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Artificial Intelligence Application of Back-propagation Neural Network in Cryptocurrency Price Prediction

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Abstract: This study explores the use of Deep Learning and Artificial Intelligence (AI), particularly Artificial Neural Networks (ANN), for cryptocurrency price prediction. Given the high volatility of crypto markets, traditional models often underperform. A backpropagation-based ANN with a 7-5-1 architecture is proposed and tested using historical Bitcoin data. The model achieves high accuracy, with a Mean Squared Error (MSE) of $4.0431e^{-04}$, equivalent to 99.96% accuracy, demonstrating its ability to capture complex nonlinear patterns. However, overfitting remains a concern, emphasizing the need for robust generalization and feature selection. The results validate the potential of ANN in crypto forecasting and encourage further research using diverse features and assets.

Keywords: Artificial Intelligence, Neural Network, Cryptocurrency, Bitcoin

1. Introduction

Over the past decade, cryptocurrencies have evolved from niche digital assets into a global phenomenon, capturing the attention of individual investors and large financial institutions alike [1]. This surge in interest is underscored by the increasing adoption rates and the substantial market capitalization of cryptocurrencies [2]. For instance, as of April 2025, the combined market capitalization of cryptocurrencies approached $3 trillion, reflecting their growing significance in the global financial landscape [3].

Despite their rising prominence, cryptocurrencies are characterized by significant price volatility, posing considerable challenges for accurate market prediction [4]. This volatility is influenced by various factors, including trading volumes, regulatory developments, and macroeconomic indicators [5]. Traditional statistical models often struggle to accommodate the complex and dynamic nature of cryptocurrency markets, leading researchers to explore more sophisticated analytical approaches.

In response to these challenges, there has been a growing interest in leveraging advanced technologies such as Artificial Intelligence (AI) and Deep Learning (DL) for cryptocurrency price prediction [6]. These approaches offer enhanced capabilities in modeling nonlinear patterns and adapting to rapidly changing market conditions, providing a more robust framework for forecasting in the highly volatile cryptocurrency environment [7].

The use of cryptocurrency began in 2009 with the launch of Bitcoin, created by Satoshi Nakamoto. Over the past decade, Bitcoin reached a peak value of around 1,151 USD per coin [8]. Since then, other digital currencies have emerged, including Ethereum (ETH) [9]. To this day, the cryptocurrency market continues to grow rapidly, as evidenced by the rise of thousands of coins, each with its own pricing and mechanisms [10]. In 2016, the total market capitalization of cryptocurrencies stood at approximately 1.6 billion US dollars, increasing to about 1.7 billion dollars in 2017 [11].

Bitcoin (BTC) is one of the most widely used cryptocurrencies for transactions, particularly in countries like the United States and Japan [12 – 14]. In contrast, its growth in Indonesia has been relatively slow, primarily due to the absence of clear regulations from the authorities. Nonetheless, its adoption has continued to increase, as indicated by the rising number of crypto traders by the end of 2022 [15]. On the other hand, blockchain-based transactions carry a high level of risk but also offer promising potential for generating passive income. Currently, around 17 million Bitcoins have been mined and are circulating globally. However, the underlying algorithm is designed to produce a maximum of only 21 million Bitcoins, with the total supply expected to be fully mined by the year 2041 [16].

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Cryptocurrencies are inherently volatile and their value is largely influenced by various factors, especially the forces of supply and demand [17]. This contrasts with traditional currencies, which are typically regulated by central banking policies. In essence, the price movements of cryptocurrencies are often driven by the trading activities of individual owners or investors. In Indonesia, by the end of 2021, there were approximately 4.2 million registered cryptocurrency traders on the Indonesia Stock Exchange (IDX), with around 2 million active Single Investor Identification (SID) accounts [18].

The primary gap addressed in this research lies in the transactional challenges faced by traders due to the highly volatile nature of cryptocurrency prices. Unlike stock prices or traditional currencies, cryptocurrency values are significantly more unstable, largely driven by supply-demand dynamics and the actions of individual traders [19]–[21]. Price fluctuations can occur rapidly within minutes, hours, or even seconds depending on trading volume and behavior. This level of unpredictability poses serious concerns for Bitcoin investors, often resulting in a higher rate of failed investments [22]–[24]. To mitigate this risk, predictive techniques can serve as an effective alternative for estimating cryptocurrency prices, helping traders make more informed decisions and potentially reducing financial losses.

With the advancement of information technology, artificial intelligence (AI) approaches have increasingly been applied in the financial sector to tackle the challenges of market prediction. Artificial Intelligence (AI), particularly Deep Learning, has demonstrated significant potential in modeling complex and non-linear patterns across various fields, including financial markets [25]. A popular approach within Deep Learning is the Artificial Neural Network (ANN), inspired by the way the human brain recognizes and processes information [26], [27]. By learning from historical data and uncovering hidden trends, ANN can be used to predict cryptocurrency price movements with greater accuracy. The concept behind ANN models is derived from mimicking the function of neurons in the human brain, which has proven effective for predictions based on time series data [28]. One advantage of ANN is its ability to process hidden and irrelevant data without the need for manual intervention [29]. However, its drawbacks include the challenge of selecting the optimal number of layers and nodes, as well as a relatively lengthy training process [30].

