

STEM approach prototype to improve classification skills in tea leaves using convolutional neural networks

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Abstract

The STEM approach integrates Science, Technology, Engineering, and Mathematics in technology-based problem solving. This study aimed to develop a valid, practical, and effective STEM-based prototype to improve students' classification skills in identifying tea leaf diseases using Convolutional Neural Networks (CNN). The study employed a Research and Development (R&D) method using the ADDIE model. The developed products included Student Worksheets (LKM) and Learning Outcome Tests (THB). The results showed that the prototype was valid, practical, and effective, with validation, practicality, and effectiveness percentages of 94.18%, 90.33%, and 94.28%, respectively. Students' classification skills improved significantly, as indicated by the increase in average scores from 49.40 to 80.77 and the paired sample t-test result of $0.000 < 0.05$. Qualitative analysis using phase portraits and N-Vivo also demonstrated improvements in classification skill indicators. Therefore, the STEM-based prototype effectively improved students' classification skills in CNN-based tea leaf disease identification.

Keywords: STEM approach; Classification skills; Tea leaf disease; Convolutional Neural Network (CNN)

1. Introduction

Tea plant (*Camellia sinensis*) is one of the important plantation commodities that plays a significant role in supporting the agroindustry sector and the economy [1]. Tea productivity and quality are highly influenced by leaf health conditions, particularly due to diseases such as *algal spot*, *brown blight*, *red spot*, and healthy leaf conditions [2]. These diseases cause changes in leaf color, shape, and texture that are difficult to identify visually, especially during the early stages of infection. Inaccurate disease identification may lead to decreased crop quality and improper disease control [3]. Therefore, a more objective and accurate identification method is needed to support the analysis of tea leaf diseases.

The advancement of digital image processing technology provides opportunities to support plant disease identification through image segmentation and classification processes [4]. Image segmentation plays an important role in separating the main object from the background, thereby affecting the quality of feature extraction and classification results [5]. However, tea leaf image segmentation still faces several challenges, including color similarity between healthy and infected leaves, lighting variations, and complex image backgrounds [6]. These challenges indicate that classification

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skills are essential in digital image analysis because the success of segmentation directly affects overall classification performance.

Classification skills are one of the essential skills in science, technology, and mathematics learning because they involve the ability to categorize, distinguish, and analyze objects systematically [7]. In the context of image processing and artificial intelligence, students are required to understand pattern recognition processes, segmentation results, and classification model performance. However, learning in higher education is still predominantly theoretical and has not sufficiently integrated real-world problems with the application of current technologies, resulting in students' classification skills not being optimally developed. Therefore, a learning approach that can connect theoretical concepts with data-driven technological applications is needed [8].

One relevant approach to address this issue is the STEM (*Science, Technology, Engineering, and Mathematics*) approach. The STEM approach enables students to actively engage in authentic problem-solving through the integration of science, technology, engineering, and mathematics concepts. In this study, the STEM approach was applied to tea leaf disease analysis through image acquisition, segmentation, and classification stages [9]. To support the image classification process, the *Convolutional Neural Network* (CNN) method was used because of its ability to automatically extract visual features and achieve strong performance in various image recognition studies.

Although the application of CNN in image processing has been widely developed, its integration into STEM-based learning focused on improving students' classification skills remains limited. Therefore, this study aims to develop a STEM approach prototype to improve classification skills in tea leaf disease identification using *Convolutional Neural Network* (CNN). The developed prototype is expected to provide a more authentic, interactive, and technology-based learning experience that can support the development of students' classification skills and align with the needs of learning in the era of smart agriculture.

2. Material and methods

2.1. STEM Approach Prototype

A prototype is an initial model or design of a product developed to test concepts, functions, and feasibility before broader implementation. In the development process, a prototype serves as an early representation of a system or product that enables evaluation, revision, and gradual improvement. According to [10] a prototype is an initial representation of a system used to visualize ideas, test concepts, and obtain user feedback before the final product is developed. In the educational context, prototypes may include learning models, instructional devices, or learning approaches designed to evaluate the effectiveness of innovative learning strategies.

