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On RBL-STEM Learning Activities: The Use of ANN Multi-Step Time Series Forecasting to Improve the Students Metacognition in Solving A Cryptocurency Volatility Based on the Fundamental, Technical and On-Chain Analysis

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ABSTRACT: Metacognitive skills refer to an individual's ability to be aware of, manage, and evaluate their own thinking processes, supporting independent learning strategies and understanding. However, the low level of metacognitive skills highlights the need for further research, particularly on how to improve them. This study aims to enhance students' metacognitive skills through a Research-Based Learning (RBL) approach and STEM learning activities by employing multi-step time-series forecasting techniques based on Artificial Neural Networks (ANN). The main focus is on designing learning activities that teach ANN Multi-Step Time Series Forecasting to address cryptocurrency volatility, analyzed using three main approaches: fundamental analysis, technical analysis, and on-chain analysis. By applying ANN to predict cryptocurrency price volatility, students are expected to better understand market dynamics and improve their decision-making abilities. The results show that RBL-STEM learning activities can be structured into six clear stages to utilize ANN Multi-Step Time Series Forecasting for improving students' metacognitive skills in solving cryptocurrency volatility issues based on these analytical approaches.

KEYWORDS: Artificial Neural Network (ANN), Cryptocurrency, Forecasting, Metacognitive, RBL-STEM, Volatility.

INTRODUCTION

In today's fast-paced and information-driven era, metacognitive skills are increasingly vital for personal and professional success. These skills, which involve self-awareness, planning, monitoring, and evaluating one’s thought processes, empower individuals to learn more effectively and adapt to diverse challenges. In education, for instance, metacognition allows students to identify their learning strengths and weaknesses, enabling them to apply tailored strategies to improve their understanding and performance. As knowledge continues to expand at an unprecedented rate, metacognitive abilities help learners prioritize information, focus on critical tasks, and engage in deeper, more meaningful learning. This is especially important as traditional rote learning becomes obsolete, and the emphasis shifts toward fostering independent, lifelong learners who can navigate and evaluate complex information landscapes.

In professional and technological contexts, metacognitive skills are equally critical. As industries increasingly rely on problem-solving, innovation, and decision-making in complex environments, individuals with strong metacognition can assess risks, anticipate outcomes, and adjust their strategies accordingly. For example, in technology-driven fields like data science or cryptocurrency markets, metacognitive skills allow professionals to reflect on their decision-making processes, evaluate outcomes, and improve future performance. Furthermore, as artificial intelligence and automation replace routine tasks, the ability to think critically and adapt becomes a key differentiator in the workforce. By fostering self-regulation, reflection, and adaptability, metacognitive skills not only enhance individual potential but also contribute to organizational success and societal progress in a world where adaptability and continuous learning are paramount.

Despite the clear benefits of metacognitive skills, their prevalence among people remains relatively low due to several factors. One key reason is the lack of awareness and explicit instruction in metacognition, both in educational and professional settings.

Traditional education systems often prioritize rote memorization and standardized testing over critical thinking and reflective practices, leaving little room for students to develop self-regulation and strategic learning skills. Additionally, many individuals are not naturally inclined to engage in self-reflection or evaluate their thought processes, often due to cultural or societal norms that prioritize outcomes over processes. In professional environments, the fast-paced nature of work, coupled with performance pressures, often discourages individuals from pausing to reflect on their decision-making and strategies. Furthermore, the absence of structured tools or guidance to foster metacognitive skills compounds the issue, leaving individuals unaware of how to consciously develop and apply these skills in their personal and professional lives.

To prevent the decline of metacognitive skills, it is essential to cultivate these abilities in students from an early age through to university level by embedding metacognitive practices into the education system. At the school level, teachers can encourage students to reflect on their learning processes by incorporating activities such as journaling, self-assessment, and goal setting, which promote self-awareness and strategic thinking. Introducing problem-based and inquiry-driven learning methods also fosters active engagement and encourages students to plan, monitor, and evaluate their learning strategies. As students transition to higher education, metacognitive training can be deepened by integrating reflective practices into coursework, offering explicit instruction on study strategies, and encouraging collaboration in problem-solving scenarios. At the university level, research-based learning (RBL) and project-based learning (PBL) approaches can help students apply metacognitive skills to real-world problems, enabling them to critically analyze their approaches and adapt strategies based on outcomes. By creating a culture of reflection and continuous improvement across all education levels, we can empower students to become lifelong learners who are better equipped to navigate complex challenges in their academic, professional, and personal lives.

Improving students' metacognitive skills by integrating cryptocurrency knowledge, a cornerstone of decentralized finance, offers a unique and practical approach to enhancing critical thinking and decision-making. Cryptocurrency markets, characterized by high volatility and rapid technological advancements, require individuals to analyze complex data and make strategic decisions. By introducing students to this domain through research-based and problem-solving activities, educators can simultaneously build their financial literacy and metacognitive abilities. For instance, students could use fundamental, technical, and on-chain analysis to evaluate cryptocurrency trends and forecast market movements, which would require them to plan their research approach, monitor their reasoning processes, and evaluate outcomes critically. Employing tools like Artificial Neural Networks (ANN) for multi-step time-series forecasting can further engage students in advanced problem-solving, compelling them to reflect on their learning strategies and refine their methods. Such activities not only deepen students’ understanding of blockchain technology and decentralized systems but also enhance their ability to adapt, analyze, and self-regulate, crucial components of metacognition. This integrative approach prepares students to navigate both the complexities of financial markets and broader real-world challenges with confidence and critical awareness.

The importance of cryptocurrency knowledge today is closely linked to advancements in blockchain technology and the growing trends of digital finance. The increasing adoption of cryptocurrency by individuals and financial institutions highlights the urgency of understanding the digital economy. Moreover, the dynamic and often unpredictable nature of cryptocurrency markets presents both significant challenges and exciting opportunities for the application of advanced analytical techniques. Cryptocurrency volatility refers to the high level of price fluctuations of cryptocurrencies over a certain period. This means that the value of cryptocurrencies can rise or fall significantly within a relatively short time. Cryptocurrency volatility can be influenced by various factors, including market sentiment, economic or political news, government regulations, or global economic conditions [11]. This necessitates sophisticated forecasting models to accurately anticipate future price movements. Therefore, a strong understanding of cryptocurrency is crucial in the ever-evolving digital economic environment, enabling individuals to make smart and informed investment decisions.

One of the breakthroughs today involves fundamental, technical, and on-chain analysis, which are essential foundations for understanding cryptocurrency volatility. When someone lacks knowledge of technical, fundamental, and on-chain analysis related to cryptocurrency, they become more vulnerable to losses caused by the high volatility in cryptocurrency markets. Without an understanding of fundamental analysis, they may be unable to evaluate the long-term value of a specific crypto asset, such as the project's prospects, the strength of the development team, or the adoption of its technology. Similarly, without technical analysis knowledge, individuals may struggle to recognize price patterns or determine appropriate entry and exit points in cryptocurrency trading. Moreover, without on-chain analysis expertise, predicting price direction and volatility in cryptocurrencies becomes more challenging. As a result, this can increase the risk of financial losses, especially if individuals are influenced by extreme price fluctuations [12].

Learning mathematics through a STEM approach can train students to integrate themselves in strengthening and expanding various mathematical thinking skills, as STEM focuses on developing critical thinking, problem-solving, collaboration, and creativity skills through the application of scientific and mathematical concepts in real-world contexts [1]. Moreover, education has undergone a significant shift in recent years. One learning approach that has been gaining increasing attention is Research-Based Learning (RBL), which is combined with the STEM approach (Science, Technology, Engineering, and Mathematics) [7].

