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Review

A survey of deep learning applications in cryptocurrency

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SUMMARY

This study aims to comprehensively review a recently emerging multidisciplinary area related to the application of deep learning methods in cryptocurrency research. We first review popular deep learning models employed in multiple financial application scenarios, including convolutional neural networks, recurrent neural networks, deep belief networks, and deep reinforcement learning. We also give an overview of cryptocurrencies by outlining the cryptocurrency history and discussing primary representative currencies. Based on the reviewed deep learning methods and cryptocurrencies, we conduct a literature review on deep learning methods in cryptocurrency research across various modeling tasks, including price prediction, portfolio construction, bubble analysis, abnormal trading, trading regulations and initial coin offering in cryptocurrency. Moreover, we discuss and evaluate the reviewed studies from perspectives of modeling approaches, empirical data, experiment results and specific innovations. Finally, we conclude this literature review by informing future research directions and foci for deep learning in cryptocurrency.

INTRODUCTION

Deep learning is an algorithm model based on various deep neural networks. The ultimate goal of deep learning is to enable machines to analyze and learn like humans and recognize data such as text, images and sound. Deep learning is a complex machine learning algorithm that has achieved significant advancements in speech and image recognition. Compared with traditional machine learning algorithms, deep neural networks need data preprocessing and feature extraction before training. In addition, deep neural networks use the cascade of multi-layer nonlinear processing units for automatic feature extraction and transformation. This enhances the ability of neural networks to discover nonlinear relationships between data and improve the learning ability regarding the original data.[1] In the past few years, based on the big data collected from information sets, parallel processing capabilities of graphics processing units (GPUs), and new families of convolutional neural networks, deep learning methods have achieved great success in many different applications, including image classification,[2] object detection,[3] time series prediction.[4]

Essential tools for deep learning have been evolving rapidly in the past few years. With ever-improving programming packages, it has become easier to implement and test new deep learning models. As an emerging field of machine learning, deep learning is currently applied in multiple scenarios, from autonomous vehicles to image recognition, hazard prediction, health informatics and bioinformatics.[5–7] In addition, several comparative studies evaluated the performance of deep learning models versus standard machine learning models, for example, support vector machines (SVM),[8] K-nearest Neighbors (KNN),[9] and generalized regressive neural networks (GRNN)[10] in economic research.

With a strong ability to process big data and learn nonlinear relationships between input features and predicted targets, deep learning models perform better in prediction tasks than linear and machine learning models in the financial field, especially in the cryptocurrency market. Cryptocurrencies are currencies generated by computer programs, distributed and circulated on the Internet based on cryptography and network P2P technology. In addition to studying the mechanism of digital currency from the perspective of computer science and cryptography, researchers have also started the economic analysis of cryptocurrency, such as the currency characteristics and asset attributes, as well as the innovation of introducing cryptocurrency to traditional monetary theory and payment methods.[11–13] Some researchers also employ machine learning and deep learning models to model the cryptocurrency market. For example, Lahmiri & Bekiros[10] compared the performance of long short term memory(LSTM) and generalized regression neural network(GRNN) in predicting cryptocurrency prices, which involves cryptocurrencies including Bitcoin, digital cash, and Ripple. They revealed that the LSTM model has better prediction performance than GRNN. Altan et al.[14] claimed that by testing their proposed model using Bitcoin, Ripple, digital cash, and Litecoin time series data, the combination of LSTM and empirical wavelet transform (EWT) improved the performance of LSTM in predicting digital currency prices.

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Table 1. CNN applications in financial research

Models	Targets	Markets	Data	Results	Innovation	References
CNN LSTM (RNN)	Investment sentiment prediction	Stock	StockTwits Investment Sentiment Data (January 1, 2015 June 30, 2015)	It is proved that CNN can overcome the problems of data mining methods in stock sentiment analysis	CNN is the best model to predict investor sentiment	Sohangir et al.[23]
CNN	Financial time series method	Stock, gold and petroleum	S&P 500 index, FTSE 100 index, petroleum and gold index (hour, daily, weekly, monthly data)	The prediction error rate of CNN is significantly reduced	Proposed new A-Trader system's investing strategy and a financial time series forecasting method.	Korczak and Hemes[24]
CNN, RNN, RCNN	Stock index forecast	Stock	106,494 Reuters Financial News (20 October 2006-21 November 2013)	While RNN has more advantages in capturing contextual data and complex time features, CNN is better at capturing text semantics.	A new model called the RCNN model is developed.	Vargas et al.[25]
CNN	Financial time series method	Futures	Taiwan Index Futures One-minute Trading Data (January 2, 2001 April 24, 2015)	The CNN model can collect certain features and classify them for the futures market.	This paper proposes a deep learning-based financial time series analysis method	Chen et al.[26]
CNN, novel neural tensor network	Stock price prediction	Stock	Reuters, Bloomberg Financial News headlines (October 2006 November 2013)	The prediction accuracy is improved by about 6%	Deep learning models were first applied to event-driven stock market forecasting	Ding et al.[27]
CNN, LSTM	Stock price prediction	Stock	daily time series from January 2010 to September 2019, include the closing prices of the S&P 500, Dow Jones, DAX, and Nikkei 225	It demonstrates how CNN maybe combined with LSTM, CEEMD, or EMD to increase prediction accuracy and exceed the competition.	The use of CEEMD-CNN-LSTM and EMD-CNN-LSTM hybrid algorithms.	Rezaei et al.[28]
CNN, LSTM	Time series analysis and financial market forecast-ing under investor sentiment	Stock	Between January 1, 2017, and July 31, 2019, six industries having a market value of up to 1.008 billion yuan and five stocks were randomly chosen from each industry.	Future stock price predictions are more accurate when investor sentiment and technical indicators based on LSTM neural networks are combined.	Combining the LSTM neural network method for price prediction with the CNN model for sentiment analysis	Jing et al.[29]
MLP, CNN, LSTM	Company financial credit ranking	Corporate Finance	Financial data of over 1761 Indian companies with IT sector from 2015 to 2020	MLP is the most efficient predictor of a company's financial situation.	Combine several deep learning models to estimate each company's credit rating from high to poor.	Pol et al.[30]

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Table 1. *Continued*

Models	Targets	Markets	Data	Results	Innovation	References
MLP, LSTM, MALSTMFCN, CNN	Financial time series method	Crypto-currency	Bitcoin and Ethereum price time series from January 1, 2017 to January 1, 2021	The CNN model performs the best among the constrained models. The LSTM neural network's average accuracy in unrestricted is 83% and 84%, respectively.	Using unrestricted models of technical, trading, and social media variables to increase prediction accuracy.	Ortu et al.[31]
CNN, DDQN	Stock index forecast	Stock	Training dataset generated by 30 stocks in the S&P 500 index from January 2, 2013 to December 31, 2019, testing dataset from January 1, 2020 to June 30, 2020	The feature map visualization in stock market prediction is realized.	Using CNN in DDQN to outperform S&P 500 index returns and analyze how does the system trade.	Brim and Flann[32]

Jiang & Liang[15] developed a convolutional neural network(CNN) model to predict the price of Bitcoin, where historical data on financial asset prices is employed to train the proposed model and pooled portfolio weights are the model's output.

There is considerable literature about cryptocurrency, and researchers have published several surveys reviewing and exploring the topic from different perspectives and application areas. Those include reviews on cryptocurrency trading systems,[16] and mining systems,[17,18] reviews on specific modeling tasks concerning cryptocurrency transactions such as knowledge discovery[19] and cryptocurrency price prediction.[20–22] A few of these studies review the cryptocurrency price prediction models from the perspective of modeling paradigms. For example, Sina et al.[21] review the cryptocurrency price prediction models that use artificial neural networks (ANN)s. Similarly, Ahmed et al.[20] focus on the traditional statistical and machine-learning techniques employed in cryptocurrency price prediction tasks. However, none of these studies review the deep learning methods involved in multiple modeling tasks in cryptocurrency, thus becoming a research gap to address in this study.

Therefore, this study comprehensively reviews the deep learning methods employed in cryptocurrency research across multiple modeling tasks, including price prediction, portfolio, bubble analysis, abnormal trading, trading regulations and initial coin offering in cryptocurrency. We first review popular deep learning models employed in multiple financial application scenarios, including CNNs, recurrent neural networks (RNNs), deep belief networks (DBNs), and deep reinforcement learning (DRL). We also give an overview of cryptocurrencies by outlining the cryptocurrency history and discussing primary representative currencies. Based on the reviewed deep learning methods and cryptocurrencies, we conduct a literature review on the new multidisciplinary area that employs deep learning models on cryptocurrency. We discuss applications of deep learning models in financial research from perspectives of modeling approaches, empirical data, experiment results and specific innovations. Finally, we point out the research challenges for future study.

This study is organized as follows. Sections, Overview of deep learning and Overview of Cryptocurrency, respectively review the deep learning methods and development path of cryptocurrency. In the Deep learning in cryptocurrency Section, comprehensively review deep learning methods employed in multiple modeling tasks related to cryptocurrency. This is followed by the Challenges and Future Directions Section, where we identify the research challenges and directions. Finally, we conclude this literature review in the Conclusion.

OVERVIEW OF DEEP LEARNING

This section overviews the deep learning methods by introducing related concepts and development over the years and reviewing fundamental deep learning models. A group of deep learning models will be mentioned in this section.

Basic concept and development process

Deep learning is a new concept in artificial neural network research originally proposed by Geoffrey & Ruslan.[33] It is a machine learning method that primarily simulates the human brain to evaluate and understand data and information. Through supervised and unsupervised learning, deep learning creates a new interpretation mechanism. Deep learning has significantly advanced artificial intelligence, which has made it possible for AI concepts and technology to be broadly accepted and used. Deep learning methods have enabled significant advancements in various fields, such as speech recognition,[34] face recognition[35] and image analysis.[36] Therefore, it has quickly emerged as one of the most crucial ideas in artificial intelligence and computer technology and has profoundly and quickly impacted how people work, learn, and

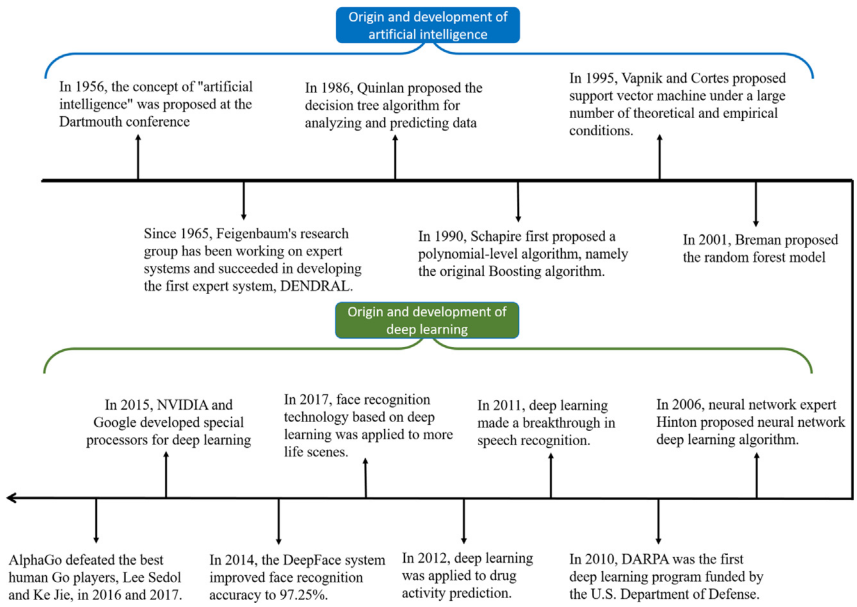

Figure 1. Development of artificial intelligence and deep learning

live. At the same time, the combination of deep learning and the financial sector has gained prominence as an emerging field of study in recent years, making advances in both theoretical and practical application.[37,38]

Deep learning methods can learn rules from vast amounts of data using neural network models, thus emerging as one of the most significant developments in artificial intelligence. It has consistently displayed high application vitality during the development process of more than ten years. To have an overview of the deep learning's history, we discuss the crucial phases in the evolution of deep learning (See Figure 1).

The idea of artificial intelligence was developed and established in the 1950s.[39] Scientists including John McCarthy, Marvin Minsky, and Claude Shannon gathered in August 1956 at Hanover's serene Dartmouth College to discuss the cutting edge of using machines to emulate human learning and other characteristics of intelligence. The Dartmouth Conference was a two-month gathering that marked the beginning of a new era in the development of artificial intelligence. Thus, 1956 also marked the birth of artificial intelligence.

Artificial intelligence has entered the "knowledge application period" since the middle of the 1970s.[40] During this time, "expert systems"-based AI algorithms started to be used by businesses worldwide, and "knowledge processing" was the principal topic of mainstream AI research. Expert systems and knowledge engineering had extraordinary global growth throughout the 1980s, and both businesses and individual users have benefited financially from using them.

From the end of the 1980s to the beginning of this century, more and more algorithms were developed and applied, such as decision tree algorithm,[41] boosting algorithm,[42] support vector machine (SVM)[43] and random forest.[44]

Hinton, a leading specialist in neural networks, created the neural network deep learning algorithm in 2006, considerably enhancing neural networks' capabilities and ushering in a new era of deep learning in both academia and business.[45] LeNets, a deep learning network developed by Hinton student Yann LeCun, is widely utilized in global banking and financial services as well as automated deposit and withdrawal equipment.[46] As a result, 2006 might be considered to be the year when deep learning really got started and the year that it really started to catch on among academics.

At the beginning of 2010, the application in the military field is an essential process for the development of many cutting-edge technologies, and deep learning is certainly no exception: DARPA is the first deep learning project funded by the US Department of Defense in 2010, which has promoted the application and popularization of deep learning in the military and defense industry to a large extent.[47] In 2011, deep learning made a breakthrough in speech recognition,[48] improving various real-world applications such as e-commerce[49] and customer service.[50]

In 2012, deep learning was applied to drug activity prediction and achieved the best results in the world. Google Brain, a deep learning-based face recognition system, made a breakthrough in 2012 by comprehending and recognizing cats' faces from numerous photos.[51] In 2017, these technologies were used in more real-world scenarios, making people's daily lives convenient.

In 2014, the DeepFace system improved the accuracy of face recognition to 97.25%, which is close to the performance of normal humans.[35] The promotion of application and the improvement of efficiency make face recognition technology reliable. At the same time, surpassing human capabilities means that deep learning is beginning to exert practical value.[36,52]

NVIDIA and Google developed particular processors for deep learning in 2015, motivating the development of deep learning technology from two aspects, hardware and software.[53] Yann et al.[1] proposed a new deep learning method, further revitalizing the research on neural networks. After that, deep learning continued to heat up.

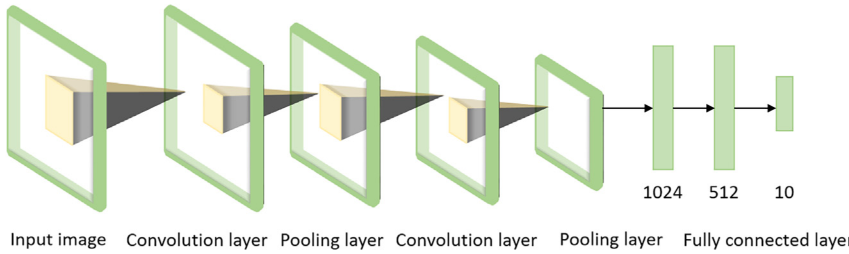

Figure 2. Convolutional Neural Network

Notes: In Figure 2, CNN consists of input, convolutional, pooling, and fully connected layers. We can see that the value of the fully connected layer is from 1024 to 512, and the final display is 10, which shows the great advantage of CNN in image processing.

