cryptocurrencies using sentiment analysis and machine learning. *Entropy* 21(6), 589. https://doi.org/10.3390/e21060589.

Vieira, E., Gomes, J., 2009. A comparison of Scopus and Web of Science for a typical university. *Scientometrics.* 81(2), 587-600. https://doi.org/10.1007/s11192-009-2178-0.

Wang, Q., Li, X.X., Yu, Y., 2018. Anonymity for Bitcoin From Secure Escrow Address. *IEEE Access* 6, 12336-12341. https://doi.org/10.1109/ACCESS.2017.2787563.

Wang, T.T., Liew, S.C., Zhang, S.L., 2021. When blockchain meets AI: Optimal mining strategy achieved by machine learning. *Int. J. Intell. Syst.* 36(5), 2183-2207. https://doi.org/10.1002/int.22375.

Wei, W.Q., Zhang, Q., Liu, L., 2021. Bitcoin transaction forecasting with deep network representation learning. *IEEE trans. emerg. top. comput. intell.* 9(3), 1359-1371. https://doi.org/10.1109/TETC.2020.3010464.

Weng, L.G., Sun, X.D., Xia, M., Liu, J., Xu, Y.Q., 2020. Portfolio trading system of digital currencies: A deep reinforcement learning with multidimensional attention gating mechanism. *Neurocomputing* 402, 171-182. https://doi.org/10.1016/j.neucom.2020.04.004.

Wu, J., Yuan, Q., Lin, D., You, W., Chen, W., Chen, C., Zheng, Z, 2020. Who are the phishers? phishing scam detection on ethereum via network embedding. *IEEE Trans. Syst. Man Cybern. Syst.* 52(2), 1156-1166. https://doi.org/10.1109/TSMC.2020.3016821.

Wu, J.J., Liu, J.L., Zhao, Y.J., Zheng, Z.B., 2021. Analysis of cryptocurrency transactions from a network perspective: An overview. *J. Netw. Comput.Appl.* 190, 103139. https://doi.org/10.1016/j.jnca.2021.103139.

Xu, M., Chen, X.T., Kou, G., 2019. A systematic review of blockchain. *Financial Innov.* 5(1), 1-14. https://doi.org/10.1186/s40854-019-0147-z.

Yasir, M., Attique, M., Latif, K., Chaudhary, G.M., Afzal, S., Ahmed, K., Shahzad, F., 2020. Deep-learning-assisted business intelligence model for cryptocurrency forecasting using social media sentiment. *J. Enterp. Inf. Manag.* https://doi.org/10.1108/JEIM-02-2020-0077.

Yue, Y., Li, X.R., Zhang, D.X., Wang, S.Y., 2021. How cryptocurrency affects economy? A network analysis using bibliometric methods. *Int. Rev. Financial Anal.* 77, 101869. https://doi.org/10.1016/j.irfa.2021.101869.

Żbikowski, K., 2016. Application of machine learning algorithms for bitcoin automated trading. In Machine intelligence and big data in industry (pp. 161-168). Springer, Cham. In: Ryżko, D., Gawrysiak, P., Kryszkiewicz, M., Rybiński, H. (eds) Machine Intelligence and Big Data in Industry. Studies in Big Data, vol 19. Springer, Cham. https://doi.org/10.1007/978-3-319-30315-4_14.

Zhang, Z.R., Dai, H.N., Zhou, J.H., Mondal, S.K., Garcia, M.M., Wang, H., 2021.

Forecasting cryptocurrency price using convolutional Neural Networks with weighted and attentive memory channels. *Expert Syst. Appl.* 183, 115378. https://doi.org/10.1016/j.eswa.2021.115378.

Zheng, B.K., Zhu, L.H., Shen, M., Du, X.J., Guizani, M., 2020. Identifying the vulnerabilities of Bitcoin anonymous mechanism based on address clustering. *Sci. China Inf. Sci.* 63(3), 1-15. https://doi.org/10.1007/s11432-019-9900-9.

Zhou, G.Q., Zhuge, J.W., Fan, Y.Q., Du, K., Lu, S.Q., 2020. A market in dream: the rapid development of anonymous cybercrime. *Mob. Netw. Appl.* 25(1), 259-270. https://doi.org/10.1007/s11036-019-01440-2.

Tables

Table 1 Definition of machine learning

Number	Article	Definition
1	Jordan and Mitchell (2015)	A learning problem can be defined as the problem of improving some measure of performance when executing some tasks, through some type of training experience.
2	Mahesh (2020)	Machine learning is the scientific study of algorithms and statistical models that computer systems use to perform a specific task without being explicitly programmed.
3	El Naqa and Murphy (2015)	Machine learning is an evolving branch of computational algorithms that are designed to emulate human intelligence by learning from the surrounding environment.