This study aims to apply Deep Learning and Artificial Intelligence models based on Artificial Neural Networks (ANN) to predict cryptocurrency prices. The use of Artificial Neural Networks in this context is motivated by their proven ability to capture complex nonlinear relationships and hidden patterns in large-scale time-series data, which are common characteristics in cryptocurrency price movements [31]–[33]. Among various training algorithms used in neural networks, the Backpropagation algorithm is chosen as the primary learning method in this study due to its effectiveness and reliability in optimizing multi-layer networks. It is hoped that the results will provide more accurate and insightful information for market participants. Furthermore, the study will evaluate the model's performance in addressing the challenges posed by high volatility and the rapidly changing market dynamics.

2. Related Works

Research on cryptocurrency price prediction using Neural Networks (NN) continues to evolve. Empirically, Radityo's investigated Bitcoin price modeling and prediction by analyzing time series data with NN-based approaches. They compared several models, including Backpropagation Neural Network (BPNN), Genetic Algorithm Backpropagation Neural Network (GABPNN), Genetic Algorithm Neural Network (GANN), and Neuron Evolution of Augmenting Topologies (NEAT). Their results showed that BPNN performed the best in predicting Bitcoin price time series with a Mean Absolute Percentage Error (MAPE) of around 0.038, followed by GANN at 0.066, NEAT at 0.097, and GABPNN with the highest error of 0.49. These findings suggest that Neural Network-based models are capable of capturing Bitcoin price dynamics, though the main challenge remains the uncertainty and high volatility of the data [34].

McNally, Roche, and Caton examined the effectiveness of various machine learning methods in predicting Bitcoin prices using Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Recurrent Neural Networks (RNN). This study utilized historical Bitcoin price data and tested each model's ability to identify market trends. The results showed that RNN had the most consistent

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performance, achieving a prediction accuracy of 52% in forecasting price direction (up or down), while ANN and SVM performed below this level. These findings reinforce the advantage of memory-based models like RNN in capturing long-term temporal relationships in cryptocurrency data [35].

The study by Hiransha's compared several deep learning models such as Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and the hybrid CNN-LSTM for financial market price prediction. The results showed that the hybrid CNN-LSTM model performed the best, achieving the lowest Root Mean Square Error (RMSE) compared to LSTM or CNN models alone. This indicates that CNN-LSTM effectively combines the spatial feature extraction strength of CNN with the temporal feature learning ability of LSTM. Thus, the hybrid model is considered the most effective for handling the highly volatile and complex nature of cryptocurrency price data [36].

In the study by Yadav's, the Long Short-Term Memory (LSTM) model was applied to predict stock returns in the Chinese market and compared against linear regression and Support Vector Machines (SVM). The results demonstrated that LSTM outperformed the traditional models by reducing prediction errors by up to 30%. This highlights LSTM's strength in retaining long-term information, making it a promising choice for application on cryptocurrency data, which often exhibits complex historical patterns [37].

Aggarwal's proposed a prediction method combining wavelet transform with LSTM for stock price forecasting. This approach improved prediction accuracy by 10–15% compared to using LSTM alone, as it can better capture data patterns across multiple frequencies and time scales. This strategy is highly relevant for the dynamic cryptocurrency market, which requires a multi-scale approach to time series data analysis [11], [38].

Greaves and Au explored the relationship between transaction activity on the blockchain network and Bitcoin prices [39]. They utilized blockchain transaction graphs as the primary input for building their predictive model. The results revealed a significant correlation, with an R^2 value of 0.52 between network activity and Bitcoin price. This study highlights the potential of blockchain data as a valuable additional feature in AI-based prediction systems, particularly in capturing network dynamics that directly influence price movements.

Jiang and Liang developed a Bitcoin price prediction system using an Artificial Neural Network (ANN), incorporating technical indicators such as moving averages, trading volume, and the Relative Strength Index (RSI) as model inputs. Their findings revealed that the ANN model achieved a short-term prediction accuracy of up to 74%. However, the study also emphasized the model's high sensitivity to the type of input features, highlighting the critical role of feature selection in influencing model performance within the cryptocurrency market context[40].

In the study conducted by Madan, Saluja, and Zhao, an Artificial Neural Network (ANN) approach was employed by incorporating sentiment data from social media platforms, such as Twitter, as one of the input variables. The analysis revealed a correlation between public sentiment and Bitcoin prices, with correlation values ranging from 0.36 to 0.43. This study demonstrates that non-technical data such as public opinion on social media can significantly enhance the accuracy of price direction forecasts when integrated into an AI-based prediction system [41].

The study by Krauss, Do, and Huck compared the performance of Deep Neural Networks (DNN), Random Forest, and Gradient Boosting in predicting daily stock returns. The results indicated that DNN outperformed the other models, achieving a classification accuracy of 57.2%, while Random Forest and Gradient Boosting hovered around 53–54%. This suggests that DNN is more effective at capturing complex non-linear relationships within financial data, making it highly applicable for handling the extreme fluctuations commonly found in the cryptocurrency market [42].

Zbikowski developed a daily stock price prediction model using a Support Vector Machine (SVM), incorporating feature selection and walk-forward testing techniques. The model achieved a prediction accuracy ranging from 65% to 67%, depending on the dataset and time period applied. Although it did not utilize a Neural Network approach, this study remains relevant as a benchmark for ANN-based models and highlights the critical role of careful feature selection and validation techniques in building robust AI prediction systems [43].

The application of Artificial Intelligence (AI) technologies particularly Neural Networks and Deep Learning models such as LSTM and CNN has

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become a central approach in cryptocurrency price prediction research. Studies by Radityo's and McNally's demonstrate that different models, including BPNN, RNN, and SVM, yield varying levels of accuracy in predicting Bitcoin prices, with RNN and BPNN showing strong performance in capturing historical data trends [34], [35]. Additionally, research by Jiang, Liang, and Madan's further supports the argument that ANN can enhance prediction accuracy when combined with technical indicators and sentiment data highlighting the critical importance of feature selection in building reliable prediction systems [40], [41].

