Culturally Tailored No-Code Machine Learning for Enhanced Educational Engagement

A Study on Nigerian High-School Students

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ABSTRACT

Despite the growing emphasis on introducing AI and ML concepts to students from kindergarten through high school, existing educational resources often lack cultural relevance for African students. This study addresses this gap by designing, developing, and evaluating AfriML, a web-based platform integrating African cultural elements for ML education. Implemented in Nigerian high schools, AfriML enables users to train, test, and export models for image, text, pose, and audio classification, recognizing African images, accents, and languages. The study assessed AfriML's effectiveness through structured surveys, pre- and post-test assessments, and semi-structured interviews, revealing significant improvements in students' ML comprehension and engagement. Challenges such as technical issues and resource limitations were noted, suggesting areas for future enhancement. The findings underscore the importance of culturally relevant educational tools in making AI and ML education more accessible and engaging for African students, recommending broader school inclusion and mobile application development for improved accessibility and language processing capabilities.

Keywords: AfriML, AI/ML Education, Cultural Relevance, No-Code ML tool, Educational Technology, Nigerian High Schools.

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List of Abbreviations

AfriML	Africa Machine Learning
AI	Artificial Intelligence
ANOVA	Analysis of Variance
API(s)	Application Programming Interface(s)
BERT	Bidirectional Encoder Representations from Transformers
CNN	Convolutional Neural Network
CSS	Cascading Style Sheet
DB	Database
DSR	Design Science Research
FAQ(s)	Frequently Asked Question(s)
Fig	Figure
FRN	Federal Republic of Nigeria
ICT	Information and Communication Technology
iOS	Iphone Operating Software
LMS	Learning Management System
ML	Machine Learning
NLP	Natural Language Processing
PC	Personal Computer
REST(ful)	Representational State Transfer(ful)
RNN(s)	Recurrent Neural Network(s)
SPSS	Statistical Package for the Social Sciences
STEM	Science Technology Engineering and Mathematics
UNESCO	United Nations Educational, Scientific and Cultural Organization
URL	Uniform Resource Locator

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1.0 INTRODUCTION

1.1 Background

Artificial intelligence (AI) and its key component, Machine Learning (ML), are continuously transforming various sectors and influencing everyone's lives (Sanusi et al., 2022; Darell and John, 2018). Consequently, there is a growing push to introduce these concepts to students from kindergarten through high school to cultivate AI-ready citizens (Wang and Johnson, 2019). Recognizing the importance of AI/ML education, numerous stakeholders have reached a consensus on its significance, leading to the implementation of several initiatives (UNESCO, 2021; Walter, 2024). For example, the non-governmental organization AI4K12 has spearheaded the development of a "5 Big Ideas" framework for AI education (Touretzky et al., 2019). This framework is designed to provide a cohesive structure for integrating AI concepts into K-12 curricula, ensuring that students grasp the fundamental principles of AI, its ethical considerations, and its practical applications. The "5 Big Ideas" include Perception, Representation and Reasoning, Learning, Natural Interaction, and Societal Impact. These ideas are designed to be accessible and engaging for students, helping them grasp complex topics through age-appropriate activities and projects (Drivas & Doukakis, 2022).

Moreover, numerous educational programs and partnerships have emerged to support this movement. Among which are: Machine Learning for Kids (ML4Kids) which is an initiative dedicated to increasing diversity and inclusion in the field of machine learning by offering educational programs and providing accessible and engaging hands-on experiences, equipping students with the skills and knowledge to pursue further studies and careers in technology and artificial intelligence (ML4Kids, 2018) . Similarly, the MIT Media Lab's "Scratch" programming environment has incorporated AI modules, enabling younger students to experiment with machine learning through visual coding interfaces (Scratch, 2007).

Integrating AI and ML into early education prepares students for future careers and also foster critical thinking, creativity, and an understanding of the technological world they inhabit (Johnson and Sarkar, 2023). As AI continues to advance, equipping the next generation with the knowledge and skills to navigate and shape this landscape becomes increasingly vital. Through collaborative efforts among educators, industry leaders, and policymakers, we can create an education system that empowers students to become informed, responsible, and innovative contributors to the AI-driven future (Sanusi et al., 2022; Limna et al., 2021).

To further enhance student engagement in AI and ML, this study proposed an ML tool called ”AfriML” Building on existing platforms (e.g., Googles Teachable Machine and Machine Learning for Kids), AfriML considered incorporating African cultural elements. This platform, AfriML, aims to introduce high school students in Africa to AI and ML concepts through culturally relevant content, models and examples. By embedding African cultural elements, AfriML seeks to create a more relatable and stimulating learning environment for African students (Ertugruloglu et al., 2024). Integrating AI and ML education with African cultural elements through AfriML will not only enhance engagement but also inspire a new generation of African innovators and leaders in technology. This initiative represents a significant step towards creating a diverse and inclusive AI landscape, fostering a future where African students can actively contribute to and shape the global technological narrative.

1.2 Problem Statement

Despite the growing recognition of the importance of introducing AI and ML concepts to students from kindergarten to high school, existing educational initiatives often lack cultural relevance, particularly for African students. This gap in culturally tailored educational resources hinders effective engagement and learning outcomes (Chisom et al., 2024). While programs like ML4Kids, Scratch and many more have made strides in making AI and ML accessible, they do not fully address the unique cultural contexts and needs of African students. To bridge this gap, AfriML was developed to integrate African cultural elements into AI and ML education, aiming to provide a more relatable and stimulating learning environment (Ertugruloglu et al., 2024).

1.3 Aim and Objectives of the Study

1.3.1 Research Aim

This study aims to design, develop and evaluate AfriML, a No-Code ML tool infused with cultural orientation to teach ML concepts to high-school students in Nigeria.

1.3.2 Objectives of the study

1. To design and develop the AfriML tool, incorporating culturally relevant elements that resonate with Nigerian high-school students.

2. To implement the AfriML tool in selected Nigerian high schools and evaluate its effectiveness in enhancing students' understanding of machine learning concepts, measuring their engagement and overall satisfaction.

1.4 Research Questions

1. How can we design and develop an ML tool infused with African cultural elements to improve high-school students' education of ML concepts?

2. How effective is AfriML in enhancing students' understanding of machine learning concepts?

3. How does the use of the AfriML tool influence students' attitudes towards learning machine learning and their motivation to pursue further studies in this field?

1.5 Scope of Research

The scope of this research encompasses the design, development, and in-depth examination of the effectiveness and implications of AfriML, a culturally tailored web-based No-Code Machine Learning (ML) platform, within the educational landscape of Nigerian high-schools. This study focus on investigating the integration of AfriML into the educational framework, evaluating its impact on their understanding of machine learning concepts, including classification algorithm. Specifically, the research will delve into identifying the specific cultural considerations essential for the effective implementation of AfriML, addressing challenges, and optimizing instructional strategies to enhance learning experiences for Nigerian high-school students.

1.5.1 Significance of the study

The significance of this study lies in its potential to address critical gaps in the intersection of education, technology, and cultural relevance, particularly within the context of high-school education in Africa. With the existence of AfriML, a culturally tailored No-Code Machine Learning (ML) platform, this research has the unique opportunity to assess its impact on their understanding of machine learning concepts, particularly in image, pose, audio, and text classification among Nigerian high-school students. By investigating the integration of AfriML and its culturally relevant elements into the educational framework, the study aims to pioneer innovative approaches that enhance educational experiences for African students. The findings of this study could have far-reaching implications for educational policymakers, technologists, and practitioners seeking to bridge educational disparities and promote inclusive learning environments in Africa.

This research will contribute to advancing the understanding of how AfriML and similar culturally relevant educational technologies can be effectively implemented to cater to the diverse cultural backgrounds and learning needs of Nigerian high-school students. By aligning the aim and objectives with the research questions shared earlier, the study provides practical insights for designing educational resources that resonate with students' cultural identities and promote meaningful learning experiences. Ultimately, the significance of this study lies in its potential to inform the development of culturally sensitive educational technologies, such as AfriML, that empower African students, foster inclusivity, and contribute to the advancement of education and STEM fields in the region.

1.6 Summary of the chapter

This research investigates the impact of AfriML, a culturally tailored No-Code Machine Learning (ML) platform, on their understanding of machine learning concepts, particularly in image, pose, audio, and text classification among Nigerian high-school students, with the overarching goal of bridging educational disparities and promoting inclusive learning environments. Through a comprehensive examination of specific cultural considerations, challenges, and opportunities associated with implementing AfriML, the study aims to pioneer innovative approaches that enhance learning experiences and promote equitable access to machine learning education for underrepresented groups in STEM fields in Africa. By providing practical insights and recommendations grounded in the existence of AfriML, this research contributes to advancing the intersection of education, technology, and cultural relevance, with the potential to inform policymaking, technological development, and educational practices aimed at fostering meaningful learning experiences for African students.

1.7 Thesis structure

This research study consists of seven chapters. The introductory chapter provides an overview of the research background, problem statement, aims, objectives, research questions, and scope of the study, highlighting its significance. Chapter two is dedicated to reviewing related research, offering a comprehensive understanding of the existing literature, conceptual frameworks, and the context of high school education in Nigeria, including educational technologies, cultural relevance, and the role of machine learning in K-12 education.

In the third chapter, the study's methodology is detailed, encompassing the study area, research design, the design and development of the AfriML tool, goals of design science research, and the stages involved in the design science research methodology. It also covers the data collection and analysis methods employed in the study. Chapter four focuses on the implementation of AfriML using the design science research framework, providing an overview of the tool, its software architecture, and the steps for its use.

Chapter five presents the research design and methodology, detailing the structure and approach of the study. Chapter six presents the results, including qualitative and quantitative analyses, and explores the overall positive experience, enhanced student engagement through cultural integration, and identifies challenges and areas for improvement.

Finally, chapter seven summarizes the key findings, draws conclusions based on the research outcomes, and provides recommendations for future research and practice. This chapter also emphasizes the study's significance and its potential implications for enhancing engagement and accessibility among Nigerian high school students using AfriML.

2.0 LITERATURE REVIEW

2.1 Introduction

Africa's diverse cultures, languages, and socio-economic conditions present distinctive educational hurdles. Challenges like unequal access to educational resources, differing linguistic environments, and disparities in learning achievements form a multifaceted context for the incorporation of internet and technology in its educational framework (Chisom et al., 2024). However, the potential of the internet to personalize educational experiences, address individual learning needs, and enhance educators' capabilities is now embodied in artificial intelligence (AI), providing hope for overcoming these challenges (Agbo et al, 2020; Seo, 2021).

In the realm of education, AI serves a dual purpose: to enhance learning outcomes (Chisom et al, 2024) and to support educators in refining their teaching methodologies (Agbo et al, 2021). The applications of AI in education are multifaceted, ranging from automating the grading of assignments (Aldriye et al, 2019) to crafting personalized curriculums tailored to individual student needs (Tapalova et al 2022). AI-based platforms have the capability to gather and analyze vast troves of student data, including their interactions with educational materials, completion times for exercises, test scores, and overall performance (Oyelere et al, 2018).

Within the rapidly evolving educational technology landscape, the intersection of cultural relevance and machine learning presents both opportunities and challenges, particularly within the context of high-school education in Africa. As advancements in technology continue to reshape educational practices (Agbo et al., 2021), there is a growing recognition of the importance of integrating culturally tailored elements into educational resources to enhance engagement, promote inclusivity, and improve learning outcomes among diverse student populations. In this literature review, we will explore the existing research and scholarship surrounding the integration of No-Code Machine Learning (ML) platforms within African educational settings, aiming to provide a comprehensive understanding of the current state of knowledge, identify gaps, and lay the groundwork for our study's investigation into the effectiveness and implications of such platforms for Nigerian high-school students.

2.2 Conceptual Framework

The conceptual framework for this study is grounded in the intersection of three key domains: high-school education, cultural relevance, and machine learning. This framework is designed to guide the development and evaluation of AfriML, an educational tool that integrates these domains to provide a culturally responsive learning experience for Nigerian high-school students.

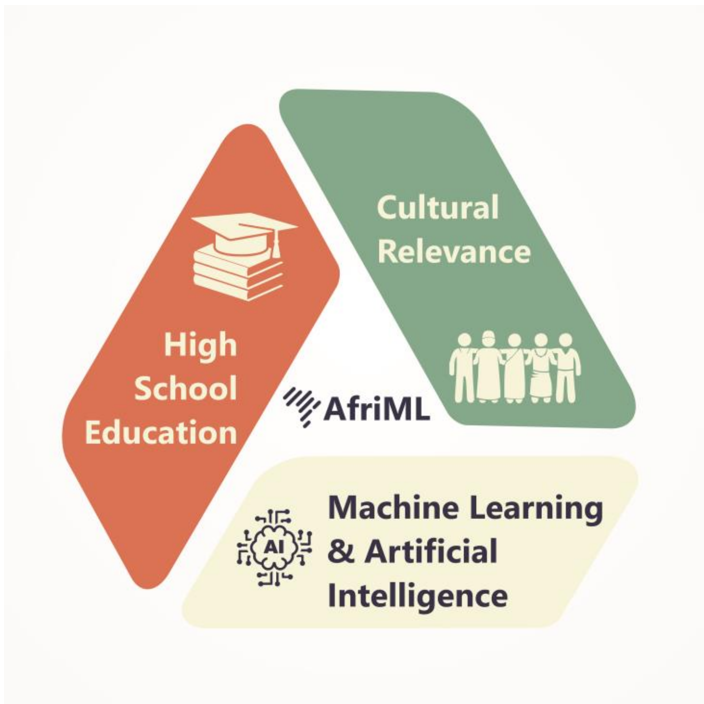

Fig 1: The Three Key Domains of AfriML

The intersection of high-school education, cultural relevance, and machine learning forms a robust framework for AfriML. This integrated approach ensures that the tool is pedagogically sound, culturally sensitive, and technologically advanced. By leveraging the strengths of each domain, AfriML seeks to bridge the gap in culturally relevant educational resources and provide an engaging, effective learning experience for Nigerian high-school students. It further underscores the importance of a holistic approach to educational technology. It highlights the need for tools like AfriML that not only teach essential skills but also respect and incorporate the cultural contexts of learners. Through this framework, the study aims to demonstrate that integrating high-school education system with cultural relevance and machine learning can create a more inclusive and impactful educational experience for students in diverse contexts.

2.3 High School Education

2.3.1 Overview of High School Education in Nigeria

In Nigeria, the high school education has historically faced significant challenges, including societal undervaluation, inadequate funding, bureaucratic obstacles, and poor policy implementation, which have contributed to its low status (Mormah, 2021). However, there has been a shift towards professionalizing teaching through various legislations and policies, such as the National Policy on Education (FRN, 2013), which mandates that teachers of all educational levels undergo specialized education to gain the necessary knowledge, skills, and attitudes. This policy aimed to ensure that teachers are well-prepared and motivated, with programs designed for both prospective and current teachers to achieve certification and meet intellectual and professional standards considering the emergence and swift invasion of various technologies for teaching and learning in the classroom (OECD, 2016). High school education in Nigeria prepares individuals for various roles within and beyond the school system, including administration, guidance and STEM fields (Mormah, 2021).

2.3.2 Educational Technologies used in High Schools

Digital technologies are becoming an integral part of the modern world, constantly intersecting with various areas of our lives, including the field of education. At the same time, digital technologies have a certain impact on the educational process and, accordingly, on the quality of education (Schmidt, 2024; Vahedian et al., 2023).

The idea of introducing AI in educational systems cannot be attributed to a single individual, as it emerged from the collaborative efforts of researchers, educators, and technologists over several decades. The concept has evolved significantly since the mid-20th century with contributions from various fields of which a significant figure in the application of AI in education is Seymour Papert, a mathematician, computer scientist, and educator. Papert (1980) co-invented the Logo programming language in the 1960s, which was designed to help children learn through computer programming. His work at the MIT Media Lab and his seminal book "Mindstorms: Children, Computers, and Powerful Ideas" (1980) were instrumental in promoting the use of computers and AI to enhance learning.

