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Computer Vision on Education: Fostering AI Literacy using RBL-STEM with Google Teachable Machine

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Abstract

This study aims to analyze the application of the RBL-STEM learning model using Google Teachable Machine as a computer vision-based learning media to improve AI literacy. The Research Based Learning-STEM (RBL-STEM) learning model is a learning model that integrates research activities in learning using the STEM approach. Convolutional Neural Network (CNN) is a branch of computer vision that uses artificial intelligence algorithms that are very effective in developing AI products to process image-shaped data. This study utilized a mixed methods approach that integrates quantitative and qualitative techniques to explore the improvement of AI literacy. The participants in this study were 139 undergraduate students of science education study program, Faculty of Teacher Training and Education, University of Jember who participated in the study were taking introductory information technology courses for science education, the sample selection method used was purposive sampling. The quantitative method utilized a pre-test and post-test design, which included the analysis of mean scores, standard deviation, and the observed increase in mean scores. The quantitative method used a survey on AI literacy. The pretest mean score was 38.33 with a standard deviation of 13.41, while the posttest mean score was 71.49 with a standard deviation of 9.37 with a Wilcoxon signed rank-test result of -8.468, indicating a significant effect of the RBL-STEM learning model on students' AI literacy. The high standard deviation on the pretest indicates that there is a large variation in the AI literacy level of the students before the learning begins. This is due to students' different backgrounds, experiences and understanding of AI technology. Some students may be familiar with AI, while others have not been exposed to it at all. This inequality causes a wide spread of scores. After the implementation of the RBL-STEM model with Google Teachable Machine, the standard deviation decreased, indicating that this learning not only improved the average AI literacy, but also made the improvement more even. The AI literacy survey results showed an average score of 3.48, indicating that 69% of students showed an understanding of AI literacy. The implementation of the RBL-STEM model of teaching with Google Teachable Machine is able to train students to conduct research integrated in learning activities, the role of Google Teachable machine as an AI-based learning media is able to improve student AI literacy because the use of AI-based learning media creates a new, interactive, and fun learning atmosphere. Based on the findings of the analysis, it can be concluded that the application of the RBL-STEM model has a significant impact in improving students' AI literacy.

Keywords: AI literacy, CNN, computer vision, google teachable machine, RBL-STEM

INTRODUCTION

To address these challenges, one of the solutions that can enhance AI literacy among undergraduate students is computer vision. Computer vision is a branch of AI that enables machines to obtain information and make recommendations from digital images, videos, and other visual data (Matsuzaka & Yashiro, 2023). Compared to other types of AI used in education, such as natural language processing in chatbots or generative AI for content creation, computer vision stands out for its ability to provide visual, interactive, and tangible learning experiences (Russell & Norvig, 2021). This makes it particularly effective in helping students understand AI systems and offering a unique and accessible way for developing AI literacy. Computer vision algorithms are constructed using convolutional neural networks (CNNs). CNNs assign learnable weights and biases to features in an image, enabling the model to identify and differentiate objects (Khan et al., 2020). Additionally, CNNs require minimal preprocessing and excel at tasks like image classification, recognition, segmentation, and retrieval, demonstrating the effectiveness of computer vision in real-world applications (Li et al., 2019). Moreover, when combined with machine learning techniques, computer vision enables predictive analytics and automated monitoring (Khan & Al-Habsi, 2020). These characteristics not only demonstrate the relevance of computer vision in AI development but also present opportunities for students to explore how AI systems operate, make decisions, and impact society. Therefore, incorporating computer vision into learning activities can serve as both a practical and engaging method to foster students' AI literacy.

However, understanding and implementing computer vision, particularly through coding, remains a significant challenge for novice students, especially those with limited technical backgrounds. Traditional machine learning education is often inaccessible to beginners because it relies heavily on complex concepts, programming skills, and a strong foundation in mathematics and statistics (Lamsal & Lamsal, 2025). As a result, exposure to AI is often limited to students with advanced computational abilities or access to formal STEM education. To bridge this gap, it is essential to introduce tools that facilitate hands-on exploration and make AI concepts more approachable. One of the tools is Google Teachable Machine, a free, web-based platform that enables learners to create and train simple computer vision models without any prior coding experience (Lamsal & Lamsal, 2025). By applying core principles of computer vision, this tool allows users to build machine learning classification models capable of recognizing objects, poses, and sounds using visual and audio data (Kurz et al., 2024; Carney et al., 2024). In educational settings, Google Teachable Machine can serve as an accessible entry point for students to explore the fundamentals of AI, such as data training, model accuracy, and bias, within an engaging and low-pressure environment. This kind of experiential learning helps foster AI literacy by encouraging students to observe, experiment with, and reflect on how machines process data and make decisions.

The use of technologies such as Google Teachable Machine should be integrated with pedagogical approaches that promote student engagement and deep exploration in learning. These are key components in enhancing AI literacy. One approach is the RBL-STEM model (Research-Based Learning integrated with STEM), which provides a flexible framework for fostering hands-on learning experiences. This model has been shown to effectively improve digital literacy skills among Indonesian undergraduate students (Gita et al., 2024). Digital literacy is a foundational element of AI literacy (Yi, 2021), RBL-STEM holds strong potential for advancing students' understanding of AI concepts and applications. In STEM education, integrating computer vision into RBL-STEM projects can provide practical, real-world applications that help students grasp how AI systems function. For example, in the agricultural sector, computer vision is widely used to classify and grade products like coffee beans based on visual features such as color, size, shape, texture, and defects (Bhargava & Bansal, 2021;

Hossain et al., 2019). These systems support harvesting (Ramos et al., 2017), postharvest sorting (de Oliveira et al., 2016), and quality control using colorimetric data (Wan et al., 2018). By engaging students in projects that apply computer vision to real-world problems, such as identifying coffee ripeness, RBL-STEM helps them explore how AI technologies operate and impact industries. These experiences make abstract AI concepts more concrete while developing students' critical thinking and technical skills. Thus, combining Google Teachable Machine with RBL-STEM offers a promising strategy for cultivating AI literacy.

