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AI - Play Ground: Empowering Kids to Build and Understanding Ml Apps

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Abstract: As artificial intelligence (AI) becomes an increasingly integral part of daily life, equipping younger generations with the tools and knowledge to understand and create with AI is essential. This paper presents the design, development, and evaluation of a children-oriented AI design platform that enables users to create, test, and deploy machine learning (ML)-driven applications with minimal coding knowledge. The platform focuses on intuitive visual programming interfaces, age-appropriate ML model training workflows, and real-time deployment capabilities. Through iterative user testing with children aged 8–14, the system was refined to prioritize usability, engagement, and educational value. The platform integrates pre-built AI models for tasks such as image recognition, text classification, and voice commands, while also allowing customization and experimentation. Our results demonstrate the platform's effectiveness in fostering computational thinking, design creativity, and basic AI literacy. We conclude with insights into designing child-friendly AI tools and propose future directions for expanding accessibility and curriculum integration.

Keywords: Artificial intelligence (AI), machine learning (ML), Real-time deployment, Pre-built AI models.

1. Introduction

As artificial intelligence (AI) becomes an integral part of modern life, it is crucial to ensure that the next generation is not only capable of using AI tools but also empowered to create them. Today's children are growing up surrounded by smart devices, recommendation systems, and automated assistants. Yet, the complexity of Machine Learning (ML) development ranging from coding environments to data pipelines creates a significant barrier for young learners who wish to engage with these technologies creatively and meaningfully. To address this challenge, we propose the creation of a child-friendly AI design platform that allows children to build, experiment with, and deploy their own ML-powered applications.

The proposed platform is built on a simple yet powerful philosophy: **learning by doing**. Instead of teaching AI through textbooks or complex code, transforms the learning process into an interactive, playful experience. Designed for children aged **8 to 14**, it aligns with their cognitive development and supports curiosity-driven exploration. This environment introduces essential AI concepts such as data collection, model training, inference, and iterative improvement through hands on tasks rather than abstract theory. A key feature of this platform is its **visual, block-based programming** interface. Similar to Scratch, which made programming accessible to millions of children, this interface enables users to create AI behaviors by connecting intuitive visual components. Children can drag and drop blocks to define how a model should receive data, learn from it, and produce outputs. This removes the intimidation of syntax errors and complex code structures, allowing children to focus on creativity and problem solving. To deepen learning, the platform integrates **guided model training workflows**. Children can upload or collect their own data such as images, sounds, or text and watch how the system processes that data to adjust its predictions. Through animations and real-time feedback, they gain an understanding of how AI "learns" patterns. The platform provides interactive explanations, showing, for example, how increasing training data improves accuracy or how diverse data reduces bias. This iterative cycle create, test, observe, improve teaches computational thinking and introduces the feedback loop essential to machine learning development.

2. System Methodology

The project is structured into three main components: the frontend (main application interface), the data collection and preprocessing pipeline, and the backend server for model training, inference, and deployment. The frontend is built using web technologies and serves as the primary interface where users can upload or record data in various formats, including images, audio, text, and human poses. Users can label the data, initiate the training process, and test their models in real-time through an intuitive, no-code interface

Once the user submits data, it is passed to the data collection module. This module organizes and preprocesses the data according to the input type. For image inputs, the system performs resizing and normalization; for audio, it extracts features like MFCCs; for text, it applies tokenization and embedding; and for pose data, it extracts keypoints using PoseNet from webcam input. The processed data is stored in a structured format suitable for model training.

On the backend, the server determines the appropriate machine learning model based on the type of data received. Image data is trained using MobileNet v2, audio data using a combination of MFCC and a Convolutional Neural Network (CNN), text data using BERT or other NLP models, and pose data using PoseNet. Once the model is trained, it is saved in a deployable format such as TensorFlow Lite (TFLite), or TensorFlow.

