ARTICLE IN PRESS

Decision Support Systems xxx (xxxx) xxx

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

LSTM-ReGAT: A network-centric approach for cryptocurrency price trend prediction

Chao Zhong, Wei Du [*], Wei Xu, Qianhui Huang, Yinuo Zhao, Mingming Wang

School of Information, Renmin University of China, Beijing 100872, PR China

ARTICLE INFO

Keywords:
Cryptocurrency
Price trend prediction
Cryptocurrency network
Graph attention network

ABSTRACT

Predicting price trends of cryptocurrencies is a challenging task due to the highly speculative cryptocurrency market. Prior studies mainly investigate predictors such as historical trading data, macroeconomic development, and public interests in cryptocurrencies for price trend prediction while ignoring the predictive role of the relations between cryptocurrencies. In fact, the price movement of a cryptocurrency may be affected by those of other cryptocurrencies, thus, incorporating cryptocurrency interrelations can further improve the prediction performance. In this paper, we propose a novel end-to-end model for price trend prediction using long short-term memory (LSTM) and relationwise graph attention network (ReGAT), in which both individual cryptocurrency features and cryptocurrency relations are considered. Specifically, a cryptocurrency network is built by using shared features between cryptocurrencies. Further, LSTM is used to profile sequential patterns of individual cryptocurrency features. To fully extract network features, ReGAT is designed to aggregate information conveyed by different types of relations while automatically differentiating their importance. Finally, the conventional and network features are concatenated to predict the price trend. The effectiveness of LSTM-ReGAT is validated using real-world cryptocurrency market data. The trading simulations for Bitcoin and portfolios reveal that our model obtains the highest profits. Our study provides insightful implications for investment decision support in cryptocurrency market.

1. Introduction

The cryptocurrency market has received increasing attention from investors. As of December 2022, there are >8000 cryptocurrencies in the market. The total cryptocurrency market capitalization has shown a significant upward trend from approximately $17 billion in 2017 to approximately $799 billion in 2022. Cryptocurrencies are viewed as pure speculative assets given their extreme volatility and bubble-like price changes [12]. Predicting cryptocurrency market performance is rather challenging and has become a prominent branch of cryptocurrency research [19].

Existing cryptocurrency studies focus either on price prediction or price trend prediction. Both streams have been studied in recent years. Price prediction mainly introduced time series forecasting to predict the maximum, minimum, or closing price in the next period [10,28]. A related but different problem is price trend prediction that aims to predict the direction of price movement with classification models [6,36,40]. Compared to price prediction, forecasting the fluctuation tendency of cryptocurrency price is of equal importance [2,40,41] and is particularly challenging considering the highly speculative cryptocurrency market [6]. This study focuses on price trend prediction. Previous studies have investigated many features to predict price trends of cryptocurrencies, such as historical price data, public interests in cryptocurrency, macroeconomic factors, and sentiment of social media [13,19]. However, these studies ignore the predictive role of relations between cryptocurrencies. The interrelations within the stock market have recently been used to predict stock price movement [9,27,32]. Similar to the stock market, there exists price co-movement between cryptocurrencies and collective behaviors in the cryptocurrency market [7,15,39], suggesting that the price movement of a cryptocurrency may be affected by those of other cryptocurrencies. Inspired by this, some studies began to utilize the relationship between Bitcoin and related Altcoins for Bitcoin price prediction [24,26]. However, the few existing attempts focus on extracting relations from time series information, making the results difficult to interpret due to the absence of explicit relationships. Overall, the potential of explicit interrelations (e.g.,

* Corresponding author.
E-mail addresses: zhongchao@ruc.edu.cn (C. Zhong), ahduwei@ruc.edu.cn (W. Du), weixu@ruc.edu.cn (W. Xu), luc123@ruc.edu.cn (Q. Huang), mingmwang@263.net (M. Wang).

https://doi.org/10.1016/j.dss.2023.113955
Received 24 June 2022; Received in revised form 26 February 2023; Accepted 28 February 2023
Available online 5 March 2023
0167-9236/© 2023 Elsevier B.V. All rights reserved.

technological relatedness, industry relatedness, and investor co-attention) between cryptocurrencies, which can provide interpretable results, was not exploited in prior studies. Besides, prior studies mainly used Bitcoin as the target cryptocurrency, and predictions of a wide set of cryptocurrencies that are significant to investors and portfolio formation are rare.

To bridge this gap, we propose to leverage various relations between cryptocurrencies for price trend prediction. Specifically, we first build a cryptocurrency network in which cryptocurrency relations are extracted from technology foundation (e.g., *PoW* and *SHA-256*), industry (e.g., *gaming* and *metaverse*), and investor co-attention (e.g., *investment portfolio*) that may affect the market performance of cryptocurrencies. To make full use of traditional time series features and cryptocurrency networks, we propose a deep learning method called LSTM-ReGAT to jointly combine the long short-term memory (LSTM) and relationwise graph attention network (ReGAT). LSTM is applied to deal with the time series features of individual cryptocurrencies following prior studies [19,22,26,31]. Based on the widely used network feature extraction technique, graph attention network [42], we propose a ReGAT to combine network features in the cryptocurrency network on top of traditional features. ReGAT adopts a hierarchical attention mechanism and is able to deal with that (1) different related cryptocurrencies have different importance, and (2) different relations are of different importance, in predicting the price trend of the target cryptocurrency. The results can be interpreted with attention values. Last, a deep neural network (DNN) architecture is used to predict the price trend of the next day. The experimental analysis with a real-world cryptocurrency market dataset shows the outperformance of our model.

In summary, the primary contributions of this study are threefold. First, this is the first attempt, as far as we know, to construct a cryptocurrency network with explicit relations between cryptocurrencies for price trend prediction. Second, the proposed end-to-end LSTM-ReGAT model can be applied to a wide set of cryptocurrencies. Third, using a real-world dataset, performance analysis of price trend prediction and trading simulations show that our model outperforms state-of-the-art baselines. The prediction results can also be interpreted with attention values, suggesting the interpretability of our model.

The remainder of this paper is organized as follows. In Section 2, we first introduce previous studies related to the price trend prediction of cryptocurrencies. We also refer to a broad set of studies related to utilizing stock interrelations for stock prediction and the interrelations in the cryptocurrency market. Section 3 formulates the research problem. Section 4 describes the proposed model. Section 5 describes the dataset. Section 6 elaborates on the experimental procedures and the empirical results. Finally, the conclusion of our work and a discussion of future work are provided in Section 7.

2. Related work

2.1. Cryptocurrency price trend predictors

Cryptocurrency price and trend prediction can utilize the same set of time series features as provided in the hybrid study that solves both problems [30,34]. Here we focus on the stream of literature on cryptocurrency price trend prediction. A comprehensive feature set including *technical, asset-based, sentiment−/interest-based*, and *blockchain-based* features was utilized for cryptocurrency price trend prediction [19].

Technical features related to historical data are the most frequently used features in cryptocurrency price trend prediction tasks. Technical features including OHLC (Open, High, Low, Close) price data, trading volume at each time epoch, and technical indicators [4,16,22,38]. Technical indicators, originally introduced in technical analysis for forecasting future price movements of stocks, were also introduced as cryptocurrency price trend predictors. Technical indicators can be calculated from the raw price data, the commonly used technical indicators such as relative strength index (RSI), moving average (MA), moving average convergence divergence (MACD), price rate of change (ROC), and on balance volume (OBV) are used to analyze the past trading activity in prior studies [2,3,18,26,36].

Asset-based features, also known as macroeconomic factors, are features derived from other financial assets such as stock market, gold prices, oil prices, and exchange rates between major fiat currencies (e.g., US dollar, EUR, and CNY). For example, asset-based features including crude oil future prices, gold future prices, and stock market indices (i.e., S&P500 future, NASDAQ future, and DAX index) were used in [34] to predict the direction of Bitcoin price trend.