Developing AI literacy among undergraduate students is essential to preparing them for active participation in the digital age, especially as artificial intelligence becomes increasingly embedded in various sectors. In Indonesia, where agriculture remains a vital part of the economy and societal development, integrating AI into agricultural practices presents both a practical need and a valuable learning opportunity. Agriculture is considered the foundation of modern human society (Gomeiro, 2018) and plays a critical role in ensuring food security and sustaining livelihoods (Ding et al., 2018). Therefore, this study aims to address the issue of classifying coffee fruits based on their maturity levels, specifically unripe, semi-ripe, ripe, and overripe. To achieve this, computer vision through image recognition is employed to facilitate the classification process. By implementing this technology, the harvesting of coffee crops can achieve optimal results, ensuring better accuracy and efficiency. Additionally, it can also provide students with insights into the applications of AI in the agricultural sector.

Research Question:

RQ1: "To what extent RBL-STEM learning model integrated with Google Teachable Machine can enhance Artificial Intelligence (AI) literacy among science education students?"

METHODS

The participants in this research are undergraduate students of the science education study program at the faculty of teacher training and education at the University of Jember in the semester period of 2024. A total of 139 students who participated in the study were taking introductory information technology courses for science education, consisting of 32% male and 68% female students. The reason for selecting students who are taking an introductory information technology for science education course is because the course characteristics related to AI which is part of one of the learning objectives in an information technology course. Additionally, students' prior programming skills and knowledge of coffee cultivation were assessed to understand their familiarity with AI concepts and coffee fruit classification, providing context for their learning progress and engagement with AI applications. An explanation of gender distribution, students' programming skills, and coffee knowledge presented in TABLE 1.

TABLE 1. Student distribution

Programming Knowledge		**Gender**		**Coffee Knowledge**	
Know Programming	Do not Know Programming	Male	Female	Know Coffee	Do not know
42%	58%	32%	68%	62%	38%

This research employs a mixed-methods approach, integrating both qualitative and quantitative techniques. The qualitative data is gathered through a questionnaire and survey, which elicits student perspectives on the role of Computer Vision using CNN in enhancing student proficiency in coffee fruit maturity classification. On the other hand, The quantitative data collection instrument is based on the ability to conduct research activities in learning which contains (1) Analysis of AI concepts on the problem of classification of coffee fruit maturity using RBL-STEM; (2) Designing AI applications based on computer vision integrated with Google Teachable Machine; (3) Making modifications based on parameters in the Google Teachable Machine application which include epoch, learning rate, and batch size to produce optimal AI applications; (4) Psychological readiness and Ethical considerations to apply AI for problem-solving by filling out surveys, highlighting the importance of valid data in AI-based coffee fruit classification (Kong et al., 2021). The AI literacy questionnaire targeted three dimensions: (1) Analysis of understanding of the use of AI in solving problems in the classification of coffee fruit maturity and its relationship with ethics in using AI; (2) Ability to integrate research activities in learning and problem solving to improve understanding of AI; (3) Self-control management using AI in daily life. The advantage of using a mixed-methods approach is the ability to generate more valid, reliable, and objective findings. The process of mixed-methods can be seen in FIGURE 1.

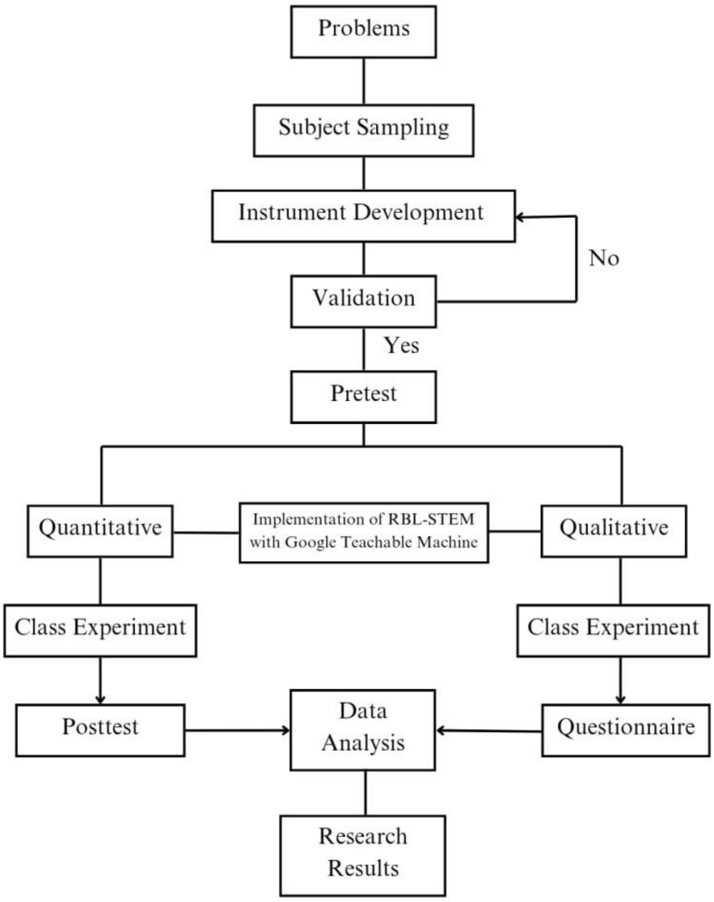

FIGURE 1. Triangulation Methods

The integration of qualitative and quantitative approaches in this study follows a triangulation method. By applying triangulation, results from qualitative and quantitative methods are compared and verified, increasing confidence in their validity. When both types of data source align, they provide a clearer and more accurate understanding of the research findings. Beyond improving accuracy, mixed methods allow for better interpretation of trends in quantitative data by providing contextual insights that would otherwise be difficult to uncover. This approach enables a holistic and in-depth analysis of complex educational phenomena, ultimately enhancing the quality of research. The instruments used in this study consisted of a student task (pretest and posttest sheets) and a questionnaire of AI literacy. Both instruments were validated by experts in the field of science education and educational technology to ensure their quality and suitability to the research objectives. The validated aspects included (1) constructivism (the correlation between active learning and knowledge construction), (2) content (the suitability of the material to the AI literacy indicators and the RBL-STEM model of teaching), and (3) language (clarity, readability, and accuracy of the use of terms for undergraduate students).