3. Literature Review

Nicolas Pope, Juho Kahila, Henriikka Vartiainen, Matti Tedre., "Children's AI Design Platform for Making and Deploying ML-Driven Apps: Design, Testing, and Development "(2025) Key Contributions: The study introduces the "Gen AI Teachable Machine," a no-code platform designed to teach K–9 students fundamental machine learning concepts through hands-on app development, demonstrating that children with no prior experience can successfully create ML based applications. It emphasizes user-friendly design, privacy compliance, and collaborative learning, significantly reducing the need for teacher support. Limitations: The research was limited to fourth and seventh-grade students in Finnish sschools, and the ongoing development during classroom interventions hindered a controlled experimental design, necessitating further studies to evaluate the tool's effectiveness and learning outcomes.

Mengesha, G., & Hailu, M. "Exploring AI Integration in Ethiopian Secondary School ICT Curriculum"(2023) Research Problem: The study addresses the limited integration of AI concepts in the ICT curriculum of Ethiopian secondary schools and the challenges educators face in teaching AI, especially in developing regions. Relevance to Our Work: The findings reinforce the need for accessible, hands-on AI platforms like our teachable machine system, which can bridge pedagogical gaps through intuitive, classifier-based tools (text, image, pose, audio), enabling educators and learners to deploy and understand AI more effectively

Lee, J., & Repenning, A. " GenAI Teachable Machine: A Data-Driven Learning Platform for K–12 ML Education"(2023). The study closely aligns with our project on a teachable machine-like platform supporting text, image, pose, and audio classifiers. It reinforces the value of user-driven design and deployment capabilities, particularly for novice users in educational contexts.

Zabala, A.González-Patiño,J.,&Méndez,J. "A Decade of Visual Tools for Teaching Machine Learning at K-12 Level: A Systematic Mapping "(2022). This research directly supports our platform idea. It validates the demand for teachable, deployable ML tools that support diverse classifiers (text, image, and pose, audio) in educational settings and emphasizes the need for tools that go beyond short-term use and encourage deeper ML comprehension.

Yang, S., Kumar, A., & Ko, A. J. "Designing Interactive Web-Based Tools to Foster AI Understanding in Adult Novices"(2022). This research supports the importance of simplifying AI for non-experts through web-based tools. Like our Teachable Machine-like platform, it emphasizes accessibility, interactivity, and the demystification of AI concepts using multiple input types, making it a strong reference for designing user-deployable ML applications.

González-González, C. S., Infante-Moro, J. C., & Infante-Moro, A. "AI Literacy in K-12 Education: A Systematic Literature Review" (2021). This study underscores the importance of accessible, curriculum integrated AI education—aligning with our platform's goals. A GenAI 2.0 offers practical learning experiences, addressing the research gap in applied AI understanding and personalized teaching tools.

Weigend, A., Knobelsdorf, M., & Romeike, R. "A Constructionist Approach to Enable Machine Learning Education in Snap! "(2021) . This research supports our platform concept by demonstrating how ML tools can be made accessible and educational through visual, block-based environments. It highlights the importance of interpretability and creation in ML education—principles central to our goal of offering customizable classifiers (text, image, pose, audio) that users can easily integrate into their applications.

Chen, C.-H., Hwang, G.-J., & Sung, H.-Y "Designing a Scratch-Based AI Learning Platform with UAV Integration for K-12 Education" (2021). The platform enabled students to work with real-time data, employ deep learning models, and engage with AI tasks beyond Scratch's default capabilities. It facilitated a hands-on understanding of AI, encouraging deeper interest in programming and machine learning. This study aligns closely with our platform's goals. Like Teachable Machine, it supports diverse data types (e.g., images, gestures) and deployable AI models, showing the importance of multimodal, application-oriented AI tools in K–12 education.