Sentiment−/interest-based features reveal the public sentiment/interest in corresponding cryptocurrencies. Sentiment features extracted from social media (e.g., Twitter and Reddit) are able to mirror the market, and were validated as significant price trend predictors in both stock market and cryptocurrency market [6,17,20,31,33,41]. Search trends indicate public interests, and Google Trends is the most widely used interest-based feature for price trend prediction [31].

Blockchain-based features refer to the blockchain information of cryptocurrency, including mining difficulty and block size. The hash rate and mining difficulty can be used to measure its supply and are therefore associated with Bitcoin price [25]. However, blockchain-based features are normally introduced for Bitcoin price trend prediction because these features are not available for most cryptocurrencies [6,19,34].

2.2. Cryptocurrency price trend prediction models

The commonly used classification models for cryptocurrency price trend prediction are machine learning and deep neural network models. Machine learning classifiers such as logistic regression (LR), neural networks (NN), support vector machines (SVM), decision tree (DT), light gradient boosting machine (LightGBM), and random forest (RF) have achieved good performance in predicting cryptocurrency price movement [2,14,40].

Deep learning algorithms are widely applied in cryptocurrency price trend prediction tasks due to their characteristics of easy feature engineering and good model performance [3,6,22,36]. Compared to traditional machine learning, deep learning does not require extensive feature engineering, and the multiple layers in deep neural networks make them more efficient at learning complex features. Widely used recurrent neural networks (RNN) variants such as gated recurrent units (GRU) and LSTM are suitable for processing time series data and have become popular choices for price trend forecasting [26,36]. Originally used for image recognition, a 1D convolutional neural networks (CNN) has recently been proposed for prediction tasks with time series data and achieved encouraging performance in cryptocurrency price trend prediction. For example, CNN got higher accuracy compared to LSTM models in [6]. A hybrid CNN-LSTM network that outperformed CNN and DNN in price trend prediction for six major cryptocurrencies was proposed in [3].

2.3. Modeling interrelations in cryptocurrency market

Cryptocurrency is developed as a financial asset. Therefore, more broadly, our work also relates to studies of modeling interrelations between financial assets (e.g., stocks) for market performance prediction. The interrelations between financial assets provide important implications for portfolio allocation and regulatory decisions [8,15,35,49]. In recent years, with the development of network analysis and graph mining techniques, many studies began to introduce complex network methods for performance prediction of financial assets [9,45,46,48], mainly stocks. These studies hold the view that stock interrelations lead to stock price co-movement considering the co-attention effect and interrelated business. Stock interrelations can be profiled in various ways. For example, co-search of supply chain partners as a proxy of investor co-attention [1], shareholding relationship between firms [9], multiple relationships (i.e., shareholding, company industry and stock topicality) among stocks [48] were utilized as useful relations for stock market prediction. These studies validated the success of stock interrelations for stock performance prediction with complex network methods such as TransR [27], graph convolutional network (GCN) [9,48], and struc2vec for time series graphs [46].

Likewise, price correlations exist between cryptocurrencies, indicating investors are making informed decisions [12]. Some other studies also unmasked this phenomenon. For example, Non-Fungible Tokens have strong co-movement with Ether and Bitcoin was found in [15]. The cross price correlations between 119 publicly traded cryptocurrencies from August 2016 to January 2018 was analyzed and multiple collective behaviors in the market of cryptocurrencies was found in [39]. The collective behaviors reveal that cryptocurrencies are strongly influenced by others [7].

Several studies have utilized cryptocurrency relations for price trend or price prediction. Bitcoin is not independent but related to other cryptocurrencies. Based on this, in [24], an Attentive LSTM network and an Embedding Network (ALEN) was proposed to capture relations between time series information of Bitcoin and selected relational cryptocurrencies (i.e., Ethereum, Ripple, Bitcoin Cash, and Litecoin) for Bitcoin price trend prediction. Results shows that cryptocurrency relations contain valuable clues for Bitcoin price fluctuation prediction. In [23], a Lead-lag Variance Kernel (LVK) was proposed to leverage the synchronous and asynchronous relationship between Bitcoin and related Altcoins for Bitcoin price prediction. The outperformance suggests the effectiveness of cross-cryptocurrency interactions for Bitcoin price prediction. Though there are several attempts of modeling relational data for cryptocurrency performance prediction, this research direction is still immature. Few studies introduced explicit interrelations such as technical/business interdependence and investor co-attention that could provide more practical implications for investing decisions.

Prior stock prediction studies have shown the effectiveness of introducing relational information from business activities [9], industry information [48], and investor co-attention [1] in benefiting stock performance prediction. Similarly, we propose that extracting relational information from technology foundation [15,51], industry information, and investor co-attention provide informative clues for cryptocurrency price trend prediction. Therefore, built upon the advanced graph mining techniques in stock prediction studies [48,50], we propose LSTM-ReGAT to deal with the multi-relations and automatically learn the different importance of relational cryptocurrencies in predicting price trends.

3. Problem formulation

For each target cryptocurrency, we combine time series data and interrelations between cryptocurrencies to predict the price trend (i.e., price movement direction) at the next timestamp. Time series features of cryptocurrency c and related cryptocurrencies in cryptocurrency network G are model inputs. It can be formulated as follows:

$$\widehat{y}_{c,t} = f_{\theta}(G, \mathbf{X}_{t-1}, \mathbf{X}_{t-2}, \dots, \mathbf{X}_{t-T}) \tag{1}$$

where c is the target cryptocurrency, t is the target timestamp, T is the time window size, $\mathbf{X}_t$ represents the features of all cryptocurrencies at time t, f_{θ} is the classification method with trainable parameter θ, and $\widehat{y}_{c,t}$ is the predicted probability that the price of cryptocurrency c will increase at time t.

4. Proposed model

The framework of LSTM-ReGAT is shown in Fig. 1. It consists of four primary modules: cryptocurrency network construction, time series information extractor, ReGAT, and prediction module. The details are provided as follows.

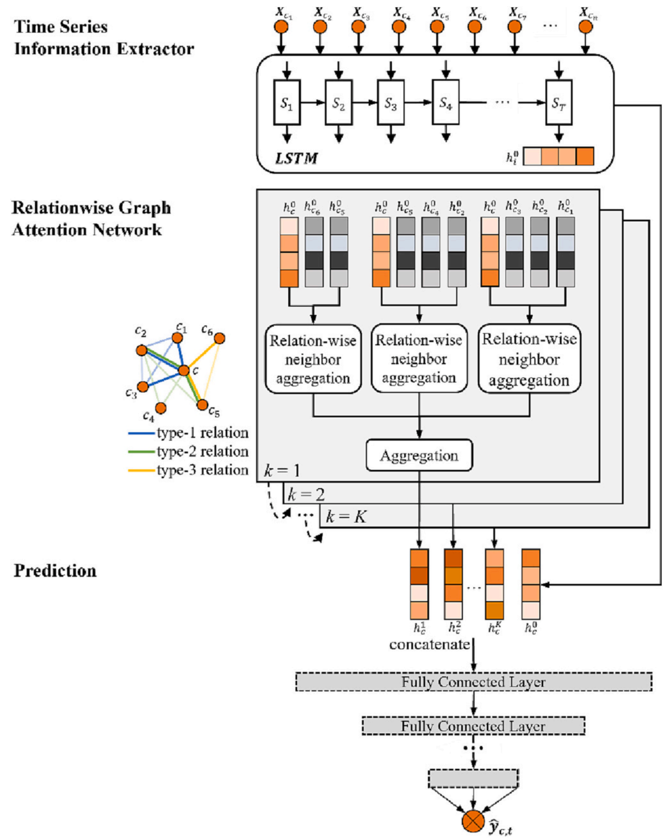


Fig. 1. The framework of LSTM-ReGAT.

4.1. *Cryptocurrency network construction*

We develop the cryptocurrency network by using shared features in terms of technology foundation, industry information, and investor co-attention. Table 1 lists the features we used for cryptocurrency network construction and example labels.

