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Bitcoin Price Prediction Model Development Using Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM)

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Abstract

Cryptocurrency is a virtual currency that can be used as a financial or economic standard, foreign currency reserve, and as a means of payment in some countries. The value that goes up and down every time is not easy to predict using logic. This is a problem for investors, besides that investors lack knowledge about the direction of crypto money movement. In addition, there is no system that can predict the price of Bitcoin, so this can cause investors to take the wrong steps in transactions and can cause losses. To avoid this risk, a system is needed that can predict bitcoin prices using data mining techniques, namely forecasting, the algorithms used are CNN and LSTM. The data used is Bitcoin closing price data from January 1, 2017, to April 26, 2023. The data is divided into 80% training data and 20% testing data. The prediction results are evaluated using MAPE which gets a MAPE value of 0.037 or 3.7% in the CNN algorithm, while the LSTM algorithm gets a value of 0.065 or 6.5%. The MAPE results of the two algorithms are in the MAPE range <10%, so it can be said that the ability of the forecasting model is very good so that it can be used as a reference to determine the prediction of bitcoin prices in the next few periods.

Introduction

Cryptocurrency is a virtual currency that can be used as a financial or economic standard, as foreign currency reserves, and as a means of payment in several countries (Стойка, 2021; Luchkin et al., 2020). The use of cryptocurrencies in investing has high volatility but also carries high risks. One type of cryptocurrency that is still popular is Bitcoin. Bitcoin has become a cryptocurrency that has the largest capitalization value compared to other cryptocurrencies. A common risk associated with investing in cryptocurrency is that the price always fluctuates every minute (Agbo & Nwadialor, 2020). Values that go up and down all the time are not easy to predict using logic, creating problems for investors who intend to buy or sell crypto. In addition, the absence of a system that can predict the price of Bitcoin causes investors to experience losses due to wrong steps in transactions. To avoid this risk, we need a system that can predict Bitcoin prices with a high degree of accuracy so that investors do not buy the wrong crypto and can provide appropriate profits. Research that has been done previously (Chen et al., 2020; Mudassir et al.,2020) namely predicting Bitcoin prices using LSTM, shows an accuracy of 93.5% and shows that LSTM can predict Bitcoin prices well. Other research conducted related to harvest prediction using CNN-RNN resulted in an accuracy value of 93%, which means that the model can work well in predicting harvests.

Based on the description above, in this study the application of data mining to predict Bitcoin prices was carried out using the Convolutional Neural Network (CNN) and Long Short-Term

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Memory (LSTM) algorithms. The use of the CNN and LSTM algorithms is because in previous studies they were able to predict and produce good accuracy. In addition, the use of the two algorithms will be compared to find out which algorithm performs better. It is hoped that the results of this research can help investors or the public make decisions about when to buy or sell their crypto. From the research conducted, it is hoped that it will provide benefits to be able to get Bitcoin price predictions in the future and as a decision support system for investors to invest in cryptocurrencies, especially Bitcoin.

The Comprehensive Theoretical Basis

Cryptocurrency

Cryptocurrency is a digital asset designed as a medium of exchange where records of individual coin ownership are stored in computerized databases using strong cryptography to secure transaction records, control the creation of additional coins, and verify transfers of coin ownership (Fokri , 2021; Khan et al., 2020)**Error! Reference source not found.**. In addition, cryptocurrency is a digital currency where transactions can be carried out in the network (online). Unlike printed paper currency, cryptocurrency is designed to solve mathematical problems based on cryptography. This currency is formed based on cryptographic technology so that it is not easily duplicated or transferred to other parties who are not the owners and do not have access to this currency (Amsyar et al., 2020).

Bitcoin

Bitcoin is a cryptocurrency that came into use in 2009. Bitcoin is a centralized digital currency, without a central bank or single administrator that can be sent from user to user on the peer-to-peer Bitcoin network without the need for intermediaries (Taskinsoy, 2021). Transactions are verified by network nodes through cryptography and recorded in a publicly distributed database called the blockchain. Bitcoin is currently a new technology and the most expensive cryptocurrency in the world, so several price prediction models are available.

Machine Learning

Machine learning is the study of computer algorithms that improve automatically through experience and use of data (Mahesh, 2020). Machine learning is part of artificial intelligence. Machine learning algorithms build models based on sample data, known as training data, to make predictions or decisions without being explicitly programmed to do so.

