A Versatile Low-Cost Kit for Teaching Novice Learners AI Using Robotics Components and a No-Code Development Playground

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Abstract

In the fast-growing field of K–12 AI education, there is an urgent need for accessible, hands-on tools that introduce AI concepts and workflows to novice learners. In recent years, a variety of AI education tools have been introduced, ranging from coding environments to physical kits and robots. To provide an alternative to existing AI education tools, this paper presents a low-cost robotics kit (<50€) designed to teach modern ML concepts through a no-code approach. The kit is grounded in maker pedagogy and designed for easy customizability to different materials commonly found in classrooms, like cardboard, wood, metal, and plastic builder kits without the need for specialized tools. For programming the robot's actions, the kit features an all-in-one development studio that is compatible with most phone, laptop, and tablet platforms and can operate with or without an Internet connection, making it applicable to a wide range of educational contexts, including ICT4D.

Introduction

Robots have a long history in K–12 education, marked by milestones like Papert's Logo Turtle in the late 1960s and LEGO Mindstorms in the late 1990s, followed by an educational robotics boom in the 2000s (Evripidou et al. 2020). Over the years, the intended learning outcomes (ILO) of robotics-based educational interventions have changed, yet common themes have remained: self-efficacy, computational thinking, creativity, motivation, collaboration, problem-solving, and broadening participation in STEM fields (Evripidou et al. 2020; Anwar et al. 2019; Pedersen et al. 2022).

With the rise of deep learning in artificial intelligence (AI), interest in integrating modern machine learning (ML) topics into K–12 curricula has grown rapidly, extending to broader audiences, including teacher training (Sanusi et al. 2022; Grover 2024; Rizvi, Waite, and Sentance 2023; Martins and Gresse Von Wangenheim 2022; Shapiro and Fiebrink 2019; Long et al. 2023; Olari et al. 2024; Zhang, Lee, and Moore 2023). This interest is driven by the significant impact of AI/ML technology on the future of work, society, and individual lives (e.g., Grover 2024; Höper and Schulte 2023). K–12 AI initiatives often focus on foundational AI techniques, such as classifiers and pattern recognition, but also on AI ethics, curriculum integration of AI, teacher training, and AI literacy (Heintz and Roos 2021; Grover 2024; Druga, Otero, and Ko 2022). Many fit the "Five Big Ideas in AI" framework established by the AI4K12 initiative (Touretzky, Gardner-McCune, and Seehorn 2023), and emphasize the critical role(s) of data in the datafied world. They often cover data collection, curation, storing, and processing, and aim at fostering data awareness and data agency among students (Olari and Romeike 2024; Höper and Schulte 2023; Vartiainen et al. 2022; Morales-Navarro et al. 2024).

Modern AI education and educational robotics have recently started to converge (Eguchi 2022). Empirical studies have shown success in using robots to teach AI principles, such as supervised learning (Williams et al. 2019) and reinforcement learning (Zhang et al. 2022; Dietz et al. 2022). A recent survey identified several promising K–12 robotics platforms suitable for AI/ML education, though many are yet to be extensively reported in the academic literature (Karalekas, Vologiannidis, and Kalomiros 2023).

A sizable body of research in craft, design, and technology education suggests that using tangible, malleable media to learn complex concepts like AI is effective because it allows learners to engage with abstract ideas in a concrete, hands-on manner (Hayes and Kraemer 2017). It helps to enhance technological literacy through conceptual knowledge of AI principles, procedural knowledge of making self-made products work with AI, and contextual knowledge of AI's impact on everyday life (Stolpe and Hallström 2024). Combining a "sense" of a machine with data-based tinkering and sensory exploration promotes integrative design thinking, encouraging students to iterate on their designs using digital and physical means (Van Mechelen et al. 2023; Cheng and Hao 2022). Tangible tools also facilitate collaborative learning by encouraging social interaction and peer learning (Niiranen 2021), as students can easily share and discuss their physical creations, leading to a deeper collective understanding of AI principles and concepts.

Existing robotics platforms for AI education have been tested in various contexts and application domains. Each have their strengths and limitations, arising from their different design aims. High-end robot kits for AI education like

NAO AI and Pepper are prohibitively expensive for large-scale adoption in schools, with five-figure price tags (Evripidou et al. 2020). Even more affordable platforms can become costly when deployed across many classrooms (Dietz et al. 2022). Many low-cost alternatives are available, too. A survey by Karalekas et al. (2023) showed that most low-cost ones rely on block-based programming to define robot actions (e.g., Williams 2021; Williams, Kaputsos, and Breazeal 2021; Dietz et al. 2022). Block-based programming is a natural choice where teachers and students have programming skills, but it limits applicability in contexts where programming is not part of the curriculum. Many popular platforms feature wheeled robots with limited options for additional actuators, sensors, or creative extensions, limiting customizability and educational versatility (Karalekas, Vologiannidis, and Kalomiros 2023). Privacy concerns arise with platforms that rely on sending data to the cloud, which potentially compromises student data privacy.

