Stock Price Prediction with Golden Cross and Death Cross on Technical Analysis Indicators Using Long Short Term Memory

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Abstract*— The stock market price movement has become an interesting topic to research due to the large profit potential. Market traders use technical analysis to forecast stock prices by analyzing stock transaction data. Because technical analysis predictions are subjective, an automated system is needed to produce more objective and faster results. In the previous, next prices were predicted by combining price and transaction volume features with technical analysis indicators such as Stochastic, Moving Average, Moving Average Convergence Divergence, and Relative Strength Index values. In most cases, the addition of the indicator's value reduces the accuracy of the forecast. This is because the value of technical analysis indicators is not useful enough when they are used directly without transformation. The transformation of technical analysis indicators to a crossing value between the fast and slow signal on these indicators, known as the golden cross and death cross, has a greater impact on stock price movement. Therefore, it is recommended to use the price and the golden cross and death cross on technical analysis indicators as inputs to improve stock price predictions. Long Short Term Memory is used in the proposed method, which is a reliable method for predicting sequence data. The stock price forecasts are based on 1200 days of trading data from the Indonesia Stock Exchange for 10 LQ45 group shares. The test was conducted by calculating the Root Mean Squared Error and the Mean Absolute Percentage Error value of the predicted close price next day.

***Keywords*—deep learning, LSTM, price prediction, stock market**

I. INTRODUCTION

In April 2021, the entire value of money managed by banks throughout Indonesia (quasi money and current accounts) is 6,206.81 trillion rupiah [1], while the average value of stock capitalization on the Indonesian Capital Market (Indonesian Stock Exchange) is 7,096.07 trillion rupiah [2]. The capitalization value of the capital market is bigger than the amount of money managed by banks, which makes it a unique appeal for investors looking to profit from the capital market. Furthermore, according to the Indonesian Stock Exchange (IDX) Decree Kep-00108/BEI/12-2020, the high level of stock liquidity and volatility of stock price changes with a limit of up to 35 percent increase in stock prices and a limit of up to 7 percent decline in stock prices per day becomes another investment magnet. In comparison, investment bank deposits pay a maximum annual interest rate of 4.88 percent [3].

The stock market price movement has become an intriguing topic to study due to the significant profit opportunities that traders can gain if they accurately estimate the movement of stock values. Traders, on the other hand, run the risk of losing money if their stock price predictions are inaccurate. Before deciding to buy, sell, or hold stocks, a trader must analyze stock trading data using the appropriate indicators in order to maximize profit and minimizing risk of loss. Data mining approaches on the features of stock price movements can be used to predict stock price increase/correction. The two types of data mining are descriptive and predictive [4], [5]. Predictive category data mining is the type of data mining that will be used in this study.

There are now a plenty of methods for developing predictive systems on the market as a result of advancements in computing technology. As [6] shows, the first method developed is usually based on template-matching on trading charts. In a review of articles on predictive systems, [7] discovered that classifiers can be used effectively to make financial data predictions. A classifier is a computer program that predicts input data and assigns labels to it. Classifiers are developed through a training process on historical data to identify patterns. As a result, based on new data, the classifier can predict the class output label. Data mining algorithms, as proposed [8] and [9], can be used to forecast stock prices.

In addition to the classifier, [10]-[15] performs the same task using a Recurrent Neural Network (RNN) derivative called Long Short Term Memory (LSTM). Because stock prices are sequential data, which is an advantage of RNN and its derivatives, LSTM was chosen as a suitable method for stock price prediction. Stock prices and previous transaction volumes are commonly used as inputs [10]-[14]. In addition, [11][13] news sentiment analysis as a feature, and [15] uses a Genetic Algorithm to select features before making predictions.

In addition to the features mentioned above, [16][17] also includes amount of analytical technical indicators that traders frequently employ to predict stock prices. These include stochastic values, the moving average (MA), the moving average convergence and divergence (MACD), the relative strength index (RSI), and others. However, sometimes the use of analytical technical indicators reduces the quality of the prediction results. This is because the values of analytical technical indicators have no meaning when applied directly to stock price fluctuations. However, stock movements will have greater significance if the intersection of fast and slow signal values from technical analysis indicators known as the golden cross and death cross is utilized, according to [18]. However, [18] only uses the crossing of the Moving Average. In addition the crossing of the Moving Average, Stochastic, MACD, and RSI will give a more accurate predictions [19].

