A combination of technical indicators and deep learning to predict price trends for short-term cryptocurrency investment

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***Abstract* —Recently, cryptocurrency investment is one of the most interesting investment channels offered on the market. Investors are always trying to find an effective prediction model to increase profit as well as reduce loss in investment. In this paper, a combination of technical indicators and deep learning is applied to predict cryptocurrency price trends in the short term. The work also used the Multi-scale Residual Convolutional (MRC) module for feature extraction and a Long Short-Term Memory (LSTM) to predict price trends. Experimental results using Bitcoin and Ethereum time-series data in time frame as 1-hour and 30-minute show that our proposed method has better accuracy in a comparison to some other methods. Moreover, an automation trading bot using the proposed model was tested on the Binance Sandbox environments and got good results.**

Keywords— price trend, technical indicators, cryptocurrency investment, multi-scale residual convolutional block, long short-term memory.

I. Introduction

In the area of the global economy, investing in cryptocurrencies has attracted a lot of attention from investors. The cryptocurrency market offers many great opportunities for investors to achieve high returns, but also contains many serious risks.

There are two analysis methodologies in investment markets: technical analysis and fundamental analysis [3]. Technical analysis is the discipline by which future movements of securities, currency pairs, and cryptocurrencies are discerned from historical patterns. In general, technical indicator is a mathematical calculation based on historic price, volume, or open interest information that is used for forecasting future financial market price movement. Fundamental analysis revolves around analyzing the true value of an asset through valuation techniques that include overall economic analysis, industry and sector analysis, and analysis of a company's financial data.

In the view of information technology researchers, many complicated models have been developed to predict cryptocurrency prices or cryptocurrency trends [1] – [6]. Finding an effective investment model for the cryptocurrency market is always a challenge for information technology researchers. First, the topic depends on too many volatile factors. Second, the return on investment is promising. And there are many potential risks that investors want to avoid.

In this study, a model for predicting cryptocurrency trends in short-term is proposed based on some technical indicators, multi-scale residual convolutional block (MRC) and long short-term memory (LSTM) method in order to support investors to make decisions in short time.

The paper is organized as follows: In section 2, related work is introduced. Section 3 presents the proposed method. In section 4, the experiments and results are shown. Finally, in section 5, the conclusions are given.

II. Related Work

Commonly, there are two main methods to enhance performance of an investment prediction system. The first is discovering suitable features that more accurately characterize different prices or trend movements. The second is finding classifiers that better classify accuracy.

Moreover, it depends on the investment purpose so that may have very different output values such as to predict price or trend in long-term or in short-term. Some of them focus on input data type (raw historical data, selected historical data, technical indicators, google trends, or special news…). Other researchers focus on building effective machine learning or deep learning models to get better performance.

Qiutong Guo et al. presented a method [1] in 2021 that tried to find an effective model to predict closing Bitcoin price. The authors proposed a combination of Multi-scale Residual Convolutional neural network and a Long Short-Term Memory model. The authors claimed that research done with better results in a comparison with Long Short-Term Memory model or Bidirectional Long Short-Term Memory.

In another method presented in 2022, Marco Ortu et al. [2] analyze important input factors for cryptocurrency price classification. The work researched some different input data such as technical trading indicators and social media indicators to predict cryptocurrency price movements. The experimental results showed that addition of technical trading indicators and social media indicators to the model leads to an effective improvement in average accuracy.

Patrick Jaquart and his team published a journal [3] focusing on predicting short-term bitcoin market using some different features such as technical, blockchain-based, sentiment-/interest-based, and asset-based features. The authors claimed that technical features remain most relevant for most methods, followed by selected blockchain-based and sentiment-/interest-based features.

As shown in [4], the work tried to develop a deep learning integration method to predict bitcoin price. The model contains two main parts: advanced deep neural network model and bootstrap aggregation method. The advanced deep neural network model is used to simulate the nonlinear complex relationship between the bitcoin price and its influencing factors. And the bootstrap aggregation method generates multiple datasets for training a set of basic models. Experimental results showed that their method obtained higher accuracy and lower error, and can well track the randomness and nonlinear characteristics of bitcoin price.

Beside a lot of deep learning methods, other approaches for cryptocurrency prediction are researching such as Support Vector machine, Ensemble algorithms (based on Recurrent Neural Networks and the k-Means clustering method) published in 2018 [5], fuzzy approach published in 2019 [6]. The work in [5] also aimed to predict the Bitcoin price direction and forecast the Bitcoin exchange rates (maximum, minimum and closing prices).