Research-Based Learning (RBL) is one of the Student-Centered Learning (SCL) methods that integrates research into the learning process [13]. Through RBL, students are given the opportunity to develop and construct knowledge by following the steps of a research process, such as seeking information, formulating hypotheses, collecting data, analyzing data, drawing conclusions, and preparing reports. This approach encourages students to connect the knowledge and skills they learn in science, technology, engineering, and mathematics to solve complex problems [2]. This learning model is also considered effective in fostering various mathematical thinking skills in students that are highly essential in the 21st century, such as metacognitive thinking skills [4].

Metacognitive thinking skills are one of the mathematical thinking abilities that enable students to think more critically about everything they process mentally [4]. Metacognitive skills can be trained and developed in various contexts, including dealing with cryptocurrency volatility. With metacognitive skills, individuals can engage in self-awareness and regulate their own thought processes, which are essential in complex and dynamic situations [14]. The better a person's metacognitive skills, the more adaptive, responsive, and proactive they will be in managing unpredictable market fluctuations, thereby improving their ability to make better investment decisions. Metacognitive skills have three main indicators: 1) planning, 2) monitoring, and 3) evaluating [3].

Table I. The indicator of metacognitive skill

No.	Indicator	Sub Indicator
1.	Planning	• The individual is able to restate the problem using their own words. • The individual is able to identify information from the problem. • The individual has ideas and is able to select the strategies to be used.
2.	Monitoring	• The individual is able to explain everything related to what has been written. • The individual is aware of their mistakes and is able to correct them.
3.	Evaluating	• The individual performs a review of their solution. • The individual is able to reflect on the problem-solving process.

In this study, the researcher will utilize Artificial Neural Networks (ANN) to enhance understanding and predict cryptocurrency volatility. ANN can be applied in cryptocurrency market analysis due to its ability to recognize complex patterns in data. The main ANN process involves data collection, preprocessing, network architecture design, training, validation, and testing before being used for prediction. In the financial world, ANN is frequently used to analyze market data, forecast asset prices, identify trading patterns, and manage risks. ANN can be a powerful tool in market analysis when used correctly. Therefore, it is expected to provide more precise and accurate predictions for investors when buying or selling their assets [6]. Similar to biological neurons in humans, ANN also performs learning processes to recognize patterns, classify, and predict data [8]. In the financial world, ANN is often employed to analyze market data, predict asset prices, identify trading patterns, and manage risks [9]. ANN is capable of learning from past data and adapting to current market conditions, thereby providing more accurate and precise predictions for investors in making their buying or selling decisions. Thus, the main goal of this research is to develop RBL-STEM learning activities into six clear stages to utilize ANN Multi-Step Time Series Forecasting for improving students' metacognitive skills in solving cryptocurrency volatility issues based on these analytical approaches.

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RESEARCH METHOD

This research employs a qualitative narrative method. The study begins with collecting and reviewing several pieces of literature related to RBL (Research-Based Learning) and STEM (Science, Technology, Engineering, and Mathematics), including an exploration of STEM-related problems. Next, a syntactical framework for the integration of RBL-STEM is developed to address these STEM problems. Learning outcomes and objectives are also presented, including the development of indicators and sub-indicators related to metacognition. The research then continues by outlining the role of the four STEM elements in solving these problems, progressing to describing each stage of RBL along with the corresponding learning activities. Finally, it includes completing the indicators and sub-indicators of metacognition, including the development of assessment instruments. The activity framework is designed to teach ANN Multi-Step Time Series Forecasting to improve students' metacognitive skills in solving cryptocurrency volatility issues based on Fundamental, Technical, and On-Chain Analysis.

RESULTS AND DISCUSSION

FRAMEWORK OF THE RBL-STEM SYNTAX

The following presents the syntactical framework of Research-Based Learning (RBL) with a STEM approach to enhance students' metacognitive skills in solving problems related to cryptocurrency volatility using fundamental, technical, and on-chain analysis. This framework is developed based on the syntax in [4]. At the initial stage of the Research-Based Learning model's syntax, problems are introduced based on open issues from the research group's focus. The researcher considers problems in fundamental, technical, and on-chain analyses concerning cryptocurrency volatility.

Knowledge of fundamental, technical, and on-chain analysis is crucial in addressing cryptocurrency volatility as it provides a comprehensive overview of the factors influencing asset prices. By combining these three types of analyses, investors can make more informed decisions and mitigate the risks associated with market fluctuations.

The framework for the integration of RBL-STEM can be seen in more detail in the following figure:

Knowledge of fundamental, technical, and on-chain analysis is essential for navigating cryptocurrency volatility. By understanding the fundamental factors that influence asset values, price movement patterns, and transaction data on the blockchain, individuals can make more accurate predictions about cryptocurrency market prices, enabling them to make wiser investment decisions.

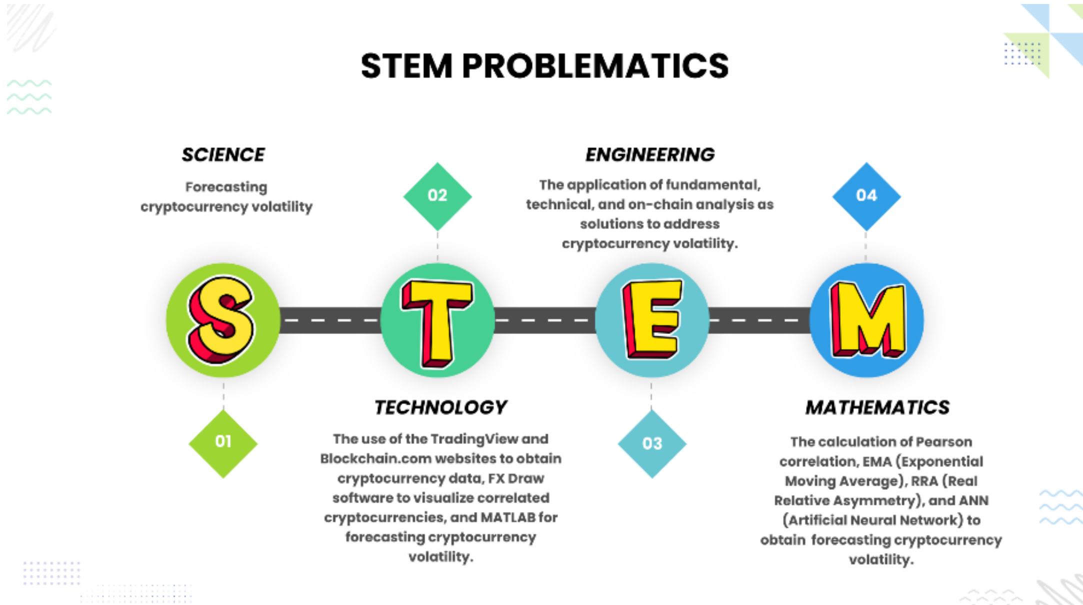

Figure 1. STEM Elements in Cryptocurrency Volatility Issues

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In this study, the following are the stages in the RBL-STEM learning model:

1. Problems related to cryptocurrency volatility.
2. Collecting cryptocurrency-related data using fundamental analysis.
3. Correlating cryptocurrency data using the Pearson Correlation formula.
4. Conducting technical and on-chain analysis of cryptocurrency volatility issues.
5. Testing and analyzing the obtained results, then generalizing or forecasting cryptocurrency trends using the ANN model.
6. Reporting research findings and observing students' metacognitive skills.