Data mining is a sub-study of machine learning which is the process of extracting and finding patterns in large data sets involving methods at the intersection of machine learning, statistics, and databases (Raghuram et al., 2023; Hirvasniemi et al., 2021). Several methods are often used for data analysis, namely regression, classification, and clustering. Regression and classification are supervised learning approaches that map an input to output based on examples of input-output pairs, while clustering is an unsupervised learning approach. Regression is used to predict continuous-valued outputs. Regression analysis is a statistical model used to predict numerical data. Classification is used to predict the number of discrete values. Meanwhile, clustering is a method for partitioning datasets into several groups called clusters (Zhou & Saeidlou, 2024).

In this study, researchers will focus on using regression models, especially CNN and LSTM to analyze time series data. Time series regression is a statistical method for predicting future values based on historical values and the dynamic transfer of relevant predictors. Regression uses the independent variable, while time series usually uses the target variable itself.

Time-Series Data

Time series data, also referred to as time-series data, is a collection of observations obtained through repeated measurements over time. The sequence of data points is indexed in time

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order. Timestamps are data collected at different points in time. These data points usually consist of successive measurements made from the same source over a time interval and are used to track changes over time (Kang et al., 2020).

Data Normalization

In the normalization stage, preprocessing is carried out on the data. Preprocessing is a step taken to prepare raw data into data that is ready to be used for the data mining process (Burdack et al., 2020). The purpose of preprocessing is to increase accuracy in processing data. Preprocessing is done to avoid imperfect datasets, there is noise in the dataset, and inconsistent data, and to speed up the processing of documents.

Convolutional Neural Network (CNN)

In deep learning, convolutional neural networks (CNNs) are a class of deep neural networks, which are generally often applied to analyze visual images (Ketkar et al., 2021)**Error! Reference source not found.**. Most convolutional neural networks are only equivariant, not invariant. CNNs are also known as shift invariant or space invariant artificial neural networks (SIANN), based on the kernel's shared-weight architecture or convolution filters that run along the input features and provide equivalent responses known as feature maps. CNN is applied in image and video recognition, recommendation systems, image classification, image segmentation, medical image analysis, natural language processing, brain-computer interfaces, and financial time series.

Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a recurrent neural network (RNN) architecture used in the field of deep learning. Unlike standard feedforward neural networks, LSTMs have feedback connections. It can process not only single data points (such as images) but also entire data sequences. LSTM networks are well suited for classifying, processing, and making predictions based on time series data, as there may be lags of unknown duration between important events in the time series (Essien & Giannetti, 2020).

Mean Absolute Percentage Error

Mean Absolute Percentage Error (MAPE) is an absolute average percentage error. In statistics, MAPE is used to measure the accuracy of estimates or predictions in forecasting methods. The MAPE value provides information on how much the forecast error is compared to the actual value of that period. The smaller the percentage error value in MAPE, the more accurate the forecasting results will be. The following formula equation (1) is the formula for calculating MAPE:

$$MAPE = \frac{1}{n}\sum_{i=0}^{n} \left|\frac{y'_i - y_i}{y_i}\right| * 100\% \quad (1)$$

Before doing MAPE, it is necessary to de-normalize the results of previous predictions. To calculate denormalization, you can use the following formula:

$$X = X' * (x_{max} - x_{min}) + x_{min} \quad (1)$$

In the MAPE calculation, the lower the MAPE value, the ability of the forecasting model used can be said to be good, and for MAPE there is a range of values that can be used as measurement material regarding the ability of a forecasting model, the range of values can be seen in Table 1.

Table 1. Comparison of Research Results

MAPE Range	Model Competence
< 10%	Very Good
10 - 20%	Good

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20 - 50%	Feasible
> 50%	Bad

For the research to be conducted, the researcher decided to use MAPE as an evaluation metric for the prediction results of the method to be used.

Literature Review

Several related studies have been conducted previously by **Error! Reference source not found.** regarding bitcoin price predictions using Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models for comparison. This study shows that the LSTM model is better than the GRU because it has good MAPE values in window sizes 12 and 7, namely 0.030 and 0.060. In research conducted by Cavalli & Amoretti (2021) regarding cryptocurrency price predictions using CNN and linear regression for comparison. The results of this study indicate that CNN produces a higher accuracy value than linear regression, namely obtaining an accuracy on ETH next day-BTX of 92.1%.