One form of educational innovation that can be developed through a prototype is the STEM approach. STEM integrates Science, Technology, Engineering, and Mathematics into a unified learning process focused on solving real-world problems [11]. This approach encourages students to connect interdisciplinary knowledge and apply it in authentic situations [12]. Through STEM-based learning, students are actively involved in exploration, experimentation, data analysis, and problem solving, which can enhance critical and analytical thinking skills. Based on these concepts, a STEM approach prototype can be defined as an initial design of a learning model or instructional device that integrates science, technology, engineering, and mathematics in the learning process. In this study, the STEM approach prototype was designed to facilitate students in understanding tea leaf classification through digital image processing technology and artificial intelligence algorithms.

2.2. Classification Skills

Classification skills refer to the ability to group objects or events based on specific characteristics so that categories with similar features can be formed [13]. These skills help students build organized knowledge structures, making it easier to understand concepts, analyze data, and make decisions. In science and mathematics education, classification skills are considered part of basic science process skills [14]. These skills involve observing object characteristics, determining classification criteria, and placing objects into appropriate categories [15].

Students with good classification skills are able to recognize patterns, compare characteristics, and establish logical relationships among objects. Therefore, classification skills become an important foundation for developing analytical thinking and problem-solving abilities. In STEM-based learning, classification skills also play an important role because the STEM approach integrates science, technology, engineering, and mathematics in solving real-world problems [16]. In this context, classification skills support data processing, system analysis, and technological problem solving through

data grouping, result interpretation, and system performance evaluation. According to [17], classification skill indicators include recording observations, identifying similarities and differences, distinguishing object characteristics, comparing characteristics among groups, determining classification criteria, and relating observational results. Based on the theoretical review and the needs of this study, the classification skill indicators used include recording observations, distinguishing object characteristics, comparing characteristics among groups, determining classification criteria, and relating observational results.

2.3. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a deep learning model designed to process image data through automatic visual feature extraction [18]. CNN learns important patterns such as color, texture, and shape using layered convolution operations, making it effective for image segmentation and classification tasks [19]. CNN architecture generally consists of convolution, activation, pooling, and fully connected layers [20]. The convolution layer extracts image features using filters, while activation functions such as *Rectified Linear Unit* (ReLU) introduce nonlinearity into the model [21]. Pooling layers reduce data dimensions while preserving important information, and fully connected layers perform the final classification process [22]. One of the main advantages of CNN is its ability to perform end-to-end learning without manual feature extraction (Widodo et al., 2025). CNN automatically adjusts filter weights during training to capture relevant visual characteristics, enabling it to handle variations in lighting, scale, and object deformation effectively [23].

CNN has been widely applied in plant image processing, particularly for leaf disease classification and image segmentation. Previous studies reported that CNN achieved high accuracy in tea leaf disease classification compared to conventional machine learning methods [24]. In addition, architectures such as *Fully Convolutional Network* (FCN) and U-Net allow CNN to perform pixel-level segmentation accurately, even with complex backgrounds [25]. In this study, CNN was used as the main method for segmenting and classifying tea leaf (*Camellia sinensis*) images by extracting relevant visual features for classification decision-making. Figure 1 illustrates the architecture used in the CNN model.