In 2016, the computer program AlphaGo defeated Lee Sedol, one of the finest human Go players.[54] The media enthusiastically hailed this victory as "truly conquering the most difficult and intelligent Go project."[55] In the game of Go, AlphaGo defeated Ke Jie, the current world No. 1 player, in 2017.[56] This victory demonstrated that humans cannot defeat artificial intelligence using deep learning technology, making deep learning technology and artificial intelligence a hot topic of discussion worldwide.

Deep learning model

In this section, we respectively review four fundamental deep learning models, including (1) convolutional neural network, (2) deep belief network and (3) deep reinforcement learning.

Convolutional neural network

Convolutional neural network (CNN) is an outstanding feedforward neural network (FFNN) recognition technique.[57] Its artificial neurons can respond promptly to surrounding units in a defined area, with an outstanding performance in large image processing and object detection.[1,58] Therefore, in recent years, the emerging CNN plays a prominent role in image recognition and analysis, which also makes people pay more attention to its research and development.[59–63]

As shown in Figure 2, CNN takes FFNN as the technical core and collects, analyses and integrates image information through the "layer by layer" neuron response recognition mode to improve the efficiency of recognition and reliable quality. In Figure 2, CNN consists of input, convolutional, pooling, and fully connected layers. The input image first reaches the convolutional layer and gets processed by the pooling layer. It then goes through the convolutional and pooling layers again and finally enters the fully connected layer. We can see that the value of the fully connected layer is from 1024 to 512, and the final display is 10, which shows the great advantage of CNN in image processing. When the input propagates to further layers, the CNN model can use this structure to decrease the amount of input parameters and obtain abstract features.[64]

CNN has been employed in various application scenarios. The proposal and development of CNN technology enable the artificial neuron response method of FFNN to process large images while also having better performance in speech recognition.[65] Moreover, Li[66] studied the critical value of CNN application in computer vision, which involves three representative research topics, including object recognition,[67] image annotation[68] and image recognition.[69] In addition, Zhou[70] has proved the universality of CNN and the probability of using it to approximate any continuous function.

Considerable studies apply CNN to corporate financing decisions and financial forecasts. Ding[27] combined neural tensor network and deep CNN to process the text information and predict stock price. The model in this study is composed of two parts, including (i) a neural tensor network that conducts event embedding training on the events extracted from the news text and (ii) a deep CNN that captures the impact of the events. Compared with the standard FFNN, the prediction accuracy of the established CNN-based model for the S&P 500 index and related individual stocks is improved by nearly 6%. Chen[26] proposed a CNN-based financial time series analysis method. Vargas et al.[25] proposed a new deep learning model, RCNN model, using 106,494 financial news from Reuters and compared its stock prediction performance with the traditional CNN and neural network (NN) models. Korczak & Hemes[24] proposed a financial time series prediction method based on CNN and accordingly developed a multi-agent stock trading system. The experiment on S&P 500 index, FTSE 100 index, oil index and gold index proved that the proposed CNN-based method significantly improves the prediction accuracy. Sohangir et al.[23] analyzed StockTwits investment sentiment data (from January 1, 2015 to June 30, 2015) to determine whether using deep learning models could improve StockTwits' sentiment analysis performance. The results show that deep learning models can effectively assist financial sentiment analysis, and CNN is the best model to predict the sentiment of StockTwits authors. Based on empirical mode decomposition (EMD) and fully integrated empirical mode decomposition (CEEMD) algorithm, Rezaei et al.[28] proposed CEEMD-CNN-LSTM and EMD-CNN-LSTM hybrid algorithms for the prediction of stock indexes. Jing et al.[29] used CNN model to classify the hidden emotional factors extracted from stock forums, which improved the accuracy of stock prediction. Pol et al.[30] used the CNN model to predict the financial data of more than 1761 Indian companies in the IT sector from 2015 to 2020 and rank the credit of each company. Ortu et al.[31] focused on the two largest cryptocurrencies by market capitalization, Ethereum and Bitcoin, during the 2017–2020 period to predict and classify the trend of price movements with CNN and other deep learning models.

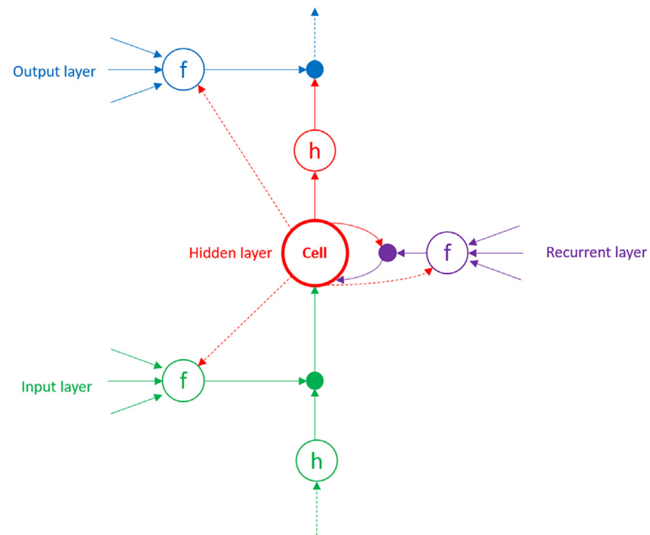

Figure 3. Recurrent Neural Network

Notes: In this model, the information flow is governed by three gates, including the input gate, the forget gate and the output gate. The input gate decides the information to store in the current state. The forget gate determines the removal of information. The output is related to the output information in current state.

In addition, the application of CNN plays an important role in quantitative trading. Quantitative trading systems can be generally divided into three parts: trading signal (pattern recognition), position control and asset management. The application of CNN in signal recognition, information collection, image analysis and other activities within these three parts is of great help to the final trading decision. For example, Brim & Flann[32] used CNN to obtain market returns that outperform the S&P 500 index and analyzed how the system trades. In order to facilitate relevant researchers to understand the research status in recent years, we create a table for comparative analysis of research from perspectives of model, data, results and innovations (See Table 1). By enumerating these studies, we find that CNN models perform well in the prediction tasks involved in various financial markets. Moreover, it can be incorporated into other models to increase their interpretability.

Recurrent neural network

Recurrent neural network (RNN) is a general term for two kinds of artificial neural networks: temporal RNN and structural RNN. Specifically, the connections between neurons of temporal RNN constitute directed graphs, while structural recurrent neural networks use similar neural network structures to build more complex deep networks recursively. These two neutral networks' training methods have slight differences even though they belong to the same algorithmic framework. Regarding operation mechanism, RNN is a kind of network constructed by the method of structural recursion.[71]

RNN models are generally used to describe sequences of dynamic behaviors that circulate states in the basic network framework and can accept a wider range of time series structure inputs. Current representative RNN include traditional RNN, LSTM neural network and gated recurrent unit (GRU) models. Unlike feedforward deep neural network (FDNN), RNN pays more attention to the feedback effect of the network. RNN has a specific memory function due to the connection between the current and previous states. In this model, the information flow is governed by three gates, including the input gate, the forget gate and the output gate. The input gate decides the information to store in the current state. The forget gate determines the removal of information. The output is related to the output information in the current state. The structure of RNN is shown in Figure 3.

Regarding specific applications of RNN, Graves et al.[34] found that RNN could essentially guide and expand the application scope in speech recognition. This neural network model promotes greater technical innovation in speech recognition when it is applied to the combination of natural language sequences or voice analysis and interpretation.

In the financial field, RNN models are widely employed in financial market prediction research involving the stock market, futures market and crude oil market. Yoshihara et al.[72] first proposed a deep learning model that combines RNN and restricted Boltzmann machine to process the text information of news events (834,882 financial news items of Keizai Shimbun from 1999 to 2008) and predict stock price movements. Xiong et al.[73] used the LSTM neural network to model the S&P 500 volatility and studied the factors affecting the S&P 500 volatility, including the macroeconomic factors and the public sentiment factor represented by Google domestic trends data (from October 19, 2004 to July 24, 2015). Heaton et al.[74] analyzed the stock prices of the S&P 500 index and 20 included companies, and proposed a hierarchical decision model for financial forecasting and classification problems, which, based on RNN models, can improve the forecasting performance of traditional financial applications. Singh et al.[75] demonstrated that deep learning with the method 2-Directional 2-Dimensional Principal Component Analysis ($(2D)^2$ PCA) can improve inventory multimedia (graph) prediction accuracy, compared with the traditional neutral network method. As the study showed that correlation coefficient between actual income and predicted income of $(2D)^2$ PCA + DNN is 17.1% higher than $(2D)^2$ PCA + RBFNN and 43.4% better than RNN in the aspect of stock prediction. Deng et al.[76] used RNN to process the characteristics of real-time financial signals and tried to build quantitative trading strategies based on structure to beat experienced financial asset traders. This study uses deep learning technology to learn and extract relevant features from dynamic market conditions automatically and, afterward, uses reinforcement learning technology to make trading decisions in unknown environments. This model can reflect both the deep structure and the circular structure, and the experiment results show that the model performance is robust in both the stock market and the commodity futures market. Moreover, some researchers find that the combination of principal component analysis (PCA) and recurrent neural network (RNN) enables the consideration of both fundamental and price information of stocks and balances the trade-off between the performance and diversity of the selected stock, thus making the prediction of the future trend of the stock market more robust.[77,78]

Recent studies have extended and applied RNN models to improve different financial market forecasting methods. Karaoglu et al.[79] improved RNN to detect excessive movement in noisy time series data streams. Berat Sezer et al.[80] proposed a stock price prediction and trading system based on neural network technical analysis indicators. Bao et al.[81] employ six market indexes, including the A-share CSI 300 index in mainland China, the Nifty 50 index representing the Indian stock market, the Hang Seng Index in Hong Kong stock market, the Nikkei 225 index in Tokyo, the S&P 500 index and the DJIA index in New York Stock Exchange, as examples. This study presents a novel deep learning framework where wavelet transforms (WT), stacked autoencoders (SAEs) and LSTM are combined to predict stock price and is proved to outperform other similar models in accuracy and profitability. Yan et al.[82] employed LSTM to predict the daily closing price of Shanghai Composite Index from January 4, 2012 to June 31, 2017, which presents better prediction accuracy for both static and trend prediction of financial time series. This experiment illustrates the applicability and effectiveness of LSTM in financial time series forecasting. Meanwhile, researchers find that the wavelet decomposition and reconstruction of financial time series can improve the generalization ability of LSTM forecasting model and the prediction accuracy of long-term dynamic trend. For example, Fischer et al.[83] applied LSTM networks to S&P 500 index time series forecasting (December 1989 to September 2015) and found that they performed better than non-categorical memory methods such as Random Forest (RF), deep neural networks (DNN), and logistic regression classifiers (LOG). Chen et al.[84] proposed a new hybrid crude oil price prediction model based on Deep Belief Network (DBN) and LSTM model and used the model to analyze and simulate the crude oil price trend. Ji et al.[85] used traditional stock financial index variables and social media text features as the input of the prediction model based on LSTM. Prachyachuwong & Vateekul[86] adopted a bidirectional encoder model composed of LSTM and Bidirectional Encoder Representation from Transformers (BERT) architecture to predict the daily activity of the Thailand stock market. Adisa et al.[87] improved LSTM model for financial prediction and found that the improved model was superior to the single classifier and ensemble classifier models.

Regarding portfolio allocation strategies, Xie et al.[88] designed a two-stage system, namely LSTMcon, which consists of an asset price prediction model and a decision strategy based on set rules. Yue et al.[89] proposed a deep reinforcement learning model based on the Markov decision process model in the context of COVID-19, including the stacked sparse denoising autoencoder (SSDAE) model and the long–short-term-memory-based autoencoder(LSTM-AE) model. Overall, the decision-making of the portfolio management process is improved from two perspectives: time series analysis and information extraction based on market observations. In order to facilitate relevant researchers to understand the research status in recent years, this section lists two tables for comparative analysis of model, data, experiment results and innovations, as shown in Tables 2 and 3. The RNN model is more widely employed in stock price prediction tasks, and multiple studies have validated the impact of different RNN model algorithms on prediction performances.

Deep belief network

Geoffrey Hinton proposed the DBN generative model in 2006.[90] It is a generative model, which can generate training data with the entire neural network according to the maximum probability by training weight among neurons. DBN can be used to create data and categorize and define the properties of data. Many researchers analyze financial data using the DBN model to assist decision-making in financial transactions and investments.

In essence, the DBN model is an efficient machine learning algorithm that enables rapid data processing and integration by using a generative model. The integration of these two functionalities has a significant breakthrough point. As a result, DBN can better illustrate the transmission mode and data characteristics of information in financial applications.

As shown in Figure 4, DBN is derived from the restricted Boltzmann machine system (RBM). Stacked with the neuronal structure of RBM, the propagation of DBN is well-ordered. Meanwhile, the deep structure of DBN corresponds naturally to the deep learning architecture, reflecting the advantages of DBN regarding technological innovation.[91]

Hinton & Salakhutdinov[33] first proposed the concept of a simple belief network and gave a prototype model. Their study proved that DBN-based neuron weight training can generate data with maximum probability, which meets the needs of computation and practical applications. Regarding financial applications, considerable studies use DBN on stock price forecasts. For example, Kuremoto et al.[92] proposed a new neural network model for time series prediction with higher accuracy. Zhu et al.[93] established an automatic stock decision support system by combining DBN with the oscillation box theory. The results show that systematic market-based trading with extreme learning machine algorithm outperforms the basic buy-and-hold strategy. Batres-Estrada[94] applies new deep learning algorithms to predict financial stock data using the S&P 500 index (January 1, 1985 to December 31, 2006). Lanbouri[95] used the financial data of 966 companies in France to combine deep learning and support vector machine (SVM) to build a financial distress prediction (FDP) model. Shen et al.[96] to extend the application of DBN models to continuous data by introducing the constant restricted Boltzmann mechanism and use the proposed model to predict the weekly exchange rates of GBP/USD, INR/USD and BRL/USD. Sharang & Rao[97] designed an intermediate frequency trading method based

Table 2. RNN applications in financial research (1)

Models	Targets	Markets	Data	Results	Innovation	References
RNN, DBN	Stock price trend prediction	Stock	834,882 Nikkei Financial News (1999–2008)	The proposed DBN combination has the lowest error rate.	RNN is combined with restricted Boltzmann machine to predict the stock market trend.	Yoshihara et al.[72]
LSTM (RNN)	Stock index forecast	Stock	Google Domestic Trends Data (October 19, 2004 July 24, 2015)	*The MAPE was 24.2%.*	The impact of public sentiment and macroeconomic factors on the volatility of the S&P 500 index.	Xiong et al.[73]
RNN	Stock price trend and stock index forecast	Stock	The S&P 500 index and the stock prices of 20 companies are included.	It improves the predictability of traditional financial applications.	A hierarchical decision model for the classification of financial forecasts is proposed.	Heaton et al.[74]
RNN, DNN	Stock price prediction	Stock	Multimedia data of Google's stock price in the NASDAQ	The correlation coefficient between actual and predicted income for DNN is 17.1% higher than for RBFNN and 43.4% higher than for RNN.	Compared with traditional neural networks, (2D) ZPCA + has improved accuracy on Google datasets	Singh and Srivastava[75]
RNN	Establish a real-time financial trading system based on deep learning	Stock and futures	The first index-based IF stock futures contract in China and the first silver (AG) and sugar (SU) futures contract in the commodity market (2014.1–2015.9)	The model has good application effect and robustness in both stock market and commodity futures market	A model consisting of deep learning and reinforcement learning is proposed	Deng et al.[76]
RNN	The performance of the model is examined in interperiod time series data	Stock	Istanbul Stock Exchange fixed time interval data	The model has good performance and has been successful in data trading.	RNN is improved to make it more suitable for time series data and detect excessive movement in noisy time series data streams	Karaoglu et al.[79]
RNN	Stock price prediction	Stock	Daily stock prices for all Do230 stocks between 1997 and 2007	In most cases, the results of the correct buy-and-hold strategy are achievable.	A stock price prediction and trading system based on neural network technical analysis index is proposed.	Sezer et a l.[80]
LSTM (RNN), WT, SAEs	Forecasts of stock prices and stock indices	Stock	CSI 300 index, NIFTY 50 Index, Hang Seng Index, Nikkei 225 index, S&P 500 index and Dow Jones Index	This model outperforms other similar models in terms of forecasting accuracy and profitability.	A deep learning framework combining wavelet transform, stacked autoencoder and LSTM is proposed to predict stock prices	Bao et al.[81]