Research conducted by (Hua, 2020) regarding bitcoin price predictions uses the LSTM method. In this study, time-series data were used for one day from January 1 2018 to May 31, 2019. From the tests carried out, Bitcoin with a hidden number of 15 neurons is more optimal with an MSE value of 0.0016, and with an epoch of 30, it is more optimal with an MSE value of 0.0019. Obtaining forecasting results In June 2019 Bitcoin rose slowly with an accuracy of 97.5% based on MAPE and 58348.44 based on MSE.

Another study conducted by Hamayel & Owda (2021) regarding cryptocurrency price predictions uses the LSTM algorithm. In this study, data was taken from the Yahoo Finance website using the Pandas Datareader library via Google Colaboratory. This study uses Nadam optimization to improve model accuracy, and tests are carried out with the number of epochs of 1, 10, and 20 respectively. The results of this study are epochs worth 20 get the best results with an RMSE value of 0.0630.

Methods

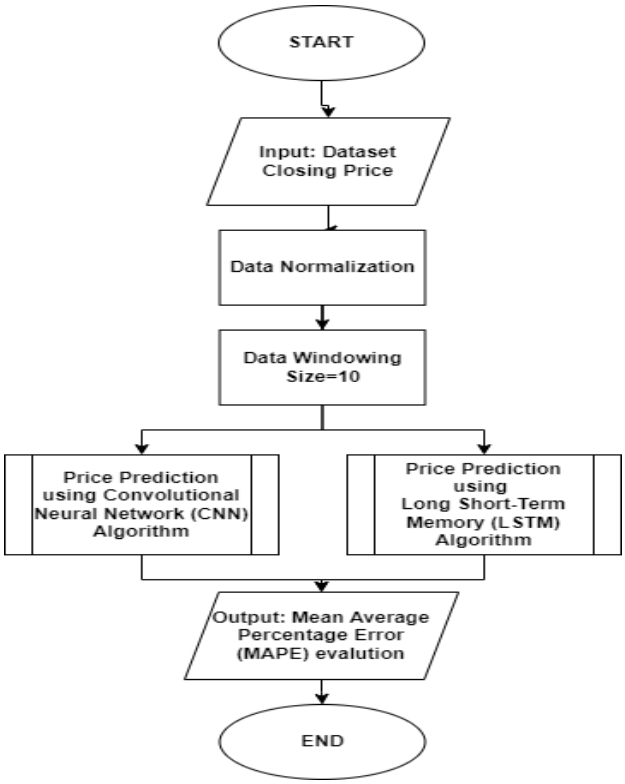

Figure 1. Experiment Stages Flow

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In this study, planning was carried out to determine the existing problem formulation, then a research study was carried out related to Bitcoin price prediction using time-series datasets. Time series data is transformed into series data that is used to make predictions. In addition, studies were carried out regarding the algorithms used in this study, namely the Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) to create a model that can be used to predict Bitcoin prices. The implementation of the CNN and LSTM algorithms is carried out through the stages which can be seen in Figure 1 as follows:

Dataset

The dataset used in developing the model is Bitcoin cryptocurrency data from January 1st, 2017, to April 26th, 2023, with a total of 2307 rows, with the value to be predicted in the closing price (USD) column, which can be seen in Table 2.

Table 2. Sample Dataset

Date	Price (USD)
01-01-2017	995. 4
02-01-2017	1017
03-01-2017	1033.3
…..	…..
24-04-2023	27509.3
25-04-2023	28298.8
26-04-2023	28859.1

Data Normalization

Data preprocessing is prepared by going through a process to handle missing or empty data in various ways such as finding the average of an attribute for the same class. After that, the data is normalized using MinMaxScaler with a range (0,1) and the following formula:

$$x^i = \frac{x - minx}{maxx - minx} \qquad (3)$$

Windows Size

The sliding window is the formation of a structure from the available time series data to reduce approximation errors, for example, the Euclidean distance or the vertical distance between the actual approximation and the time series. Here the windows_size used is equal to 10.

Prediction using the CNN Algorithm

There are many convolutional CNNs, one of which is a 1-dimensional Convolutional Neural Network (CNN). This 1-D CNN is a layer that is more suitable for time-series data. The following are the stages in creating a 1D-CNN prediction model:

CNN Architecture Model

First of all, the Conv1D model is defined as it will use a 1D CNN. Here, a 1D convolutional layer is added to the model. The following layers are contained in this model architecture: The first layer has 128 filters, kernel size 2, ReLU (Rectified Linear Unit) activation function, and dataset input to the model. This layer serves to capture local patterns in the data. A 1D max-pooling layer is added with pool size 2. Max pooling reduces the spatial dimension of the feature map. Layer Flatten to flatten the 2-dimensional feature map into a 1-dimensional vector. This is an important step before adding fully connected layers. A fully connected layer with 64 units and a ReLU activation function is added. This layer captures higher-level features from the feature vectors that have been averaged in the previous layer. Output layer with 1 data neuron, for regression results where the model predicts the next time-series value as the output of the model. This model is compiled with the Adam optimizer and the loss

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function mean squared error (MSE). Adam is a popular optimizer algorithm, and MSE is usually used for regression.