More educational technology tools have been created and integrated in schools, also invention and innovation is still high among which Oshodi (2022) investigated as

1. Learning Management Systems (LMS): It offers various tools such as communication tools, student assessment tools, attendance submissions, performance evaluations and other supporting classroom learning and teaching tools, students can be divided into various groups and classes. It could also host digital libraries, simulated online laboratories etc. These tools allow easy traceability, personalized learning experience, transparency, and proficient implementation of learning objectives. Examples include Brightspace, Moodle, blackboard learn, e-learn, google classroom, LinkedIn learning, Coursera, canvas, etc (Chung et al., 2013).

2. Gamification: is the use of game dynamic mechanics and framework into a non-gaming environment like business, sports and learning, the goal is to make learning fun and educative at the same time, gamification motivates students as they are already comfortable with the gaming environment. Examples include medieval Swansea, ribbon hero etc. (Stott & Neustaedter, 2013).

3. Digital libraries: are repositories that store materials and information in electronic format on a database, the information stored are easily accessed from any part of the world. Examples include google books, open library, world digital library etc. (Seadle & Greifeneder, 2007).

4. Smart Classroom is a technology-enhanced learning classroom, it supports and promotes teaching and learning digitally by integrating technology in classrooms. They include the use of technology such as specialized software, multimedia technology, hardware, audio, audio-visual technologies etc. (Saini & Goel, 2019)

Oshodi Ismaila in 2022 who carried out a research to determine how educational technologies has impacted education in Nigeria, highlighted more examples of educational technology tools like social media, note-taking and referencing tools, text to speech and speech to text technologies, cloud technologies etc., concluded that the future of educational technology may include SmartDesk and Machine Learning in education. He further said that other future use of educational technologies include improved usage of artificial intelligence in education, virtual classroom and augmented reality, digital workspace, laboratories, and many more innovations (Oshodi, 2022).

2.4 Culture Relevance

In nature, things can be grouped into three types: natural, mechanical, and social systems. Social systems, made by people, include things like schools and how people live together. Schools, being a part of society, are connected to its culture, which is how people live and what they believe. Education and culture are closely linked. As our society changes, so does our culture, and this affects how we teach and learn. Culture shapes education, and education passes on culture to the next generation (Ertugruloglu et al., 2024).

2.4.1 Impact on Education

To understand and improve education, we need to think about the culture it comes from, especially in Africa. Cultural relevance, emphasizes the importance of incorporating cultural considerations and contextual factors into educational practices. Highlighting language relevance, Bamgbose (2011) emphasized the crucial inclusion of indigenous languages within the digital sphere, arguing that such integration not only broadens resources available to users but also elevates the stature and relevance of these languages. Despite the presence of some African languages on the internet, the actual content available in these languages remains scarce, as noted by the World Bank Group (2021). Hence, there arises a pressing need to translate digital resources and materials into African languages to facilitate their growth and broader accessibility, as advocated by Wierenga and Carstens (2021). This endeavor not only broadens access to resources but also fosters cultural preservation, communication, and socioeconomic development. Integrating cultural relevance into educational technologies, such as No-Code ML platforms, holds promise for creating culturally sensitive learning resources that resonate with diverse learners and communities, thereby contributing to equitable and inclusive education.

2.4.2 Elements of Culture Identification (Artifacts, Accents, Language)

Material culture encompasses all physical and tangible objects created by people, shaping the physical possibilities and opportunities within a society. It includes artifacts such as adornments, buildings, and weapons, alongside the skills for their use and the values attached to them. Nonmaterial culture consists of behavior patterns and artifacts forming the universal structure of culture. Social norms dictate expected behaviors, while folkways, mores, and laws represent customs, moral values, and formalized norms, respectively. Beliefs reflect perceptions of reality, and values guide judgments of what is desirable. Cognitive culture helps individuals navigate social situations, and language systematizes communication of feelings and ideas (Eshleman & Cashion, 1983).

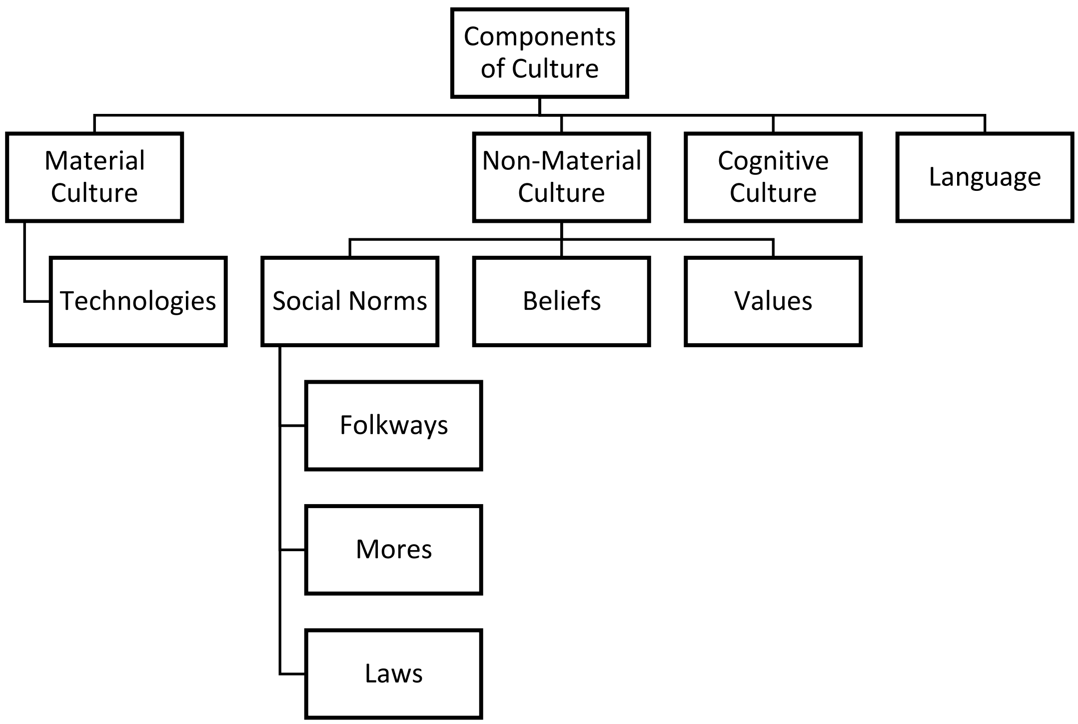

Fig 2: Components of Culture by Eshleman & Cashion in 1983

2.5 Machine Learning in K-12

Machine learning, provides the computational framework for analyzing and interpreting data to facilitate personalized learning experiences. Experts in computing (Tedre et al., 2021) have noticed that the way we teach about computers in schools is changing. They have also observed that more and more, younger students are learning about a special kind of computer technology called machine learning, even as young as in elementary and middle school (Sanusi & Oyelere, 2020). A study by Livia et al (2020) found about 30 different programs teaching kids about machine learning and neural networks in school. Some of these programs include using tools like Wolfram Alpha, Google's Teachable Machine, and IBM's Watson (Sanusi et al., 2023). These programs help kids understand how things like picture recognition, streaming recommendations, and voice commands work. By learning about machine learning, students can better understand the technology they use every day and how it affects their lives. These lessons also prepare them to be smart users of technology and to understand things like data collection and online advertising. Teaching machine learning to students is different from teaching them about regular computer programming (Sanusi et al., 2023), and it's becoming an important area of research in education. In this study, machine learning techniques are employed within an African culture-tailored No-Code ML platform to adapt educational content and instructional strategies to the cultural backgrounds and learning needs of Nigerian high-school students.

2.5.1 Concepts of Machine Learning (Data Classification)

Machine learning (ML), a vital part of artificial intelligence (AI), uses statistical methods to enable computers to learn and make decisions autonomously. ML includes supervised, unsupervised, semi-supervised, and reinforcement learning. In supervised learning, the goal is to optimize models to predict class labels from input features, with classification predicting similar information based on a categorical target variable. These algorithms are used in image, pose, text, and audio classification, as well as predictive modeling and data mining (Alnuaimi & Albaldawi, 2024).

1. **Image and Pose Classification:** With the arrival of the era of big data and the improvement of computing power, deep learning has swept the world. Traditional image classification methods are difficult to deal with the huge image data, and cannot meet the requirements of people on the accuracy and speed of image classification, the image classification method based on convolutional neural network breaks through the bottleneck of the traditional image classification method, and becomes the mainstream algorithm of image classification, how to effectively use convolutional neural network to classify images has become a hot spot of research in the field of computer vision at home and abroad (Hua & Chunzhong 2024).

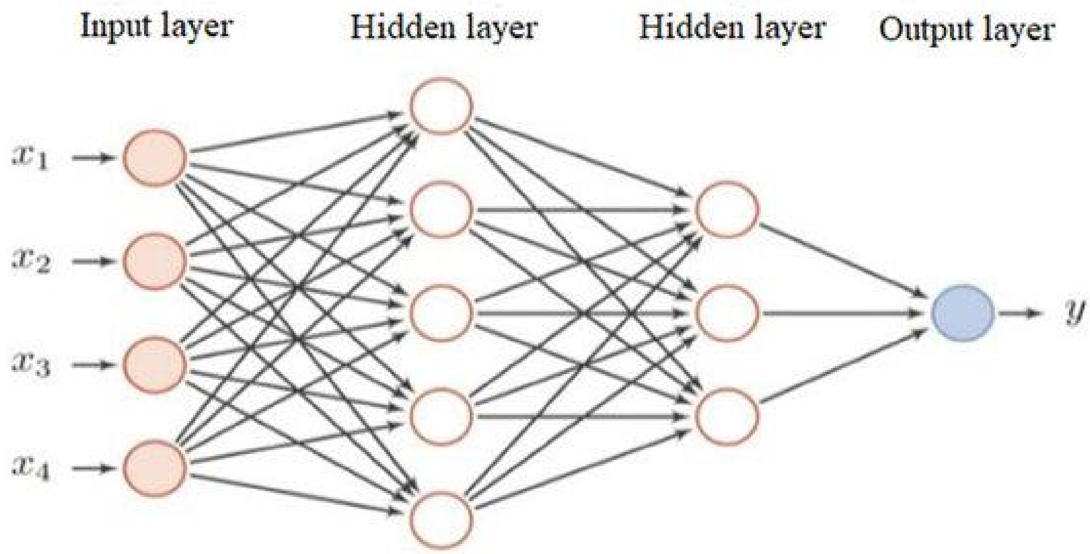

Fig 3. Multilayer feed-forward neural network structure (Source: Hua & Chunzhong 2024)

2. **Audio Classification:** Deep learning offers diverse methods for classifying audio signals. It can identify and categorize different types of sounds, including speech, music, and environmental noises. These models excel at learning intricate audio patterns and, when trained on extensive datasets, can achieve high levels of accuracy. To utilize deep learning for audio classification, the audio signals must be appropriately represented. Techniques for this include spectrograms, Mel-frequency Cepstral coefficients, linear predictive coding, and wavelet decomposition. After transforming the audio signal into a suitable representation, it can be processed by a deep learning model. There are various deep learning models available for this classification task. (Zaman et al., 2023).

3. **Text Classification:** Text classification involves categorizing text into specific groups based on certain criteria, essentially assigning a category to a piece of text using pre-existing knowledge. This process can be divided into two main types: binary classification and multi-class classification. Binary classification can be used to accomplish multi-class classification as well. Text classification tasks can also be categorized into single-label and multi-label tasks, depending on whether the text belongs to one category or multiple categories simultaneously. Text classification has a wide range of applications, including topic classification (determining if a document is about technology, sports, or lifestyle), spam detection (identifying if an email is

spam), and sentiment analysis (evaluating whether a tweet conveys a positive or negative opinion), among others. (Wang, 2023)

2.5.2 Existing No-Code Platforms

There are several no-code platforms available for machine learning and AI, designed to enable users to create and deploy models without needing to write code. Here are some popular ones:

1. Google AutoML: A suite of machine learning products that enables developers with limited machine learning expertise to train high-quality models (Poulakis et al., 2024).

2. Teachable Machine: A web-based tool that makes creating machine learning models fast, easy, and accessible to everyone (Pujari et al., 2022).

3. Lobe: A Microsoft tool that helps you train machine learning models with a visual interface (Robert, 2020).

4. ML4Kids: A web-based tool that makes creating machine learning models fast, easy, and accessible to everyone but primarily used for kids in UK (Sanusi et al., 2023).

5. LearningML: Both web-based and PC based machine learning tool used to create ML models for data classification (Rodriguez et al., 2020).

6. Generation AI: A web-based tool that trains image models fast, easy, and accessible (Pope et al., 2023).

These platforms are designed to make machine learning accessible to a broader audience, enabling users to leverage AI technologies without needing deep programming skills. They represent a recent development within this domain, democratizing access to machine learning concepts and empowering users to explore and apply these technologies regardless of their technical expertise. As the landscape of educational technology continues to evolve, it is essential to recognize the role of innovation in shaping the future of teaching and learning, with a focus on accessibility, flexibility, and empowerment for all stakeholders.

2.6 Summary of chapter

This chapter presents a comprehensive examination of the intersection between high-school education, cultural relevance, and machine learning within the context of high school education in Africa, highlighting Nigerian students as focus. It commences by exploring the Africa and beaming the spotlight on Nigerian high school education, which has continuously evolved due to the innovations of educational technologies and creation of policies to enhance the education system. The chapter went further to underscore the significance of incorporating cultural relevance into educational practices, emphasizing the importance of cultural affirmation, representation, and inclusivity in fostering meaningful learning experiences for diverse student populations, including those in Nigeria.

Furthermore, the chapter synthesizes existing ML technologies and explained how the structure of AfriML flow. It concluded by explaining no-code platforms and existing examples. By synthesizing diverse perspectives and empirical findings, the literature review lays the groundwork for the study's investigation into the effectiveness and implementation of AfriML for high-school students in Nigeria, contributing to advancing our understanding of how educational technology can be leveraged to promote inclusive, culturally responsive education in the country.

3.0 METHODOLOGY

3.1 Introduction

The methodology to be employed in this study aims to design, develop and evaluate AfriML within the educational context of Nigerian high-school students. By implementing Design Science Research method and quantitative research method, the study seeks to capture insights into the interplay between cultural relevance, technology integration, and learning experience. This introduction outlines the key components of the methodology, including research design, data collection methods, and analysis techniques, to elucidate the process of inquiry and ensure rigor in the study's findings.

3.2 Study Area

The study focuses on assessing the impact of AfriML, a culturally tailored No-code Machine Learning (ML) platform, on learning experience, engagement, and accessibility among students in Nigerian schools. Nigeria, as the most populous country in Africa, presents a diverse educational landscape with a wide range of socio-cultural contexts, making it an ideal study area to investigate the effectiveness of AfriML in addressing educational challenges and promoting inclusive learning environments.

3.3 Study Design

Implementing a robust methodology is crucial to ensure the quality and effectiveness of research. For this study, the Design Science Research (DSR) method was employed, which is a contemporary and efficient approach to problem-solving that focuses on generating substantial knowledge through the creation of artifacts (Hevner et al., 2004). This approach is particularly effective for this study as it allows for the triangulation of data, enhancing the reliability and depth of the findings.

In alignment with our aim to design, develop, and evaluate the AfriML tool, DSR was chosen due to its dual focus: developing practical solutions and producing valuable theoretical outcomes

(Oyelere & Suhonen, 2016). This methodology is particularly well-suited for our objectives of incorporating culturally relevant elements, implementing the tool in Nigerian high schools, and assessing its educational impact.

3.3.1 Design and Development of the AfriML Tool

As stated by Briggs & Schwabe, (2011), DSR aims to generate design knowledge, which includes understanding how prototypes should be constructed or arranged to achieve specific goals. This is achieved through a thorough process of refining problems, developing solutions, and applying concrete scientific techniques (Agbo et al., 2019).

AfriML tool was developed using culturally relevant elements specific to Nigerian high-school students. This tool integrates African artifacts, accents, and languages to teach machine learning (ML) concepts. According to DSR principles, the development process involved a well-defined and consistent method, allowing for continuous refinement and improvement to address practical educational challenges and enhance the research knowledge base (Hevner et al., 2004).

