




## AfriML: A Culturally Relevant AI Tool for Teaching Machine Learning Concepts

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### Article Info

### Abstract

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This paper introduces AfriML, a culturally relevant artificial intelligence tool designed to enhance machine learning (ML) education through African cultural contexts. While tools like Teachable Machine and LearningML simplify ML concepts, they often lack cultural integration. AfriML addresses this gap by using artifacts from major Nigerian ethnic groups (Hausa, Igbo, Yoruba, Ibibio, and Efik) to teach ML classification problems. The tool was implemented with students at a tertiary institution and evaluated using a survey to assess learners' confidence, satisfaction, and perceptions of cultural relevance. Results showed a significant increase in confidence scores from 2.43 to 3.28. Participants also reported improved understanding of ML classification (mean = 3.09) and rated the tool's effectiveness at 3.36. Cultural relevance was rated positively (mean = 3.45). These findings suggest that AfriML supports both conceptual understanding and cultural engagement in ML education. Future work will expand AfriML's cultural scope and its impact across broader educational contexts.

#### Keywords

Machine learning  
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Adaptive learning  
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## Introduction

Artificial intelligence (AI) has emerged as a transformative force, particularly in education, with schools gradually adopting various approaches to teaching and learning AI to enhance student engagement, experiences, and learning outcomes (Sanusi & Oyelere, 2020). To create effective and ethically responsible AI-integrated learning environments, it is important to consider the views and experiences of the learners involved (Mogavi et al., 2023). Rather than teaching AI in isolation, education in this field should be transdisciplinary, connecting to other areas of the curriculum and the community context in which students are situated (Aliabadi et al., 2023).

Culturally responsive computing education connects students' cultural backgrounds with computer science, enabling them to recognize the importance and relevance of their culture within the field (Miller, 2014). Adapting AI pedagogy to diverse cultural contexts is critical for teaching AI effectively across various populations. Without such adaptation, AI education risks confusion, cultural biases, and resistance, as learners may struggle to see the relevance of the content (Samuel et al., 2023). Despite recent advancements, most AI tools are designed within Western frameworks, often overlooking the specific needs and challenges faced by students in African educational settings (Boateng, 2024; Prabhakaran et al., 2022). This lack of representation impacts how AI concepts are taught, as existing tools often lack cultural elements that could enhance students' understanding and retention (Moremoholo, 2023).

Integrating cultural context into AI education can make concepts more meaningful, potentially enhancing deeper connections and interest in the subject matter. While current AI resources focus on active learning and technological engagement, they often lack adaptability to diverse classroom needs (Druga et al., 2022). This highlights the importance of developing culturally relevant AI tools to enhance student engagement and retention. Although machine learning (ML) is rapidly becoming an essential field globally, teaching it effectively in Africa presents unique challenges, as the educational system must align with global trends while incorporating African cultural elements. While existing tools like Google Teachable Machine, LearningML, mBlock, and ML4K (Gresse von Wangenheim et al., 2021) provide valuable educational resources, they often fall short in culturally relevant engagement for students in African contexts. These tools are primarily designed and tested within Western frameworks, which limits their capacity to foster meaningful connections for African learners (Oyelere et al., 2022).

To address this gap, this study introduces AfriML, an AI tool designed to teach ML concepts specifically classification, using African cultural elements to support students' understanding and retention. AfriML contextualize machine learning education within familiar African cultural elements. By creating a culturally resonant learning environment, AfriML not only enhances comprehension but also supports students' identity and belonging within the field of AI. This research holds significant potential for advancing the field of AI education by developing a culturally adaptive approach to teaching machine learning in Nigeria. AfriML's integration of African cultural artifacts into AI education sets a precedent for localized educational tools, underscoring the importance of culturally responsive computing.

The primary cultural focus is on artifacts from Nigeria's main ethnic groups (Hausa, Igbo, Yoruba, Ibibio, and Efik), with future studies potentially expanding the approach to other African cultures. This study addresses the following research questions:

- RQ1. How effective is AfriML in enhancing students' understanding of machine learning concepts?
- RQ2. What impact does the use of culturally familiar elements have on students' engagement and satisfaction with learning AI concepts?
- RQ3. What are students' perceptions of their knowledge improvement and user experience satisfaction with AfriML?

This paper is organized into several parts. The literature review first examines the role of cultural elements in enhancing learning tools and then reviews existing tools for AI pedagogy. The methodology section outlines the research design using the Design Science Research (DSR) framework and the research procedure. The results present the analysis of findings, followed by a discussion of their significance. The limitations of the study are addressed in a separate section, and the paper concludes with recommendations for future research.

## Literature Review

### Insights from Literature on the Role of Cultural Elements in Enhancing Learning Tools

In recent years, integrating cultural elements into educational tools has been recognized for enhancing learning experiences. For instance, Vadivel et al. (2020) examined the impact of culturally themed educational tools in Southeast Asian secondary schools, revealing that culturally relevant themes in digital learning environments significantly improved students' engagement and learning outcomes. A cultural theme refers to incorporating specific cultural elements, such as traditions, values, practices, and stories, into educational materials and activities. By aligning with students' social, cultural, and linguistic contexts, integrating cultural elements in educational tools enhances engagement. Culturally responsive personalized learning (CRPL) promote flexible, student-centered experiences that respect diverse backgrounds, ultimately improving educational quality and inclusivity in diverse classrooms (Ober et al., 2023).

Developing culturally based English instructional materials (CBEIM) for Grade VII students (Afifah & Zuchdi, 2018) significantly enhanced both English language learning and students' internalization of cultural values. Through expert evaluations, CBEIM proved effective, showing improved student outcomes in experimental classes compared to controls. This underscores the value of incorporating culture into educational materials to boost engagement and learning outcomes. Brion (2022), highlighting the benefits of cultural integration within professional development (PD), proposed a Culturally Proficient Professional Development (CPPD) framework with a culturally responsive Multidimensional Model of Learning Transfer (MMLT). By aligning PD with cultural elements, educators can better support diverse student needs and enhance learning transfer, addressing issues like stagnating student outcomes.

