Integrating AI-Based Image Analysis for Objective Assessment in CBET Practical Examinations

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Abstract

Technical and Vocational Education and Training (TVET) in Kenya plays a vital role in equipping learners with practical skills essential for economic development. However, competency-based practical assessments in TVET institutions face challenges such as human bias, inconsistencies, and inefficiencies due to manual evaluation methods. This study investigated the potential of Artificial Intelligence (AI)-based image recognition to automate and enhance the accuracy, objectivity, and efficiency of CBET practical assessments. A mixed-methods approach was employed, including a baseline survey of 50 students and 10 trainers to assess AI awareness and perceptions, followed by the development and testing of an AI-powered image recognition system for evaluating AutoCAD practical tasks. Results indicate moderate AI awareness but high willingness for AI training among participants. The AI model demonstrated improved consistency and time efficiency compared to traditional instructor-led assessments. The findings demonstrate that AI-driven assessment tools offer fast and consistent evaluations, enabling timely feedback delivery even in large TVET classes. This scalability significantly reduces instructor workload while maintaining uniform standards across assessments. By facilitating fast, reliable, and scalable competency evaluations, AI can enhance skill development and employability in Kenya's TVET sector, contributing to narrowing the digital divide through broader adoption of advanced technologies in TVET.

Keywords: Artificial Intelligence, TVET, Assessments, CBET, Skills, Practical

Introduction

Background of Study

Technical and Vocational Education and Training (TVET) plays a crucial role in Kenya's economic development by equipping learners with practical skills that are needed for the current labor market. Ao of 2023 Kenya had over 238 public TVET institutions accredited by the Technical and Vocational Education and Training Authority (TVETA), with an enrollment of more than 500,000 trainees across various disciplines such as engineering, ICT, business, and hospitality. The Kenya Vision 2030 blueprint identifies TVET as a key driver in addressing youth unemployment by enhancing the development of a skilled workforce.

Kenya embarked on a comprehensive education reform, leading to the introduction of the Competency-Based Curriculum (CBC). The CBC aims to equip learners with practical skills, foster creativity, and promote critical thinking to better prepare them for the dynamic demands of the 21st century. The curriculum emphasizes the development of competencies over rote memorization, encouraging learners to apply knowledge in real-life situations(Okeyo & Mokua, 2023). This shift represents a significant departure from the previous system, focusing on nurturing individual talents and abilities.

CBET assessments in Kenya primarily focus on practical skill evaluation through direct observation, portfolios, projects, and standardized practical exams. While these methods align with competency-based learning, they face several limitations, including human bias, lack of standardized evaluation criteria, scalability issues, and high resource demands. These challenges hinder the efficiency and reliability of CBET assessments, making it difficult to ensure that graduates meet industry requirements(Simiyu et al., 2023).

Artificial Intelligence (AI) is rapidly transforming industries worldwide, and Africa is no exception. Home to the largest and fastest-growing workforce in the world, Africa is poised to play a crucial role in the global AI ecosystem.(Çela et al., 2024) AI is increasingly being integrated into various sectors, including finance, agriculture, and healthcare. However, its adoption in Technical and Vocational Education and Training (TVET) institutions remains relatively low. Given TVET's critical role in equipping learners with industry-relevant skills, understanding the level of AI adoption in these institutions is essential for bridging the digital divide and fostering sustainable economic growth.

Image recognition is a computer vision technique that allows machines to interpret and categorize the content of images and visual inputs. It involves the use of algorithms and machine learning models to detect and identify objects, features, or patterns within an image. This technology is widely used in various applications, such as facial recognition systems, autonomous vehicles, medical image analysis, and photo tagging on social media platforms. Despite the widespread use of AI-powered image recognition in various other fields, its application in practical assessments and examinations remains largely unexplored. (Tweissi et al., 2022)