Training Model

After defining the model architecture to be used, the next step is to train the model using the previously prepared dataset. The batch size for training is 64, which means the model weights are updated after processing each batch of 64 samples. The epoch size used is 200, which means adjusting the model to the training data for 200 periods, using a batch size of 64. The 20% testing data is used as validation data to evaluate the performance of the model during the training process.

Prediction using the LSTM Algorithm

LSTM is well suited for classifying, processing, and making predictions based on time series. The stages in making predictions using the LSTM algorithm are:

LSTM Model Architecture

First of all, the LSTM model is defined as it will be used. Each layer in the LSTM model will be followed by a dropout layer that serves to prevent overfitting before proceeding to the next layer. The following layers are contained in this model architecture:

The first layer has 32 units, set return sequence as output for the next layer, input dataset to the model, followed by a dropout layer of 0.2. The second layer has 64 units, set return sequence as output for the next layer, followed by a dropout layer of 0.2. The third layer has 128 units, no return sequence is set because it will produce a single output, followed by a layer dropout of 0.5. Fully connected dense layer with 1 data neuron, for regression results where the model predicts the next time-series value as the output of the model.

Output layer with 1 data neuron, for regression results where the model predicts the next time-series value as the output of the model. The learning rate value is set to 0.001. This value controls how fast the model learns during training. The model is compiled with the Adam optimizer and the loss function mean squared error (MSE). Adam is a popular optimizer algorithm, and MSE is usually used for regression.

After defining the model architecture to be used, the next step is to train the model using the previously prepared dataset. The batch size for training is 64, which means that the model weights are updated after processing each batch of 64 samples. The epoch value is 5, which means adjusting the model to the training data for 5 periods, using a batch size of 64. The 20% testing data is used as validation data to evaluate the performance of the model during the training process.

Performance Measurement Method

The prediction results of each model will be compared with 20% testing data using a graph, to see whether the direction of the model prediction results is following the testing data or not, the direction of the graph resembles or not. In the next stage, the previous results will be evaluated using MAE, but the final evaluation results will be carried out using MAPE. MAPE is an evaluation calculation used to measure how precise or accurate a prediction is used. The MAPE formula can be seen in Equation 1. Before doing MAPE, denormalization of the previous prediction results is required. This aims to restore the initial value before normalization and these results are considered as the final result data of a prediction. The denormalization formula can be seen in Equation 2. There are data needed in the calculation of MAPE such as prediction data and predicted actual data, namely closing price (USD), then after that the MAPE value can be calculated.

Results and Discussion

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The implementation of the system for predicting Bitcoin prices is carried out using the Python programming language with the import libraries used, namely NumPy, Pandas, TensorFlow, Keras, Matplotlib, MinMaxScaler, Dropout, Dense, LSTM, Conv1D, MaxPooling1D, flatten and sequential. The dataset used in the research is the closing price of Bitcoin and its date which will then be preprocessed to validate, if there is empty data it will be removed and not included in the next process.