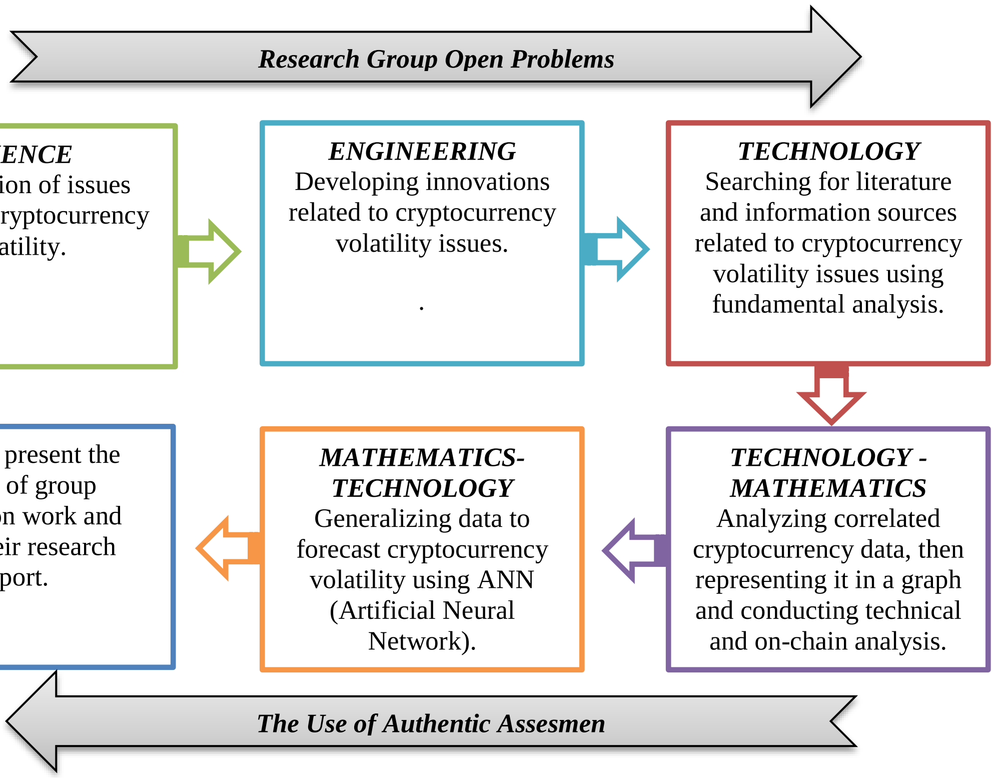

Figure 2. RBL-STEM Framework in Developing Forecasting Cryptocurrency Volatility

Learning Outcomes and Objectives

1. **Learning Outcomes**

The expected learning outcomes include the enhancement of students' metacognitive skills through the application of research-based learning methods with an innovative STEM approach.

2. **Learning Objectives**

The learning objectives resulting from Research-Based Learning with a STEM approach will enable learners to develop knowledge and skills in the fields of science, technology, engineering, and mathematics.

These objectives are outlined as follows:

SCIENCE-Students are expected to:

- Understand the issues of volatility in cryptocurrency.
- Analyze cryptocurrency data using the TradingView website.

TECHNOLOGY- Students are expected to:

- Use websites such as CoinMarketCap, TradingView, and Dexscreener to obtain the latest cryptocurrency value data.
- Use MATLAB software to identify correlated cryptocurrencies, calculate RRA values, and implement ANN. Then, use software like FX Draw or Draw.io to represent the data in graphs based on correlated cryptocurrency data.

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ENGINEERING-Students are expected to:

- Understand fundamental, technical, and on-chain analysis as solutions to address cryptocurrency volatility.

MATHEMATICS – Students are expected to:

- Identify cryptocurrencies that are correlated with each other.
- Obtain a cryptocurrency with the smallest RRA value.
- Then, determine the output weights from the ANN model to forecast cryptocurrency trends.

Research-Based Learning with a STEM Approach in Forecasting Cryptocurrency Volatility

1) Science Elements

In facing cryptocurrency volatility, one requires a deep understanding and data-driven analysis to predict the highly dynamic and often unpredictable price movements. Factors influencing this volatility, such as market news, regulatory changes, technology adoption, and investor sentiment, can be analyzed using a scientific approach [18]. This approach involves data collection, the use of mathematical and statistical models, and hypothesis testing to understand patterns and trends in cryptocurrency price movements. In this way, cryptocurrency volatility becomes not just a random phenomenon, but something that can be studied and predicted through a systematic scientific method.

2) Engineering Elements

In this context, fundamental, technical, and on-chain analysis are crucial solutions for addressing volatility in cryptocurrency. Fundamental analysis involves evaluating the intrinsic value of a crypto asset based on economic, financial, and underlying project factors [15]. Technical analysis focuses on historical price movement patterns and statistical indicators to predict future price movements. Meanwhile, on-chain analysis uses data directly from the blockchain, such as transaction volume and wallet activity, to identify trends and market behavior. Understanding these three types of analysis makes it easier to make more informed and strategic investment decisions in the volatile cryptocurrency market [19].

Then, in this context market behavior of cryptocurrencies will also be analyzed using the Cointelegraph website, which can be accessed at https://cointelegraph.com/, and to analyze cryptocurrency price changes, the TradingView website can be accessed at https://id.tradingview.com/.

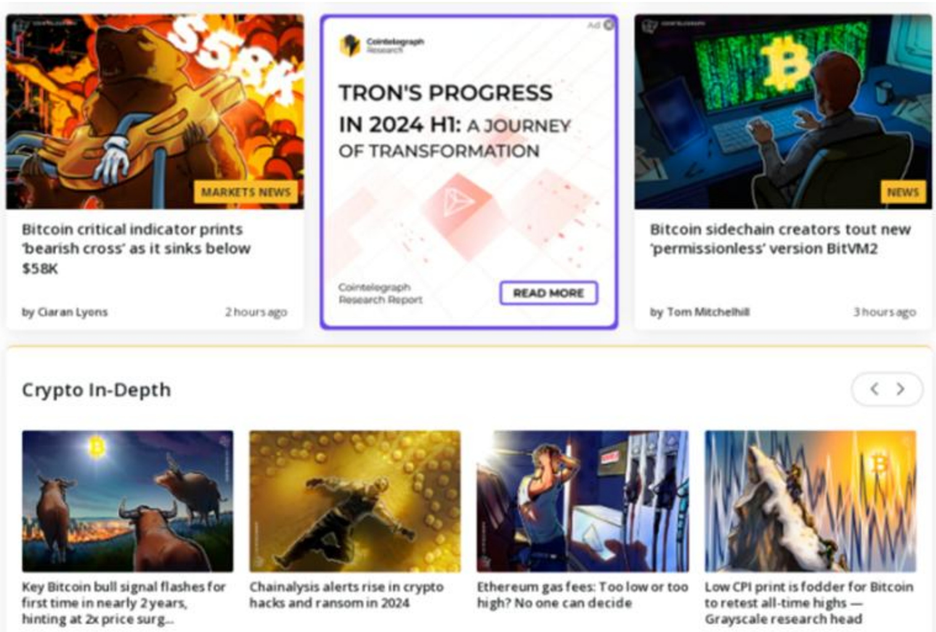

Figure 3. Latest News on CoinTelegraph

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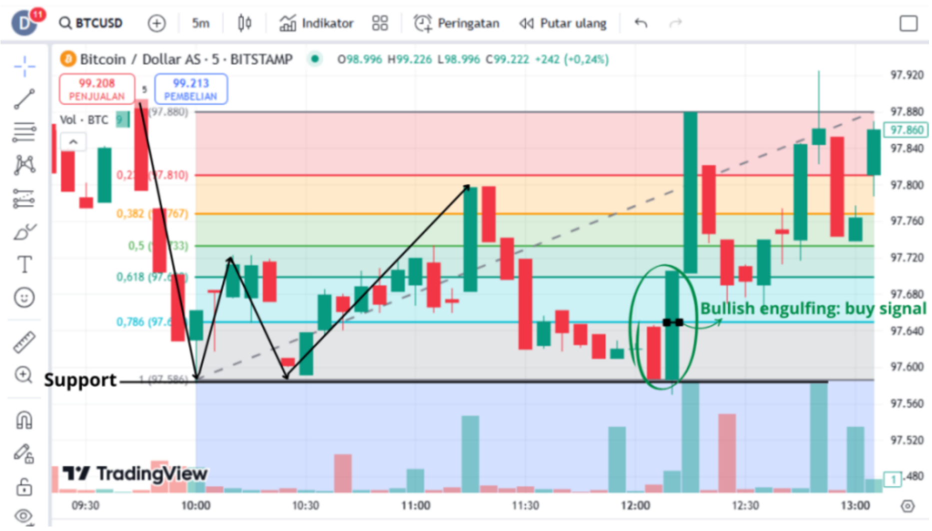

