Cryptocurrency Price Forecasting based on Hybrid CEEMDAN-EWT Deep Learning Method

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Abstract – The prediction of cryptocurrency price has appealed to many researchers in recent years because of its importance to investment strategies. Considerable fluctuation in cryptocurrency prices has called on research communities to design models of high accuracy in price prediction. Owing to seasonal effects and the need to satisfy several unrealistic requirements, it is difficult to predict the prices accurately by means of traditional statistical methods. This has caused machine learning, especially ensemble and deep learning, to be accepted widely for the prediction of cryptocurrency price. his paper presents a novel hybrid method for cryptocurrency price forecasting by integrating Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), Empirical Wavelet Transform (EWT), and a Gated Recurrent Unit (GRU) deep learning model. Accurate price prediction is crucial for effective investment strategies, yet the highly volatile, nonlinear, and nonstationary nature of cryptocurrency data poses significant challenges. Traditional statistical and standalone machine learning models often fail to capture complex patterns and are prone to overfitting. To address these issues, the proposed method employs a decomposition-based preprocessing strategy combined with deep learning to enhance prediction accuracy. The process begins by applying CEEMDAN to decompose the original cryptocurrency price series into several Intrinsic Mode Functions (IMFs). These subseries are more stationary and manageable for forecasting. However, the first IMF, which contains the highest frequency components, remains noisy and irregular, adversely affecting model accuracy. To mitigate this, EWT is utilized as a denoising technique specifically applied to the first IMF. EWT reduces randomness and removes noise, transforming the high-frequency subseries into a smoother, more predictable form. Following preprocessing, each denoised and decomposed subseries is individually forecasted using a GRU neural network. GRU is chosen for its ability to capture long-term dependencies in sequential data with lower computational complexity compared to alternatives like LSTM. The final prediction is obtained by aggregating the forecasts from all subseries. This approach leverages the strengths of decomposition for data simplification, wavelet-based denoising for noise reduction, and deep learning for pattern recognition. The method is evaluated using real-world Bitcoin daily closing price data, with performance measured through Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). Experimental results demonstrate that the proposed CEEMDAN-EWT-GRU model significantly outperforms both single models (e.g., SVR, ANN, RF, LSTM, GRU) and existing hybrid methods (e.g., EMD-GRU, CEEMDAN-LSTM, CEEMDAN-GRU, CEEMDAN-EWT-LSTM). The model achieves the lowest error metrics, with a MAPE of 0.28%, RMSE of 258.33, and MAE of 195.82, highlighting its superior forecasting capability. Key findings indicate that hybrid decomposition methods consistently surpass single models, CEEMDAN offers better decomposition quality than EMD or EEMD, and denoising the highest-frequency IMF with EWT further enhances prediction accuracy. The integration of CEEMDAN, EWT, and GRU provides a robust framework for handling the inherent noise and nonstationarity of cryptocurrency markets.

Keywords: Cryptocurrency, Decomposition, Deep learning

1. Introduction

From the introduction of Bitcoin in 2008, many investors and regulators were attracted to the area of cryptocurrencies. Such great popularity of cryptocurrency is attributed to its characteristics that significantly differ from traditional financial assets. The value of these currencies depends on the confidence of the algorithms that underly them, rather than on tangible assets. This makes cryptocurrencies independent of higher authorities and results in less cost of transactions [1].

Predicting cryptocurrency prices accurately will have significant effects on economy and many technical advantages. Therefore, numerous scholars have proposed different approaches to developing and improving methods for the prediction of cryptocurrency price, including statistical methods, e.g., GARCH [2] and autoregressive integrated moving average (ARIMA) [3]. Though, the

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approaches mentioned above identify only the linear patterns in the time series of cryptocurrencies and suppose that variables are normally distributed. These are not realistic in the case of cryptocurrencies [4]. Machine learning approaches are capable of extracting nonlinear patterns and use huge datasets with no assumption of any prior understanding of the data. Nevertheless, even the conventional machine learning methods, e.g., support vector machines (SVM) [5] or multilayer perceptron (MLP) neural networks [6] have problems such as vulnerability to overfitting. In addition, they do not use the full potential of capturing high-level hidden patterns from cryptocurrency sequential data. To resolve such challenges, several researchers have employed forecasting models that work based on deep learning; these models can demonstrate better performance compared to conventional machine learning methods [4,5]. This was recently supported by Murray et al.'s [7] findings showing that gated recurrent unit (GRU) neural networks and long short-term memory (LSTM) show less error than different statistical and machine learning methods in their predicting tasks.