III. PROPOSED METHOD

The objective of this study is developing an effective model to predict price trends for short-term cryptocurrency investment. Based on previous related works, important technical indicators are selected and after that apply Multi-Scale Residual Convolutional neural network and a Long Short-Term Memory model to classify the price trend in short-term (1-hour time frame and 30-minute time frame).

A. *Technical Indicators*

In this work, five technical indicators are applied as following:

- Coppock Curve: a long-term price momentum indicator used to recognize major downturns and upturns in a market index.
- Relative Strength Index (RSI): a momentum indicator that measures the magnitude of recent price changes. It is normally used to evaluate whether stocks or other assets are being overbought or oversold.
- Stochastic Relative Strength Index (RSI): the same as RSI, but the indicators move more quickly
- Price Rate of Change (ROC): the percentage change in price between the current price and the price a certain number of periods ago
- Moving average convergence divergence (MACD): is used for measuring the strength of a trend by using two moving average prices.

The window size indicates the number of previous values used to evaluate the indicator at time *t*. Table. 1 shows technical indicators and its association factors.

TABLE I. SOME TECHNICAL INDICATORS

Technical Indicators	Window size
Coppock Curve	10
Relative Strength Index (RSI)	10
Stochastic Relative Strength Index (Stochastic RSI)	10
Price Rate of Change (ROC)	10
Moving average convergence divergence (MACD)	5

The five selected indicators are important in investment. The Coppock curve provides the long-term buy and sell signals. And other indicators give signal points that start to increase or decrease. So, the combination of the five indicators contains both short-term and long-term signals, which include more short-term information.

These technical indicators are calculated based on real market data (also called historical data). The historical data contain some attributes such as: the Date of observation, Open price, High price, Low price, and Close price, Volume, and Market cap. Historical data of cryptocurrency can be downloaded from the Binance website [7].

B. *Price movement classification*

The output of the model has two classes and is described as following:

- Up (value 1): It is an upward movement and shows an increase in price.
- Down (value 0): It is a downward movement and shows a falling price.

Trends in the real environment change continuously from up trend to down trend and vice versa because of many market factors. For that reason, predicted trends are necessary for short-time investors.

C. *Multi-scale Residual Convolution and Long Short – Term Memory combination model for trend prediction*

Qiutong Guo et. al [1] proposed a hybrid approach of multi-scale residual (MSR) and long short-term memory (LSTM) to predict Bitcoin closing price in 2021. This method has two main parts: using the MSR module to detect effective features and using LSTM to forecast the price. The work used historical price as input of the model. Experimental results showed that their method significantly outperformed a variety of other network structures.

Based on the good result of the Qiutong Guo's research teams, we adapted it for our research purposes. The main differences here are:

- The inputs of our model are technical indicators instead of only closing price.
- The outputs of our model are two classes illustrating uptrend and downtrend instead of price.

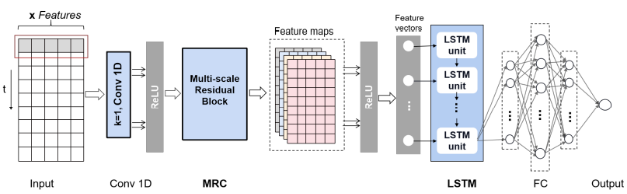

Fig. 1. Architecuture of the MRS-LSTM model [1].

The architecture of the proposed network is shown in the Fig. 1 and can be explained as following: First, the input matrix contains 5 technical indicators for each data point (Coppock Curve, Relative Strength Index, Stochastic Relative Strength Index, Price Rate of Change, and Moving average convergence divergence). Second, a 2D convolutional layer. Next is a long short-term memory layer, a fully connected layer, and an output layer.

The input matrix of our proposed method contains 5 features, 40 input data points to predict the (40+1) point price trend as shown in Fig. 2. And Fig. 3 illustrates the input and the output of our proposed method. The output includes two percentage values corresponding to the probability of downtrend (0) and the probability of uptrend (1). A decision is made based on the highest value of the output.