Figure 4. Support Line-Based Candlestick Pattern Analysis for Bullish Engulfing and Buy Decision

3) **Technological Elements**

The technology available for students includes access to the CoinMarketCap website, which can be visited at https://coinmarketcap.com/id/. This platform allows students to explore a wide range of cryptocurrencies in detail. By utilizing the information provided on the website, students can analyze different digital assets, which are then selected as representative samples to deepen their understanding of the fluctuations and volatility associated with cryptocurrency markets.

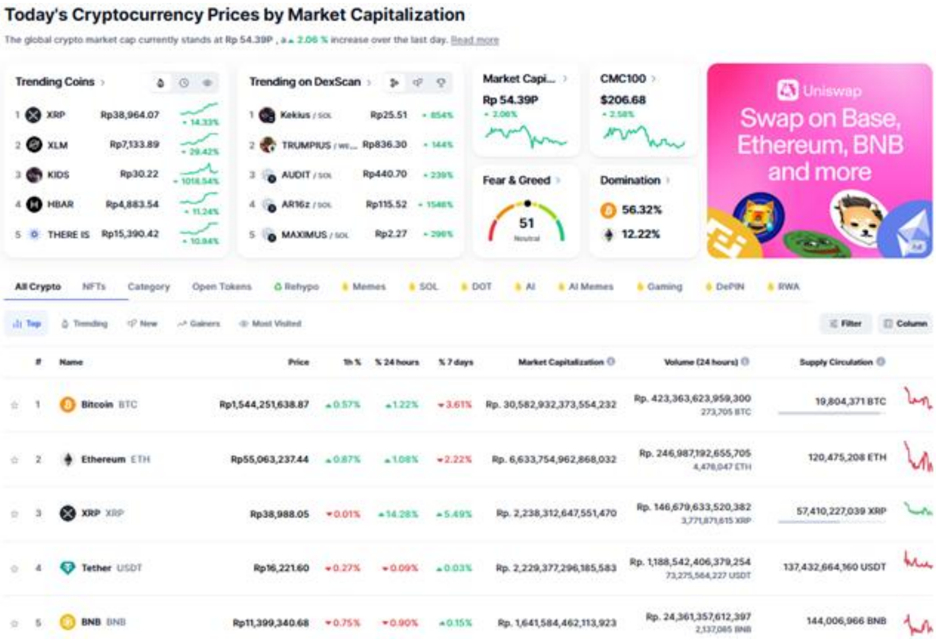

Figure 5. Collecting cryptocurrency data using the CoinMarketCap website

Additionally, the use of FX Draw applications and MATLAB software is included as part of the technological elements. MATLAB software is used to determine the results of cryptocurrencies that are correlated. Students are directed to create a new script. The input written by students represents the connection between points in a graph. Subsequently, students use commands such as "plot," "subplot," and "figure" to produce output in the form of a graph image corresponding to the input. Then, this is generalized into a graph using the FX Draw application.

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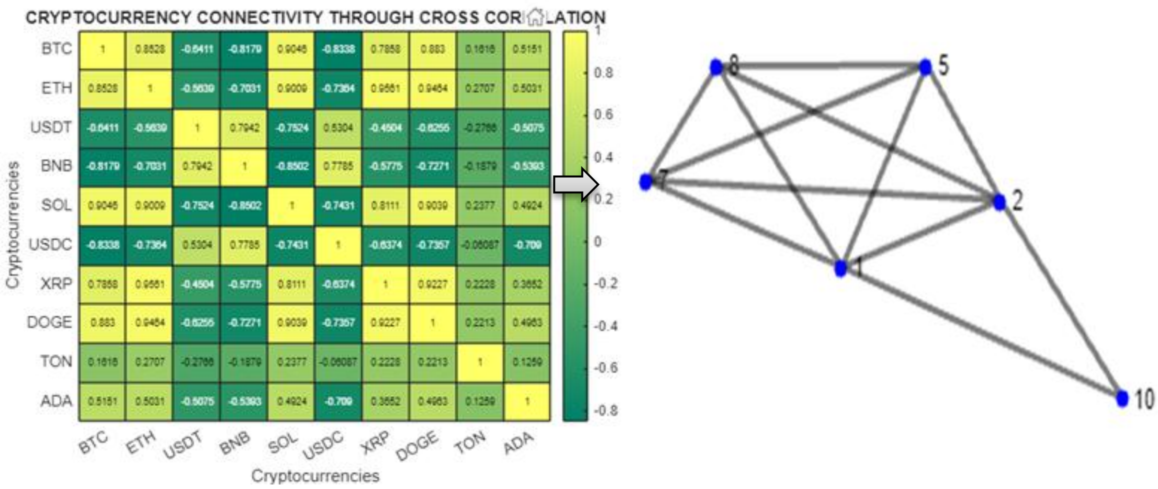

Figure 6. Determining correlation matrices using MATLAB online and its representation

After determining the graph for several correlated coins, fundamental and technical analyses are conducted, followed by on-chain analysis. On-chain analysis is used to estimate cryptocurrency volatility, marking a significant change in how financial analysts interpret signals and market dynamics. In this regard, the website https://blockchain.com/id/ can be accessed to gain an understanding of demand dynamics, network pressure, and potential price fluctuations in cryptocurrencies.

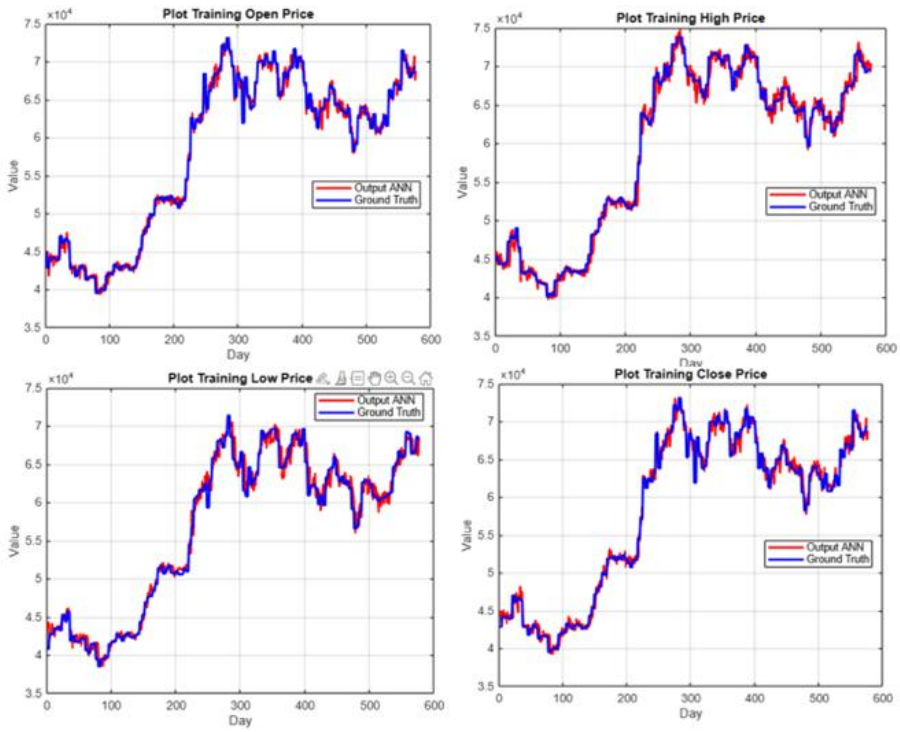

Figure 7. Forecasting results of cryptocurrency using training data from Artificial Neural Network (ANN) model