Recognizing that culturally responsive instruction can bridge the literacy achievement gap for students from diverse backgrounds, Au (2007) proposed a model of culturally responsive instruction centered on hybridity and inclusivity.

This aligns with the idea that integrating cultural elements enhances engagement and comprehension, especially for students from varied backgrounds. Finally, Brown et al. (2021) explore the integration of culturally relevant elements in virtual reality (VR) for science education, showing that embedding culturally meaningful content in VR can positively influence students' perceptions of science in their communities. This approach allows students to connect personal and cultural knowledge with scientific concepts, enhancing engagement and their valuation of science.

### **Existing Tools for AI Pedagogy**

AI holds great promise for education, with applications from personalized learning to automated grading, predictive analytics, and intelligent tutoring systems (Algahtani, 2024). Integrating AI into educational practices has significantly shifted how educators and students interact with technology. This development has introduced several instructional resources and platforms for teaching complex machine-learning subjects in schools. There are various educational tools and platforms in existence for the teaching of ML as shown in Table I. This section presents an overview of some of the tools.

Teachable Machine is a web-based application developed by Google that simplifies the training of machine learning models, (Carney et al., 2020; de Oliveira et al., 2022) requiring no prior machine learning expertise (Carney et al., 2020; de Oliveira et al., 2022). It enables the teaching of a computer to identify sounds, sights, and poses, possible without writing code (Kurz et al., 2024; Smilkov et al., 2019). DeepScratch was introduced as an extension of the Scratch programming language (Alturayef et al., 2020), covering more advanced machine learning concepts, specifically deep learning. It allows users to train a model by choosing the dataset, the architecture of the neural network, and the hyperparameters.

A web-based visual programming environment called Milo was developed by Rao et al. (2018), Milo is a tool for data science and ML education that requires no prior programming knowledge. Using user-created block, Milo generates JavaScript-comparable source code that runs entirely within the browser. An interactive web program that recognizes sketches to teach middle school pupils image recognition was developed by Mahipal et al. (2023). Using DoodleIt, students draw lines on a canvas, and the item they draw is recognized by a convolutional neural network (CNN) that has been trained beforehand.

ChemAIstry, an interactive tool for children to demonstrate machine learning training and classification was designed by Martin et al. (2024). In ChemAIstry, students select everyday objects, such as a lab coat, to determine which items are acceptable in a chemistry lab. Similarly, LearningML, created by García et al. (2020) for supervised learning pedagogy, consists of ML platform where learner-labeled data is used to build ML models, and a programming platform where learners can create innovative applications that use these ML models to detect texts, photos, sounds, or numbers. Although these tools are unique and offer practical approaches to teaching machine learning, a notable gap remains, none were developed with consideration of the cultural background of the intended users. This research develops AfriML, a tool that integrates cultural elements, such as images, audio, and text into ML education to enhance learning in Nigerian tertiary institutions.

Table 1. Educational Tools for Machine Learning and AI

Tool	Description	Unique Feature	Educational Applications
Google Teachable Machine	A web-based interface for training ML classification models without coding, using webcam, images, or sound.	Simplifies ML model training without coding, making it highly accessible for beginners.	Demonstrating ML concepts in real-time, enabling students to see the immediate impact of their inputs on the model's performance.
DeepScratch	An extension to Scratch for building and learning about deep learning models with built-in datasets or pre-trained models.	Integrates deep learning capabilities directly into the Scratch environment, simplifying complex concepts.	Teaching deep learning concepts in a simplified manner, allowing students to work with built-in datasets or pre-trained models.
Milo	A web-based visual programming environment for Data Science Education.	Emphasizes data science education through visual programming, facilitating data-driven learning.	Teaching data science concepts through visual programming, enabling students to perform interactive data analysis.
DoodleIt	A platform for creating interactive and educational doodles using AI technologies.	Focuses on interactive and engaging AI-driven doodle creation.	Enhancing creativity and engagement in learning through interactive AI-powered doodling activities.
ChemAlstry	An educational tool designed to teach chemistry concepts using artificial intelligence.	Demonstrates the principles of model training and classification using a decision tree classifier with interactive and age-appropriate tasks.	Engaging K–8 students in machine learning concepts, allowing them to understand the impact of their training data on the classifier's output, and encouraging reflections on AI ethics.
LearningML	A platform aimed at teaching supervised ML in K–12.	Specifically designed for K–12 education, focusing on supervised ML, making it suitable for younger learners.	Introducing supervised ML concepts to K–12 students, allowing them to create and understand ML models through hands-on practice.

## Methodology

### Research Design

This research employed a Design Science Research framework (DSR) to navigate the development and evaluation process of AfriML. Design Science Research is a problem-solving approach aimed at advancing human knowledge by developing innovative artifacts (Vom Brocke et al., 2020). DSR uniquely underscores the creation of innovative artifacts to solve practical-oriented problems. The DSR methodology is perfect for this study because it strongly emphasizes producing and assessing artifacts meant to address identified issues.

This research adopted the DSR framework presented by Peffers et al. (2020) to develop AfriML. The framework consists of the following activities: Problem Identification and motivation, Objectives of a solution, Design and development, Demonstration, Evaluation, and Communication, as shown in Figure 1. The adopted methodology defines several steps. As a result, the research process followed the six-step procedure suggested.

