Integrating Computer Vision and Deep Learning for Sustainable Development in Engineering Education: A Case Study in Electronics and Circuits Laboratories

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Abstract

With the promotion of global educational equity and quality education under the United Nations Sustainable Development Goals (SDGs), technology-assisted instruction has become a critical pillar in engineering education. This study aims to apply computer vision and deep learning technologies to electronics circuit lab teaching, enhancing learners efficiency and addressing fairness issues in experimental assessment. Traditional assessment methods for electronics experiments focus on experiment success or failure, which may fail to accurately reflect the efforts of some students. To address this, the study developed an intelligent experimental assessment system based on computer vision, capable of accurately identifying the number and position of components amidst environmental noise. Combined with deep learning for experiment classification, the system provides dynamic scoring and subsequent operational suggestions based on the recognition results, thereby improving learners understanding and interest in electronics experiments. The system leverages image processing to filter external noise and accurately extract key experimental features. To enhance adaptability and versatility, the system supports automated recognition and scoring across various experimental scenarios. Experimental results demonstrate that this system not only reduces the workload of educators but also significantly increases learner engagement and learning outcomes. The study contributes to integrating technological innovation into engineering education, achieving the SDGs vision of educational equity and quality education.

Keywords: Technology-Assisted Engineering Education, Computer Vision in Experimental Assessment, Deep Learning for Fair Scoring, Sustainable Development in Education

1. Introduction

With the implementation of the Education 4.0 policy, the integration of technology in education has become a key driver in achieving the Sustainable Development Goals (SDGs) [1], [2]. Launched by the United Nations in 2015, the SDGs aim to address global social, economic, and environmental challenges while ensuring a sustainable pathway for future generations [3]. Among these goals, SDG4 is particularly relevant to education, as it emphasizes accessible, inclusive, and high-quality education for all [4], [5]. This goal aligns closely with the aims of engineering education, especially in the context of improving hands-on experimental learning environments such as electronics and circuit laboratories.

Higher education institutions play a vital role in achieving these goals by fostering innovation and promoting equitable learning environments [6]. The exponential growth in sustainability-related publications reflects academia's increasing engagement in addressing the 2030 Agenda [7]. However, the challenge remains to translate these global goals into practical applications within specific educational contexts. For engineering education, this means integrating intelligent systems to improve instructional quality, assessment fairness, and learning outcomes.

In this light, SDG4's emphasis on lifelong learning and equitable access intersects with the evolving needs of engineering disciplines. Objectives such as advancing gender equality, fostering employability, and creating supportive learning environments directly relate to the goals of foundational technical courses, including electronics and circuit experiments [8], [8], [10]. These laboratory-based courses provide opportunities not only for technical knowledge acquisition but also for developing critical thinking and problem-solving skills in alignment with SDG9 (Industry, Innovation, and Infrastructure) and SDG12 (Responsible Consumption and Production) [11], [12], [13].

As noted in [14], education and media are key drivers of sustainable development mindsets. In engineering education, which addresses complex real-world problems, fostering such mindsets is particularly essential. Despite this, traditional laboratory courses face challenges in delivering innovative and resource-efficient teaching. Electronics and circuit laboratories, in particular, encounter persistent issues related to outdated assessment methods, inefficient feedback mechanisms, and unequal learning opportunities [15], [16]. These issues limit student engagement and hinder the realization of sustainability objectives within the classroom.

A relevant illustration of hands-on STEM education's importance can be seen in the "miniXplore" initiative by the Technical Museum Vienna [17]. While targeting early learners, this program exemplifies how interactive, fail-safe, and explorative environments can stimulate interest and creativity—values equally crucial in engineering education. Electronics laboratories, as foundational courses, must evolve toward similar learner-centered, feedback-rich models that align with SDGs and modern educational expectations.

However, electronics laboratory courses often rely on binary grading—either the circuit works or it doesn't—which fails to reflect students' efforts or partial correctness. This creates motivational barriers, particularly for beginners. The increasing class sizes exacerbate the issue, making manual grading labor-intensive and less consistent [18], [19]. GenAI tools offer a promising solution by providing real-time diagnostic feedback, automated scoring, and adaptive learning support. In this context, the integration of computer vision and AI technologies into electronics experiments not only aligns with sustainable education objectives but also directly addresses fairness, efficiency, and learner engagement [20], [21].

This study builds upon these foundations by developing an intelligent experimental assessment system that leverages deep learning and computer vision. The system is designed to recognize components and their placement on breadboards, assess correctness, and offer dynamic, personalized feedback. This supports students in understanding errors, refining skills, and achieving better learning outcomes. Moreover, the system aligns with the goals of Industry 4.0 and future transitions toward Industry 5.0 by promoting competency-based learning, automation in assessment, and data-informed feedback loops [22], [23].