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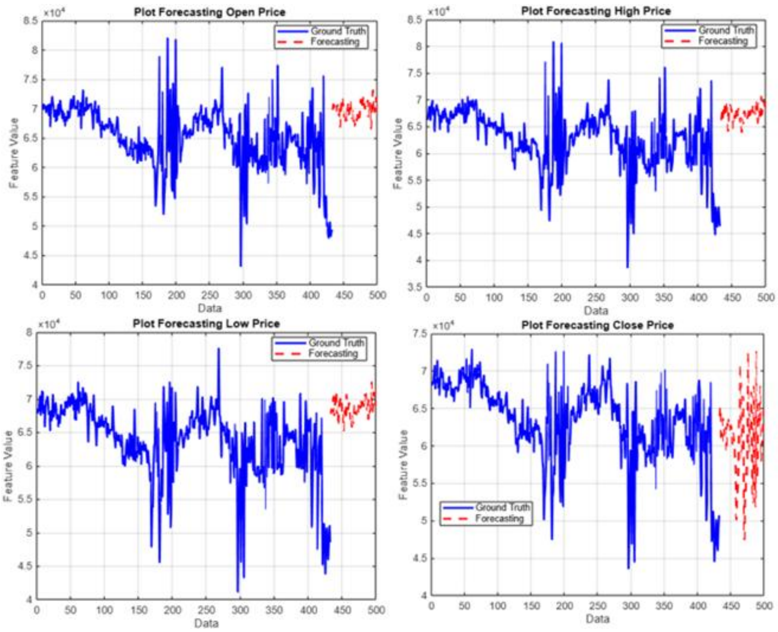

Figure 8. Cryptocurrency forecasting using the Artificial Neural Network (ANN) model

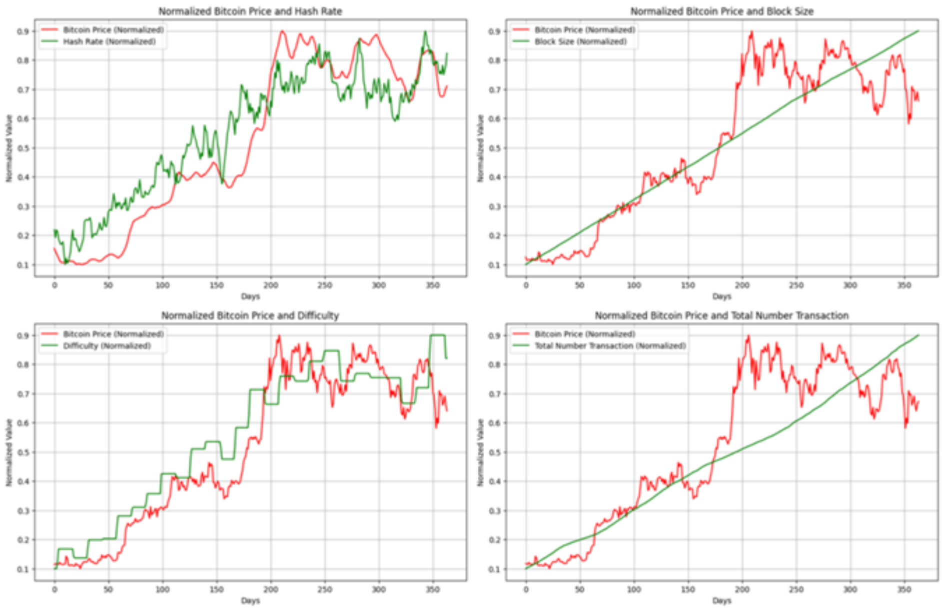

Figure 9. On-Chain Analysis results of normalized data using the Google Colab website

4) Mathematical Elements

Several mathematical elements are involved in the steps students take. One of these is used to identify price trends in time-series data, particularly in financial market analysis or predictive data using the Exponential Moving Average (EMA). The systematic steps are as follows:

The first dataset will utilize Bitcoin data from January 1 - Desember 18, 2024. As previously mentioned, the SMA value for this dataset will first be calculated based on the selected time period. A 20-day period is chosen, and then using Equation 1:

$$SMA = \frac{\sum \text{Closing price in an } n - \text{period}}{n}$$

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With $n =$ the period used . It will be calculated SMA for the BTC dataset in the interval from October 1 to October 20, 2024, as shown in Table 1, resulting in:

$$SMA = \frac{1276803{,}309}{20} = 63840{,}16543$$

Table II. Closing Prices over 20 Periods of Days

Date	Close Price
01 October 2024	60837,00781
02 October 2024	60632,78516
03 October 2024	60759,40234
04 October 2024	62067,47656
05 October 2024	62089,94922
06 October 2024	62818,95313
07 October 2024	62236,66016
08 October 2024	62131,96875
09 October 2024	60582,10156
10 October 2024	60274,5
11 October 2024	62445,08984
12 October 2024	63193,02344
13 October 2024	62851,375
14 October 2024	66046,125
15 October 2024	67041,10938
16 October 2024	67612,71875
17 October 2024	67399,83594
18 October 2024	68418,78906
19 October 2024	68362,73438
20 October 2024	69001,70313

The previously calculated SMA value becomes the initial EMA value. Once the initial EMA value is obtained, subsequent EMA values for this dataset can be calculated using Equation 2:

$$EMA = (Close - Previous\ EMA) \times Multiplier + EMA\ Previous \qquad (2)$$

Where "Close" is today's closing price, and the Multiplier is calculated $= \frac{2}{n+1}$, Multiplier For this case, a Multiplier of $= \frac{2}{20+1} =$ 0,0952 is used. Next, we will calculate the EMA for the next 3 days, namely October 21, 22, and 23, as follows:

$EMA_{21}Oktober = (67367{,}851 - 63840{,}165) \times 0{,}0952 + 63840{,}165 = 64176{,}001$

$EMA_{22}Oktober = (67361{,}406 - 64176{,}001) \times 0{,}0952 + 64176{,}001 = 3488{,}655$

$EMA_{23}Oktober = (66432{,}195 - 3488{,}655) \times 0.0952 + 3488{,}655 = 68935{,}764$

Similarly, EMA values for periods of 50 and 100 can be calculated using the same steps, with Multipliers of 0.0392 and 0.0198, respectively. Mathematical elements are also involved in the steps where students generalize previous results into the ANN model for forecasting existing data using the following steps:

Algoritma *Backpropagation*

Input : Soil moisture data (x), initial weights (W^0), initial biases (β^0), learning rate (α), error tolerance (ϵ), epoch

Output : MSE, W_{new}, β_{new}

Step 1: Feedforward Phase

The input to the hidden layer is calculated as :

$h_i = \beta + \sum_{i=0}^{n} x_i \times w_{ij}$,

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where n is the number of inputs, β is the bias, x_i are the inputs, and w_{ij} are the weights connecting the inputs to the hidden layer.

Step 2: Calculating the Output

The input to the output layer is calculated as:

$$y_{in_i} = \beta + \sum_{i=0}^{n} w_{i,j} \times h_i$$

where h_i is the output from the hidden layer, w_{ij} are the weights connecting the hidden layer to the output layer, and β is the bias.