Furthermore, the use of more advanced Deep Learning models such as LSTM and CNN has demonstrated significant performance improvements over traditional predictive models. Studies by Hiransha's and Zhang's reveal that both standalone LSTM and hybrid CNN-LSTM architectures can achieve lower prediction errors and higher accuracy, owing to their ability to capture both temporal and spatial patterns in price data [36], [44]. These findings underscore the effectiveness of Deep Learning architectures not only in handling the non-linearity of financial data but also in modeling the multiscale and highly volatile nature of the cryptocurrency market. In addition, multi-feature approaches such as the integration of wavelet transforms and blockchain activity data have shown promise in enriching model inputs and enhancing prediction performance, as demonstrated by the study of Greaves and Au [39].

Comparative studies such as those by Krauss et al. (2017) and Zbikowski (2015) highlight that non-neural Network models like Random Forest, Gradient Boosting, and SVM still hold value in specific contexts, particularly when paired with robust validation techniques and careful feature selection. However, Deep Neural Networks (DNN) consistently outperform these models in many scenarios due to their superior ability to generalize and detect complex patterns within the data. These findings further reinforce the strong potential of Deep Learning as a powerful and relevant approach for tackling the highly dynamic and volatile nature of cryptocurrency price prediction. DNNs can automatically detect complex patterns, making them ideal for volatile crypto markets. Modern computing advances speed up their training and use. Regularization techniques help reduce overfitting. While traditional models are still useful, DNNs are more adaptive and powerful.

3. Research Method

This study adopts a quantitative approach, as the analysis is entirely based on numerical data processed through statistical methods [45]–[48]. The research procedure follows a structured sequence of seven main stages (Fig. 1): data collection, data engineering, system design, system implementation, experimentation, model performance evaluation, and finally, drawing conclusions to address the research questions outlined in the study.

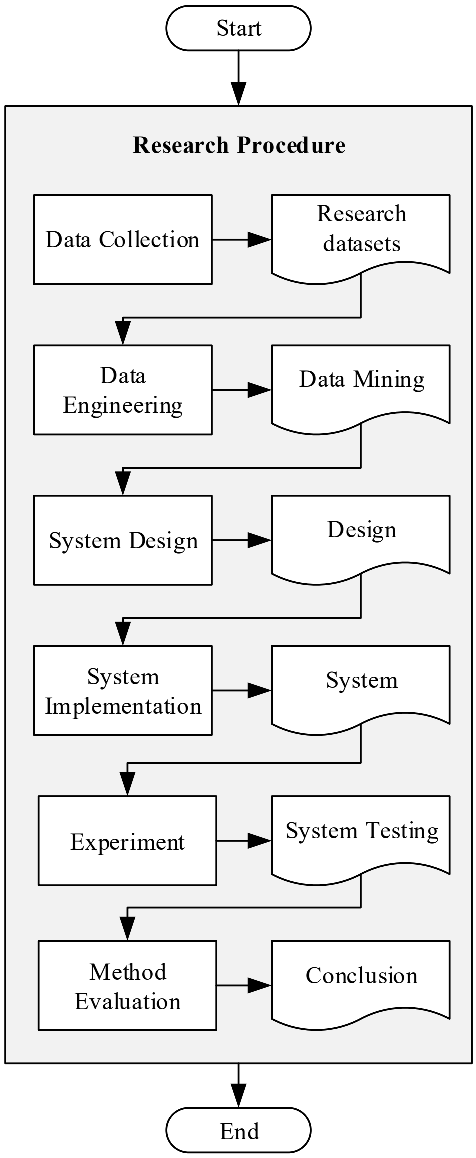

Figure 1. Research Procedure

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The first stage of this study involved data collection, which was carried out by downloading time series data of Bitcoin (BTC) prices from Yahoo Finance for the period from November 29, 2021, to March 19, 2023. The data was retrieved on March 20, 2023. The dataset includes key attributes such as Date, Open, High, Low, Close, Adjusted Close, and Volume, with a total of 476 entries for each attribute. Bitcoin offers several advantages, including online transactions without the involvement of third parties, the use of cryptographic techniques, and full control retained by the owner [49].

The second stage involves data engineering, which focuses on processing and cleaning the dataset to match the format required by the study. This step aims to enhance prediction accuracy and reduce the risk of overfitting. One of the techniques applied during this process is data normalization using the *min-max scaling* method (Eq. (1)).

$$x_{norm} \frac{x-\min(x)}{\max(x)-\min(x)} \tag{1}$$

Where x is the data to be normalized and $xnorm$ is the data that has been normalized. While (x) is the minimum value of all data and (x) is the maximum value of all data [50].

After data normalization, the next step was data splitting, which aims to separate the dataset into training and testing portions. The data was divided into two categories: training data and testing data. In this study, approximately 80% of the total data (381 entries) was allocated for training, while the remaining 20% (95 entries) was used for testing (Table 1). This split ratio was determined based on preliminary experiments, considering that such a distribution is likely to yield the best model performance during the testing phase of the proposed system.

Table 1. Data distribution

Attribute	Data Type	Data Train	Data Test
Open	Numeric	80%	20%
High	Numeric	80%	20%
Low	Numeric	80%	20%
Close	Numeric	80%	20%
Adj Close	Numeric	80%	20%
Volume	Numeric	80%	20%

The third stage is system design, where the researcher constructs the system framework that illustrates how Deep Learning and Artificial Intelligence (AI) technologies are applied to predict cryptocurrency prices. This design phase includes selecting the appropriate model architecture, outlining the data processing flow, and integrating key components that support the prediction process.