To remain responsive to industrial and educational evolution, many universities have adopted Competency-Based Education (CBE) and Competency-Based Curriculum (CBC) approaches [24], [25]. These models aim to equip students with real-world skills and provide flexible learning paths. This study contributes to such efforts by offering a system that not only evaluates student performance with precision but also supports curriculum innovation. Through the integration of intelligent technologies, this research proposes a scalable and sustainable approach to laboratory instruction, thereby addressing educational equity, resource efficiency, and pedagogical innovation in engineering education [26], [27], [28], [29], [30], [31].

The introduction of AI-based systems in electronics laboratories represents a practical and impactful step toward achieving SDG4 in engineering education. This study presents a concrete implementation of such a system, with evidence supporting its effectiveness in promoting fairness, accuracy, and student engagement in assessment practices.

To address these challenges, this study developed an intelligent grading and learning assistance system specifically designed for electronics and circuit laboratory courses by integrating computer vision and deep learning technologies. The system aims to enhance teaching efficiency, ensure educational equity, and promote sustainable resource use, aligning with relevant Sustainable Development Goals (SDGs). The primary objective is to transform the teaching methods of electronics and circuit laboratory courses through technological innovation. The specific goals include:

1. Promoting Educational Fairness through a Diversified Grading Mechanism (Aligned with SDG 4: Quality Education)

Traditional binary grading mechanisms overlook the effort and details involved in experimental processes [32], [33]. As illustrated in Fig. 1, this system leverages computer vision technology to analyze component placement, quantity, and connections during experiments, providing granular grading. For example, students who complete most of the operations correctly but fail due to minor errors can receive near-full marks, objectively reflecting their learning outcomes and promoting educational fairness.

2. Integrating Innovation with Foundational Education to Support Engineering Education Innovation (Aligned with SDG 9: Industry, Innovation, and Infrastructure)

The system incorporates deep learning models to automatically identify multiple types of experiments. By analyzing the types, quantities, and layouts of components, the system can accurately distinguish different experiments and offer specific operational suggestions [34]. This not only enhances the system's flexibility and versatility but also promotes the application of knowledge and innovative practices in electronics and circuits, laying the groundwork for future intelligent laboratories [35].

3. Enhancing Resource Utilization Efficiency and Reducing Experimental Material

Traditional manual grading often requires repeated debugging and adjustments, increasing hardware equipment and material consumption. This system minimizes material waste through digital grading and assistance, helping students identify and correct errors at an early stage [36]. Its automation significantly reduces time and human resource costs in teaching, further advancing the sustainable use of educational resources [37].

4. Improving Student Learning Experiences and Stimulating Innovative Thinking

Another core function of the system is to provide detailed improvement suggestions based on grading results. For example, when students fail due to improper wiring, the system can combine image data to analyze specific errors, helping students quickly identify and correct problems [38], [39]. This design not only lowers the learning barrier but also inspires students' interest and enthusiasm for electronics and circuit experiments, enhancing their innovative capabilities in the engineering field [40].

5. Supporting the Development of Sustainable Educational Models

The proposed system aligns with the requirements of SDGs by improving educational quality while focusing on efficient resource utilization and promoting innovative technologies [41]. It offers feasible solutions for future engineering education, fostering deeper integration between education and societal needs [42].

In the future, this system can be expanded to other engineering education courses, such as mechanical design, materials testing, and automation control, enabling broader educational innovation [43]. By integrating with virtual laboratory and remote education technologies, the system can provide cost-effective engineering education solutions for regions with limited educational resources, promoting educational equity and inclusivity [44], [45].

2. Using artificial intelligence and deep learning to promote the sustainable development of engineering education

Artificial intelligence (AI) plays a crucial role in advancing sustainable practices within Industry 4.0 technologies. AI simulates human intelligence to perform tasks such as learning, reasoning, problem-solving, and decision-making [46]. The emergence of AI tools is transforming engineering practice, research, and education [47]. Early milestones include the Turing Test, which evaluates whether a machine can mimic human intelligence [48]. Turing emphasized that computer-assisted teaching should refine students thought processes and help overcome learning challenges [49]. By the 1960s, computer-based teaching experiments began, offering personalized instruction, such as adapting linear algebra lessons to individual learning paces [50]. Later advancements added tailored content and real-time feedback, significantly improving instructional effectiveness [51]. Today, AI-powered systems analyze text and images to provide meaningful feedback, making automated grading widely applicable in education and enhancing assessment efficiency and accuracy.

Higher education is undergoing significant transformation due to advancements in information technology [52]. Remote learning enabled by modern communication technologies has redefined the roles of teachers and students, positioning students as active learners who use technology to solve problems innovatively [53]. AI advancements are reshaping engineering education by analyzing student data to identify individual needs and create personalized learning paths. Deep learning enhances automated assessment systems, enabling efficient evaluation and targeted feedback. These tools support personalized learning, automate problem-solving, and transform how students grasp complex concepts and how educators guide learning [54], [55].