Table 3. RNN applications in financial research (2)

Models	Targets	Markets	Data	Results	Innovation	References
LSTM (RNN)	Forecast the daily closing price of the Shanghai Stock Exchange Composite Index	Stock	Daily Closing Price of Shanghai Composite Index (January 4, 2012 June 31, 2017)	LSTM performs well for both static and dynamic trend prediction of financial time series.	According to the complex characteristics of financial time series, a new time series forecasting model is proposed.	Yan and Ouyang[82]
LSTM (RNN), DNN	Forecast stock price volatility	Stock	S&P 500 Index (December 1989 to September 2015)	The LSTM network performs better than RAF, DNN, and LOG	The LSTM network is applied to financial time series forecasting, and portfolio strategy.	Fischer and Krauss[83]
LSTM (RNN), DBN	Forecasting Crude oil prices	Crude Oil	2409 WTI Crude Oil Market Price Data (July 23, 2007 February 24, 2017)	The model improves the prediction accuracy	This paper proposes a novel hybrid crude oil price prediction model based on deep learning.	Chen et al.[84]
Doc2Vec, SAE-LSTM, wavelet transform	Stock price volatility forecast	Stock	From January 2010 to November 2019, investors' comments and company news on the top 15 pharmaceutical listed companies.	It eliminates the interference of random noise brought by stock market volatility to stock prediction.	Fusion of traditional financial features and social media text features derived from social media	Ji et al.[85]
BERT, LSTM	Stock and futures price volatility prediction	Stock and futures markets	Economic topics in Thai news headlines from 2014 to 2020, and Thai stock market data	Simultaneously improving numerical and textual information enhances predicting performance and exceeds all baselines.	A deep learning model consisting of LSTM and from Transformer (BERT) is proposed.	Prachyachuwong and Vateekul[86]
LSTM	Company financial credit score prediction	Corporate Finance	Credit score dataset provided by credit reporting agencies	The optimized LSTM model outperforms the single classifier model and the classifier model.	A method for optimizing deep learning algorithm parameters is given to close the gap left by LSTM prediction.	Adisa et al.[87]
LSTM	Price prediction	Gold and Bitcoin	The prices of gold and bitcoin over a five-year trading period from September 11, 2016 to September 10, 2021	The accuracy rate in the gold and bitcoin markets reached 98.5% and 98.8% respectively	Designs a two-stage system LSTMcon, which consists of an asset price forecasting model based on an ensemble rule	Xie et al.[88]
MDP, SSDAE, LSTM-AE	Quantitative portfolio management	Stock	OHCLV data from January 1, 2007 to January 1, 2018	In terms of Sharpe and Sortino ratios, the suggested portfolio management approach beats other models.	A deep reinforcement learning model for COVID-19 quantitative portfolio management is built using a Markov decision process model.	Yue et al.[89]

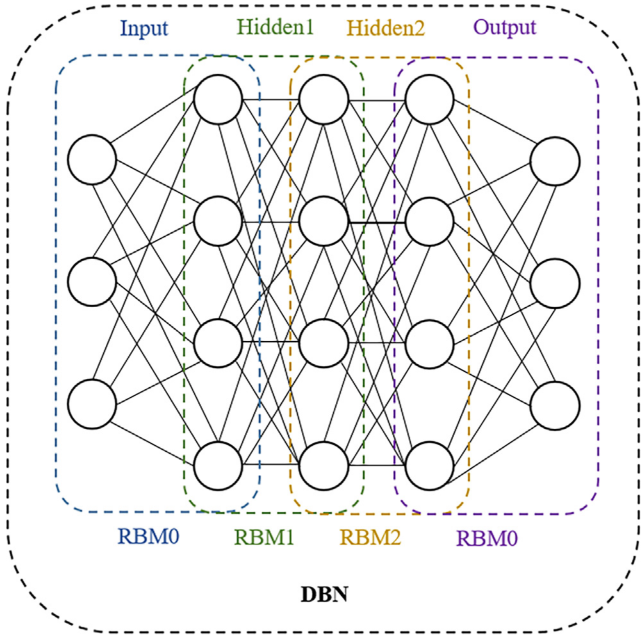

Figure 4. Deep Belief Network

Notes: As shown in Figure 4, DBN is derived from the Restricted Boltzmann Machine system (RBM). Stacked with the neuronal structure of RBM, the propagation of DBN is well-ordered. Meanwhile, the deep structure of DBN corresponds naturally to the deep learning architecture, reflecting the advantages of DBN regarding technological innovation [91].

on the daily and biweekly average prices of US treasury futures over a five-year and ten-year term. They employed DBN model, which is composed of stacked restricted Boltzmann machines, to predict the weekly trend in the price of an asset portfolio. In addition, they devised trading strategies respectively based on the constructed prediction model and the random classifier model. To better understand the researches over the years, we create a table to summarize the model, data, results and innovations in DBN in Table 4. The DBN model has been used in the multifaceted subject of finance, particularly in forecasting company financial problems.

Deep reinforcement learning

Deep reinforcement learning (DRL) combines reinforcement learning (RL) and deep learning. The reinforcement learning algorithm sets the goals for DRL, while the deep learning algorithm provides the learning mechanism. DRL entails agents that observe states and take actions to gather long-term rewards. It also uses approximations or strategies to solve RL problems when the state space is too large or the action space is continuous. DRL has the powerful representation ability of neural networks to deal with high-dimensional inputs.[66]

Deep learning enables RL to be extended to previously intractable decision problems, namely environments with high-dimensional states and action spaces. There are two outstanding works in the DRL field. First the DRL development started by developing an algorithm that could learn directly from image pixels to play a series of video games on the Atari 2600 platform beyond learning ability of the human average.[100] This study provides a solution to the instability of function approximation techniques in RL. It also demonstrates that RL agents can be trained on raw high-dimensional observations based only on reward signals. The second outstanding achievement is the development of the hybrid DRL system AlphaGo, which defeated the human world champion in Go[101] after IBM's Watson DeepQA system defeated the best human chess player 20 years ago.[102] Unlike the DeepQA system's manual rules, AlphaGo consists of neural networks trained using supervised and reinforcement learning and traditional heuristic search algorithms.

DRL is an end-to-end perception and control system from the standpoint of system structure, and its learning process can be summarized as follows: (1) The agent interacts with the environment every moment to obtain a high-dimensional observation. The agent then uses deep learning to interpret the observation to derive a representation of a particular state feature. (2) The agent then evaluates the value function of each action based on the expected return and maps the current state to the corresponding action using a specific strategy. (3) The environment responds to this action and receives the subsequent observation. The best method for achieving the objective can finally be found by repeating the abovementioned procedure.[103]

Currently, DRL algorithms have been applied to a wide range of problems, such as robotics, where the control strategy of the robot can now be learned directly from camera inputs in the real world,[104] subsequent controllers are either manually designed or learned from low-dimensional features of the robot state. In a step toward more powerful agents, DRL has been used to create agents that can meta-learn,[105] enabling them to adapt to complex visual environments that have not been seen before.[106]

Table 4. DBN applications in financial research

Models	Targets	Markets	Data	Results	Innovation	References
DBN	Stock price trend prediction	Stock	The data are smoothed.	The new DBN combination proposed in this chapter has the lowest error rate.	A new neural network model for time series forecasting with high accuracy is proposed.	Kuremoto et al.[92]
DBN	Stock price prediction	Stock	Historical trading data for the 400 stocks in the S&P 500 index	The model constructs systematic trading that outperforms the basic buy-and-hold strategy.	An automatic stock decision support system is established by using DBN and oscillatory box theory.	Zhu et al[93]
DBN	Stock price prediction	Stock	S&P 500 Index (January 1, 1985 to December 31, 2006)	The results obtained by deep neural networks are better and more stable than the basic results.	New deep learning algorithms are used to predict financial stock data	Batres-Estrada[98]
DBN	Forecast of financial distress of the company	Corporate Finance	Financial data for 966 French firms	The classification accuracy of the model is 76.8%	Deep learning and support vector machine are combined.	Lanbouri and Achchab[95]
DBN	Exchange rate price forecast	Foreign exchange	Weekly data for the three exchange rates GBP/USD, Indian Rupee/USD, and Brazilian real/USD	Compared with traditional methods, FFNN is more suitable for forecasting exchange rates and their effects.	An improved DBN algorithm (FFNN) is proposed to forecast the exchange rate	Shen et al.[96]
DBN	Forecast of the weekly movement direction of the Treasury portfolio	Treasury bond futures	Daily and two-week average price data for 5 and 10-year Treasury futures.	The portfolio has a trade size of 10 units and a profit of 10 units, which is about 90,000 dollars.	Using the DBN of stack-constrained Boltzmann mechanism, an intermediate frequency trading strategy is designed	Sharang and Rao[97]
DBN	Financial time series methods	Stock	Sample of financial series data of closing prices of all stocks in Shanghai and Shenzhen stock markets during the 100 working days prior to October 20, 2012	The accuracy of financial data samples selected by DBN model in quantitative decision analysis of financial time series data can reach 90.54%	Presents an improved modeling based on DBN and decision algorithm	Zeng et al.[99]

DRL algorithms based on model-free approaches can generally be categorized as value-based and policy-based RL. Deep Q-network (DQN) is a common value-based RL method that solves the confused representation of high-dimensional state inputs by employing the maximum Q value as the low-dimensional action outputs.[107] In contrast, policy-based RL is easier to implement in the continuous action space problem than value-based RL. This algorithm also prevents the policy deterioration due to value function mistake.[108] Model-based RL, as opposed to model-free RL, requires less ongoing contact with the environment and learns a value function or policy in a data-efficient manner. Consequently, they can be applied to different scenarios.[109]

Using some algorithms that allow agents to learn how to create profits in any market sector, DRL is utilized in finance to boost earnings in financial markets. The main task of DRL is to collect data to design models with low latency and low cost training in financial markets. Using deep reinforcement learning enables the agent (the algorithm) to learn how to make profitable transactions, which also enables the methodology changes and the unique representation of the financial Markov decision process (FMDP).[110] Liu et al.[111] used the deep deterministic policy gradient (DDPG) algorithm as an alternative to exploring the optimal policy in the dynamic stock market. The algorithmic component of DDPG handles large action state spaces, pays attention to stability, eliminates sample correlation, and improves data utilization. The results show that the proposed model is robust in balancing risks and performs better than the Dow Jines Industrial Average and min-variance

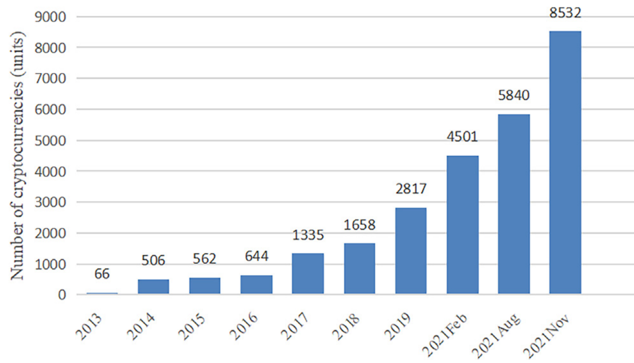

Figure 5. Number of cryptocurrencies from 2013 to 2021 (https://www.statista.com/statistics/863917/number-crypto-coins-tokens/)

portfolio allocation method. Li et al.[112] designed a new adaptive deep deterministic reinforcement learning framework (Adaptive DDPG) for optimal trading strategies in stock markets. The model combines optimistic and pessimistic deep RL, which relies on negative and positive forecast errors. The model can obtain better portfolio profits based on Dow Jones stocks in complex market situations. Li et al.[113] studies DRL methods and their applications in stock decision-making mechanisms. The experiments with three classical DRL models (Deep Q-Network, Double DQN and Dueling DQN) show that the DQN model enables us to obtain better investment strategies to optimize stock trading returns. Raj Azhikodan et al.[114] focused on the DRL automatic monitoring oscillation of securities trading, and they used a recursive convolutional neural network (RCNN) method to predict stock values from economic news. The primary focus of the DRL model's application is stock market prediction, and more research is necessary to fully understand its use (See Table 5).

OVERVIEW OF CRYPTOCURRENCY

To have an overview of cryptocurrency, we review the development path of cryptocurrency and introduce the main cryptocurrencies.

The evolution of cryptocurrency

The traditional monetary system is the collection of laws, regulations, legal structures, and organizations that the government uses to issue currency for use in economic activity. The major participants in this system are the central bank, the Treasury, the Mint and commercial banks. And three main different trading instruments are the legal tender, commodities and the asset backed by commodities from a historical perspective. Traditional monetary systems may be significantly vulnerable to bandwagon effects, where prices fluctuate under the impact of consumer behaviors. In addition, central banks may cause inflation by printing and devaluing money. As a result, traditional monetary systems are not convenient for purchase and cannot always satisfy the assumptions like infinite subdivision and relative stability of value.

The concept of exchanging money in digital form has become popular due to the drawbacks of conventional monetary exchange systems. The digital currency systems aim to improve the stability of the financial market and assist consumers by addressing problems like inflation and low yields. This concept can dramatically bring about economic benefits by enhancing operation efficiency, enabling convenience access and saving the cost of carry. The implementation of digital currency systems is also confronted with the question of whether the system should be based on the central bank or decentralized by replacing the central bank with a new monetary system.

David Chaum created the e-cash cryptosystem back in 1983.[117] Twelve years later, he created DigiCash, another encryption system, to conceal financial transactions.[118] Wei Dai employed the cryptosystem to create a new payment mechanism with a primary decentralization characteristic in 1998, the same year the word "cryptocurrency" first surfaced.[119]

The first and most prominent cryptocurrency is Bitcoin, launched by.[120] Satoshi Nakamoto invented Bitcoin and made the source code available to the world. Bitcoin, altcoins, and tokens are the top three cryptocurrencies that are actively active on the market. Cryptocurrency technology is taking financial markets one step closer to the future by decentralizing money and releasing it from hierarchical power structures. With cryptocurrency technology, consumers and businesses execute transactions digitally through a peer-to-peer network.

In the short time since its birth, the cryptocurrency market has experienced exponential growth and widespread popularity (Figure 5). In recent years, cryptocurrencies have grown in popularity and received global media attention, attracting investors, academics, governments, regulators, and speculators. The future of Bitcoin, or any cryptocurrency, is not confined to any particular discipline; Instead, it transcends each domain.[121]

Litecoin was Launched in October of 2011. WordPress was the first retailer to accept Bitcoin payments in 2012.[122] Many businesses now accept these digital currencies as payment for their goods and services. Moreover, some of them have developed their own digital currencies. El Salvador became the first nation to accept Bitcoin as legal money in June 2021. Following Resolution 215 in August 2021, Cuba recognized Bitcoin as a legal tender.[123] By November 2021, there are 8,532 cryptocurrencies, up from 66 in November 2013.