This study applies the six-phase RBL-STEM model (Ridlo et al., 2024) and selects specific RBL syntaxes that best support the intended learning outcomes (Ridlo et al., 2021). The six phases include: (1) understanding AI concepts and applications; (2) formulating a problem on coffee fruit maturity classification; (3) designing a solution using computer vision tools; (4) modifying model parameters to improve performance; (5) analyzing prediction results; and (6) reporting findings and reflections. In this study, students first should have understanding regarding AI concepts and its application. They identified a real-world problem in the agricultural sector, classifying coffee fruit ripeness, then designed and implemented a project using Google Teachable Machine to build a classification model. Data analysis was conducted by testing model accuracy, and the results were presented through filling out surveys. These selected syntaxes were chosen to promote AI literacy by fostering critical thinking, collaboration, and technical skills in an authentic learning context. The main characteristic of RBL in teaching and learning activities is the integration between the research and learning process in the classroom activities. In this study, this integration is reflected in the learning process, as illustrated in FIGURE 2.

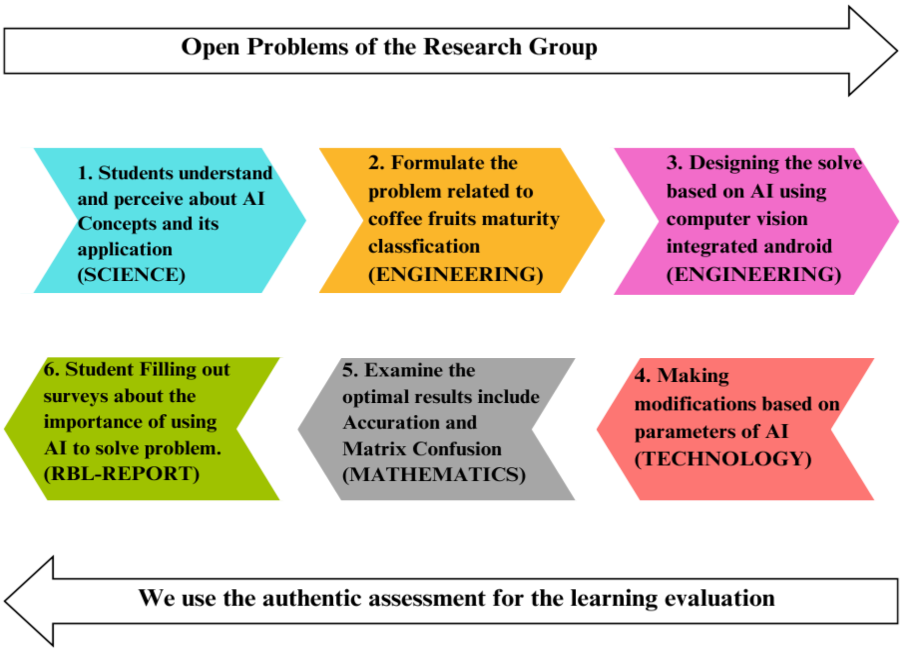

FIGURE 2. Syntax of RBL-STEM integrated with CNN and Computer Vision

RESULTS AND DISCUSSION

The validation results of the instruments used in this study showed that both the student task sheet and the AI literacy questionnaire had a high level of validity. Validation was conducted by three experts by assessing three main aspects, namely content, constructivism, and language. On the student task instrument, the following results were obtained: 82.5% for the content aspect, 90.5% for the constructivism aspect, and 85% for the language aspect. Meanwhile, on the AI literacy questionnaire instrument, the validation results showed that the content aspect scored 85%, the constructivism aspect 87%, and the language aspect 91%. Overall, these results indicate that both instruments have met the criteria of strong content validity and are suitable for use in conducting research. The high score on the constructivism aspect indicates that the instrument supports the research-based active learning approach, while the high language aspect ensures that the instrument is easily understood by students as respondents. the result of validation described on TABLE 2.

TABLE 2. Average Score of Pretest - Posttest of Scientific Literacy

Instrument	Content	Construct	Language
Student Task	82.5%	90.5%	85%
Questionnaire	85%	87%	91%

Analysis of AI concepts in RBL-STEM approach is carried out with project-based assignments that are oriented towards research activities. The results of the AI literacy test in the form of average score data before and after the implementation of the RBL-STEM model were analyzed for mean, Standard Deviations (SD) and mean difference. The Wilcoxon signed-rank test was applied, with a maximum score of 100 points. The results are described in TABLE 3. Furthermore, this research will present indicators of AI literacy embedded with problems posed. Indicators of AI Literacy are given in TABLE 4.

TABLE 3. Means, standard deviations, and Wilcoxon signed-rank test Z-scores

Pretest		Posttest		Result	
Mean	**SD**	**Mean**	**SD**	**Mean Difference**	**Wilcoxon signed rank-test**
38.33	13.41	71.49	9.47	33.16	-8.46

Note. N = 139; *p < 0.05; **p < 0.01; ***p < 0.001.

TABLE 4. Element, Descriptions and Indicators of AI literac

Element	Description	Indicators
Analysis of AI concepts	Analysis of AI concepts on the problem in coffee fruit maturity classification using RBL-STEM	Students' ability to understand, identify and analyze important details to find representations (ideas) for solutions.
Designing AI applications	Designing AI applications based on computer vision integrated with Google Teachable Machine	Students' ability to make appropriate designs and steps to solve the problem by creating a simple computer program through computer vision integrated with Google Teachable Machine.
Making modifications based on parameters of AI	Making modifications on Google Teachable Machine	Students' ability to modify the parameters in the Google Teachable Machine application which include epoch, learning rate, and batch size to produce optimal AI applications. These parameters modified will produce different results which are Accuration (Regresion coefficient value) and Confusion Matrix. Students must modify these parameters until find the optimal accuracy of the results
Psychological readiness and Ethical considerations to apply AI	Filling out surveys on the importance of valid data in developing AI-based applications in coffee fruit maturity classification.	Students’ ability to demonstrate their knowledge about AI Literacy by understanding the concepts, designing application based on AI, and solve problem using AI application

The complete AI Literacy analysis includes four important components used to evaluate students’ cognitive abilities in understanding and applying AI. The results provide a comprehensive distribution of pretest and posttest scores, as described in TABLE 5

TABLE 5. Analysis of Element AI literacy

Element of AI Literacy	Pretest Score	Posttest Score
Analysis of AI concepts	30.52	78.24
Designing AI applications	42.25	77.58
Making modifications based on parameters of AI	44.35	67.58
Psychological readiness and Ethical considerations to apply AI for problem-solving	36.21	62.57