3.3.2 Goals of Design Science Research

As outlined by Oyelere & Suhonen (2016), DSR has two main goals:

1. Developing the tool: Creating a practical solution, in this case, the AfriML tool, to effectively teach ML concepts with cultural artifacts identification models infused.

2. Producing Theoretical Outcomes: Generating theoretical knowledge that contributes to the scientific body of knowledge, particularly in the context of educational technology and cultural integration.

3.3.3 Evaluation and Refinement

The outcome of DSR can manifest as a product, process, technology, tool, methodology, technique, procedure, or a combination of these elements (Venable & Baskerville, 2012). In this study, the AfriML tool represents the product of DSR, designed to enhance students' understanding of ML concepts through culturally relevant educational content, thereby achieving both practical and theoretical research objectives. Throughout the research process, the DSR method facilitates the systematic evaluation and refinement of the AfriML tool. This iterative process ensures that the tool not only meets the educational needs of Nigerian high-school students but also adheres to high standards of usability and effectiveness.

3.4 Stages in Design Science Research Methodology

According to Johannesson & Perjons (2014), the Design Science Research (DSR) approach contains five phases. These phases are iterative and interconnected, often requiring revisiting and refining previous phases based on the outcomes of later phases.
These phases are:

1. Explicate the Problem: The first step towards any research is the identification of the problem. In the Design Science Research (DSR) framework, the problem being studied for a solution should be practical and significant (Johannesson & Perjons, 2012). The problem that motivated the development of AfriML, a culturally tailored No-Code Machine Learning (ML) tool, is that existing educational initiatives often lack cultural relevance, particularly for African students. This gap results in ineffective engagement and disparities in learning outcomes. While programs like ML4Kids and Scratch have made strides in making AI and ML accessible, they do not fully address the unique cultural contexts and needs of African students. AfriML was developed to integrate African cultural elements into AI and ML education, aiming to provide a more relatable and stimulating learning environment for Nigerian high-school students.

2. Define the Requirements: This step establishes the procedures to be followed in order to solve the identified problem. The goal is to create a prototype that provides a solution to the practical problem outlined in the explication of the problem. From the literature review, it is evident that traditional teaching methods in underdeveloped and developing countries are less engaging and motivational, which makes them less effective for children's education. The requirements for AfriML include incorporating culturally relevant elements, ensuring an effective, interactive, and motivational learning process, and making the learning application easy to use. These considerations were integrated into the design and development of the AfriML tool to ensure it meets the educational needs of Nigerian high-school students.

3. Design and Develop an Artifact/Prototype: As a solution to the research problem, a prototype is developed at this step. The AfriML tool was designed and developed to incorporate culturally relevant elements that resonate with Nigerian high-school students. This No-Code ML tool enables students to engage with machine learning concepts through familiar cultural references, including African artifacts, accents, and languages. The prototype allows students to learn about machine learning concepts such as classification algorithms in a way that is interactive and relatable. The tool was designed to be web-based, making it easily accessible to students with varying levels of technological access.

4. Demonstrate the Artifact: At this stage, the developed tool, AfriML, is applied in real-world settings to evaluate its effectiveness in solving the practical problem identified in the first step of the DSR framework. The AfriML tool was implemented in selected Nigerian high schools, targeting high-school students. During this demonstration phase, the usability and effectiveness of the tool in enhancing students' understanding of machine learning concepts were assessed. Students interacted with the tool, and their feedback and engagement levels were recorded to determine the tool's practical impact.

5. Evaluate the Artifact: After the demonstration and application of the prototype in real-world settings, the developed artifact is evaluated based on the results obtained. The evaluation involves comparing the results and findings with the objectives of the solution to measure and analyze the extent to which the solution is supported by the artifact. This phase requires a proper understanding of the analysis techniques for the findings. Researchers will have enough information after this phase to decide whether to revert to the design and development phase to improve effectiveness or to leave further refinement for future study. The evaluation of AfriML focused on measuring students' engagement, understanding of machine learning concepts, and overall satisfaction with the tool. The findings provide insights into the tool's effectiveness and areas for potential improvement.

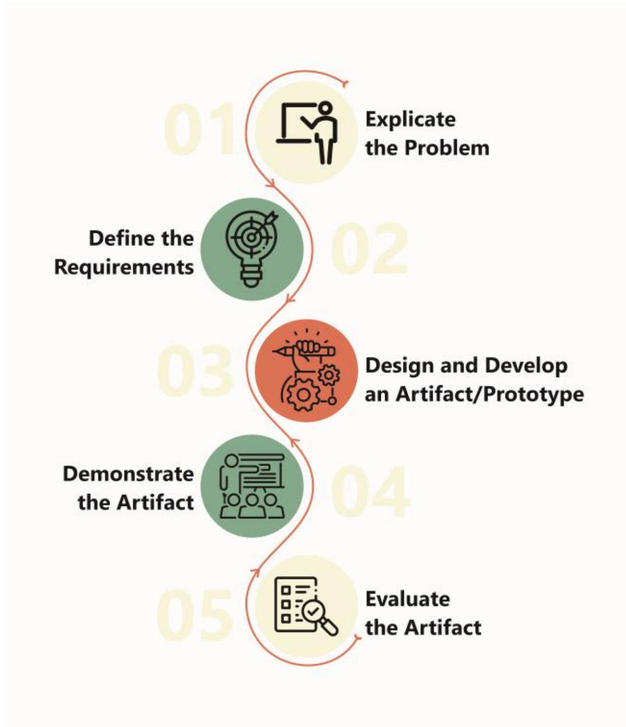

Fig 4: Stages of Design Science Research Methodology (Johannesson & Perjons, 2014)

3.5 Data Collection Method

1. **Surveys**: Administer structured surveys to gather data on students' engagement, and usability experiences.

2. **Pre- and Post-Tests**: Conduct pre-tests and post-tests to measure students' knowledge and understanding of ML concepts before and after using AfriML.

3. **Interviews**: Conduct semi-structured interviews and discussions with students, and teachers. Explore their experiences, perceptions, and suggestions regarding the platform. Gather insights on specific cultural considerations, challenges, opportunities, and customization needs associated with AfriML.

3.6 Data Analysis Methods

1. Qualitative Data: Employ thematic analysis (Prokopis, 2024) to identify patterns, themes, and insights from qualitative data. Code the transcripts, categorize responses, and extract key themes related to the research objectives and questions.
2. Quantitative Data: Conduct descriptive and inferential statistical analysis to examine relationships, correlations, and differences between variables. Utilize statistical tests such as t-tests, ANOVAs, and regression analyses to assess the impact of AfriML.

3.7 Summary of Chapter

In conclusion, the methodology outlined in this introduction establishes a structured and rigorous framework for examining the effectiveness and implementations of AfriML in African education system using Nigerian high-school students as a case-study. Through the use of quantitative approach, the study endeavors to generate robust empirical evidence that can inform educational practices and contribute to the advancement of knowledge in the intersecting fields of high school education, cultural relevance, and machine learning. By leveraging AfriML's existence, this research aims to provide valuable insights into how such platforms can enhance learning experiences and promote inclusivity within the educational landscape of African countries.

4.0 IMPLEMENTATION OF AfriML USING DESIGN SCIENCE RESEARCH FRAMEWORK

This study aims to design, develop and evaluate a No-Code ML tool infused with cultural orientation to teach ML concepts to high-school students in Nigeria by integrating the software development process with the Design Science Research (DSR) framework. AfriML was developed as a solution to the identified problem of the lack of culturally relevant educational resources in AI and ML education for African students. The tool was developed following the stages of the DSR framework, ensuring it effectively incorporates African cultural elements to make the learning process more engaging and effective for Nigerian high-school students.

4.1 Design and Development of AfriML Tool

4.1.1 Overview of AfriML Tool

AfriML is a user-friendly web-based application designed to make machine learning accessible to everyone, especially students and educators. It allows users to train their own machine learning models without any coding experience similar to Google Teachable Machine. Users can create models for image, audio, text and pose classification by simply uploading their data or by recording samples directly through the web interface. For example, to create an image recognition model, users can upload photos or use their webcam to capture images. Once sufficient data is collected, users can label the data accordingly. The platform then trains the model using the provided samples. After training, users can test the model directly and also its African cultural relativity based on the internal African model within the web interface. They can upload new images, record new sounds, add new texts or perform new poses to see how well the model performs. The results are displayed in real-time, providing immediate feedback on the model's accuracy and also cultural accuracy. This intuitive platform is perfect for creating educational tools and interactive projects, helping to demystify machine learning concepts with cultural awareness.

AfriML also supports exporting the trained models for use in various applications. Users can download the models in TensorFlow Lite for mobile applications. This feature enables users to integrate their custom machine learning models into their own projects, expanding the tool's utility beyond the ML platform. AfriML integrates cultural identification models particularly artifacts identifier for images, accent detector for audio and language detection for text classification.

In addition to practical model creation, it also offers educational resources to help users understand machine learning concepts. The platform includes tutorials, documentation, and examples that explain how machine learning works and how it can be applied in different contexts. These resources are designed to be easy to follow and provide a comprehensive introduction to machine learning.

4.1.2 Steps of Using AfriML

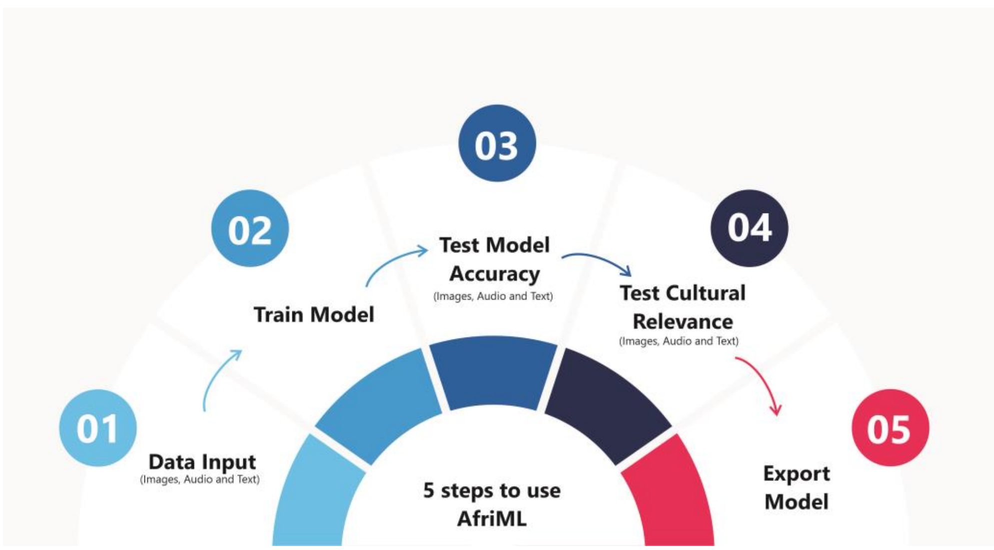

Fig 5: Five steps to use AfriML

1. Data Input

a. Access AfriML: Open your web browser and go to the AfriML (https://afriml.com/) website.

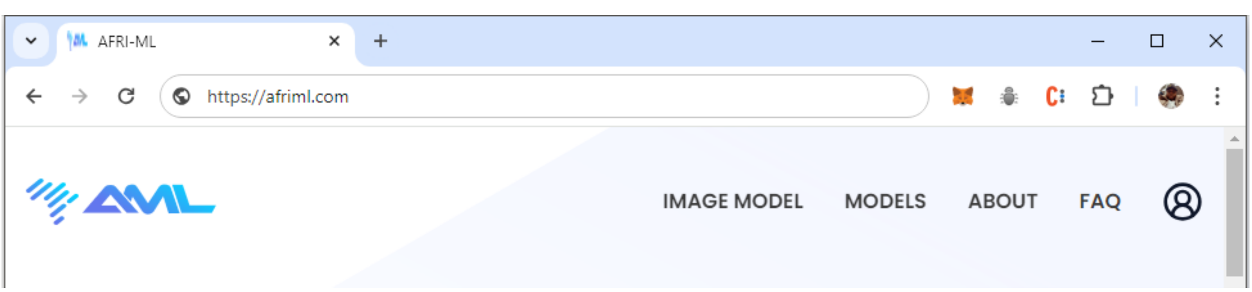

Fig 6: Website URL input

b. Select Project Type: Choose the type of project you want to create: Image Project, Audio Project, Text Project or Pose Project.

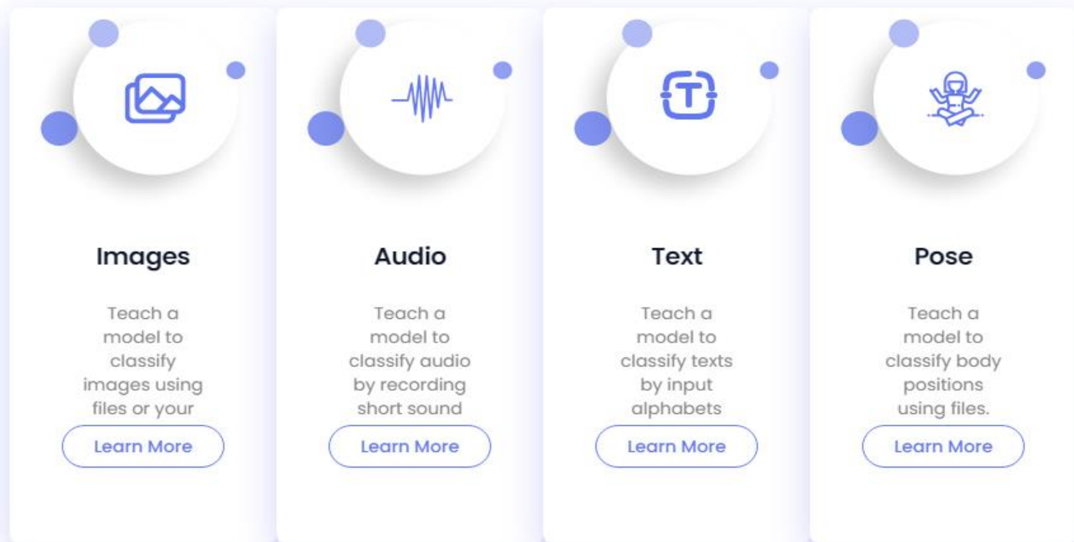

Fig 7: The Four Models of AfriML

c. Create Classes: For an image project, you might create classes like "Cat" and "Dog". For an audio project, you might create classes like "Clapping" and "Whistling". For a text project, you might create classes like “Shakespeare” and “Jonson”. For a pose project, you might create classes like "Standing" and "Sitting".

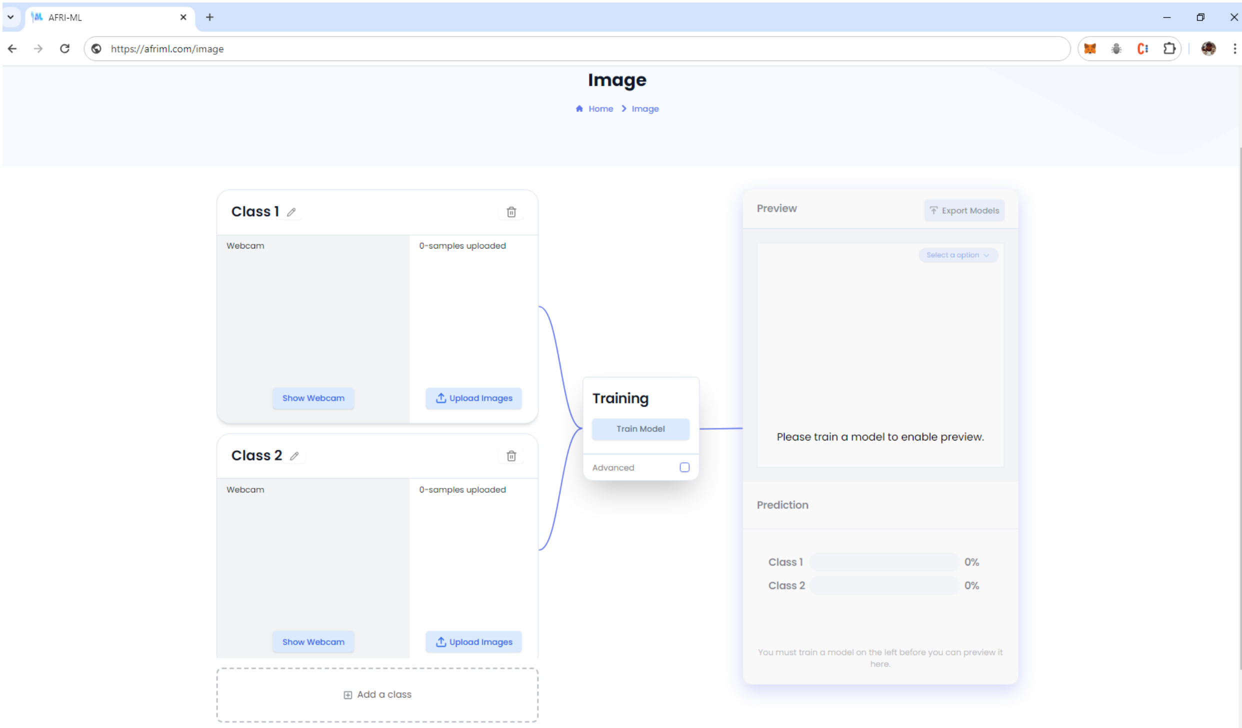

Fig 8: Image Model Page on AfriML

d. Gather Data: Use your webcam or microphone to record data directly.