Cryptocurrency investment has become more dependable due to the advancement of cryptocurrency research. However, considering the cryptocurrency market's high risk and high volatility, the cryptocurrency market's security and regulation are still vital. To stop crypto hijacking, there are considerable studies on the security of cryptocurrencies. Conrad et al.[124] investigated the cryptocurrency security structure and

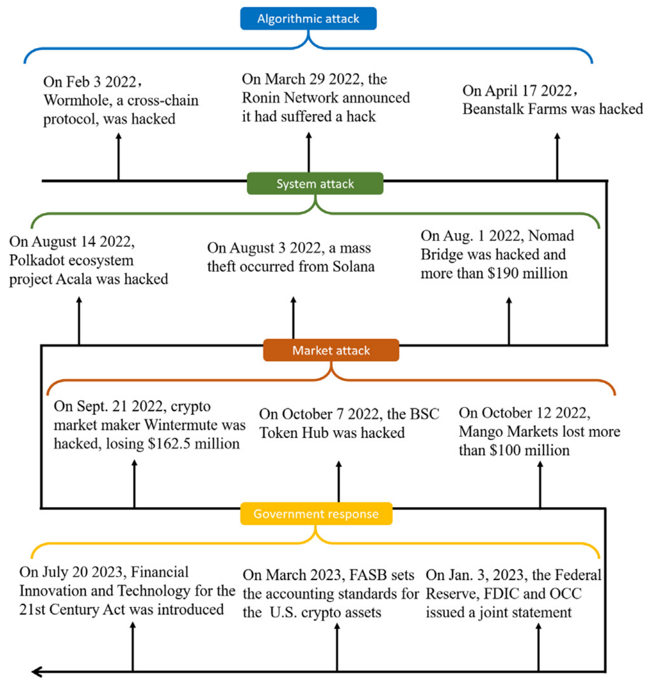

Figure 6. Security and regulation events in the cryptocurrency market in 2022 and 2023

discovered that security architecture is a complicated idea that incorporates security components of software, hardware, and operating systems in addition to procedures. McLean et al.[125] sought to create security models that "describe any formal statement of a system's confidentiality, availability, or integrity requirements.". Many researchers focus on the effectiveness of cryptocurrency mining by lowering the cost of mining. For example, Gundaboina et al.[126] conducted statistical data analysis in a Dogecoin mining benchmark and found that the hashing algorithm determines mining cost. Mining companies are trying to use renewable energy to replace traditional energy and reduce the carbon footprint. Figure 6 summarizes the security and regulations that affected the cryptocurrency market in 2022, and the government regulatory policies for cryptocurrency risk events in 2023.

On February 3, the Wormhole system, which links Ethereum and Solana, was breached by hackers, who took 120,000 ETH with a market value of more than 320 million dollars. On March 29, the NFT game Axie Infinity revealed that its side chain Ronin Network had been compromised, causing losses of up to 620 million in the form of 173,600 ETH and 25.5 million USDC. An algorithmic stable-coin project called Beanstalk Farms was targeted on April 17, and the attack-related losses totaled 182 million USD dollars (https://www.bruegel.org/policy-brief/decentralised-finance-good-technology-bad-finance). On August 1, a compromise of the Nomad Bridge cross-chain technology resulted in the theft of more than 190 million USD dollars in cryptocurrency.[127] On August 3, a large-scale theft occurred in the Solana system, causing a loss of much to 8 million in tokens from the wallets of several users. Due to the iBTC/aUSD pool, hackers also attacked the Polkadot ecological project Acala on August 14. As a result, more than 1.2 billion ecological stable-coins (AUSD) were created, which severely unanchored AUSD and caused a 70% price decline. Crypto market manufacturer Wintermute was attacked on September 21 and suffered a loss of roughly 162.5 million USD dollars (https://www.cshub.com/attacks/news/wintermute-loses-160-million-in-hack). On October 7, market manipulation by attackers resulted in a 100 million loss for the BNB Chain cross-chain bridge BSC Token Hub.[128] A hack on October 12th cost Mango Markets, a DeFi platform with headquarters in Solana, more than 100 million USD dollars.[129] Since the beginning of 2023, governments and regulators have begun to strengthen risk control in the cryptocurrency market. On January 3, the Federal Reserve, the Federal Deposit Insurance Corporation (FDIC) and the Office of the Comptroller of the Currency (OCC) issued a joint statement emphasizing that risks related to crypto assets cannot be transferred to the banking system. The Financial Accounting Standards Board (FASB) proposed an exposure draft on crypto assets in March 2023, which stipulates that entities must measure certain crypto assets at fair market value and recognize changes in fair value net income during each reporting period. The Financial Innovation and Technology for the 21st Century Act (FIT21) was proposed on July 20, 2023 to establish a regulatory framework for digital asset markets in the United States that provides clear rules for market participants and protects investors and consumers.

Traders in the cryptocurrency industry panicked and feared the onset of a "Lehman moment" in November 2022 after FTX, one of the biggest cryptocurrency exchanges in the world, collapsed. The timing of the incident, which had a significant impact on the cryptocurrency market, is reviewed in this survey.

As shown in Figure 7, between May 7 and May 13, 2022, numerous bitcoin decoupling incidents caused the cryptocurrency algorithm to ultimately enter a death spiral and progressively approach the brink of collapse.[130] Following this event, crypto lending company Celsius ultimately suspended withdrawals on June 13 due to its usage of on-chain leverage and the derivative stETH. A few days later, Celsius applied

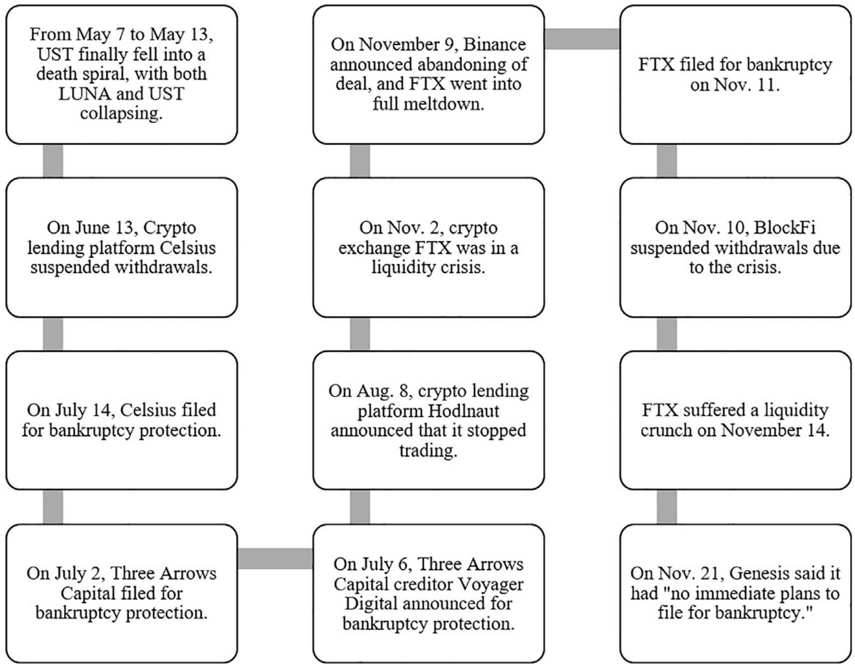

Figure 7. FTX failure and related events (all taking place in 2022)

for bankruptcy protection. Due to its significant holdings in GBTC and stETH, Three Arrows Capital also requested federal bankruptcy protection on July 2, using the Luna incident as the catalyst. In addition, the incident prompted Three Arrows' creditor, Voyager Digital, to declare bankruptcy after suffering significant losses due to Three Arrows' failure on a 670 million debt.[131] According to Hodlnaut's financial report as of August 8, the company had a funding gap of around 193 million. Its outstanding debt was 391 million Singapore dollars when its assets were valued as 122 million, or about 281 million Singapore dollars when its assets were valued as 88 million (https://finance.yahoo.com/news/hodlnaut-owes-us-200-mln-070407468.html). The massive funding shortfall forced the platform to suspend trading.

At the beginning of November, the disclosure of a massive hole in the financial sheet of cryptocurrency market maker Alameda intensified the panics in the cryptocurrency market. The bitcoin exchange FTX experienced a liquidity issue—large withdrawals due to social panic increase as the panic grew. When Coin An, the company that was going to purchase FTX, stated that it was pulling out of the agreement on November 9, FTX went into a complete meltdown. FTX declared bankruptcy on November 11.[132] The demise of FTX also influenced the cryptocurrency market. Due to the issue at creditor FTX, BlockFi did not choose to exit, but unfortunately, on November 28, sought bankruptcy protection. Due to the demise of FTX and cash flow issues, cryptocurrency brokerage Genesis asked for a 1 billion emergency loan on April 14 and ceased accepting withdrawals on April 16. Genesis on November 21 claimed "no immediate plans to file for bankruptcy" and that as of December 8, it was still in the recovering period.[133]

The main cryptocurrencies

Cryptocurrency is a digital currency created based on a specific encryption algorithm. It is an open-source blockchain technology architecture, which enables to generate, manage, exchange, circulate and even destroy divisible digital units according to a certain logic according to complete user management.[134] Such digital units are also generally called points, tokens, coins, tokens, or cryptocurrencies.

In 2009, when Bitcoin first became available, it had virtually no rivals. However, by 2011, new varieties of cryptocurrencies had begun to appear. There are currently tens of thousands of distinct cryptocurrency varieties. The top 10 cryptocurrencies (See Table 6 [134]) by market capitalization by March 3, 2023, are shown below (https://www.investing.com/crypto/currencies):

- Bitcoin (BTC): The first cryptocurrency developed in 2009 is called Bitcoin. It utilizes blockchain technology and is decentralized and independent of all governments and central banks. More than 18.8 million Bitcoin tokens were in use as of September 2021, with a limit of 21 million.
- Ethereum (ETH): Ethereum is also a blockchain network, much like Bitcoin. ETH is created with a proof-of-work algorithm as well. However, unlike Bitcoin, there is no upper limit for the creation of ETH.
- Tether Coin (USDT): The USDT is the cryptocurrency pegged to the USD dollar, which also invests in the blue. Users can use SWIFT to transfer money to Tether provided bank accounts or the Bitfinex exchange to convert their money to USDT.

Table 5. DRL applications in financial research

Models	Targets	Markets	Data	Results	Innovation	References
DDPG	Investment portfolio allocation	Stock	Daily data of Dow 30 stocks	The adaptive DDPG outperforms the baseline in terms of return on investment and Sharpe ratio.	The adaptive DDPG is compared with the traditional portfolio allocation strategy	Li et al.[112]
DQN, DRL	Stock market trading strategy	Stock	Daily data for 10 stocks from 2000 to 2018	The DQN model works best in stock market investment decisions.	The feasibility of DRL in the field of financial strategy is demonstrated and three classical DRN models are compared.	Li et al.[115]
RCNN, DRL	The realization of automatic trading mechanism	Stock	95,947 news headlines for 3,300 companies	It proves that deep reinforcement learning can learn the skills of stock trading.	Neutral network models based on deep deterministic policy gradients are trained to choose the action of selling, buying, or holding a stock	Azhikodan et al[114]
DRL	Stock market trading strategy	Stock	Historical daily prices of the Dow 30 stocks from January 1, 2009 to September 30, 2018	The proposed deep reinforcement learning method outperforms both baselines in terms of Sharpe ratio and cumulative return	A deep reinforcement learning agent model is trained and an adaptive trading strategy is obtained	Liu et al.[116]

- Binance Coin (BNB): The total amount issued is still 200 million. BNB is an Ethereum-based decentralized blockchain digital asset created by Ethereum.
- USD Coin (USDC): USD coin (USDC) is a stablecoin that runs on the Ethereum blockchain and other blockchains. Its 1:1 parity with the dollar makes USDC a reliable medium of trade. The purpose of stablecoins like USDC is to facilitate quicker and less expensive transactions.
- XRP: Ripple LABS is the company behind XRP. XRP cannot be mined, unlike Bitcoin and many other cryptocurrencies. Instead, there is a limited supply of it. XRP transactions are cheaper and faster than Bitcoin transactions due to the Ripple network's transaction verification method.
- ADA: The blockchain platform used by ADA, called Cardano, is a member of the third generation of blockchain platforms. Due to its reliance on reliable evidence (PoS), Cardano's network may be more effective and durable because it does not require the intricate PoW computations and substantial power consumption necessary to mine coins like Bitcoin.
- Polygon (MATIC): MATIC is an Indian blockchain scalability platform dubbed "Ethereum's Internet of Blockchains" that aspires to build a multi-chain ecosystem of Ethereum-compatible blockchains.
- Dogecoin: Dogecoin was introduced in 2013 and uses a PoW mechanism to operate on the blockchain network, much like Bitcoin and Ethereum. However, the total amount of coins that may be mined is limitless compared to Bitcoin's 21 million coin restriction.
- Binance USD (BUSD): A stable asset backed by USD that is listed and traded on Binance issued and managed by Paxos Trust Company, and subject to New York State Department of Financial Services regulation.

DEEP LEARNING IN CRYPTOCURRENCY

In this section, we comprehensively review the application of deep learning methods in cryptocurrency research across multiple modeling tasks, including price prediction, portfolio construction, bubble analysis, abnormal trading and initial coin offering.

Cryptocurrency price prediction

A variety of deep learning algorithms have been applied in the prediction of cryptocurrency prices. Ryotaro et al.[8] used many machine learning algorithms ANN, SVM, LSTM, Ridge Regression, Heterogeneous Autoregressive model Realized Volatility (HARRV) and other models for comparative analysis. Among them, the prediction model based on LSTM has received a lot of attention and extension. Abdullah Ammer & Aldhyani[137] found that LSTM has an accurate and good effect on the prediction of cryptocurrency after empirical studies in different

Table 6. Information of major cryptocurrencies

Names	Codes	Price (USD)	Value	Volume (24h)	Proposed time
Bitcoin	BTC	22370.8	432.52B	26.19B	2009
Ethereum	ETH	1565.29	191.84B	9.76B	2013
Tether coin	USDT	1.0002	71.14B	38.07B	2014
Binance coin	BNB	290.51	45.99B	466.23M	2017
USD Coin	USDC	0.9996	43.17B	4.33B	2018
XRP	XRP	0.36601	18.78B	1.06B	2013
Ada coin	ADA	0.3367	11.67B	388.80M	2015
Polygon	MATIC	1.166	10.19B	544.08M	2017
Dogecoin	DOGE	0.075592	10.03B	531.91M	2013
Binance USD	BUSD	0.9997	9.68B	7.85B	2019

periods; Fang et al.[142] used LSTM model to present the characteristics of real-time tick data in cryptocurrency trading system and analyzed the trade-off between model accuracy and training frequency.

Hybrid models based on LSTM have gradually developed. First, D'Amato et al.[138] combined RNN-Jordan neural network and LSTM to predict cryptocurrency price volatility, which verified that the model can provide more vital prediction ability; Based on the hybrid prediction model of RNN and LSTM, Kumari Priya et al.[139] focused on analyzing how LSTM network upgraded traditional algorithms in the field of price prediction. Tanwar et al.[141] considered the interdependence between parent currencies and adopted the hybrid model of GRU and LSTM to better predict the price of litecoin. Parekh et al.[143] proposed a hybrid and robust model DL-Gues considering the interdependence between cryptocurrencies and market sentiment; Hansun et al.[140] compared three commonly used deep network structures, namely LSTM, BiLSTM and GRU, using multiple prediction model methods, and found that the latter two could provide similar robust and accurate predictions.