According to Kong et al. (2021), AI literacy involves several key aspects. These include (1) Analysis of AI concepts on the problem of classification of coffee fruit maturity using RBL-STEM; (2) Designing AI applications based on computer vision integrated with Google Teachable Machine; (3) Making modifications based on parameters in the Google Teachable Machine application which include epoch, learning rate, and batch size to produce optimal AI applications; (4) Filling out surveys on the importance of valid data in AI-based coffee fruit classification. The results presented in the table clearly indicate a significant improvement in students' AI Literacy after conducting RBL-STEM in their learning. The pretest and posttest scores of the four indicators demonstrate a consistent upward trend, suggesting that implementation of RBL-STEM with Google Teachable Machine had a positive impact on students' academic achievement. On pretest scores, students obtain low scores especially in indicators of analysis of AI Concept and Psychological readiness and Ethical considerations to apply AI for problem-solving, which in 30.52 and 36.21, indicates that students had low understanding of what AI is and its benefit to solving real-world problems. Although they already know and have had exposure to AI in educational context, it does not mean they can assist AI into their academic learning in the classroom and show off psychological readiness. These results indicate that RBL-STEM integrated Google teachable machine was effective in enhancing students' AI Literacy, which is reflected in their posttest outcomes. The consistent improvement across all cases of indicator supports the conclusion that RBL-STEM provided meaningful support to the students. It can be inferred that the instructional approach or educational strategy implemented was instrumental in facilitating improved AI literacy and knowledge retention, as evidenced by the increased posttest scores.

AI Literacy measurement also involves qualitative methods using questionnaires to determine the understanding of the use of AI in solving real-world problems, especially in coffee fruit classification. The questionnaire on AI Literacy includes three indicators: Analysis of AI comprehension in solving problems, ability to integrate research activities in learning and problem solving, and self-control management using AI in everyday life. Each of these indicators has sub-indicators or supporting factors. The result of the questionnaire on AI literacy served in the mean value for each indicator, as shown in TABLE 6.

TABLE 6. The result of the questionnaire of AI literacy

Indicators	Factors	Mean Value	
Analysis of understanding of the use of AI in solving problems	Use and apply AI	4.71	3.88
	Know and understand AI	3.68	
	Detect AI	3.58	
	AI Ethics	3.56	
Ability to integrate research activities in learning and problem solving	Problem Solving	3.27	3.21
	Learning	3.15	
Self-control management using AI in daily life	AI Persuasion Literacy	3.25	3.35
	Emotion Regulation	3.45	
Average Score			3.48

AI Literacy has been enhanced among science education students after conducting RBL - STEM with Google Teachable Machine into learning activities in the classroom on solving coffee fruits classification. The enhancement can be seen through posttest scores that all of the indicators have increased significantly. Besides on the posttest score, qualitative methods based on questionnaire results remain to be considered. Questionnaire involves three indicators presented in Table 6, and it can be seen that the first indicator obtains the highest scores among the others. Students can understand what AI is, its benefits and its ethics. Understanding AI concepts is essential for students developing AI literacy. Based on that, students already assist AI in their learning activities to support and encourage their knowledge and capability to solve problems in their learning activities, even real-world problems. Despite all the ease of AI supporting students' learning, problems remain that students can not control themselves to not rely on AI fully, it can be seen on the third indicator, indicating that students emphasize using AI to solve all of the problems without trying to solve based on their creativity. Lastly, the second indicator got the lowest scores among the others, indicating that students need to optimize their ability to conduct research activities to solve problems over AI. Artificial intelligence brought students further to solve problems easier, make students can catch new learning experiences, and bring students to adapt with the digital age as well. Students already know and understand how to solve problems using AI with research activities in their learning, however there is a need to optimize students self-control management.

The student of this research was conducted in the science education study program for undergraduate students. RBL-STEM is used as a learning model to achieve indicators of AI literacy. The employment of Computer Vision in the present study, which pertains to the classification of coffee fruits utilizing Google Teachable Machine (GTM) and Research-Based Learning (RBL-STEM) approach, furnishes students with profound insight into the underlying physics principles of this technology. Among the most salient concepts is optics, particularly the interaction of light with object surfaces. Students already know and understand physics concepts about optical and colorimetric wavelengths of light, however there is no extension into the real-world problems. The classification process utilizes the color and texture of the coffee fruit, determined by the wavelength of light reflected and absorbed by the fruit surface. Light is an electromagnetic wave that can propagate without passing through a medium. Light is divided into invisible light and visible light; this is due to the different wavelengths of light. Colors (visible light) can be seen by the eye because there is a reflection of color from the light source (sunlight). The reflected color is the color captured by the eyes and recognized as a color, the illustration can be seen in FIGURE 3. This phenomenon can be elucidated through optical theory, where the color variations detected by the camera are influenced by the light spectrum used and the lighting angle applied during image capture.