- For images, click on the "Show Webcam" button to take pictures.

- For audio, click on the "Mic Icon" button to capture sounds.

- For text, type or paste the words, sentence or paragraph, click on the "Add Text" button to add text sub-classes.

- For poses, use the webcam to capture different body positions.

- Alternatively, you can upload existing files from your computer (images, audio and doc/txt files).

- Ensure you have enough samples for each class to train the model effectively (at least 20-30 samples per class is recommended).

e. Label Data:

- Make sure each set of data is correctly labeled with the class it belongs to. This is crucial for the model to learn accurately.

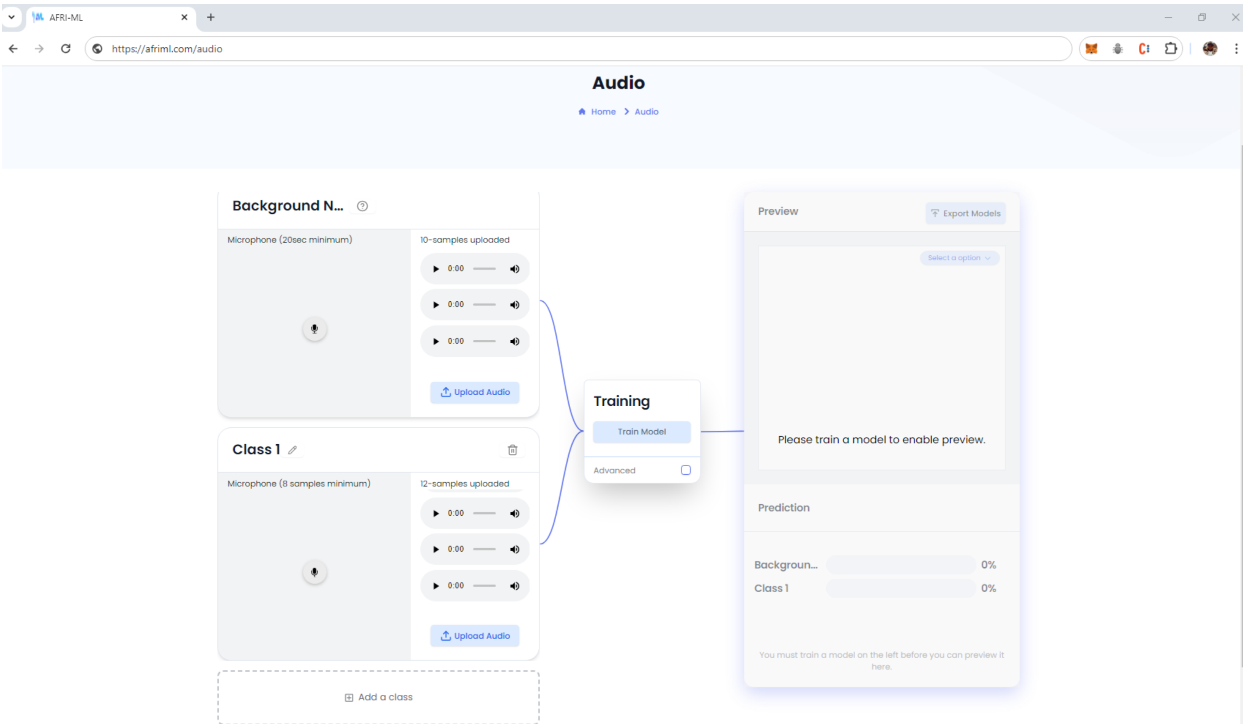

Fig 9: Audio Model Page on AfriML (Audio Data uploaded)

2. Train Model

a. Check the samples you have collected to ensure they are clear and correctly labeled. The default settings like the number of epochs (training cycles) is 10 and it usually work well for beginners and students.

b. Click on the “Train Model” button.

c. The training process will begin, and you’ll see a process icon. This may take a few seconds to a few minutes, depending on the amount of data and the complexity of the model.

d. To activate the cultural model testing model, simply check the “Advanced” checkbox. This will set the platform to enable the cultural model to await testing on the preview/test tab immediately.

3. Test Model Accuracy

a. Switch to Preview/Testing Tab: Once training is complete, switch to the “Preview” tab.

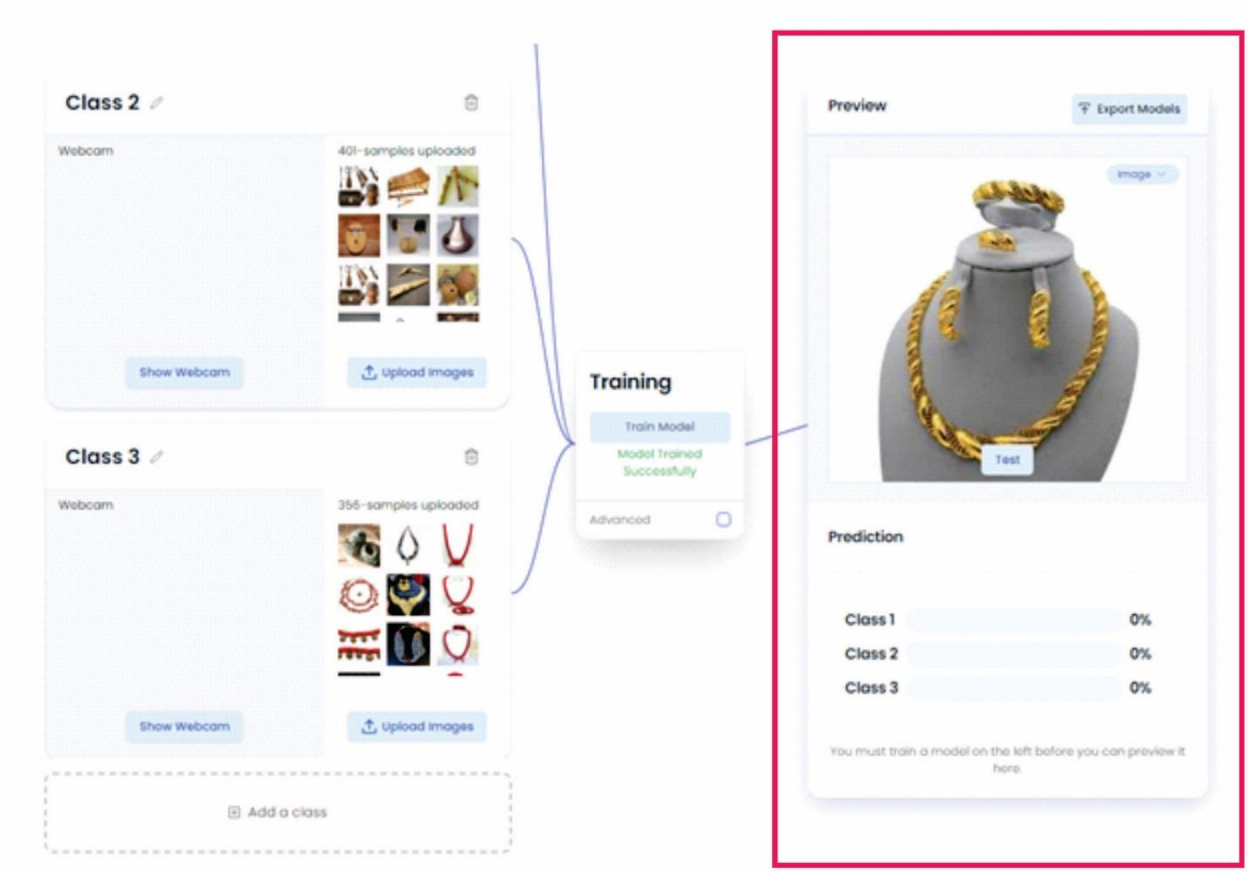

Fig 10: Image Model Trained and ready for testing on AfriML

b. Test with New Data:

- For image projects, you can use the webcam to test new image captures, live-feed testing or upload new files.

- For audio projects, use the microphone to record new sounds or upload new files.

- For text projects, use the notepad to input new texts or upload new files.

- For pose projects, use the webcam to perform new poses or upload new files.

c. Observe Results:

- The platform will display the model's predictions in real-time, showing how confident it is about each class.

- Check the accuracy and reliability of the model's predictions.

d. Refine Data (Optional):

- If the model is not performing well, you might need to gather more data or correct any mislabeled samples.

- Retrain the model with the updated dataset if necessary.

4. Test Cultural Relevance

AfriML has three (3) African cultural agents who are represented as "Characters". These agents/models are activated when the "Advanced Checkbox" is checked. Their primary aim is to determine if the test input is culturally inclined to African culture, particularly in image, accent and language.

a. Otieno: is an African artifact detector. It was trained using at least 5,000 images of Nigerian cultural artifacts such as jewelries, music instrument, work tools, crafts, masks, games, fabrics, textiles etc. Its job is to test every input on the preview tab to determine its cultural relevance. Based on its rich and vast model coverage it comes to live if cultural relevance particularly image-wise is detected at 90% or more.

b. Rukky: is an African accent detector. It was trained with more than 2,000 voice recording of Africans (currently Nigerians) reading out sentences. This model was trained using supervised machine learning model, particularly neural networks. Its rich and classified database was a contribution to this research by SautiDB (v1.2, 2023). It comes alive if a speaker or user's accent matches at least 90% to an African.

c. Melo: is an African language detector created with boundaries to 3 Nigerian languages for the purpose of this research. Its database was a contribution from these languages dictionaries. Its function is to test and then predict the language of a user's data input. It appears when the prediction rate hits 90% or more while testing the model.

5. Export Model

- After you are satisfied with the model's performance, click on the "Export Model" button.

Fig 11: Preview Tab indicating the export button on AfriML

- Follow the prompts to download the model files to your computer. It will download the trained model based on the classification model you created.

- Deploy the model within your application.

- Test the integrated model to ensure it works correctly in the real-world environment.

By following these detailed steps, beginners can successfully create, train, test, and deploy machine learning models using AfriML, making the process of learning and applying machine learning both accessible and practical.

4.1.3 Learn Section

This page serves a very vital role in educating users on how to use AfriML. It serves as a library to learn about machine learning concepts and also displays existing projects done using AfriML as a tool.

FAQ Section: This section contain questions and answers related to using AfriML

Tutorials Section: This section contains tutorial videos to watch to gain insight and understanding about AfriML.

Projects Section: This section contains overview of projects related to machine learning and artificial intelligence.

4.2 Software Architecture of AfriML

The features described in AfriML is a complex system with multiple components. We achieved this through a multi-tier software architecture that encompasses both front-end and back-end components. Here is the current architecture:

4.2.1 Client Tier (Front-End)

This is the user interface that the target audience will interact with. It is purely a web-based interface for the platform.

Web Interface: A user-friendly and responsive web interface using HTML, CSS, and Javascript. Putting into consideration modern front-end frameworks like React and Tailwind was used to create a dynamic and interactive user experience.

Model Building Interface: An intuitive interface for users to input data, upload files, and train their machine learning models. This interface would allow users to select the type of model (image, audio, text and pose) and customize if they want to test the cultural relevance of their data input.

File Upload and Webcam/Microphone/Clipboard Integration: This functionality was implemented to allow users to upload image, audio and doc/csv data. If users want to use webcam/microphone for input, appropriate APIs and libraries were integrated and used.

4.2.2 Application Logic Tier

This is where most of the processing, logic, and communication occur.

Backend APIs: RESTful APIs was developed using Python (using Django frameworks). These APIs handle user requests, data processing, and communication with the database.

ML Model Integration: Machine learning libraries were integrated specifically TensorFlow to enable users to train their models. Also algorithms like deep learning, computer vision, ANN, and linear regression were implemented as required.

Model Training: the logic to train models was implemented based on user-provided data. The system was built for high school students, so the flexibility for users to choose parameters, algorithms, and training options are minimal. The system also provide feedback on model performance.

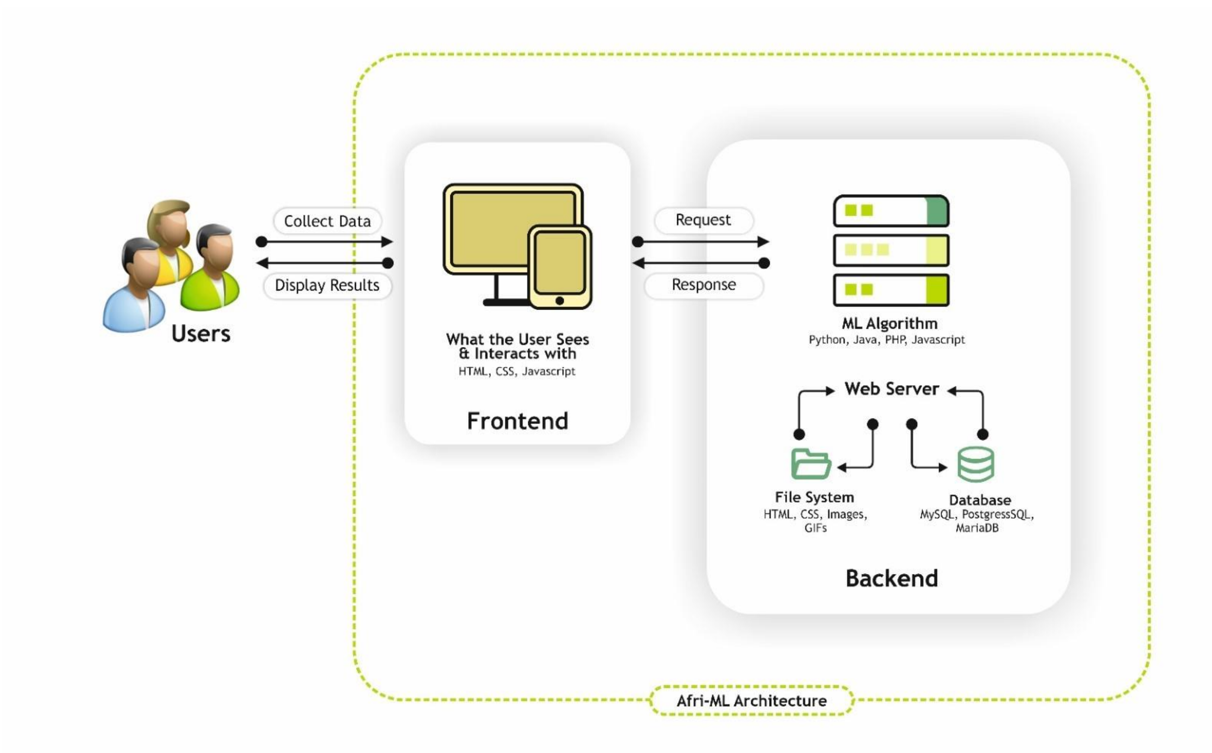

Fig 12: Software Architecture of AfriML

4.3 African Culture Detecting Agents

AfriML, a No-Code ML tool infused with cultural orientation was possible by introducing African cultural detecting agents called Otieno – African Image Detector, Rukky – African Accent

Detector, and Melo – African Language Detector. This section deals with the how they work, their model creation and dataset used.