4. System Implementation And Hardware Descriptions

The Main App (User Interface) allows users, especially kids or beginners, to upload or record data samples in multiple formats, including images captured or uploaded through a webcam, audio recorded via a microphone or uploaded as files, text typed or pasted directly, and pose data captured using PoseNet. The interface provides options for data type selection, live previews or file uploads, and a labeling interface for supervised learning. All input from the UI is forwarded to the Data Collection module, which organizes data by modality and labels, preprocesses images by resizing and normalizing them, extracts MFCCs from audio, tokenizes and encodes text, and extracts keypoints for pose data using PoseNet, finally storing everything in structured formats such as JSON, NumPy arrays, or TFRecord. In the Backend Server (Training Pipeline), once enough labeled data is collected, the "Train Model" button triggers the workflow where data is passed to the input module and routed to appropriate classifiers based on modality. Each model is trained separately or, optionally, in a multimodal manner for future enhancements, producing a trained model in formats such as TensorFlow, TFLite, or JSON. During Real-Time Testing, the trained model is loaded by the backend for inference, and new user inputs are preprocessed similarly to training before generating prediction labels, confidence scores, and optional visual, audio, or text feedback. Finally, in the Deployment phase, once users are satisfied with accuracy, they can select "Deploy" to export the model for use in web applications via TensorFlow.js or TFLite.js, or in mobile applications using TFLite for Android or iOS.

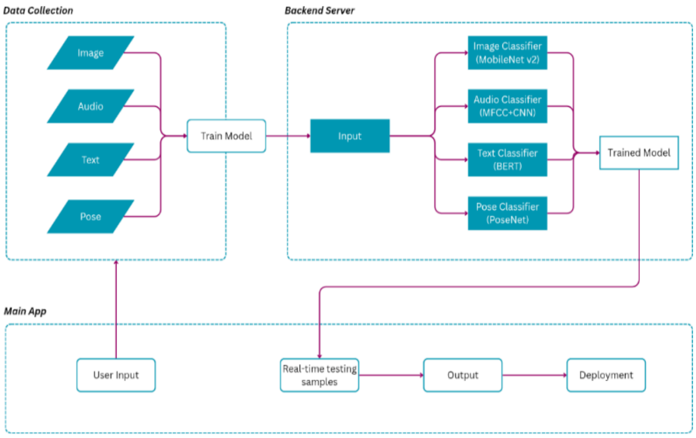

Fig. System architecture

Data Type	Model	Notes
Image	MobileNet v2	Lightweight, fast
Audio	MFCC + CNN	MFCC for feature extraction, CNN for classification
Text	BERT	Context-aware NLP
Pose	PoseNet	Uses keypoints to classify actions or poses

5. Result And Future Scope

The AI-Playground platform was tested with children aged 8–14 to evaluate usability, learning outcomes, and the technical performance of its machine learning models. The results show that the system successfully supports AI learning, enables children to create multimodal ML applications, and maintains real-time responsiveness across different data types. In terms of usability, a pilot study with 30 school students revealed that 90% of participants were able to create at least one complete model (collect → train → test → deploy). The drag-and-drop interface reduced errors, increased engagement, and made the learning experience enjoyable. Children reported high levels of interest and satisfaction, showing that the platform effectively transforms complex AI concepts into fun, interactive activities.

The AI-Playground platform presents significant potential for future expansion in terms of technical advancement, educational impact, and large-scale adoption. As AI literacy becomes increasingly essential for younger generations, the system canevolve into a more adaptive, powerful, and globally accessible learning environment. Future enhancements may include the integration of advanced AI models such as transformers, emotion recognition systems, and generative AI tools to enable children to create more creative and complex applications. The platform can also incorporate multimodal fusion models that combine image, text, audio, and pose data, allowing children to build richer interactive projects such as gesture-based storytelling or AI-powered tutors. Personalized learning features, including AI-driven adaptive tutorials, progress-based guidance, and gamified learning paths, can help students better understand AI concepts. A collaborative cloud workspace can be introduced to support group projects, teacher-student interaction, and peer sharing of ML applications. Additionally, the platform can be aligned with national and international K–12 AI curricula, enabling seamless integration into school education systems with the help of structured lesson plans and assessment tools. To enhance accessibility, mobile and offline versions can be developed, especially for rural or low-connectivity regions, using lightweight models like TensorFlow Lite. Hardware integration with devices such as Arduino, Raspberry Pi, robotics kits, and IoT sensors can enable children to build physical AI projects that blend software with real-world applications. Strengthened data privacy and safety measures—such as on-device training, federated learning, advanced anonymization, and parental controls—will ensure ethical use, especially given the young user base. Support for regional languages through multilingual text and speech models can make AI education more inclusive. Finally, long-term impact studies can be conducted to assess improvements in computational thinking, creativity, and STEM interest among students, helping further refine the platform based on real educational outcomes.