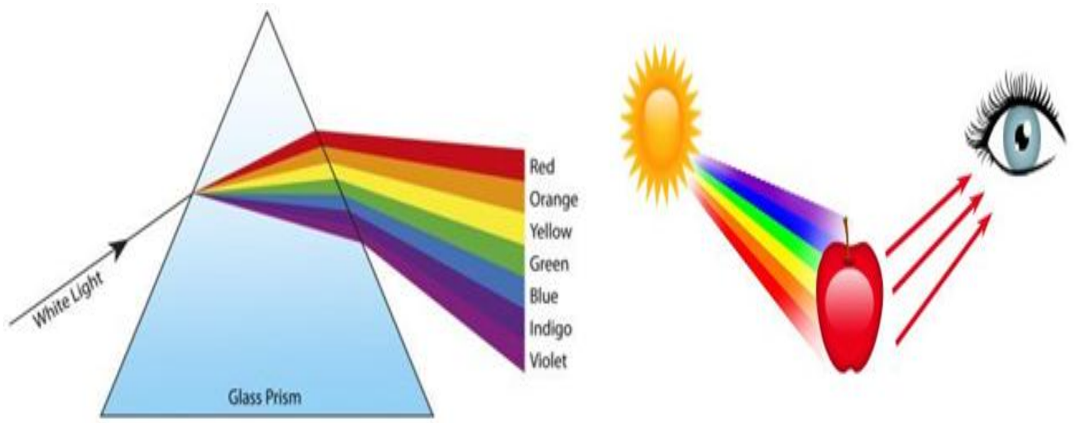

FIGURE 3. Light Reflected and Recognized as Colors

In addition to optics, the concepts of image resolution and sharpness play an instrumental role in the success of AI-based classification systems. The quality of the image produced by a camera is contingent on physical factors, including light diffraction, camera sensor quality, and lens quality. Higher image resolution facilitates the discernment of textural details in coffee fruits, thereby enhancing the model's capacity to accurately differentiate between ripe and unripe fruits. Within a learning environment, students can conduct experiments with diverse resolutions and lighting conditions to discern how these physical parameters influence the performance of Computer Vision systems. Moreover, the concepts of kinematics and dynamics can be linked to image processing in Computer Vision systems. For instance, when coffee fruits are analyzed in motion, such as during a fall or rotation on a table, changes in the position and angle of light can affect the classification results. This experiential learning approach offers an opportunity for students to comprehend how an object's movement can influence the precision of AI-based recognition systems. Based on figure 3, the illustration of colors recognition is conducted in this research to recognize ripeness of coffee fruits through its colors using camera integration with Google Teachable Machine based on Convolutional Neural Network (CNN). Implementation of image recognition can be seen in Figure 4 below. Students are required to brainstorm a problem that could be solved with AI-enabled tools. Then, the lecturer demonstrates the use of Google Teachable Machine (for image, sound, and pose recognition), which is powered by CNNs algorithm through computer vision. This tool is either open-source or institutionally subscribed, ensuring accessibility for all participants.

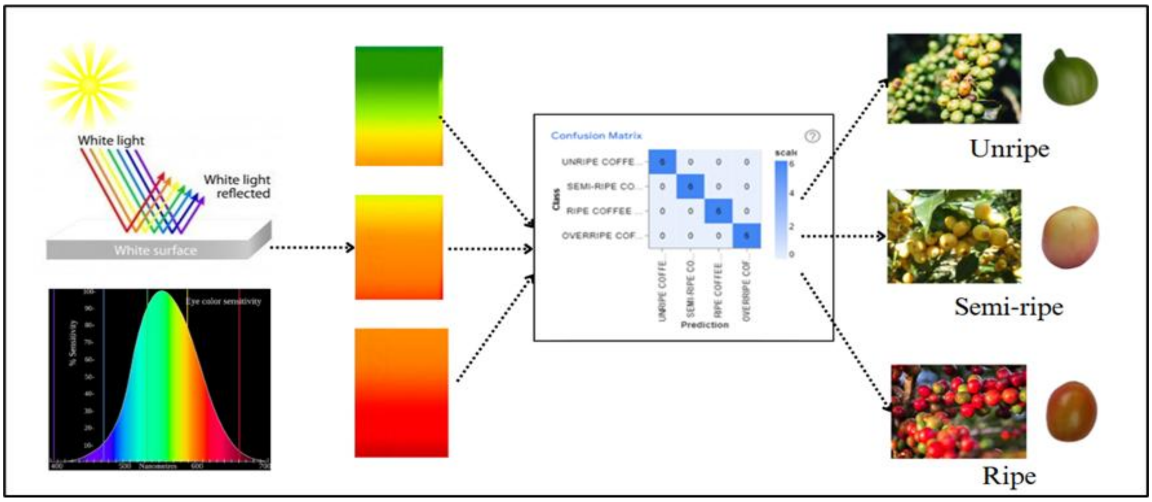

FIGURE 4. Implementation CNN in Light Reflection into Colors

In this research, the ripeness of coffee fruit classification was chosen as the topic of the problem. The dataset of images used in Google Teachable Machine was collected manually using a camera. Students took images of each category of coffee fruits and then uploaded it to Google Teachable Machine. In this platform, students can modify, create, and train the model by resetting the epoch, batch size, and learning rate to produce the optimal regression coefficient value and confusion matrix results. In addition, the lecturer guided students to consider the ethical implications of their AI-based solutions and how to mitigate these concerns. Students were supposed to discuss ethical implications not only for the final solution product, but also for data collection, data processing, and other stages of the overall AI. To enhance AI literacy, students integrate the concept of Convolutional Neural Networks (CNNs), a subset of machine learning specialized in image recognition and classification. This process involves using Google Teachable Machine, a computer vision application powered by CNN algorithms. An illustration of implementing computer vision is described in FIGURE 5.

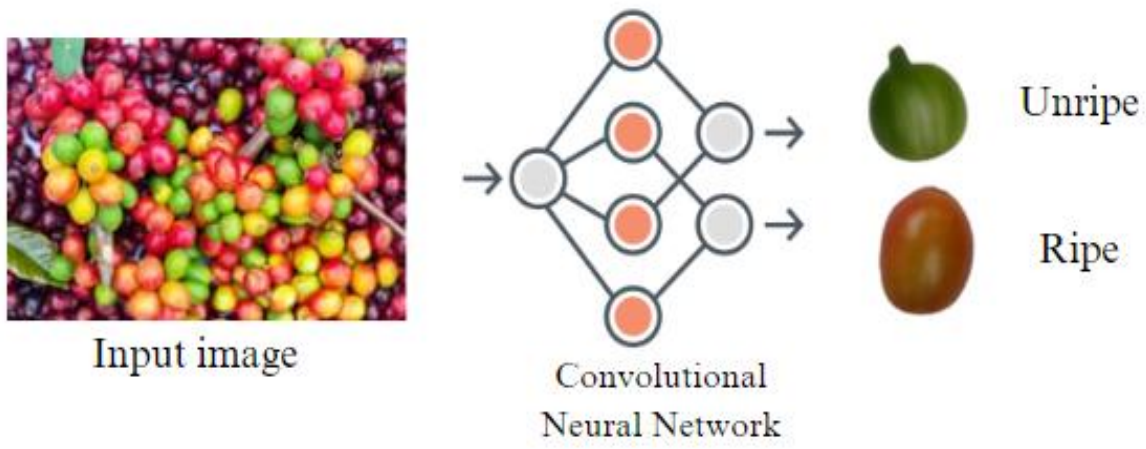

FIGURE 5. Illustration of Implement Computer Vision

A framework design of the development CNN-based computer vision applications using Google Teachable Machine is illustrated in FIGURE 6. The first stage in designing a CNN-based computer vision application using the Google Teachable Machine platform involves collecting original data of Robusta and Arabica coffee fruit images. The collected images are classified into four maturity stages: unripe, semi-ripe, ripe, and overripe. Robusta and Arabica coffee were selected due to their significance as key commodities in Jember. Once the images are gathered, they are uploaded to the Google Teachable Machine platform, where classification labels are assigned accordingly. On this platform, students can refine and train their models by adjusting key parameters such as Epoch, Batch Size, and Learning Rate. These adjustments help improve the model's accuracy, optimize the regression coefficient, and enhance the confusion matrix results. By experimenting with different settings, students gain hands-on experience in developing AI models while also understanding the impact of parameter tuning on performance.