4.3.1 Otieno

Otieno is a character in the AfriML tool that serves as an integral part of the image classification model, specifically tailored to enhance the educational experience of Nigerian high-school students by incorporating culturally relevant elements. It was crucial to design Otieno not only to function effectively but also to engage students by providing a familiar and relatable results. Otieno operates by leveraging a trained image classification model that utilizes an extensive dataset of African images, including categories such as fabric, games, sculptures, jewelry, and tools. This dataset was meticulously curated to ensure it accurately represents the rich and diverse visual culture of Africa (particularly Nigeria), thereby making the learning process more relevant and exciting for the students.

The technical implementation of Otieno involves using state-of-the-art machine learning algorithms that can accurately classify images based on the predefined African categories. When a student uploads an image to test a model trained on AfriML, Otieno's model processes the image and determines whether it matches any of the African categories in the dataset. This functionality is encapsulated within Otieno, who then provides feedback to the user, indicating the degree of resemblance or match with the African model. The interface designed for Otieno includes visual cues and explanations that help students understand the cultural significance of the classified images, thus fostering a deeper connection and appreciation for their heritage.

Ensuring the robustness and accuracy of Otieno's image classification required a comprehensive approach to data collection and model training. The dataset was sourced from various repositories, including museums, cultural archives, and community contributions, to capture the true essence of African visual art and artifacts. Advanced convolutional neural networks (CNNs) were employed to train the model, ensuring high accuracy and performance. Additionally, Otieno's integration into the AfriML platform involved seamless interaction with the user interface, providing real-time feedback and educational insights. This blend of technical precision and cultural relevance makes Otieno a unique and powerful tool in the AfriML suite, bridging the gap between modern AI technology and African cultural education.

4.3.2 Rukky

Rukky is the character dedicated to the audio classification model within the AfriML platform, designed to detect and recognize accents from various African languages. The creation of Rukky required an in-depth understanding of both machine learning techniques and the linguistic diversity of Africa. Rukky's model is trained to identify accents from Igbo, Hausa, Yoruba, Efikibibio, Nigerian-Western, and other categories, providing students with a culturally resonant tool for audio classification. This feature not only enhances the educational value of the tool but also promotes an appreciation for the linguistic richness of Africa.

Implementing Rukky involved several technical challenges, such as sourcing high-quality audio data for training the model and ensuring accurate accent detection. The audio dataset was compiled by SautiDB (2023) from native speakers across different regions, encompassing various dialects and pronunciations to create a robust training set. Using deep learning techniques, particularly recurrent neural networks (RNNs) and convolutional neural networks (CNNs) for audio processing, Rukky's model was trained to recognize subtle differences in accents and provide precise classifications. The character Rukky, encapsulating this functionality, interacts with users by analyzing their audio inputs when testing a trained model and offering feedback on the detected accent, thereby making the learning process interactive and culturally relevant.

Integrating Rukky into the AfriML platform required careful attention to user experience and interface design. The goal was to create an intuitive and engaging interface where students could easily upload or record their audio samples. Rukky then processes these samples in real-time, providing immediate feedback on the detected accent. This interactive feature helps students not only understand machine learning concepts related to audio classification but also fosters a sense of cultural identity by highlighting the unique characteristics of African accents. The technical sophistication and cultural sensitivity embedded in Rukky make it a standout feature of AfriML, promoting both educational advancement and cultural pride among Nigerian high-school students.

4.3.3 Melo

Melo is a pivotal character in the AfriML platform, responsible for the text classification model that detects languages within the training dataset. Specifically, Melo is trained to recognize Igbo, Hausa, and Yoruba, which are prominent African languages. The creation of Melo involved a combination of advanced natural language processing (NLP) techniques and a deep understanding of these languages. The objective was to provide a tool that not only educates students about machine learning concepts related to text classification but also reinforces their linguistic heritage.

The technical implementation of Melo involved collecting extensive textual data in Igbo, Hausa, and Yoruba to train the language detection model. This data was sourced from literary works, online resources like language dictionaries, and contributions from native speakers to ensure a diverse and representative dataset. Utilizing NLP algorithms, particularly those based on transformer models such as BERT (Bidirectional Encoder Representations from Transformers), Melo's model was trained to accurately identify and classify text samples in the specified languages. The character Melo encapsulates this functionality, providing students with feedback on the language detected in their text inputs, thus making the learning process more interactive and culturally aligned.

Integrating Melo into the AfriML platform involved seamless interaction with the user interface where students can input or upload text samples for classification. Melo processes these samples and delivers real-time feedback on the detected language, helping students understand the nuances of text classification and language detection. Additionally, the interface intends to include educational content about the cultural and linguistic significance of Igbo, Hausa, and Yoruba, enriching the students' learning experience. The combination of technical rigor and cultural relevance in Melo's design ensures that it serves as both an educational tool and a means of cultural preservation. By embedding these elements into the AfriML platform, Melo helps foster a deeper connection to African languages and cultures among Nigerian high-school students, making machine learning both accessible and meaningful.

5.0 RESEARCH DESIGN AND METHODOLOGY

This chapter details the approaches utilized for an initial assessment of the AfriML tool, designed for high school students, based on the literature review. We will cover the research setting, data collection techniques, and analytical methods used in the study.

5.1 Study Context

The study was conducted in four high schools in two states in Northern Nigeria and the FCT (Abuja), aiming to evaluate the effectiveness of the AfriML tool, which was specifically designed for high-school students in Africa. AfriML integrates African cultural elements into its curriculum to make machine learning (ML) concepts more relatable and engaging for students.

To reiterate, the objective of this study is to design, develop, and assess AfriML—a culturally-oriented, no-code ML tool—to teach high-school students in Nigeria the fundamental concepts of machine learning. The study seeks to determine the tool's effectiveness in enhancing students' understanding of ML concepts, influencing their attitudes towards learning ML, and motivating them to pursue further studies in this field.

The participants, high-school students aged between 13 to 17, were selected to ensure a representative sample that could provide comprehensive feedback on the tool's usability and educational impact. These students were chosen based on their basic understanding of English and their familiarity with computer technology, which are essential for engaging with the AfriML tool effectively.

Data collection was conducted through a combination of structured surveys, pre- and post-test assessments, and semi-structured interviews. The surveys gathered data on students' engagement, usability experiences, and overall satisfaction with the AfriML tool (Xia et al., 2022). Pre- and post-test assessments measured the students' knowledge and understanding of ML concepts before and after using AfriML, allowing for a comparative analysis of their learning progress. Additionally, interviews with the students' respective teachers who guided them during this research provided deeper insights into the students' experiences, perceptions, and suggestions for improvement, particularly focusing on the cultural relevance and practical applications of the tool.

This comprehensive approach ensured that the study captured both quantitative and qualitative data, providing a well-rounded evaluation of AfriML's educational impact and its potential to be a sustainable part of the curriculum in Nigerian high schools. Figure 13 below shows students exploring AfriML tool.

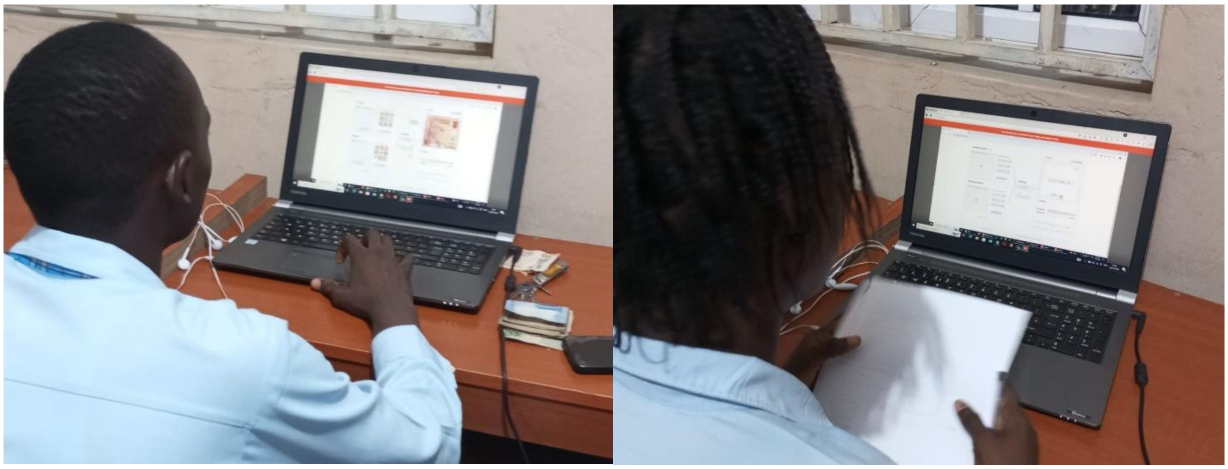

Fig 13: Students Exploring AfriML Tool

5.2 Study Ethics

The study is qualitative and quantitative in nature, focusing on the evaluation of the AfriML tool. Prior to participation, informed consent was obtained from the school authority and parents/guardians of the high-school students involved in the research. All participants voluntarily contributed to the study.

Before participation, both the students and their teachers were briefed about the purpose of the study. They were informed about how AfriML integrates African cultural elements to teach machine learning concepts. The students were given instructions on how to access and use the AfriML tool.

Participants were provided ample time to explore and use AfriML for their learning purposes before the survey and interviews. The learning environment was informal, allowing students to engage with the tool at their own pace and in settings that they found comfortable and conducive to learning.

All interviews were recorded with the consent of the teachers. To maintain confidentiality, the participants were assured that all information gathered would be analyzed anonymously, and individual identities would not be revealed. All recordings and transcriptions were securely stored, and the data was used solely for the purpose of this research.

Adhering to these ethical guidelines, the study ensured that the participants' rights and well-being were protected throughout the research process.

5.3 Study Instruments

The study employed a mixed-methods approach, combining both quantitative and qualitative data collection methods. Using the Design Science Research (DSR) approach as a guide, the research aimed to evaluate the effectiveness of the AfriML tool in teaching machine learning concepts to high-school students.

5.3.1 Quantitative Approach

1. Pre- and Post-Tests:

- Participants: 40 high-school students.

- Purpose: To measure the students' knowledge and understanding of machine learning concepts before and after using the AfriML tool.

- Method: Standardized tests administered before the introduction of AfriML and after the students had sufficient time to use and learn from the tool.

2. Surveys:

- Participants: 40 high-school students.

- Purpose: To gather data on students' engagement, usability experiences, and overall satisfaction with the AfriML tool.

- Method: Structured surveys with a mix of multiple-choice and open-ended questions, designed to capture detailed feedback on the students' learning experiences. Some of the items used in the questionnaire were adapted from Xia et al. (2022).

5.3.2 Qualitative Approach

Semi-Structured Interviews:

- Participants: 4 teachers.

- Purpose: To gather in-depth insights into the teachers' experiences with the AfriML tool, including its impact on student engagement, the integration of cultural elements, and any challenges encountered during implementation.

- Method: Interviews were conducted with four teachers who have integrated AfriML into their classroom activities. The introductory questions were generic, aimed at understanding the participants' backgrounds and their experiences with technology in their teaching processes. This was followed by questions specifically focused on their experiences with AfriML and the research goals. All interviews were conducted remotely via Zoom (online meeting platform) and were recorded using inbuilt zoom recorder.

Participants were asked about their experiences using AfriML, including their opinions, suggestions, limitations, and difficulties encountered. The recordings were transcribed, organized, and analyzed to derive valuable inferences from the data set. The transcribed data was read multiple times to ensure a thorough understanding and to facilitate accurate analysis. To identify the main features of the data, notes were made in the form of codes by highlighting relevant text. Initial patterns or themes were identified from the coded data, forming the basis of the thematic analysis. It was ensured that the themes identified were appropriate and sufficient to meet the research objectives. The themes were named and defined to distinguish different aspects of the data. A formal report was then written, summarizing the thematic analysis after themes were carefully identified, named, and defined.

Combining these quantitative and qualitative methods, the study ensured a comprehensive evaluation of AfriML, capturing both measurable outcomes and detailed experiences. This approach allowed for a robust analysis of the tool's effectiveness in enhancing machine learning education in a culturally relevant manner.

5.4 Data Analysis

5.4.1 Quantitative Analysis

The primary data, collected via printed questionnaires, pre-tests, and post-tests, were analyzed using quantitative methods. IBM SPSS Statistics (version 29) was utilized to code and analyze these questionnaires and tests to provide quantitative justifications for the research questions (Wohlin and Runeson, 2021). The primary focus was to analyze the effectiveness of the AfriML tool in enhancing students' understanding of machine learning concepts and their engagement with the learning process.

Paired Sample T-Test

This study adopted the paired sample t-test, which is commonly used to compare the means of two interrelated datasets. This statistical test was appropriate for comparing the students' knowledge and understanding of ML concepts before and after using AfriML. By determining whether the mean difference of the two datasets (pre-test and post-test results) is significantly different from zero, the impact of AfriML on students' learning outcomes was assessed.

The t-score was computed by dividing the mean of the difference by the standard deviation of the difference. A paired t-test value equal to zero would indicate no significant impact of AfriML on students' ML knowledge. The significance level adopted for this study was 10%. If the statistical significance value was less than 10%, the null hypothesis (no impact) was rejected, indicating a significant effect of the AfriML tool on students' learning.

Reliability analysis (Cronbach's Alpha)

Cronbach's Alpha is a statistical measure used to assess the internal consistency or reliability of a set of scale or test items. It evaluates how closely related a group of items are as a single construct, essentially indicating the extent to which the items measure the same underlying concept (Bansal et al., 2011). It was employed to validate how the various indicators accurately measured each individual construct related to student motivation and attitude towards using AfriML and ML which result was 0.809. It was also used to validate the reliability of the pre and post test results of the students which result was 0.655. A high Cronbach's alpha value (typically above 0.7) suggests that the items have a high level of internal consistency, while a low value indicates potential issues with the scale's reliability.

Analysis of Variance (ANOVA)

ANOVA is a statistical method used to compare the means of three or more groups to determine if there are any statistically significant differences among them. By analyzing the variances within each group and between groups, ANOVA helps to identify whether the observed variations in the data are due to actual differences in group means or are simply the result of random chance (McDonald, 2009). This technique was employed to measure attitude and motivation of the students via their reply on Section G of the survey questionnaire.

Regression Analysis

Regression analysis is a statistical tool used to examine the relationship between a dependent variable and one or more independent variables. This method allows researchers to understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed (Frost, 2013). In this study, students' engagement was the dependent variable and their satisfaction was the independent variable. This was used to measure the relationship between students' engagement and satisfaction.

5.4.2 Qualitative Analysis

In this study, a thematic coding approach was used to analyze the data collected from teacher interviews regarding their use of the AfriML tool. Qualitative data collection often requires interpretation, meaning that the data needs to be explained and categorized in several ways. Thematic coding, a type of qualitative analysis, is used to analyze the classifications and patterns that emerge from the data (Alhojailan, 2012). According to Braun & Clarke (2006), thematic coding involves several phases, including:

- Becoming familiar with the data
- Generating Codes
- Generating initial themes
- Reviewing themes
- Defining and naming themes
- Producing the report

Identified Themes

Three major themes have been identified that closely align with the objectives and research questions of this study. Each major theme encompasses a series of relevant subthemes, which provide further depth and context:

1. Overall Positive Experience

- **Highly Favorable Reception:** Teachers generally had a highly positive reception of AfriML. They appreciated the user-friendly interface, the comprehensive dataset provided, and the overall user experience. The tool was described as interesting, engaging, and easy to navigate.

2. Enhanced Student Engagement through Cultural Integration

- **Significant Student Engagement:** AfriML significantly engaged students in the learning process. The practical sessions, which included text, audio, and image classifications, as well as accent detection, were enjoyable and interactive for students. This hands-on experience captured their interest and facilitated their learning.