Step 3: Appliying the Activation Function

The output is activated using the log-sigmoid function:

$$\hat{y}_m = \frac{1}{1 + e^{-yin_m}}$$

Step 4: Calculating the output Error

The error for each output is calculated as:

$$\delta k_i = (y - \hat{y}_i)^2$$

The Mean Squared Error (MSE) is calculated as:

$$MSE = \frac{\sum_{i=0}^{n}(y - \hat{y}_i)^2}{n}$$

Where y is the target output, $\hat{y}_i$ is the predicted output, and n is the number of samples.

Step 5: Backpropagation Error (Output Layer to Hidden Layer)

The error propagated from the output layer back to the hidden layer is calculated as:

$$\delta j_i^j = \beta \sum_{i=0}^{n} w_{ij} \times \delta_{k_i}$$

where β is the bias, w_{ij} are the weights, and δ_{k_i} is the error at the output layer.

Step 6: Backpropagation Error (Hidden Layer to Input Layer)

The error propagated from the hidden layer back to the input layer is calculated as:

$$\delta j_i^j = \sum_{i=0}^{n} w_{ij} \times \delta k_i$$

Step 7. Updating Weights and Biases

The weights and biases are updated as follows:

- Weights: $W_{new} = W_{old} + \alpha \times \delta k_i \times h_i$ where α is the learning rate.
- Biases: $\beta_{new} = \beta_{old} + \alpha \times \delta j_i + x_i$

Step 8: Check Stopping Criteria, the number of epochs has reached the maximum limit, or The MSE is less than or equal to a predefined threshold (ϵ).

Step 9. Repeat or Terminate, if the stopping criteria are not met, return to **Step 1** and repeat the process.

Illustration: Given a data set x that has been normalized and formed into a vector. The vector will be the input of Artificial Neural Networks (ANN). Some of the parameters used in ANN are such as weights (W^0 and W^1), biases (β^0 dan β^1), learned ratio $\alpha = 0.1$, and target y.

$$x = \begin{bmatrix} 98 & 98 & \cdots & 96 \\ 98 & 98 & \cdots & 88 \\ \vdots & \vdots & \vdots & \vdots \\ 96 & 88 & \cdots & 85 \end{bmatrix}; x^1 = [98; \quad 98; \quad \cdots; \quad 96]; y = \begin{bmatrix} 88 \\ 87 \\ \vdots \\ 85 \end{bmatrix}$$

$$W^0 = \begin{bmatrix} 0.2 & 0.1 & 0.3 & 0.2 & 0.1 & 0.3 & 0.2 & 0.1 & 0.3 & 0.2 & 0.1 & 0.3 \\ 0.1 & 0.3 & 0,2 & 0.1 & 0.3 & 0.2 & 0.1 & 0.3 & 0.2 & 0.1 & 0.3 & 0.2 \end{bmatrix}$$

$$W^1 = [0.1; 0.2]; \beta^0 = [0.1; 0.1]; \beta^1 = 0.1; \alpha = 0.1$$

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Step 1. Feedforward Phase

$$h^1_{1,1} = \beta^0_1 + x^1_1 \times w^0_{1,1} = 0.1+98\times 0.2 = 19.7$$
$$h^1_{1,2} = \beta^0_1 + x^1_2 \times w^0_{1,2} = 0.1+98\times 0.2 = 19.7$$
$$\vdots$$
$$h^1_{1,12} = \beta^0_1 + x^1_1 \times w^0_{1,1} = 0.1+98\times 0.2 = 19.7$$
$$h^1_1 = [19.7 \quad 9.9 \quad 29.5 \quad 19.5 \quad 9.9 \quad 29.2 \quad 19.5 \quad 9.8 \quad 28.9 \quad 19.3 \quad 9.7 \quad 28.9]$$
$$h^1_{2,1} = \beta^0_2 + x_1 \times w^0_{2,1} = 0.1+98\times 0.1 = 9.9$$
$$h^1_{2,2} = \beta^0_2 + x_2 \times w^0_{2,2} = 0.1+98\times 0.3 = 29.5$$
$$\vdots$$
$$h^1_{2,12} = \beta^0_2 + x_{12} \times w^0_{2,12} = 0.1+96\times 0.2 = 0.2620$$
$$h^1_2 = [9.9 \quad 29.5 \quad 19.7 \quad 9.8 \quad 19.5 \quad 19.5 \quad 9.8 \quad 29.2 \quad 19.3 \quad 9.7 \quad 28.9 \quad 19.3]$$

Step 2. Calculating the Output ($\hat{y}_{in}$)

$$\begin{aligned}\hat{y}_{in} &= \beta^1_1 + w^1_1 \times h^1_{1,1} + \cdots + w^1_1 \times h^1_{1,12} + w^1_2 \times h^1_{2,1} + \cdots + w^1_2 \times h^1_{2,12} \\ &= 0.1+0.1\times 19.7+\cdots+0.1\times 28.9+0.1\times 9.9+\cdots+0.1\times 0.262 \\ &= 76.09\end{aligned}$$

Step 3. Appliying the Activation Function

The output is activated using the log-sigmoid function

$$\hat{y} = \frac{1}{1+e^{-\hat{y}_{in}}} = \frac{1}{1+e^{-76.09}} = 1$$

Step 4. Calculating the output Error

$$\delta k = (y-\hat{y})^2 = (88-1)^2 = 7569$$
$$\delta k = MSE = 7569$$

Step 5. Backpropagation Error (Output Layer to Hidden Layer)

$$\delta j^0_1 = \beta^0_1 + w^1_1 \times \delta k = 0.1+0.1\times 7569 = 757$$

Step 6. Backpropagation Error (Hidden Layer to Input Layer)

$$\delta j^1_1 = w^0_{1,1} \times \delta k + w^0_{1,2} \times \delta k + w^0_{1,3} \times \delta k + \cdots + w^0_{1,12} \times \delta k = 1.8166e^4$$
$$\delta j^1_2 = w^0_{2,1} \times \delta k + w^0_{2,2} \times \delta k + w^0_{2,3} \times \delta k + \cdots + w^0_{2,12} \times \delta k = 1.8166e^4$$

Step 7. Updating Weights and Biases

Weight between input layer and hidden layer

$$\begin{aligned}w\_new^0_{1,1} &= w^0_{1,1} + \alpha \times \delta k + h_{1,1} \\ &= [1.4915; \quad 0.7495; \quad 2.2335; \quad 1.4764; \quad 0.7495; \quad 2.2107; \quad 1.4764; \\ &\quad 0.7420; \quad 2.188; \quad 1.4612; \quad 0.7344; \quad 2.188]\end{aligned}$$

$$\begin{aligned}w\_new^0_{2,1} &= w^0_{2,1} + \alpha \times \delta k + h_{1,2} \\ &= [0.7495; \quad 2.2335; \quad 1.4915; \quad 0.7420; \quad 2.2335; \quad 1.4764; \quad 0.7420; \\ &\quad 2.2107; \quad 1.4612; \quad 0.7344; \quad 2.188; \quad 1.4612]\end{aligned}$$

$$W\_new^0 = \begin{bmatrix} w\_new^0_{1,1} \\ w\_new^0_{1,1} \end{bmatrix} = \begin{bmatrix} 1.4915 & 0.7495 & 2.2335;\ldots & 2.188 \\ 0.7495 & 2.2335 & 1.4915;\ldots & 1.4612 \end{bmatrix}$$

Weight between hidden layer and output layer

$$w\_new_1^1 = w_1^1 + \alpha \times \delta k = 2.2484e^3$$
$$w\_new_2^1 = w_2^1 + \alpha \times \delta k = 1.5064e^3$$
$$W\_new^1 = \left[w\_new_1^1 ; w\_new_2^1 \right] = \left[2.2484e^3 ; 1.5064e^3 \right]$$