Therefore, this paper will propose stock price predictions using price and the golden cross/ death cross Stochastic, MACD, and RSI values as inputs. The study was based on 1200 days trading data from 10 LQ45 Indonesian Stock Exchange stocks and predictions using the LSTM method, which is able to accurately predict data series.

II. Literature Review

A. Stocks

Stocks serve as proof of ownership of a company's capital. The holder is entitled to dividends in proportion to the number of stocks owned. On the Stock Exchange, stock in a Public Limited Liability Company (Inc.) can be purchased. It can be obtained through an initial public offering (IPO), or through a secondary market known as the stock market. Stock exchange prices fluctuate up and down in accordance with economic laws, which dictate that prices rise when demand is high and fall when demand is low. Profits can be earned by shareholders (investors) in two ways: through dividend distribution or through the growth of stock prices on the stock market (capital gain).

Stock investors are interested in the movement of stock prices in order to earn capital gains. Long-term stock investors with a holding period of more than one year use mostly fundamental analysis to determine which stocks offer the best prospects for capital gains. Fundamental techniques are used to analyze stocks from the standpoint of the company's fundamental health and performance. Meanwhile, short-term stock investors (traders) use mostly technical analysis, which is an examination of the daily fluctuations in stock prices without regard for the company's fundamentals, in order to maximize capital gains.

B. Technical Analysis

Technical analysis is a technique for analyzing historical stock trading data in order to forecast future stock prices. Technical indicators used in stock trading data analysis include the following:

- Daily Stock Price

  Daily stock prices are classified into several categories, including opening, closing, highest, lowest, and average. Because the average price is not always readily available via the trading platform, the average stock price is typically represented by a typical price. $p_{typical}$ as in (1), where p_{close} denotes the closing price, p_{min} denotes the lowest price, and p_{max} denotes the highest price.

$$p_{typical} = \frac{p_{close} + p_{\min} + p_{\max}}{3} \quad (1)$$

- Transaction volume

  The Transaction volume is the number of shares traded in one day. The greater the volume of sales transactions, the price will rise, and vice versa.

- Moving Average (MA)

  Moving Average in n days denoted MA_n formula as shown in equation (2) is the average price over the previous n-1 days (p_n-1) to today's price (p_0).

$$MA_n = \frac{p_{n-1} + p_{n-2} + \ldots + p_0}{n} \quad (2)$$

In addition to the basic Moving Avaerage, a Weighted Moving Average was also developed. and Exponential Moving Average. Exponential Moving Average for n days denoted by EMA_n is defined by equation (3).

$$EMA_n = \left(\frac{2}{n+1}\right)p_n + \left(\frac{n-1}{n+1}\right)EMA_{n-1} \quad (3)$$

- Stochastic

  The stochastic value is a momentum indicator that oscillates between overbought and oversold conditions. The stochastic value is a mathematical expression that describes the relationship between the closing price and the distance between the highest and lowest prices. These connections are what generate buy and sell signals, as well as overbought and oversold conditions. This indicator contains two signal lines: the fast line (%K) and the slow line (%D). %K is defined by equation (4),

$$\%K = \left(\frac{p_{close} - p_{\min n}}{p_{\max n} - p_{\min n}}\right)100 \quad (4)$$

where p_{close} denotes the day's closing price, $p_{\min n}$ denotes the lowest price over the last n periods, $p_{\max n}$ denotes the highest price over the last n periods, and n denotes the observation period. While %D is simply %K with a longer duration, it is possible to think of %D as the Moving Average of %K.

When the stochastic value exceeds 80, an overbought condition exists, and when the stochastic value falls below 20, an oversold condition exists. A buy signal is formed when the %K stochastic value crosses up the %D stochastic value (golden cross). On the other hand, a sell signal is formed when the %K stochastic crosses down (death cross).