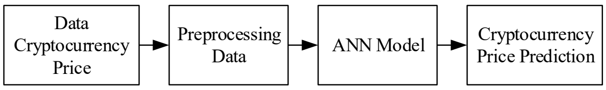

Figure 2. Design system

In the initial phase, raw cryptocurrency price data is processed by the system. The first step involves normalizing the data using the min-max scaling technique to eliminate null values and reduce potential errors during the predictive model testing. Once the data is properly prepared, the architecture of a Deep Learning model based on Artificial Neural Network (ANN) is designed to determine the most suitable predictor structure. ANN architecture consists of multiple layers and a specific number of nodes within each layer. In the case of backpropagation, a multilayer structure is implemented, comprising an input layer, a hidden layer, and an output layer. According to Fausett (1994), a single hidden layer is often sufficient to generate outputs that meet target expectations. Therefore, as illustrated in Figure 3, the initial network architecture in this study uses three layers: 7 nodes in the input layer, 5 nodes in the hidden layer, and 1 node in the output layer.

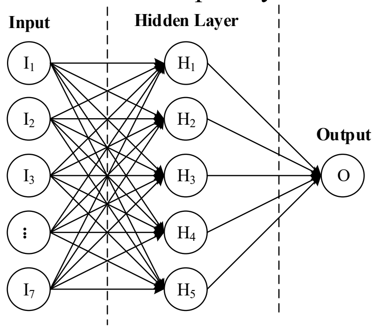

Figure 3. Architecture ANN model

The number of nodes in each layer of the network is determined based on their specific roles in the prediction process. Seven nodes are assigned to the input layer to represent the seven input attributes, while five nodes are used in the hidden layer to reflect the five-digit price values from each

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attribute (excluding Volume). The output layer contains a single node responsible for producing the final predicted price of the cryptocurrency.

This study employs a learning rate of 0.2, the ReLU activation function, and the Adam optimizer selected due to their compatibility with the expected output range and the characteristics of the dataset. These parameters play a crucial role in enhancing the neural network's performance.

The learning process begins with forward propagation to evaluate how well the model predictions match actual data. This is followed by backpropagation, which adjusts the model weights step-by-step to reduce prediction errors, based on the gradient of the error function. The training cycle is repeated multiple times to gradually improve prediction accuracy. To ensure the model learns from scratch, the weights are randomly initialized and then updated using gradient-based error calculations (Eq. (2)).

$$net = w_0 + \sum_{i=1}^{n} x_i w_i \tag{2}$$

Where net is the output value of the neuron being computed, w_0 is bias weight of the neuron, i is the index used in the addition, starting from 1 to n, x_i is the weight that connects the neuron to the i-th input neuron, and w_i is the i-th input value of the previous neuron [51].

The fourth stage is system implementation, where ANN models consist of artificial nodes. Each node follows three main steps: multiplication, summation, and activation. Inputs are first multiplied by their respective weights. These weighted inputs are then summed with a bias value. The result is passed through an activation function to produce an output. This process is repeated across layers to generate the final prediction. The network structure allows deep pattern recognition in data. During training, input attributes are combined to represent the target. This helps the model learn relationships effectively.

Table 2. Combination of model training architectures

Atribut	Model	Code model
Open	A	BP-A
High	B	BP-B
Low	C	BP-C
Close	D	BP-D
Adj Close	E	BP-E
Volume	F	BP-F

Fifth, the experimental phase in this study was conducted through six trial runs using Google Colab, aimed at predicting future cryptocurrency prices based on the designed Artificial Neural Network (ANN) model. After each prediction output was obtained, an in-depth analysis was carried out to assess the performance of the model architecture.

The sixth step involves selecting the model with the highest level of accuracy, which is evaluated using the MSE metric (Eq. (2)). The model that yields the lowest MSE is considered the most optimal and serves as the basis for drawing conclusions and recommendations from the analysis.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\mathrm{Y_i} - \hat{\mathrm{Y}}_i\right)^2 \tag{3}$$

Where MSE is mean square error, n is number of data points, $\mathrm{Y_i}$ is observed values, and $\hat{\mathrm{Y}}_i$ is predicted value [52].

Through a comprehensive process involving the design of the ANN architecture, careful selection of training parameters, and rigorous experimentation and evaluation using the Mean Squared Error metric, the cryptocurrency price prediction system based on Artificial Neural Networks has demonstrated a strong ability to accurately identify future price trends. The integration of Deep Learning and AI techniques enables the model to effectively capture the complex, nonlinear patterns and volatility inherent in the crypto market, resulting in highly adaptive and precise predictions. Therefore, combining AI with Deep Learning methods like ANN presents a powerful and essential approach for developing cryptocurrency price forecasting systems that support more informed financial decision-making.