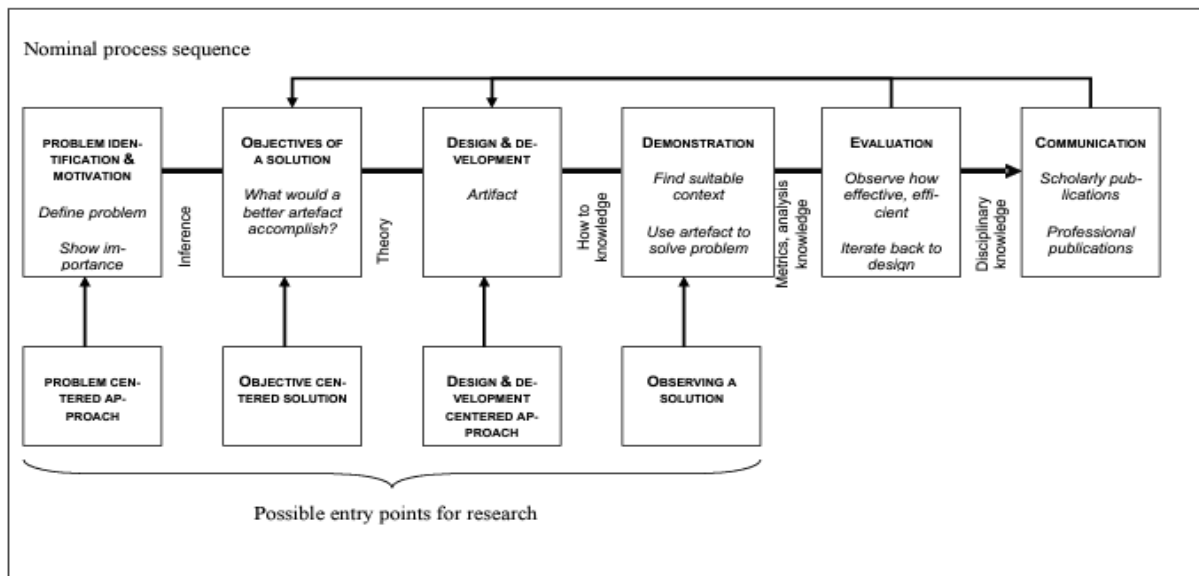


Figure 1. Design Science Research Process (DSRP) Model

### Problem Identification and Motivation

The increasing need for culturally relevant resources in Machine Learning (ML) education highlights a significant gap in the current learning environment. This research addresses the challenge of integrating cultural elements into ML education in Nigerian higher institutions. This research problem is substantiated through a literature review that explores existing studies on the integration of cultural elements in education and their impact in enhancing learning outcomes. The motivation to tackle this issue stems from the importance of enhancing ML literacy among Indigenous populations while ensuring the learning process resonates with their cultural identities and experiences.

### Objectives of the Solution

This research aims to develop AfriML a tool that integrates cultural elements into Machine Learning (ML) education for Nigerian tertiary institutions. The specific objectives of this study are to:

- i. Identify African cultural artifacts that can be incorporated into ML educational tool.
- ii. Adapt existing ML tool to integrate these cultural elements effectively.
- iii. Assess the effectiveness of AfriML in enhancing ML education and fostering cultural relevance among students.

### Design and Development

This research builds on and extends related work. With its user-friendly interface, the platform offers features that empower learners to build their own Machine learning categorization models. It enables users to train classifiers for any number of given classes, putting them in control of their learning process. The platform provides a single interface for data collection, pre-processing, model training, evaluation, and classification. It also includes a pre-trained model using an African dataset, enabling the identification of African artifacts. One notable feature of the

platform is the African relics detector, which can identify texts written in African languages such as Hausa, Igbo, Yoruba, Ibibio, and Efik.

The artifact developed in this research is AfriML, built upon Google's Teachable Machine framework. It teaches ML concepts using African cultural elements. The development process includes data collection, Data Organization and Labeling, classifier algorithm selection, and tool development. African-related images (fabrics and textiles, games, jewelry, masks, sculpture, musical instruments, etc.) and texts were collected. The audio dataset includes native African accents in Hausa, Igbo, Yoruba, Efik, and Ibibio, collected from SautiDB. SautiDB is an innovative digital repository platform dedicated to collecting different African accents; it enables users to contribute to the ongoing initiative of cultural digital curation by recording their voices.

The collected data were organized and labeled appropriately to create a structured dataset fit for training ML models. After that, the Machine learning classifier model was trained for artifact detection and recognition. Finally, artifact detection was integrated into an interactive platform that provides educational content on ML concepts. The platform includes data gathering, organizing, labeling, and classifier output modules.

### **Demonstration**

This phase involved implementing and pilot testing the AfriML tool with students in a Nigerian higher institution to demonstrate the tool's effectiveness in teaching ML concepts. AfriML was demonstrated to 100 level undergraduate students of Modibbo Adama University, Yola, a tertiary institution in Nigeria. Since Machine learning is not currently offered as a dedicated undergraduate course at the institution, AfriML was introduced in the CSC102 (Introduction to Problem Solving) class. CSC102 covers algorithm concepts in problem-solving processes and their implementation strategies. The session included an explanation of how technological advancement has led to the effective use of AI in problem-solving. We highlighted how algorithms are the backbone of any AI tool, including the one we have developed. Subsequently, we presented AfriML as an instrument for solving problems, explaining how the tool can be used to solve classification problems and the importance of using contextualized datasets of African origin.

AfriML provides users with various features. Users can select from several options, such as an Accent Detector, Language Text Detector, and Artifacts Detector. For the Accent Detector, users upload audio files, users upload text files for the Language Text Detector, and for the Artifacts Detector, users upload images. Every other process remains the same. The following explains the process of setting up and using the tool for training a machine learning model to recognize different classes of objects. Here is a breakdown of the process:

- i. **Creating and Naming Classes:** The user begins the process by defining and naming the different categories (or classes) that the model will be trained to recognize, as shown in Figure 2.
- ii. **Data Collection:** The data collection process follows; the user needs to collect data for each named class, as shown in Figure 3. The data can be collected by uploading files from the user's local computer or using a webcam

to capture data in real-time. Both methods involve a simple button click to start the data collection process. The data collected will serve as input for the next phase, which is the model training phase.