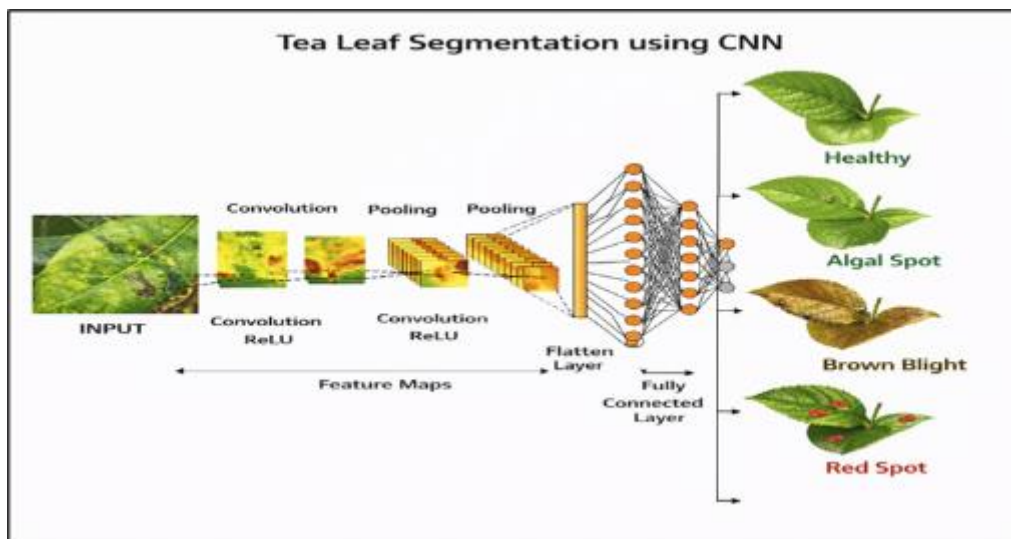


Figure 1 Illustration of the CNN Architecture

2.4. Methods

The development process was carried out through the five stages of the ADDIE model, namely analysis, design, development, implementation, and evaluation, as shown in Figure 1. This study used the ADDIE development model as a procedure for designing a STEM approach learning prototype. The ADDIE model consists of the analysis, design, development, implementation, and evaluation stages. Figure 2 presents the flow of the ADDIE development stages according to [26].

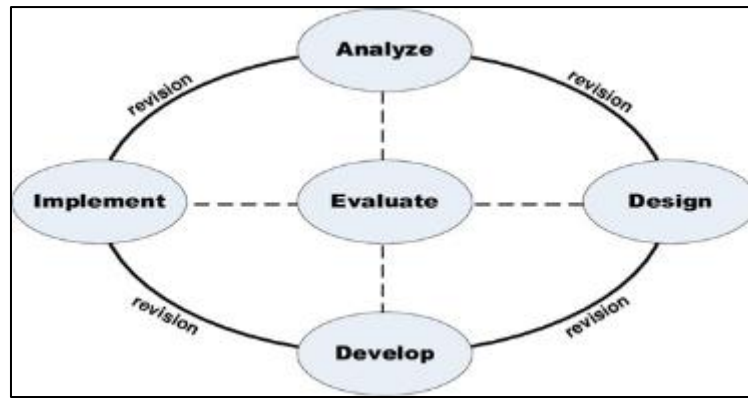


Figure 2 ADDIE Development Stages

Data collection in this study was conducted using several research instruments, including learning device validation, observation of learning implementation, collection of learning outcome data, activity observation, and response questionnaires. The research data were analyzed quantitatively using the SPSS application through the paired sample t-test statistical analysis.

3. Results and discussion

3.1. RBL-STEAM Implementation

This STEM approach prototype requires students to be more active in the learning process through exploration and image classification analysis activities. During the learning stages, students were directed to analyze tea leaf classification problems and design CNN-based solutions. The researchers addressed the problem of tea leaf classification using CNN, as shown in Figure 3.

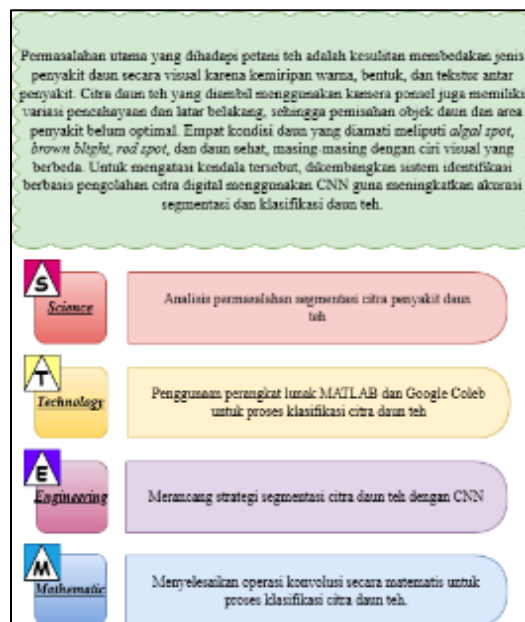


Figure 3 Framework of STEM Approach Activities

The expected outcome of this study is the development of a STEM-based learning prototype using Convolutional Neural Networks (CNN) to improve tea leaf image classification skills systematically and accurately. The research stages include: (a) analyzing tea leaf image problems and their visual data, (b) designing tea leaf image segmentation strategies using CNN, (c) conducting mathematical classification processes through iterative procedures, (d) utilizing MATLAB software to support further classification processes, and (e) drawing conclusions regarding the classification and segmentation problems of tea leaf images using CNN.