Problem Statement

Despite the critical role of Competency-Based Education and Training (CBET) in preparing learners for industry-specific skills, assessing practical competencies remains a major challenge in Kenya's TVET institutions. Current approaches for CBET practical assessments often rely on physical instructor supervision, paper-based checklists, and oral evaluations, which are prone to human error, bias, and inconsistencies(Henri et al., 2017). This is compounded by the rising student enrollment and limited instructor-to-student ratio, as a result, practical assessments lack standardization, efficiency, and real-time feedback, limiting their ability to accurately measure student competency and readiness for the job market. Advancements in Artificial Intelligence (AI) and Image Recognition offer a promising solution to enhance CBET practical assessments by providing automated, objective, and real-time evaluations of students' practical tasks. However, the adoption of AI-driven assessment tools remains low in Kenya's TVET sector. This study explored how AI-based image recognition can be leveraged to automate, standardize, and improve the efficiency of CBET practical assessments. By implementing AI-driven assessment systems, institutions can enhance assessment accuracy, reduce instructor workload, and provide instant feedback to learners, ultimately improving skill acquisition and employability outcomes

Objectives of the Study

Main Objective

The main objective of this study was to investigate the use of AI-based image recognition for automating and enhancing the accuracy, efficiency, and standardization of CBET practical assessments in Kenya's TVET institutions.

Specific Objectives

- To analyze the existing CBET practical assessment methods in TVET institutions.
- To explore existing knowledge, perceptions, and readiness for AI integration in CBET practical assessments.
- To develop and evaluate an AI-based image recognition system for verifying and assessing CBET practical tasks.
- To assess the effectiveness of AI-driven image recognition in improving accuracy, objectivity, and efficiency in CBET practical assessments.

Literature Review

Methods of Practical Assessments in CBET

Competency-Based Education and Training (CBET) emphasizes hands-on learning to ensure that learners acquire practical skills relevant to industry needs. In Kenya's Technical and Vocational Education and Training (TVET) institutions, practical assessments are crucial for evaluating students' competencies. However, these assessments rely on traditional methods, which pose challenges in terms of objectivity, efficiency, and scalability(Khan et al., 2022).

Instructor Observation and Manual Grading

Instructor-led observation is the primary method used for competency-based education and training (CBET) assessments, where instructors directly evaluate students as they perform tasks, assigning grades based on predefined rubrics(Macheso et al., 2024). While this method allows for hands-on evaluation, it is highly prone to human bias, inconsistencies, and subjectivity, as different instructors may interpret performance criteria differently, leading to potential disparities in grading(Jonsson, 2014). Moreover, the growing number of students in TVET institutions has made individualized assessment increasingly difficult, particularly due to limited instructor-to-student ratios, which can compromise the depth and accuracy of evaluations. The reliance on manual grading also makes the process time-consuming and labor-intensive, increasing instructor workload and potentially delaying feedback to students. Additionally, fatigue and cognitive overload among assessors may further impact grading consistency, raising concerns about fairness and reliability in competency evaluations(Macheso et al., 2024). Addressing these limitations necessitates the integration of automated assessment tools and AI-driven evaluation frameworks to enhance objectivity, efficiency, and scalability in CBET assessments.

Checklists and Rubric-Based Evaluations

One of the most commonly used assessment methods is checklists and rubric-based evaluations, where instructors use structured criteria to assess students' practical skills. This approach ensures standardization and transparency, making it possible to evaluate different aspects of a given task systematically. However, rubric-based assessments are often subject to human interpretation, leading to inconsistencies in grading(Rahman et al., 2014). Instructors may assign different scores based on subjective evaluations, creating disparities in assessment outcomes. Additionally, manually filling out rubrics for multiple students is time-consuming, particularly in institutions with large class sizes. Additionally, they still rely on manual grading, which is time-consuming and susceptible to errors and inconsistencies(Henri et al., 2017).

Practical Demonstrations and Oral Examinations

Another common approach in TVET institutions is practical demonstrations and oral examinations, where students perform tasks in front of an examiner while responding to related questions. This method provides an opportunity for real-time evaluation, allowing instructors to assess practical skills alongside theoretical understanding. It ensures that students can apply their knowledge effectively and demonstrate problem-solving abilities in real-world scenarios. However, this approach is labor-intensive, requiring significant time and resources(Henri et al., 2017b). Individual assessment of students can be exhausting for instructors, particularly when dealing with large student populations. Additionally, variations in instructor judgment may lead to grading inconsistencies, raising concerns about fairness and standardization.

AI for Educational Assessment

The recent advancement in the realms of Artificial Intelligence has opened up frontiers for improvements in the way technology can transform education. One of the key areas in education where AI in technology can positively improve effectiveness is online assessments. From automated item generation to personalized assessments, AI has the potential to revolutionize the way we teach, assess, and learn(Khan et al., 2023).