- Relative Strength Index (RSI)

  The RSI Oscillating Indicator, denoted $\Re_{si}$, is a technical indicator that oscillates between overbought and oversold conditions. It is defined by equation (5),

$$\Re_{si} = 100 - \left(\frac{100}{1+\Re_s}\right) \quad (5)$$

where $\Re_s$ is the ratio of the average daily closing price increase to the daily average daily closing price decrease. If $\Re_{si}$ is greater than 70, the signal is overbought; if $\Re_{si}$ is less than 30, the signal is oversold. When it is oversold and breaks above the 30 level, a buy signal is generated; when it is overbought and breaks below the 70 level, a sell signal is generated.

Fig. 1. Golden Cross and Death Cross illustration. a. Golden Cross on the Stochastic indicator, %K curve (blue) crossing up %D curve (red). b. Death Cross on the Stochastic indicator, %K curve (blue) crossing down %D curve (red) c. Golden Cross on the RSI indicator, RSI curve (purple) crossing up MA_{14} RSI curve (yellow). d Death Cross on the RSI indicator, RSI curve (purple) crossing down MA_{14} RSI curve (yellow). e. Golden Cross on MACD indicator, MACD curve (blue) crossing up EMA_9 MACD curve (blue). f. Death Cross on MACD indicator, MACD curve (blue) crossing down EMA_9 MACD curve (blue).

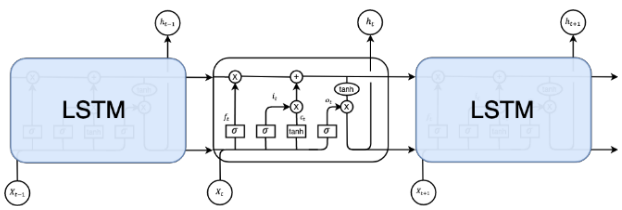

Fig. 2. LSTM architecture

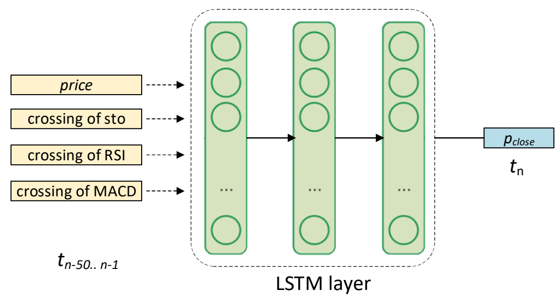

Fig. 3. LSTM architecture for stock price prediction

- Moving Average Convergence Divergence (MACD)

  MACD identifies the momentum of a stock price. *MACD* is the difference between EMA_{12} and EMA_{26} as equation (3), so

$$MACD = EMA_{12} - EMA_{26} \quad (6)$$

- Golden Cross and Death Cross

  The golden cross and death cross are the crossings of long period and short period signals on an analytical technical indicator value. Long period signals are relatively long averages of signals than short period signals. Long period signals represent a more stable average of a technical indicator's value than shorter period signals, which are more volatile.

  A golden cross occurs when a short period signal crosses above a long period signal. A golden cross indicates that prices will increase because signals with short periods are greater than signals with long periods. This means that the value of a technical analysis indicator is currently greater than the average value.

  A death cross occurs when a short period signal crosses below a long period signal. A death cross indicates that there will be a price correction because signals with short periods are smaller than signals with long periods. This means that the value of a technical analysis indicator is currently lower than the average value.

  Fig 1 shows additional information about crossing on the value of technical analysis. The intersection of *%K* and *%D* values determines the crossing of stochastic values. If *%K* crosses up *%D* (Fig 1a), it is called a golden cross; if *%K* crosses down *%D*, it is called a death cross (Fig 1b).

  The RSI value crossing is calculated by crossing the RSI and MA_{14} RSI values. When RSI crosses up MA_{14} RSI (Fig 1c), it is referred to as a golden cross; when RSI crosses down MA_{14} RSI, it is referred to as a death cross (Fig 1d).

  MACD crossing is calculated by combining the MACD and EMA_9 MACD values. If MACD crosses up EMA_9 MACD (Fig 1e), it is referred to as a golden cross; if MACD crosses down EMA_9 MACD, it is referred to as a death cross (Fig 1f).

C. Long Short Term Memory (LSTM)

Hochreiter and Schmidhuber [20] are the first to mention LSTM in 1997. The LSTM is also known as a neural network with adjustable architecture, meaning that the shape of the network may be changed based on the application. The Recurrent Neural Network (RNN) method is a variant of the LSTM technique. RNN stands for recurrent neural network, and it is a type of iterative neural network that is designed to handle sequential input.