In addition, considering the practical problems related to investment, Kim et al.[144] proposed to construct a SAM (Segment Anything Model)-LSTM model based on an attention mechanism to predict the price trend of bitcoin, which is composed of several LSTM modules for on-chain variable groups and the attention mechanism. Park & Seo[145] proposed an LSTM model and input features, including sellProfit (the profit that can be obtained when selling a specific amount of cryptocurrency), buyProfit (the profit that can be obtained when buying a specific amount of cryptocurrency) and maxProfit (the maximum profit that can be obtained between sellProfit and buyProfit) to help investors make investment decisions. In the first stage, the LSTM network is used to extract structured information from financial news, and in the second stage, a machine learning model with structured financial news input is employed to predict bitcoin prices. Luo et al.,[146] considering the multi-scale properties of cryptocurrency prices, matched different machine learning algorithms like LSTM and Extreme Learning Machines (ELM). with the corresponding multi-scale components and built an integrated prediction model based on machine learning and multi-scale analysis.

Regarding other deep learning methods, Schnaubelt[148] applied deep reinforcement learning to optimize limit order configuration on cryptocurrency exchanges. Lahmiri & Bekiros 10 applied deep feedforward neural network (DFFNN) to analyze and forecast high-frequency price data of bitcoin. Akyildirim et al.[150] used ANN, SVM, Random Forest and Logistic Regression to analyze the predictability of the 12 most liquid cryptocurrencies. Jana et al.[151] proposed a regression framework based on differential evolution to predict the one-day price of bitcoin based on the fusion of MLP, Random Forest, Support vector regression(SVR) and other algorithms. In particular, considering the epidemic's impact, Ftiti et al.[152] developed the HAR model to measure price volatility based on various deep learning algorithms. Oyedele et al.[149] used relevant performance indicators to evaluate and benchmark the performance of CNN, DFFNN and gated recurrent unit (GRU) models based on Boosted Tree. From the studies mentioned above, we can conclude that the price prediction for various cryptocurrencies has been conducted using a wide range of deep learning algorithms. The most recent research has improved the prediction accuracy and efficiency by combining various algorithmic techniques (See Tables 7 and 8).

Cryptocurrency portfolio construction

Deep learning methods have also been widely employed in cryptocurrency portfolio construction, especially portfolio management based on the DRL model.[15,154,153] For example, Estalayo et al.[155] allocated cryptocurrency portfolios around a combination of deep learning (DL) models and multi-objective evolutionary algorithms (MOEA) and, using its predictive ability, made accurate *ex ante* estimates of portfolio returns and risks. Sockin & Xiong[215] facilitated decentralized bilateral trading of certain goods or services between cryptocurrency users across asset allocations using blockchain technology.

LSTM models have also been widely employed in cryptocurrency portfolio research. Osifo & Bhattacharyya[156] compared the LSTM, autoregressive integrated moving average(ARIMA), moving average(MA), cumulative moving average (CMA), artificial neural networks (ANN) models in the risk control of pair trading in the cryptocurrency space. Gu et al.[157] used LSTM to learn the temporal information of historical transactions and make price predictions. Aguayo Moreno & Garcia Medina[158] constructed LSTM and GARCH hybrid models and found that deep learning models, including LSTM and MLP algorithms, and their different variables could better reduce the value at risk and enhance

Table 7. Research on cryptocurrency price prediction literature (1)

Models	Data	Results	Innovation	References
ANN, LSTM, SVM, HARRV, Ridge regression	Minute sampling of bitcoin returns over 3-h intervals	The ridge regression model performs best, supporting the assumption of autoregressive dynamics of the HARRV model.	A variety of deep learning algorithms are applied, and the prediction findings are used for dynamic risk hedging	Miura et al.[8]
LSTM	It contains data from 2013 to 2018 for five cryptocurrencies including bitcoin.	The root-mean-square error of the model prediction results is small, and good accuracy is achieved	The LSTM is trained to learn and forecast the highest price for a future time using the highest price of Bitcoin on past dates.	Mittal and Bhatia[135]
LSTM	From 7 December 2020 to 26 September 2021 USDP,BTG, OKB, TEL, AUDIO	Both LSTM and a single network integration based on LSTM can provide relatively accurate prediction of cryptocurrency.	Using LSTM and a single network ensemble based on LSTM to compare the returns on investment of these cryptocurrencies	Buyrukoğlu[136]
LSTM	AMP, Ethereum, EOS, and XRP from May 2015 to April 2022	LSTM has the most superior performance.	The implementation of a novel deep learning technique based on LSTM yields	Ammer and Aldhyani[137]
RNN—Jordan, SETAR	Bitcoin, Ripple, and Ethereum	RNN-Jordan method better reflects the high volatility of cryptocurrencies.	By capturing complicated data interactions, it outperforms conventional methods in terms of accuracy.	D'Amato et al.[138]
RNN, LSTM	Bitcoin	The model takes into account crucial information from the past, and the suggested model performs better and is more effective.	The price of any cryptocurrency is predicted in this research using a hybrid RNN and LSTM prediction model.	Priya et al.[139]
RNN, LSTM	Bitcoin, Ethereum, Cardano, T-Ether, and Binance	BiLSTM and GRU have similar performance results in terms of accuracy	Multivariate forecasting models were used, while the process robustness was assessed through different RNN models	Hansun et al.[140]
GRU, LSTM	Litecoin and Zcash	Hybrid models based on GRU and LSTM can be used in real-time scenarios and are well trained and evaluated using standard datasets.	The suggested model incorporates emotional aspects and takes into account how parent currencies are interdependent.	Tanwar et al.[141]
RMSprop, LSTM	Real-time tick data in cryptocurrency trading systems	Models that are more effective than those of individual assets due to the generic properties of cryptocurrencies also find a trade-off between model accuracy and training frequency.	The characteristics of the cryptocurrency market in a high-frequency environment are analyzed and presented	Fang et al.[142]

(*Continued on next page*)

Table 7. *Continued*

Models	Data	Results	Innovation	References
DL-GuesS, GRU, LSTM, VADER	Historical prices of Dash, Litecoin, and Bitcoin	The proposed DL-GuesS outperforms traditional systems in predicting cryptocurrency prices.	Proposed DL-GuesS model considering price history and recent Twitter sentiment.	Parekh et al.[143]

capital allocation for the uniform portfolio. Hashemkhani Zolfani et al.[161] used return forecasts obtained in autoregressive integrated moving average (ARIMA), long short-term memory (LSTM) and random forest regression (RFR) models as return-related criteria, based on PROMETHEE II,A cryptocurrency portfolio allocation model is proposed. Current literature generally uses the DRL model to construct portfolios in the cryptocurrency market with an optimized investment performance. In addition, the involved studies focus on the diversification of portfolio risks (See Tables 9 and 10).

Cryptocurrency bubble analysis

Cryptocurrency trading is a challenging research area due to its characteristics of high volatility[216] power-law bubble dynamics[217] and impacts other markets.[218] Speculative trading of cryptocurrencies on social media has become increasingly common, leading to sentiment-driven "price bubbles".[219] Such bubbles are characterized by rapid price increases in a short period, often driven by exuberant investor behavior,[217] and can be associated with substantial risk.

Cryptocurrency bubbles and crashes are essential research directions, and correspondingly, the measurement and monitoring of bubbles also emerge as important research topics. Soloviev & Belinskiy[163] proposed an economic Planck constant to investigate the statistical properties and characteristic distribution of the global cryptocurrency market and found that the introduced economic quality and the maximum eigenvalue of the correlation matrix can act as the quantum indicator – a predictor of the decline of the cryptocurrency market. Shahzad et al.[164] argued that the connectivity of cryptocurrency returns under extreme shocks may be stronger and more complex, revealing the returns' interdependence based on median and right tail between cryptocurrencies under normal and extreme market conditions. Chowdhury et al.[165] explain the occurrence of cryptocurrency bubbles and crashes and reveal interdependence and contagion effects.

The cryptocurrency price fluctuates significantly in crisis, posing a research challenge for price prediction. Deep learning algorithms have been widely employed to predict cryptocurrency prices in a bubble period. Livieris et al.[166] combined LSTM, BiLSTM, and CNN models to build an integrated model for hourly price prediction and movement of cryptocurrency, achieving an improved price prediction accuracy in the crisis period. El-Berawi et al.[167] proposed a new model to predict and classify cryptocurrency's price and movement direction based on RNN, GRU, LSTM, and MLP. The proposed model has made a promising breakthrough in movement classification through adaptive dynamic feature selection and external reliable factors with potential predictability. From the perspective of investor behavior, Ghasemieh & Kashef[168] proposed an integrated model based on CNN, which significantly increases the resistance of the model under critical stock market conditions, especially in the early stage of COVID-19. Guarino et al.[169] used BTC and ETH data from January 1, 2015, to December 31, 2018, to analyze the behavior of DRL-based trading agents during the financial bubble. Pagnotta[170] developed a Bitcoin's security model and extended it to allow consumers choose between Bitcoin and fiat currency while balancing the three goals, including maximizing currency price, system security and social welfare of transactions. The results showed the adaptability of Bitcoin's security model, given amplified price volatility. Sawhney et al.[171] proposed a CryptoBubbles model for a new multispan recognition task related to bubble detection. They employed a dataset containing more than 400 cryptocurrencies from 9 exchanges. Also, they developed a novel span identification task and dataset for foam detection based on the power-law dynamics of cryptocurrencies and user behavior on social media.

To explore the driving factors of cryptocurrency bubbles, Cross et al[172] constructed a time-varying parameter model considering stochastic volatility and heavy-tailed distribution and verified that the news effect was an essential factor affecting cryptocurrency returns. In the context of the COVID-19 pandemic, Montasser et al.[173] conducted a DDTW-based test and clustering of 18 cryptocurrencies by exploring their similarities in market efficiency and found that COVID-19 was the core factor leading to price bubbles. Deep learning models have been used in the literature on cryptocurrency bubbles to simulate the distribution of extreme losses to identify price bubbles as well as the direction of price movement (See Table 11).

Abnormal trading in cryptocurrency

Regarding abnormal trading detections, researchers first employed K-means clustering and SVM models.[174–176] For example, Monamo et al.[174] used the Trimmed K-means algorithm to detect unsupervised cybercrimes, successfully detecting some known fraudulent activities and improving the detection rate for known fraudulent elements. Pham & Lee,[175] Martin et al.[176] used a variety of supervised and unsupervised learning methods, including K means clustering, Mahalonobis distance, stochastic gradient descent (SGD) and SVM for anomaly detection in Bitcoin transaction network. Apart from K-means clustering and SVM models, researchers also found that graph neural network is more accurate than traditional non-graph-based methods in constructing abnormal transaction detection framework. In addition, many scholars also pay attention to semi-supervised learning methods. Patel et al.[177] proposed a method based on semi-supervised learning, which introduces the automatic signature of blockchain transactions and includes personalized identification of abnormal transactions. Kim et al.[179]

Table 8. Research on cryptocurrency price prediction literature (2)

Models	Data	Results	Innovation	References
CPD-Attention mechanism, SAM-LSTM	BTC prices from March 27, 2018 to November 16, 2021	The model enables price prediction models to predict unseen price ranges.	A SAM-LSTM-based prediction model is proposed	Kim et al.[144]
LSTM	BTC, ETH, ADA, DASH, LTC, and XMR	The proposed model's accurate response percentage has increased by roughly 13%–21%, according to experimental findings, which has significantly enhanced performance.	A deep learning model containing sellProfit, buyProfit, and maxProfit input features is presented with a criterion for which action is most beneficial at any given time.	Park and Seo[145]
LSTM, Extreme learning machine	The bitcoin price series from 2017/11/24 to 2020/4/21 and 2020/4/22 to 2020/11/27 are used as training and prediction datasets.	The prediction accuracy of the integrated model can reach 95.12%.	Multi-scale components to create an integrated prediction model based on machine learning and multi-scale analysis, taking into account the multi-scale features of bitcoin values.	Luo et al.[146]
LSTM, CNN, Random forest	980 news articles containing bitcoin between June 6, 2011 and May 13, 2019	The proposed forecasting system produces a substantially greater time-out rate of return than the buy-and-hold approach.	By applying the LSTM network to sentiment analysis	Jakubik et al.[147]
DRL	Currency pairs BTC/USD, ETH/USD, ETH/BTC from January 1, 2018 to June 30, 2019	When compared to the execution of a single market order, the model produces a better order placement strategy that lowers the average total under execution by 37.71%	apply deep reinforcement learning to the optimal limit order placement problem	Schnaubelt[148]
DFFNN	High frequency dataset of Bitcoin intraday price data from January 1, 2016 to March 16, 2018	The proposed algorithm has advantages in terms of prediction accuracy.	Three distinct training strategies for deep feedforward neural networks are evaluated	Lahmiri et al.[10]
CNN, Boosted trees, DFFNN, GRU	BTC, ETH,BNB, LTC, XLM, and DOGE data from January 1, 2018 to December 31, 2021	The CNN model gave a consistent and high explained variance score (on average) of 0.97 and had the minimum mean percentage error (0.06).	Study performance evaluation using improved tree-based methods and DL genetic algorithms to forecast closing prices of various cryptocurrencies.	Oyedele et al.[149]
ANN, SVM, Random forest, logistics regression	From April 1, 2013 to June 23, 2018, BCH, BTC,DSH, EOS, ETC, ETH, IOT, LTC, OMG, XMR, XRP and ZEC	There is some predictability of price trends in the cryptocurrency market, as evidenced by the average categorization accuracy of the algorithms being regularly over the 50% cutoff.	using ANN, SVM, RL, and logistic regression techniques, with past price data and technical indications serving as model features.	Akyildirim et al.[150]

(*Continued on next page*)

Table 8. *Continued*

Models	Data	Results	Innovation	References
MLP, SVR, Random forest	Bitcoin data from January 10, 2013 to February 23, 2019	In both static and dynamic forecasting instances, the suggested method statistically outperforms all other competing models.	A regression framework based on differential evolution is proposed to predict the day-ahead price of bitcoin	Jana et al.[151]
HAR model	Bitcoin, Ethereum, ETC, and XRP data from April 2018 to June 2020	Times of crisis, especially the coronavirus disease pandemic, increase the volatility of cryptocurrency volatility.	Use high-frequency data and the HAR model to validate investors' sensitivity to unfavorable news in chaotic periods.	Ftiti et al.[152]

proposed a security mechanism based on analyzing blockchain network traffic statistics to detect malicious events through data collection and anomaly detection functions.