AI-based assessments have already been successfully implemented in various industries, demonstrating their reliability and effectiveness in evaluating practical competencies. In the medical field, AI verifies surgical procedures by analyzing movements and ensuring precision, helping medical trainees refine their techniques(Campbell et al., 2024). Similarly, in the manufacturing sector, AI-powered image recognition is used to inspect assembly processes for defects, ensuring quality control and reducing errors. In the education sector, AI-driven proctoring tools monitor students during examinations to prevent cheating and maintain academic integrity (Owan et al., 2023). These applications highlight the potential of AI to improve assessment processes across different disciplines, further supporting its adoption in CBET practical evaluations.

In TVET AI-driven image recognition could be used to assess hands-on skills, such as welding, carpentry, and engineering tasks, by analyzing images or videos of student performances against predefined competency standards(Çela et al., 2024). The integration of AI in practical assessments could not only enhance fairness and objectivity but also provide real-time feedback, helping learners improve their skills more effectively. However, challenges such as data privacy concerns, algorithm biases, and infrastructure limitations must be addressed to ensure successful adoption and implementation in educational institutions(Khan et al., 2023).

Methodology

Introduction

This chapter presents the methodological approach adopted to investigate the development and application of an AI-powered image recognition model for enhancing practical assessments in Technical and Vocational Education and Training (TVET). The methodology covers the two key phases of the study: the initial baseline survey to assess participants' knowledge, perceptions, and readiness for AI integration, and the subsequent development, training, and testing of the AI model. It also outlines the mixed-methods research design, data collection procedures, model evaluation criteria, and the quasi-experimental approach used to compare AI-based assessments with instructor-led evaluations. Together, these components provide a structured foundation for assessing the feasibility, accuracy, and practical relevance of AI in TVET assessment environments.

Research Design

This study employed a mixed-methods research design, integrating both qualitative and quantitative approaches to gain a comprehensive understanding of AI-based assessment in Competency-Based Education and Training (CBET). The design was implemented across two phases. In the first phase, a descriptive qualitative approach was used to gather insights from participants through a baseline questionnaire. This phase aimed to explore existing knowledge, perceptions, and readiness for AI integration in practical assessments, particularly within the context of image recognition technologies. The qualitative data collected provided context-specific insights into the current gaps, challenges, and expectations of end-users in TVET institutions.

The second phase adopted a quasi-experimental design to quantitatively evaluate the performance of an AI-powered image recognition model developed for assessing AutoCAD practical tasks. The model was trained and tested on a dataset of real-world assessment images, and its performance was compared against traditional instructor-led evaluations. Key metrics such as accuracy, consistency and score were used to measure the effectiveness of the AI system. The comparison helped determine the viability and reliability of using AI in automated practical assessments.

By combining qualitative exploration with quantitative validation, this research design facilitated a holistic examination of both the user context and technical performance, ensuring that the findings are both actionable and grounded in real-world practice.

Target Population

The target population for this study is the trainers and students of TVET institutions in Kenya.

Sampling Techniques and Sample Size

A purposive sampling technique was used to select the institution, trainers and students. The sample size consisted of 10 TVET instructors and 50 diploma students at Nkabune Technical Training Institute, a public TVET Institution located in Meru, Kenya.

Data Collection Methods

A structured questionnaire was used to collect data for the baseline survey. The questionnaire covered six main thematic areas which include AI Awareness and Knowledge, Current Assessment Methods, Perceived Effectiveness of Current Methods, Perceived Benefits of AI in Assessments, and Institutional Readiness

Data Analysis

Both qualitative and quantitative data analysis methods are employed. Statistical analysis was conducted using SPSS and Python to examine the effectiveness of AI-based assessments. Descriptive statistics, such as mean scores and standard deviations, are used to evaluate AI accuracy compared to instructor evaluations.

AI Model Development

A supervised machine learning model based on image recognition was developed using Python and OpenCV. The model was trained to recognize and evaluate specific features of AutoCAD drawings such as dimensions, alignment, symmetry, and object completeness.

Evaluation Metrics

The comparative analysis of AI vs. manual assessment was based on accuracy: Comparison of mean scores and correlation between manual and AI scores. Consistency: Standard deviations of scores and inter-rater reliability using Cohen's Kappa and correlation coefficients (R^2). Time Efficiency: Average time taken by each method for assessment.