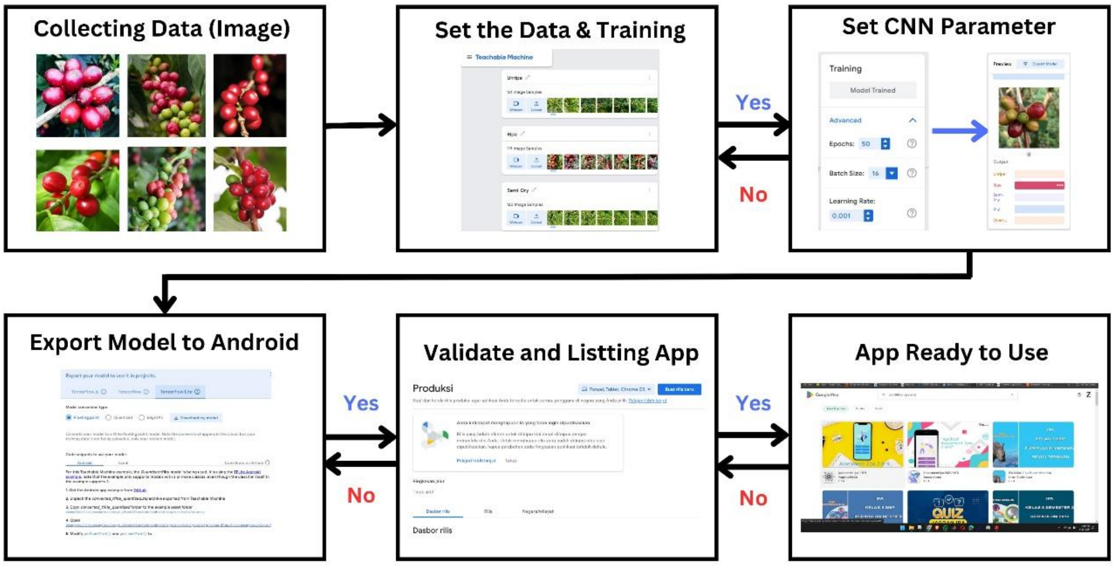

FIGURE 6. Framework design of Development Computer Vision Application based on Google Teachable Machine

Analysis of AI concepts in RBL with a STEM approach is carried out with project-based assignments within the research activities. In the process, students apply AI concepts to design computer vision system based on Google Teachable Machine. Student's assessments were designed to evaluate a comprehensive understanding of AI based on RBL-STEM-based learning scenarios. Pre- and post-tests were administered to measure the impact of this approach on AI literacy. The result found a significant effect on AI literacy. The analysis of AI literacy consists of four key components, including (1) analyzing the AI concepts relevant to the problem, (2) designing AI applications for AI-based product development, (3) modifying CNN parameters to optimize performance, and (4) assessing psychological readiness and ethical considerations in AI implementation.

The first stage involved grasping essential AI concepts for developing AI-driven solutions. Students examined the physical and visual characteristics of coffee fruit maturity, including how color variations indicate ripeness. They also studied CNN fundamentals and how machine learning models process image data. When designing AI applications for image recognition, students focused on gathering high-quality image data representing different maturity levels of coffee fruits. They experimented with key model parameters such as dataset size, number of training epochs, learning rate, and batch size to refine their models. To improve classification accuracy, students modified CNN parameters within Google Teachable Machine, gaining hands-on experience in optimizing AI models. According to research results, students performed best in designing AI applications, while their lowest scores were in understanding AI ethics and psychological readiness for AI adoption.

Students perceived a significant improvement in their ability to design AI products through the implementation of RBL-STEM in learning activities. It showed in the result both the test items and the overall student survey, which indicated significant improvement in students' AI literacy skills. The use of the RBL model facilitates students in developing AI Literacy skills by integrating research activities in which students are able to create AI-based. Meanwhile, the STEM approach helps students develop and integrate Science skills in terms of coffee plant quality, using technology in making products in the form of Google Teachable Machine-based applications, and engineering processes, which involve reverse engineering to identify obstacles and make modifications for optimal application performance.