There are considerable studies on the detection of credit card fraud,[220] financial statement fraud[221] and insurance fraud.[222] However, there are only a few studies on the detection systems for securities market fraud and illegal activities.[223] For example, James et al.[180] calculated intraday realized volatility within a 30-min trading transaction moving window and designed an adaptive framework to detect illegal trading behavior to fill the gap in this field. Rabieinejad et al.[182] proposed a two-stage deep learning-based Ethereum threat search model through real Ethereum transaction datasets from 2017 to 2019, where they employed deep neural networks for attack detection and classification of attacks of different degrees. The model achieves 97.72% accuracy in Ethereum attack detection and 99.4% accuracy in attack classification. Aziz et al.[181] proposed a transaction fraud detection method based on an optical gradient enhancement machine (LGBM) to detect fraudulent transactions on Ethereum and compared eight different machine learning methods, logistic regression, random forest, classifier and MLP classifier. The results showed that the LGBM model outperformed the other models with a slightly better performance in the specified dataset scenarios. For processing heterogeneous information, Liu et al.[183] built a heterogeneous graph transformation network based on CNN for contract anomaly detection and employed this model to detect financial fraud on the Ethereum platform. Fan et al.[184] built a lightweight identifier independent engine (LION) for anomaly detection in P2P networks of cryptocurrency blockchains. Gu et al.[185] used the web crawler to collect transaction data and obtain the influential factors on the turnover based on LSTM. They calculated the deviation between the predicted and the real transaction amounts and provided a basis for detecting the abnormal transaction amount.

Ethereum is a cryptocurrency transmission system, and because of the confidentiality provided by Ethereum, it can be challenging to identify a user's wrongdoing if fraud occurs.[181] The results showed that the accuracy of the method was 96.3%.

Yan et al.[186] reviewed the perception methods of abnormal behavior of public blockchain in recent years and summarized three dimensions to perceive abnormal behavior. First, be aware of various abnormal behaviors at the blockchain network level that are not directly related to laws and regulations in physical space; Second, be aware of the abnormal behavior of the subjects in the blockchain; Third, be aware of the risks of public blockchain service behavior, that is, to concentrate on the behavioral risks that violate the laws and regulations related to physical space under the premise of the proper use of blockchain. To keep market transactions efficient and equitable, it is especially crucial to identify abnormal trading activity in the cryptocurrency market. Currently, the majority of research develops deep learning-based algorithms to detect abnormal trading behaviors. The identification efficiency has been improved in recent research by using blockchain-related technologies such as smart contracts (See Tables 12 and 13).

Regulation of cryptocurrency transactions

Cybersecurity has recently become an important research topic, considering cryptocurrencies' high volatility and significant implications for developing dynamic and long-term corporate governance and business regulation.[224] With fintech development, technological innovation can help mitigate structural problems, risks, and regulatory challenges in the cryptocurrency market.[225] The anonymity and decentralization characteristics of blockchain and smart contracts may provide new opportunities for tax evaders, criminals and cheaters. Bartoletti et al.[187] conducted a comprehensive investigation on Ponzi schemes in Ethereum, analyzing their behaviors and impacts from different perspectives. Suggestions and suggestions for improvement to potential users and regulatory authorities. Hua et al.[188] used supervised machine learning to predict unidentified transaction types, which played an essential role in organizational norms and avoiding regulatory vacuums. Pedersen[189] explained the Social Network effect, excess volatility, momentum and reversal effect, meme trading, the effect of repeated news, expected spillover and the transaction price between people with social relations in portfolio holdings based on belief formation in social network. In network security analysis, Ebrahimi et al.[190] significantly improved the detection of hacked cryptocurrency assets across multiple foreign languages based on Contrastive Learning based Knowledge Tracing (CLKT) and DRL.

Anti-money laundering has also recently emerged as a critical research topic. Paula et al.[191] used autoencoder to mark outliers in export enterprises, including statistical data of customs inspection, export volume and tax, where they identified 20 high-risk companies with fraud. Charitou et al.[192] combined sparse autoencoder and generative adversarial network (GAN) for anti-money laundering in online gambling.

Table 9. Research on cryptocurrency portfolio construction (1)

Models	Data	Results	Innovation	References
CNN, DRL	12 most traded cryptocurrency assets	The performance of the model strategy is compared to three benchmarks and three other portfolio management algorithms with positive results.	In this paper, we propose a model-free convolutional neural network that takes the historical prices of a group of financial assets as input and outputs the weights of this portfolio.	Jiang and Liang[15]
DRL, MDP	10 Cryptocurrencies with Transaction Costs data from 2011/10/01 to 2011/10/20	The BTC buy-and-hold strategy has a cumulative yield of 93%.	A state-of-the-art DRL algorithm implementation framework called FinRL has been created enabling users to train trading agents in the pipeline. An automatic backtesting module is also offered to assess trading performance.	Liu et al.[153]
DRL, CVaR	Data on the cryptocurrency market from 2015 to 2021 was used	When the economic structure collapses, it captures the nonlinear compound effect of many risk shocks on the risk distribution and directs investment in the financial market with hightail risk.	Based on CVaR risk measurement and a deep reinforcement learning optimization framework, a new bitcoin portfolio model framework is created.	Cui et al.[154]
DRN, MultiObjective Evolutionary Algo rithms(MOEA)	BTC, ETH, LTC, XRP, DSH, XLM, HMR	The proposed framework utilizes a multi-layer deep recurrent neural network regression model, which can provide more accurate prediction estimates.	The allocation of a bitcoin portfolio using a multi-objective evolutionary algorithm and deep learning model. Additionally, its capacity for forecasting can produce precise ex ante assessments of portfolio returns and dangers.	Estalayo et al.[155]
LSTM, ARIMA, CMA, ANN	10 cryptocurrencies including bitcoin from January 1, 2018 to September 1, 2019	Bitcoin shows a fantastic investment opportunity with a buy-and-hold Sharpe ratio of 2.85, a return of 78.52%, and no volatility.	Paired trading using cryptocurrencies adds an edge to traders.	Osifo and Bhattacharyya[156]
RNN, LSTM, GRU	Ethereum	Deep learning is more effective than traditional methods in predicting transaction value.	It is proved that the deep learning-based method is suitable for forecasting large-scale and long-term data scenarios	Gu et al.[157]

Weber et al.[193] used graph convolutional neural network to identify illegal bitcoin transactions; Mohan et al.[194] introduced graph convolutional decision forest, which combines the potential of evolutionary graph convolutional network and deep neural decision forest, and improves the efficiency of the model to identify money laundering behaviors. Hua et al.,[188] Zhang & Trubey[195] used multiple models such as logistic regression (LR) and random forest (RF) to model anti-money laundering events and regulate cryptocurrencies. Moreover, the research results of Raiter,[196] Ruiz & Angelis[197] show that random forest can be used in the anti-money laundering architecture of financial institutions due to its accuracy and interpretability characteristics.

XGBoost algorithm is also often used to improve the computational efficiency of tax evasion discrimination.[198] Vassallo et al.[226] proposed Adaptive stacked Extreme Gradient Enhancement (ASXGB), which is an improvement of extreme gradient enhancement (XGBoost) to better deal with dynamic environments. Jullum et al.[199] constructed and validated a supervised learning model based on the XGBoost algorithm to determine which transactions should be further investigated by AML investigators. The active learning solution proposed by 9 to match the

Table 10. Research on cryptocurrency portfolio construction (2)

Models	Data	Results	Innovation	References
LSTM, GARCH	From January 1, 2020 to June 30, 2020 BTC, ETH, BCH and other 10 currencies	It is found that the deep learning model can better recover the structure of realized variance, and the model can achieve more accurate prediction.	Major cryptocurrency volatility is predicted by GARCH, LSTM, and hybrid models, where the LSTM model's properties are based on the GARCH family of parameters.	Moreno and Garcia Medina[158]
Stochastic spanning, Mildly explosive framework with multiple bubbles	Bitcoin, Ethereum, XRP and Litecoin USD closing prices	The optimal enhanced portfolio consists of 90% cryptocurrency and 10% traditional assets.	It is investigated whether cryptocurrencies offer diversification benefits to risk averse individuals via a stochastic spanning approach.	Anyfantaki et al.[159]
High frequency trading, gorithmic trading	10 cryptocurrencies including BCH returns from July 1, 2018 to August 31, 2018	The results of the study surface the large-scale use of automated trading algorithms and extremely fast trade execution in this market seems to be a standard based on media reports.	In the study, intraday trading patterns incorporating algorithmic trading and their effects on the European cryptocurrency market are examined.	Petukhina et al.[160]
PROMETHEE II, ARIMA, LSTM, RFR	From 2017/01/01 to 2022/01/01 data of Bitcoin	The performance of the model results confirms that the proposed model is superior to other proposed models in terms of average return rate (=0.017) and standard deviation (=0.036).	Using ARIMA, LSTM and RFR models to predict returns, VaR and C-VaR as risk related criteria, the cryptocurrency portfolio allocation model is proposed based on PROMETHEE II	Zolfani et al.[161]
Model review		The distribution between research objects and approaches, datasets, research trends, and some startup chances that are still available in cryptocurrency trading are studied.	A comprehensive overview and analysis of the research work on cryptocurrency transactions is provided. The defined nomenclature and the current state of the art are presented.	Fan et al.[16]
Model review		Apply big data to cryptocurrency trading strategy	To find research gaps in bitcoin price prediction and portfolio management, cryptocurrency trading algorithms carried out a bibliometric analysis and a systematic review.	Ruiz Roque da Silva et al.[162]

performance of a fully supervised baseline includes XGBoost, local outlier factor (LOF), KNN, principal component analysis (PCA), single-class support vector Machine (OCSVM), cluster-based outlier factor (CBLOF) and other algorithm models.

Alarab et al.[200] adopted an ensemble learning method and combined it with a supervised learning model to predict legal and illegal transactions, which achieves a higher accuracy level than classical learning methods, such as Random Forest, Adaboost, and External Trees. In addition, the LSTM model has also been employed in anti-money laundering modeling. Alarab & Prakoonwit[201] developed a classification model that combines long and short-term memory with Graph Convolutional Network(GCN), which, under the same experimental settings, has better performance than the LSTM and the GCN model. Jensen & Iosifidis[202] proposed to combine LSTM and GRU to determine anti-money laundering alerts on cryptocurrency transaction records. They automatically replaced predefined rules with the potential features extracted from transaction records from January 1, 2020, to January 31, 2022. The experiment results show an improved accuracy in detecting banks' money laundering alerts. Current research on the regulation of the cryptocurrency industry focuses on identifying and monitoring

Table 11. Research on cryptocurrency bubble analysis

Models	Data	Results	Innovation	References
Network measures of complexity, Random matrix theory	Daily returns of 24 global cryptocurrency price time series from 2013 to 2018	The market effect as a whole is captured by the highest eigenvalue, which is very susceptible to crash occurrences. Both the largest eigenvalue of the correlation matrix and the new economic quality can serve as quantum indicators that foretell the market fall for Bitcoin.	The possibility of using recursive measures of complexity, entropy measures, network measures and quantum measures to detect dynamic changes in complex time series is explored.	Soloviev and Belinskiy[163]
LASSO, Network analysis	Data for 50 cryptocurrencies from January 1, 2015 to September 30, 2020	The connectivity of cryptocurrency returns under extreme shocks may be stronger and more complex.	Reveal media-based and right-tail-based return interdependence between cryptocurrencies under normal and extreme market conditions.	Shahzad et al.[164]
Quantile vector autoregressive model	Closing prices of six cryptocurrencies from June 1, 2016 to May 31, 2021	Explains the existence of cryptocurrency asset interdependence and contagion effects during bubble and crash periods.	Separating dependency, contagion, and asset rotation effects by concentrating on currencies with higher market capitalization measures directional spillovers.	Chowdhury et al.[165]
Ensemble learning, CNN, LSTM	BTC, ETH and XRP from January 1, 2018 to August 31, 2019	Ensemble learning and deep learning can effectively benefit each other to develop powerful, stable, and reliable predictive models.	Ensemble learning strategies are combined with advanced deep learning models for predicting hourly prices and movements of cryptocurrencies.	Livieris et al.[166]
RNN, GRU, LSTM, MLP	BTC, ETH, USDT, and BNB data over the years	The neural network's input data has the best ability to predict prices, and the use of adaptive feature selection approaches significantly enhances classification performance.	A prediction model based on deep learning during the bubble period is proposed to predict and classify the price of cryptocurrency and its movement direction.	El-Berawi et al.[167]
CNN, Ensemble models	20 stocks from 2000 to 2021	The experimental results show that the integrated CNN model using GAF greatly improves the prediction accuracy of the model under key market conditions.	An integrated CNN-based model is proposed that is highly resilient to stock market crashes, especially in the early stage of the COVID-19 pandemic	Ghasemieh and Kashef[168]
ZI/MI traders, DRL	January 1, 2015 to December 31, 2018 BTC, ETH	The ZI/MI factor is easier to interpret than the CI factor, and GGSMZ proves to be a decision support tool for investors.	A trading agent mechanism GGSMZ based on neurofuzzy mechanism is introduced. The behavior of ZI/MI trading agents during financial bubbles is analyzed.	Guarino et al.[169]
Security model	Ethereum and Litecoin	Consumers could be holding economies with essentially useless bitcoin, and a systemic attack could jeopardize bitcoin's ability to move.	Show how Bitcoin's security-model can embed price volatility amplification and develop models that let consumers choose between Bitcoin and fiat currencies	Pagnotta[170]

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Table 11. *Continued*

Models	Data	Results	Innovation	References
NLP, Hyperbolic learning	Prices from March 1, 2016 to April 7, 2021	The utility of CryptoBubbles is demonstrated, and CryptoBubbles and our hyperbolic model are publicly released.	The multi-span crypto bubble prediction task and dataset of CryptoBubble are proposed to explore the power-law dynamics of social media hype.	Sawhney et al.[171]
Time-varing parameter model	Bitcoin, Ethereum, Litecoin, and XRP data during the 2017–2018 cryptocurrency bubble	During the 2018 crypto crash, the negative news effect was a significant driver of crypto returns.	It generalizes the asset pricing model with correlation between return and volatility, considers time-varying parameters, and explains the importance of time-varying returns and volatility maybe formally verified in this new model.	Cross et al.[172]
Dynamic Time Warping(DTW)	Daily closing prices of 18 major cryptocurrencies for 2017 2018	Comparing the cryptocurrency bubble period to the COVID 19 pandemic, the results suggest that this one had the greatest impact on cryptocurrency market efficiency.	DTW paths are used to study the lead lag relationship between different cryptocurrencies	Montasser et al.[173]

Table 12. Research on abnormal cryptocurrency trading (1)

Models	Data	Results	Innovation	References
Trimmed, kmeans	230,686 transactions from Genesis Block to blockchain on April 7, 2013	Trimmed k-means provides excellent results and improves the detection rate for known fraud elements.	This paper investigates the simultaneous clustering of objects and fraud detection by trimmed k-means in a multivariate setting to detect fraudulent activity in Bitcoin transactions	Monamo et al.[174]
K-means, Mahalanobis distance, SVM	All Bitcoin transactions from the creation of the network until April 7, 2013	The algorithm used is able to identify certain abnormal transaction data.	The automated nature of a variety of unsupervised learning methods is used to elaborate on useful feature observation and the extraction of input networks	Pham and Lee[175]
Logistics regression, K-means, SVM, GAT2VEC	Three datasets	Detect the most suspicious users and transactions, match the dataset and adapt machine learning methods.	A graph structure analysis of the Bitcoin network is performed to identify potential anomalies and unusual user activities using a social network approach.	Martin et al.[176]
GNN, GAT	Transaction data on Ethereum blockchain from August 2, 2016 to January 15, 2017	Graph neural network algorithm has higher anomaly detection accuracy.	An anomaly detection framework for Ethereum blockchain based on OCGNN is proposed.	Patel et al.[177]
RNN, RF	About 3000 transaction data of Ethereum	Manual signing of unusual transactions by the model still greatly improves the usability of the digital signature process.	An automatic digital signature method for blockchain transactions based on RNN is proposed in order to construct a customized anomalous transaction detection system, and the user's local environment is used to operate and store the customized data in the anomaly detection model.	Podgorelec et al.[178]
OC-SVM, AutoEncoder	639,360 pieces of Bitcoin data were collected, of which 39.4% of the data belonged to Normal	The Age-based detection engine performs better in detecting anomalies than the semi-supervised (OC-SVM) and supervised (LR, GB, RF, and DNN) learning methods.	A security mechanism based on analyzing blockchain network traffic statistics is proposed to detect malicious events through data collection and anomaly detection functions.	Kim et al.[179]
NN-DTW	A grid of 1800 trade prices is used to calculate intraday realized volatility over a 30min trade by trade moving window.	The NN DTW model correctly identifies 90% of suspected illegal transactions in the validation sample and achieves a type I error rate of 38% on average.	The flexibility of dynamic temporal warping and extreme value theory are used in an adaptive framework to identify large-scale trade data and illicit trading patterns.	James et al.[180]