3.2. Validity, Practicality, and Effectiveness of the STEM Approach Prototype

The first stage of the ADDIE model is the analysis stage, which aims to identify and determine learning needs through the analysis of objectives and the scope of the material to be developed. This stage includes learning outcome analysis, material analysis, and students' learning needs analysis. The learning outcome analysis was conducted to identify students' competencies, particularly in understanding tea leaf image classification concepts and the application of Convolutional Neural Networks (CNN) as the basis for developing the learning prototype. The material analysis aimed to identify and systematically organize the main concepts related to digital image processing, tea leaf image segmentation, and CNN that would be implemented in the STEM approach prototype. Furthermore, the students' learning needs analysis was conducted to obtain information regarding students' characteristics, prior knowledge, and difficulties in understanding digital image processing and machine learning, so that an appropriate learning approach could be determined to improve students' classification skills.

The second stage of the ADDIE model is the design stage, which focuses on designing the STEM-based learning prototype. This stage was conducted based on the results of the learning outcome analysis, students' characteristics, and learning needs in tea leaf classification using Convolutional Neural Networks (CNN). The learning objectives were formulated to help students understand digital image processing concepts and the application of CNN in tea leaf classification. The STEM approach was integrated through science, technology, engineering, and mathematics aspects, where the technology aspect involved the use of MATLAB and Google Colab, while the mathematics aspect included convolution operations in image processing. The learning activities were systematically arranged from problem analysis, image preprocessing, to CNN model implementation using the VGGNet architecture. Based on this design, the initial prototype of the learning tools was developed, including Student Worksheets (LKM) and Learning Outcome Tests (THB) in the form of pretests and posttests. The evaluation results showed that the learning design was aligned with the learning outcomes and supported the improvement of students' classification skills. Figure 4 presents the initial design of the LKM and THB.



Figure 4 Initial Design of LKM and THB

The third stage is the development stage, which involves realizing the results of the analysis and design into a STEM-based learning prototype applicable to tea leaf classification using Convolutional Neural Networks (CNN). The developed learning tools included Student Worksheets (LKM) and Learning Outcome Tests (THB) in the form of pretests and posttests. After the learning tools were developed, validation was conducted by expert lecturers on the learning tools, student activity observation sheets, STEM approach implementation observation sheets, and student response questionnaires. The validation results showed that the learning tools obtained an average score of 3.76 with a percentage of 94.18%, indicating that the prototype was categorized as valid and feasible for implementation in the next stage.

The fourth stage is the implementation stage, which involves applying the STEM approach prototype in the learning process to determine its practicality and effectiveness. The implementation was conducted with 35 students of the Mathematics Education Study Program at the University of Jember. The practicality test was carried out through observations of learning implementation by seven observers and obtained an average score of 3.67 with a percentage of 92.25%, indicating that the prototype was categorized as highly practical.

Table 1 Recapitulation Results of the STEM Approach Prototype Validation

Validation Result	Average Score	Percentage
Learning Device	3.75	93.75%
Student Activity Observation Sheet	3.75	93.75%
STEM Approach Implementation Sheet	3.80	95.08%
Student Response Questionnaire	3.77	94.33%
Overall average score	3.76	94.18%

The effectiveness test was evaluated based on students' learning outcomes, student activity observations, and student response questionnaires. The learning outcome data obtained from the posttest showed that 33 out of 35 students (94.28%) achieved the minimum mastery criterion; therefore, the learning device was considered to meet the effectiveness indicator. Student activity observation was conducted in three learning phases, namely the introduction, main activity, and closing, using an observation sheet assessed by seven observers. The recapitulation results showed an average score of 3.61 with a percentage of 90.33%. Overall, student activity was categorized as highly active ($90\% \leq P \leq 100\%$), indicating that the learning device was effective in enhancing student engagement during the learning process. The recapitulation results are presented in Table 2.