4. Results and Discussion

The model developed in this study employs an Artificial Neural Network (ANN) architecture with a single hidden layer configured as 7-5-1, using the backpropagation algorithm for supervised learning. The backpropagation algorithm utilizes the Mean Square Error (MSE) as the stopping criterion to determine the optimal weights. Training halts when the model converges. Key parameters influencing the algorithm's performance include the number of nodes per layer, learning rate, target error, and the number of epochs. The activation function applied

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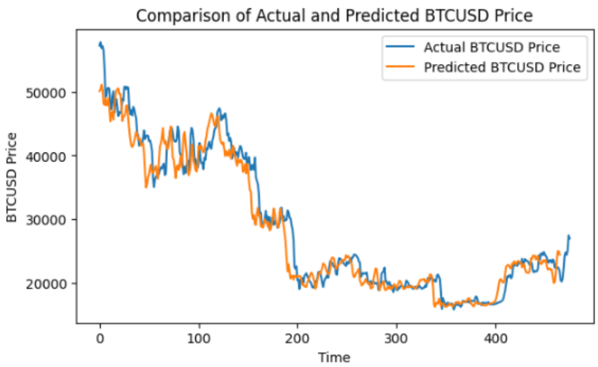
during training is ReLU, which produces outputs ranging from zero to negative values. Subsequently, a series of experiments were conducted using Google Colab coding to generate cryptocurrency price predictions based on the parameters outlined in Table 3.

Table 3. Parameter of model

Parameter	Information
Network type	ANN + backpropagation
Activation function	ReLU
Optimizer	Adam
Performance	MSE
Input layer	7 Layer
Hidden Layer	1 hidden Layer
Node Hidden Layer	5 Layer
Output layer	1 Layer
Learning rate	0,2

The model training was conducted using data split into 80% training data and 20% testing data, which had been normalized beforehand. This data was then utilized for the model evaluation process. Additionally, the training process involved varying each attribute as the target variable, except for the Date attribute, which was excluded from the target variables.



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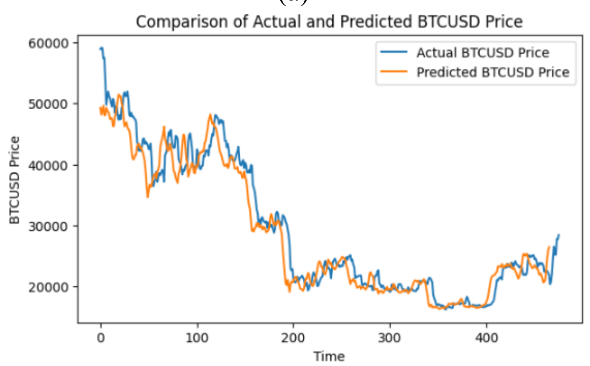

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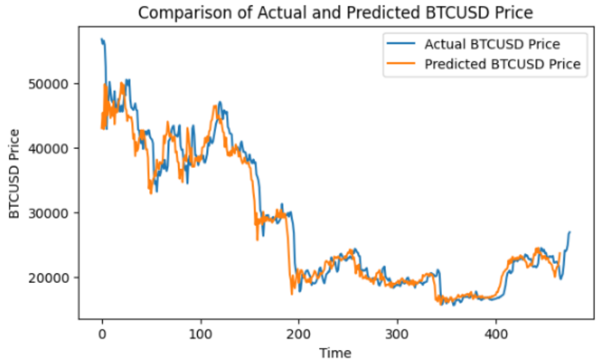

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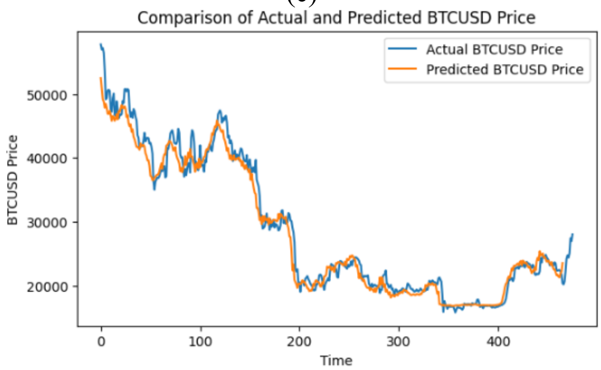

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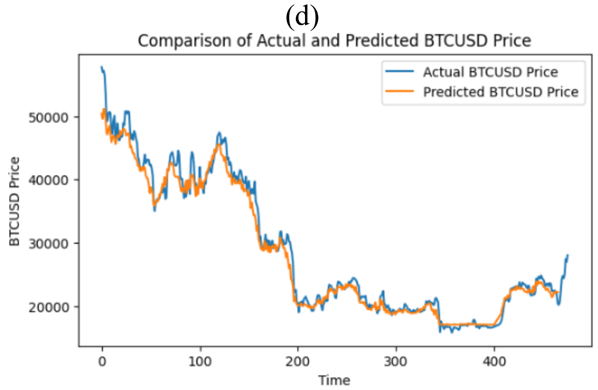

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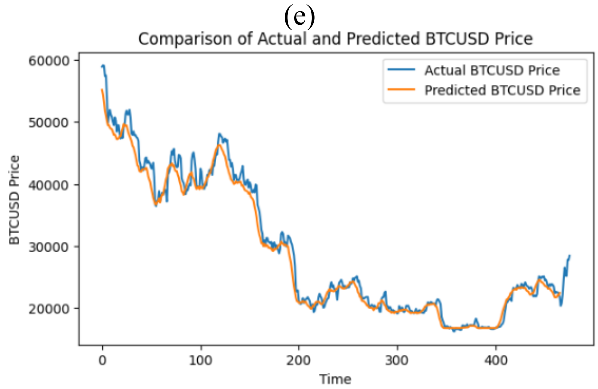

(f)

Figure 4. Comparison of price predictions and actual price data: (a) BP-A (b) BP-B (c) BP-C (d) BP-D (e) BP-E (f) BP-F