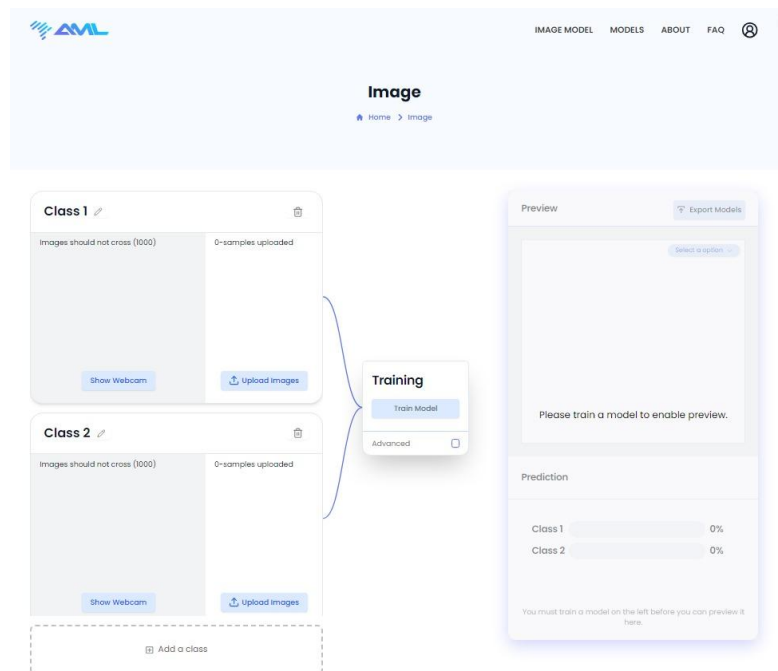


Figure 2. Creating and Naming Classes

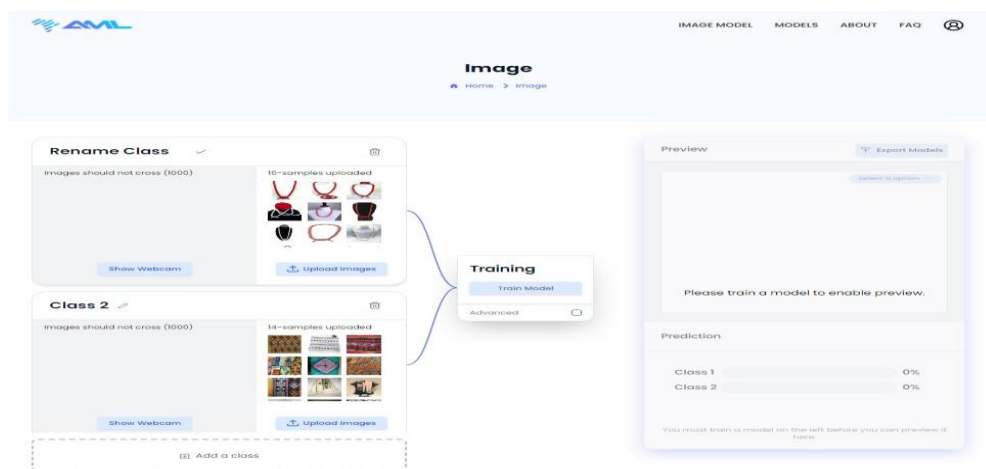


Figure 3. Data Collection and Training

iii. **Model Training:** After collecting the necessary data, the user proceeds to the model training phase. This is initiated by clicking the training button, as shown in Figure 3. During this phase, the model learns to recognize the patterns and features of each class based on the collected data.

iv. **Preview Panel Expansion:** Once the model has finished training, a preview panel on the interface that expands to the right displays the features and capabilities of the trained model.

v. **Feeding New Data to the Model:** Users can now test the model by providing new data. By clicking the upload

button, they can upload files using a webcam or directly from their computers. The model will then categorize the new data into one of the predefined classes as shown in Figure 4.

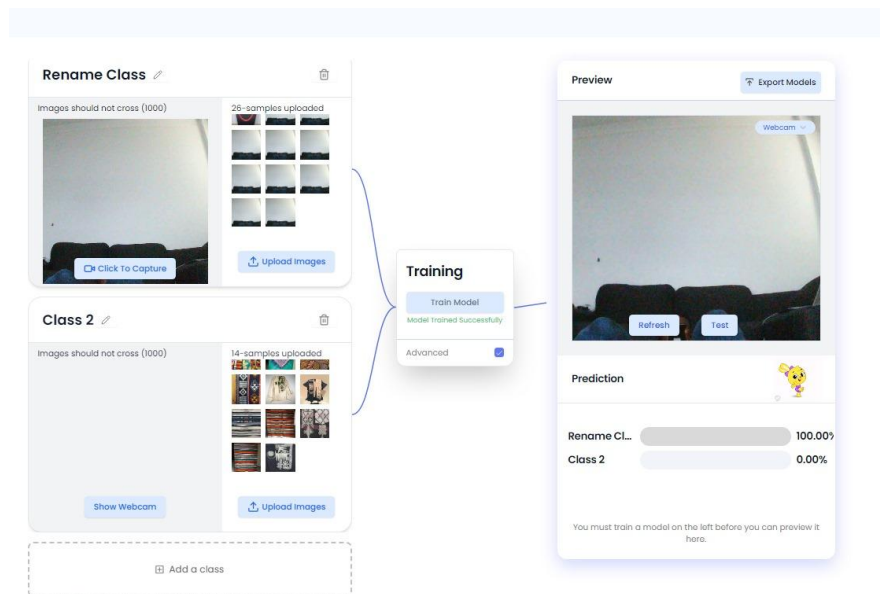


Figure 4. Feeding New Data to the Model

vi. African Artifact Detector Option: Users can check whether the new data is categorized as an African artifact by clicking the "advance" button to activate the relic detector feature. When users activate this feature, if the image, text, or audio matches an African artifact, a prediction GIF image is displayed, tagging it as such, as shown in Figure 5.