The rationality of used relations for cryptocurrency network construction is as follows.

4.1.1. *Technological foundation*

Algorithm and *platform* reveal cryptocurrency interrelations in terms of technological foundation. Cryptocurrencies are technologically related in terms of blockchain technologies (e.g., SHA-256 and PoW), and these interrelationships may provide useful blockchain features for cryptocurrency trend prediction [19,34]. Besides, some cryptocurrencies are related in terms of the underlying blockchain platforms or ecosystems, and their market performance may be affected by technological dependence [37]. For example, the market performance of Theta Network and Enjin Coin built upon Ethereum may be affected by

Table 1
Features for cryptocurrency network construction.

Cryptocurrency interrelations	Features
Technological foundation	**Algorithm**: *PoW, Hybrid-PoW&PoS, PoS, Scrypt, SHA-256,* etc. **Platform**: *BNB Chain, Ethereum Ecosystem, Cosmos Ecosystem, BNB Smart Chain, Polygon Ecosystem,* etc.
Industry	**Industry**: *DeFi, Payments, Medium of Exchange, Enterprise Solutions, Web3,* etc.
Investor co-attention	**Investment portfolio**: *Kenetic Capital Portfolio, Pantera Capital Portfolio, DCG Portfolio, Alameda Research Portfolio, Hashkey Capital Portfolio,* etc.

Ethereum fees [15].

4.1.2. Industry

Industry information helps to extract industrial interrelations between cryptocurrencies. Cryptocurrencies have been utilized as a viable finance system in different industries such as social media, travel, hotel, gaming, and education. Given the information diffusion and related business activities within the industry, industrial relations have been validated as an important company relationship for predicting stock price trends [32,48]. Industry information can also serve as a proxy of investor attention, for example, the positive performance of metaverse tokens in gaming/metaverse industry due to the recent investor attention to metaverse projects [43].

4.1.3. Investor co-attention

Co-investment relations in *investment portfolios* are introduced as a proxy for investor co-attention. Investor co-attention reveals information dissemination among investors and can be associated with investment habits [23]. Such information was proved useful in analyzing stock co-movements [1]. Likewise, we introduce investor co-attention as useful information for cryptocurrency price trend prediction.

The cryptocurrency network, denoted as $G = (C, E)$, consists of node set C and edge set E. It is also associated with an edge type mapping function $\psi : E \rightarrow \mathscr{R}$ where $\mathscr{R}$ is the set of relation types. Fig. 2 illustrates an example cryptocurrency network centered on Bitcoin Cash. We use the specific shared attributes as relation labels to preserve the original semantics in cryptocurrency network, for example, *Bitcoin Cash* $\overset{PoW}{\rightarrow}$ *Bitcoin* represents that Bitcoin Cash and Bitcoin share *PoW algorithm* as technology foundation. The specific labels such as *PoW* and *SHA-256* are used to denote relations to preserve the original semantics in cryptocurrency network. Multi-relations can exist between two cryptocurrencies if they share multiple features. Note that even we do not assign edge weights in cryptocurrency network construction, the proposed method automatically captures the unequal effects between the two cryptocurrencies. The attention weight from cryptocurrency i to cryptocurrency j on relation (*i. e.*, $\alpha_{i,\,j}^{r}$) is ex-post information and calculated by learnable model parameters. Fig. 2 illustrates that Bitcoin's price movement affects the one of Bitcoin Cash differently than in the opposite direction along PoW relation, i.e., $\alpha_{BTC,\,BCH}^{PoW} \neq \alpha_{BCH,\,BTC}^{PoW}$.

4.2. Time series information extractor

We use LSTM to profile the dynamic changes of each cryptocurrency in a time window and output an initial embedding for each cryptocurrency. In each timestamp t, a list of traditional features $\mathbf{x}_t^c$ of a cryptocurrency c are extracted as the input of LSTM. In this study, we use a wide range of traditional features, including technical features, interest-based features, and asset-based features summarized from previous studies. LSTM outputs the vector $h_c^0 \in R^F$ in the final state as the initial embedding of a cryptocurrency c.

4.3. Relationwise graph attention network

ReGAT is proposed to utilize both traditional features and structural information in a cryptocurrency network. The basic idea of ReGAT is to aggregate neighbor information into a focal cryptocurrency, and then combine all neighbors with different relation types to achieve accurate cryptocurrency embedding. Considering that both neighbor cryptocurrencies and relations contribute differently when predicting the price trend of a focal cryptocurrency, we introduce attention mechanisms in both steps, i.e., hierarchical attention, to distinguish neighbors and relations when embedding cryptocurrencies.

4.3.1. Relationwise neighbor aggregation

Relationwise neighbor aggregation aggregates the neighbor information of a specific relation type. Given a focal cryptocurrency c, we define relationwise neighbors $N_{c,\,r}$ as a set of neighbor cryptocurrencies that connect node c via relation r. For each cryptocurrency, relationwise neighbors contribute differently when learning node embedding for price trend prediction. For example, in Fig. 2, Litecoin and Bitcoin have different importance in predicting the price trend of Bitcoin Cash under PoW relation. Therefore, we introduce attention mechanism, i.e., cryptocurrency-level attention, to learn meaningful neighbors to form a cryptocurrency embedding.

For each relation $r \in \mathscr{R}$, we aggregate the relationwise neighbors into a focal cryptocurrency c at the kth iteration as $\mathbf{h}_c^{k,\,r}$:

$$\mathbf{h}_c^{k,r} = \sum_{j \in N_{c,r}} \alpha_{cj}^{k} \mathbf{e}_j^{k-1} \tag{2}$$

$$\mathbf{e}_j^{k-1} = \delta\left(\mathbf{W}_1 \mathbf{h}_j^{k-1} + \mathbf{b}_1\right) \tag{3}$$

where $N_{c,\,r}$ is the neighbor set of cryptocurrency c with relation r, α_{cj}^{k} is the cryptocurrency-level attention score assigned to each neighbor cryptocurrency at the kth iteration, and $\mathbf{h}_j^{k-1}$ is the embedding of cryptocurrency j at the $(k-1)$th iteration. $\mathbf{W}_1 \in R^{F \times F}$ and $\mathbf{b}_1 \in R^F$ are learnable parameters. F is embedding size.

At each iteration, with the embedding of cryptocurrency c and cryptocurrency j, the attention score is calculated using a fully connected layer.

$$\alpha_{cj}^{k} = \frac{exp\left(v_{cj}\right)}{\sum_{n \in N_{c,r}} exp\left(v_{cn}\right)} \tag{4}$$

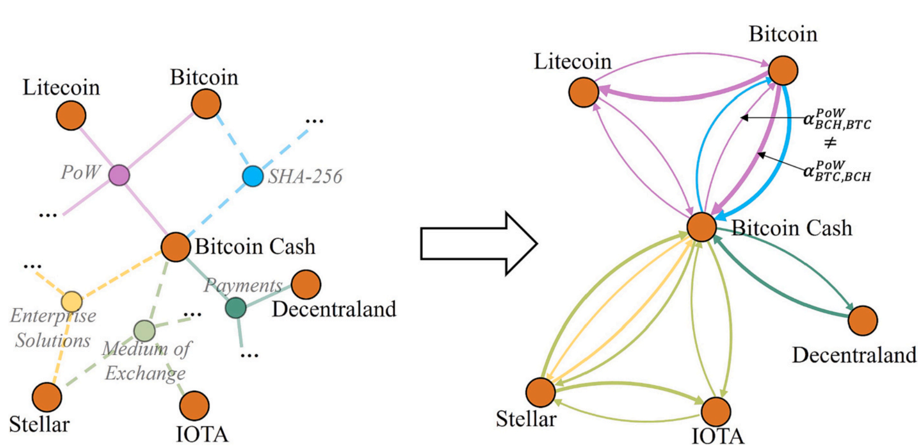


Fig. 2. An example cryptocurrency network.

$$v_{cj} = \mathbf{W}_2 concat\left(\mathbf{e}_j^{k-1}, \mathbf{e}_c^{k-1}\right) + \mathbf{b}_2 \quad (5)$$

where $\mathbf{W}_2 \in R^{1\times 2F}$ and $\mathbf{b}_2 \in R^1$ are learnable parameters.