To provide an alternative to the platforms above, we have developed an AI education platform designed for K–12 children to learn ML concepts through hands-on robotics projects. The platform combines robotics with a "Teachable Machine" type image classifier, and lets learners define what robotics actions do different classifier results trigger.

Our platform's design philosophy is slightly different from many current approaches. Firstly, it presents a low cost physical kit (<€50) that is easily customizable without tools and adaptable to various DIY media, such as wooden construction kits for younger children (ages 3-7), metallic kits for older students (ages 8+), plastic stackable blocks, and cardboard creations. Secondly, its no-code solution offers an all-in-one development environment for controlling the robot. This environment is compatible with popular operating systems, including Apple, Windows, Android, and Linux, and can be used on phones, tablets, and laptops. Thirdly, designed to be classroom safe and GDPR-compliant, the system requires no Internet connection, ensuring students' data privacy. Fourthly, the platform is designed to unlock "open design" opportunities not limited to predefined technical or material solutions, and it supports cumulative competences. It encourages imagination, creativity, and personal expression in ML-driven robotics projects. Fifthly, the system is self-explanatory and assumes no prior knowledge of making, automation, electronics, robots, AI, or ML.

Intended Learning Outcomes

Our robotics kit is designed to teach AI concepts through hands-on robotics building activities, using robotics as a medium for AI education. It shares similarities with the ILOs of many "Teachable Machine" initiatives, such as Google's Teachable Machine (Carney et al. 2020), MIT's Personal Image Classifier and App Inventor (Tang et al. 2019), and GenAI Teachable Machine (Pope et al. 2024), which combine pre-trained image classification models with the learner's own training data, transfer learning, and possibly some ways to deploy the new models. Unlike fully virtual AI education initiatives, our platform integrates those ILOs in a physical robotics environment, with an aim to strengthen the students' understanding of causality and world modeling, aligning with the "Five big ideas in AI" framework (Touretzky, Gardner-McCune, and Seehorn 2023). Unlike classical K–12 computational thinking initiatives, our kit requires no classical programming to achieve the ILOs, making it accessible in educational contexts where programming is not part of the curriculum or where it has yet to be covered. The ILOs we target intersect with AI4K12 and DSCF guidelines in a number of ways, as presented by Touretzky et al. (2023).

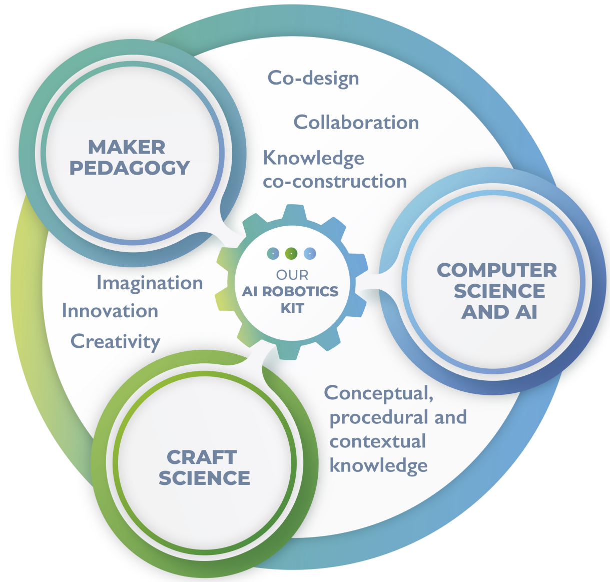


Figure 1: Boundary-crossing between digital and material through meta-design.