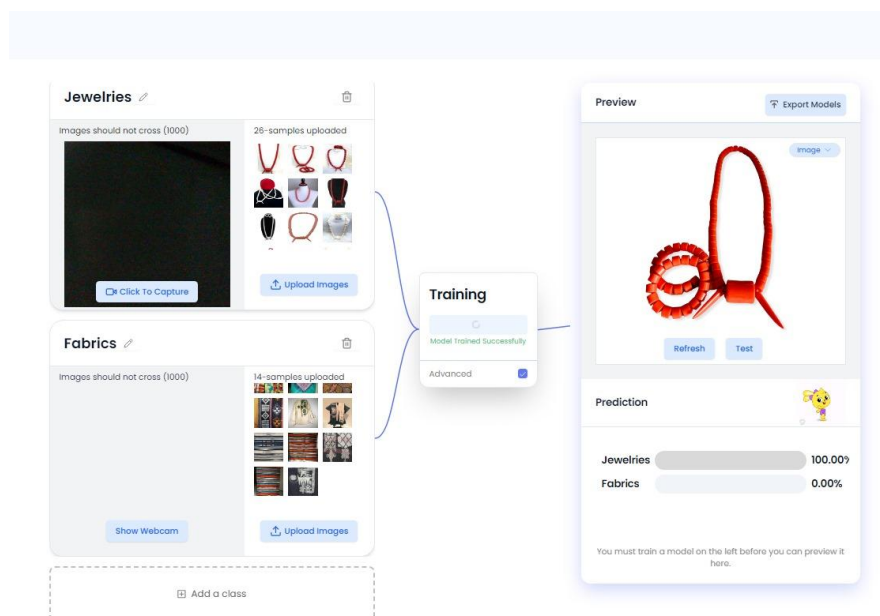


Figure 5. African Artifact Detector Option

vii. Exporting the Trained Model: Users can export the trained model for use in other applications.

## Research Procedure

The participants were students with varying levels of prior ML experience, representing diverse cultural backgrounds across the institution's communities. This diversity supported the study's goal of creating a culturally inclusive learning tool. To assess the effectiveness of AfriML, we conducted structured surveys with 247 respondents to evaluate their improvement in understanding ML concepts. These surveys measured comprehension, engagement, and the perceived relevance of ML content.

The demographics of the participants were as follows: 57% were female, and 43% were male. The age distribution revealed that 78.14% of respondents were between 18 and 25 years old, 19.43% were under 18, 2.02% were between 26 and 35 years old, and only 0.40% were over 45 years old. This age distribution indicates a majority of young adult participants, with fewer respondents under 18 and very few in the 26 - 35 age group. Sessions were conducted in a controlled environment within computer labs, ensuring consistent access to technology and minimizing external disruptions. The controlled setting provided uniformity in learning conditions, allowing a focused evaluation of AfriML's impact on participants' understanding of ML concepts.

A structured survey was developed to assess the impact of AfriML. This primary research instrument, a self-administered questionnaire, evaluated students' perceptions and experiences about their knowledge improvement and understanding of ML using AfriML. The questionnaire consisted of four sections: demographic information, consisting of three items; ML knowledge improvement and user experience satisfaction, composed of 6 items; the relevance of culturally integrated content in learning ML, consisting of 4 items; and lastly, feedback and suggestions for improvement, consisting of three items. The research instrument utilizes Likert scale. Particular attention was given to aligning the questionnaire with the objectives of enhancing ML education and incorporating African cultural elements. The questionnaire underwent a validation process involving a panel of experts, including educational technology and AI experts. We selected the experts based on their scholarly and practical expertise. The questionnaire was reviewed to ensure relevance, comprehension, and effectiveness in answering the research questions. The experts provided feedback to refine the questionnaire and ensure it effectively met the study's goals. Descriptive data analysis was performed to assess the effectiveness of the AI tool. The collected data was analyzed using mean and standard deviation to know the users' improvement ratings, confidence level, perception about improvement in their knowledge, and overall satisfaction with AfriM.

## Results

### ML Knowledge Improvement and User Experience Satisfaction

This section details the responses to survey questions designed to measure participants' improvement in ML knowledge and overall satisfaction with the AfriML tool as shown in Figure 6. Participants' confidence in understanding ML concepts showed noticeable improvement after using AfriML. Before using the tool, the mean confidence level was 2.43 with a standard deviation (SD) of 1.04, indicating a moderate level of self-assessed ML knowledge. After engaging with the tool, confidence increased to a mean of 3.28 (SD = 1.05). This shift reflects a positive change in students' self-assessed understanding of ML concepts.

Participants reported a moderate level of improvement in their understanding of the ML classification concept after using AfriML, with a mean rating of 3.09 (SD = 1.04). This result suggests that users found the tool effective in clarifying the classification concept, indicating that AfriML's instructional approach was helpful. In terms of the tool's overall effectiveness in facilitating ML learning, participants gave an average rating of 3.36 (SD = 1.08), reflecting a generally positive perception, though some variability in experiences were observed.

AfriML's user experience was rated highly by participants, with a mean score of 4.08 (SD = 0.77), suggesting that users found the tool enjoyable and easy to navigate. Additionally, the likelihood of recommending AfriML to others was rated even higher, with a mean score of 4.39 (SD = 0.83), further reinforcing the positive reception and perceived value of the tool.