Advancements in AI and deep learning have expanded the potential of technology-assisted education to support sustainable engineering education [56]. For instance, Guo et al. highlighted that AI can automate data analysis to support decision-making and management processes, advancing SDGs [57]. Wang et al. identified four development areas for ChatGPT in manufacturing engineering: human-machine collaboration, knowledge management, design innovation, and engineering skills education [58]. Daun and Brings argued that ChatGPTs ability to generate code shifts the focus of software engineering education toward software design and architecture [59]. These technologies enhance teaching efficiency and foster innovation by optimizing resources and reducing repetitive tasks. Compared to traditional methods, technology-assisted education offers unparalleled flexibility and access to diverse content. Although face-to-face interaction may decrease, AI promotes personalized learning and provides teachers with effective support, particularly for students with special needs, thereby fostering equity and inclusivity [60].

Automated scoring systems have significantly advanced, achieving reliability on par with human evaluation [61]. AI-driven text scoring systems address inconsistencies in open-ended question evaluation and improve teaching efficiency. For instance, Wang et al. proposed a BiLSTM-based essay scoring system, while Li et al. developed a smartphone-based scoring tool using DeepLabv3+ [62]. In programming education, automated tools like Code Assessment Extension efficiently grade C++ assignments, meeting the rising demand in engineering disciplines [63]. Studies on AI applications, such as GPT-4 in discourse evaluation and manuscript review, show alignment with human reviewers, particularly for low-quality submissions [64]. Despite these advancements, challenges persist, including ensuring academic integrity and addressing student hesitations toward adopting AI tools. Research highlights factors like trust and concerns over automation influencing technology adoption [65], [66].

Understanding the psychological, cultural, and technical factors influencing AI adoption can improve its accessibility and acceptance. By addressing students concerns, educators can better integrate AI tools into learning environments, ensuring alignment with students engagement and readiness [67]. AI and deep learning technologies enhance teaching efficiency, redefine teacher-student interactions, and support personalized learning, automated assessments, and experimental teaching. These tools promote equitable resource distribution, enabling students to develop innovative skills and adapt to industry demands. By reducing repetitive tasks, educators can focus on advanced teaching and innovation, fostering sustainable education models [68]. As technology advances, AI and deep learning are set to drive engineering education, integrating technology with education and supporting global sustainability goals.

3. System Design and Implementation

This study leverages deep learning models to perform structured analysis of circuit boards. Based on the error types and component placement information output by the model, it generates operational recommendations. These recommendations include examples of correct wiring, possible error cause prompts (such as component polarity issues), and are visually presented to users within the system interface. Furthermore, to ensure the accuracy of the recommendations, the system dynamically calibrates itself using historical data, optimizing the model's classification and recommendation capabilities. This study highlights the potential applications of AI and deep learning in electronic circuit experiment education. These technologies not only optimize teaching processes but also reshape educational assessment paradigms [69], [70]. By leveraging intelligent systems, educators can reduce the burden of grading and experiment result validation, allowing them to focus more on fostering students' innovative abilities. Simultaneously, students benefit from diverse and adaptive learning environments, enabling them to acquire experimental skills more effectively while enhancing their learning interest and efficiency. More importantly, the application of AI and deep learning offers sustainable development opportunities for engineering education [71], [72]. The efficiency and versatility of intelligent teaching systems enable a more equitable distribution of educational resources, narrowing the educational gap between urban and rural areas or under-resourced regions. Additionally, these technologies facilitate a shift towards data-driven educational models through automated data analysis and real-time feedback, laying a solid foundation for the future of engineering education. As these technologies continue to mature, AI and deep learning are set to become indispensable drivers of progress in engineering education, contributing to the achievement of global educational sustainability goals [73], [74].

3.1 Overall System Architecture and Intelligent Methodology

This system leverages deep learning models to perform structured analysis of circuit boards. Based on the error types identified by the model and the placement information of components, it generates operational recommendations. These recommendations include examples of correct wiring, potential error cause hints (such as incorrect component polarity), and are visually presented to users through the system interface. Furthermore, to ensure the accuracy of the suggestions, the system dynamically calibrates using historical data, optimizing the model's classification and recommendation capabilities.

In introductory electronic circuit education, expecting learners to directly execute experiments based on complex circuit schematics is impractical [75]. To lower the learning curve, many electronic circuit textbooks adopt breadboard circuit diagrams, as seen in resources provided by platforms like ELECTROTHOUGHTS, Makezine, and Taiwan’s IoT education platform CAVEDU. Breadboard circuit diagrams provide beginners with an intuitive and operationally accessible reference, helping learners comprehend the connections between circuit components clearly while cultivating good practices for maintaining tidy and legible circuit boards, which lays a strong foundation for advanced learning.