- **Data-driven problem formulation.** Students learn to articulate a problem or an opportunity in a way amenable to a data-driven, robotics-based solution (linking classifier results with physical actions.)
- **Working with data.** Students gain hands-on experience on how to define classes necessary for solving a problem, collecting and organizing data, labeling, cleaning, and curating data for training classifiers. They understand the importance of diverse, clean, and well labeled data in improving the model's performance.
- **ML workflows.** Students become familiar with the entire ML workflow, involving data preparation, training the model, deployment in robotics systems, testing, and iterative refinement.
- **Limitations and weaknesses of ML.** Students learn to interpret confidence levels and understand that ML predictions are probabilistic. They develop understanding of brittleness, uncertainty, long tail, opacity, and softness related to ML models.
- **Causality and actions.** By connecting classification results to trigger physical actions, students create a "world model" that defines how the system perceives and responds to its surroundings. They learn about the tangible

Concept	Learned at Which Stage	Description of Activity
Input	Robot design	Children design a robot equipped with a camera to perceiving its environment.
Class	Model design	Children create class containers to group similar examples (“cats”, “dogs”).
Label	Model design	Children give class containers descriptive names (“cat”, “dog”, “nothing”).
Training data	Data collection	Children determine the types of data necessary for solving the problem.
Sample	Data collection	Children collect examples to populate the class containers.
Curation	Data preprocessing	Children add, move, and delete samples to improve the training results.
Training	Model training	As classes are populated with samples, children use the tool to train the classifier.
Classifier	Model training	The training process generates a classifier that maps inputs to the labeled classes.
Confidence	Testing	Children interpret classification result as a probabilistic confidence score 0%–100%
Actions	Action design	Children connect classification results to triggers for physical actions.
Actuators	Action design	Children connect electrical components to MCU to implement physical actions.
Output	Action design	Children apply different levels of delay to smooth out erratic output behaviors.
Causality	Action testing	The classification results impact the physical environment through robot actions.
Model limits	Action testing	The robot’s ”world model” is limited to classification results and action triggers.
Generalization	Deployment	Children analyze their robot’s ability to apply its classifier to new, unseen inputs.
ML workflow	All stages	Children learn to navigate through the ML workflow and turn their design ideas into concrete ML-driven robots.

Table 1: Key AI Concepts Involved

consequences of AI in the physical world.

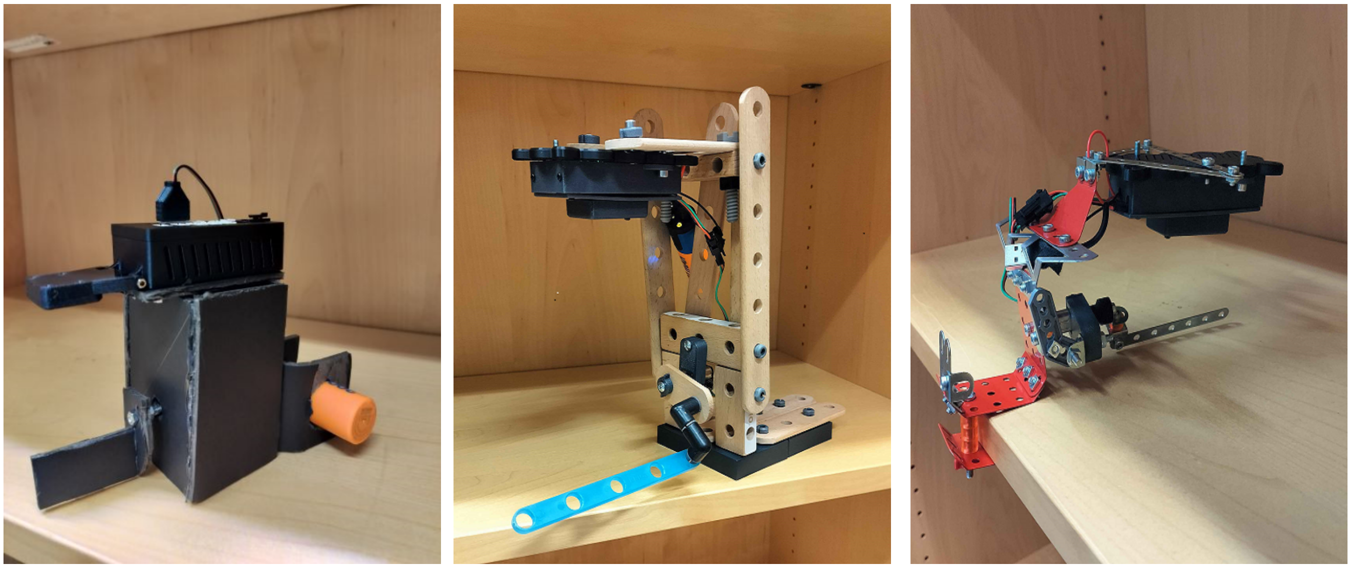
- **Rapid prototyping.** Students learn to make swift adjustments and improvements through immediate feedback and rapid and responsive design cycles, enhancing their problem-solving and iterative design skills.
- **Personalized learning technology.** Students learn to construct their own easy-to-approach technology, promoting self-directed learning and deepening their understanding of ML/AI.
- **Integration of design thinking and technological literacy.** Students learn to apply design thinking principles to create tools that incorporate ML into their immediate environment, enhancing their understanding of real-world AI/ML applications.
- **Holistic experimentation and adaptation.** Students learn how to combine different technologies and materials to a ML-driven product. They evaluate the suitability of various technologies for ML-driven actions and adapt their designs accordingly.
- **Ethical understanding of AI in robotics.** Students learn to identify and analyze ethical questions related to AI, including accountability, various types of bias, and the societal impacts of autonomous systems.