Table 1 Literature search sentence

Topic	Retrieval statement
Machine learning	TS = ("machine learning" OR " Supervised Learning" OR "Support Vector Machine" OR "Random Forest" OR "Classification Tree" OR "Discriminant analysis" OR "Data Fluctuation Network" OR "Recurrent Neural Network" OR " Convolutional Neural Network" OR "Long-Short Term Memory" OR "Wavelet-Based Neural Networks" OR "Feed-Forward Deep Network" OR "Back propagation neural network" OR "Generative Adversarial Network" OR "Artificial Neural Network" OR "Radial Basis Function Network" OR "Kernel-based Extreme Learning" OR "Simulated-Based Neural Network" OR "REGRESSION" OR "bayes" OR "Conditional Demand Analysis" OR "genetic programming" OR "particle swarm algorithm" OR "radial basis function" OR "decision tree" OR "case based reasoning" OR "k nearest neighbor" OR "Clustering" OR "self organising map" OR "expectation maximization" OR "restricted Boltzmann machine" OR "gaussian mixture" OR "model low density separation" OR "generative models" OR "graph based methods" OR "semi-superverised" OR "q learning" OR "temporal difference" OR "deep adversarial network" OR "reinforced" OR "Ensemble Empirical Mode Decomposition" OR "Extreme Gradient Boosting" OR "Ensemble Methods" OR "statistics based learning " OR "logistic regression" OR "naive bayes" OR "discriminant analysis" OR "data envelop analysis" OR "isotonic separation" OR "mahalanobis taguchi" OR "Auto-Encoder" OR "automated machine learning" OR "deep neural networks" OR "Deep Learning" OR "Genetic Algorithm" OR "group method of data handling " OR "rough sets" OR "Agent-Based Algorithmic Learning" OR "Restricted Boltzmann Machine" OR "Particle Swarm Optimization" OR " Soft Computing" OR "Deep Stacking

	Network" OR "fuzzy sets" OR " LSTM" OR "neural network" OR "neural networks"))
Cryptocurrency	TS= ("bitcoin" OR "cryptocurrenc*" OR "crypto-currenc*" OR "litecoin" OR "ethereum" OR "digital currenc*" OR "initial coin offerings" OR "Virtual assets"))
Type	DT= (Article OR Review)

Table 2 Top ten most cited articles in this field[4]

Rank	Title	Article	Topic	Algorithms	Cited
1	Price clustering in Bitcoin	Urquhart (2017)	the Inefficiency of Bitcoin	Random Walk	43
2	Volatility estimation for Bitcoin: A comparison of GARCH models	Katsiampa (2017)	Volatility Estimation for Bitcoin	GARCH	42
3	Bitcoin, gold and the dollar–A GARCH volatility analysis	Dyhrberg (2016)	Financial Asset Capabilities of Bitcoin	GARCH	39
4	On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?	Bouri et al. (2017)	the Hedge and Safe Haven Properties of Bitcoin	Dynamic Conditional Correlation	40
5	An empirical study on modeling and prediction of Bitcoin prices with Bayesian Neural Networks based on blockchain information	Jang and Lee (2017)	Modeling and Prediction of Bitcoin Prices	Bayesian Neural Networks	37
6	Can volume predict Bitcoin returns and volatility? A quantiles-based approach	Balcilar et al. (2017)	Predict Bitcoin Returns and Volatility	Quantiles-Based Approach	33
7	Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions	Bouri et al. (2017)	Bitcoin's Function	Wavelet-Based Quantile-in-Quantile Regressions	31
8	The economics of Bitcoin price formation	Ciaian et al. (2016)	Bitcoin Price Formation	Multivariate Vector Auto Regressive	30

[4] Note: ① The data in this table are calculated by CiteSpace. ②Cited refers to the number of times that each paper is cited by the literatures in the sample (including 363 articles, other 11 reviews are ignored).

9	Exploring the dynamic relationships between cryptocurrencies and other. financial assets	Corbet et al. (2018)	intensity of spillovers	measurement of volatility spillovers	30
10	Predicting the price of Bitcoin using machine learning	McNally et al. (2018)	Prediction of Bitcoin Prices Direction	Recurrent Neural Network LSTM	29

Table 3 Top ten Journals with the most papers published in this field

Number	Journal	Counts	Proportion	JCR
1	*IEEE Access*	43	9.885%	Computer Science, Theory & Methods
2	*Finance Research Letters*	20	4.640%	Business, Finance
3	*Mathematics*	11	2.529%	Mathematics
4	*Physica A Statistical Mechanics and Its Applications*	11	2.529%	Physics, Multidisciplinary
5	*Applied Soft Computing*	10	2.299%	Computer Science, Interdisciplinary Applications
6	*Expert Systems with Applications*	10	2.299%	Operations Research & Management Science
7	*Plos One*	9	2.069%	Multidisciplinary Sciences
8	*Entropy*	8	1.839%	PHYSICS, MULTIDISCIPLINARY
9	*Financial Innovation*	8	1.839%	BUSINESS, FINANCE
10	*Research in International Business and Finance*	7	1.609%	Business, Finance

Table 4 Application of linear model in cryptocurrency[5]

Number	Author	Title	Journal	Topic	Algorithm
1	Sebastiao and Godinho (2021)	Forecasting and trading cryptocurrencies with machine learning under changing market conditions	*Financial Innovation*	Prediction	LM RF
2	Uras et al. (2020)	Forecasting Bitcoin closing price series using linear regression and Neural Networks models	*PeerJ Computer Science*	Prediction	LR NN
3	Song et al. (2019)	Cluster analysis on the structure of the cryptocurrency market via Bitcoin-Ethereum filtering	*Physica A: Statistical Mechanics and its Applications*	Market Structure	LR Cluster MST
4	Michalski et al. (2020)	Revealing the Character of Nodes in a Blockchain with Supervised Learning	*IEEE Access*	Other	DT NN LM SVM
5	Cohen (2020)	Forecasting Bitcoin Trends Using Algorithmic Learning Systems	*Entropy*	Prediction	Darvas Box LR
6	Mohamed et al. (2022)	Price Prediction of Seasonal Items Using Machine Learning and Statistical Methods	*CMC-Computers Materials & Continua*	Prediction	SVR LR RF ARIMA

5 Note: The algorithms involved in the table are abbreviated, LR refers to Linear Regression; LM refers to Linear Model; DT represents Decision Tree; NN refers to Neural Network; MST refers to Minimum Spanning Tree; SVR refers to Support Vector Regressor; RF refers to Random Forest and AR refers to Autoregressive; SVM refers to Support Vector Machine.