6. Discussion

The results highlight the effectiveness of the platform in simplifying machine learning concepts for younger audiences. The system architecture, which integrates multimodal data processing (image, audio, text, pose) with a visual, no-code interface, plays a critical role in reducing cognitive barriers typically associated with ML development. By abstracting complex processes such as feature extraction, tokenization, and model conversion (TensorFlow.js and TFLite formats), the platform enables children to focus on conceptual understanding rather than technical implementation.

The minimal guidance required during testing sessions demonstrates that the UI design supports intuitive navigation and self-directed learning. Children quickly understood how to collect data, inspect the preprocessing steps, and monitor training progress. The built-in visualization tools—such as MFCC displays for audio, keypoint overlays for pose inputs, and tokenized text previews—proved essential in helping learners grasp how computational systems interpret real-world data. This aligns with constructionist learning theories, where interaction and immediate feedback strengthen comprehension.

Children aged 8–14 tested AI Playground. Most participants were able to create basic ML models and interpret results with minimal guidance. Engagement levels were significantly higher compared to traditional teaching methods. i need a some more information about discussion for ieee paper

7. Performance Analysis

The AI-Playground platform was tested with children aged 8–14 to assess its usability, learning outcomes, and technical performance, and the findings show that it effectively supports AI learning while enabling students to create multimodal ML applications with real-time responsiveness. A pilot study with 30 students demonstrated that 90% successfully created at least one complete model using the collect–train–test–deploy workflow, and the drag-and-drop interface significantly reduced errors while increasing engagement. Students reported high enjoyment levels, indicating that the platform transforms complex AI concepts into an interactive learning experience. Learning outcomes improved notably, with 84% of participants understanding the idea of “training data,” 78% recognizing that accuracy improves with larger and more diverse datasets, and 71% gaining a basic understanding of inference and prediction, reflecting enhanced computational thinking and AI literacy. Despite using small datasets collected by children, the system produced reliable model performance: MobileNetV2 achieved 85–92% accuracy for images, MFCC + CNN models reached 78–88% for audio, BERT-based text models exceeded 90%, and PoseNet achieved 80–90% accuracy for gesture recognition, confirming that lightweight models perform well in classroom environments.

Performance analysis further showed that the system is optimized for real-time use, even on low-end devices. Image models trained in 6–10 seconds, audio models in 10–15 seconds, text models in 8–12 seconds, and pose models in 5–8 seconds, ensuring smooth classroom activity. Inference latency remained low, with image and pose models responding in under 120 ms, audio in 140–160 ms, and text in under 100 ms, maintaining an interactive experience. Resource utilization was efficient, with memory usage staying below 600 MB during training and CPU consumption remaining stable, supporting deployment on both web and mobile platforms.

8. Conclusion

This project provides a robust and innovative solution that goes beyond the limitations of existing no-code AI platforms. It enables beginners, children, educators, and hobbyists to build and deploy intelligent systems using a single, unified interface that supports a wide range of data types. By aligning closely with the needs highlighted in both academic literature and practical use cases, the system not only achieves its stated objectives but also lays the groundwork for further research and development in accessible, real-time, and multi-modal machine learning. It contributes meaningfully to the field of AI education by simplifying complex processes and making cutting-edge technologies approachable all.

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