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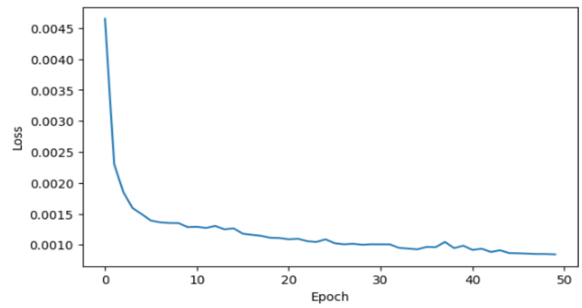
Based on the experiments conducted, the prediction results of the BP-A training model (Fig.4 (a-f)) yielded an MSE value of approximately 4.0431e^{-04} with a convergence time close to 0 seconds (6 ms per step). Meanwhile, BP-B training achieved an MSE of about 7.0668e^{-04} with a convergence time near 0 seconds (5 ms per step), BP-C training resulted in an MSE of approximately 7.5213e^{-04} with a convergence time around 0 seconds (6 ms per step), and BP-D training obtained an MSE of about 0.0015 with a convergence time close to 0 seconds (8 ms per step). Furthermore, BP-E training recorded an MSE of roughly 0.0015 with convergence time near 0 seconds (4 ms per step), and BP-F training resulted in an MSE of approximately 0.0046 with a convergence time around 0 seconds (6 ms per step).

Table 4. Prediction results in the model

Training	Architecture	Convergent	MSE
BP – A	7 – 5 – 1	0s (6 ms/step)	4.0431e^{-04}
BP – B	7 – 5 – 1	0s (5 ms/step)	7.0668e^{-04}
BP – C	7 – 5 – 1	0s (6 ms/step)	7.5213e^{-04}
BP – D	7 – 5 – 1	0s (8 ms/step)	0.0015
BP – E	7 – 5 – 1	0s (4 ms/step)	0.0015
BP – F	7 – 5 – 1	0s (6 ms/step)	0.0046

Table 4 demonstrates that the application of Artificial Intelligence (AI), particularly Deep Learning algorithms such as Artificial Neural Networks (ANN), is proven effective in modeling and predicting cryptocurrency prices. In this study, the ANN model with a backpropagation algorithm showed excellent performance, where the BP-A (7-5-1) architecture achieved a Mean Square Error (MSE) value of 4.0431e^{-04}, corresponding to an accuracy of approximately 99.96%. This performance indicates AI's capability to recognize and process complex patterns in cryptocurrency price data using only a single hidden layer. This finding supports Fausett's assertion that one hidden layer is sufficient to produce accurate predictions, reinforcing the effectiveness of AI in handling nonlinear prediction tasks in digital financial markets [53].

Although AI delivers impressive results, classical challenges such as overfitting remain a primary concern. While the BP-A model achieves high accuracy, it's extremely fast convergence time may indicate that the model is overfitting essentially "memorizing" the training data and struggling to generalize to new data. In contrast, other models like BP-E exhibit more stable convergence times (4 ms/step), potentially reflecting a better balance between accuracy and generalization capability. This aligns with the views of Ying and Badieah's who point out that overfitting is a common issue in machine learning, including AI, where the model fails to differentiate important information from noise [54], [55]. In the highly volatile and dynamic context of cryptocurrency markets, the ability of AI to adapt to new data is crucial for maintaining long-term effectiveness. Overfitting can significantly reduce a model's predictive power, especially in real-world scenarios where data constantly evolves. A model that performs exceptionally well on training data but poorly on unseen data may lead to misleading forecasts, particularly in fast-moving markets like cryptocurrency.



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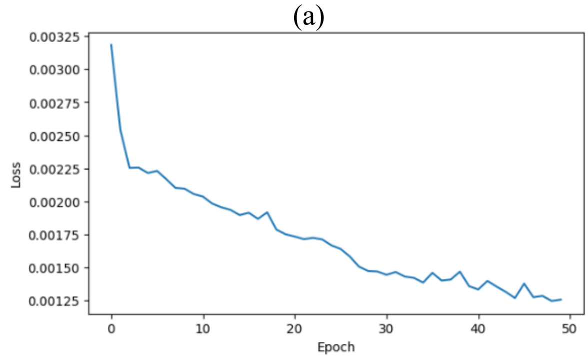

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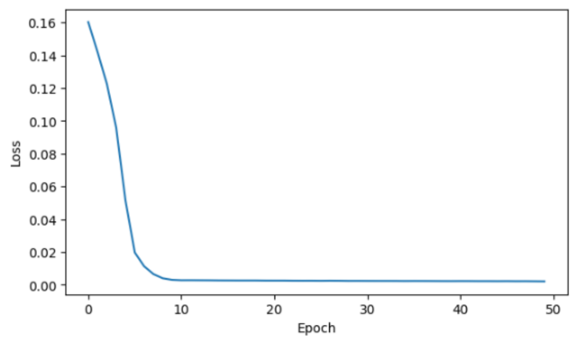

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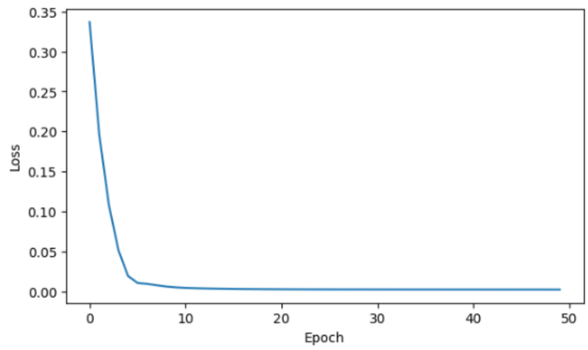