7	Mills and Nower (2019)	Preliminary findings on cryptocurrency trading among regular gamblers: A new risk for problem gambling?	*Addictive Behaviors*	Risk Management	LR
8	Saad et al. (2020)	Toward characterizing blockchain-based cryptocurrencies for highly accurate predictions	*IEEE Systems Journal*	Prediction	LM NN
9	Chen et al. (2020)	Bitcoin price prediction using machine learning: An approach to sample dimension engineering	*Journal of Computational and Applied Mathematics*	Prediction	NN LM EM SVM
10	Poongodi et al. (2020)	Prediction of the price of Ethereum blockchain cryptocurrency in an industrial finance system	*Computers & Electrical Engineering*	Prediction	LM SVM
16	Akyildirim et al. (2021)	Prediction of cryptocurrency returns using machine learning.	*Annals of Operations Research*	Prediction	SVM LM NN EM
11	Crowcroft et al. (2021)	Leveraging the users graph and trustful transactions for the analysis of Bitcoin price	*IEEE Transactions on Network Science and Engineering*	Factor	AR LR
12	Levulyte and Sapkauskiene (2021)	Cryptocurrency in context of fiat money functions	*Quarterly Review of Economics and Finance*	Ability of Cryptocurrencies	Cluster LR
13	Borges and Neves (2020)	Ensemble of machine learning algorithms for cryptocurrency investment with different data resampling methods	*Applied Soft Computing*	Investment Strategy	EM LM DT

					SVM
14	Nikic (2018)	Perception of user Interests for the development of Bitcoin, the new payment technology in the see countries	*Transformations in Business & Economics*	Adoption	LR
15	Yasir et al. (2020)	Deep-learning-assisted business intelligence model for cryptocurrency forecasting using social media sentiment	*Journal of Enterprise Information Management*	Prediction	NN SVM LM
17	Serrano (2021)	The random Neural Network in price predictions	*Neural Computing & Applications*	Prediction	LR LSTM RNN
18	Gagarina et al. (2019)	Social and psychological predictors of youths' attitudes to cryptocurrency	*Behavioral Sciences*	Adoption	LR
19	Steinert and Herff (2018)	Predicting altcoin returns using social media	*Plos One*	Prediction	LR
20	Alonso et al. (2021)	Cryptocurrency mining from an economic and environmental perspective	*Energies*	Factor	LR
21	Mohamed et al. (2022)	Price Prediction of Seasonal Items Using Machine Learning and Statistical Methods	*CMC-Computers Materials & Continua*	Prediction	SVR LR RF Ridge model ARIMA

Table 5 Application of decision trees in cryptocurrency[6]

Number	Author	Title	Journal	Topic	Algorithm
1	Lahmiri and Bekiros (2020a)	Intelligent forecasting with machine learning trading systems in chaotic intraday Bitcoin market	*Chaos, Solitons & Fractals*	Prediction	NN SVM DT
2	Michalski et al. (2020)	Revealing the Character of Nodes in a Blockchain with Supervised Learning	*IEEE Access*	Other	DT EM NN LM SVM
3	Ferdous et al. (2021)	A survey of consensus algorithms in public blockchain systems for crypto-currencies	*Journal of Network and Computer Applications*	Suitability of Consensus Algorithms	DT
4	Abu Al-Haija and Alsulami (2021)	High performance classification model to identify ransomware payments for heterogeneous Bitcoin networks	*Electronics*	Identify Ransomware Payments	NN DT
5	Chen et al. (2021b)	The determinants of Bitcoin's price: Utilization of GARCH and machine learning approaches	*Computational Economics*	Determinants of Bitcoin's Price	GARCH DT SVM
6	Nerurkar et al. (2021)	Supervised learning model for identifying illegal activities in Bitcoin	*Applied Intelligence*	Identifying Illegal Activities in Bitcoin	DT
7	Qiu et al. (2021)	A directed edge weight prediction model using DT ensembles in industrial Internet of things	*IEEE Transactions on Industrial Informatics*	Prediction	DT RF

[6] Note: The algorithms involved in the table are abbreviated, LM refers to Linear Model; DT represents Decision Tree; NN refers to Neural Network; RF represents Random Forest; GB represents Gradient Boosting; SVM refers to Support Vector Machine.