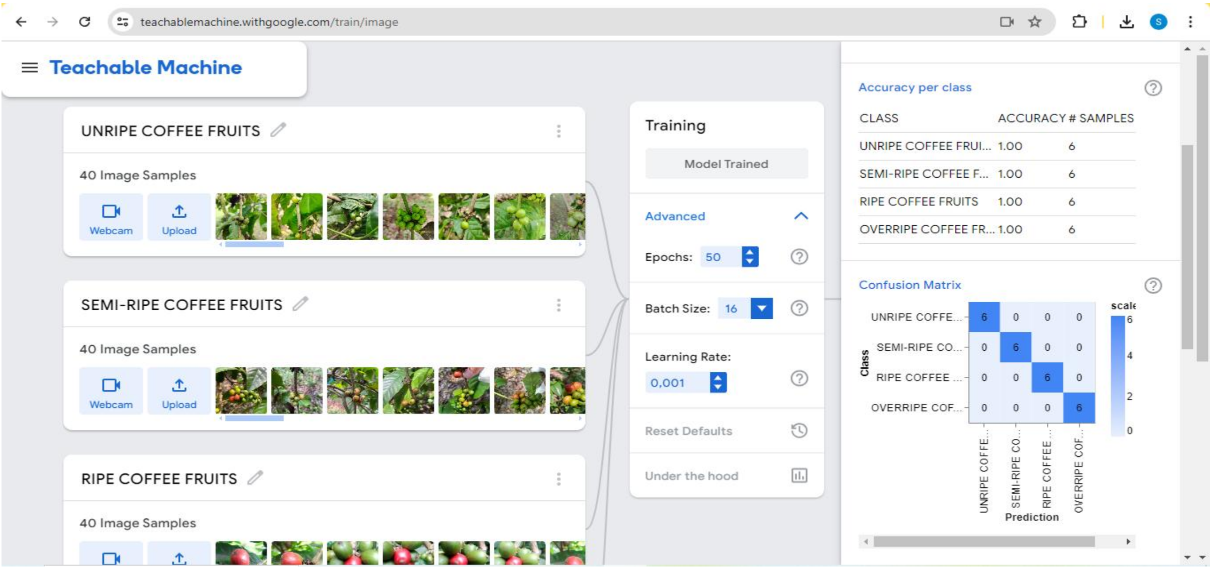

FIGURE 7. Result Interface of Google Teachable Machine in Image Recognition

In the AI ethics section, students are also taught good ethics in using AI including in the process of collecting coffee fruit data from original data. AI ethics is also emphasized in student honesty when developing applications, ensuring they do not falsifying important parameters in AI. The mathematical aspects related to numerical analysis in the CNN process was involving epochs, learning rates and batch sizes. These parameters affected the results as presented in the FIGURE 7. The result demonstrates that RBL-STEM is an effective and efficient collaboration in developing student competence in using AI to solve coffee fruit maturity classification problems. This study also proves that AI literacy improved through the implementation of the RBL-STEM learning model.

The implementation of a RBL model with a STEM approach plays an important role in enhancing students' literacy. It supports their interest in learning and researching AI by providing hands-on experience with Google Teachable Machine platforms. Additionally, it also encourages students to develop their higher order thinking, creative thinking, critical thinking, and computational thinking skills, which are fundamental for developing AI solutions. To determine their understanding, this study also conducted qualitative techniques using surveys. The surveys allow students to explore how AI can be used to address real-world challenges, with a focus on accurately classifying coffee fruit maturity. The survey results include four important factors including the ability to use and implement AI, knowledge and understanding of AI, the ability to identify AI-driven tasks and processes, and the importance of understanding ethical AI usage. Additionally, the ability to integrate research activities also includes problem solving skills and a deep understanding about image recognition, which is the basis for making AI using CNN techniques and supporting 21 century skills (Ab Kadir, 2017 ; Fensham & Bellochi, 2013). Problem solving skills are crucial to build research activities carried out by students in designing AI-based applications. Students will not be able to plan, implement, evaluate, and develop AI-based products that have been made without strong problem solving skills (Sanders, 2002; Schultz & Seele, 2002; Gamayun & Korniichuk, 2020). The ability to be persuasive in using AI and regulating student emotions is needed to avoid cheating in using the data analyzed or being trained data in making AI-based applications. In this case, honesty is needed in taking data, and using data.

CONCLUSION

This study aims to improve the artificial intelligence (AI) literacy of science education students through the application of the Research-Based Learning (RBL) learning model integrated with the STEM approach, using Google Teachable Machine as a computer vision-based learning media. This study focuses on the utilization of AI to solve real problems in agriculture, specifically in the classification of coffee fruit maturity levels. The results showed a significant improvement in students' AI literacy, as indicated by the increase in pretest to posttest scores, as well as mastery of AI concepts through CNN-based projects. Students not only understand the working principles of AI and its ethical concepts, but also demonstrate the ability to build, train, and optimize AI models using Google Teachable Machine with parameters such as epoch, batch size, and learning rate, to achieve a correlation coefficient above 0.9. In addition to improved AI literacy, students also developed 21st century skills such as critical thinking, problem solving, and scientific research. However, students' psychological readiness scores for AI use were still low, indicating the need for support in the form of digital ethics workshops and training.

The RBL-STEM approach with AI technology support has important pedagogical implications, especially for physics and science educators. It encourages active, contextualized and exploratory learning that strengthens mastery of scientific content as well as technological literacy. The use of Google Teachable Machine allows students to directly experience the application of science and physics concepts in AI systems, such as classification of experimental images or modeling of physics phenomena. However, this study has limitations in the context of the classification object (coffee fruits), limited generalizability of results, risks of technological evolution, and ethical challenges related to data privacy and equal access to technology. Therefore, further studies are needed to adapt and test this approach in a broader educational context and population, as well as strengthen teacher readiness and supporting policies for the integration of AI literacy in STEM education.

LIMITATION

This study has several limitations that should be considered, particularly regarding its transferability to other topics, reproducibility, and access to technology in varied educational contexts. Firstly, not all physics topics may be suitable for the integration of Google Teachable Machine and the RBL-STEM approach to enhance AI literacy. For example, topics such as electricity or mechanics, which involve complex mathematical modeling and abstract reasoning, may not align well with the image-based classification capabilities. Therefore, the instructional approach used in this study may require adaptation before being applied. Secondly, reproducibility is limited by contextual factors, including students' prior exposure to technology or digital literacy. In this study, the participants were undergraduate students from a single university who had sufficient support and guidance to engage with the programming activities. However, in different settings, especially those with limited instructor expertise and less digital exposure, the outcomes may be different. Thirdly, access to technology or the internet remains a challenge. Google Teachable Machine requires consistent internet connectivity and modern devices. In educational institutions or regions with limited resources, students may struggle to fully engage with AI-integrated instructional designs. As a result, the generalizability of this study's findings to under-resourced or technologically constrained environments may be limited. Future research should consider involving a broader range of scientific topics, more diverse student populations, and varied institutional contexts. Longitudinal studies could also provide valuable insights into the sustained development of students' AI literacy through the integration of AI tools like Google Teachable Machine in STEM education.