However, when the range of values changes between layers in an architecture, RNNs exhibit vanishing and exploding gradients. When dealing with vanishing and exploding gradients, the LSTM was developed and designed to address the issue of gradient vanishing in RNNs. Fig 2 depicts the LSTM architecture as an input layer, an output layer, and a hidden layer. The hidden layer is composed of memory cells, each of which contains three gates: an input gate, a forget gate, and an output gate. The input gate specifies the amount of data that should be retained in the cell state. This prevents the cell from storing unnecessary data. The duration of the value's storage in the memory cell is determined by forget gate functions. The Output Gate's purpose is to determine how much content or value from a memory cell will be used in the output calculation.

The LSTM architecture consists of [14]:

- Memory cell : stores state
- Front gate: controls what to learn
- Forget gate: controls what to forget
- Exit gate: controls the amount of content to modify

The LSTM unit can decide to store the existing memory through the gate according to the equation (7),

$$\begin{pmatrix} i \\ f \\ o \\ x \end{pmatrix} = \begin{pmatrix} sigm \\ sigm \\ sigm \\ \tanh \end{pmatrix} T_{2n,4n} \begin{pmatrix} z_t^{l-1} \\ z_{t-1}^{l} \end{pmatrix}$$

$$c_t^l = f \circ c_{t-1}^l + i \circ x \tag{7}$$

$$z_t^l = o \circ \tanh(c_t^l)$$

where $c^l{}_t$ is the cell's memory vector, i represents input gates, f represents forget gates, o represents output gates, h represents hidden state, and x represents modulation gates. As a result, this memory allows you to perform the following operations: *.forget* (wipe memory), *.input* (add memory), and *.output* (restore from memory).

III. Research Methodology

A. Data Setup

The sample is a stock with a big market capitalization, making price control difficult for a group of people. The LQ45 group, which is the leading stock group in IDX, has been expanded to include ten stocks. Furthermore, shares in the metal, mining, energy, and plantation industries are not available because their prices are determined by commodities market prices. Table I lists the ten equities that were chosen as research subjects. The dataset used is transaction data from November 9, 2021 through 1,200 transaction days.

B. Technical Analysis Indicator Features and Output

The output of this research is a closing price prediction based on four transaction variables: price, stochastic, RSI, and MACD indicator for 1200 days. According to technical analysis, stock prices will rise if a "golden cross" is produced on technical indicators, and stock prices would be corrected if a "death cross" is formed on technical indicators [19].

As a result, the Stochastic value is determined by the intersection of $\%K$ and $\%D$ values. If $\%K$ crosses up $\%D$, it is called a golden cross; if $\%K$ crosses down $\%D$, it is called a death cross. The RSI value is then calculated by crossing the RSI and MA_{14} RSI values. If RSI crosses up MA_{14} RSI, it is called a golden cross; if RSI crosses down MA_{14} RSI, it is dubbed a death cross. Finally, the MACD value is calculated by adding the MACD and EMA_9 MACD values together. If MACD crosses up EMA_9 MACD, it is called a golden cross; if MACD crosses down EMA_9 MACD, it is dubbed a death cross.

C. LSTM architecture

The LSTM architecture of this research can be seen in Fig 3. The input consists of 4 input features for 1,200 days divided into 960 training sections and 240 testing sections. Each section consists of 50 data input series to predict the next 1 data. The input then followed by 3 LSTM layers of 96 cells each with epoch=50 and batch size=32. The output is the predicted closing price for the next day.

D. Error Value Calculation

The predicted error value is found by calculating the Root Mean Squared Error (*RMSE*) obtained by equation (8),

$$RMSE = \sqrt{\frac{\Sigma(y_i - \hat{y}_i)^2}{n}} \tag{8}$$

where

y : actual value

$\hat{y}$: predicted value

i : order of data in database

n : the number of data.

In addition to *RMSE*, the error value of the prediction results is also found by calculating the Mean Absolute Percentage Error (MAPE) obtained by equation (9),

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - F_i}{Ai}\right|100\% \tag{9}$$

where

n : number of data

A_i : actual data value

F_i: predicted value

IV. Testing and Result Analysis

A. Experimental Scenario

The experiment is carried out by splitting the dataset into two parts: training and testing. The training dataset contains 960 days of transaction data, while the testing dataset contains the most recent 240 days.