The single head attention can also be extended to multi-head attention to deal with the variance of heterogeneous graph [44]. The attention mechanism is replicated by concatenation to obtain multi-head attention for M heads as:

$$\mathbf{h}_c^{k,r} = W_3 \bullet concat\left[\mathbf{h}_c^{k,r,m}\right]_{m=1,\dots,M} + b_3 \quad (6)$$

where $\mathbf{h}_c^{k,\ r,\ m}$ is the m-head output, and $W_3 \in R^{F\times MF}$ and $b_3 \in R^F$are learnable parameters.

4.3.2. Relation aggregation

Further, ReGAT fuses embeddings achieved by each relation type. Relation-level attention is introduced to automatically learn the importance of different relations. All relationwise embeddings $\mathbf{h}_c^{k,\ r}$ are aggregated to $\mathbf{h}_c^k$ (as)

$$\mathbf{h}_c^k = \sum_{r\in\mathscr{R}} \beta_{cr}^k \mathbf{h}_c^{k,r} \quad (7)$$

where β_{cr}^k is the relation-level attention score assigned on relation r at the kth iteration.

4.4. Prediction

In the prediction stage, for cryptocurrency c, we concatenate the embedding results of all ReGAT iterations and the initial embedding output by LSTM. Therefore, we have

$$\mathbf{h}_c = concat\left[\mathbf{h}_c^k\right]_{k=0,\dots,K} \quad (8)$$

where K is the number of ReGAT iterations, $\mathbf{h}_c^0$ is the LSTM output and $\mathbf{h}_c^k$ ($k = 1, \dots, K$) is the output of the k-th ReGAT iteration.

A DNN model $\mathscr{G}$ is used to predict the price trend of each cryptocurrency:

$$\hat{y}_{c,t} = \mathscr{G}(\mathbf{h}_c) \quad (9)$$

where $0 \le \hat{y}_{c,t} \le 1$ indicates the increase probability of cryptocurrency c at date t. The final layer uses the sigmoid function as the activation function.

5. Dataset

We first crawled the daily prices and trading information from CoinMarketCap.com from March 30, 2020 to December 20, 2022, for a total of 995 days. Fig. 3 plots the price fluctuations of two representative cryptocurrencies, i.e., Bitcoin and Ethereum, over the selected time span. As we can see from Fig. 3, the time span that covers both bull market and bear market can fully represent the cryptocurrency market. A total of 645 cryptocurrencies with observations were collected.

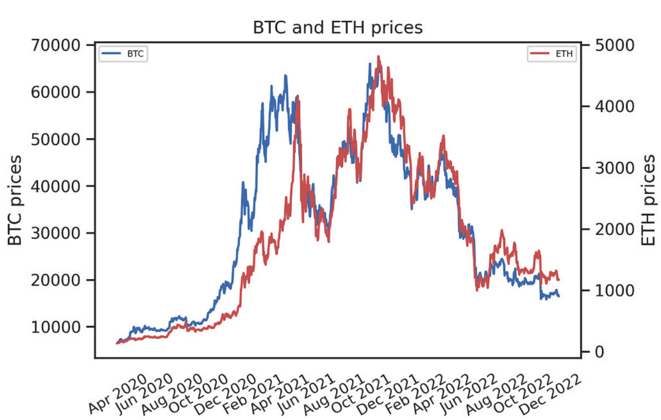


Fig. 3. Bitcoin (BTC) and Ethereum (ETH) price fluctuations in our dataset.

For each cryptocurrency, a wide set of traditional features, i.e., technical features, asset-based features, and interest-based features, in the given time span were collected to profile the dynamic changes. A summary of traditional features is provided in Table 2.

Besides the basic technical features collected from CoinMarketCap.com, technical indicators listed in Table 2 were calculated to analyze the past trading activities of each cryptocurrency. Asset-based features indicating macroeconomic development including *Nasdaq, S&P 500, Dow Jones 30, FTSE 100, Crude Oil Future Prices, VIX, Gold Price,* and *Gold Future Price* were crawled from the Wind Database and Investing.com. In addition, the exchange rates between several major currencies (i.e., GBP, CNY, and EUR) and US dollars are included. Interest-based features reflect public attention to cryptocurrencies. Following a previous study, we use the Google Trends index for each corresponding cryptocurrency to measure public attention [11].

Table 3 provides the summary statistics of asset-based features and interest-based features. The summary statistics of technical features are not presented because technical indicators for each cryptocurrency are not comparable.

For each cryptocurrency, features (i.e., *algorithm*, *platform*, *industry*, and *investment portfolio*) were collected from CoinMarketCap.com to build the cryptocurrency network. For the 645 cryptocurrencies, there are 23 algorithms, 24 platforms, 52 industries, and 31 investment portfolios in total. The resulting cryptocurrency network has 645 nodes and 66,564 edges.

6. Experiment

6.1. Experimental setting

In the present study, we use the cryptocurrency network combined with daily historical time series data of cryptocurrencies as raw inputs to the model, to predict the price trend of each cryptocurrency of the next day. The target of experiment is formulated as follows:

$$y_{c,t} = \begin{cases} 1, if\ close_{c,t} > close_{c,t-1} \\ 0, otherwise \end{cases} \quad (10)$$

where $close_{c,\ t}$ refers to the closing price of cryptocurrency c on day t.

To evaluate the predictive performance, performance metrics including Accuracy, Precision, Recall, F1, False Positive Rate (FPR), area under the receiver operating characteristic (AUC), and average precision (AP) are used in this study. F1, AUC, and AP are comprehensive metrics that evaluate the overall performance of prediction models.

6.2. Baselines

To compare the model performance, we selected four most widely

Table 2
Summary of traditional time series features.

Data category	Features
Technical features	***Basic technical features:*** *trading volume, market capitalization, OHLC price data.* ***Technical indicators:*** *last five lagged returns, exponential moving average of the close prices, cumulative sum of the last 3 and 5 days of returns, RSI, William's percentage, MACD, OBV.*
Asset-based features	*Nasdaq, S&P 500, Dow Jones 30, FTSE 100, Crude Oil Future Prices, VIX, Gold Prices, Gold Future Prices, USD/GBP, USD/CNY, and USD/EUR*
Interest-based features	*Google Trends Index.*

Table 3
Summary statistics of asset-based features and interest-based features.

Features	mean	median	min	max	std
Nasdaq	12,593.851	12,755.640	7360.580	16,057.440	1907.194
S&P 500	3933.603	3965.340	2470.501	4796.561	511.721
Dow Jones 30	31,666.597	32,778.640	20,943.510	36,799.650	3491.674
FTSE 100	6868.298	7037.470	5415.500	7672.400	566.811
Crude Oil Future Prices	69.018	70.730	−37.630	123.700	24.950
VIX	24.224	23.140	15.010	57.060	6.088
Gold Price	1809.522	1803.400	1571.310	2063.810	83.782
Gold Future Prices	1482.650	1806.100	1591.400	2058.400	82.399
USD/GBP	0.772	0.758	0.704	0.936	0.049
USD/CNY	6.665	6.552	6.308	7.301	0.275
USD/EUR	0.890	0.876	0.811	1.043	0.058
Google Trends Index	24.920	21.000	7.000	100.000	18.489

used classification models in previous studies (i.e., LR, SVM, RF, and DNN) and two deep learning models for time series data (i.e., LSTM and CNN) as baselines. The inputs of aforementioned models include technical features, asset-based features and interest-based features. We also performed an ablation study of LSTM-ReGAT to validate the key design.