					GB DT Extreme GB Light GBM
8	Sun et al. (2020)	A novel cryptocurrency price trend forecasting model based on Light GBM	*Finance Research Letters*	Prediction	GB DT Light GBM
9	Zhou et al. (2020)	A market in dream: the rapid development of anonymous cybercrime	*Mobile Networks and Applications volume*	Identifying Illegal Activities	DT

Table 6 Application of neural network in cryptocurrency[7]

Number	Author	Title	Journal	Topic	Algorithm
1	Akyildirim et al. (2021)	Prediction of cryptocurrency returns using machine learning	*Annals of Operations Research*	Prediction	SVM LM NN EM
2	Alessandretti et al. (2018)	Anticipating cryptocurrency prices using machine learning	*Complexity*	Prediction	NN EM
3	Weng et al. (2020)	Portfolio trading system of digital currencies: A deep reinforcement learning with multidimensional attention gating mechanism	*Neurocomputing*	Investing Strategy	RL NN
4	Chen et al. (2020)	Bitcoin price prediction using machine learning: An approach to sample dimension engineering	*Journal of Computational and Applied Mathematics*	Prediction	NN LM EM SVM
5	Chowdhury et al. (2020)	An approach to predict and forecast the price of constituents and index of cryptocurrency using machine learning	*Physica A: Statistical Mechanics and its Applications, 124569.*	Prediction	NN EM
6	Ferdiansyah et al. (2019)	A LSTM-Method for Bitcoin price prediction: A case study yahoo finance stock market	*In 2019 International Conference on Electrical Engineering and Computer Science (ICECOS)*	Prediction	NN

[7] Note: The algorithm involved in the table is expressed in the form of abbreviation, LM refers to Linear Model; DT refers to Decision Tree; NN refers to Neural Network; RF represents Random Forest; GRU represents Gated population Unit; EM refers to Ensemble Model; RL refers to Reinforcement Learning; MLP refers to Multilayer Perceptron; DNN refers to Deep Neural Network; RNN refers to Recurrent Neural Networks; BNN refers to Bayesian Neural Network; FNN refers to Feedforward Neural Networks.

7	Jay et al. (2020)	Stochastic Neural Networks for cryptocurrency price prediction	*IEEE Access*	Prediction	NN
8	Ji et al. (2019)	A comparative study of Bitcoin price prediction using deep learning	*Mathematics*	Prediction	NN
9	Lahmiri and Bekiros (2019)	Cryptocurrency forecasting with deep learning chaotic Neural Networks	*Chaos, Solitons & Fractals*	Prediction	NN
10	Lahmiri and Bekiros (2020a)	Intelligent forecasting with machine learning trading systems in chaotic intraday Bitcoin market	*Chaos, Solitons & Fractals*	Prediction	NN SVM DT
11	Lamothe-Fernandez et al. (2020)	Deep learning methods for modeling Bitcoin price	*Mathematics*	Prediction	NN
12	Lucarelli and Borrotti (2020)	A deep Q-learning portfolio management framework for the cryptocurrency market	*Neural Computing and Applications*	Investing Strategy	NN RL
13	Mallqui and Fernandes (2019)	predicting the direction, maximum, minimum and closing prices of daily Bitcoin exchange rate using machine learning techniques	*Applied Soft Computing*	Prediction	NN SVM
14	Michalski et al. (2020)	Revealing the character of nodes in a blockchain with supervised learning	*IEEE Access*	Other	DT EM NN LM SVM
15	Mudassir et al. (2020)	Time-series forecasting of Bitcoin prices using high-dimensional features: a machine learning	*Neural Computing and Applications*	Prediction	NN SVM

		approach.			
16	Saad et al. (2020)	Toward characterizing blockchain-based cryptocurrencies for highly accurate predictions	*IEEE Systems Journal*	Prediction	LM NN
17	Sattarov et al. (2020)	Recommending cryptocurrency trading points with deep reinforcement learning approach	*Applied Sciences*	Investing Strategy	RL NN
18	Uras et al. (2020)	Forecasting Bitcoin closing price series using linear regression and Neural Networks models	*PEERJ Computer Science*	Prediction	NN
19	Valencia et al. (2019)	Price movement prediction of cryptocurrencies using sentiment analysis and machine learning	*Entropy*	Prediction	NN SVM EM
20	Yasir et al. (2020)	Deep-learning-assisted business intelligence model for cryptocurrency forecasting using social media sentiment	*Journal of Enterprise Information Management*	Prediction	NN SVM LM
21	Nakano et al. (2018)	Bitcoin technical trading with artificial Neural Network	*Physica A: Statistical Mechanics and its Applications*	Investing Strategy	NN
22	Seo and Kim (2020)	Hybrid forecasting models based on the Neural Networks for the volatility of Bitcoin	*Applied Sciences*	Prediction	NN
23	Patel et al. (2020);	A deep learning-based cryptocurrency price prediction scheme for financial institutions	*Journal of information security and applications*	Prediction	LSTM GRU
	Tanwar et al. (2021)	Deep learning-based cryptocurrency price prediction scheme with inter-dependent relations	*IEEE Access*	Prediction	LSTM GRU
24	Alonso-Monsalve et al. (2020)	Convolution on Neural Networks for high-frequency trend prediction of cryptocurrency	*Expert Systems with Applications*	Prediction	CNN Hybrid CNN-

		exchange rates using technical indicators			LSTM Network MLP
25	Alkhodhairi et al. (2021)	Bitcoin candlestick prediction with deep Neural Networks based on real time data	*CMC-Computers Materials & Continua*	Prediction	NN LSTM GRU
26	Livieris et al. (2021)	A dropout weight-constrained recurrent Neural Network model for forecasting the price of major cryptocurrencies and cci30 index	*Evolving Systems*	Prediction	RNN
27	Wei et al. (2021)	Bitcoin transaction forecasting with deep network representation learning	*IEEE Transactions on Emerging Topics in Computing*	Prediction	DNN
28	Cocco et al. (2021)	Predictions of Bitcoin prices through machine learning based frameworks	*PeerJ Computer Science*	Prediction	BNN
29	Livieris et al. (2021)	An advanced CNN-LSTM model for cryptocurrency forecasting	*Electronics*	Prediction	CNN-LSTM
30	Kurbucz (2019)	Predicting the price of Bitcoin by the most frequent edges of its transaction network	*Economics Letters*	Prediction	FNN
31	Atsalakis et al. (2019)	Bitcoin price forecasting with neuro-fuzzy techniques	*European Journal of Operational Research*	Prediction	Hybrid Neuro-Fuzzy Controller
32	Jang and Lee (2018)	An empirical study on modeling and prediction of Bitcoin prices with Bayesian Neural Networks based on blockchain information	*IEEE Access*	Prediction	BNN
33	Tsimpourlas et al.	Embedding and classifying test execution traces	*IET Software*	Other	NN