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REFERENCES

Bhargava, A. and Bansal, A. (2018). Fruits and vegetables quality evaluation using computer vision: A review. *Journal of King Saud University – Computer and Information Sciences*, 33(3), pp. 243–257. doi: https://doi.org/10.1016/j.jksuci.2018.06.002

Carney, M., Webster, B., Alvarado, I., Phillips, K., Howell, N., Griffith, J., Jongejan, J., Pitaru, A. and Chen, A. (2020). Teachable Machine: Approachable web-based tool for exploring machine learning classification. Extended Abstracts of the 2020 *CHI Conference on Human Factors in Computing Systems*, pp. 1–8. doi: https://doi.org/10.1145/3334480.3382894

Dafik. Kadir, N., Maryati, T., Sufirman, N. and Ridlo, Z.R. (2023). The analysis of the implementation of RBL-STEM learning materials in improving student's meta-literacy ability to solve wallpaper decoration problems using local antimagic graph coloring techniques. *Heliyon*, 9(6), p.e17433. doi: https://doi.org/10.1016/j.heliyon.2023.e17433

de Oliveira, E.M., Leme, D.S., Barbosa, B.H.G., Rodarte, M.P. and Pereira, R.G.F.A. (2016). A computer vision system for coffee beans classification based on computational intelligence techniques. *Journal of Food Engineering*, 171, pp. 22–27. doi: https://doi.org/10.1016/j.jfoodeng.2016.01.001

Ding, Y., Wang, L., Li, Y. and Li, D. (2018). Model predictive control and its application in agriculture: A review. *Computers and Electronics in Agriculture*, 151, pp. 104–117. doi: https://doi.org/10.1016/j.compag.2018.06.004

Gita, R.S.D., Adhim, F., Jayawardana, H. and Hariyanto, F. (2024). Development of Android-based E-learning platform with RBL-STEM approach to improve digital literacy. *Jurnal Penelitian Pendidikan IPA*, 10(10), pp. 7597–7605. doi: https://doi.org/10.29303/jppipa.v10i10.8901

Gomiero, T. (2018). Agriculture and degrowth: State of the art and assessment of organic and biotech based agriculture from a degrowth perspective. *Journal of Cleaner Production*, 197, pp. 1823–1839. doi: https://doi.org/10.1016/j.jclepro.2017.03.237

Hossain, M.A. and Alam Sajib, M.S. (2019). Classification of image using convolutional neural network (CNN). *Global Journal of Computer Science and Technology*, pp.13–18. doi: https://doi.org/10.34257/gjcstdvol19is2pg13

Kasinidou, M. (2023). AI literacy for all: A participatory approach. *In: Proceedings of the 2023 Conference on Innovation and Technology in Computer Science Education*, Vol. 2, pp.607–608. doi: https://doi.org/10.1145/3587103.3594135

Khan, A., Sohail, A., Zahoora, U. and Qureshi, A.S. (2020). A survey of the recent architectures of deep convolutional neural networks. *Artificial Intelligence Review*, 53. doi: https://doi.org/10.1007/s10462-020-09825-6

Khan, A.I. and Al Habsi, S. (2020). Machine learning in computer vision. *Procedia Computer Science*, 167, pp.1444–1451. doi: https://doi.org/10.1016/j.procs.2020.03.326

Kong, S.-C., Cheung, W.M.-Y. and Zhang, G. (2021). Evaluation of an artificial intelligence literacy course for university students with diverse study backgrounds. *Computers and Education: Artificial Intelligence*, 2, p.100026. doi: https://doi.org/10.1016/j.caeai.2021.100026

Kurz, T.L., Jayasuriya, S., Swisher, K., Mativo, J., Pidaparti, R. and Robinson, D.T. (2024). The impact of Teachable Machine on middle school teachers' perceptions of science lessons after professional development. *Education Sciences*, 14(4), p.417. doi: https://doi.org/10.3390/educsci14040417

Lamsal, R.R. and Lamsal, S. (2025). Introducing image classification through no-code Teachable Machine platform: An intuitive approach for novice learners. *Preprint on ResearchGate*.

Matsuzaka, Y. and Yashiro, R. (2023). AI-based computer vision techniques and expert systems. AI, 4(1), pp.289–302. doi: https://doi.org/10.3390/ai4010013

Ramos, P.J., Prieto, F.A., Montoya, E.C. and Oliveros, C.E. (2017). Automatic fruit count on coffee branches using computer vision. *Computers and Electronics in Agriculture*, 137, pp.9–22. doi: https://doi.org/10.1016/j.compag.2017.02.011

Ridlo, Z.R., Dafik. Waluyo, J. and Yushardi. (2024). Exploring the impact of makerspace-based learning materials on students' computational thinking skills: Using machine learning to address challenges in smart coffee agroforestry. *Edelweiss Applied Science and Technology*, 8(5), pp.52–73. doi: https://doi.org/10.55214/25768484.v8i5.1630

Ridlo, Z.R., Indrawati. Afafa, L., Bahri, S., Kamila, I.S. and Rusdianto. (2021). The effectiveness of research-based learning model of teaching integrated with computer simulation in astronomy course in improving student computational thinking skills. *Journal of Physics: Conference Series*, 1839(1), p.012027. doi: https://doi.org/10.1088/1742-6596/1839/1/012027

Russell, S.J. and Norvig, P. (2021). Artificial Intelligence: A modern approach. 4th ed. Pearson.

Sagala, T.R., Aulia, M.P., Haryanti, S.R. and Joharis, M. (2025). Improving AI literacy competence among European students: Implementation recommendations for Indonesian student. *International Journal of Educational Development*, 2(2), pp.57–67. doi: https://doi.org/10.61132/ijed.v2i2.300

Sarwanti, S., Sariasih, Y., Rahmatika, L., Islam, M.M. and Riantina, E.M. (2024). Are they literate on ChatGPT? University language students' perceptions, benefits and challenges in higher education learning. Online Learning, 28(3), pp.105–130. doi: https://doi.org/10.24059/olj.v28i3.4599

Tzirides, A.O., Zapata, G., Kastania, N.P., Saini, A.K., Castro, V., Ismael, S.A. and Kalantzis, M. (2024). Combining human and artificial intelligence for enhanced AI literacy in higher education. *Computers and Education Open*, 6, p.100184. doi: https://doi.org/10.1016/j.caeo.2024.100184

Wan, P., Toudeshki, A., Tan, H. and Ehsani, R. (2018). A methodology for fresh tomato maturity detection using computer vision. *Computers and Electronics in Agriculture*, 146, pp.43–50. doi: https://doi.org/10.1016/j.compag.2017.05.017

Yi, Y. (2021). Establishing the concept of AI literacy. *JAHR*, 12(2), pp.353–368. doi: https://doi.org/10.1007/s13198-020-00930-7