LR, **SVM**, **RF**, and **DNN**: **LR** is developed from linear regression to solve classification problems with high interpretability [19]. **SVM** classifies samples through a hyperplane and applies kernel functions to solve nonlinear problems [40]. **RF** is a popular ensemble model of decision trees that avoids the overfitting of a single decision tree [18]. **DNN** is a basic model of deep learning, which consists of multiple fully connected layers [36]. These models do not deal with time series data, so technical features, asset-based features and interest-based features of the previous day were used as model input. Note that compared to basic technical features, technical indicators provided in Table 2 can be applied to a given timeframe and provide more historical information.

LSTM and **CNN**: LSTM and CNN can extract time series information from historical data. Following [3], all filters in CNN are vertically shaped, ensuring that each filter works on a single feature over time. LSTM proposed an input gate, output gate and forget gate to address the vanishing gradient problem in traditional RNN [22]. Inputs of LSTM and CNN include technical features, asset-based features, and interest-based features of T (days)

ReGAT-Only, **LSTM-GAT** and **LSTM-ReGAT-Singlehead**: These models serve as variants of LSTM-ReGAT, which can be used to verify the modules of time series extractor, relationwise graph attention network and multi-head attention mechanism. ReGAT-only model removes the time series information extractor (i.e., LSTM) and directly inputs features from the previous day into the ReGAT module. In LSTM-GAT, the ReGAT module is replaced with the graph attention networks architecture [42]. Therefore, LSTM-GAT treats different relations as homogeneous and does not consider the importance of different relations. LSTM-ReGAT-Singlehead removes the multi-head attention mechanism in LSTM-ReGAT, i.e., $M = 1$.

6.3. Implementation details

To prevent data snooping, we performed out-of-time sample and experimental data sets were strictly split according to the dates. The ratio of training, validation, and test set is approximately 8:1:1. For each target cryptocurrency, the first 795 days of data were used as the training set, the next 100 days of data serve as the validation set, and the last 100 days of data serve as the test set. The validation set is used to tune hyperparameters.

We randomly initialized parameters and optimized the model with Adam [21]. For the proposed LSTM-ReGAT, we set the learning rate to 0.0001, the embedding size F to 64 [44], the dropout rate to 0.3, and the number of epochs to 20. The hyperparameters of T, K and M are tuned within {2, 3, 4, 5, 6, 7, 14, 21, 28}, {1, 2, 3, 4}, and {2, 4, 6, 8} separately, and optimal performance achieves when the time window length T is set to 6 days, the number of ReGAT iterations K=2, and the number of attention head M=6. Fig. 4 plots the parameter sensitivity analysis. The results show that: (1) LSTM-ReGAT requires historical data with a suitable time window size, and data that is too old may add noise to the model; (2) the best performance achieves when is K set to 2, which means that including 1-order and 2-order neighbors helps to capture network information well; (3) Multiple head will improve the prediction performance, but a large number of attention heads may introduce redundancy. The best performance achieves when M=6.

Key parameters for each model are provided in Table 4. In the prediction stage, we used the DNN model with two hidden layers, and the number of neurons in each layer was 256 and 128. For fair comparison, the time window was set as 6 days for LSTM and CNN. Learning rate, dropout rate, and the number of epochs in DNN, LSTM, and CNN are the same with LSTM-ReGAT, and are not repeated in Table 4. To obtain reliable results, we performed 10 repeated runs and took the average of all the performance measures. To avoid overfitting, we apply L2 regularization (weight decay = 0.001) and early stopping strategy.

6.4. Performance comparison

Table 5 shows the performance comparison of different models. In order to compare the performance of LSTM-ReGAT and baselines, we marked the best results in bold.

The observations are summarized as follows.

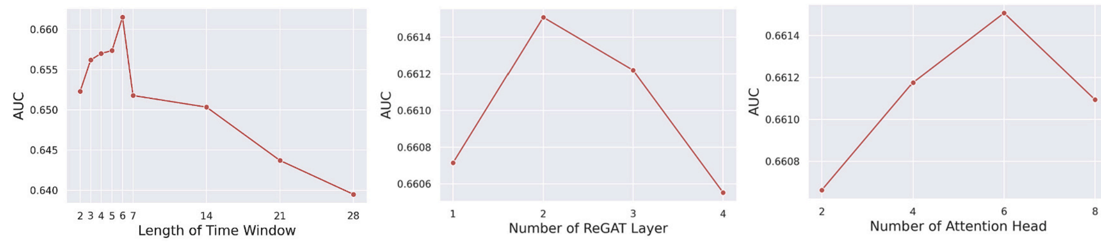
First, among conventional models (i.e., LR, SVM, RF, DNN, LSTM, and CNN), SVM performs worst, and LSTM performs best in terms of two comprehensive metrics, i.e., AUC and AP. The outperformance of deep learning models indicates its ability in learning complex feature interactions and sequential historical information.

Second, compared with conventional models, LSTM-ReGAT performs best in nearly all evaluation metrics. LSTM-ReGAT outperforms the best LSTM by 1.05% (AUC) and 1.93% (AP). Compared with the worst SVM, our model improves 31.5% (AUC) and 38.6% (AP). Note that LSTM-GAT has the best Recall score while medium precision score, which means LSTM-GAT allows for more false positives. The outperformance of our model indicates the superiority of LSTM-ReGAT in price trend prediction.

Third, LSTM-ReGAT also outperforms ReGAT-Only, LSTM-GAT and LSTM-ReGAT-Singlehead, which validates the design of time series information extractor, the solution for dealing with heterogeneous relations and multi-head attention mechanism.

Last, note that even with the absence of time series information extractor and ReGAT for heterogeneous relation, ReGAT-Only, LSTM-GAT and LSTM-ReGAT-Singlehead are competitive compared to traditional models. This indicates that the constructed cryptocurrency network provides significant information for price trend prediction.

In summary, these results validate the contributions of cryptocurrency network in predicting cryptocurrency price trend. Combined with the constructed cryptocurrency network and the key designs of LSTM-ReGAT, the prediction performance can be improved compared to the state-of-the-art models.



(a) Length of time window T (b) Number of ReGAT layer K (c) Number of attention head M

Fig. 4. Parameter sensitivity analysis.

Table 4
Parameter setting of models.

Model	Key parameters	
LSTM-ReGAT/ LSTM-GAT	Learning rate: 0.0001	Embedding size F=64
	Time window length T=6	Dropout rate: 0.3
	The number of epochs: 20	The number of iterations K=2
	The number of attention head M=6	
	The number of neurons in DNN: 256, 128	
LR	L2 norms	
SVM	Kernel type: RBF	Kernel coefficient: 1
	Regularization parameter: 10	
RF	The number of trees: 10	The maximum depth of the tree: 5
	The function to measure the quality of a split: Gini	
DNN	The number of neurons in DNN: 256, 128	
LSTM	Embedding size: 64	Time window length: 6
CNN	Convolutional layers: 5	Time window length: 6
	The kernel sizes of each layer: (5,1), (3,1), (3,1), (3,1), (3,1)	
	The number of kernels of each layer: 16, 32, 48, 64, 80	

6.5. *The roles of different relations in price trend prediction*

The importance of different relations varies in price trend prediction and can be measured with the attention mechanism. For clarity, we use ReGAT with single head attention to show relation importance. All attention scores are averaged over the test dataset. Taking Bitcoin Cash (BCH) as an example, Table 6 provides the attention scores distributed on different relations and the top 5 neighbors with the highest scores along each relation when predicting BCH's price trend.

Results show that our model can learn the attention scores of different relations automatically. Bitcoin is among the top 5 neighbors along PoW relation (102 neighbors in total) and SHA-256 relation (29 neighbors in total) when predicting BCH's price trend, suggesting the influence power of Bitcoin as the leading cryptocurrency using PoW and SHA-256 algorithm. While for Bitcoin, the attention score of PoW relation ranks 10th out of all 25 relationships. Under PoW relation, the attention score of Bitcoin's attention to BCH and BCH's attention to Bitcoin were respectively 0.0242 and 0.0109. Under SHA-256 relation, the attention score of Bitcoin's attention to BCH and BCH's attention to Bitcoin were respectively 0.1165 and 0.0561. The results show that the influence of Bitcoin on BCH under PoW and SHA-256 relation is greater than the reverse direction.