Because of the sporadic nature of the cryptocurrency market, the data of cryptocurrency price is highly volatile. Therefore, a single forecasting method cannot provide a precise prediction of cryptocurrency price. As a result, a number of scholars have suggested the use of hybrid methods through integrating artificial intelligence methods with data preprocessing strategies. Nowadays, one of the commonly used methods of data preprocessing is the decomposition-based method, which has demonstrated an appropriate performance in predicting results [8,9,10]. The decomposition-based hybrid methods employ decomposition techniques to decompose original data into a number of more relatively stationary subseries. After that, for each subseries, a forecasting model is created, and the obtained results are integrated in order to achieve the final forecasting outcomes. The accuracy of cryptocurrency price forecasting could be enhanced through decomposing into several more relatively stationary subseries and then forecasting each subseries individually.

To predict cryptocurrency price, a number of decomposition-based hybrid methods have been used in the literature, for instance Empirical Mode Decomposition [8], Ensemble Empirical Mode Decomposition (EEMD) [9], Complementary EEMD (CEEMD) [10], and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) [11]. The outcomes of the experiments demonstrated the higher effectiveness of the decomposition-based hybrid methods in enhancing the forecasting accuracy in comparison with individual models. For example, for the purpose of predicting cryptocurrency price, Arslan et al. [8] integrated EMD, as a data decomposition method, with Long Short-Term Memory (LSTM) networks. In their model, EMD decomposes the original data, while LSTM constructs the forecasting models for each subseries. They showed that the combination of EMD and LSTM is able enhance the accuracy in predicting cryptocurrency prices. In another study, Khaldi et al. [9] designed a hybrid method using EEMD decomposition in order to predict cryptocurrency price. They decomposed the original time series into a number of components using EEMD, and then employed ELMAN for the prediction of each component.

The combination of the decomposition technique and the artificial intelligence has resulted in a considerable enhancement of forecasting models; though, there is still much room for raising the accuracy level in predicting cryptocurrency prices. The highest frequency series generated using CEEMDAN is still highly volatile and includes some noises. Remember that the most difficult series to predict is the highest frequency series [12]; this can further decline the accuracy of forecast. The majority of the methods already proposed in the literature for the prediction of cryptocurrency price rely only on a single data decomposition method and do not take into consideration the highest frequency problem. For example, in [8, 9, 10] the authors used only EMD, EEMD, and CEEMDAN to decompose their data. This confines the accuracy of predictions produced by their methods since they have not properly dealt with the complexity of the problem of highest frequency series. This problem could be handled through applying the denoising technique of Empirical Wavelet Transform (EWT) to the highest frequency series produced by CEEMDAN [12]. IMF 1, as the highest frequency series, is the most irregular subseries and shows a high randomness. As a result, EWT, which is a signal processing technique, can lessen the randomness and eliminate the noises in the input data of IMF 1. This significantly increases the accuracy of forecasting outcomes. EWT has the capacity of removing noises and unrelated information in the data [12]. In addition, it has been found useful in different applications. For instance, the researchers in [12] applied EWT to the removal of the noises that may exist in the wind speed data. EWT is able to embody the original data into a number of modes and prevent the noisy residuals. Furthermore, the use of EWT for denoising the original data enhances the accuracy of the cryptocurrency price predictions.

Accordingly, the present paper developes a method for the prediction of cryptocurrency price by means of a novel hybrid CEEMDAN-EWT deep learning GRU method. At first, the original cryptocurrency price data are transformed by CEEMDAN into some subseries. Afterward, EWT denoises the highest frequency series that CEEMDAN has produced. The prediction difficulty can be further decreased by lessening the noise in the highest frequency series. When data are preprocessed by CEEMDAN-EWT, GRU is then used to forecast each of the subseries individually. Finally, the prediction outcomes of each subseries are integrated to acquire the final result. To the best of our knowledge, no study has combined CEEMDAN, EWT denoising technique, and GRU yet for the prediction of cryptocurrency price.