This research focuses on the commonly used solderless breadboard as the core object for system recognition and evaluation. Regarding the application of computer vision in electronic circuit experiments, this study accounts for the fact that a single circuit design can involve hundreds of possible wiring configurations. For instance, experiments utilizing integrated circuits (ICs) may present diverse scenarios due to variations in pin connections, IC orientation, and wiring across rows, which increase the complexity of recognition tasks. Such uncertainties often lead traditional recognition systems to encounter false negatives or detection errors. To address these issues, this study imposes specific constraints on the placement rules of circuit board components to ensure the recognition system effectively processes experimental results and delivers accurate assessments. Moreover, the complexity of circuit board wiring is a major challenge for computer vision recognition; therefore, experimental conditions are designed to minimize unnecessary wiring interference [76], [77], [78].

To enhance recognition efficiency, the study introduces AI and deep learning technologies for component localization and analysis in electronic circuit experiments. Through deep learning models, such as convolutional neural networks (CNNs), the study achieves high-precision recognition and positioning of breadboard components [79], [80]. The adaptability of deep learning allows the system to handle diverse component arrangements, overcoming limitations faced by traditional computer vision systems and improving overall recognition stability and accuracy. This intelligent system not only boosts teaching efficiency but also creates a more learner-friendly environment, lowering the barriers to learning [81].

In specific experiments, the computer vision system identifies components based on a structured left-to-right, top-to-bottom arrangement on the circuit board. Components are divided into three sections: upper, middle, and lower, according to the board's separation regions. This structured approach ensures accurate relative positioning among components, especially in dense layouts where misplacement could lead to recognition errors and affect grading results [82]. To mitigate these issues, this study assumes users follow provided standard component distribution guidelines and that all components are functional, ensuring a stable and controlled experimental environment.

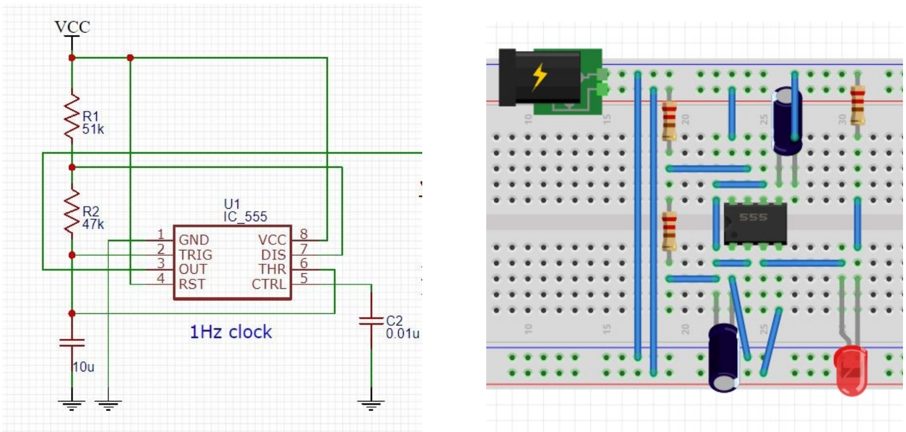

Fig 1. Circuit Diagram and Breadboard Circuit Diagram

3.2 Experimental Setup and Assumptions

Data preprocessing is a critical step in successfully implementing electronic circuit recognition [83]. Since images captured during experiments may be affected by noise, including external objects on the circuit board or variations in lighting conditions, the study employs a series of AI-based image processing techniques to ensure clean and suitable data inputs for the recognition system. To achieve this, the images are first converted to grayscale during preprocessing, which helps reduce computational load. This is followed by the application of Otsu's binarization algorithm combined with Gaussian blur to remove unnecessary details and enhance the clarity of the images [84], [85]. Morphological operations, such as opening operations, are used to effectively remove minor noise while preserving key features of the image. Finally, Canny edge detection and contour-finding techniques accurately identify the circuit board's boundaries and component regions. Notably, the integration of deep learning introduces additional possibilities for data preprocessing. By using deep learning models for feature extraction, the system achieves more precise component localization and contour detection, automatically adapting to different experimental environments and lighting conditions [86]. Furthermore, leveraging the capabilities of convolutional neural networks, the study automates the classification and analysis of data during experiments, significantly improving the efficiency of data processing [87], [88].

Beyond identifying components and circuit boundaries, the system extends its computer vision capabilities into an integrated assessment and feedback mechanism. Once components and their relative positions are extracted through edge detection and contour recognition, the system matches the observed layout against predefined templates stored in the experiment database. These templates represent correct circuit configurations and are indexed by experiment type, component quantity, and functional layout.

Through this comparison process, the system automatically evaluates the correctness of each component's type, placement, polarity, and connectivity. A dynamic scoring algorithm then calculates a partial or full score based on the level of match with the expected configuration. In addition to numerical scores, the system generates qualitative feedback by identifying the specific errors in the student's setup. For instance, if a capacitor is placed in the wrong row, the system flags the discrepancy and overlays a highlighted guide showing the correct placement directly on the circuit image interface.