Ethical Considerations

Informed consent was obtained from all participants. Student identities were anonymized in both manual and AI assessments additionally Institutional approval was sought before conducting experiments involving academic assessment.

Results Analysis and Discussions

The baseline study questionnaire was administered to 50 students and 10 trainers. The key areas analyzed include AI awareness, current assessment methods, perceptions of AI-based assessments, perceived benefits, institutional readiness, and training willingness. Below is a detailed analysis.

The Baseline Survey

The section presents the results and discussions of the baseline survey.

AI Awareness and Knowledge Levels

We examined the level of AI awareness and knowledge among participants.

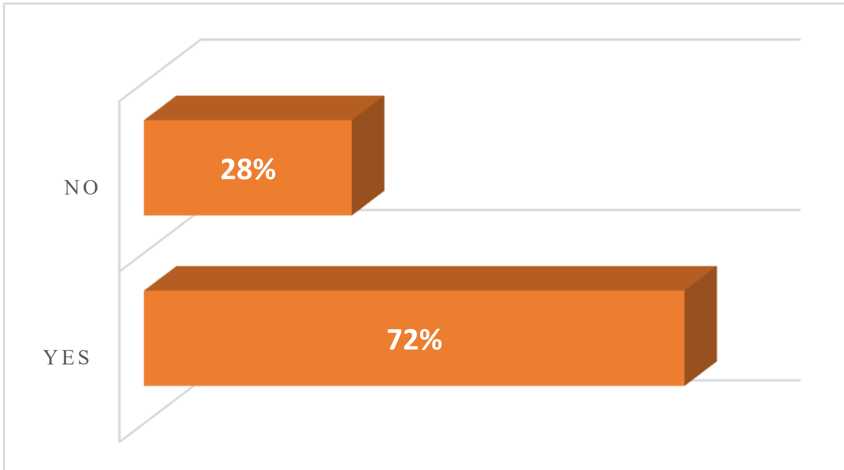

Figure 1: AI awareness among participants

The bar chart indicates that a significant proportion of participants are aware of AI, with about 72% responding "Yes" and 28% responding "No". This suggests that while AI is known to many, a substantial group remains unaware, highlighting the need for AI literacy programs.

AI Knowledge Levels Among Participants

Next, we examined how well participants understand AI concepts. The AI knowledge distribution shows that most participants rate their knowledge as low or moderate, with very few considering themselves highly knowledgeable. This suggests that training programs will be crucial before implementing AI-based assessments.

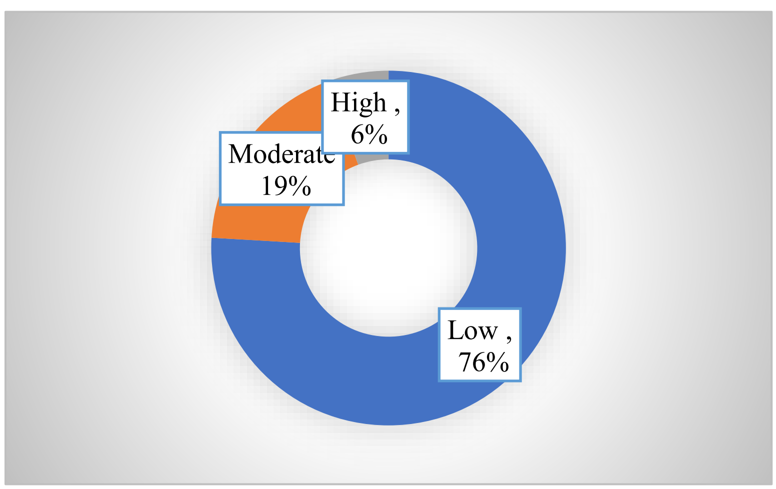

Figure 2: AI knowledge levels among participants

Current Assessment Methods Used

We analyzed the methods currently employed in assessments. The analysis indicated that manual observation is the most commonly used assessment method, followed by video recordings and peer assessments. AI-based assessments are currently rare, reinforcing the need for exploring AI integration in CBET institutions.