	(2021)	using Neural Networks			
34	Tian et al. (2022)	Landscape estimation of solidity version usage on Ethereum via version	*International Journal of Intelligent Systems*	Other	DNN
35	Zhang et al. (2021)	Forecasting cryptocurrency price using convolutional Neural Networks with weighted and attentive memory channels	*Expert Systems with Applications*	Prediction	CNN
36	Nghiem et al. (2021)	Detecting cryptocurrency pump-and-dump frauds using market and social signals	*Expert Systems with Applications*	Detecting Frauds	NN
37	Lee (2020)	Chaotic type-2 transient-fuzzy deep neuro-oscillatory network (ct2tfdnn) for worldwide financial prediction	*IEEE Transactions on Fuzzy Systems*	Prediction	RNN
38	Jana et al. (2022)	Taming energy and electronic waste generation in bitcoin mining: Insights from Facebook prophet and deep neural network	*Technological Forecasting and Social Change*	Prediction	Facebook's Prophet algorithm DNN
39	Chen (2022)	Cryptocurrency Financial Risk Analysis Based on Deep Machine Learning	*Complexity*	Prediction	DNN
40	Hwang et al. (2022)	Code-Targeted Convolutional Neural Network Architecture for Smart Contract Vulnerability Detection	*IEEE ACCESS*	vulnerability detection	CNN

Table 7 Application of SVM in cryptocurrency[8]

Number	Author	Title	Journal	Topic	Algorithm
1	Akyildirim et al. (2021)	Prediction of cryptocurrency returns using machine learning	*Annals of Operations Research*	Prediction	SVM LM NN EM
2	Borges and Neves (2020)	Ensemble of machine learning algorithms for cryptocurrency investment with different data resampling methods	*Applied Soft Computing*	Investing Strategy	EM LM SVM
3	Chen et al. (2020)	Bitcoin price prediction using machine learning: An approach to sample dimension engineering	*Journal of Computational and Applied Mathematics*	Prediction	NN LM EM SVM
4	Lahmiri and Bekiros (2020a)	Intelligent forecasting with machine learning trading systems in chaotic intraday Bitcoin market	*Chaos, Solitons & Fractals*	Prediction	NN SVM DT
5	Mallqui and Fernandes (2019)	Predicting the direction, maximum, minimum and closing prices of daily Bitcoin exchange rate using machine learning techniques	*Applied Soft Computing*	Prediction	NN SVM

[8] Note: The algorithms involved in the table are abbreviated, LR refers to Linear Regression; LM refers to Linear Model; DT represents Decision Tree; NN refers to Neural Network; RF refers to Random Forest; EM refers to Ensemble Model.

6	Michalski et al. (2020)	Revealing the Character of Nodes in a Blockchain with Supervised Learning	*IEEE Access*	Other	DT EM NN LM SVM
7	Mudassir et al. (2020)	Time-series forecasting of Bitcoin prices using high-dimensional features: a machine learning approach	*Neural Computing and Applications*	Prediction	NN SVM
8	Peng et al. (2018)	The best of two worlds: Forecasting high frequency volatility for cryptocurrencies and traditional currencies with Support Vector Regression	*Expert Systems with Applications*	Prediction	SVM Other
9	Poongodi et al. (2020)	Prediction of the price of Ethereum blockchain cryptocurrency in an industrial finance system	*Computers & Electrical Engineering*	Prediction	LM SVM
10	Sun et al. (2020)	A novel cryptocurrency price trend forecasting model based on Light GBM	*Finance Research Letters*	Prediction	SVM Other EM
11	Valencia et al. (2019)	Price movement prediction of cryptocurrencies using sentiment analysis and machine learning.	*Entropy*	Prediction	NN SVM EM
12	Yasir et al. (2020)	Deep-learning-assisted business intelligence model for cryptocurrency forecasting using social media sentiment	*Journal of Enterprise Information Management*	Prediction	NN SVM LM

13	Sebastiao and Godinho (2021)	Forecasting and trading cryptocurrencies with machine learning under changing market conditions	*Financial Innovation*	Prediction	LM RF SVM
14	Aggarwal et al. (2020)	A complete empirical ensemble mode decomposition and support vector machine-based approach to predict Bitcoin prices	*Journal of Behavioral and Experimental Finance*	Prediction	SVM
15	Wu et al.(2022)	Who Are the Phishers? Phishing Scam Detection on Ethereum via Network Embedding	*IEEE Transactions on Systems Man Cybernetics-Systems*	detecting phishing scams	SVM
16	Kim et al. (2021)	Predicting Ethereum prices with machine learning based on Blockchain information.	*Expert Systems with Applications*	Prediction	ANN SVM