6.6. *Trading simulation*

We conducted two types of trading simulations to further verify the model performance: one for the most popular cryptocurrency Bitcoin and another for portfolio formation.

(1) **Trading simulation for Bitcoin**

Trading was carried out with a daily frequency. To simplify the trading process, we use the Bitcoin trading strategy in [47] based on price movement. Increase probability (p_t) on each day is used to generate trading signal S_t (1 = buy, 0 = sell) following a Bernoulli distribution, $S_t \sim B(1, p_t)$. In other words, the probability of buying bitcoin at day t is p_t.

We compared four strategies for Bitcoin trading, i.e., random strategy, momentum strategy, Baseline Strategy and LSTM-ReGAT Strategy.

Random Strategy: Assumes a 50% chance of buying Bitcoin on day t, i.e., $p_t^R = 0.5$.

Momentum Strategy: Assumes that positive (negative) returns are presumed to be followed by continued positive (negative) returns. We define the *momentum* equal to the percent of days with positive returns

Table 6
The top 5 neighbors with the highest scores under each relationship.

Relation type	Attention score	Top5 neighbor cryptocurrencies
Enterprise Solutions	0.240	LTO Network, Horizen, Hedera, Ontology, BlackCoin.
PoW	0.223	Dimecoin, StrongHands, Bytecoin, Elastos, **Bitcoin.**
Medium of Exchange	0.203	StrongHands, Bytecoin, DeepOnion, ReddCoin, PIVX.
SHA-256	0.167	Elastos, **Bitcoin**, Peercoin, Litecoin Cash, Syscoin.
Payments	0.165	StrongHands, Dimecoin, Bytecoin, TIME, DeepOnion.

Table 5
Performance comparison of different models.

Model	AUC	AP	Accuracy	Precision	Recall	F1	FPR
LR	0.5057	0.4504	0.5568	0.5914	0.0258	0.0494	0.0144
SVM	0.5028	0.4487	0.5554	0.6691	0.0093	0.0184	**0.0037**
RF	0.5263	0.4610	0.5411	0.4846	0.3875	0.3986	0.3347
DNN	0.5740	0.5111	0.5605	0.5102	0.4652	0.4834	0.3625
LSTM	0.6546	0.6103	0.6227	0.5998	0.4671	0.5250	0.2516
CNN	0.6297	0.5788	0.5994	0.5681	0.4777	0.5070	0.3023
ReGAT-Only	0.5774	0.5126	0.5658	0.5169	0.4272	0.4660	0.3225
LSTM-GAT	0.6597	0.6205	0. 6193	0.5854	**0.5152**	0.5453	0.2968
LSTM-ReGAT-Singlehead	0.6582	0.6183	0.6255	0.5998	0.4820	0.5345	0.2589
LSTM-ReGAT	**0.6615**	**0.6221**	**0.6297**	**0.6041**	0.4997	**0.5469**	0.2600

in the past, i.e., $p_t^M = momentum_t$.

Baseline Strategy: We choose the output of the best baseline model, i.e., LSTM-GAT, as the increase probability on each day to make investment decisions.

LSTM-ReGAT Strategy: The output of the LSTM-ReGAT model, $\hat{y}_{c,t}$, is used as the probability of buying bitcoin at day t to make investment decisions.

During the simulation, we began with $1. The best baseline model and LSTM-ReGAT were trained using training data, and trading simulations were performed on test data (100 days). The average end-of-period balance across 10,000 repetitions is calculated as follows. The two equations are for when shorting is not allowed and when shorting is allowed.

$$\text{Shorting not allowed}: Balance_{\mathscr{T}} = \prod_{t=1}^{\mathscr{T}} (1 + S_t R_t) \tag{11}$$

$$\text{Shorting allowed}: Balance_{\mathscr{T}} = \prod_{t=1}^{\mathscr{T}} ((1 + R_t)S_t + (1 - R_t)(1 - S_t)) \tag{12}$$

where R_t is the Bitcoin return on day t, and $\mathscr{T}$ is the final day of test data.

Table 7 provides the average final balance generated with different strategies. Results of shorting not allowed and shorting allowed are both provided. The improvement ratios over Random Strategy are provided in brackets. During the test period, the Bitcoin price dropped from $21,769 to $16,439, a drop of 24.45%. Results show that Random Strategy and Momentum Strategy perform worst. LSTM-ReGAT Strategy performs best with the average final balance of 1.005 (shorting not allowed) and of 1.305 (shorting allowed).

(2) **Trading simulation with investment portfolios.**

Furthermore, we validated the role of the cryptocurrency network in building portfolios. Portfolio theory advocates diversification to reduce risk and maintain high returns. Adding diversification in cryptocurrencies helps increase the Sharpe ratio and reduce the total risk [29]. In our cryptocurrency network, the closely connected nodes have strong risk correlations because they share the same attributes. Therefore, closely connected cryptocurrencies in the network should avoid being selected into the same portfolio.

A popular community detection algorithm, Louvain [5], is used to identify closely connected cryptocurrencies. Louvain is an unsupervised community detection algorithm based on modularity optimization. We chose Louvain because it does not require specification of the number of communities or the expected size of community. Through Louvain, the network is divided into 7 communities, containing 252, 153, 131, 49, 33, 22, 5 respectively. Cryptocurrencies within the same community are treated as sharing similar risks. Therefore, we set the number of cryptocurrencies in a portfolio as C=7. Cryptocurrency c has a probability $\eta_{c,t}$ of being selected in the portfolio at day t. Total balance is allocated to each cryptocurrency in the portfolio by weight $w_{c,t}$. Cryptocurrency c is decided whether to be bought or not with a probability $p_{c,t}$. Here, we used three baseline strategies and the cryptocurrency network separately to create investment portfolios. The details are provided as follows.

Random Strategy-Portfolio: Samples cryptocurrencies and assigns total balance randomly, i.e., $\eta_{c,t}^R = 1/N$, and $w_{c,t}^R = 1/C$.

Momentum Strategy-Portfolio: Samples cryptocurrencies and assigns total balance according to *momentum* scores, i.e., $\eta_{c,t}^M = momentum_{c,t} / \sum_{j=1}^N momentum_{j,t}$, and $w_{c,t}^M = momentum_{c,t} / \sum_{j \in P^M} momentum_{j,t}$, where P^M is the portfolio selected by the momentum strategy.

Baseline Strategy-Portfolio: Samples cryptocurrencies and assigns total balance according to the output of the best baseline model, i.e., $\eta_{c,t}^B = \hat{y}_{c,t} / \sum_{j=1}^N \hat{y}_{j,t}$, and $w_{c,t}^B = \hat{y}_{c,t} / \sum_{j \in P^B} \hat{y}_{j,t}$, where P^B is the portfolio selected by the baseline strategy.

Cryptocurrency Network-Portfolio: We combine the LSTM-ReGAT output and the cryptocurrency network to sample cryptocurrencies and assign total balance. Within each community, the cryptocurrency with the highest increase probability $\hat{y}_{c,t}$ has the highest probability of being selected. Therefore, $\eta_{c,t}^C = \hat{y}_{c,t} / \sum_{j \in \Phi_i} \hat{y}_{j,t}$, $w_{c,t}^C = \hat{y}_{c,t} / \sum_{j \in P^C} \hat{y}_{j,t}$, where Φ_i is the set of cryptocurrencies in i-th community, and P^C is the portfolio selected by the cryptocurrency network and LSTM-ReGAT.

Table 8 provides the trading simulation results with portfolios. Besides average final balance, we calculated the standard deviation of daily returns to represent the volatility of a portfolio as a measure of portfolio risk. Whether shorting is allowed or not, Cryptocurrency Network-Portfolio performs best in terms of both average final balance and average volatility. These results demonstrate the good performance of combing LSTM-ReGAT and cryptocurrency network for portfolio formation.