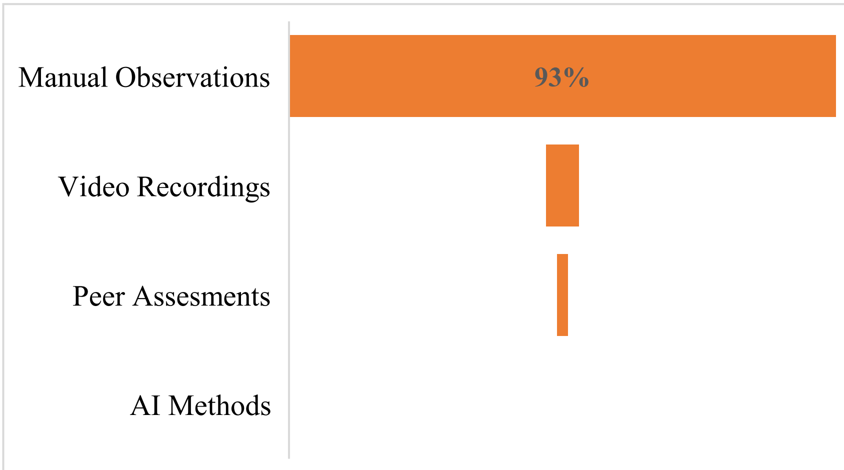

Figure 3: Current assessment methods

Effectiveness of Current Assessment Methods

We examined how participants perceive the effectiveness of their current methods. The results show a balanced distribution, with many respondents rating current methods as Neutral (26%) or effective (24%). However, a significant portion finds them ineffective (33%), suggesting opportunities for improvement through AI.

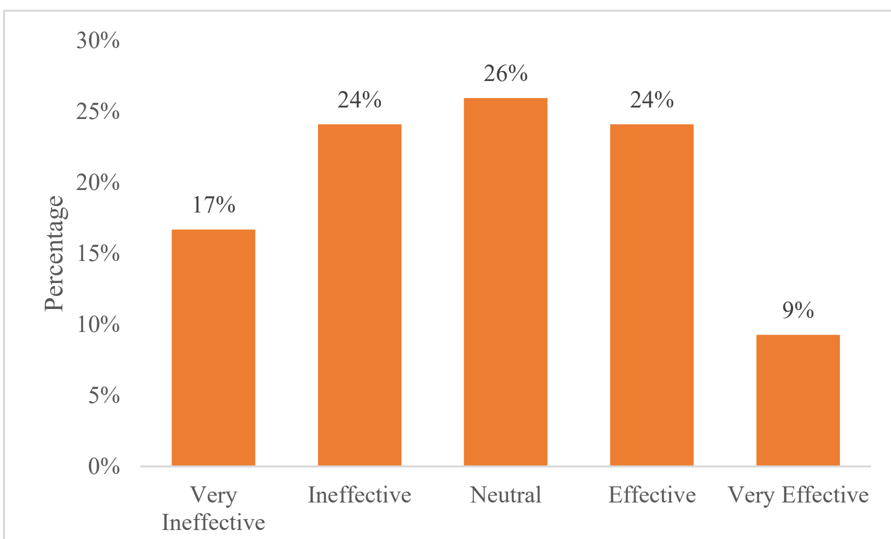

Figure 4: Perceived effectiveness of the current methods

Perceived Benefits of AI in Assessment

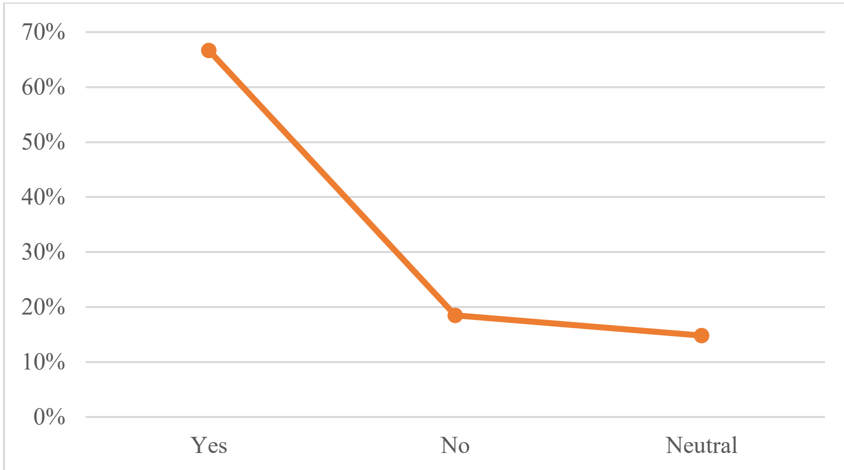

Figure 5: Perceived Benefits of AI in Assessment

We analyze whether participants believe AI could improve assessments. The majority of respondents believe AI can improve assessments (68%), but a notable percentage (20%) are uncertain, indicating the need for more awareness and training.