This dynamic feedback loop is further enhanced by an AI-driven error classification module trained on historical data from previous users. By recognizing recurring error patterns, such as reversed polarity for LEDs or incomplete wiring connections, the system proactively suggests targeted instructional prompts and corrective tutorials. These are presented in real-time during the lab session, allowing students to reflect on mistakes and apply corrections immediately, thus reinforcing learning through active experimentation.

Additionally, the system logs each student's interaction data and error history, which can be used to adapt the difficulty level of future tasks or recommend supplementary exercises. This personalized feedback strategy not only increases engagement but also ensures a deeper understanding of the circuit design principles, fulfilling the system's dual function as both an evaluator and an intelligent tutor.

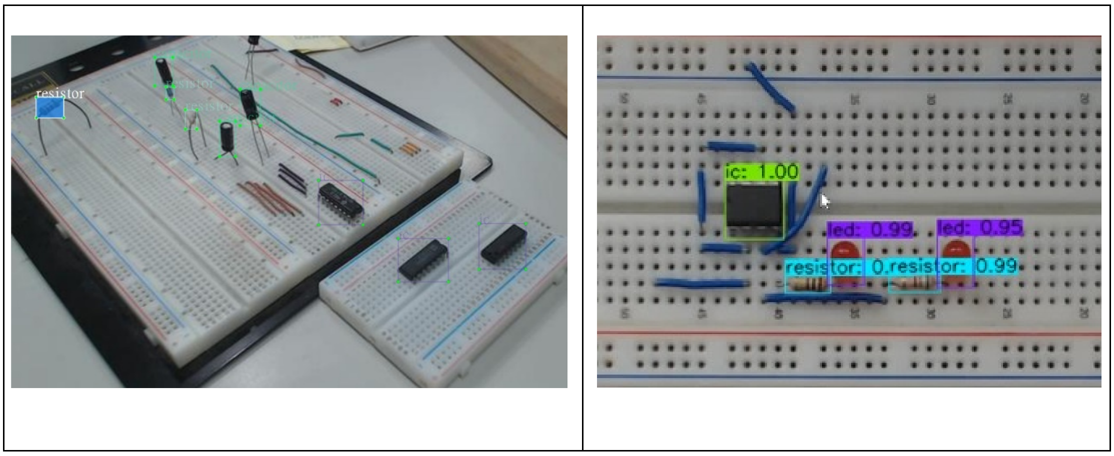

Fig 2. The Process by which an AI-assisted System Performs Component Identification and Error Detection on a Circuit Board.

3.3 Computer Vision Pipeline and AI-Based Preprocessing

This study targeted undergraduate students from the College of Engineering at a university in Taiwan, involving a total of 84 participants. The students were divided into a control group (CG) and an experimental group (EG), with 42 students in each group to ensure balanced and representative sampling. The control group followed a traditional lecture-based teaching approach, focusing on foundational knowledge of electronics and circuit experiments, where the instructor guided students to complete experimental tasks during class. In contrast, the experimental group utilized an intelligent learning assistance system integrating AI and deep learning technologies. This system served as an instructional medium to support students learning and operational tasks during experiments. At the beginning of the course, a pre-test was administered to all participants using a standardized skill assessment scale to measure their baseline knowledge and experimental skills. During the initial phase of the course, the same instructor delivered unified foundational knowledge to all students. This ensured a common baseline of understanding, mitigating the potential influence of initial disparities on subsequent experimental outcomes. As the course progressed, differences in instructional models emerged. Students in the control group performed electronics and circuit experiments using the traditional method, with the instructor responsible for guidance and evaluation. Meanwhile, students in the experimental group completed their experiments with the intelligent learning assistance system. This system leveraged computer vision technologies to provide real-time analysis and feedback on students' experimental operations, offering targeted suggestions and corrective directions. It enabled students to identify and rectify errors promptly. Beyond operational assistance, the system also facilitated a detailed and diversified evaluation of students based on their experimental process. At the end of the course, all students underwent a post-test based on a unified assessment framework. The evaluation included measuring their mastery of experimental skills and their ability to apply theoretical knowledge. Additionally, feedback was collected from the experimental group on their experience with the intelligent system, which helped refine the systems functionalities and applicability. Through a systematic comparison of the control and experimental groups, this study investigated the application of AI and deep learning technologies in teaching electronics and circuit experiments. It analyzed their effectiveness in enhancing learning outcomes, optimizing resource utilization, and promoting educational equity, providing empirical support for the innovation of future engineering education models.