7. Conclusions and future works

This paper proposes LSTM-ReGAT to predict cryptocurrency price trends by combining traditional cryptocurrency features with network information. There are several methodological implications of our research. First, in contrast with prior studies that focused on traditional cryptocurrency features, we innovatively explore the relational information between cryptocurrencies and propose a new network-centric model in the price trend prediction scenario, which provides a new angle for understanding the price fluctuations of cryptocurrencies. Based on prior studies [1,15,48,51], we proposed to utilize technology foundation, industry information, and investor co-attention to profile cryptocurrency associations, and such information is validated as useful relational information in predicting the cryptocurrency market. Second, to fully extract network information, we design a ReGAT model that introduces hierarchical attention to aggregate information conveyed by different types of relations while automatically differentiating their importance. It is an easily implementable approach without the need to manually assign weights to the relations between cryptocurrencies. Third, with the cryptocurrency network and LSTM-ReGAT, we provide viable trading strategies for both single cryptocurrency and portfolio formation, future scholars could continue to investigate the investment portfolios based on our research framework. The trading simulations in our study have verified the role of the cryptocurrency network in building diversified portfolios.

Our findings also have several managerial implications for investors, corporations, and regulators. First, our research can provide investors with trading references to increase their returns in the volatile cryptocurrency market. They could further rationalize their investment portfolios to diversify risks with the support of the cryptocurrency network. Second, retailers and large corporations could replicate the research

Table 7
Trading simulation result for Bitcoin.

Trading strategy	Average final balance	
	Shorting not allowed	Shorting allowed
Random Strategy	0.882 (–)	1.008 (–)
Momentum Strategy	0.843 (−4.42%)	0.919 (−8.82%)
Baseline Strategy	0.959 (8.73%)	1.191 (18.15%)
LSTM-ReGAT Strategy	1.005 (13.94%)	1.305 (29.46%)

Table 8
Trading simulation results of portfolios.

Trading strategy	Average final balance (Average volatility)	
	Shorting not allowed	Shorting allowed
Random Strategy-Portfolio	0.870 (0.0298)	0.975 (0.0388)
Momentum Strategy-Portfolio	0.794 (0.0278)	0.898 (0.0358)
Baseline Strategy-Portfolio	1.220 (0.0277)	1.382 (0.0349)
Cryptocurrency Network-Portfolio	1.307 (0.0255)	1.480 (0.0327)

framework for decision support when deciding whether to adopt cryptocurrencies as a means of payment given the highly volatilely nature of cryptocurrencies. Third, the cryptocurrency network and our method also provide indicators to predict the potential systemic risks associated with cryptocurrencies, and regulators can implement safeguards to ensure financial stability.

This study has some limitations. First, LSTM is applied to our work given its popularity. Other models such as Transformer and GRU can be tested to enhance prediction performance. Second, our study focuses on a broad set of cryptocurrencies, making portfolio construction another feasible research direction. The cryptocurrency network can not only help predict cryptocurrency performance but also act as a proxy of risks shared between cryptocurrencies. Future research could further explore the strategic role of the cryptocurrency network in building portfolios. This can provide investors with more valuable insights in real investment scenarios.

CRediT authorship contribution statement

Chao Zhong: Writing – original draft, Conceptualization, Software, Methodology, Resources, Validation, Visualization, Data curation. **Wei Du:** Project administration, Conceptualization, Methodology, Resources, Writing – original draft, Supervision. **Wei Xu:** Supervision, Methodology, Resources. **Qianhui Huang:** Writing – original draft, Writing – review & editing. **Yinuo Zhao:** Investigation, Writing – review & editing. **Mingming Wang:** Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare that there is no conflict of interest.

Data availability

Data will be made available on request.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant No. 71901208), and Fundamental Research Funds for the Central Universities and the Research Funds of Renmin University of China (No. 22XNA036).