Willingness to Undergo AI Training

Finally, we examined whether participants are open to AI-related training. The results showed that 83% of respondents are willing to undergo AI training, which is a positive indicator for AI adoption in assessments.

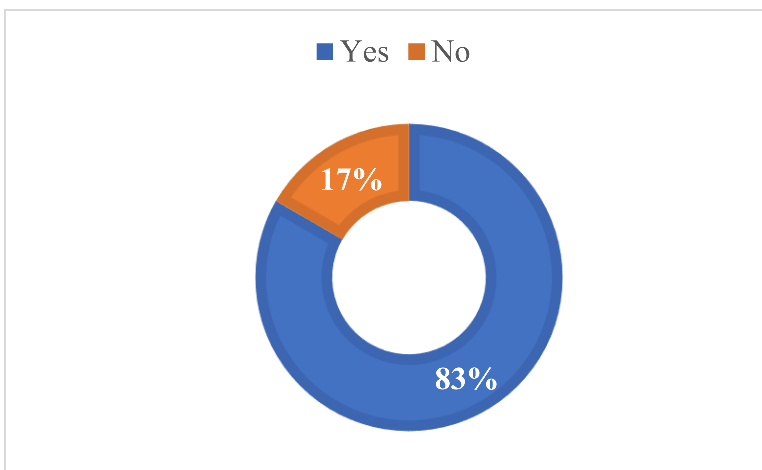

Figure 6: Willingness to undergo AI training

Development, Training and Testing of the Image Recognition Model

The second stage involved creation, training and testing of the AI machine learning Image recognition model for assessing practical examination. 20 students and three trainers were involved in this stage. Computer AIDED design and specifically AutoCAD subject was used for the experiment. The students were given an examination to draw an AutoCAD drawing. The assessment was done using two methods in the first method three trainers marked the task using manual observation/checklist method. The scores for each trainer were recorded and averaged. A CNN based AI model was developed and trained to recognize key features in the AutoCAD drawings and predict assessment scores. After training, the model was tested on unseen drawings. The AI model was used to do the assessment three times and the scores averaged. Analysis was then done based on three main metrics, Accuracy of the assessment method, time taken to perform the assessment, consistency of the manual assessment as compared to the consistency of the AI model.

Descriptive Statistics

Table 1: Summary Table for All Grades

	Trainer 1	Trainer 2	Trainer 3	AI 1	AI 2	AI 3
Mean	82.9	83.2	83.0	84.1	84.3	83.9
Median	83	83	83	84	84	84
Std Dev	3.4	3.6	3.5	2.2	2.1	2.3
Min	76	77	75	80	81	79
Max	90	91	89	88	89	88

Accuracy of the Assessment Method

The AI model showed slightly higher average scores compared to the human trainers, indicating a high degree of agreement and reliability in its grading. The mean scores for the trainers ranged from 82.9 to 83.2, while the AI scores ranged from 83.9 to 84.3. Similarly, the median scores for the trainers were all 83, whereas the AI consistently gave a median score of 84 across all three runs. These results suggest that the AI model was able to assess the practical tasks with an accuracy level comparable to human evaluators. The small difference in mean and median scores reflects that the AI closely approximates human judgment while maintaining a slight margin of generosity. The similarity in score distribution supports the validity of AI as an accurate tool for assessing practical AutoCAD tasks.

Consistency of the Assessment Method

The AI model demonstrated superior consistency when compared to manual assessments by trainers. This was most evident in the standard deviation values. For the human trainers, the standard deviation ranged between 3.4 and 3.6, indicating variability in scoring among different assessors. In contrast, the AI assessments had significantly lower standard deviations between 2.1 and 2.3, indicating less fluctuation in scores. In terms of score range, trainers gave scores between 75 and 91, showing a wider spread, whereas AI scores fell within a tighter band of 79 to 89. This narrower range of AI results further demonstrates the model's ability to apply assessment criteria uniformly across all students. The reduced variation and tighter score range indicate that the AI model is less prone to subjective bias and is more consistent in its evaluation, making it a reliable tool for repetitive and large-scale assessments.