Table 8 Application of clustering methods in cryptocurrency[9]

Number	Author	Title	Journal	Topic	Algorithm
1	Papadamou et al. (2021)	Herding behavior and price convergence clubs in cryptocurrencies during bull and bear markets	*Journal of Behavioral and Experimental Finance*	Herding Behavior	Cluster
2	Kondor et al. (2014)	Do the rich get richer? An empirical analysis of the Bitcoin transaction network	*Plos One*	Bitcoin Transaction Network	Degree Distribution Degree Correlations Cluster
3	Gidea et al. (2020)	Topological recognition of critical transitions in time series of cryptocurrencies	*Physica A: Statistical Mechanics and its Applications*	Topological Recognition	K-Means
4	Song et al. (2019)	Cluster analysis on the structure of the cryptocurrency market via Bitcoin-Ethereum filtering	*Physica A: Statistical Mechanics and its Applications*	Structure of the Cryptocurrency Market	MST
5	Giron et al. (2021)	Steganographic analysis of blockchains	*Sensors*	Steganographic Analysis of Blockchains	Steganographic Analysis
6	Mallqui and Fernandes (2019)	Predicting the direction, maximum, minimum and closing prices of daily Bitcoin exchange rate using machine learning techniques	*Applied Soft Computing*	Prediction	ANN SVM EM RNN K-Means
7	Guru and	Self-restrained energy grid with data analysis	*Energy Sources Part A-*	Self-Restrained	Cluster

[9] Note: The algorithms involved in the table are abbreviated, EM refers to Ensemble Model; ANN refers to Artificial Neural Network; SVM refers to Support Vector Machine; RNN refers to Recurrent Neural Network; MST refers to Minimum Spanning Tree.

	Kumar (2020)	and blockchain techniques	*Recovery Utilization and Environmental Effects*	Energy Grid	
8	Zheng et al. (2020)	Identifying the vulnerabilities of Bitcoin anonymous mechanism based on address clustering	*Science China-Information Sciences*	Identifying the Vulnerabilities	Heuristic Cluster
9	Xu et al. (2019)	A systematic review of blockchain	*IEEE Access*	Review	Cluster
10	Guerra et al. (2020)	Bitcoin analysis and forecasting through fuzzy transform	*Axioms*	Prediction	Cluster
11	Chang and Svetinovic (2020)	Improving Bitcoin ownership identification using transaction patterns	*IEEE Transactions on Systems, Man, and Cybernetics: Systems*	Bitcoin Ownership Identification	Cluster
12	Wang et al. (2018)	Anonymity for Bitcoin from secure escrow address	*IEEE Access*	Tracing Bitcoin Transaction	Cluster
13	Meiklejohn et al. (2016)	A fistful of Bitcoins: characterizing payments among men with no names	*Communications Of the ACM*	Anonymous	Heuristic Clustering
14	Lahmiri and Bekiros (2020b)	Randomness, informational entropy, and volatility interdependencies Among the major world markets: the role of the covid-19 pandemic	*Entropy*	COVID -19 Pandemic	Hierarchical Cluster
15	Gerlach et al. (2019)	Dissection of Bitcoin's multiscale bubble history from January 2012 to February 2018	*Royal Society Open Science*	Price Character	Cluster
16	Mao et al. (2019)	Visual and user-defined smart contract designing system based on automatic coding	*IEEE Access*	Smart Contract Designing System	K-Means

17	Manavi et al. (2020)	Demythifying the belief in cryptocurrencies decentralized aspects. A study of cryptocurrencies time cross-correlations with common currencies, commodities and financial indices	*Physica A: Statistical Mechanics and its Applications*	Price Character	Hierarchy Cluster
18	Bayhan et al. (2019)	Smart contracts for spectrum sensing as a service	*IEEE Transactions on Cognitive Communications and Networking*	Smart Contracts	K-Means
19	Shayegan et al. (2022)	A Collective Anomaly Detection Technique to Detect Crypto Wallet Frauds on Bitcoin Network	*Symmetry-Basel*	detect fraud	Trimmed_Kmeans
20	Lorenzo and Arroyo (2022)	Analysis of the cryptocurrency market using different prototype-based clustering techniques	*Financial Innovation*	Price Character	Partitional clustering algorithms

Table 9 Application of reinforcement learning in cryptocurrency[10]

Number	Author	Title	Journal	Topic	Algorithm
1	Lucarelli and Borrotti (2020)	A deep Q-learning portfolio management framework for the cryptocurrency market	*Neural Computing and Applications*	Investing Strategy	NN RL
2	Sattarov et al. (2020)	Recommending cryptocurrency trading points with deep reinforcement learning approach.	*Applied Sciences*	Investing Strategy	RL NN
3	Weng et al. (2020)	Portfolio trading system of digital currencies: A deep reinforcement learning with multidimensional attention gating mechanism.	*Neurocomputing*	Investing Strategy	RL NN
4	Ma et al. (2021)	Security reinforcement for Ethereum virtual machine	*Information Processing & Management*	Security Reinforcement	FISCO-BCOS-EVM
5	Sattarov et al. (2020)	Recommending cryptocurrency trading points with deep reinforcement learning approach	*Applied Sciences-Basel*	Investing Strategy	DRL

[10] Note: The algorithms involved in the table are abbreviated, MDP refers to Markov Decision Process; RL refers to Reinforcement Learning; DRL refers to Deep Reinforcement Learning; NN refers to Neural Network.