Table 2 Recapitulation of Student Activity Observation Results

Assessed Aspects	Avarage Score	Percentage
Introduction	3.56	89.12%
Main Activities	3.71	92.75%
Closing	3.57	89.25%
Overall average score	3.61	90.33%

The student response questionnaire was administered in printed form to 35 students. The recapitulation results showed an average percentage of 95.53%, as presented in Table 3. This value falls within the range of $80\% \leq Pr \leq 100\%$, indicating a very positive category. Based on these results, the STEM-based learning prototype was considered effective.

Table 3 Summary of Data from Student Response Questionnaire Results

Assessed Aspects	Percentage
Enjoyable learning components	97.85%
Learning components are considered new	92.14%
Students are interested in participating in the learning process	91.42%
The language used is clear and easy to understand	92.85%
Students understand each problem presented	97.14%
Students are attracted to the presentation (text, images, and layout)	98.57%
Students enjoy discussing with group members	100%
Students are able to process observation results	94.28%
Overall average score	95.53%

The fifth stage is the evaluation stage, which is conducted continuously in each phase of the ADDIE model to ensure that the developed learning device meets the criteria of validity, practicality, and effectiveness. In the analysis stage, the

evaluation showed that the learning needs, learning outcomes, and materials were in accordance with students' characteristics and the topic of tea leaf classification using CNN. In the design stage, the STEM prototype design, including the LKM and THB, was found to be aligned with the learning objectives and supportive of computational classification skills. In the development stage, expert validation indicated that the learning device was feasible with minor revisions. In the implementation stage, the evaluation showed that the learning device was practical to use in classroom settings, received positive responses from students, and was effective in improving learning outcomes and students' classification skills. Overall, the STEM approach prototype was considered valid, practical, and effective in improving students' tea leaf image classification skills using CNN.

3.3. Improvement of Classification Skills

This section presents the improvement in students' classification skills after the implementation of the STEM approach prototype. The improvement was analyzed based on the results of the Learning Outcomes Test (THB) administered before and after the learning process. The analysis focused on five indicators of classification skills, namely recording each observation, distinguishing object characteristics, comparing features between groups, determining the basis of classification, and connecting the results of observations. The distribution of students' pre-test and post-test scores is presented in Figure 5, while Figure 6 shows the percentage of improvement in students' classification skills after the implementation of STEM-based learning activities.