Statistical Agreement Analysis

To evaluate the reliability and alignment between human trainers and the AI image recognition model. Intraclass Correlation Coefficient (ICC) was used to measure inter-rater reliability by quantifying the degree of agreement among different graders when scoring the same set of AutoCAD drawings. The ICC for the three trainers was 0.65 (95% CI: 0.50–0.78), which falls under the category of moderate agreement. This indicates that while trainers were fairly consistent, there were notable variations in how each interpreted and scored the student outputs. Such variability is expected due to human subjectivity, fatigue, or differing levels of strictness.

The AI assessment had an ICC of 0.82 (95% CI: 0.72–0.90), indicating high agreement. This demonstrates the AI model's strong internal consistency, as its evaluation criteria are algorithmically defined and applied uniformly across assessments, free from subjective influence.

Time Efficiency Analysis

The evaluation of time efficiency between manual and AI-based grading methods revealed a significant advantage in favor of the AI model. The average time taken for manual grading by human trainers was 14.49 minutes per student, while the AI grading system completed the same assessment in just 0.87 minutes. This substantial difference of 13.62 minutes saved per assessment translates to a time reduction of approximately 94%.

With the AI system performing assessments in a fraction of the time, educators can significantly reduce the hours spent on repetitive grading tasks. This is especially valuable when handling large student cohorts, such as in technical institutions or national examinations, where time and consistency are critical.

Instructor Perception Scores

Instructors rate AI-based assessments positively (3-5) but show more variation compared to students. Some instructors prefer manual grading methods as they allow for direct interaction and personalized feedback. Concerns include initial setup challenges, AI reliability, and lack of transparency in grading. Instructors hesitate to fully adopt AI, especially for evaluating subjective or complex skills.

Student Perception Scores/ Student Satisfaction

Most students rate AI-based assessments positively (4-5), showing a preference for quick and objective grading. Traditional manual assessments receive mixed ratings (2-5), with some students appreciating instructor feedback but others dissatisfied with perceived subjectivity.

The analysis clearly demonstrates that AI grading is far more time-efficient than manual grading, reducing assessment time by around 94% per student. This efficiency gain holds transformative potential for education systems seeking to scale up practical assessments while maintaining reliability. In doing so, AI not only accelerates operations but also empowers human educators to deliver more value where it matters most guiding and nurturing student growth.

Conclusion and Recommendations

Conclusion

This study explored the transformative potential of AI-based image recognition in enhancing the accuracy, objectivity, and efficiency of CBET practical assessments in Kenya's TVET institutions. By addressing challenges such as human bias, grading inconsistencies, and limited scalability, the AI-powered system demonstrated improved consistency and faster evaluation times compared to traditional methods. The positive response from both students and trainers indicates a readiness for AI integration, particularly when supported with relevant training and infrastructure.

The findings underscore that AI can significantly reduce instructor workload while enabling timely, standardized feedback in large classes. As Kenya's TVET sector continues to grow, adopting AI-driven tools for practical assessments can promote fairer evaluations, improve skill acquisition, and increase employability among graduates. Broader adoption of such technologies can also help bridge the digital divide, positioning TVET as a leader in educational innovation.

Recommendations

R1	Institutions offering CBET assessments should implement AI grading systems to manage large student populations efficiently and reduce manual workload for trainers.
R2	Institutions and Assessment bodies should develop a unified grading rubric to align AI assessment with curriculum objectives and human grading standards.
R3	For the successful implementation of AI in assessment, trainers must be equipped with the necessary skills to understand and work alongside the AI system. TVET institutions should structure courses and workshops to help build capacity among academic staff.
R4	While the AI system demonstrated high agreement with trainers, some discrepancies were noted further development and fine-tuning of the model are necessary.
R5	A hybrid approach that integrates AI and human assessment should be adopted, where AI performs the initial evaluation and human assessors review the results. This will ensure fairness while maintaining efficiency.
R6	AI assessment systems should be evaluated through long-term studies comparing them with traditional methods to understand their impact on learning outcomes and guide future improvements.
R7	Seamless integration of AI tools into existing Learning Management Systems to provide seamless grading, instant feedback, and streamlined academic processes.
R8	As institutions move toward greater reliance on AI in academic assessments, it is crucial to develop policies and ethical frameworks governing its use. These policies should address issues such as transparency, bias mitigation, data privacy, and the role of human oversight