6	Li et al. (2021a)	Take Bitcoin into your portfolio: a novel ensemble portfolio optimization framework for broad commodity assets	*Financial Innovation*	Investing Strategy	RL
7	Rakkini and Geetha (2021)	Deep learning classification of Bitcoin miners and exploration of upper confidence bound algorithm with less regret for the selection of honest mining	*Journal of Ambient Intelligence and Humanized Computing*	Bitcoin Mining Mechanism Design	RL
8	Kumari and Tanwar (2021)	Multiagent-based secure energy management for multimedia grid communication using Q-learning	*Multimedia Tools and Applications*	Multimedia Communication	RL
9	Wang et al. (2021)	When blockchain meets AI: Optimal mining strategy achieved by machine learning	*International Journal of Intelligent Systems*	Optimal Mining Strategy	MDP
10	Lim et al. (2021)	Performance optimization of criminal network hidden link prediction model with deep reinforcement learning	*Journal of King Saud University - Computer and Information Sciences*	Criminal Network Analysis	DRL

11	Chen et al. (2021a)	Effective management for blockchain-based agri-food supply chains using deep reinforcement learning	*IEEE Access*	Management for Blockchain-Based Agri-Food Supply Chains	DRL
12	Schnaubelt (2022)	Deep reinforcement learning for the optimal placement of cryptocurrency limit orders	*European Journal of Operational Research*	Optimal Placement of Cryptocurrency Limit Orders	DRL
13	Kumari and Tanwar (2021)	A Reinforcement-Learning-Based Secure Demand Response Scheme for Smart Grid System	*IEEE Internet of Things Journal*	optimal price decisions	Q-SDRM(secure demand response management)

Figures

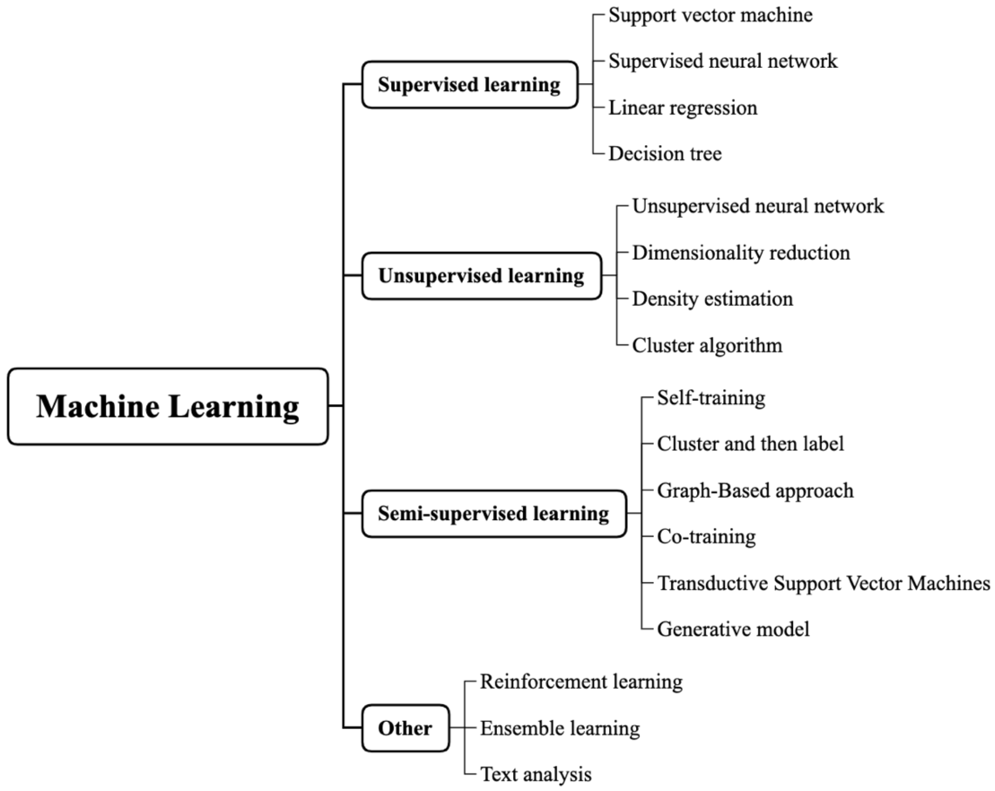

Figure 1 Classification of machine learning algorithms

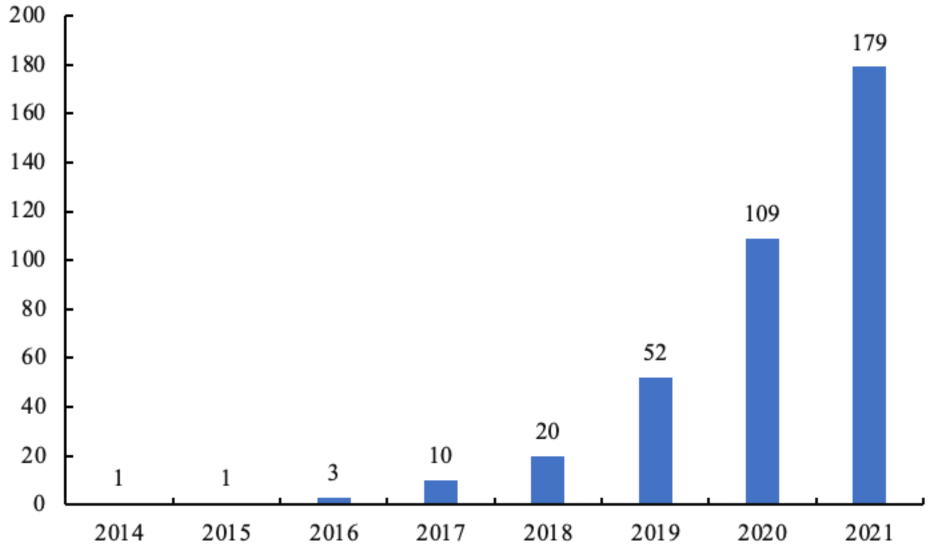

Figure 2 Schematic diagram of changes in the number of articles published from 2014 to 2021[11]