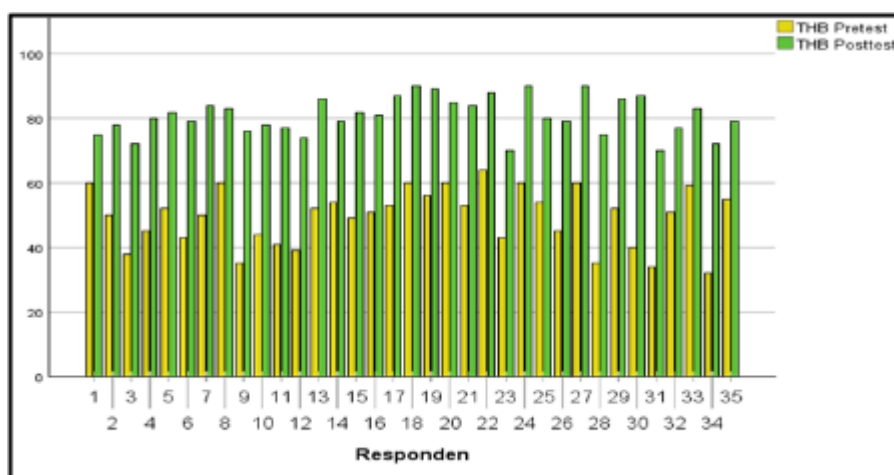


Figure 5 Graph of Distribution of Pretest and Posttest Scores

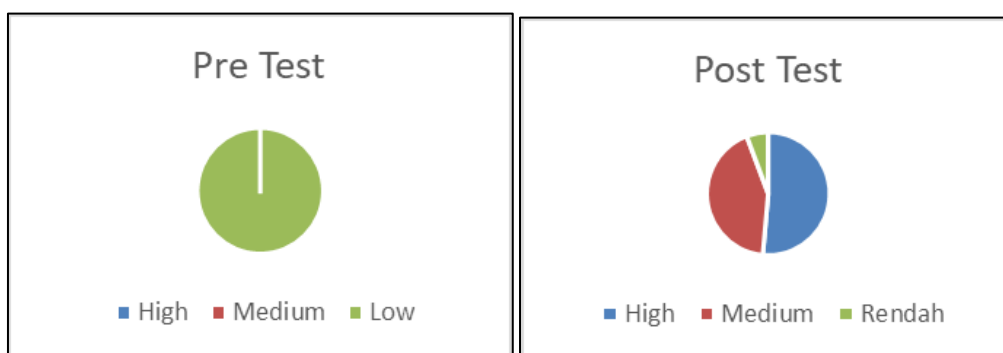


Figure 6 Percentage of Students' Classification Skills Level

The percentage results of the pretest and posttest showed that in the pretest stage, no students were classified into the high or medium classification skill categories, meaning all students were in the low category (100%). In contrast, the posttest results showed a significant improvement, with 51.42% of students in the high category, 42.85% in the medium category, and only 6% remaining in the low category. The next step was conducting a normality test to ensure that the data met the assumptions required for the paired sample t-test. This test was carried out using SPSS software. The results of the normality test are presented in Table 4.

Table 4 Normality Test Results

Tests of Normality						
	Kolmogorov-Smirnov ^a			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
THB Pretest	0.127	35	0.166	0.946	35	0.088
THB Posttest	0.077	35	0.200*	0.967	35	0.359

Based on the normality test results, the significance value of the Kolmogorov-Smirnov test was 0.166 for the pretest data and 0.200 for the posttest data, while the Shapiro-Wilk test yielded values of 0.088 for the pretest and 0.359 for the posttest. All significance values were greater than 0.05, indicating that the data were normally distributed. Since the sample size was less than 50, the decision was primarily based on the Shapiro-Wilk test, which has higher accuracy for small samples. Therefore, the data met the normality assumption, allowing further analysis using the parametric paired sample t-test. The paired sample statistics are presented in Table 5.

Table 5 Paired Sample Statistics

Paired Samples Statistics					
		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	THB Pretest	49.40	35	8.829	1.492
	THB Posttest	80.77	35	5.786	0.978

Based on Table 5, the mean score of the pretest was 49.40, while the mean score of the posttest was 80.77, with a total of 35 respondents. This indicates an improvement in scores after the learning process. Furthermore, Table 6 presents the correlation results of the paired samples.

Table 6 Paired Sample Correlations

Paired Samples Correlations				
		N	Correlation	Sig.
Pair 1	THB Pretest & THB Posttest	35	0.713	.000

Based on the results in Table 6 with a sample of 35 students, the correlation coefficient between the pretest and posttest was 0.713 with a significance value of < 0.05 . These results indicate a strong and significant relationship between the pretest and posttest scores. Furthermore, Table 7 presents the results of the paired sample t-test.

Table 7 Paired Sample Test

Paired Samples Test									
		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	THB Pretest - THB Posttest	-31.371	6.208	1.049	-33.504	-29.239	-29.898	34	0.000

The test results in Table 7 show that the significance value (Sig. 2-tailed) is 0.000, which is lower than 0.05. Therefore, it can be concluded that there is a significant difference between the pretest and posttest scores before and after the treatment. The decision is based on the criterion that if the p-value is < 0.05 , then H_0 is rejected and the difference is

considered significant. This means that learning using the prototype for tea leaf classification with Convolutional Neural Networks has a significant effect on improving students' classification skills.

4. Conclusion

Based on the research findings, the development of a STEM-based learning prototype to improve students' classification skills in tea leaf analysis using CNN was carried out through the five ADDIE stages (analysis, design, development, implementation, and evaluation). The STEM activity framework includes image problem analysis, segmentation design using CNN, mathematical classification, MATLAB utilization, and conclusion drawing. The results showed that the developed device was highly valid (94.18%), highly practical (92.25%), and highly effective (94.28% of students achieved mastery). In addition, the paired sample t-test revealed a significant improvement from a pretest mean score of 49.40 to a posttest mean score of 80.77 with Sig. 0.000 < 0.05. Therefore, it can be concluded that the STEM-based prototype is effective in improving students' classification skills.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare that they have no conflict of interest.

Statement of ethical approval

This research was approved by the Research Ethics Committee of Universitas Jember.

Statement of informed consent

All participants gave their informed consent before participating in this study.

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