The rest of the article is organized as follows. Section 2 provides the theoretical background of the research. Then, Section 3 explains the framework of the method proposed in this study. Next, Section 4 presents the experiments conducted. Finally, Section 5 concludes the whole study.

2.Theoretical background

This section elaborates on the theoretical background of the methods used in the present research.

2.1. Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN)

CEEMDAN is a signal processing method capable of decomposing nonlinear and nonstationary data into a number of Intrinsic Mode Functions (IMF) series. These series are more stable and stationary. CEEMDAN is built on top of the Empirical Mode Decomposition algorithm [13]. EMD was created by Huang et al. [14], with the problem of mode mixing. Therefore, Ensemble Empirical Mode Decomposition (EEMD) was designed to resolve this problem [15]. On the other hand, EEMD suffers from some limitations, too, such as high computational costs [16]. Therefore, CEEMDAN was designed in order to improve EEMD through the addition of adaptive noise into the residual signal after EMD decomposition, instead of the direct addition of noise to the original signal [17]. EEMD and CEEMDAN are different primarily because they differ in their approach to the addition of white-noise components. What EEMD performs is decomposing each signal realization with noise independently into modes; the residuals acquired from each realization do not depend upon each other. CEEMDAN, on the other hand, adds noise to the residual attained from the preceding iteration, not the original noise. This algorithm employs that noise's mode that corresponds to the iteration attained with EMD, not the noise itself. It leads to adaptive noise that is averaged at each iteration and does not introduce additional input to the original signal. In comparison with EEMD, the computational cost of CEEMDAN is lower and also it has shown decomposition results of higher quality.

2.2. Empirical Wavelet Transform

Empirical wavelet transform (EWT) is a technique of adaptive signal processing. It constructs wavelet functions and empirical scaling with considering the signal frequency spectrum [18]. EWT basically calculates the Fourier segment and forms a series of wavelet filters for the purpose of extracting various modes from the given signal. The steps involved in EWT are described as follows:

Applying the FFT to the original signal x(t) in order to measure its frequency spectrum x(ω) and then identifying the maxima in the spectrum x(ω) and the frequencies that correspond to them. Assume that the spectrum comprises P maxima with frequencies ωi, $i = 1, 2, \ldots. P$. In this situation, the maxima should be sorted in a decreasing order considering their magnitude. Segmenting the Fourier spectrum. To split the spectrum (0, π) into $N(N \leq P)$ sections, the first $(N - 1)$ maxima are chosen, excluding 0 and π. For each segment, the boundary of Ωi is defined as the midpoint between two consecutive maxima.

$$\Omega_i = \frac{\omega_i + \omega_{i+1}}{2} \tag{1}$$

This process results in a set of boundaries $\Omega = \{\Omega i\}, i = 1, 2, \ldots, N - 1$.

Creating an adaptive wavelet filter bank incorporating a low-pass filter (scaling function) φ□n(ω) and (N − 1) bandpass filter (wavelet functions) ψ□n(ω) with the use of the identified boundaries.

$$\hat{\varphi}_n(\omega)=\begin{cases} 1 if |\omega| \leq (1-\gamma)\omega_n. \\ \cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma\omega_n}\left(|\omega|-(1-\gamma)\omega_n\right)\right)\right] \\ if (1-\gamma)\omega_n \leq |\omega| \leq (1+\gamma)\omega_n. \\ 0 otherwise \end{cases} \tag{2}$$

$$\hat{\psi}_n(\omega)=\begin{cases} 1 if (1+\gamma)\omega_n \leq |\omega| \leq (1-\gamma)\omega_{n+1}. \\ \cos\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma\omega_{n+1}}\left(|\omega|-(1-\gamma)\omega_{n+1}\right)\right)\right] \\ if (1-\gamma)\omega_{n+1} \leq |\omega| \leq (1+\gamma)\omega_{n+1}. \\ \sin\left[\frac{\pi}{2}\beta\left(\frac{1}{2\gamma\omega_n}\left(|\omega|-(1-\gamma)\omega_n\right)\right)\right] \\ if (1-\gamma)\omega_n \leq |\omega| \leq (1+\gamma)\omega_n. \\ otherwise \end{cases} \tag{3}$$

$$\beta(x)=\begin{cases} 0 if x \leq 0 \\ and \beta(x)+\beta(1-x)=1 \forall x \in [0,1] \\ 1 if x \geq 1 \end{cases} \tag{4}$$