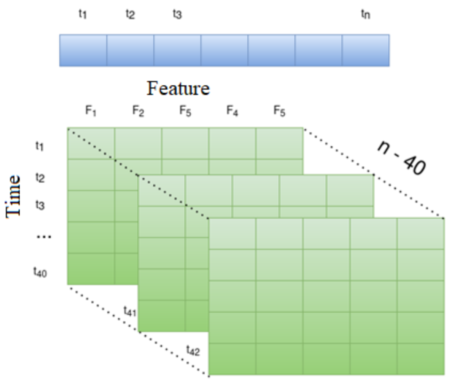

Fig. 2. The input matrix.

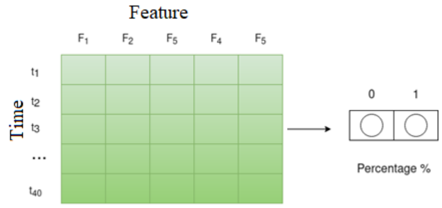

Fig. 3. The input and output of our implementation model.

Thus, by improving the original model in [1] based on new input and output, our proposed model not only keeps the advantages of the original model but also obtains better accuracy results for cryptocurrency trends prediction.

IV. Experiments

A. Dataset

The work uses Bitcoin and Ethereum historical data available on Binance [7]. The dataset was collected using Python-Binance library [8]. The raw dataset includes the daily Close price, Open price, High price, Low price, Volume, and Market cap of Bitcoin and Ethereum over USDT from 1 September 2019 to 22 June 2022. Short explanations of raw data are shown in Table II and Fig. 4 illustrates some samples of the raw data from the BTC dataset.

TABLE II. Raw Historical Dataset

Name	Description	Data type
Date	Date of observation	Date
Open	The price at which the cryptocurrency first trades upon the opening of a trading period	Number
High	The highest price at which the cryptocurrency traded during the course of the trading period	Number
Low	The lowest price at which the cryptocurrency trades over the course of a trading period	Number
Close	The last price at which the cryptocurrency traded during the trading period	Number
Volume	Number of cryptocurrency trades completed	Number
Market Cap	The aggregate market value	Number

	Open	High	Low	Close	Volume	Market Cap
Date						
2021-05-18	0.486954	0.515599	0.470384	0.476115	4.802903e+09	6.172964e+10
2021-05-19	0.476435	0.684735	0.218267	0.333123	1.507262e+10	4.319498e+10
2021-05-20	0.330252	0.433192	0.296253	0.400194	1.241548e+10	5.189730e+10
2021-05-21	0.398124	0.411975	0.314766	0.359382	7.452862e+09	4.660975e+10
2021-05-22	0.358717	0.360517	0.318169	0.342371	5.243222e+09	4.440825e+10

Fig. 4. Some samples of the raw data from the BTC dataset

The raw dataset of historical market price is pre-processed including some main ordered tasks: smoothing, labeling, technical indicators calculation, normalizing. In the smoothing step, raw data will be cleaned by removing noisy data by using Savitzky–Golay filter [9]. In the labeling step, the data sample is labeled as 0 or 1 (it means downtrend or uptrend) based on the Close value. Next, technical indicators are calculated using Open, Close, High, and Low values based on equations in [10][11]. Finally, technical indicators are normalized to the range of [-1.0..1.0] in order to improve the performance of the learning model.

After the data preprocessing phase, the dataset is partitioned into training set, validation set, and test set. The dataset is spitted into a test set and a training model dataset. The test set in case of the 1-hour time frame and in case of the 30-minute time frame are the last 1,000 data samples and the last 3,000 data samples, respectively. The training model dataset is further divided into a training set (80%) and a validation set (20%) for evaluating performance and avoiding overfitting. Numbers of data samples for experiments are shown in Table III.

TABLE III. Experimental Dataset

	Number of data samples in 1-hour time frame	**Number of data samples in 30-minute time frame**
Training set	18,400	36,800
Validation set	4,600	9,200
Test set	1,000	3,000
Total	**24,000**	**49,000**

Fig.5 shows the class distribution and the data set for hourly frequency. Fig.5 also demonstrates that it is a balanced classification in the case of hourly frequency.