- **Improved Understanding through Cultural Relevance:** The integration of African cultural elements within AfriML was a notable aspect that enhanced the learning experience. Students were able to connect with the content more deeply because it included familiar cultural artifacts, languages, and accents, making the tool more relatable and interesting.

- **Importance of Cultural Relevance in Education:** The need for culturally relevant educational resources was underscored. Teachers noted that integrating African cultural elements into educational tools can enhance the learning experience by making it more meaningful and relatable for students. These tools can bridge the gap between traditional education and students' cultural backgrounds, fostering a deeper understanding and appreciation of the content.

3. Challenges and Areas for Improvement

- **Implementation Challenges:** Several challenges were encountered during the implementation of AfriML. Limited availability of computer systems posed difficulties in providing individual access to students. Additionally, the tool's limited accessibility on mobile devices hindered students' ability to use AfriML outside the classroom.

- **Suggestions for Enhancement:** Participants provided constructive feedback for improving AfriML. Suggestions included developing a mobile application for wider accessibility, adding interactive features such as a question-and-answer bot, and incorporating engaging tools like African games to capture students' attention and enhance their knowledge of African culture.

- **Sustainability and Future Use:** There was a strong interest in the continued use of AfriML. Teachers expressed their willingness to integrate it into their curriculum and recommend it to colleagues and other schools. They believed that with further improvements, AfriML could become a valuable asset in enhancing the teaching and learning process, particularly in ICT education.

6.0 RESULTS

6.1 Qualitative Analysis

Using Braun & Clarke's (2006) thematic analysis approach, I organized the feedback from all four teachers into distinct themes. This process involves becoming familiar with the data, generating codes, generating initial themes, reviewing themes, defining and naming themes, and producing the report.

6.1.1 Becoming Familiar with the data

I have conducted a thorough review of the interview transcripts for all four teachers and have identified several key points and recurring patterns. This detailed analysis has provided valuable insights into common themes and perspectives among the educators.

6.1.2 Generating Codes

Several recurring themes emerged from the interviews which are:

- Positive Experience: The overall reception of AfriML was highly favorable.
- Student Engagement: The tool significantly engaged students in the learning process.
- Cultural Integration: The integration of African cultural elements enhanced the learning experience.
- Challenges: Implementation faced certain challenges that need addressing.
- Suggestions for Improvement: Participants provided constructive feedback for enhancing the tool.
- Importance of Cultural Relevance: Emphasized the necessity of culturally relevant educational tools.
- Future Use and Recommendations: There was a strong interest in continued use and recommendations for AfriML.

6.1.3 Generating Initial Themes

Based on the analysis of the codes, the following initial themes and subthemes have been derived:

6.1.3.1 Overall Positive Experience

- Highly Favorable Reception: The teachers generally had a highly favorable reception of AfriML. They appreciated the interface, the dataset provided, and the overall user experience. The tool was described as interesting, engaging, and easy to navigate.

"After the whole class session, I was asking them how they understood the whole class, they responded by saying 'interesting and engaging'." [Teacher 1]
"Seeing how a program runs after much theory classes. The feeling from the student was satisfying." [Teacher 2]

"Overall learning, was good, because of the broadness, so you know, it's very, very, very good website." [Teacher 3]
"AfriML is a special website." [Teacher 3]

"Okay, it was very, very, very fantastic, and students are the happy." [Teacher 4]

6.1.3.2 Enhanced Student Engagement through Cultural Integration

- Significant Student Engagement: AfriML significantly engaged students in the learning process. The students found the practical sessions with the tool enjoyable and interactive. The hands-on experience with text, audio, and image classifications, as well as accent detection, captured their interest and facilitated their learning.

"For me, I think what the students responded to more after showing them the various dataset, was the identification of the artifacts, during the training they focus more on the artifacts, as they saw their tribal cultural elements." [Teacher 1]

"When they were running the program, using the beads, naira notes, the audio, sounds, and after running it, when they were trying to test run and after running the program seeing it work they were happy." [Teacher 2]

"AfriML website helped the students to differentiate a Yoruba beads from an Igbo beads, a Hausa native attire from a Yoruba attire." [Teacher 3]

"So, as they saw it, it was very very interesting, and they were very happy as it was used in programming." [Teacher 4]

- Improved Understanding through Cultural Relevance:

The integration of African cultural elements within AfriML was a notable aspect that enhanced the learning experience. Students were able to connect with the content more deeply because it included familiar cultural artifacts, languages, and accents. This cultural relevance made the tool more relatable and interesting for the students.

"Initially before the class commence they were not too familiar with the whole machine learning, they couldn't understand how the model work ... how they were able to navigate around the AfriML interface, about five of them stood out… " [Teacher 1]

"Yes, they really understood it. So, they wish they had the opportunity to have time to go over the program at home." [Teacher 2]

"It's actually boosted their interest in machine learning." [Teacher 2]

"It is a government secondary school, machine learning hasn't been well taught to the students so I had to explain from the basics. The students were so interested, willing and passionate in learning so it was easy for them to use AfriML without having issues." [Teacher 3]

"Really, really, because it was just their first contact with machine learning … they were able to explain a lot of things that make me very very happy concerning it." [Teacher 4]

- Importance of Cultural Relevance in Education

The necessity of culturally relevant educational tools was emphasized. Teachers highlighted that tools incorporating African cultural elements can make learning more meaningful and relatable for students. Such tools can bridge the gap between traditional education and the students' cultural backgrounds, fostering a deeper understanding and appreciation of the content.

"Yes more educational tools should be created or added, as it add to the beauty and uniqueness of the model, it can be very useful in future to come." [Teacher 1]

"Yes, it will, it will be very relevant to African students " [Teacher 2]

"I believe if more educational tools are added to AfriML so many people will learn about their culture and other state culture it can help to broaden their knowledge about their culture and other ethnic groups." [Teacher 3]

6.1.3.3 Challenges and Areas for Improvement

- Implementation Challenges: Several challenges were encountered during the implementation of AfriML. These included the limited availability of computer systems, which led to difficulties in providing individual access to students. Additionally, the tool's accessibility on mobile devices was a concern, as it limited the students' ability to use AfriML outside the classroom.

"The challenge faced was lack of more systems for them to use, since we were limited to one, I would have love it if they had practice using individual systems instead of clustering together viewing when we had the Practical lessons." [Teacher 1]

"The fact it wasn't assessable on phone, my reason are these are student that would have continue it using the model at home with their parents phone or for those that owns one would have use it during the class." [Teacher 1]

"The challenges was only the network issue and the excitement from the student did not allow them to copy at least ten from a class and paste instead they just copy everything and upload due to excitement just because they want to see how the program runs." [Teacher 2]

"When I started, I used a lot of images, it took a very long time before the model was able to train … So I had to use less number of images for each class I noticed it was faster to train the model." [Teacher 3]

"our major challenge is with the issue of light (power supply)." [Teacher 4]

- Suggestions for Enhancement

The participants provided constructive feedback to enhance AfriML. Suggestions included developing a mobile application for wider accessibility, adding interactive features such as a question-and-answer bot, and incorporating more engaging tools like African games to capture students' attention and improve their knowledge of African culture.

"I would suggest if it possible to add a bot that can talk and respond to question ask that are relating to African culture, language, items and other engaging tools like African games it would capture the attention of the student and help them to improve in their knowledge of African culture." [Teacher 1]

"For Nigeria school level I think nothing should be added." [Teacher 2]

"I believe if other models are added for the website to be more entertaining at the same time educating, for example a video model." [Teacher 3]

"So, if it is done as application such that, the application will be able to use on devices like handsets to be a little bit better." [Teacher 4]

- Sustainability and Future Use

There was a strong interest in the continued use of AfriML. Teachers expressed their willingness to integrate it into their curriculum and recommend it to colleagues and other schools. They believed that with further improvements, AfriML could become a valuable asset in enhancing the teaching and learning process, particularly in ICT education.

"Introducing AfriML to school isn't out of place, I believe it would improve their understanding on machine learning and give them a first hand knowledge, to as many that would go in the path of coding and website designing." [Teacher 1]

"I think it should be part of the curriculum because it going to boost the interest of our culture to Nigeria students and its going to make Nigeria students gets interest in programming." [Teacher 2]

"Definitely, I will recommend AfriML." [Teacher 2]

"Yes, I believe so, AfriML can be and will be part of the students curriculum from next school session." [Teacher 3]

"Yes, for me, I would continue using AfriML and also encourage my students to use the website continuously to help improve their knowledge." [Teacher 3]

"Due to electricity instability in Nigeria I'll try to use the website at least twice or three times a week." [Teacher 3]

"As soon as it is ready for use been it online or it is in the form of app we will download and begin to use and also recommend for others." [Teacher 4]

6.2 Quantitative Analysis

6.2.1 Paired T-Test Sample for Pre and Post Test

Paired Samples Test

		Paired Differences							Significance	
					95% Confidence Interval of the Difference					
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	One-Sided p	Two-Sided p
Pair 1	PreTest Scores - PostTest Scores	-1.69900	.99232	.15690	-2.01636	-1.38164	-10.829	39	<.001	<.001

Table 1: Paired Sample Test for Pre and Post Test

Interpretation

Mean Difference: The average improvement in students' scores from pre-test to post-test is 1.699 points, suggesting that students generally performed better after using the AfriML tool.

Standard Deviation and Standard Error: The relatively low standard deviation (0.99232) and standard error (0.15690) indicate that the differences in scores are fairly consistent across students, and the sample mean difference is a reliable estimate of the population mean difference.

Confidence Interval: The 95% confidence interval does not include zero, reinforcing that the improvement in scores is statistically significant. We can be confident that the true average improvement in scores lies between 1.38164 and 2.01636 points.

t-Statistic and p-Value: The very high t-statistic (-10.829) and the extremely low p-value (<0.001) provide strong evidence that the observed improvement in scores is not due to random chance. The results are statistically significant at any conventional significance level (e.g., 0.05, 0.01, or 0.001).

6.2.2 ANOVA for Students' Motivation and Attitude

ANOVA

		Sum of Squares	df	Mean Square	F	Sig
Between People		73.785	38	1.942		
Within People	Between Items	.533	4	.133	.360	.837
	Residual	56.267	152	.370		
	Total	56.800	156	.364		
Total		130.585	194	.673		

Grand Mean = 1.35

Table 2: ANOVA for Students' Motivation and Attitude

Interpretation: The ANOVA results indicate that there is no significant difference in the way students rated the various statements regarding their motivation and attitude towards ML in Section G of the survey. The high p-value (0.837) for the F-statistic implies that the variability between the items is not statistically significant compared to the variability within respondents. This suggests that students' attitudes and motivations are consistently similar across the different survey items in this section.

The grand mean of 1.35 and the good internal consistency (Cronbach's alpha = 0.809) suggest that students generally agree with the positive statements about their motivation and attitude towards ML, and their responses are reliable.

6.2.3 Regression Analysis Comparing Engagement and Satisfaction

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.407[a]	.166	.094	.461

a. Predictors: (Constant), Did the cultural elements in AfriML make learning more relatable for you?, On a scale of 1-5, how engaging did you find the AfriML tool overall?, How often did you use the AfriML tool during the study period?

b. Dependent Variable: On a scale of 1-5, how satisfied are you with the AfriML tool overall?

Table 3: Model Summary for Regression Analysis comparing Engagement and Satisfaction

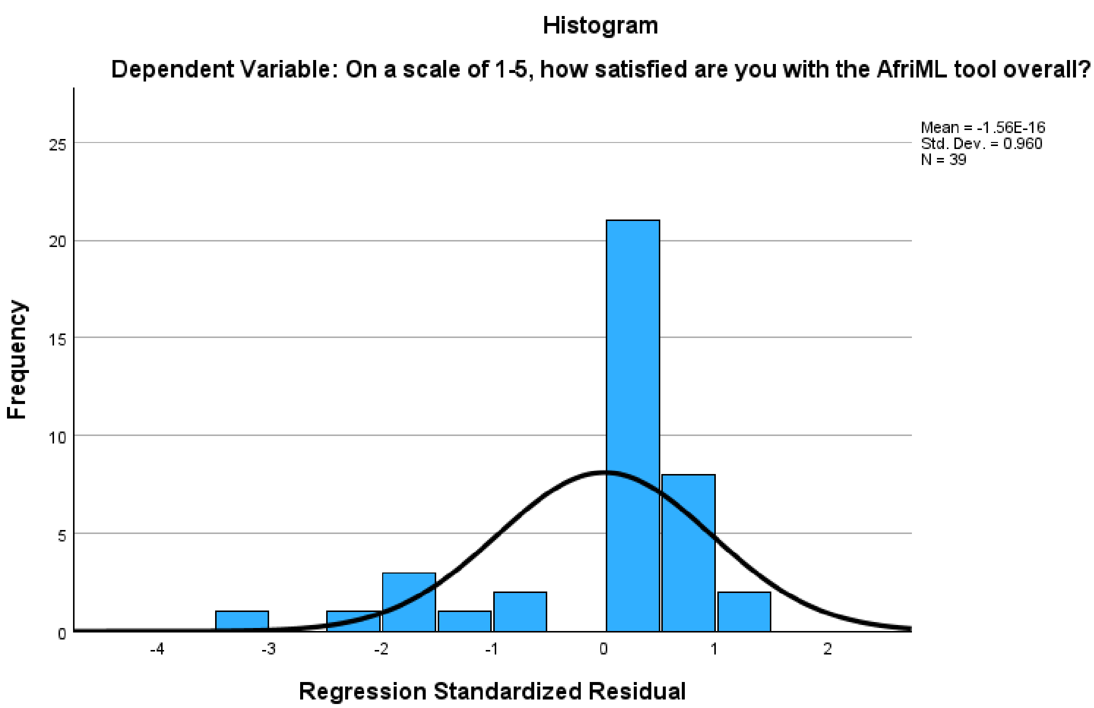

Fig 14: Histogram for Regression Analysis comparing Engagement and Satisfaction

Interpretation: The regression analysis indicates that there is a moderate positive relationship between students' engagement with the AfriML tool and their overall satisfaction. The engagement factors explain about 16.6% of the variance in satisfaction, highlighting that other factors not included in this model play a significant role in determining satisfaction.

The adjusted R Square value suggests that the model could be improved by refining the predictors or including additional relevant variables. The standard error indicates that while the model provides some insight into the factors influencing satisfaction, there is still substantial variability that is not accounted for.

In summary, the results suggest that enhancing engagement with the AfriML tool, particularly through culturally relatable elements, can positively influence students' satisfaction. However, to fully understand the determinants of satisfaction, further research incorporating additional variables would be beneficial.

7.0 DISCUSSION AND CONCLUSION

7.1 Discussion

In the realm of AI education, integrating culturally relevant elements into learning tools has become increasingly important (Chisom et al., 2024). AfriML, a no-code web-based platform akin to Google Teachable Machine, which facilitates model training, testing, and exporting for image, text, pose, and audio classification is designed to teach high-school students machine learning (ML) concepts. A distinguishing feature of AfriML is its incorporation of African cultural elements, allowing it to recognize African images, accents, and languages. This study applied a design science research methodology to develop and evaluate AfriML, aiming to enhance students' understanding of ML concepts by using culturally specific elements that resonates with African students.

The effectiveness of AfriML was assessed through various methodologies, including classroom trials and teacher feedback. The platform's design was influenced by educational research principles, user experience design, and considerations for privacy and data protection. The use of culturally relevant characters was shown to significantly improve students' engagement and understanding of ML concepts. This supports the observations of Ertugruloglu et al. (2024) and Chisom et al. (2024), who highlighted the transformative potential of AI in making education more inclusive, particularly within African contexts. The platform's minimalistic user interface was intentionally designed to avoid overwhelming students with too many options, thus promoting experimentation and exploration.

Prior to the development of AfriML, existing ML education tools such as ML4Kids, Scratch, AutoML, Lobe, and LearningML primarily focused on providing user-friendly interfaces for creating ML models without requiring extensive technical knowledge. While these platforms made ML more accessible, they often lacked the cultural context necessary to fully engage students from diverse backgrounds. Recent literature, including studies by including Mahipal et al. (2023) and Martin et al. (2024) have explored innovative tools like DoodleIt and ChemAIstry, which teach ML concepts through specialized software, yet they do not specifically address cultural adaptation in their educational frameworks.