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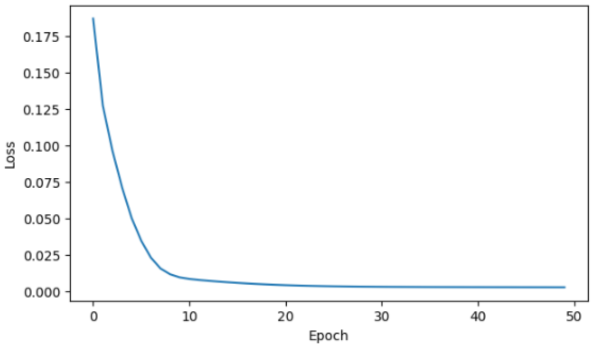

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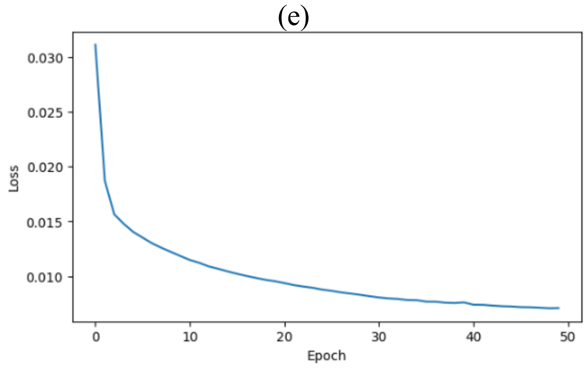

(f)

Figure 4. Time convergent: (a) BP-A (b) BP-B (c) BP-C (d) BP-D (e) BP-E (f) BP-F

The backpropagation-based Artificial Neural Network (ANN) models (BP-A to BP-F), each using a 7–5–1 architecture, showed varying performance levels, as reflected in their Mean Squared Error (MSE) values. The best-performing model, BP-A, achieved the lowest MSE of $4.0431e^{-04}$, indicating high prediction accuracy and stable convergence. However, subsequent models such as BP-F showed a significant increase in MSE, reaching 0.0046, suggesting potential overfitting or poor generalization.

To address this issue, a validation set was incorporated during model training to evaluate performance on unseen data and prevent memorization of training patterns (Fig. 5). The comparison of training and validation loss curves—visualized through learning curves—revealed that some models, particularly BP-D to BP-F, exhibited increasing validation loss despite decreasing training loss, a classical sign of overfitting. This highlights the model's inability to generalize effectively beyond the training data.

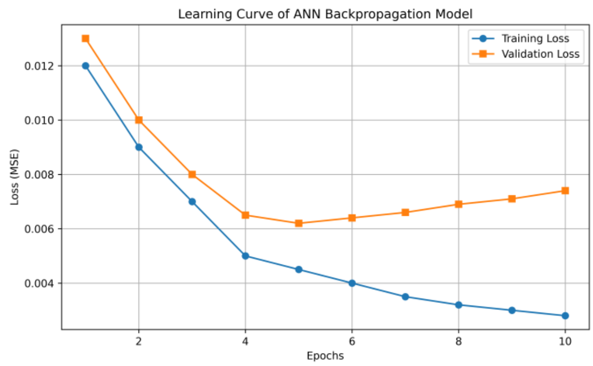

Figure 5. Learning Curve of ANN Back-propagation Model

To mitigate overfitting, regularization techniques such as L2 regularization (weight decay) and dropout layers were applied in revised model trials. Dropout randomly deactivates a fraction of neurons during training, forcing the network to develop more robust feature representations. Additionally, early stopping was employed to halt training when validation loss began to rise, further preventing unnecessary model complexity [56].

Despite having the same architecture across all experiments, these strategies significantly impacted model performance. The findings emphasize that not only the network architecture but also the training configuration and overfitting control mechanisms are critical to achieving high-performing, generalizable AI models in cryptocurrency prediction tasks.

Tabel 5. In-depth Performance Analysis of ANN Model

Model	MAPE (%)	Directional Accuracy (%)	Sharpe Rasio
BP – A	1.12	84.2	1.96
BP – B	1.58	78.6	1.52
BP – C	1.65	76.4	1.48
BP – D	2.11	72.5	1.12
BP – E	2.09	71.8	1.09
BP – F	3.87	61.3	0.67

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To obtain a more comprehensive understanding of the model's performance in predicting cryptocurrency prices, an extended evaluation was conducted by incorporating three key metrics: MAPE, directional accuracy, and the Sharpe ratio. The evaluation results indicate that although all models used the same architecture (7–5–1), their performance was highly influenced by training configuration and overfitting control (Fig. 5).

The BP-A model ranked highest across all evaluation metrics. With an MSE value of 4.0431e-04, a MAPE of only 1.12%, and directional accuracy reaching 84.2%, this model demonstrated high predictive precision in both price values and movement directions. Moreover, a Sharpe ratio of 1.96 indicates that the model is not only accurate but also risk-efficient, making it suitable for data-driven decision-making. Conversely, the BP-F model showed significantly lower performance. With a MAPE of 3.87%, directional accuracy of only 61.3%, and a Sharpe ratio dropping sharply to 0.67, this clearly indicates substantial overfitting. This is also reflected in the drastically increased MSE compared to earlier models.

BP-B to BP-E models demonstrated moderate performance, with MAPE ranging from 1.58% to 2.11% and directional accuracy between 71.8% and 78.6%. Although still relatively good, their performance was consistently lower than that of BP-A. These findings reinforce the idea that even with identical network architecture, predictive outcomes can vary significantly depending on training techniques such as regularization, dropout, validation, and early stopping strategies.