Bias between input layer and hidden layer

$$\beta\_new_1^0 = \beta_1^0 + \alpha \times \delta j_1^1 = 1.8167e^3$$
$$\beta\_new_2^0 = \beta_2^0 + \alpha \times \delta j_2^1 = 1.8167e^3$$
$$\beta\_new^0 = \left[\beta\_new_1^0 ; \beta\_new_2^0 \right] = \left[1.8167e^3 ; 1.8167e^3 \right]$$

Bias between hidden layer and output layer

$$\beta\_new_1^1 = \beta_1^1 + \alpha \times \delta j_1^0 = 75.8$$

Since the maximum number of epochs is 1, the algorithm is stopped. The output results obtained are:

$$MSE = 7569; W\_new^0 = \begin{bmatrix} 1.4915; & 0.7495; & 2.2335; \ldots & 2.188 \\ 0.7495; & 2.2335; & 1.4915; \ldots & 1.4612 \end{bmatrix}$$

$$W\_new^1 = \left[2.2484e^3 ; 1.5064e^3 \right]; \beta\_new^0 = \left[1.8167e^3 ; 1.8167e^3 \right]; \beta\_new_1^1 = 75.8$$

3.1 Research-Based Learning (RBL) with STEM Approach for ANN Multi-Step Time-Series Forecasting

This section will discuss in more detail the six stages of the research-based learning model with a STEM approach. Based on Figure 2, these six stages illustrate how students engage in the learning process using a research-based learning model with a STEM approach to apply ANN Multi-Step Time-Series Forecasting. This model aims to enhance metacognitive skills in understanding cryptocurrency volatility, based on fundamental, technical, and on-chain analysis [17].

Step 1: (Science) The fundamental issue addressed is the volatility in cryptocurrency, where students must understand the price fluctuations in the crypto market to facilitate analysis in subsequent stages.

Table III. Learning Activities in RBL-STEM Stage 1

The First Stage	Learning Activities
(Science) Presentation of issues related to volatility in cryptocurrency to students.	• The lecturer asks students if they have ever heard of cryptocurrency before.
	• The lecturer provides an overview of volatility in cryptocurrency and then asks the students if they understand the core issue.
	• The lecturer instructs the students to write down any information they consider important to solve the previously presented problem.

Stage 2: (Engineering) Understanding fundamental, technical, and on-chain analysis, as these three advanced analyses are essential solutions for addressing cryptocurrency volatility [16].

Table IV. Learning Activities in RBL-STEM Stage 2

Second stage	Learning Activities
(Engineering) Students obtain solutions for forecasting volatility using fundamental, technical, and on-chain analysis	• The lecturer guides the students to discuss solutions for volatility in cryptocurrency.
	• The lecturer instructs the students to write down the information they deem important to solve the given problem

Stage 3: (Technology) The use of the website coinmarketcap.com to analyze several cryptocurrencies and then obtain data related to the cryptocurrencies.

Table V. Learning Activities in RBL-STEM Stage 3

The Third Stage	Learning Activities
(Technology) Students search for literature and information sources related to the volatility issues of cryptocurrency using fundamental analysis	• The lecturer guides the students in using the website coinmarketcap to obtain data related to cryptocurrencies.
	• Students group the cryptocurrency data based on its features.

Stage 4: (Technology-Mathematics) Determining the cryptocurrencies that are correlated using MATLAB, then representing them in a graph and conducting technical and on-chain analysis.

Table VI. Learning Activities in RBL-STEM Stage 4

The Fourth Stage	Learning Activities
(Technology-Mathematics) Students analyze the correlated cryptocurrency data, then represent it in a graph and perform technical and on-chain analysis.	• Students are guided by the lecturer to use MATLAB software to find correlated cryptocurrencies by generating an adjacency matrix, then transferring it to FX Draw software to create a graph of the correlated cryptocurrencies.
	• Students represent the correlated cryptocurrencies in a graph.
	• Students perform an analysis of the dynamics of cryptocurrency activity and trends by accessing the Blockchain.com website to obtain data and processing the data using Google Colab.

Stage 5: (Mathematics-Technology) Students generalize the data that has been generated for forecasting cryptocurrency volatility using an ANN model.

Table VII. Learning Activities in RBL-STEM Stage 5

The Fifth Stage	Learning Activities
(Mathematics-Technology) Students generalize data to perform forecasting of cryptocurrency volatility using an ANN (Artificial Neural Network).	• The lecturer guides the students in determining the smallest RRA value from the existing cryptocurrency data. There are several options, one of which is using MATLAB software.
	• Students use MATLAB software to obtain the cryptocurrency with the smallest RRA value.
	• The lecturer guides the students in training and testing cryptocurrency data for forecasting cryptocurrency volatility using the ANN model.

Stage 6: This is the report stage where students present their solution to the volatility issues in cryptocurrency.

Table VIII. Learning Activities in RBL-STEM Stage 6

The Sixth Stage	Learning Activities
Students present the results of their group discussion and write their research report related to metacognitive skills.	• Students develop a research report on the use of the ANN multi-step time-series forecasting model for volatility issues in cryptocurrency based on fundamental, technical, and on-chain analysis.
	• Students give a presentation in front of the class to conduct a focus group discussion
	• The lecturer evaluates and clarifies all the results of the students' research activities.
	• The lecturer observes the students' metacognitive thinking skills using an observation sheet.

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Framework for Material Development

After the stages of learning activities are developed, follow-up research involves R&D using the 4-D development model, which includes four stages for creating learning tools: Define, Design, Develop, and Disseminate. Below is an explanation of each stage:

- Define: This stage involves preliminary analysis, student analysis, material concept analysis, task analysis, and determining the learning objectives to be achieved.
- Design: At this stage, learning tools to be developed are designed, including creating Student Task Designs (RTM), Student Worksheets (LKM), and Metacognitive Skills Tests. These tools use a research-based learning model with a STEM approach to study time-series forecasting of cryptocurrency volatility using metacognitive skill indicators.
- Develop: At this stage, the learning tools are validated by validators for testing the validity of the developed tools. The results of field trials and revisions from validators are used as feedback to produce the final tools ready for use in learning. Trials are conducted with undergraduate Mathematics Education students at FKIP, University of Jember.
- Disseminate: At this stage, dissemination is carried out among undergraduate Mathematics Education students at FKIP, University of Jember.

  This 4-D research is conducted separately in the study, so the results will be published in different papers.

DISCUSSION

The development of a framework for STEM-RBL learning activities utilizing ANN multi-step time-series forecasting to improve students' metacognitive skills in addressing cryptocurrency volatility is highly significant and serves as a starting point for the Research and Development (R&D) research format. This paper will act as a guide for researchers to take further actions in their studies. At least two additional research activities can be conducted subsequently: (1) the development of RBL-STEM learning materials using the 4D development model, and (2) studying the RBL-STEM learning materials to enhance students' metacognitive skills in solving cryptocurrency volatility problems using ANN multi-step time-series forecasting. We consider learning activities that integrate RBL-STEM to be highly effective in fostering metacognitive skills, aligning with the findings of previous studies [10].

Metacognitive skills are crucial in the context of cryptocurrency, particularly as digital currencies gain increasing popularity in the modern era. The volatile and dynamic nature of cryptocurrency markets demands a high level of self-awareness, strategic planning, and critical reflection—key components of metacognition. These skills enable individuals to analyze complex data, evaluate risks, and adapt to market fluctuations effectively. For instance, by applying metacognitive strategies, investors can plan their decision-making processes by understanding market trends, monitor their investment choices in real-time, and evaluate the outcomes to refine future strategies. Moreover, the fast-paced and decentralized nature of cryptocurrency requires individuals to continuously learn and adapt, making metacognition an essential tool for navigating uncertainties and making informed decisions. By fostering metacognitive skills, individuals can not only mitigate risks associated with market volatility but also capitalize on opportunities, ensuring they stay ahead in the rapidly evolving digital financial landscape [9].