Finally, establishing the extracted modes as the output of the scaling function and wavelet functions. Figure 1 illustrates the EWT method.

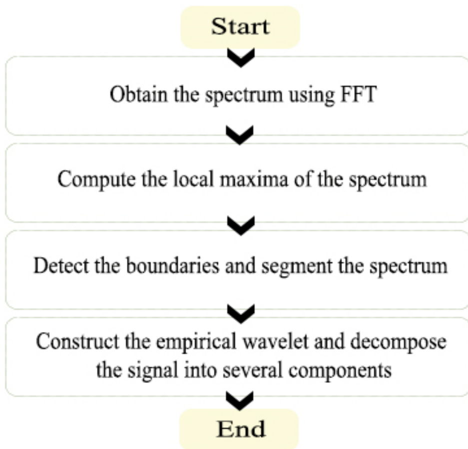

Fig 1: the steps of the EWT method.

2.3. Gated Recurrent Unit

In 2014, Cho et al. designed Gated Recurrent Unit (GRU) with the aim of adaptively capturing the dependencies of various time scales. GRU comprises the update gate and the reset gate. The former controls the extent to which the status information of the previous moment is brought into the current state. The latter, on the other hand, controls the extent to which the status information of the previous moment can be ignored [7]. Figure 2 depicts the structure of a GRU neuron.

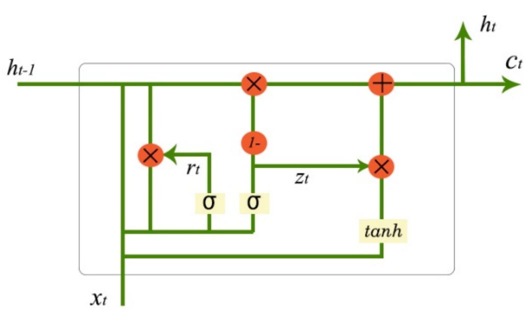

Fig. 2: the structure of a GRU neuron.

3.The framework of the proposed method

The present paper develops an approach hybridized with CEEMDAN, EWT, and GRU to forecast cryptocurrency price. Figure 3 shows the general framework of the method proposed in this study. The method consists of the following stages:

•**Stage 1**: The original data of cryptocurrency price is preprocessed by means of CEEMDAN into a number of subseries, i.e., Intrinsic Mode Functions (IMFs). The present research uses CEEMDAN because it generates better decomposition outcomes and also it is more computationally efficient than EEMD and CEEMD.

• **Stage 2**: The first IMF series CEEMDAN produces in the preceding stage is the series of highest irregularity, which can decline the accuracy of the prediction model. To deal with that series, the denoising technique of EWT is applied to the first IMF. This stage involves the preprocessed of the original IMF1 data with the use of EWT and also the acquiring of several meaningful empirical modes, as well as the residual. Afterward, the residual is removed because of its noisy signals, and the rest of the modes are aggregated in order to create a new series of IMF1 that is entirely denoised. The denoising of IMF1 reduces the negative effects of randomness and irregularities upon it. This will make IMF1 more appropriate for prediction functions and also it could be modeled effortlessly.

• **Stage 3**: In this stage, the GRU forecasting method is applied to the prediction of all subseries acquired by CEEMDAN-EWT.

• **Stage 4**: To attain the final forecasting outcomes, all the forecasting results obtained for each of the subseries are added together.