AfriML fills this gap by explicitly integrating African cultural elements into its educational content, thereby enhancing relatability and engagement for African students. This approach is supported by Pope et al. (2024), who emphasize the value of no-code AI education tools in making complex concepts accessible. Additionally, Sanusi (2021) underscored the importance of contextualizing ML education to improve understanding and retention, a principle that AfriML embodies.

While previous research has often focused on technical aspects or the general utility of ML education tools, there has been limited exploration into how these tools impact students' attitudes, engagement, and motivation specifically in the context of high-school education. This study contributes to filling that gap (Nasir & Hand, 2006) by demonstrating that culturally relevant tools like AfriML can significantly enhance learning outcomes. The paired t-test, ANOVA and Regression analysis conducted in this study confirmed that AfriML not only enhances students' comprehension of ML concepts but also positively influences their attitudes and motivation towards learning more about the field which also introduces a new dimension by contextualizing ML education within a cultural framework.

AfriML's approach of combining educational technology with cultural specificity offers a novel and effective means of teaching ML concepts. This aligns with the broader trend in educational research advocating for culturally responsive teaching methods to boost engagement and comprehension. The success of AfriML underscores the importance of designing educational tools that are not only technically proficient but also culturally sensitive, ensuring that they meet the diverse needs of students across different regions. Future research should continue to explore this intersection, further validating the efficacy of culturally tailored educational technologies.

7.1.1 Research Question One

How can we design and develop an ML tool infused with African cultural elements to improve high-school students' education of ML concepts?

- Design Strategy: The AfriML tool was developed as a hybrid of similar ML web-based platforms by integrating African cultural elements such as artifacts images, accents, and languages as models and dataset. African Image model (Otieno) was trained using Fastai, specifically employing a ResNet152 architecture. African Accent model (Rukky) was trained using an audio dataset obtained from SautiDB, the dataset features were extracted using Librosa, which are then used to train a neural network with TensorFlow. African Language Model (Melo) was trained using the Hugging Face Transformers library to train a robust word database of 3 languages (Igbo, Hausa, Yoruba) with a pre-trained DistilBERT model. This design strategy aimed to make the learning experience more relatable and engaging for Nigerian high-school students.

- Implementation Feedback: Teachers and students responded positively to the cultural elements, noting that these features enhanced their connection to the material and made the learning process more enjoyable. The diversity of cultural elements, including visual and audio components, was particularly appreciated. This was achieved by using structured surveys, pre- and post-test assessments, and semi-structured interviews for 4 schools, 40 high-school students and 4 teachers of these schools.

- Impact on Learning: The cultural relevance of the tool was crucial in improving students' understanding of ML concepts. Students were able to relate to the content better, which facilitated a deeper comprehension of the subject matter. Also, their teachers testified to the impact it made on the students' knowledge and performance.

7.1.2 Research Question Two

How effective is AfriML in enhancing students' understanding of machine learning concepts?

This study found that the AfriML tool significantly enhanced students' understanding of machine learning (ML) concepts. The tool's effectiveness was evident in multiple dimensions, as captured through both quantitative and qualitative data.

- Effectiveness: The AfriML tool demonstrated high efficacy in improving students' comprehension of ML concepts. This was primarily evidenced by the results of the pre- and post-tests administered to students, which revealed a substantial increase in their understanding following the use of the tool. The paired t-test results provided robust statistical support for this improvement, showing a highly significant difference in the pre-test and post-test scores ($t(39)$ =

-10.829, $p < .001$). The mean difference of -1.69900, with a 95% confidence interval ranging from -2.01636 to -1.38164, indicates a clear enhancement in students' knowledge and understanding of the tool.

- Teacher Observations: Teachers reported notable improvements in students' grasp of ML concepts after engaging with AfriML. They observed that students were not only able to understand theoretical aspects more deeply but also demonstrated a heightened ability to apply these concepts in practical scenarios. The interactive features and practical applications embedded in the AfriML tool played a crucial role in this learning process. According to the teachers, students showed increased enthusiasm and engagement, often expressing their interest in exploring further aspects of ML. This enthusiasm was attributed to the culturally relevant content, which made the learning experience more relatable and accessible.

- Quantitative Data: The paired t-test data corroborated the qualitative observations, providing a quantitative basis for the tool's effectiveness. The statistical analysis confirmed that the use of AfriML significantly improved students' understanding of ML concepts. The improvement was not just in their theoretical knowledge but also in their ability to apply ML principles in diverse contexts, as facilitated by the practical, hands-on nature of the tool. These findings underscore the value of integrating culturally relevant educational tools like AfriML into the curriculum, as they can lead to meaningful improvements in student engagement and learning outcomes.

7.1.3 Research Question Three

How does the use of the AfriML tool influence students' attitudes towards learning machine learning and their motivation to pursue further studies in this field?

- Positive Attitudes: The use of the AfriML tool positively influenced students' attitudes towards machine learning. The ANOVA analysis for "Students' Motivation and Attitude" showed that the variance between different participants' attitudes was significant, with a Sum of Squares between people of 73.785, indicating variability in responses. However, the Sum of Squares for items was relatively low (0.533), suggesting that the differences in response to individual items were not substantial. This indicates that, while students had varying levels of overall engagement, there was a general consensus on their positive attitude toward the tool's content and delivery.

- Motivation: The interactive features and culturally relevant content of the AfriML tool were key factors in enhancing student motivation. The Mean Square between items (0.133) and the resulting low F value (0.360) indicate that there were no significant differences in how different aspects of the tool influenced motivation. This consistency suggests that the tool's various components—such as image, text, pose, and audio classification, including African cultural elements—were uniformly effective in engaging students. The lack of significant variance (Sig value of 0.837) further supports the conclusion that the students were generally motivated by the tool's content.

- Teacher Feedback: Teachers observed that students were more engaged and motivated after using AfriML. They noted that the tool's inclusion of culturally familiar elements helped demystify complex machine learning concepts, making them more approachable and relatable. This increased understanding led to a heightened interest in the tool, as students could see the practical applications of what they were learning. Teachers also reported a notable increase in students' enthusiasm for exploring machine learning further, indicating a positive shift in their attitudes towards the subject.

7.2 Conclusion

In this study, the AfriML tool was designed, developed, and implemented to enhance the understanding of machine learning (ML) concepts among high-school students in Nigeria. Using the Design Science Research (DSR) methodology, this research integrated culturally relevant elements into the AfriML tool, making it relatable and engaging for the students. The initial evaluation involved collecting feedback from students and teachers through structured surveys, pre- and post-test assessments, and semi-structured interviews.

The study revealed that incorporating African cultural elements into ML education can significantly improve students' engagement and comprehension. The quantitative data showed notable improvements in students' understanding of ML concepts, as evidenced by the pre- and post-test results. Qualitative feedback from teachers highlighted that students found the tool motivating and relatable, enhancing their learning experience.

Students reported a preference for learning through the culturally enriched content provided by AfriML, which made complex ML concepts more accessible and interesting. This approach not only facilitated a better understanding of the subject matter but also increased students' enthusiasm and motivation to pursue further studies in the field of machine learning.

However, some challenges were identified, such as technical difficulties with voice recognition and language processing, and limited access to necessary resources like devices and stable power supply. These challenges indicate that further improvements are needed to enhance the tool's usability and accessibility. Teachers suggested developing AfriML as a mobile application to improve accessibility and usability and enhancing its language processing capabilities to better handle diverse African accents and languages.

The implications of this study suggest that integrating modern technology, combined with culturally relevant content, can significantly improve educational outcomes and the overall learning experience for high-school students. The recommendations for educators based on these findings include incorporating culturally relevant elements and modern technologies, like those used in AfriML, into the learning process to increase student engagement, interactivity, and improve learning outcomes. By doing so, educational tools like AfriML can play a crucial role in making education more inclusive, engaging, and effective for students in diverse cultural settings.

7.3 Limitation and Future Work

This study faced several limitations. The sample size was limited due to logistical constraints and resource limitations, which restricted the generalizability of the findings. Future studies should involve a larger group of students across diverse regions and school types to draw more robust and reliable conclusions.

Additionally, while AfriML was tested in four high schools in Nigeria, the implementation was confined to these specific schools. Future research should expand to include a broader range of schools, including public institutions and those in rural areas, to assess the tool's effectiveness in varying educational environments and with students who may have less exposure to technology.

Technical limitations also emerged, particularly concerning the tool's voice recognition and language processing capabilities. These issues underscore the need for further development to enhance AfriML's ability to accurately recognize and process diverse African accents and languages.

The AfriML tool, as currently developed, relies on a web-based platform. Future work should include developing a mobile application version for both Android and iOS platforms to increase accessibility and usability. This would ensure that more students, regardless of their access to specific types of devices, can benefit from the tool.

In addition, while the study focused on high-school students, exploring the tool's applicability and effectiveness for different educational levels could provide valuable insights. Evaluating its use in primary schools, vocational training centers, and higher education institutions could help in understanding its broader impact and adaptability.

Lastly, the study highlighted the importance of integrating culturally relevant content to enhance learning experiences. Future research should continue to explore and incorporate diverse cultural elements to ensure that educational tools are inclusive and relatable for students from various backgrounds.

Addressing these limitations and expanding the scope of future studies will help to refine the AfriML tool, ensuring it can be a sustainable and effective part of the educational curriculum across different contexts and regions.

7.4 Recommendations

- Develop a Mobile Application: To improve accessibility and usability in low-resource settings.

- Enhance Language Processing: Improve the tool's ability to recognize and process a wider range of African languages and accents.

- Formal Curriculum Integration: Collaborate with educational authorities to integrate AfriML into the school curriculum.

- Teacher Training and Resources: Provide training and resources to teachers to effectively use AfriML in their classrooms.
- Ongoing Feedback and Improvement: Establish a feedback mechanism to continuously gather input from users and make iterative improvements to the tool.

REFERENCE

A. Stott, and C. Neustaedter, “Analysis of gamification in education(2013): 36.,” Surrey, BC, Canada 8 , vol. 8, no. 36, 2013.

Agbo, F. J., Oyelere, S.S., Suhonen, J. & Tukiainen, M., (2019). Identifying potential design features of a smart learning environment for programming education in Nigeria. International Journal of Learning Technology IJLT Vol 14, No. 4, pp. 331-354 https://www.inderscienceonline.com/doi/abs/10.1504/IJLT.2019.106551.

Agbo, F. J., Oyelere, S. S., & Bouali, N. (2020). A UML approach for designing a VR-based smart learning environment for programming education. In 2020 IEEE Frontiers in Education Conference (FIE) (pp. 1-5). IEEE. https://ieeexplore.ieee.org/abstract/document/9273956/

Agbo, F. J., Oyelere, S.S., Suhonen, J. & Tukiainen, M. (2021). iThinkSmart: Immersive virtual reality mini games to facilitate students’ computational thinking skills. Koli Calling '21: 21st Koli Calling International Conference on Computing Education Research (1-3) ACM. https://doi.org/10.1145/3488042.3489963

Aldriye, Hussam & Alkhalaf, Asma & Alkhalaf, Muath. (2019). Automated Grading Systems for Programming Assignments: A Literature Review. International Journal of Advanced Computer Science and Applications. 10. 10.14569/IJACSA.2019.0100328.

Alhojailan, M. I. (2012). Thematic analysis: A critical review of its process and evaluation. West East Journal of Social Sciences, 1(1), 39-47.

Alnuaimi, Amer & Albaldawi, Tasnim. (2024). An overview of machine learning classification techniques. BIO Web of Conferences. 97. 00133. 10.1051/bioconf/20249700133.

Bamgbose, A. (2011). African languages today: The challenge of and prospects for empowerment under globalization. Paper presented at the Selected Proceedings of the 40th Annual Conference on African Linguistics, 1-14.

Bansal, Prashant & Stewart, Rachel & Entezari, Vahid & Snyder, Brian & Grinstaff, Mark. (2011). Contrast Agent electrostatic attraction rather than repulsion to glycosaminoglycans affords a greater contrast uptake ratio and improved quantitative CT imaging in cartilage. Osteoarthritis and cartilage / OARS, Osteoarthritis Research Society. 19. 970-6. 10.1016/j.joca.2011.04.004.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative research in psychology, 3(2), 77-101.

Briggs, Robert & Schwabe, Gerhard. (2011). On Expanding, the Scope of Design Science in IS Research. 92-106. 10.1007/978-3-642-20633-7_7.

C. H. Chung, L. A. Pasquini, and C. E. Koh, "Web-based learningmanagement system considerations for higher education," Learning andPerformance Quarterly , vol. 1.4 , pp. 24-37, 2013.

Chisom, Onyebuchi & Unachukwu, Chika & Osawaru, Blessing. (2024). REVIEW OF AI IN EDUCATION: TRANSFORMING LEARNING ENVIRONMENTS IN AFRICA. International Journal of Applied Research in Social Sciences. 5. 637-654. 10.51594/ijarss.v5i10.725.

Darrell, West & John, Allen. (2018). How artificial intelligence is transforming the world. https://www.brookings.edu/articles/how-artificial-intelligence-is-transforming-the-world/

Drivas, Thanassis & Doukakis, Spyridon. (2022). Introducing the Fundamentals of Artificial Intelligence to K-12 Classrooms According to Educational Neuroscience Principles. 1-7. 10.1109/SEEDA-CECNSM57760.2022.9932989.

Ertugruloglu, Oya & Gülcan, Nur & Abidoğlu, Ülkü. (2024). The Impact of Culture on the Education System: The Impact of Culture on the Education System. International e-Journal of Educational Studies. 8. 10.31458/iejes.1436091.

Eshleman, Ross J and Cashion G Barbara (1983) – Sociology - An. Introduction -- U.S.A. - Little Brown and Co Ltd.

Federal Republic of Nigeria (2013). National Policy on Education. 6thEdition. Lagos, NERDC Press.

Frost, J. (2013). Regression Analysis: An Intuitive Guide for Using and Interpreting Linear Models. Available at: (https://dokumen.pub/regression-analysis-an-intuitive-guide-1nbsped.html)

Generation AI (2023): https://tm.generation-ai-stn.fi/

Google AutoML (1990s): https://cloud.google.com/automl

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. MIS quarterly, 75-105.

Hua, Weiqi & Li, Chunzhong & Wang, Xinsheng. (2024). Review of Convolutional Neural Network Models and Image Classification. Academic Journal of Science and Technology. 10. 178-184. 10.54097/644jqv20.

Johannesson, Paul & Perjons, Erik. (2014). An Introduction to Design Science. 10.1007/978-3-319-10632-8.

Johnson, Nathan & Sarkar, Sayani. (2023). Integrating AI and ML Education in Small Liberal Arts Institutions: Curriculum and Pedagogical Considerations. International Journal on Cybernetics & Informatics. 12. 1-17. 10.5121/ijci.2023.120401.

LearningML (2019): https://web.learningml.org/en/home/

Limna, Pongsakorn & Jakwatanatham, Somporch & Siripipattanakul, Sutithep & Kaewpuang, Pichart & Sriboonruang, Patcharavadee. (2022). A Review of Artificial Intelligence (AI) in Education during the Digital Era. 1. 1-9.

Lobe (2020): https://www.lobe.ai/

M. K. Saini, and N. Goel, " How smart are smart classrooms? A review of smart classroom technologies.," ACM Computing Surveys (CSUR), vol.52.6, pp. 1-28, 2019

Mahipal, V., Ghosh, S., Sanusi, I. T., Ma, R., Gonzales, J. E., & Martin, F. G. (2023, January). DoodleIt: A novel tool and approach for teaching how CNNs perform image recognition. In Proceedings of the 25th australasian computing education conference (pp. 31-38).

Martin, F., Mahipal, V., Jain, G., Ghosh, S., & Sanusi, I. T. (2024, March). ChemAIstry: A Novel Software Tool for Teaching Model Training in K-8 Education. In Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1 (pp. 792-798).