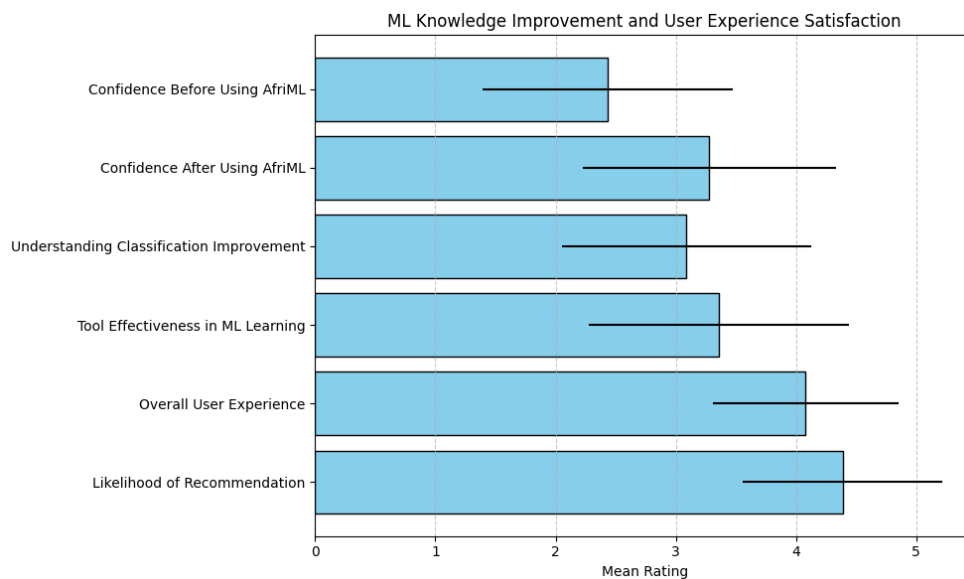


Figure 6. ML Knowledge Improvement and User Experience Satisfaction

### Cultural Context in ML Learning

This section presents responses to items measuring the relevance, clarity, and helpfulness of cultural elements in the ML learning experience with AfriML as shown in Figure 7. Participants rated the cultural relevance of AfriML with a mean of 3.45 (SD = 1.03), indicating a positive appreciation for the incorporation of African cultural context in the learning process. Students also acknowledged the clarity and relatability that these cultural elements brought to ML concepts, at an average rating of 3.34 (SD = 1.07). This suggests that the use of familiar artifacts helped make abstract ML concepts more accessible and intuitive.

In terms of engagement, participants reported high levels of interest and focus, with a mean rating of 3.43 (SD = 0.98), demonstrating that the culturally contextualized content contributed positively to their learning experience. Moreover, the usefulness of cultural elements in helping students grasp ML concepts was affirmed with a mean score of 3.47 (SD = 0.97), highlighting the educational value of integrating cultural context into the instructional design.

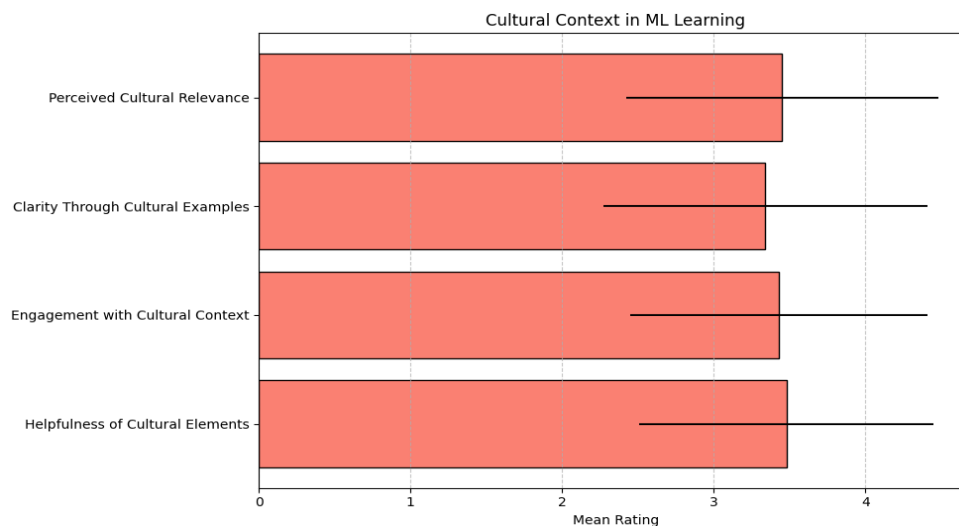


Figure 7. Cultural Context in ML Education

## Discussion

This discussion explores each survey item in-depth, linking the findings to relevant studies in the field and examining how AfriML impacted students' understanding of ML concepts, engagement, and user satisfaction. The results are discussed in relation to each research question, demonstrating the benefits of integrating culturally familiar elements within ML education. Figure 6 shows the mean ratings and standard deviations across various metrics, including confidence before and after using AfriML, improvement in understanding classification, tool effectiveness, overall user experience, and likelihood of recommendation. Figure 7 illustrates mean ratings for cultural context-related items, including perceived cultural relevance, clarity of ML concepts through cultural examples, engagement with ML content, and the helpfulness of cultural elements in grasping ML concepts.

Each chart includes error bars representing the standard deviation, which emphasize the variability in responses and serve as a visual guide to the consistency of student feedback across each category. The error bars extend above and below each bar by the standard deviation, showing how much individual responses varied around the mean. Longer error bars indicate greater variability in responses, suggesting a wider range of opinions, while shorter error bars reflect more consistency, with most ratings closer to the mean.

### RQ 1: How Effective is AfriML in Enhancing Students' Understanding of Machine Learning Concepts?

The results show that AfriML effectively enhanced students' ML knowledge, particularly in the concept of Classification. Students' self-assessed confidence in understanding ML concepts increased significantly after using AfriML, from a mean score of 2.43 (SD = 1.04) before usage to 3.28 (SD = 1.05) after usage. This improvement highlights AfriML's effectiveness in facilitating learning, as it aligns with prior research by Kaswan et al. (2024), which suggests that interactive, AI-based educational tools can positively impact students' confidence levels. The structured approach provided by AfriML, particularly through culturally relevant artifacts, likely contributed to this boost in confidence by providing students with a familiar framework to understand ML concepts better.

Supporting these findings, the study by Kelly et al. (2023) highlights that confidence in using AI tools tends to increase with familiarity and experience. They observed that students who engage more regularly with AI tools report higher confidence levels, even in the absence of formal training. This parallels AfriML's impact, as its structured and culturally relevant approach likely made the ML concepts more accessible and less intimidating for students. By embedding familiar artifacts into its instructional design, AfriML provides students with a framework that helps bridge new ML concepts with prior cultural knowledge, thus reinforcing both understanding and confidence.