Researchers predict that RBL-STEM learning activities, structured into six clear stages to utilize ANN Multi-Step Time Series Forecasting in solving cryptocurrency volatility issues through fundamental, technical, and on-chain analytical approaches, can be highly effective in improving students' metacognitive skills. These stages guide students through a comprehensive learning process, integrating research-based and STEM principles with advanced financial analysis tools. By engaging with the dynamic and complex challenges of cryptocurrency markets, students are encouraged to plan their strategies, monitor their progress, and evaluate their solutions—key components of metacognitive development. Through hands-on experience with ANN models, students not only enhance their understanding of financial forecasting and blockchain technology but also develop critical thinking, problem-solving, and self-regulation skills. This structured learning framework ensures that students are not only equipped with technical knowledge but also foster the ability to reflect on and adapt their learning processes, making it an impactful approach for 21st-century education [20].

CONCLUSION

This study has described how the syntax of RBL (Research-Based Learning) is integrated with the STEM approach. The main result is a framework for research-based learning activities with a STEM approach: the use of multi-step time-series forecasting with Artificial Neural Networks (ANN) to solve cryptocurrency volatility issues in order to enhance students' metacognitive skills through fundamental, technical, and on-chain analysis, structured into six stages and their respective learning activities. Included in this study is the development of a test instrument framework related to students' metacognitive skills. With these research findings, subsequent studies related to the development of tools and analysis of RBL-STEM implementation can be easily conducted.

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REFERENCES

1. Bowman, M., Debray, S. K., and Peterson, L. L. 1993. Reasoning about naming systems. . Izza, R., Dafik, Kristiana, A. I., Mursyidah, I. L. 2023. Research Based Learning and STEM Learning Activities: The Use of Local (a,d)-edge Antimagic Coloring to Improve the Students Combinatorial Thinking Skills in Solving a Disjoint Union Graph Line Motif Batik Design Problem. Journal of Mathematics And Applications, 4(2).
2. Mursyidah, I. L., Dafik, Kristiana, A. I., & Izza, R. 2023. Development of RBL-STEM Learning 52 Tools to Improve Students' Computational Thinking Skills Solving Rainbow Antimagic Coloring Problems and Their Application to Traffic Flow Problems with Spatial Temporal Graph Neural Network. International Journal of Current Science Research and Review. 6(1), 634-644. https://doi.org/10.47191/ijcsrr/V6-i1-69.
3. Kusumawardani, I., Slamin, Kristiana, A. I., Dafik. 2022. Kerangka Aktivitas Pembelajaran Berbasis Riset Dengan Pendekatan Stem: Penerapan Materi Resolving Efficient Dominating Set Dalam Meningkatkan Keterampilan Metakognisi Mahasiswa Pada Penyelesaian Masalah Penempatan Led Di Vertical Farming. Thesis.
4. Kristiana, A. I., Dafik, Ridlo, Z. R., Prihandini, R. M., & Adawiyah, R. 2022. Research Based Learning and STEM Learning Activities: The Use of R-Dynamic Coloring to Improve the Students Meta-literacy in Solving a Tessellation Decoration Problem. European Journal of Education and Pedagogy, 3(4), 52–60. https://doi.org/10.24018/ejedu.2022.3.4.381
5. Fang, F., Chung, W., Ventre, C., Basios, M., Kanthan, L., Li, L., & Wu, F. 2024. Ascertaining price formation in *cryptocurrency* markets with machine learning. *The European Journal of Finance*, *30*(1), 78-100.
6. Bandyopadhyay, I. 2024. Implementation Of An Artificial Intelligence And Machine Learning Powered Financial Decision-Support System For Stock Market Speculators. *Educational Administration: Theory and Practice*, *30*(4), 203-209.
7. Humaizah, R., Dafik, I M Tirta, Z R Ridlo, Susanto Susanto. 2022. Research-Based Learning Activity Framework with STEM Approach: Implementing Strong Dominating Set Technique in Solving Highway CCTV Placement to Enhance Students' Metaliteracy. Pancaran Pendidikan FKIP Universitas Jember. 11(1), 89-102. https://doi.org/10.25037/pancaran.v11i1.386
8. Farid, Z., Assimeddine, M., Abdennouri, M., Barka, N., & Sadiq, M. H. (2024). Flotation Enhancement of sedimentary phosphate ores by cornstarch as an environmental depressant: Modeling and analysis using full factorial design (FFD) and artificial neural network (ANN) approaches. *Environmental Functional Materials*.
9. Kaur, M., Kumar, A., & Mittal, A. K. (2024). Mapping the knowledge structure of artificial neural network research in the stock market: a bibliometric analysis and future research pathways. *Benchmarking: An International Journal*.
10. Medina, M. S., Castleberry, A. N., dan Persky, A. M. 2017. Strategies for improving learner metacognition in health professional education. *American Journal of Pharmaceutical Education*. 81(4)
11. Woebbeking, F. (2021). Cryptocurrency volatility markets. *Digital Finance*, *3*(3–4), 273–298. https://doi.org/10.1007/s42521-021-00037-3
12. Catania, L., Grassi, S., & Ravazzolo, F. (2018). *Centre For Applied Macro-And Petroleum Economics (CAMP) Predicting the* Volatilitas *of Cryptocurrency Time-Series*. http://www.bi.no/camp

13. Hidayah, R. (2018). Implementasi Research Based Learning- Rbl Pada Mata Kuliah Media Pembelajaran: Penelitian Kelas Pada Mahasiswa Calon Guru SD. *Jurnal Bidang Pendidikan Dasar*, *2*(2). https://doi.org/10.21067/jbpd.v2i2.2307
14. Setyadi, D., Matematika, P., Kristen, U., & Wacana, S. (2018). *Proses Metakognisi Mahasiswa Dalam Memecahkan Masalah Matematika (Studi Kasus Pada Mahasiswa Pendidikan Matematika UKSW)*. https://doi.org/10.15294/kreano.v9i1.13505
15. Shrotriya, L., Badala, J., Khatwani, R., Chinmulgund, A., Mishra, M., & Bedarkar, M. (2023). Cryptocurrency algorithmic trading with price forecasting analysis using powerBI. *International Journal of Engineering, Science and Technology*, *15*(4), 1–8. https://doi.org/10.4314/ijest.v15i4.1S
16. Tyshchenko, V., Achkasova, S., Naidenko, O., Kanyhin, S., & Karpova, V. (2023). Development Of Recurrent Neural Networks For Price Forecasting At Cryptocurrency Exchanges. *Eastern-European Journal of Enterprise Technologies*, *5*(4(125)). https://doi.org/10.15587/1729-4061.2023.287094
17. Sovia, R., Yanto, M., Budiman, A., Mayola, L., & Saputra, D. (2019). Backpropagation neural network prediction for cryptocurrency bitcoin prices. *Journal of Physics: Conference Series*, *1339*(1). https://doi.org/10.1088/1742-6596/1339/1/012060
18. Conrad, C., Custovic, A., & Ghysels, E. (2018). Long- and Short-Term Cryptocurrency Volatility Components: A GARCH-MIDAS Analysis. *Journal of Risk and Financial Management*, *11*(2), 23. https://doi.org/10.3390/jrfm11020023
19. Caporale, G. M., Gil-Alana, L., & Plastun, A. (2018). Persistence in the cryptocurrency market. *Research in International Business and Finance*, *46*, 141–148. https://doi.org/10.1016/j.ribaf.2018.01.002
20. A'yun, Q., Slamin, Kristiana, A. I., & Dafik. (2023). Development of Learning Tools Based on RBL and STEM on The Topic of Rainbow Vertex Antimagic Coloring. *AIP Conference Proceedings, 2679*. https://doi.org/10.1063/5.0111258