References

Campbell, J., Ansell, K., & Stelzer, T. (2024). Evaluating IBM's Watson natural language processing artificial intelligence as a short-answer categorization tool for physics education research. *Physical Review Physics Education Research*, *20*(1), 010116. https://doi.org/10.1103/PhysRevPhysEducRes.20.010116

Çela, E., Vajjhala, N. R., Eappen, P., & Vedishchev, A. (2024). *Artificial Intelligence in Vocational Education and Training* (pp. 1–16). https://doi.org/10.4018/979-8-3693-8252-3.ch001

Henri, M., Johnson, M. D., & Nepal, B. (2017a). A Review of Competency-Based Learning: Tools, Assessments, and Recommendations. *Journal of Engineering Education*, *106*(4), 607–638. https://doi.org/10.1002/jee.20180

Henri, M., Johnson, M. D., & Nepal, B. (2017b). A Review of Competency-Based Learning: Tools, Assessments, and Recommendations. *Journal of Engineering Education*, *106*(4), 607–638. https://doi.org/10.1002/jee.20180

Jonsson, A. (2014). Rubrics as a way of providing transparency in assessment. *Assessment & Evaluation in Higher Education*, *39*(7), 840–852. https://doi.org/10.1080/02602938.2013.875117

Khan, S., Ahmed, R. R., Streimikiene, D., Streimikis, J., & Jatoi, M. A. (2022). THE COMPETENCY-BASED TRAINING &Amp; ASSESSMENT, AND IMPROVEMENT OF TECHNICAL COMPETENCIES AND CHANGES IN PEDAGOGICAL BEHAVIOR. *E+M Ekonomie a Management*, *25*(1), 96–112. https://doi.org/10.15240/tul/001/2022-1-006

Khan, S., Blessing, L., & Ndiaye, Y. (2023). *Artificial Intelligence for Competency Assessment in Design Education: A Review of Literature* (pp. 1047–1058). https://doi.org/10.1007/978-981-99-0428-0_85

Macheso, I. S., Kati, R. O., & Wafula, R. W. (2024). Implementation of Competency Based Assessment in Kenya: Extent of Utilization of Competency Based Assessment Tools and Types. *International Journal of Research and Innovation in Social Science*, *VIII*(VI), 3124–3134. https://doi.org/10.47772/IJRISS.2024.806236

Okeyo, S. M., & Mokua, Z. O. (2023). Preparedness of Teachers for Implementing Competency-Based Curriculum System of Education in Public Secondary Schools in Nyamira South Sub- County. *East African Journal of Education Studies*, *6*(2), 406–418. https://doi.org/10.37284/eajes.6.2.1387

Owan, V. J., Abang, K. B., Idika, D. O., Etta, E. O., & Bassey, B. A. (2023). Exploring the potential of artificial intelligence tools in educational measurement and assessment. *Eurasia Journal of Mathematics, Science and Technology Education*, *19*(8), em2307. https://doi.org/10.29333/ejmste/13428

Rahman, A. bt A., Hanafi, N. binti M., Mukhtar, M. bt I., & Ahmad, J. bin. (2014). Assessment Practices for Competency based Education and Training in Vocational College, Malaysia. *Procedia - Social and Behavioral Sciences*, *112*, 1070–1076. https://doi.org/10.1016/j.sbspro.2014.01.1271

Simiyu, K. A., Injendi, Dr. J., & Mukonyi, D. P. (2023). TVET Trainers Involvement in Attaining Kenya Vision 2030: Issues and Challenges. *International Journal of Latest Technology in Engineering, Management & Applied Science*, *XII*(VIII), 93–101. https://doi.org/10.51583/IJLTEMAS.2023.12810

Tweissi, A., Al Etaiwi, W., & Al Eisawi, D. (2022). The Accuracy of AI-Based Automatic Proctoring in Online Exams. *Electronic Journal of E-Learning*, *20*(4), 419–435. https://doi.org/10.34190/ejel.20.4.2600