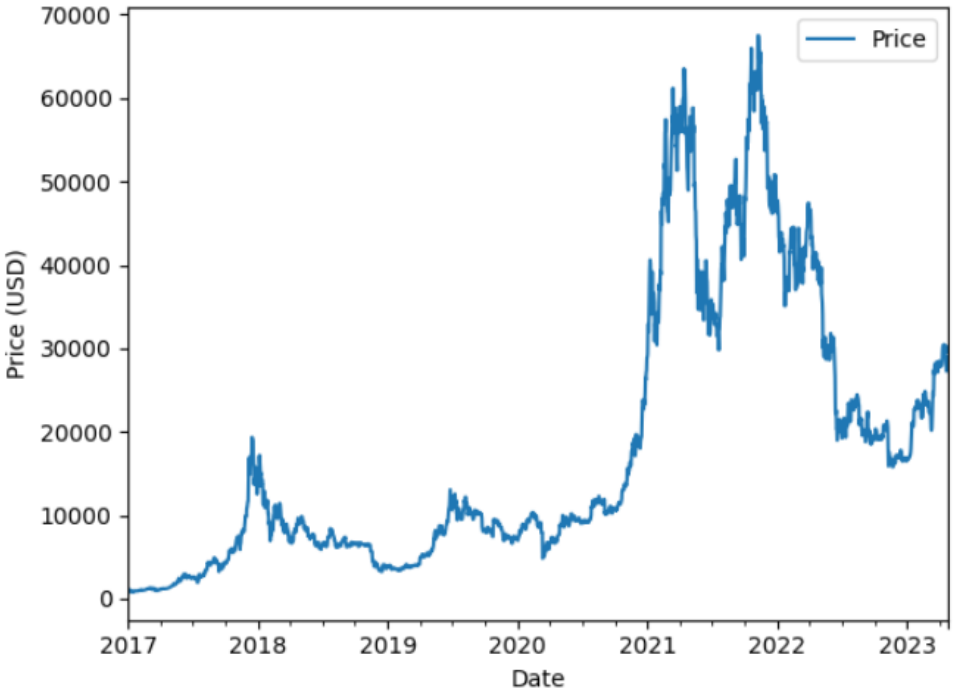

Figure 2. Dataset (Bitcoin Price) Graph

After inputting data and checking for empty data, the next step is to normalize the data using MinMaxScaler. After normalization, data transformation is carried out into a sliding window which means the formation of a structure from the available time series data.

In the sliding window result, there is a window step in the form of an array of 0-10 and window indexes. After the data is transformed, then split the data into train data and test data which will be used for the next process of predicting using the CNN and LSTM methods.

Implementation Result of CNN Method

The CNN algorithm consists of several layers, namely Conv1D, MaxPooling1D, Flatten, pooling, and Dense. The Conv1D layer is a 1-dimensional convolutional layer with 128 output channels, which have 384 parameters, which are weights and biases that can be learned.

In these results, there are total params, trainable params, and non-trainable params. Total params is the total weight owned by the model, the number of params produced is 33,281. Trainable params are parameters/connections whose weights can change according to the training process, which is generated in this study, namely 33,281. Meanwhile, Non-trainable parameters are weight/parameter values that do not change or are locked in value, in this study that is 0.

Next, the model was trained with batch size = 64 and 200 epochs. The testing data was used as validation data during the training process. As a result, the model obtained an MSE value of 0.000448.

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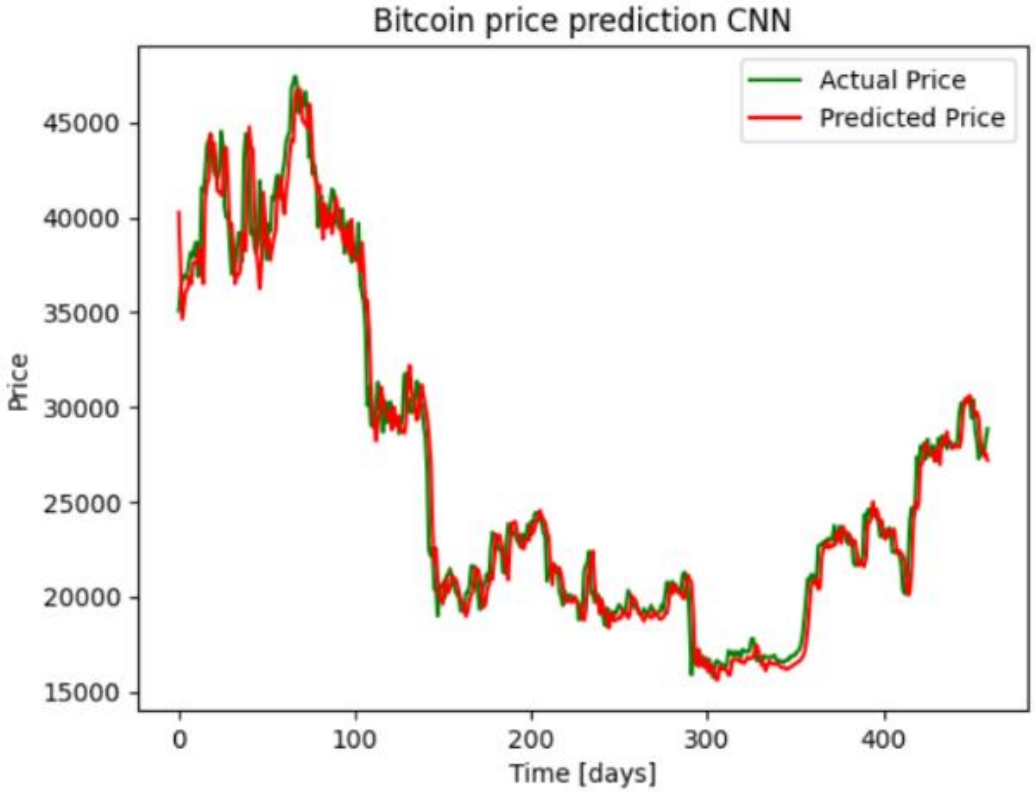