Table 13. Research on abnormal cryptocurrency trading (2)

Models	Data	Results	Innovation	References
RF, MLP, LGBM	9841 lines of known fraudulent and valid transactions through Ethereum	LGBM algorithm shows slightly better performance in the specified dataset scenario up to 98.60% accuracy up to 99.03% after parameter optimization	This paper proposes an LGBM-based transaction fraud detection method, along with other algorithms such as RF and MLP, to classify Ethereum fraud detection datasets with limited attributes	Aziz et al.[181]
DNN, Kmeans, Decision Tree, RF	Real Ethereum transaction dataset from 2017 to 2019	The model achieved 97.72% accuracy in Ethereum attack detection and 99.4% accuracy in attack classification	Deep neural networks are used in a two-stage deep learning-based Ethereum threat search model to detect attacks, and supervised and unsupervised techniques are combined to classify attacks.	Rabieinejad et al.[182]
SVM, CNN, RCNN, GCN, GAT, S_HGTNs	There were 1251 normal contracts and 131 fraudulent contracts on Ethereum	The proposed model outperforms the conventional model in the classification results with a low standard deviation, demonstrating the model's validity and stability.	A heterogeneous graph variant network (S_HGTNs) suitable for smart contract anomaly detection is constructed to detect financial fraud on Ethereum platform	Liu et al.[183]
LION (Lightweight and Identifier-Oblivious Engine)	Bitcoin P2P security research provides information	The detection accuracy of the model for attack prototypes and real-world anomalies exceeds 97% F1-score.	Build the LION model for anomaly detection in the P2P network of cryptocurrency blockchain, and conduct data-driven research and evaluation on LION	Fan et al.[184]
LSTM	Complete trading data for the 5 stable top 10 exchanges on CoinMarketCap	The test results indicated that some abnormal transaction amounts were related to policy changes and industry events, while other abnormal transaction amounts were suspected to be related to illegal acts.	By examining the relationship between the quantity of each transaction and other transactional information, it was possible to identify the significance of various transactional elements. From a time series forecasting standpoint, LSTM is utilized to examine irregular transactions.	Gu et al.[185]
Model Review		The ideas of public blockchain and joint blockchain, as well as the current methods for identifying anomalous activity, are explained in depth.	The existing mainstream blockchain security-related datasets are summarized and analyzed to provide reference for the research of blockchain security awareness.	Yan et al.[186]

money laundering, Ponzi schemes, hacker assaults, and other related activities. It has been proven that semi-supervised and unsupervised learning enables high prediction accuracy in related modeling tasks (See Tables 14 and 15).

Initial coin offering in cryptocurrency

Initial coin offering (ICO), a concept similar to initial public offerings (IPOs), refers to raising money for popular digital currencies like Bitcoin and Ethereum. The forecast of ICO financing success rate and the detection of ICO fraud are the two key components of the research on cryptocurrency ICO.

Table 14. Research on cryptocurrency regulations (1)

Models	Data	Results	Innovation	References
Monte Carlo simulation, Online Solidity Decompiler	Statistics of 184 contracts on Ethereum	The majority of chain structured contracts used in ponzi schemes barely differ in terms of multiplicative factors, etc. It is possible to create new Ponzi schemes by altering current ones.	Ponzi schemes on Ethereum have been comprehensively investigated, analyzing their behavior and impact from different perspectives.	Bartoletti et al.[187]
Decision Tree, RF, GBNN	Contains approximately 395 million transactions involving 957 unique clusters	The average cross validation accuracy is 80.42% and F1-score is 79.64%.	The genuine level of Bitcoin anonymity was examined to ascertain the extent to which users/or organizations' identities inside the Bitcoin ecosystem could be revealed by utilizing supervised machine learning techniques.	Sun Yin et al.[188]
Belief Formation in a Social Network	GameStop Price, volatility, turnover, and interest data from January 5, 2020 to March 5, 2022	The zealous and rational views of investors dominate over time, and the securities market has phenomena such as social network spillovers, the huge effect of influencers and thought leaders.	Closed-form solutions for prices, portfolios, and beliefs are presented with four types of investors	Pedersen [189]
CLKT, DRL, GANs, BiLSTM	862,715 projects, 761,993 hacker forum posts, and 100,722 DNM products from 2016 to 2019	Cybersecurity managers may benefit from focusing on Russia to identify sophisticated hacking assets.	The model makes advantage of the novel adversarial Deep representation learning (ADREL) technique, which creates multilingual text representations using GANs. It has application in the study of hacker assets using the most recent cross-language knowledge transfer techniques.	Ebrahimi et al.[190]
CRISP-DM, GBM, Deep Learning AutoEncoder, PCA	H2O R package data set	From the characteristic attributes of exporting firms, the model is able to detect anomalies for at least 20 exporters.	The model for export fraud suspect identification is unsupervised. Deep learning autoencoders are around 20 times faster at dimension reduction than PCA.	Paula et al.[191]
SSGAN, LR, RF, MLP	The credit card fraud dataset contains 2492 transactions (2000 normal transactions and 492 fraudulent transactions)	The proposed architecture achieves better classification results than the existing anti-money laundering detection system, and the F1 score is improved by 3.64%	Introduced and used in fraud detection systems and other classification tasks with imbalanced data is a system architecture based on semi-supervised generative adversarial networks and sparse autoencoders (SAE).	Charitou et al.[192]
RF, GCN, RNN	A time series graph of over 200K Bitcoin transactions (nodes), 234K directed payment flows (edges), and 166 node features	The results show the superiority of random forest, and also suggest algorithmic work that combines the respective capabilities of random forest and graph methods.	The AML community receives a big dataset of labeled transaction data. To create a safe and open financial system, the experimental findings employing various techniques, such as graph convolutional networks, are shared.	Weber et al.[193]

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Table 14. *Continued*

Models	Data	Results	Innovation	References
GDL, GCN, Deep neural decision forest, Knowledge distillation (KD)	203,769 Bitcoin transactions (21% were flagged as legitimate and 2% as illegitimate)	Knowledge distillation (KD) was applied in the proposed method to obtain the best results.	The proposed model provides a new view of combining random forests with dynamic graph learning methods	Mohan et al.[194]

Chuanjie et al.[203] classified ICOs into different topics such as finance, media, information, professional services, health and society, and natural resources based on a Latent Dirichlet Allocation(LDA) model and proved that different topic models can be used to help predict whether ICOs will be successful. Dio & Tam[205] managed to reduce investment risk through an automated deep learning system that classifies ICOs by predicting their success. This DL system consists of two neural network architectures: the first network primarily uses a bidirectional LSTM attention network to build ICOs white paper, and the second uses graphical neural networks (GNNs) and LDA to construct ICOs website structure. Based on the multiple regression model of 3838 ICO samples from 108 countries, Bellavitis et al.[212] found that the spillover effect of regulation causes a short-term increase in the number of low-rated ICOs in other countries and a long-term drop in the number of ICOs. Xu et al.[206] found that previous studies mainly used project-related factors to predict the success of ICOs, which ignored social factors such as team information and expert evaluation. Therefore, they studied the impact of heterogeneous team knowledge and expert evaluation on the success of ICOs, and designed a new knowledge measurement method based on knowledge-based theory (KBT). This study also proposed a bidirectional recurrent neural network based on an attention mechanism to extract features from online implementations in reviews. Wang et al.[207] constructed a document analysis deep regression model (DADRM) based on almost all 5,534 ICO projects as of September 2019 to extract deep text and layout features from white papers to evaluate the effectiveness of the proposed framework in predicting the amount of successful ICO funding. Experiments show that the model not only extracts the text content but also retains the original two-dimensional structure of the document, which can significantly reduce the prediction error. Regarding the influential factors on ICOs, Belitski & Boreiko[213] found that the amount of ICO funding, number of investors, hard cap achievement and token ranking have the most significant impact on the probability of ICO funding success, while other factors such as continuous investors, token pre-sale, bonus sale and ownership share off under also explain the performance of ICO to a certain extent. In addition, recent research has found that ICO investors are influenced significantly by emotions when making investment decisions.[214]

Many researchers identify subtle warning signs hidden beneath the surface with well-designed neural network systems. Bian et al.[208] used natural language processing technology to analyze the characteristics of the 2251 digital currencies and associated the life and price changes of cryptocurrencies with these characteristics by the LSTM model. The experiment results proved that the proposed system could identify scam ICO projects with an accuracy of 0.83. Besarabov & Kolev[210] proposed a convolutional architecture model based on the LSTM and CNN to extract spatial meaning from the data. In the experiments, the proposed method reduced the error of Ethereum value prediction by 26% compared with the traditional LSTM model. Hornuf et al.[211] divided ICO fraud into internal and external fraud and proposed a dummy variable regression model to analyze the degrees and reasons of fraud in 1393 ICO samples. Zheng et al.[209] extracted language features from ICO white papers and used cutting-edge machine learning and deep learning algorithms to train prediction models. They adjusted the weights and Loss functions of unbalanced samples using SVM, Bayes, logistic regression, decision trees, and other techniques using SMOTE-XGBoost and Focal Loss-XGBoost methodologies. The accuracy rate is finally 82%, which is better than those traditional methods without a weight adjustment. Beyond the prediction efficiency of traditional models, deep learning algorithms in cryptocurrency IPOs have been proved to play a significant role in IPO fraud monitoring, IPO success rate prediction, and creating better information asymmetry in the IPO market according to the most recent surveys (See Tables 16 and 17).

CHALLENGES AND FUTURE DIRECTIONS

Deep learning in cryptocurrency may still face some research challenges and need corresponding future efforts. Table 18 presents these challenges, including the impact of extreme risk events, data storage efficiency, data quality characteristics, data time lag, interactive behavior of cryptocurrency nodes, and multi-level multi-objective subject modeling. Meanwhile, we propose development directions worthy of research for each of these challenges.

First, existing models should be developed to account for the impact of extreme events. For example, in the crisis phase, market speculation is likely to result in high volatility of cryptocurrencies. Current studies generally focus on daily volatility measures calculated based on the variation between high and low prices realized throughout the day, which are also suitable for predicting intraday returns in stock and futures market. Zhang et al.[235] conducted the multifractal detrend volatility analysis based on the overlapping sliding window (OSW-MF-DFA) method to study the multifractal behavior of CSI 300 index and S&P 500 index due to the sudden impact of the COVID-19 pandemic. Based on the long short-term memory method, the time-varying Hurst exponent is added to the gated recurrent unit (GRU) neural network model to significantly improve the prediction accuracy of time series. In addition, other risk events, such as the COVID-19 pandemic, have significantly altered the market efficiency of the biggest trading cryptocurrencies. The implied price risk makes predicting prices, spot bubbles, and managing currencies extremely difficult. Repeating the experiment on a larger dataset over a more extended time from the data analysis

Table 15. Research on cryptocurrency regulations (2)

Models	Data	Results	Innovation	References
Bayes Logistic regression Decision Tree, RF, SVM, ANN	The analysis data contained 3922 alerts and the test data contained 2157 alerts.	In modeling money laundering events, it is revealed that SVM and ANN algorithms are superior to logistic regression.	According to the data and model specification used, the advantages of machine learning algorithms in modeling money laundering events are revealed	Zhang and Trubey[195]
AML, ANN, Logistic Regression, Random Forest, SVM	Synthetic dataset developed by the PaySim simulator	The random forest technique provides the best accuracy compared to other.	Compare multiple machine learning models to analyze the tools that can be used in the anti-money laundering (AML) architecture of financial institutions	Raiter[196]
RF Decision Tree	The distribution of the Bitcoin dataset has 46,564 transactions (4,545 illegal transactions and 42,019 legal transactions)	The decision tree algorithm has high classification scores and seems to be the most appealing method.	To explore how to anonymize launderers cryptocurrency money with the help of machine learning (ML)	Pettersson Ruiz and Angelis[197]
LGBA, XGBoost	Composed of 203,795 transactions, 4,544 were marked as illegal transactions and 42,018 as legal transactions	The LGBA and XGBoost outperform the Random Forest algorithm in distinguishing between exchange and account level illegal exercises.	Two algorithm structures are employed in this paper's discussion of the usage of deep learning algorithms in tax evasion discrimination exercises.	Ahmed[198]
XGBoost	Anonymized data for a series of alert transactions between April 1, 2014 and December 31, 2016	The model achieves 95% and 80% accuracy of reported transactions and is superior to the bank's current approach in terms of fair measurement of performance.	A new performance measure is proposed specifically to compare the proposed approach with the existing AML systems of banks	Jullum et al.[199]
XGBoost, LOF, KNN, PCA, OCSVM, CBLOF, ABOD, IF, Active learning	Bitcoin data published by Elliptic	The active learning solution is able to match the performance of the fully supervised baseline by using only 5% of the labels.	It emphasizes the risk of studies using artificial data being deceptive and the value of using real-world datasets when conducting experiments so that conclusions may be trusted.	Lorenz et al.[9]

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Table 15. *Continued*

Models	Data	Results	Innovation	References
Ensemble Learning	Bitcoin data published by Elliptic	The model is able to predict legal/illegal transactions with an accuracy of 98.13% and an F1 score equal to 83.36%.	A comparison of the effectiveness of traditional supervised learning techniques to predict legal and unlawful transactions in the network is carried out using a recently made dataset from the Bitcoin blockchain.	Alarab et al.[200]
Temporal GCN, LSTM	203,769 partially flagged transactions, 21% were legal and 2% of which as flagged as illegal.	The model shows a significant improvement over previous studies, with an accuracy of 97.77%	The Temporal-GCN model is proposed as a combination of LSTM and GCN models for detecting illegal transactions in the Bitcoin transaction graph, known as elliptical data.	Alarab and Prakoonwit[201]
GRU, LSTM	66,610 unique AML alerts queried between Jan 1, 2020 and Jan 31, 2022	The model can reduce the number of false positive alarms generated by the traditional AML system by more than 33.3%, while retaining 98.8% of all true positive alarms.	It is suggested to use a strategy based on LSTM to establish and enhance bank anti-money laundering alerts. The goal is to substitute established criteria with latent features that are automatically retrieved from the transactions' sequence.	Jensen and Iosifidis[202]

standpoint is advisable. Moreover, to efficiently implement this task, we can employ semi-supervised learning models, feature selection techniques and streaming data technologies to deal with the extreme events in cryptocurrency market. Yue et al.[227] use feature selection techniques to evaluate the predictive performance of different factors on bitcoin returns during Covid-19 pandemic period. By evaluating the accuracy of three machine learning models: one-dimensional convolutional neural network (1D-CNN), Bidirectional deep learning Long Short-Term Memory (BLSTM) neural network, and Support Vector Machine model, the results shows outperformance of 1D-CNN model and reveal the importance of investor sentiment to improve the accuracy of return prediction under extreme events. Other external shock events such as money laundering activities and terrorist attacks can also affect the liquidity and stability of the cryptocurrency market. Patel and Richter[236] investigated the impact of the outcome of monthly terrorist attacks on the monthly returns of 1,178 cryptocurrencies over the period from 2014 to 2018. The results show that the terrorist attacks are negatively correlated with cryptocurrency returns. Froehlich et al.[237] pointed out that the financial fraud involves the systematic manipulation of the cryptocurrency market, decreasing investor confidence in the cryptocurrency market and increasing the vulnerability of the market. Due to the volatile and uncertain financial markets, existing deep learning methods are challenged in prediction tasks considering the impact of shock events.[238]

Second, the applications of deep learning in cryptocurrency field also have the data sparsity problems. To begin with, due to asymmetric information, the difficulty of data shortage is a critical issue in model training. If a big training sample size is not employed, then learning abstraction through precise language definition is less effective.[239] Additionally, the over-reliance on convolutional neural networks (CNNs), particularly for video recognition, may experience exponential inefficiency, which can be avoided by capsules, which more efficiently capture important spatial hierarchical relationships than CNNs while requiring less data. Data augmentation, transfer learning, recursive classification algorithms, and synthetic data generation are some techniques used to enable DL to implement modeling tasks based on smaller available datasets. In addition, given a relatively small number of training examples, techniques like few-shot learning have already begun to show improvement in language processing and picture classification tasks, which inspires the further development of deep learning modes in the cryptocurrency field. Li et al.[228] conducted embedding enhancement based on contrast learning to solve the few-shot learning problem in the analysis of cryptocurrency influencers. This study shows that contrast learning can solve the problem of fewer shots when analyzing cryptocurrency influencers, and address the challenges associated with analyzing cryptocurrency influencers with limited label data.