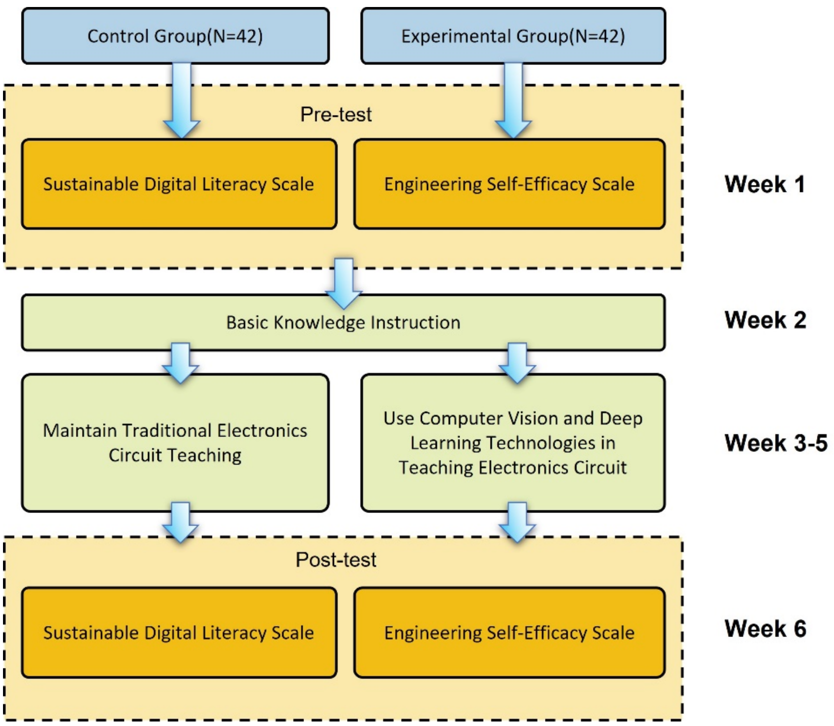

Fig 3. Research Flowchart

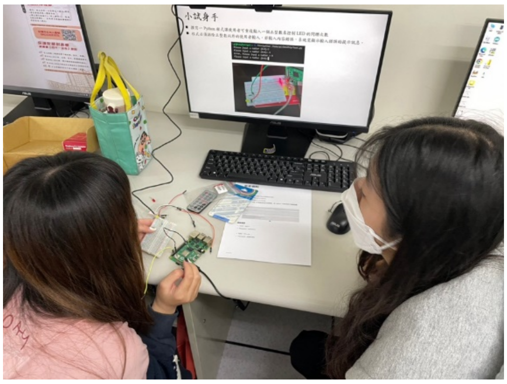

Fig 4. Experimental Group Course in Progress

4. Experimental Questionnaire and Analysis

This study involved 84 undergraduate engineering students, equally divided into experimental and control groups, to evaluate the impact of an intelligent assistive system on their digital literacy, laboratory operational skills, and engineering self-efficacy in electronics and circuits laboratory courses. The assessment framework was based on dimensions such as technical application proficiency, experimental operation skills, and error diagnosis and correction abilities.

Technical application proficiency evaluated students' familiarity with simulation software, hardware testing instruments, and hands-on operational performance in digital environments. Experimental operation skills measured students' accuracy in identifying components, wiring, and tool usage, providing a comprehensive view of their foundational competencies. Error diagnosis and correction abilities focused on students' capacity to use system prompts for troubleshooting and resolving experimental issues. Additionally, the dimension of digital media information management skills was used to evaluate students' ability to search for, evaluate, and apply experiment-related information.

The engineering self-efficacy scale measured students' confidence in performing technical tasks, their problem-solving abilities, and their motivation for engaging in engineering learning. Engineering task confidence assessed students' ability to complete operations such as component placement and debugging. Problem-solving abilities evaluated their confidence in resolving experimental challenges, while motivation for engineering learning reflected their persistence and enthusiasm for engineering tasks. Self-efficacy, as the belief in one's ability to perform tasks, plays a critical role in students success and persistence [89], [90].

To address the social aspects of engineering education, the study also included an online social behavior dimension to evaluate teamwork and resource sustainability awareness, measuring students' ability to collaborate, divide tasks, and solve problems effectively, as well as their attitudes toward efficient resource usage and material conservation.

4.1 Data Analysis Results

To analyze the experimental data, pre-test and post-test scores from all scales were compared between the experimental and control groups. Levene's test confirmed homogeneity of variance, validating the use of ANOVA for statistical analysis.

For digital literacy skills (as shown in Table 1), the experimental group demonstrated substantial gains in technical application proficiency ($F = 84.53$, $p < 0.01$), indicating an enhanced ability to use laboratory tools effectively. Experimental operation skills also improved significantly ($F = 81.23$, $p < 0.05$), reflecting greater accuracy in component identification, wiring, and tool usage. Error diagnosis and correction abilities showed notable improvements ($F = 90.32$, $p < 0.01$), as students in the experimental group resolved errors more efficiently with the aid of real-time feedback.