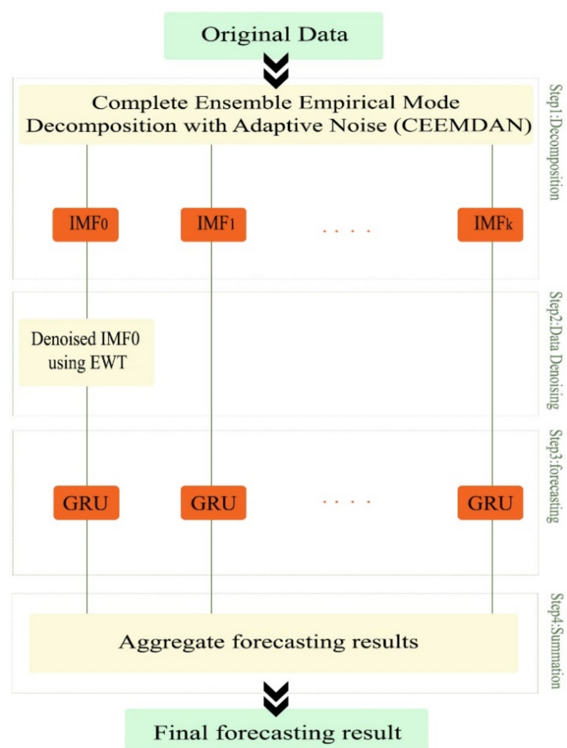

Fig. 3: The framework of the proposed method

4. Experimental results

4.1. Dataset

The BITCOIN price dataset was used in this research to examine the performance of the proposed method. The current study collected the data from www.yahoo.com (the daily closing prices of the BTC). The first 80% of the data was specified for training purposes and the rest for testing. With the use of the training data set, the model was developed; then, the testing dataset was used to examine the prediction capacity. The plots of Bitcoin price dataset are illustrated in Figure 4. This figure shows that the BITCOIN data presents nonstationary and nonlinear features. This causes the establishment of accurate cryptocurrency price forecasts to be difficult.

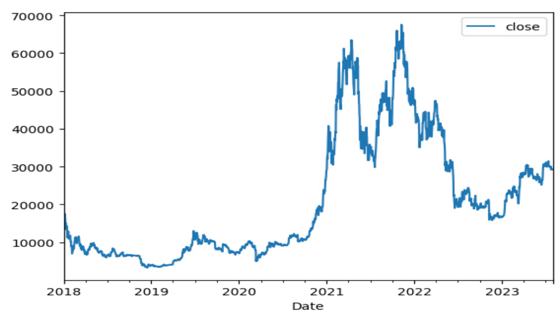

Fig. 4: The Bitcoin price dataset

4.2. Experimental settings

The experiments of the present research were run in COLAB. This study used the pyEMD package in python to implement CEEMDAN, and also the ewtpy package and Keras were used to implement EWT and GRU, respectively. Adam was employed as the optimizer in order to configure GRU since Adam has been found more effective than other stochastic optimization methods. The learning rate of GRU was fixed at 0.001, and the method was trained for 100 epochs. Furthermore, some preliminary experiments were done for the purpose of determining the ideal number of hidden neurons and batch size of the proposed method. In the experiments, different combinations of neurons and batch sizes, e.g., the values of 32, 64, and 128, were examined. The results confirmed outperformance of the model when it was configured with 128 neurons and a batch size of 64 over the other combinations. As a result, these two values were selected to train the proposed method.

4.3. Evaluation metrics

The current paper covered three common evaluation metrics: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE), which are defined as follows [12]:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{5}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{n}\left|\frac{y_i^{pre} - y_i}{y^{\max}}\right| \tag{6}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{n}\left|y_i^{pre} - y_i\right| \tag{7}$$

Where y_i stands for the real cryptocurrency price value at time *i*. $\hat{y}_i$ is the forecasted cryptocurrency price value at time *i*, *N* denotes the number of data points, and $y^{\max}$ represents the maximum value of the whole data. Lower values of the above-noted evaluation metrics indicate more acceptable performance of the forecasting method. Moreover, this study uses percentage of improvement [12] for the aim of evaluating the enhancement of the proposed method compared to other methods. This percentage is computed as follows [12]:

$$P_{RMSE} = \frac{RMSE_1 - RMSE_2}{RMSE_1} * 100\% \tag{8}$$

$$P_{MAPE} = \frac{MAPE_1 - MAPE_2}{MAPE_1} * 100\% \tag{9}$$

$$P_{MAE} = \frac{MAE_1 - MAE_2}{MAE_1} * 100\% \tag{10}$$

4.4. Results

The proposed method initially used CEEMDAN in order to transform the original data into a number of subseries. The BTC price data showed nonlinearity and nonstationary characteristics; as a result, CEEMDAN was applied to the decomposition of the original data into a number of Intrinsic Mode Functions (IMF) in a way that lower nonlinearity and fewer nonstationary characteristics could be created. Figure 5 depicts the IMFs extracted from CEEMDAN for the dataset. As the figure shows, the first IMF has the highest frequency, whereas the last series of IMF has the lowest frequency. This last series is similar to the trend of the series. As IMF 1 is the most disordered and irregular series, such conditions can influence both the stability and accuracy of the proposed model. For the reduction of the difficulties that may arise in the process of forecasting, EWT was used to denoise the first IMF. EWT decreased the randomness and fluctuation of the first IMF. This made the modeling of the series easier and also improved the learning capacity and forecasting accuracy.

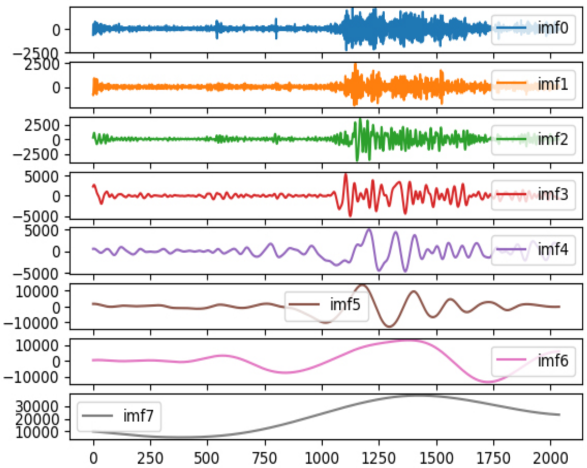

Fig. 5: The IMFs extracted from CEEMDAN decomposition

When the data was preprocessed, GRU was used to predict all the series, and the series were then summed up together to attain the final forecasting outcomes. This indicates the capability of the method in accurate prediction. For the evaluation of the CEEMDAN-EWT-GRU method, its performance was compared with that of nine forecasting methods: SVR, ANN, RF, LSTM, GRU, EMD-GRU, CEEMDAN-LSTM, CEEMDAN-GRU, CEEMDAN-EWT-LSTM. The first five methods are single forecasting methods, while the rest are hybrid decomposition methods combining a single data preprocessing technique for the aim of decomposing the original data and deep learning models (LSTM and GRU) in order to forecast all the decomposed subseries separately. Table 1 compares the simulation results. To demonstrate the forecasting capacity of the proposed method, the improvement percentages of the other benchmarking methods were computed, and the obtained results are presented in Tables 2. The bold values in Tables 1 and 2 signify the forecasting method with the lowest error in the corresponding dataset, and the values given in the last row denote the average values of each evaluation metric. The results revealed that:

Table 1: Comparative experiment results for BTC dataset.

Forecasting methods	**Metrics**		
	MAPE	RMSE	**MAE**
SVR	1.42	1515.06	**961.48**
ANN	5.34	4199.17	**3610.62**
RF	1.04	1009.60	**703.89**
LSTM	0.67	670.51	**454.44**
GRU	0.65	634.60	**442.96**
EMD-GRU	0.38	393.84	**256.93**
CEEMDAN-LSTM	0.34	303.40	**234.49**
CEEMDAN-GRU	0.31	290.56	**216.06**
CEEMDAN-EWT-STM	0.30	270.84	**205.49**
Proposed Method	**0.28**	**258.33**	**195.82**

1. GRU is able to attain higher accuracy than the other single forecasting methods (SVR, ANN, RF and LSTM). As Tables 1 and 2 demonstrate, GRU has the smallest MAPE, RMSE, and MAE among the single forecasting methods. As a result, GRU can be marked out as the base forecasting technique for the prediction of each subseries in the proposed method.