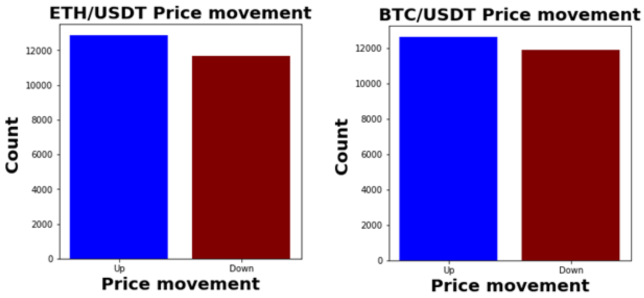

Fig. 5. Crypto currency price hourly movement for Bitcoin and Ethereum

B. *Setting experiments environment*

Our experiments were executed on Linux Mint 20.3 Cinnamon with 16 GB RAM and one GPU card (NVIDIA GTX 1060Ti 12 GB). We used TensorFlow- GPU 2.8.0 and Keras 2.8.0 operated with Python 3.8.10. Moreover, some factors are set as following:

- The optimization function: the Adam optimization algorithm.
- The loss function: binary cross-entropy
- The batch size: 64
- The initial learning rate is 0.01 and decreases to 0.3 times the origin rates every 40 epochs for a total 200 epochs.

C. *Experimental results*

We tested some experiments with:

- Cryptocurrency type: Bitcoin (BTC) and Ethereum (ETH)
- Time Frame: 1- hour frame and 30-minute frame
- Input feature: price, technical indicators
- Model: MRS-LSTM model.

To evaluate performance, some measurements are used including accuracy, recall, precision, and F1 score.

1-hour time frame experiments

Table IV shows a comparison of features of technical indicators (proposed feature) and price feature in a 1-hour time frame. The results highlight better performance of features of technical indicators compared to price features in all measurements and both Bitcoin and Ethereum.

TABLE IV. COMPARISON OF TECHNICAL INDICATORS FEATURE AND PRICE FEATURE IN 1-HOUR TIME FRAME

Crypto currency	Feature	Accuracy	Recall	Precision	F1 Score
BTC	Price	0.566	0.5812	0.5853	0.5832
	Technical Indicators	0.624	0.625	0.63	0.627
ETH	Price	0.5350	0.54	0.5232	0.5481
	Technical Indicators	0.638	0.6292	0.6367	0.6282

Fig. 6 illustrates confusion matrix based on price feature of both Bitcoin and Ethereum in 1-hour time frame with 1,000 test samples.

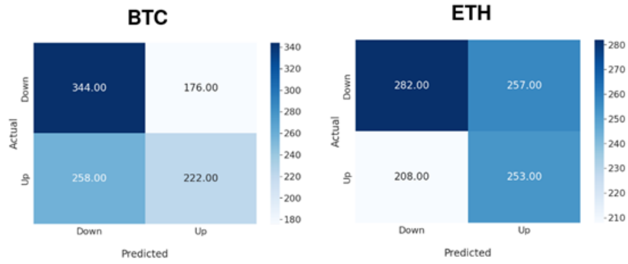

Fig. 6. Confusion matrix based on price feature of both Bitcoin and Ethereum in 1-hour time frame

Fig. 7 illustrates confusion matrix based on technical indicators feature of both Bitcoin and Ethereum in 1-hour time frame with 1,000 test samples.

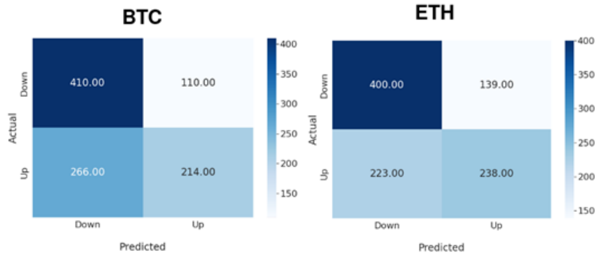

Fig. 7. Confusion matrix based on techincal indicators feature of both Bitcoin and Ethereum in 1-hour time frame

30-minute time frame experiments

Table V shows a comparison of technical indicators feature (proposed feature) and price feature in a 30-minute time frame. The results highlight better performance of features of technical indicators compared to price features in all measurements and both Bitcoin and Ethereum.

TABLE V. COMPARISON OF TECHNICAL INDICATORS FEATURE AND PRICE FEATURE IN 30-MINUTE TIME FRAME

Crypto currency	Feature	Accuracy	Recall	Precision	F1 Score
BTC	Price	0.5617	0.565	0.56	0.56
	Technical Indicators	0.6403	0.6294	0.6553	0.6196
ETH	Price	0.581	0.58	0.58	0.58
	Technical Indicators	0.6583	0.6526	0.6603	0.6514

Confusion matrices based on features of price and features of technical indicators of both Bitcoin and Ethereum in a 30-minute time frame with 3,000 test samples are shown in Fig. 8 and Fig.9, respectively.