However, improvements in digital media information management skills were not statistically significant ($p = 0.54$). This may be attributed to the convenience of the machine vision guidance system, which reduced the need for students to independently search for and manage experiment-related information. The automated guidance likely minimized reliance on external resources, resulting in limited variation in this dimension.

Collaborative learning and resource sustainability awareness, measured using the online social behavior scale, also exhibited marked improvement ($F = 76.45$, $p < 0.05$; $F = 73.24$, $p < 0.05$). These results highlight the systems effectiveness in fostering teamwork and promoting resource-conscious practices in laboratory environments.

Table 1. ANOVA Analysis on Sustainable Digital Literacy Skills Scale

variable	SS	df	MS	F	p	Partial η^2
Technical Application Proficiency	72.60	1	72.60	84.53	0.002**	0.496
Experimental Operation Skills	144.62	1	143.12	81.23	0.013*	0.486
Error Diagnosis and Correction Abilities	146.86	1	146.83	90.32	0.009**	0.512
Digital Media Information Management Skills	69.83	1	0.84	69.83	0.54	0.010
Collaborative Learning and Teamwork	147.27	1	147.27	76.45	0.043*	0.518

Resource Sustainability Awareness	146.12	1	146.10	73.24	0.041*	0.501

Note. *p < .05, **p < .01, ***p < .001

For engineering self-efficacy (as shown in Table 2), the experimental group demonstrated significant improvements across all dimensions. Engineering task confidence increased notably ($F = 45$, $p < 0.001$), reflecting enhanced technical skill mastery. Problem-solving abilities showed significant gains ($F = 41.4$, $p < 0.001$), indicating better error resolution strategies. Motivation for engineering learning also improved ($F = 24.48$, $p < 0.001$), suggesting that the system created a supportive and engaging learning environment.

Table 2. ANOVA Analysis on the Engineering Self-Efficacy Scale

variable	SS	df	MS	F	p	Partial η^2
Engineering Task Confidence	150	1	150	45	<.001***	0.35
Problem-Solving Abilities	133	1	132.88	41.4	<.001***	0.333
Motivation for Engineering Learning	136.4	1	136.42	24.48	<.001***	0.228

Note. *p < .05, **p < .01, ***p < .001

4.2 Discussion and Implications

The findings demonstrate that the intelligent assistive system significantly enhanced students technical skills, digital literacy, and self-efficacy, as well as their teamwork and resource sustainability awareness (as shown in Tables 3 and 4). The experimental group consistently outperformed the control group, underscoring the system's effectiveness in addressing both technical and social learning challenges. For instance, in error diagnosis and correction, the control group's scores showed minimal change (pre-test: 3.01, post-test: 3.03), whereas the experimental group exhibited substantial improvement (pre-test: 2.17, post-test: 4.02). These results highlight the limitations of traditional instruction and the advantages of intelligent systems in developing essential problem-solving capabilities.

Table 3. Pre-test and Post-test Mean and Standard Deviation of the Sustainable Digital Literacy Skills Scale

variable	EG(N=42)				CG(N=42)			
	Pre-test		Post-test		Pre-test		Post-test	
	M	SD	M	SD	M	SD	M	SD
Technical Application Proficiency	3.01	0.50	4.01	0.49	3.96	0.48	3.02	0.50

Experimental Operation Skills	3.03	0.33	4.03	0.50	3.54	0.49	3.04	0.73
Error Diagnosis and Correction Abilities	2.17	0.49	4.02	0.51	3.01	0.50	3.03	0.41
Digital Media Information Management Skills	3.00	0.48	3.10	0.49	3.02	0.47	3.03	0.46
Collaborative Learning and Teamwork	2.73	0.49	4.01	0.50	3.00	0.25	3.02	0.48
Resource Sustainability Awareness	3.02	0.48	4.02	0.49	3.41	0.50	3.03	0.24

Table 4. Pre-test and Post-test Mean and Standard Deviation of Self-Efficacy

variable	EG(N=42)				CG(N=42)			
	pretest		posttest		pretest		posttest	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Engineering Task Confidence	15.3	1.91	21.8	3.01	15.4	1.6	22.5	3.08
Problem-Solving Abilities	16.6	1.91	19.8	2.12	16.7	1.3	17.3	1.33
Motivation for Engineering Learning	12.8	1.92	15	2.39	12.5	2.1	12.5	2.46

Beyond individual outcomes, the system fostered collaboration and sustainability awareness, preparing students to approach engineering challenges with a socially responsible perspective. By equipping students with tools to effectively leverage digital resources and promoting innovative laboratory practices, the system aligns with the goals of sustainable engineering education.