To obtain a closing price prediction model, we conducted training. The model was put to the test on data that had not been included in the training process. The RMSE and MAPE values are used to calculate the stock price prediction error value. The error value will be compared to the commonly used features, namely the price feature alone and the price feature combined with volume features, to ensure the quality of the prediction.

B. Experimental Results

Fig 4 illustrates one of the ten-stock trials. Figure 4a shows the original (red) and predicted (blue) prices for an ASII stock code using only the price feature of the LSTM. The MAPE is 2.96 percent, and the RMSE value is 192.32. Using LSTM with proposed features, such as price, stochastic, RSI, and MACD value, Fig 4b shows the original price (red) and predicted price (blue) for the ASII stock code. The MAPE is 2.09 percent, and the RMSE value is 158.47.

Fig. 4 shows that stock prediction using LSTM with technical indicators is better than stock prediction using only the price feature, based on both visual and quantitative results.

C. Result Analysis

The test is conducted by calculating the prediction error value using LSTM with only price features, price features combined with volume, and proposed technical analysis indicator features. Table II shows the RMSE value, while Table III shows the MAPE value.

The proposed method's RMSE experiment value is always lower than the two other methods, indicating that the prediction results have the best small error. The error of all predictions, The RMSE, and The MAPE, with the proposed method is always lower than the other method, as shown in Fig 5 and Fig 6. This means that the proposed prediction method is more accurate than other methods.

The MAPE average experiment value is 2.30 percent, indicating that the prediction results are accurate when compared to predictions using only the price feature or a combination of price and volume features, which have MAPEs of 3.03 percent and 2.63 percent, respectively.

Furthermore, the 0.33 percent standard deviation indicates that the proposed method produces more consistent prediction results for any stock than other methods with standard deviations of 1.00 percent and 0.38 percent, respectively.