2. In comparison with the single forecasting methods, the hybrid decomposition methods are able to significantly enhance the performance of cryptocurrency price forecasting. For example, the MAPE values of the hybrid decomposition methods (EMD-GRU, CEEMDAN-LSTM, CEEMDAN-GRU, CEEMDAN-EWT-LSTM, and the proposed CEEMDAN-EWT-GRU) are 0.38–0.28; these values are lower than those of the single forecasting methods (SVR, ANN, RF, LSTM, and GRU). Original data of cryptocurrency price are highly volatile and nonstationary; this has made it difficult to predict cryptocurrency data using only one method. The decomposition of the original BTC data into a number of more relatively stationary subseries causes the quality of the input data of the forecasting model to be improved and each subseries can be predicted with higher effectiveness. As a result, the hybrid decomposition methods outperform the single forecasting ones.

3. After comparing various approaches to data decomposition, CEEMDAN was found to be superior to EMD. For example, the average MAPE of CEEMDAN-LSTM equals 1.72%, whereas that of EMD-LSTM and EEMD-LSTM equal 2.43% and 1.89%, respectively. CEEMDAN, as an improved version of the EMD and EEMD, outperformed these two in decomposition capacity.

4. CEEMDAN-EWT-GRU outperforms CEEMDAN-GRU. It is able to raise the prediction accuracy of the CEEMDAN-GRU by over 0.096%. Denoising the IMF1 produced by CEEMDAN can reduce the undesirable effects of irregularities and randomness on IMF1. This will make IMF1 more appropriate for prediction tasks and its modeling is simple. As a result, applying the EWT denoising technique to smoothing and denoising IMF1 can improve the prediction accuracy of cryptocurrency prices.

5. The proposed CEEMDAN-EWT-GRU method outperformed all the prediction methods considered in this study regarding the forecasting results. The average MAPE values of this method are all less than 1.5%, which reveals the high forecasting capability of the method. CEEMDAN-EWT-GRU integrates the advantages of EWT denoising,

CEEMDAN decomposition, and deep learning-GRU forecasting method. This has made it superior to the benchmarking methods. The method proposed in this paper is capable of decomposing the nonstationary and nonlinear data of cryptocurrency prices into a number of more relatively stable subseries by means of CEEMDAN. It denoises the highest frequency subseries produced by CEEMDAN in order to attain higher accuracy in prediction tasks. As a result, CEEMDAN-EWT-GRU could be used effectively to predict cryptocurrency price with a high accuracy.

Table 2: Percentage improvement of proposed method compared to other state-of-the-art methods for BTC dataset.

Forecasting methods	Metrics		
	MAPE	RMSE	**MAE**
SVR	80%	82%	**79%**
ANN	94%	93%	**94%**
RF	0.73%	0.74%	**0.72%**
LSTM	0.58%	0.61%	**0.56%**
GRU	0.56%	0.59%	**0.55%**
EMD-GRU	0.26%	0.34%	**0.23%**
CEEMDAN-LSTM	0.17%	0.14%	**0.16%**
CEEMDAN-GRU	0.096%	0.11%	**0.093%**
CEEMDAN-EWT-STM	0.066%	0.046%	**0.047%**

5. Conclusion

The accurate prediction of cryptocurrency price ensures that investment strategy operates reliably and efficiently. Because of the nonlinear and nonstationary characteristics of the data related to cryptocurrency price, it is not easy to forecast cryptocurrency price with high accuracy. This paper develops a hybrid CEEMDAN-EWT-GRU method applicable to the prediction of cryptocurrency price. CEEMDAN in the proposed method decomposes the original data of cryptocurrency price, whereas EWT denoises the first IMF produced by CEEMDAN. Then, GRU forecasts all the subseries produced by CEEMDAN-EWT. Finally, the last step is dedicated to the aggregation of the prediction results of each subseries through summation in order to achieve the final prediction outcomes. Real-world data were used to evaluate the performance of the method. The experimental results confirmed the superiority of CEEMDAN-EWT-GRU over the other benchmark methods examined in this study. Therefore, the method could effectively be applied to the prediction of cryptocurrency price.

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