Figure 3. CNN Method Prediction Result Compared to Bitcoin Prices Graph

Figure 3 is the result of the CNN method prediction, the figure shows the comparison of the actual price and the CNN prediction price of the Bitcoin price. The prediction price pattern has almost completely followed the actual price. The price difference with the largest difference is on day 38 where the actual price is in the range of 44400 USD while the predicted price is in the range of 38000 USD.

Implementation Result of LSTM Method

Implementation using the LSTM algorithm is done by building an LSTM model using 4 layers. The first layer has 32 units. The first layer is also followed by a dropout layer worth 0.2 which serves to prevent overfitting. In the next layer, there are 64 units and also followed by a dropout layer worth 0.2. The next layer has 128 with a dropout layer of 0.5. The last layer is a fully connected layer with one neuron (unit). This layer is used for regression where the model will predict one continuous value.

In these results, there are total params, trainable params, and non-trainable params. Total params is the number of weights owned by the model, the number of params produced is 128, 129. Trainable params are parameters/connections whose weights can change according to the training process, the ones produced in this study are 128, and 129. Meanwhile, Non-trainable params are the weight/parameter values that do not change or are locked in value, in this study that is 0.

Next, the model was trained with batch size = 64 and 5 epochs. The testing data was used as validation data during the training process. As a result, the model obtained an MSE value of 0.001160.

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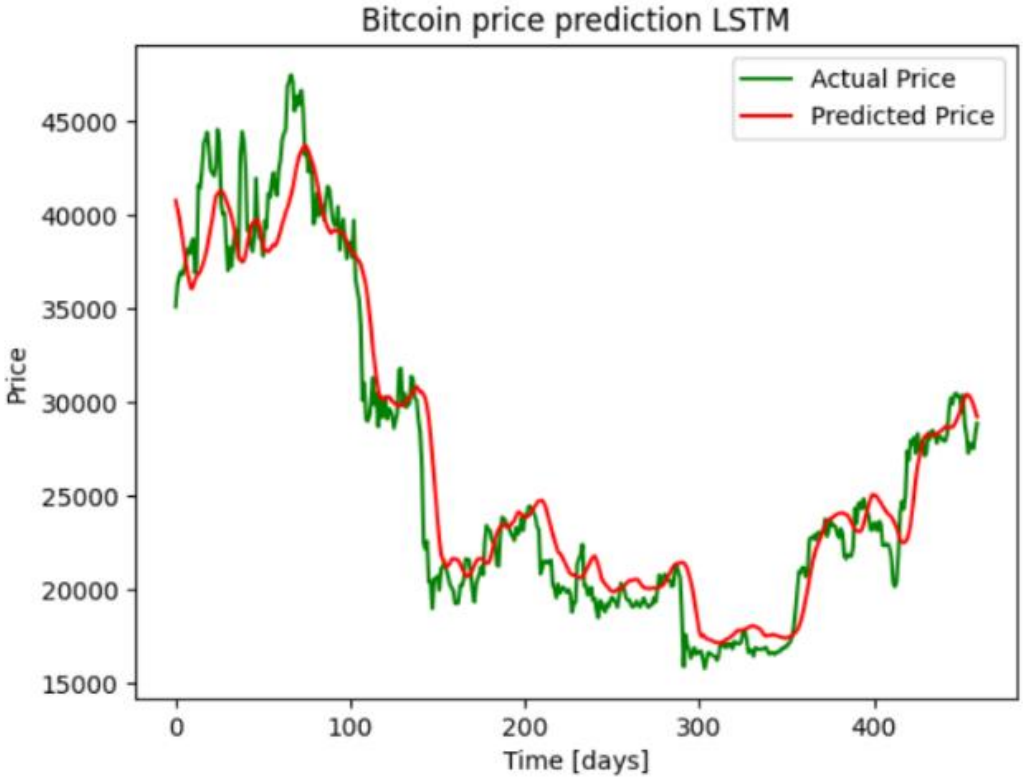

Figure 3. LSTM Method Prediction Result Compared to Bitcoin Prices Graph

Figure 4 is the prediction result of the LSTM method, the figure shows a comparison of the actual price and the LSTM prediction price of the Bitcoin price. The prediction price pattern has followed the actual price. The price difference with the largest difference is on day 145 where the actual price is in the range of 20000 USD while the predicted price is in the range of 29000 USD.