McDonald, J. H. (2009). Handbook of Biological Statistics (2nd ed.). Sparky House Publishing, Baltimore, Maryland

ML4Kids (2017) https://machinelearningforkids.co.uk/#!/about

Mormah, Felicia. (2021). Teacher education in Nigeria and the emerging technologies in the 21st century classroom. African Educational Research Journal. 9. 641-647. 10.30918/AERJ.93.19.049.

Nasir, N. S., & Hand, V. (2006). Exploring Sociocultural Perspectives on Race, Culture, and Learning. Review of Educational Research, 76(4), 449-475.

OECD (2016). Education working papers, no 170, OECD publishing, Paris http//dx.doi.orlio,17871102456c7cc. Retrieved August 10, 2019.

Oshodi, Ismaila. (2022). A review of the impact of Education Technology in developing countries (A case study of Nigeria). 10.13140/RG.2.2.10596.30084.

Oyelere, S. S., & Suhonen, J. (2016, March). Design and implementation of MobileEdu mlearning application for computing education in Nigeria: A design research approach. In 2016 International Conference on Learning and Teaching in Computing and Engineering (LaTICE) (pp. 27-31). IEEE.

Oyelere, S. S., Suhonen, J., Wajiga, G. M., & Sutinen, E. (2018). Design, development, and evaluation of a mobile learning application for computing education. Education and Information Technologies, 23(1), 467-495.

Papert Seymour (1980). Mindstorms: Children, Computers, and Powerful Ideas" (1980). Retrieved from: https://worrydream.com/refs/Papert_1980_-_Mindstorms,_1st_ed.pdf

Pope, Nicolas & Vartiainen, Henriikka & Kahila, Juho & Laru, Jari & Tedre, Matti. (2024). A No-Code AI Education Tool for Learning AI in K-12 by Making Machine Learning-Driven Apps.

Poulakis, Yannis & Doulkeridis, Christos & Kyriazis, Dimosthenis. (2024). A Survey on AutoML Methods and Systems for Clustering. ACM Transactions on Knowledge Discovery from Data. 18. 10.1145/3643564.

Prokopis, A. C. (2024). Thematic Analysis through Artificial Intelligence (AI). The Qualitative Report. 29. 560-576. 10.46743/2160-3715/2024.7046.

Pujari, Yogendra Prasad & Prasad, Dumpa & Malleswari, Naga & Gupta, Neha. (2022). Implementation of Machine Learning Based Google Teachable Machine in Early Childhood Education. International Journal of Early Childhood Special Education. 14. 4132-4138.

Robert H. B. (2020). Microsoft Lobe: Image Recognition Made Simple. Available at https://rehoyt.medium.com/microsoft-lobe-image-recognition-made-simple-4bbcf99b8bb5

Rodríguez, Juan & Moreno-León, Jesús & Román-González, Marcos & Robles, Gregorio. (2020). LearningML: A Tool to Foster Computational Thinking Skills Through Practical Artificial Intelligence Projects. Revista de Educación a Distancia (RED). 20. 10.6018/red.410121.

Sanusi, Ismaila & Oyelere, Solomon. (2020). Pedagogies of Machine Learning in K-12 Context. 1-8. 10.1109/FIE44824.2020.9274129.

Sanusi, I. T. (2021). Intercontinental evidence on learners' differentials in sense-making of machine learning in schools. In Proceedings of the 21st Koli Calling International Conference on Computing Education Research (pp. 1-2).

Sanusi, I. T., Oyelere, S. O., Vartiainen, H., & Suhonen, J. & Tukiainen, M. (2022). A systematic review of teaching and learning machine learning in K-12 education. Education and Information Technologies. 28. 1-31. 10.1007/s10639-022-11416-7.

Sanusi, I. T., Olaleye, S. A., Agbo, F. J., & Chiu, T. K. (2022). The role of learners' competencies in artificial intelligence education. Computers and Education: Artificial Intelligence, 3, 100098.

Sanusi, Ismaila & Sunday, Kissinger & Oyelere, Solomon & Suhonen, Jarkko & Vartiainen, Henriikka & Tukiainen, Markku. (2023). Learning machine learning with young children: Exploring informal settings in an African context. Computer Science Education. 34. 10.1080/08993408.2023.2175559.

Sanusi, Ismaila & Omidiora, Joseph & Oyelere, Solomon & Vartiainen, Henriikka & Suhonen, Jarkko & Tukiainen, Markku. (2023). Preparing Middle Schoolers for a Machine Learning-Enabled Future Through Design-Oriented Pedagogy. 10.1109/ACCESS.2023.3269025.

SautiDB (v1.2, 2023): https://zenodo.org/records/7646394

Schmidt, Kirill. (2024). Digital Technologies in the Educational Process: Challenges and Risks. Общество: социология, психология, педагогика. 62-67. 10.24158/spp.2024.4.8.

Scratch (2007): https://scratch.mit.edu/about

M. Seadle and E Greifeneder, "Defining a digital library.," Library HiTech, vol. 2007

Seo, K., Tang, J., Roll, I. *et al.* The impact of artificial intelligence on learner–instructor interaction in online learning. *Int J Educ Technol High Educ* **18**, 54 (2021). https://doi.org/10.1186/s41239-021-00292-9

Tapalova, Olga & Zhiyenbayeva, Nadezhda & Gura, Dmitry. (2022). Artificial Intelligence in Education: AIEd for Personalised Learning Pathways. Electronic Journal of e-Learning. 20. 639-653. 10.34190/ejel.20.5.2597.

Teachable Machine (2009): https://teachablemachine.withgoogle.com/

Tedre, Matti & Toivonen, Tapani & Kahila, Juho & Vartiainen, Henriikka & Valtonen, Teemu & Jormanainen, Ilkka & Pears, Arnold. (2021). Teaching Machine Learning in K-12 Computing Education: Potential and Pitfalls.

Touretzky, D., Gardner-McCune, C., Martin, F., & Seehorn, D. (2019). Envisioning AI for K-12: What should every child know about AI?. In Proceedings of the AAAI conference on artificial intelligence (Vol. 33, No. 01, pp. 9795-9799).

UNESCO: Beijing Consensus on Artificial Intelligence and Education. (2021) Retrieved from: https://teachertaskforce.org/knowledge-hub/beijing-consensus-artificial-intelligence-and-education#:~:text=One%20of%20the%20recommendations%20governments,and%20working%20conditions%20are%20protected.

Vahedian Movahed, Saniya & Dimino, James & Farrell, Andrew & Irankhah, Elyas & Jain, Garima & Mahipal, Vaishali & Rayavaram, Pranathi & Salas, Erika & Sanusi, Ismaila & Wolkowicz, Kelilah & Narain, Sashank & Martin, Fred. (2023). Developing AI Educational Tools for Children.

Walter, Y. Embracing the future of Artificial Intelligence in the classroom: the relevance of AI literacy, prompt engineering, and critical thinking in modern education. Int J Educ Technol High Educ 21, 15 (2024). https://doi.org/10.1186/s41239-024-00448-3

Wang, N., & Johnson, M. AI Education for K-12: Connecting AI Concepts to High School Math Curriculum. Workshop on Education in Artificial Intelligence K-12, 28th International Joint Conference on Artificial Intelligence, (). Retrieved from https://par.nsf.gov/biblio/10440200.

Wang, Zhaoguo. (2023). Deep Learning Based Text Classification Methods. Highlights in Science, Engineering and Technology. 34. 238-243. 10.54097/hset.v34i.5478.

Wierenga, R., & Carstens, W. (2021). Digitising Afrikaans: Establishing a protocol for digitalizing historical sources for Early Afrikaans (1675–1925) as a possible template for indigenous South African languages. Journal of the Digital Humanities.

Wohlin, C. and Runeson, P. (2021) 'Guiding the selection of research methodology in industry-academia collaboration in software engineering', Information and Software Technology, 140 pp. 106678. Available at: https://doi.org/10.1016/j.infsof.2021.106678

World Bank Group. (2021). Teaching young children in the language they speak at home is essential to eliminate learning poverty. World Bank. https://www.worldbank.org/en/news/press-release/2021/07/14/teaching-young-children-in-the-language-they-speak-at-home-is-essential-to-eliminate-learning-poverty

Xia, Q., Chiu, T. K., Lee, M., Sanusi, I. T., Dai, Y., & Chai, C. S. (2022). A self-determination theory (SDT) design approach for inclusive and diverse artificial intelligence (AI) education. Computers & Education, 189, 104582.

Zaman, Khalid & Sah, Melike & Direkoglu, Cem & Unoki, Masashi. (2023). A Survey of Audio Classification Using Deep Learning. IEEE Access. 11. 1-1. 10.1109/ACCESS.2023.3318015.

APPENDICES

APPENDIX I

Pre Test Quiz for Students

Section A: Basic Concept and Meaning of ML

1. What is Machine Learning?
a) Teaching machines to do things on their own
b) Making machines from metal
c) Writing books by hand
d) Talking to machines

2. What is 'training data' in Machine Learning?
a) Data for teaching the computer
b) Data for cleaning machines
c) Data for building houses
d) Data for cooking

3. What is a 'model' in Machine Learning?
a) A machine part
b) A way to predict things
c) A type of fabric
d) A computer game

4. All of these use ML applications except:
a) Youtube
b) Traffic Light
c) Google
d) Calculator

APPENDIX II

Post-Test Quiz for Students

Section A: Basic Concept and Meaning of ML

1. What is the main goal of machine learning?
a) To build physical machines
b) To cook food automatically
c) To train machines to get better at tasks without explicit programming
d) To write books

2. Which of these steps is NOT part of the machine learning process?
a) Collecting data
b) Building houses
c) Selecting a training model
d) Evaluating the model

3. What is 'supervised learning'?
a) Learning with a teacher present
b) A type of learning where the model learns from labeled data
c) Learning in a classroom
d) Learning through playing games

4. What is a key difference between machine learning and traditional programming?
a) Machine learning uses only numerical data.
b) Traditional programming is done manually without computers.
c) Machine learning is more automated and learns from data.
d) Traditional programming requires no data

5. Which of these is a type of machine learning?
a) Reinforced reading
b) Manual learning
c) Semi-supervised learning
d) Machine writing

Section B: Application of ML Concepts

6. How does machine learning help in finance?
a) By cooking food faster
b) By evaluating risks and predicting the best investments
c) By building stronger bank vaults
d) By making faster cars

7. In which industry is machine learning used for self-driving cars?
a) Farming
b) Textile
c) Automotive
d) Fishing

8. How does machine learning help in e-commerce?
a) By predicting customer churn
b) By packing products faster
c) By increasing the weight of packages
d) By reducing internet speed

9. Which task can machine learning NOT help with?
a) Space exploration
b) Sending emails manually
c) Predicting customer preferences
d) Evaluating financial risks

Section C: Practical Applications and Understanding of Machine Learning

10. What does 'unsupervised learning' do?
a) Uses labeled data to train
b) Discovers patterns within data
c) Needs a teacher to guide it
d) Only works with numbers

11. What is 'classification' in supervised learning?
a) Sorting data into numerical values
b) Sorting data into categories
c) Mixing data randomly
d) Ignoring data

12. Which algorithm is commonly used in unsupervised learning?
a) Decision trees
b) K-Means clustering
c) Logistic regression
d) Linear regression

13. Which industry benefits from machine learning for customer insights?
a) Construction
b) Education
c) Marketing
d) Mining

14. What helps improve machine learning models by automatically tuning them?
a) AutoML
b) Manual adjustment
c) Handwritten notes
d) Traditional coding

1.1 APPENDIX III

SURVEY ON AFRIML

Section A: Demographic Information

Name:

Age:

Gender:

Grade Level:

Tribe:

Previous experience with AI/ML concepts:

None Beginner Intermediate Advanced

Section B: Engagement

1. How would you rate your interest in AI/ML before using AfriML?

Very Low 1 2 3 4 5 Very High

2. How often did you use the AfriML tool during the study period?

Never 1 2 3 4 5 Very Often

3. Which features of AfriML did you find most engaging? (Select all that apply)

Image Classification
Audio Classification
Text Classification
Pose Classification
Testing the Africanism of your environment (through pictures, audio and texts)
Watching AI/ML and Tutorial Videos

4. On a scale of 1-5, how engaging did you find the AfriML tool overall?

Not Engaging 1 2 3 4 5 Very Engaging

5. Did the cultural elements in AfriML make learning more relatable for you?

Strongly Disagree 1 2 3 4 5 Strongly Agree

Section C: Usability

6. How easy was it to navigate through the AfriML tool?

Very Difficult 1 2 3 4 5 Very Easy

7. Did you encounter any technical issues while using AfriML?

Yes No Maybe

8. If yes or maybe, please describe the technical issues you faced:
9. How intuitive was the user interface of AfriML?

Very Unintuitive 1 2 3 4 5 Very Intuitive

10. Were the instructions and tutorials clear and helpful?

Strongly Disagree 1 2 3 4 5 Strongly Agree

Section D: Satisfaction

11. On a scale of 1-5, how satisfied are you with the AfriML tool overall?

Very Dissatisfied 1 2 3 4 5 Very Satisfied

12. How likely are you to recommend AfriML to your peers?

Very Unlikely 1 2 3 4 5 Very Likely

13. What did you like most about the AfriML tool?
14. What did you like least about the AfriML tool?
15. How could AfriML be improved to better suit your learning needs?

Section E: Educational Impact

16. Did using AfriML improve your understanding of ML concepts?

Strongly Disagree 1 2 3 4 5 Strongly Agree

17. On a scale of 1-5, how much has your knowledge of ML concepts increased after using AfriML?

Not at all 1 2 3 4 5 Greatly

18. Did the AfriML tool influence your attitude towards learning machine learning?

Strongly Disagree 1 2 3 4 5 Strongly Agree

19. Are you more likely to pursue further studies in AI/ML after using AfriML?

Very Unlikely 1 2 3 4 5 Very Likely

20. What additional features or content would you like to see in AfriML?

Section F: Cultural Relevance

21. How important do you think it is to have culturally relevant educational tools?

Not important at all 1 2 3 4 5 Very important

22. Did the incorporation of African cultural elements help you understand ML concepts better?

Strongly Disagree 1 2 3 4 5 Strongly Agree

23. Which among these of a cultural element in AfriML that you found particularly helpful?

Artifacts Detector

Accent Detector

Language Detector

24. How well did AfriML reflect your cultural background and experiences?

Not well at all 1 2 3 4 5 Very well

25. Would you like to see more educational tools that incorporate your cultural heritage?

Strongly Agree 1 2 3 4 5 Strongly Disagree

Section G: Motivation and Attitude towards ML

26. How much do you agree with the following statement? “I look forward to using machine learning concepts I learned from AfriML in my daily life.”

Strongly Agree 1 2 3 4 5 Strongly Disagree

27. How much do you agree with the following statement? “I think it would be very wise to use the machine learning knowledge gained from AfriML in my daily life.”

Strongly Agree 1 2 3 4 5 Strongly Disagree

28. How much do you agree with the following statement? “I enjoy learning machine learning concepts using the AfriML tool.”

Strongly Agree 1 2 3 4 5 Strongly Disagree

29. How much do you agree with the following statement? “I found learning machine learning with AfriML fun and engaging.”

Strongly Agree 1 2 3 4 5 Strongly Disagree

30. How much do you agree with the following statement? “Learning machine learning with AfriML holds my attention well and makes the subject interesting.”

Strongly Agree 1 2 3 4 5 Strongly Disagree

APPENDIX IV

Interview Questions for Teachers on Zoom

1. Can you describe your overall experience with the AfriML tool in your classroom?
2. How do you think the integration of African cultural elements affected students' engagement with learning machine learning concepts?
3. What specific cultural elements did you notice in AfriML, and how did students respond to them?
4. Did you observe any improvements in students' understanding of ML concepts after using AfriML? If so, please elaborate.
5. What challenges did you encounter while implementing AfriML in your teaching?
6. How did students with different levels of prior knowledge in AI/ML respond to the AfriML tool?
7. Do you believe that AfriML could be a sustainable part of the curriculum? Why or why not?
8. What suggestions do you have for improving the AfriML tool to better support teaching and learning?
9. In your opinion, how important is it to have educational tools that are culturally relevant to African students?
10. How likely are you to continue using AfriML or recommend it to other teachers? Why?