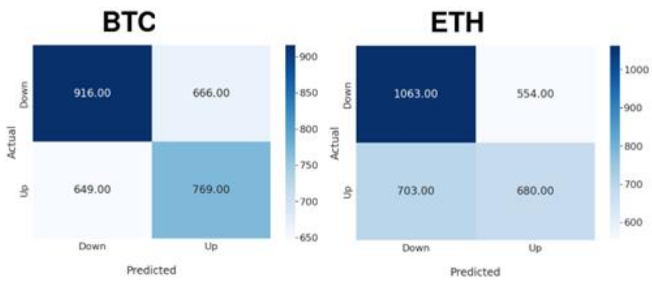

Fig. 8. Confusion matrix based on price feature of both Bitcoin and Ethereum in 30-minute time frame

Fig. 7 illustrates confusion matrix based on technical indicators feature of both Bitcoin and Ethereum in 30-minute time frame with 3,000 test samples.

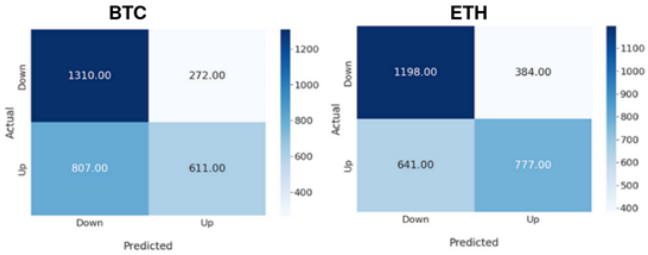

Fig. 9. Confusion matrix based on techincal indicators feature of both Bitcoin and Ethereum in in 30-minute time frame

D. *Profitability in testing on Binance Sandbox*

After successfully testing our implementation model. We created an automation trading bot using our implementation model. Our trading bot was tested on Binance Sandbox environments [12] for Spot order.

A simple trading strategy is set as: ***buy Bitcoin and Ethereum when model prediction up; sell all Bitcoin and Ethereum when model returns down prediction***. Using the present dataset sampled by a 1-hour time frame, we evaluated the prediction performance using a half-an-hour sampling step. The length of the testing dataset was 1,000-period steps for 1-hour time frames and 3,000-period steps for 30-minutes time frame. The trading results measured on a an-hour trading scale are given in Table. VI, and the trading results measured on a half-an-hour trading scale are given in Table. VII.

TABLE VI. PROFITABILITY FOR BTC AND ETH OF NEXT 1,000 1-HOUR TIME STEPS

Feature	BTC	ETH
Price	1.0377	0.805
Technical Indicators	1.2364	1.2682

TABLE VII. PROFITABILITY FOR BTC AND ETH OF NEXT 3,000 30-MINUTE TIME STEPS

Feature	BTC	ETH
Price	1.0377	0.805
Technical Indicators	1.2364	1.2682

These results highlight good results in real test environments. In the first case, the profitability factor of Bitcoin and Ethereum over USDT of next 1,000 1-hour time steps. Market reference values were 1.2364 for BTC/USDT and 1.2682 for ETH/USDT value of 1 represents 100% of the initial investment budget as shown in the Table VI. While the profitability factor of BTC and ETH over USDT of next 3,000 30-minutes time steps. Market reference values were 1.5662 for BTC/USDT and 1.7071 for ETH/USDT value of 1 represents 100% of the initial investment budget.

V. CONCLUSION

This work has proposed a model applying technical indicators and Multi-Scale Residual Convolution and Long Short – Term Memory combination model to predict price trends for short-term cryptocurrency investment. Two main adjustments are input as significant technical indicators and output as trend movements to be consistent with the original research objectives.

Based on the experimental results, the proposed method returns higher accuracy. Moreover, to test profitability in real investment conditions, a bot was created and tested with a simple short-term investment strategy in the Binance Sandbox environments for Spot order. The test profitability results also show that the investment is profitable and higher than the model using the input as Price.

On the basis of the obtained results, the research can be developed in the following directions:

- Finding effective features suitable for different investment types (such as: long-term period or short-term period)
- Finding effective models for different market trends.

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