Moreover, data quality is necessary for the training of machine learning models. Deep learning models need to pay more attention to the correlated features between different data groups, rather than merely considering the numbers of features.[240] These characteristics hurt machine learning for financial forecasting. Because the data may over-fit the square error and the model and purposefully fit some "noise" in the

Table 16. Research on cryptocurrency ICO (1)

Models	Data	Results	Innovation	References
LDA	ICO data between May 31, 2016 and August 20, 2018	Three subjects have a significantly higher percentage of successful white papers than the other nine topics when comparing the proportion of successful and unsuccessful ICOs among the ten topics.	It has been demonstrated and confirmed that the LDA model is effective for evaluating ICO white papers and that it is able to separate ICOs into various categories, aiding in the creation of prediction models.	Chuanjie et al.[203]
BloHosT,LS	Case study	It is proved that BloHosT achieves a higher ROI in tourism than the traditional framework	A single unified cryptocurrency-enabled application is proposed as the platform for BloHosT, which would allow for the registration of tourist users.	Bodkhe et al.[204]
GNN,Bi−LSTM	JavaScript generated website data	Classifying risky ICOs precisely, although recall is low.	Two neural network topologies, natural language processing, and visualization methods were investigated in order to categorize ICOs.	Di Dio and Tam[205]
A-BiRNN	The 5717 projects included 3119 failed projects and 1167 successful projects.	The proposed method is effective at predicting the success of ICOs because its accuracy is more than 6% greater than that of the existing models.	It offers helpful suggestions for ICO platforms and investors to assess the quality of cryptocurrency projects, hence enhancing the information symmetry of the ICO market.	Xu et al.[206]
RoBERTa, RCNN,DADR	Almost all 5,534 ICO Mprojects as of September 2019	Our model preserves the document's original two-dimensional structure in addition to extracting the text content, which can greatly minimize prediction error.	A Document Analysis Deep Regression model (DADRM) is constructed to innovatively extract deep text and layout features from white papers.	Wang et al.[207]
Graph learning	116,293,867 external transactions and internal transactions from January 1, 2018 to March 31, 2018	Experimental results on Ethereum transaction records show that I2GL significantly outperforms other state-of-the-art methods.	This paper proposes I2GL, a recognition inference method based on big picture analysis and learning.	Liu et al.[116]

estimation process, non-stationary data, for example, will invalidate the prediction results in training, and the corresponding prediction error may underestimate the size of the error that will occur when the model is used to predict the future.

Meanwhile, although numerous models and algorithms serve as the foundation for many real-world issues, little research has been done in heterogeneous environments. Regarding the decision making in the real world, the agent might only have access to few information in the real world. However, the final model must be built on the comprehensive representation of all the variables, which data is always unstructured and heterogeneous. These unstructured financial data include information from financial web pages, stock data, and the creation of financial taxonomies. The goal of aggregating multivariate heterogeneous data is to realize knowledge interaction at multiple levels by establishing multi-dimensional and multi-granularity associations between data, information, and knowledge pieces. To lessen the effect of heterogeneous data on modeling, new deep learning algorithms must find and use correlations without relying on spatial information. Lin et al.[229] proposed an agent-based, open source, large-scale network simulator, including network topology, packet loss, heterogeneous latency,

Table 17. Research on cryptocurrency ICO (2)

Models	Data	Results	Innovation	References
ICORATING LDA, LSTM	, 2,251 pastICO projects	Under the optimal setting, the proposed system is able to identify scam ICO projects with 0.83 accuracy.	ICORATING, a learning based cryptocurrency rating system, is introduced. Supervised learning models are used to correlate the lifespan and price changes of cryptocurrencies with these features.	Bian et al.[208]
NLP, XGBoost, SVM, Bayes, logistic Regression, Decision Tree	The ICO evaluation website screened icos in the scam category for fraud samples	An AUC of 0.94 and an accuracy of 82% are achieved, which is better than other traditional standard methods, and the results provide important implications for ICO fraud detection.	The results help potential ICO investors' investment decisions, and ICO trading institutions can utilize this model to improve the platform's professionalism and legitimacy by spotting fake ICOs.	Zheng and Wang[209]
LSTM, CNN	The first type of data is historical market cycle data, and the second type of data is from the Ethereum blockchain.	The LSTM method reduces the error by a factor of 4, and the error is further decreased by 26% by using convolutional architecture, modeling of spatial datasets, and blockchain account distribution histograms.	The standard approach to asset value prediction is market analysis based on LSTM neural networks. Blockchain technology enables experiments to access vast amounts of public data.	Besarabov and Kolev[210]
Probit Regression	Data of 1393 ICO projects	The extent of fraud in ICOs and whether disclosure prior to the offering predicts fraud are examined.	Probit regressions were run using three different dependent variables: confirmed fraud, suspected fraud, unknown fraud.	Hornuf et al.[211]
Multiple regression	Sample of 3838 icos in 108 countries	A national regulatory prohibition on ICOs causes a short-term boost in the quantity of low-quality ICOs abroad and a long-term drop in the quantity of ICOs.	We investigate how regulatory spillovers affect entrepreneurship globally. In general, more regulation results in more options on the market.	Bellavitis et al.[212]
Multiple regression	Data on 166 ICOs and over 300,000 donor addresses that sent money to ICOs in Bitcoin or ether between 2013 and 2017	The three boundary criteria forecast the amount of money for an ICO, the number of investors, the attainment of the hard cap, and token ranking. The effectiveness of ICOs is also explained by additional factors like serial investors, token presales, etc.	This study further advances recent research on initial coin offerings (icos) to understand the set of characteristics that drive ICO performance and reduce information asymmetry.	Belitski and Boreiko[213]

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Table 17. *Continued*

Models	Data	Results	Innovation	References
NLP, ANN	5033 ICO white papers were collected.	ICO investors are largely driven by emotions when making investment decisions.	37 potential variables and their verified effects on ICOs were found by looking for information about ICO characteristics on various websites and textually analyzing these white papers.	Sapkota and Grobys[214]

gossip protocol with reliable broadcast quality. Through DAG-based data structure, the consensus protocol shows robust and prominent performance measures (includes confirmation time, tip pool size and consensus time) which can be used to model interdependence of data series under different network environments, as well as attack conditions.

Thirdly, real-time trading is one of the most challenging obstacles in the cryptocurrency market. Within a predetermined time horizon, the algorithm must be able to track any changes and perform effectively in trading. Any previously trained model, however, could perform poorly when the dataset's dynamics change. The algorithm must be repeatedly trained in order to retain good performance. On the other hand, deep learning algorithms and architectures take longer and need more resources to train. As a result, investors may pass on a lot of lucrative opportunities. It is essential for deep learning models to acquire and react to real-time data to build investor confidence quickly. Investors' ability to trust DL models will be considerably aided by using more sensitive and granular algorithms, like high-performance computing (HPC) in financial markets, along with faster incremental learning, progressive neural networks, and other techniques. Murphy et al.[230] discussed the use of two types of linear regression models, least squares and autoregressive, based on predictors such as social media and economic data to calculate the volatility of a given cryptocurrency and its price. The results showed that the use of high-performance computing techniques allows regression models to predict cryptocurrency prices more accurately.

Additionally, considerable studies show that, despite the production of increasingly sophisticated and complicated algorithms today, the accuracy of predictions has not considerably increased as a result of deep learning algorithms.[241,242] Contrarily, some algorithms' ability to recognize patterns and make predictions is even worse than that of old-school classical models. Therefore, researchers must select algorithms based on their properties when applying them to various modeling tasks. Specifically, ensemble learning combines various weak supervised models to create a more robust supervised model, where the combined weak classifier can correct an error even if a weak classifier makes a wrong prediction. Rao et al.[231] combined three classic ensemble learning algorithms (ensemble averaging, bagging, and stacking) to predict the hourly value of major cryptocurrencies. The proposed ensemble method is evaluated using traditional DL strategies combining LSTM, bidirectional (BiLSTM), and convolutional layers to achieve more accurate predictions. They found that ensemble learning is a successful approach to handling financial datasets.

Currently, the modeling of cryptocurrency nodes' behavior is confined by strict and idealistic hypotheses. The current work on detecting anomalous behavior on blockchain typically begins at a single information node, ignoring the interaction behavior data across nodes or chains.[243] Smart contracts, which alter the response connection between nodes in cryptocurrencies and affect currency prices, are less frequently modeled. The new interaction can be the start of an attack. Therefore, quickly recognizing any hazards that could arise from interacting activities is critical. New research directions emerge related to modeling interaction behavior, designing smart contracts between different data on the chain, assessing the dynamic features of the interaction behavior, and developing an identification technique that can self-adapt to changes in the chain's behavior. Du et al.[232] employed change-point detection techniques to maintain stable forecasting performance in the unseen price range. Specifically, to achieve feature extraction and fusion of multivariate data, they first incorporate the external factor fusion component into the time series prediction module by using multi-level attention networks based on the Transformer. Meanwhile, to increase efficiency and accuracy in the change point detection module, CNN-LSTM-based classifier is employed to identify change points.

Other challenges include multi-objective, multi-level model design and application. Most neural network architectures employed so far have been specially trained to learn and execute a single modeling task rather than performing multiple tasks. Regarding multi-objective architectures, transfer learning and encompass learning have been employed in other domains[233] and can also be employed in future cryptocurrency research. More specifically, multi-objective learning is one field where each agent has a unique related aim to optimize. For instance, in the cryptocurrency market, it is essential to consider the profits and risks of investment, assess the timeliness of the asset portfolio, and guarantee the liquidity of the currency basket. However, The global optimum can only be reached if agents permit others to accomplish their tasks satisfactorily. Multi-task learning is a comparable direction when agents excel not just on a particular task but also on related other tasks.[234]

CONCLUSION

This study comprehensively reviews the deep learning methods employed in cryptocurrency research across multiple modeling tasks, including price prediction, portfolio, bubble analysis, abnormal trading, trading regulations and initial coin offering in cryptocurrency. Overall, our study contributes to the multi-disciplinary research on cryptocurrency and deep learning from four aspects.

Table 18. Challenges and future directions

Challenges	Future directions	Models	Examples
Extreme risk events disruption in cryptocurrency market	Study cryptocurrency market efficiency under high volatility or under shocks from other extreme events	Semi-supervised learning models and data streaming techniques	Ben Hamadou et al.[227]
Data shortage and over-reliance on CNN models in the cryptocurrency field	Improve language processing and image classification tasks	Data augmentation, transfer learning, recursive classification algorithms, few-shot learning and synthetic data generation	Li et al.[228]
Data quality and heterogeneity characteristics that may arise from the data	Aggregate multivariate heterogeneous data to achieve multi-level knowledge interaction	Agent-based, DAG-based learning	Lin et al.[229]
Acquisition and tracking of real-time transaction data	Take models to catch up with real-time data and react to it to quickly build investor confidence	High performance computing (HPC), as well as faster incremental learning, progressive neural networks	Murphy et al.[230]
Lack of accuracy in the prediction through deep learning algorithms	Choose algorithms based on their properties when applying them to various modeling tasks	Ensemble learning and other algorithms	Rama Rao et al.[231]
Ignorance of interactive behavior data across nodes or chains	Design smart contracts to model the dynamic characteristics of interaction behavior, between different data on the chain	Identification technique that can self-adapt to changes in the chain's behavior	Du et al.[232]
Multi-objective, multi-level model design and application	Maximize agent utility by modeling multi-task learning, and focus on global optimum	Multi-objective architectures, transfer learning and encompass learning	Poyatos et al.[233] and Ni et al.[234]

- We conduct a literature review on the deep learning models employed in multiple financial application scenarios.
- We give an overview of the cryptocurrency history and the primary representative currencies.
- We comprehensively review the deep learning models in cryptocurrency research regarding multiple modeling tasks, including price prediction, portfolio, bubble analysis, abnormal trading, trading regulations and initial coin offering in cryptocurrency.
- We discuss the reviewed studies from perspectives of modeling approaches, empirical data, experiment results and specific innovations and, based on that, conclude this study with a research outlook, which is to use deep learning models in cryptocurrency research.

We first review popular deep learning models employed in multiple financial application scenarios, including convolutional neural networks, recurrent neural networks, deep belief networks, and deep reinforcement learning. We also give an overview of cryptocurrencies by outlining the cryptocurrency history and discussing primary representative currencies. Based on the reviewed deep learning methods and cryptocurrencies, we conduct a literature review on the new multidisciplinary area that employs deep learning models on cryptocurrency. The literature review shows that many researchers have used ANN, SVM, LSTM, and other models for cryptocurrency price prediction. These models have produced numerous LSTM-based derivative models, such as the SAM-LSTM model 142, which have higher accuracy than conventional prediction models. The most frequently employed deep learning models in the analysis of the Bitcoin asset portfolio include DRL, LSTM, RF, etc. Moreover, some researchers compare the model performance of these deep learning models with that of GARCH and other time series models 232. Some researchers employ RNN, GRU, LSTM, and MLP analytical models to investigate cryptocurrency market bubbles in the COVID-19 outbreak 233. Researchers have recently started using SVM, LSTM, and other algorithms to identify abnormal trading behaviors in the cryptocurrency market. In related empirical studies, DRL, XGBoost, and other models have also been used to supervise cryptocurrency market transactions. Some researchers have also combined deep learning models to increase the model's accuracy 214, 240, 241. Regarding ICO, many deep learning models have been applied to the cryptocurrency ICO practice to determine the success of the ICO and the possibility of fraud.

We discuss applications of deep learning models in financial research from perspectives of modeling approaches, empirical data, experiment results and specific innovations. We conclude this comprehensive literature review with the research challenges in cryptocurrency research that can hopefully be addressed with deep learning models, including data sparsity, multi-objective modeling and heterogeneous information processing.

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DECLARATION OF INTERESTS

The authors declare no competing interests.

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