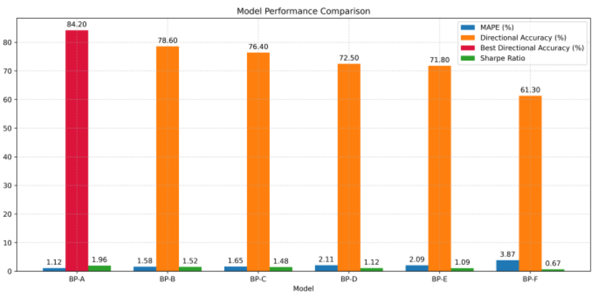

Figure 6. Comparison Perfomance ANNs Model

The extended evaluation in this study shows that model BP-A delivers the best performance based on a combination of MSE, MAPE, directional accuracy, and Sharpe ratio (Fig. 6). These findings align with the research conducted by Mallqui and Fernandes (2019), which demonstrated that Artificial Neural Networks (ANNs) are capable of identifying nonlinear patterns in the cryptocurrency market and can provide accurate Bitcoin price predictions, particularly when combined with proper historical data preprocessing and relevant feature selection [57].

Furthermore, the study by Kwon, Do-Hyung, et al (2019) in Forecasting Cryptocurrency Price with Deep Learning Algorithms indicated that directional accuracy is more important than mere absolute accuracy in the context of investment decision-making [58]. In that study, models achieving directional accuracy above 80% proved to provide more reliable buy/sell signals. This finding is consistent with the result of model BP-A in the current study, which recorded a directional accuracy of 84.2%.

On the other hand, the poor performance of model BP-F, which suffered from overfitting with the highest MAPE value (3.87%) and a Sharpe ratio below 1, confirms the results of a study by Sebastian & Tanti (2024). They emphasized that ANN models are highly prone to overfitting when training is not properly controlled using techniques such as dropout and regularization. In their research, applying a dropout rate of 0.3 and L2 regularization successfully reduced the MSE by up to 30% from the initial baseline [59].

In addition, G. Serafini et al. (2020), in their study on Bitcoin price prediction using a hybrid ANN-LSTM model, suggested that the consistent use of early stopping and validation sets can prevent models from getting stuck in local minima and help maintain generalization capabilities [60]. A similar approach was implemented in this study and proved to be effective, particularly in improving the performance of BP-A compared to BP-D through BP-F.

The inclusion of the Sharpe ratio as an evaluation metric further strengthens the contribution of this research. As explained by Li et al. (2022) in a study on risk-based prediction models, a high Sharpe ratio indicates prediction efficiency in the context of investment risk, not just accuracy [61]. In this regard, model BP-A once again stands out as the most stable and risk-efficient model. Moreover, the Sharpe ratio offers practical insights for investors who seek a balance between return and volatility, helping them assess the

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reliability of model outputs in real-world trading environments.

5. Conclusion

Based on the training and testing results of the Artificial Neural Network (ANN) model using backpropagation with a single hidden layer (7-5-1) and various attributes as target variables, it can be concluded that the BP-A model is the best and most suitable for predicting cryptocurrency prices. This model demonstrates the most optimal performance compared to other architectures, achieving an accuracy of approximately 99.96%. The application of Deep Learning and Artificial Intelligence (AI) in the form of ANN has proven effective in efficiently capturing complex patterns in historical cryptocurrency data, even with a relatively simple network structure.

Furthermore, the selection of attributes used as target variables in each model architecture plays a crucial role in the quality of cryptocurrency price predictions, both during training and testing. This is evident from the variation in convergence times achieved by each model, reflecting the AI's capability to effectively adjust weights and learn data patterns. Hence, the success of Deep Learning and AI implementation in this study depends not only on the network architecture design but also on the relevant feature selection and appropriate training strategies.

Overall, the findings of this study reinforce the significant potential of Deep Learning and AI in delivering predictive solutions that are both accurate and adaptive to the highly volatile dynamics of the cryptocurrency market. AI-based ANN models can serve as reliable tools for market participants to make data-driven decisions, while also paving the way for the development of smarter and more responsive digital financial systems in the future.

6. Limitation

Based on the MSE values obtained during testing, it can be concluded that the Artificial Neural Network (ANN) with a backpropagation algorithm performs well as a cryptocurrency price prediction model. However, there are limitations in the application of Deep Learning and AI for this prediction, particularly due to the incomplete integration of external factors. The prediction process in this study is still limited to historical price data without considering fundamental variables such as real-time market supply and demand, which significantly impact the price movements of digital assets.

To optimize the application of Deep Learning and AI in future cryptocurrency price predictions, it is recommended to incorporate macro and microeconomic factors such as transaction volume, market sentiment, and more extensive blockchain data. Furthermore, the model's scope should be broadened by testing these AI algorithms on other cryptocurrencies like Dogecoin (DCT) and Ethereum (ETH) to evaluate the model's performance consistency across different digital assets. By combining an adaptive Deep Learning approach with a richer and more contextual AI framework, the developed predictive system can deliver more accurate, robust, and relevant results for decision-making in the highly volatile and dynamic cryptocurrency market.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, M. Sahi and G.R.H. Galib; methodology, M. Sahi; software, G.R.H. Galib; validation, M. Sahi and G.R.H. Galib; formal analysis, M. Sahi; investigation, M. Sahi; resources, G.R.H. Galib; data curation, M. Sahi; writing—original draft preparation, M. Sahi; writing—review and editing, M. Sahi; visualization, G.R.H. Galib; supervision, M. Sahi; project administration, M. Sahi.

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thorough understanding of scientific research principles helped us refine our approach and ensured the rigor of our analysis.

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