The increase in students' self-assessed confidence scores indicates that AfriML's design, combining interactive AI-based learning with culturally relevant elements, not only supports conceptual understanding but also aligns with broader trends observed by Kelly et al. (2023) in AI education. This integration of cultural context and structured learning may thus be a vital component in successfully boosting students' confidence and engagement with ML concepts.

Students rated their improvement in understanding classification concepts at a mean of 3.09 (SD = 1.04), reflecting a moderate enhancement in comprehension. This finding aligns with prior research showing that contextualized learning experiences particularly those integrating culturally familiar elements can enhance conceptual understanding by making abstract concepts more relatable (Casillo et al., 2024). Yu & Denham (2019) work further supports this perspective; their culturally relevant augmented reality math game demonstrated how embedding familiar cultural elements in educational tools can make complex subjects, such as math, more accessible. By using relatable, immersive scenarios, the game effectively bridged abstract mathematical concepts with students' cultural contexts, leading to improvements in arithmetic fluency and adaptive number knowledge. Similarly, AfriML leverages cultural artifacts to contextualize ML classification concepts, likely bridging theoretical ideas with tangible examples that resonate with students lived experiences. This culturally relevant framework may have contributed to a deeper cognitive connection, as students could more readily grasp abstract ML concepts through a familiar lens. This approach suggests that culturally anchored educational tools, like AfriML, not only make learning more engaging but also facilitate better understanding by connecting complex theories with culturally relevant representations, thereby improving students' conceptual grasp of ML classification.

AfriML was rated with a mean effectiveness score of 3.36 (SD = 1.08), indicating a generally positive perception of the tool's ability to support ML learning. This result supports findings from Zawacki-Richter et al. (2019), who emphasized the importance of AI tools in enhancing learning outcomes through accessible and user-centered design. Further supporting this finding, Edwards-Fapohunda and Adediji (2024) observed that AI-powered educational tools, when well-implemented, enhance engagement and individualization in learning experiences, improving accessibility and deepened conceptual understanding. AfriML's integration of cultural artifacts likely contributed to its perceived effectiveness by making abstract ML concepts more understandable and engaging, similar to AI-driven distance learning tools that promote tailored, impactful learning interactions.

Additionally, Barua et al. (2022) discuss the role of AI tools in educational support for diverse learners, emphasizing the need for customized assistive designs to enhance learning for those with varying levels of background

knowledge. This insight is relevant to AfriML, as the variation in effectiveness scores suggests that while the tool was beneficial for most students, some may have required additional scaffolding. These findings highlight the potential for future iterations of AfriML to incorporate more instructional support to accommodate differences in prior ML exposure and learning needs.

## **RQ 2: What Impact Does the Use of Culturally Familiar Elements Have on Students' Engagement and Satisfaction with Learning AI Concepts?**

Participants rated the cultural relevance of AfriML highly, with a mean of 3.45 (SD = 1.03), reflecting appreciation for the cultural context in the ML learning experience. This aligns with research by Likourezos et al. (2019), who found that incorporating culturally relevant content can increase relatability, resulting in more effective engagement. By using African cultural artifacts as examples within ML concepts, AfriML provided students with a familiar framework that may have improved their focus and connection to the material. Kieran and Anderson (2019) and Likourezos et al. (2019) further support the value of cultural relevance in learning, highlighting how integrating culturally responsive pedagogy with Universal Design for Learning (UDL) can enhance students' educational experiences by treating cultural diversity as a learning strength. This perspective resonates with AfriML's use of African cultural artifacts, which likely made machine learning concepts more accessible and engaging for students. The high mean rating for cultural relevance suggests that students connected well with the material, likely due to this familiar context. When students' backgrounds are intentionally included, educational tools become more relatable, increasing students' focus and satisfaction.

Similarly, Brown et al. (2019) emphasize the positive effects of culturally relevant education (CRE) in STEM settings, where theory-to-practice alignment can bridge cultural context with technical learning. By embedding familiar cultural elements into complex ML concepts, AfriML's design reflects the CRE principles that Brown et al. found effective in supporting student engagement and comprehension. AfriML's cultural approach may thus serve as a bridge, transforming abstract machine learning theories into meaningful examples grounded in students' own cultural frameworks. Contextualizing learning within students' cultural backgrounds can facilitate greater engagement, understanding, and overall satisfaction in educational experiences.

The clarity Mean ratings of 3.34 (SD = 1.07) for cultural artifacts in explaining ML concepts suggest that culturally contextualized learning aids comprehension by making concepts more intuitive. Casillo et al. (2024) support this, noting that culturally relevant examples help bridge the gap between complex concepts and learners' everyday experiences. The findings indicate that AfriML's approach of contextualizing ML with cultural elements might have allowed students to better visualize and internalize complex ML ideas, thus facilitating deeper understanding.

This result also aligns with Shao et al. (2019), who discuss how cultural relevance shapes cognitive processes, noting that culturally familiar materials improve intuitive understanding by aligning learning content with students' implicit and explicit cultural frameworks. AfriML's use of African cultural artifacts in teaching ML concepts provides an understandable context, potentially enhancing clarity by linking complex ML ideas to students' everyday experiences. Shao et al. (2019) underscore that when learning materials resonate with learners' cultural

backgrounds, comprehension and retention of challenging content improve. In this way, AfriML's culturally contextualized approach may enhance students' ability to visualize, internalize, and engage deeply with ML concepts.

Engagement levels were rated at a Mean of 3.43 (SD = 0.98), underscoring that the integration of cultural context enhanced students' interest. This engagement aligns with research by Kaswan et al. (2024), which highlights the role of personalized, interactive learning tools in maintaining student focus and interest. Students' heightened engagement through culturally familiar elements suggests that AfriML made the learning experience more enjoyable and immersive, a crucial factor in sustaining attention, particularly in technically demanding subjects like ML.