5. Discussion

In today's digital era, individuals must not only recognize when information is needed but also effectively locate, evaluate, and utilize that information. This study extends traditional digital literacy by incorporating principles of sustainable engineering literacy into electronics and circuit laboratory education. Beyond technical competencies, sustainable engineering literacy encourages students to consider the broader implications of engineering practices, such as resource efficiency and ethical responsibility. By fostering both technical and sustainability-focused skills, the intelligent grading and learning assistance system supports the goals of innovative and inclusive engineering education.

Sustainable Digital Literacy Skills

The findings reveal that while technical application proficiency, experimental operation skills, and error diagnosis improved significantly, digital media information management skills did not show substantial gains. This outcome may be attributed to the convenience offered by the machine vision guidance system, which minimized the need for students to independently search for and manage experiment-related information. The structured feedback and automated processes likely reduced opportunities for students to engage with broader digital resources, limiting the development of resource management competencies. These results suggest that while intelligent systems enhance efficiency and reduce learning barriers, they may inadvertently restrict the growth of critical skills related to autonomous information handling.

To address this limitation, future system designs could incorporate tasks that encourage students to seek, evaluate, and integrate external information. For example, integrating features that require students to analyze data beyond the system's direct guidance could foster deeper engagement with digital resources, bridging the gap between structured assistance and independent digital literacy development.

Engineering Self-Efficacy

The system significantly enhanced engineering self-efficacy, with improvements noted in task confidence, problem-solving abilities, and learning motivation. The real-time feedback and automated grading empowered students to overcome challenges and boosted their confidence in conducting experiments, underscoring the importance of actionable feedback in sustaining engagement and fostering a growth mindset [91].

Regarding problem-solving abilities, the system encouraged iterative learning by allowing students to detect and correct errors, reinforcing their theoretical understanding and resilience in facing engineering challenges. However, overly difficult tasks or rigid guidance may hinder engagement, highlighting the need for balanced instructional design. Motivation also increased due to reduced frustration and a sense of steady progress. The relevance of system-supported experimental tasks to real-world applications further strengthened student enthusiasm and persistence in engineering learning [92].

6. Discussion

This study investigated the integration of computer vision and deep learning technologies into electronics and circuit laboratory education. The results demonstrated that AI-powered assessment systems can enhance teaching efficiency, support sustainable use of educational resources, and cultivate students' engineering literacy. By addressing limitations in traditional laboratory instruction, particularly binary grading and lack of real-time feedback, the system improved students' ability to troubleshoot, iterate, and apply theoretical concepts in hands-on settings.

Students exhibited significant gains in engineering self-efficacy, including increased task confidence, better problem-solving abilities, and stronger motivation to engage in experimental learning. These improvements can be attributed to the system's ability to deliver immediate diagnostic feedback and personalized guidance. However, the structured nature of the feedback may reduce students' opportunities to independently manage learning resources, potentially affecting their development of digital information management skills.

This limitation suggests that while intelligent systems can provide critical scaffolding, designers must consider how to preserve a balance between guidance and learner autonomy. Furthermore, the system was evaluated primarily in a university electronics lab environment, which may not fully reflect broader educational contexts or subject domains. The focus on breadboard-based component recognition limits its generalizability to other types of engineering laboratories.

Future research should investigate the applicability of such intelligent systems in other engineering domains, including mechanical, civil, or chemical engineering experiments. The integration of remote-access or virtual laboratory modules could also promote inclusivity by supporting students in geographically or economically disadvantaged settings. In addition, longitudinal studies are needed to assess how such systems influence students' long-term skills in innovation, independent problem-solving, and sustainable thinking.

7. Conclusion

This research presents a practical and effective approach to integrating intelligent technologies into engineering education, specifically in the context of electronics and circuit laboratories. Through the combination of computer vision, deep learning, and a dynamic feedback mechanism, the proposed system addresses the longstanding limitations of traditional laboratory instruction, including rigid assessment formats and lack of timely guidance.

The implementation of the system demonstrated clear benefits in student engagement, self-efficacy, and experimental accuracy. These improvements reflect the system's capacity to foster personalized learning pathways, reduce student frustration caused by repetitive failure, and support the development of essential engineering competencies. Moreover, the system contributes to broader educational goals aligned with the Sustainable Development Goals (SDGs), particularly SDG 4 (Quality Education), by enhancing learning accessibility, assessment fairness, and instructional quality.

By automating the assessment process while maintaining pedagogical integrity, the system not only improves the efficiency of instruction but also reduces faculty workload, allowing educators to focus more on mentoring and higher-level conceptual teaching. The system's adaptability also presents an opportunity to serve as a blueprint for similar AI-based tools in other STEM fields.

In the future, efforts should focus on expanding the system's domain coverage, improving its interoperability with remote learning environments, and integrating data-driven learning analytics to further personalize student feedback. These enhancements will ensure that AI-driven educational tools not only meet current instructional needs but also evolve to address emerging educational challenges in the era of Industry 5.0 and lifelong learning.

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