References

[1] A. Agarwal, A.C.M. Leung, P. Konana, A. Kumar, Cosearch attention and stock return predictability in supply chains, Inf. Syst. Res. 28 (2017) 265–288.
[2] E. Akyildirim, A. Goncu, A. Sensoy, Prediction of cryptocurrency returns using machine learning, Ann. Oper. Res. 297 (2021) 3–36.
[3] S. Alonso-Monsalve, A.L. Suárez-Cetrulo, A. Cervantes, D. Quintana, Convolution on neural networks for high-frequency trend prediction of cryptocurrency exchange rates using technical indicators, Expert Syst. Appl. 149 (2020).
[4] G.S. Atsalakis, I.G. Atsalaki, F. Pasiouras, C. Zopounidis, Bitcoin price forecasting with neuro-fuzzy techniques, Eur. J. Oper. Res. 276 (2019) 770–780.
[5] V.D. Blondel, J.-L. Guillaume, R. Lambiotte, E. Lefebvre, Fast unfolding of communities in large networks, J. Statist. Mech.: Theory Experim. 2008 (2008) P10008.
[6] S. Cavalli, M. Amoretti, CNN-based multivariate data analysis for bitcoin trend prediction, Appl. Soft Comput. 101 (2021).
[7] H. Chaudhari, M. Crane, Cross-correlation dynamics and community structures of cryptocurrencies, J. Comput. Sci. 44 (2020), 101130.
[8] W. Chen, M. Jiang, W.-G. Zhang, Z. Chen, A novel graph convolutional feature based convolutional neural network for stock trend prediction, Inf. Sci. (N. Y). 556 (2021) 67–94.
[9] Y. Chen, Z. Wei, X. Huang, Incorporating corporation relationship via graph convolutional neural networks for stock price prediction, in: Proceedings of the 27th ACM International Conference on Information and Knowledge Management, Association for Computing Machinery, New York, NY, USA, 2018, pp. 1655–1658.
[10] Z. Chen, C. Li, W. Sun, Bitcoin price prediction using machine learning: an approach to sample dimension engineering, J. Comput. Appl. Math. 365 (2020).
[11] T. Chuffart, Interest in cryptocurrencies predicts conditional correlation dynamics, Financ. Res. Lett. 46 (2022), 102239.
[12] S. Corbet, B. Lucey, A. Urquhart, L. Yarovaya, Cryptocurrencies as a financial asset: a systematic analysis, Int. Rev. Financ. Anal. 62 (2019) 182–199.
[13] E. Demir, G. Gozgor, C.K.M. Lau, S.A. Vigne, Does economic policy uncertainty predict the bitcoin returns? An empirical investigation, Financ. Res. Lett. 26 (2018) 145–149.
[14] H.A. Dolatsara, E. Kibis, M. Caglar, S. Simsek, A. Dag, G.A. Dolatsara, D. Delen, An interpretable decision-support systems for daily cryptocurrency trading, Expert Syst. Appl. 203 (2022).
[15] S. Gunay, K. Kaskaloglu, Does utilizing smart contracts induce a financial connectedness between Ethereum and non-fungible tokens? Res. Int. Bus. Financ. 101773 (2022).
[16] H. Guo, D. Zhang, S. Liu, L. Wang, Y. Ding, Bitcoin price forecasting: a perspective of underlying blockchain transactions, Decis. Support. Syst. 151 (2021), 113650.
[17] C.-S. Ho, P. Damien, B. Gu, P. Konana, The time-varying nature of social media sentiments in modeling stock returns, Decis. Support. Syst. 101 (2017) 69–81.
[18] S. Inder, S. Sharma, Predicting the movement of cryptocurrency "bitcoin" using random Forest, in: Communications in Computer and Information Science, Springer Science and Business Media Deutschland GmbH, 2021, pp. 166–180.
[19] P. Jaquart, D. Dann, C. Weinhardt, Short-term bitcoin market prediction via machine learning, J. Finan. Data Sci. 7 (2021) 45–66.
[20] Y. Bin Kim, J.G. Kim, W. Kim, J.H. Im, T.H. Kim, S.J. Kang, C.H. Kim, Predicting fluctuations in cryptocurrency transactions based on user comments and replies, PLoS One 11 (2016) e0161197–e0161197.
[21] D.P. Kingma, J. Ba, Adam: A method for stochastic optimization, ArXiv Preprint ArXiv (2014), 1412.6980.
[22] D.H. Kwon, J.B. Kim, J.S. Heo, C.M. Kim, Y.H. Han, Time series classification of cryptocurrency price trend based on a recurrent LSTM neural network, J. Inform. Process. Syst. 15 (2019) 694–706.
[23] A.C.M. Leung, A. Agarwal, P. Konana, A. Kumar, Network analysis of search dynamics: the case of stock habitats, Manag. Sci. 63 (2017) 2667–2687.
[24] P. Li, S. Gong, S. Xu, J. Zhou, Y. Shanqing, Q. Xuan, Cross Cryptocurrency Relationship Mining for Bitcoin Price Prediction, ArXiv Preprint ArXiv (2022), 2205.00974.
[25] X. Li, C.A. Wang, The technology and economic determinants of cryptocurrency exchange rates: the case of bitcoin, Decis. Support. Syst. 95 (2017) 49–60.
[26] Y. Li, Z. Zheng, H.N. Dai, Enhancing bitcoin price fluctuation prediction using attentive LSTM and embedding network, Appl. Sci. (Switzerland). 10 (2020).
[27] J. Liu, Z. Lu, W. Du, Combining enterprise knowledge graph and news sentiment analysis for stock price volatility prediction, in: Proceedings of the Annual Hawaii International Conference on System Sciences, IEEE Comp. Soc, 2019, pp. 1247–1255.
[28] M. Liu, G. Li, J. Li, X. Zhu, Y. Yao, Forecasting the price of bitcoin using deep learning, Financ. Res. Lett. 40 (2021), 101755.
[29] W. Liu, Portfolio diversification across cryptocurrencies, Financ. Res. Lett. 29 (2019) 200–205.
[30] I.E. Livieris, N. Kiriakidou, S. Stavroyiannis, P. Pintelas, An Advanced CNN-LSTM Model for Cryptocurrency Forecasting, Electronics (Basel), 2021.
[31] E. Loginova, W.K. Tsang, G. van Heijningen, L.P. Kerkhove, D.F. Benoit, Forecasting directional bitcoin price returns using aspect-based sentiment analysis on online text data, Mach. Learn. (2021).
[32] J. Long, Z. Chen, W. He, T. Wu, J. Ren, An integrated framework of deep learning and knowledge graph for prediction of stock price trend: an application in Chinese stock exchange market, Appl. Soft Comput. 91 (2020), 106205.
[33] M.Á. López-Cabarcos, A.M. Pérez-Pico, J. Piñeiro-Chousa, A. Šević, Bitcoin volatility, stock market and investor sentiment. Are they connected? Financ. Res. Lett. 38 (2021), 101399.
[34] D.C.A. Mallqui, R.A.S. Fernandes, Predicting the direction, maximum, minimum and closing prices of daily bitcoin exchange rate using machine learning techniques, Appl, Soft. Comput. 75 (2019) 596–606.
[35] D.G. McMillan, Cross-asset relations, correlations and economic implications, Glob. Financ. J. 41 (2019) 60–78.
[36] M. Ortu, N. Uras, C. Conversano, S. Bartolucci, G. Destefanis, On technical trading and social media indicators for cryptocurrency price classification through deep learning, Expert Syst. Appl. 198 (2022).
[37] N.P. Patel, R. Parekh, N. Thakkar, R. Gupta, S. Tanwar, G. Sharma, I.E. Davidson, R. Sharma, Fusion in cryptocurrency Price prediction: a decade survey on recent advancements, architecture, and potential future directions, IEEE Access 10 (2022) 34511–34538.
[38] T. Shintate, L. Pichl, Trend prediction classification for high frequency bitcoin time series with deep learning, J. Risk Finan. Manag. 12 (2019) 17.
[39] D. Stosic, D. Stosic, T.B. Ludermir, T. Stosic, Collective behavior of cryptocurrency price changes, Phys. A: Statist. Mech. Appl. 507 (2018) 499–509.
[40] X. Sun, M. Liu, Z. Sima, A novel cryptocurrency price trend forecasting model based on LightGBM, Financ. Res. Lett. 32 (2020).
[41] F. Valencia, A. Gómez-Espinosa, B. Valdés-Aguirre, Price movement prediction of cryptocurrencies using sentiment analysis and machine learning, Entropy. 21 (2019).
[42] P. Veličković, G. Cucurull, A. Casanova, A. Romero, P. Lio, Y. Bengio, Graph attention networks, ArXiv Preprint ArXiv (2017), 1710.10903.
[43] D. Vidal-Tomás, The new crypto niche: NFTs, play-to-earn, and metaverse tokens, Financ. Res. Lett. 47 (2022), 102742.
[44] X. Wang, H. Ji, C. Shi, B. Wang, Y. Ye, P. Cui, P.S. Yu, Heterogeneous graph attention network, in: The World Wide Web Conference, Association for Computing Machinery, New York, NY, USA, 2019, pp. 2022–2032.

[45] D. Wu, X. Wang, S. Wu, Jointly modeling transfer learning of industrial chain information and deep learning for stock prediction, Expert Syst. Appl. 191 (2022), 116257.
[46] J. Wu, K. Xu, X. Chen, S. Li, J. Zhao, Price graphs: utilizing the structural information of financial time series for stock prediction, Inf. Sci. (N. Y). 588 (2022) 405–424.
[47] P. Xie, H. Chen, Y.J. Hu, Signal or noise in social media discussions: the role of network cohesion in predicting the bitcoin market, J. Manag. Inf. Syst. 37 (2020) 933–956.
[48] J. Ye, J. Zhao, K. Ye, C. Xu, Multi-graph convolutional network for relationship-driven stock movement prediction, in: 2020 25th International Conference on Pattern Recognition (ICPR), 2021, pp. 6702–6709.
[49] I. Yousaf, R. Nekhili, M. Gubareva, Linkages between DeFi assets and conventional currencies: evidence from the COVID-19 pandemic, Int. Rev. Financ. Anal. 81 (2022), 102082.
[50] K.C. Yuen, S. Chung, P. Balsebre, C. Prachaseree, Stock Price Prediction with StemGNN and Dynamic Time Warping, 2021.
[51] L. Zhao, S. Sen Gupta, A. Khan, R. Luo, Temporal Analysis of the Entire Ethereum Blockchain Network, in: Proceedings of the Web Conference 2021, Association for Computing Machinery, New York, NY, USA, 2021, pp. 2258–2269.

Chao Zhong is a master student at School of Information, Renmin University of China. His research interests include network analysis and deep learning. His research has been published in *Journal of Electronic Commerce Research*.

Wei Du is an associate professor at School of Information, Renmin University of China. She received her Ph.D. from City University of Hong Kong. Her research interests include recommender systems, social network analysis, and knowledge graph. Her research has been published in *Decision Support Systems*, *International Journal of Electronic Commerce*, and *Scientometrics*.

Wei Xu is a professor at School of Information, Renmin University of China. He received his Ph.D. from Chinese Academy of Sciences. His research interests include quantitative investment, e-commerce and fintech. His research has been published in *Decision Support Systems*, *Internet Research*, *Information Processing and Management* and *Information Sciences.*

Qianhui Huang is an undergraduate student at School of Information, Renmin University of China. Her research interests include fintech and risk management.

Yinuo Zhao is an undergraduate student at School of Information, Renmin University of China. Her research interests include fintech and artificial intelligence.

Mingming Wang is an associate professor at School of Information, Renmin University of China. Her research interests include information economy and information management. Her research has been published in *Electronic Commerce Research* and *The Journal of Supercomputing.*