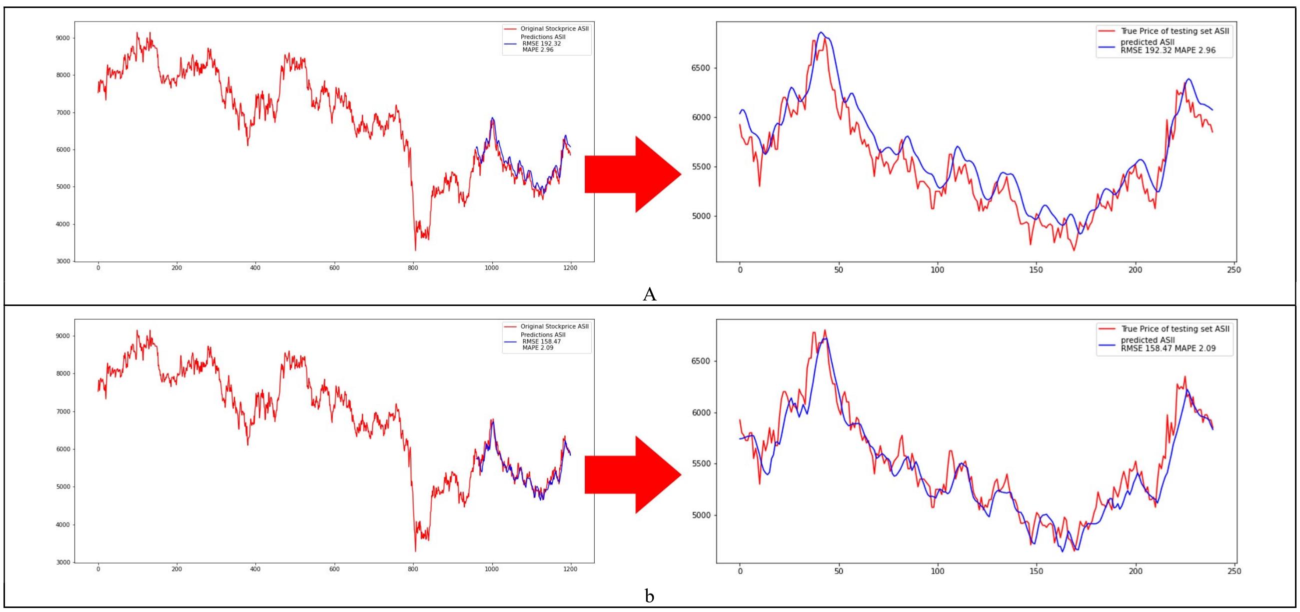

Fig. 4. ASII stock price prediction experimental results. Red original price, blue predicted price. a. Stock Price Prediction using LSTM with price feature only (code ASII, RMSE 192.32, MAPE 2.96%). b. Stock Price Prediction using LSTM with technical analysis indicator features (code ASII, RMSE 158.47, MAPE 2.09%)

TABLE I. ROOT MEAN SQUARED ERROR (RMSE) OF PRICE STOCK PREDICTION USING LSTM

Code	RMSE		
	price feature only	price&vol features	proposed method
ACES	63.88	54.36	48.41
ASII	192.32	198.35	158.47
BBNI	220.64	249.55	182.26
BBTN	81.31	63.63	58.95
BSDE	39.57	38.18	35.97
ERAA	34.82	19.52	18.42
KLBF	38.25	39.95	36.53
PWON	17.98	16.60	16.50
SMGR	294.08	321.39	295.19
TLKM	87.41	96.54	82.70

TABLE II. MEAN ABSOLUTE PERCENTAGE ERROR (MAPE) OF PRICE STOCK PREDICTION USING LSTM

Code	MAPE		
	price feature only	price&vol features	proposed method
ACES	3.23	2.90	2.44
ASII	2.96	2.71	2.09
BBNI	3.19	3.13	2.46
BBTN	4.24	2.92	2.79
BSDE	2.78	2.67	2.39
ERAA	5.08	2.69	2.53
KLBF	1.81	1.84	1.69
PWON	2.71	2.51	2.50
SMGR	2.31	2.62	2.19
TLKM	1.97	2.21	1.90
Average	**3.03**	**2.62**	**2.30**
Stdev	**1.00**	**0.37**	**0.33**

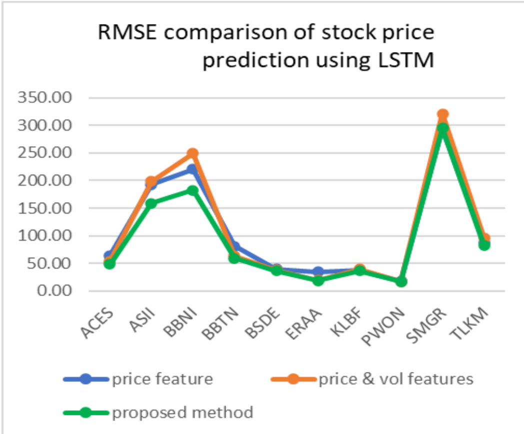

Fig. 5. RMSE comparison of stock price prediction using LSTM

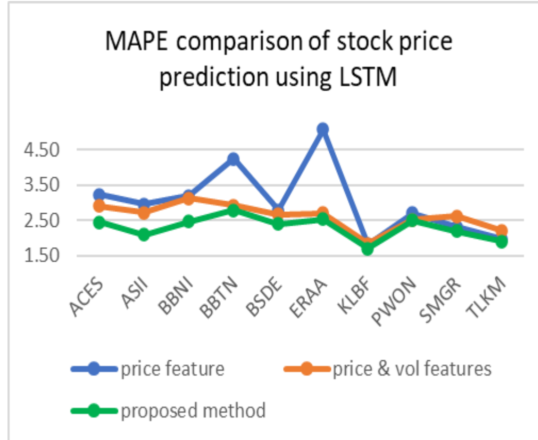

Fig. 6. MAPE comparison of stock price prediction using LSTM

V. Conclusion and Future Work

Stock price prediction using technical indicators resulted in a lower error value than either the input price only or the price combined with volume. The golden cross and death cross of the Stochastic, RSI, and MACD are recommended technical indicator features because their values indicate whether prices will be rising or will be correcting on the next. The purpose of this paper is to learn about the significance of using golden cross and death cross technical analysis indicators in improving prediction performance. The approach uses LSTM, a good method for data series. Further research on the effect of combining the golden cross and death cross features with other data series-appropriate methods can be conducted in the future.

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