Comparative Discussion of Evaluation Results Using CNN and LSTM

From the results of the implementation that has been carried out in the Python programming language in predicting the price of bitcoin using the CNN method, we have very good results, and LSTM getting good prediction results. The dataset used in this study is closing price data in sequence from January 1, 2017, to April 26, 2023. The dataset is divided into train data and test data with details, namely 80% of the first data, from January 1, 2017, to January 18, 2022, as train data, while 20% of the last data, from January 19, 2022, to April 26, 2023, as test data. In this study, the CNN model uses epoch = 200 and batch_size = 64, while the LSTM model uses epoch = 5 and batch_size = 64. The Bitcoin price prediction results on both CNN and LSTM methods show a comparison of the actual price and the predicted price of the Bitcoin price. The predicted price pattern has followed the actual price. The following in Table 3 are the evaluation results using the CNN and LSTM methods.

Table 3. Comparison of Research Results

Method	MAPE value
Convolutional Neural Network (CNN)	6.1%
Long Short-Term Memory (LSTM)	5.6%

Table 3 shows the comparison of research results using CNN and LSTM methods. When validating using test data, the CNN method gets an MSE value of 0.000448. The prediction

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price pattern is almost very close to the actual price. The prediction results are evaluated using the MAPE calculation which gets a value of 0.037 or 3.7%.

At the time of validation using the LSTM method test data, the MSE value was 0.001160, the value showed good results because the movement of loss was close to zero or less than one and the accuracy continued to increase showing good results as the epoch progressed **Error! Reference source not found.**. The prediction results are evaluated by MAPE, the MAPE value obtained is 0.065 or 6.5%.

In addition to the fluctuating price movements of Bitcoin, other factors affect the dataset, namely the price of Bitcoin experienced a very significant price spike from 2020 to early 2021 due to increased institutional interest, recognition as a legal digital asset, and the influence of the COVID-19 pandemic. The impact of these factors caused the price of Bitcoin to increase drastically. From the results of the MAPE evaluation, the CNN and LSTM methods get very good forecasting results, so the two methods can be used as a reference to determine the prediction of bitcoin prices in the next few periods.

Conclusion

Based on the results of implementing the CNN and LSTM algorithms in predicting Bitcoin prices, the following conclusions can be drawn: In implementing the CNN and LSTM algorithms in predicting Bitcoin prices, namely by planning research predicting Bitcoin prices using the CNN and LSTM algorithms. The next stage is initialization by preparing a dataset in the form of Bitcoin closing price data from January 1, 2017, to April 26, 2023. The performance results of the CNN and LSTM algorithms in predicting Bitcoin prices are that both algorithms get very good prediction accuracy in the evaluation calculation using MAPE. The CNN algorithm gets a value of 0.037 or 3.7%, while the LSTM algorithm gets a value of 0.065 or 6.5%. The MAPE results of the two algorithms are in the MAPE range <10%, which can be said that the ability of the model is very good so that it can be used as a reference to find out bitcoin price predictions in the next few periods.

References

Agbo, E. I., & Nwadialor, E. O. (2020). Cryptocurrency and the African economy. *Economics And Social Sciences Academic Journal*, *2*(6), 84-100.

Amsyar, I., Christopher, E., Dithi, A., Khan, A. N., & Maulana, S. (2020). The challenge of cryptocurrency in the era of the digital revolution: A review of systematic literature. *Aptisi Transactions on Technopreneurship (ATT)*, *2*(2), 153-159. https://doi.org/10.34306/att.v2i2.96

Burdack, J., Horst, F., Giesselbach, S., Hassan, I., Daffner, S., & Schöllhorn, W. I. (2020). Systematic comparison of the influence of different data preprocessing methods on the performance of gait classifications using machine learning. *Frontiers in bioengineering and biotechnology*, *8*, 260. https://doi.org/10.3389/fbioe.2020.00260

Cavalli, S., & Amoretti, M. (2021). CNN-based multivariate data analysis for bitcoin trend prediction. *Applied Soft Computing*, *101*, 107065.