The result is also consistent with Berti (2021), who highlights how virtual reality and similar immersive technologies can create meaningful, contextually rich experiences that improve engagement and learning outcomes. In AfriML, culturally familiar elements may have provided an analogous immersive experience by presenting ML concepts in ways that resonate personally with students, making the material more relatable and compelling. Similarly, Chu and Mazalek (2019) emphasize the benefits of embodied, narrative-driven interactions with cultural artifacts, noting that such frameworks can help learners contextualize and make personalized connections to material. The Tangible and Embodied Narrative Framework (TENF) they propose uses interactive narratives to deepen engagement with cultural heritage, an approach that parallels AfriML's use of African cultural elements. By offering students a culturally relevant framework, AfriML may have helped sustain their attention in a complex technical domain by making the content feel accessible and personally meaningful. This supports the observation that students found the culturally contextualized ML content engaging, aligning with research that shows the value of personalization and cultural relevance in educational technology.

The mean of 3.48 (SD = 0.97) for the perceived usefulness of cultural elements indicates that students found these contextual features valuable in grasping ML concepts. This aligns with findings from Cen et al. (2023) and Oyelere et al. (2022), which suggest that incorporating familiar, understandable examples in educational tools can significantly enhance comprehension and learning outcomes. By using culturally relevant artifacts and examples, AfriML allowed students to approach ML concepts from a familiar perspective, likely making complex ideas more accessible and reducing the cognitive load associated with unfamiliar content. This contextualized approach may have helped demystify ML principles, stimulating a deeper grasp of technical content and underscoring the potential of culturally attuned tools to improve educational outcomes.

### **RQ 3: What Are Students' Perceptions of Their Knowledge Improvement and User Experience Satisfaction with AfriML?**

AfriML received a high rating for overall user experience, with a mean score of 4.08 (SD = 0.77), indicating that students found the tool enjoyable and easy to use. This high rating aligns with studies like Vlachogianni and Tselios (2022), who found that positive user experience directly correlates with learning effectiveness in educational technologies. The integration of cultural elements alongside user-friendly interfaces enhanced students' satisfaction

and comfort in using AfriML. This supportive design may have facilitated a smoother learning experience, promoting both engagement and ease of comprehension, crucial factors in sustaining attention and interest in ML.

Students' likelihood of recommending AfriML to others scored even higher, with a mean of 4.39 (SD = 0.83), suggesting that they valued the tool's approach and effectiveness in ML education. Similar study, such as the one by Cen et al. (2023), highlight that recommendations are often rooted in perceived effectiveness and satisfaction. AfriML's positive reception suggests that it fulfilled students' learning expectations, making it a tool they are likely to endorse to peers, especially for ML learning in culturally relevant contexts.

The findings indicate that AfriML's approach of integrating culturally familiar elements within ML education has the potential to make learning more relatable, engaging, and effective for Nigerian students. The increases in confidence, satisfaction, and engagement reinforce the value of contextualizing ML education within a cultural framework, supporting existing literature that emphasizes culturally relevant pedagogy as a means of enhancing educational outcomes (Kaswan et al., 2024; Zawacki-Richter et al., 2019). AfriML demonstrates that culturally contextualized AI tools not only support knowledge acquisition but also promote positive user experiences, ultimately contributing to more inclusive and effective ML education in Nigerian higher institutions. Future research should consider expanding this approach by incorporating a broader range of cultural artifacts and evaluating their applicability across other regions and educational contexts.

## Limitations of the Study

This study offers valuable insights into the potential of integrating culturally relevant elements in ML education, but there are a few limitations that should be considered. First, the dataset used in training the AfriML model was limited to a relatively small set of African cultural artifacts. The limited availability of digitized and publicly accessible African cultural data remains a major challenge and may have constrained the tool's ability to reflect the full diversity of African heritage. Second, the study focused on cultural contexts relevant to Nigerian students. While effective for this target group, these contexts may not resonate equally with learners from other African countries. Finally, the study involved a relatively small sample of Nigerian tertiary students, which restricts the generalizability of the findings to broader populations.

## Conclusion

This research developed AfriML, an AI-based tool designed to enhance ML education for Nigerian tertiary students by integrating culturally familiar elements. The primary goal was to create a learning tool that leverages African cultural artifacts to increase student engagement and facilitate the understanding of ML concepts in a meaningful, contextually relevant way. The results indicate that AfriML effectively improved students' understanding of ML concepts, with users reporting substantial engagement and satisfaction due to the incorporation of culturally relevant materials. The descriptive analyses demonstrate that culturally familiar elements had a positive impact on student engagement and satisfaction, with high mean ratings across these areas. These findings support the notion that a culturally contextualized approach to teaching ML can improve not only knowledge retention but also students'

overall learning experience.

In addition, AfriML's emphasis on blending ML education with cultural familiarity proved to resonate with students, enhancing their motivation and willingness to recommend the tool to others. Feedback highlighted the tool's innovative and beneficial approach, though user suggestions point to areas for future refinement. This research underscores the potential of integrating culturally relevant elements in AI-driven educational tools to make ML education more accessible, relatable, and effective.

## Recommendations

This study recommends that AfriML be expanded to incorporate cultural artifacts, languages, and practices from a broader range of African ethnic groups. Such an expansion would enhance inclusivity and ensure that the tool resonates with learners across diverse cultural contexts on the continent. Higher education institutions in Nigeria and Africa more widely are encouraged to integrate AfriML into machine learning and introductory programming curricula as a means of bridging the gap between abstract concepts and students lived experiences. Formal adoption in classroom settings would strengthen comprehension and engagement while reinforcing the local relevance of artificial intelligence education.

Further research should also include longitudinal studies to evaluate the sustained impact of AfriML on student learning outcomes, confidence, and cultural identity in artificial intelligence education. In addition, the design principles underpinning AfriML could be adapted for other STEM disciplines where abstraction often challenges learners, such as mathematics, data science, and engineering. Extending its application across disciplines would amplify its contribution to culturally responsive pedagogy in Africa.

## Statements and Declarations

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