[11] Picture Description: the time range is from 2014 to 2021. The selection basis is that the first literature we retrieved appeared in 2014. In the process of revising this paper, 2022 has not ended, and the number of relevant research results will gradually increase. The picture only reflects the changes in the number of article achievements, not the number of literature reviews, in order to correspond to the analysis below.

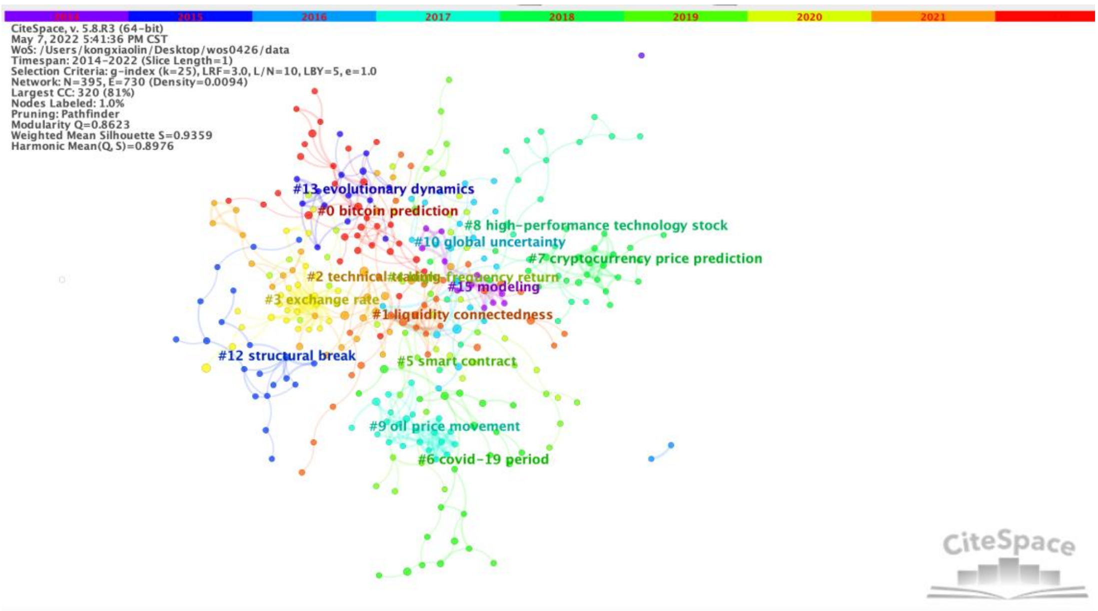

Figure 3 Co-citation networks in the cryptocurrency field[12]

[12] The time range of the sample literature in the cited network is from 2014 to 2022. The network adopts Pathfinder algorithm to prune the network. The larger the node diameter, the more times the article is cited. If two articles are cited by one document at the same time, the two articles will be connected by a line and they form a co-cited relationship.

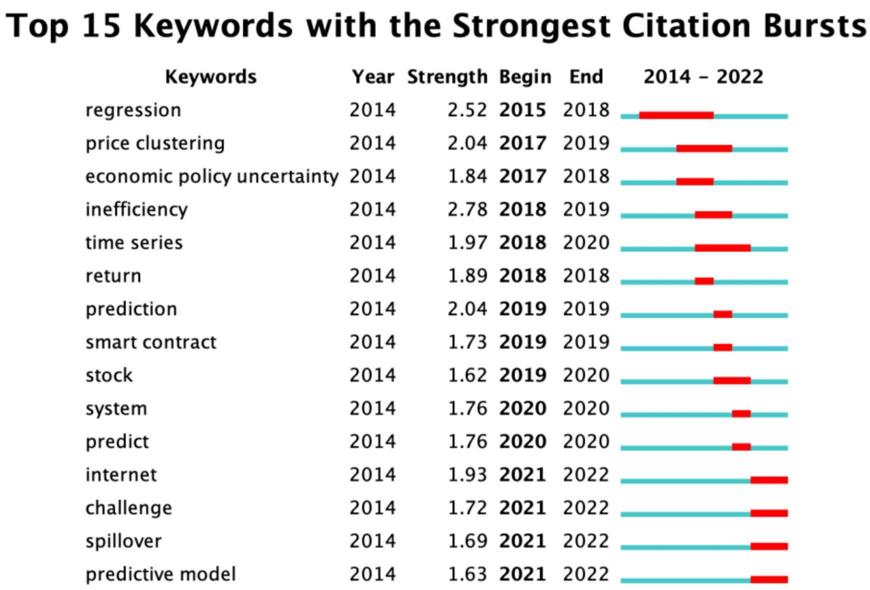

Figure 4 Bursts of topics in this field[13]

[13] Parameter setting: minimum duration is 1; gamma is 0.7.