Chen, Z., Li, C., & Sun, W. (2020). Bitcoin price prediction using machine learning: An approach to sample dimension engineering. *Journal of Computational and Applied Mathematics*, *365*, 112395. https://doi.org/10.1016/j.cam.2019.112395

Essien, A., & Giannetti, C. (2020). A deep learning model for smart manufacturing using convolutional LSTM neural network autoencoders. *IEEE Transactions on Industrial Informatics*, *16*(9), 6069-6078. https://doi.org/10.1109/TII.2020.2967556

ISSN: 2716-3865 (Print), 2721-1290 (Online)

Fokri, W. N. I. W. M. (2021). Classification of cryptocurrency: a review of the literature. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *12*(5), 1353-1360.

Hamayel, M. J., & Owda, A. Y. (2021). A novel cryptocurrency price prediction model using GRU, LSTM and bi-LSTM machine learning algorithms. *AI*, *2*(4), 477-496. https://doi.org/10.3390/ai2040030

Hirvasniemi, J., Klein, S., Bierma-Zeinstra, S., Vernooij, M. W., Schiphof, D., & Oei, E. H. (2021). A machine learning approach to distinguish between knees without and with osteoarthritis using MRI-based radiomic features from tibial bone. *European radiology*, *31*, 8513-8521.

Hua, Y. (2020). Bitcoin price prediction using ARIMA and LSTM. In *E3S Web of Conferences* (Vol. 218, p. 01050). EDP Sciences.

Kang, Y., Hyndman, R. J., & Li, F. (2020). GRATIS: GeneRAting TIme Series with diverse and controllable characteristics. *Statistical Analysis and Data Mining: The ASA Data Science Journal*, *13*(4), 354-376. https://doi.org/10.1002/sam.11461

Ketkar, N., Moolayil, J., Ketkar, N., & Moolayil, J. (2021). Convolutional neural networks. *Deep Learning with Python: Learn Best Practices of Deep Learning Models with PyTorch*, 197-242.

Khan, M. Z., Ali, Y., Sultan, H. B., Hasan, M., & Baloch, S. (2020). Future of currency: a comparison between traditional, digital fiat and cryptocurrency exchange mediums. *International Journal of Blockchains and Cryptocurrencies*, *1*(2), 206-224. https://doi.org/10.1504/IJBC.2020.109003

Luchkin, A. G., Lukasheva, O. L., Novikova, N. E., Melnikov, V. A., Zyatkova, A. V., & Yarotskaya, E. V. (2020, August). Cryptocurrencies in the global financial system: problems and ways to overcome them. In *Russian Conference on Digital Economy and Knowledge Management (RuDEcK 2020)* (pp. 423-430). Atlantis Press. https://doi.org/10.2991/aebmr.k.200730.077

Mahesh, B. (2020). Machine learning algorithms-a review. *International Journal of Science and Research (IJSR).[Internet]*, *9*(1), 381-386. https://dx.doi.org/10.21275/ART20203995

Mudassir, M., Bennbaia, S., Unal, D., & Hammoudeh, M. (2020). Time-series forecasting of Bitcoin prices using high-dimensional features: a machine learning approach. *Neural computing and applications*, 1-15.

Raghuram, A., Ssentongo, A., Pereira, L. M., Kuang, Y., Uyei, J., & Park, P. (2023, December). 2378. Use of Natural Language Processing to Extract Published Real World Data on a COVID Vaccine and Antiviral Treatment. In *Open Forum Infectious Diseases* (Vol. 10, No. Supplement_2, pp. ofad500-1999). US: Oxford University Press. https://doi.org/10.1093/ofid/ofad500.1999

Taskinsoy, J. (2021). Bitcoin: A New Digital Gold Standard in the 21st Century?. *Available at SSRN 3941857*. https://dx.doi.org/10.2139/ssrn.3941857

Zhou, B., Lu, B., & Saeidlou, S. (2024). A hybrid clustering method based on the several diverse basic clustering and meta-clustering aggregation technique. *Cybernetics and Systems*, *55*(1), 203-229. https://doi.org/10.1080/01969722.2022.2110682

Стойка, М. (2021). Cryptocurrency–definition, functions, advantages and risks. *Підприємництво і торгівля*, (30), 5-10. https://doi.org/10.36477/2522-1256-2021-30-01

ISSN: 2716-3865 (Print), 2721-1290 (Online)