By implementing ML concepts into physical, real-world contexts, our platform can be used in learning interventions that requires students to think in terms of causal systems, and engage with tangible, embodied learning. This approach brings together data-driven thinking and craft education, strengthening students’ awareness of how computational processes perceive the world and affect it (Touretzky, Gardner-McCune, and Seehorn 2023).

Learning by Making with AI

Building on the educational theories of Jean Piaget’s constructivism and Seymour Papert’s constructionism, learning through making develops awareness and understanding through interactive, open-ended, student-driven and multidisciplinary experiences (Williams 2020; Resnick 2017). Maker pedagogy provides learners with the time, space and affordances needed to develop cross-boundary skills, knowledge, and ways of thinking. In maker-centered learning tasks, students imagine, design, and create projects that align the learning content with hands-on application. The focus is not just on the artifacts learners make but on the connections, community, and the meaningful knowledge learners develop (Papert and Harel 1991).

Unlike many existing instructional approaches that emphasize scripted, build-a-thing exercises or step-by-step coding tasks, maker pedagogy in AI education encourages open-ended, real-life problems for which no “right” or ”ready-made” answers exist; learners are encouraged to explore multiple solutions and approaches instead (Vartiainen, Tedre, and Valtonen 2020). Students are motivated to collaboratively design and develop innovative solutions using the tools and thinking models of the disciplines involved (Krajcik and Blumenfeld 2006). The opportunity to collaboratively try out ideas, followed by the need to tinker with workable solutions fosters creativity and critical thinking, allowing students to learn from failure and multidisciplinary feedback, and then iterate on their designs (Davies and Seitamaa-Hakkarainen 2024; Kahila et al. 2024). Engaging in tool-mediated activities helps learners to construct and reconstruct their understanding by testing their



(a) Cardboard robot. (b) Wooden robot. (c) Metal robot.

Figure 2: Three desk cleaning robots, built using cardboard (2a), children's wooden builder kit (2b), and children's metal builder kit (2c). The MCU+camera unit face downward to classify items on a surface, and the robot then activates a blade to sweep trash in one direction and office supplies in another.

ideas through prototypes. Analyzing the results helps them refine designs and conceptions, engaging in metacognitive reasoning to bridge the gap between their current artifact and their desired solution (Kahila et al. 2024). Externalizing ideas through "objects-to-think-with" as coined by Papert (1980), makes the ideas tangible and shareable, helping communication and collaborative development of ideas and designs together with others (Ackermann 2004). Problem-solving process in making helps learners develop resilience, persistence, and adaptability, which are essential skills in the rapidly changing technological landscape (Ioannou and Gravel 2024).

In AI education maker pedagogy bridges emerging and traditional technologies by integrating digital tools like AI and ML coding platforms with physical materials, tools, and nondigital activities (Blikstein and Worsley 2016). This hybridization helps students appreciate the evolution of technology and understand how modern technologies can interact with other media and common DIY materials and tools (Kafai and Peppler 2011). Hands-on experience with various technologies prepares students for future technological advancements (Martin 2015), especially in a world where sensors, actuators, computing, and AI are increasingly embedded in material and digital objects (Vartiainen et al. 2020).

In maker pedagogy, there is a balance between conceptual, procedural, and contextual learning. Conceptual learning involves understanding the underlying principles and theories, providing students with data-driven reasoning skills and comprehension of AI and ML in everyday contexts (Williams 2020). Procedural learning focuses on the steps and processes required to complete tasks, ensuring that students can apply their knowledge and skills in practical situations (Hsu, Baldwin, and Ching 2017)—such as understanding the model training workflow and how AI and ML can be harnessed for their needs. Contextual learning emphasizes the importance of situating learning within real-world contexts, making knowledge more relevant and meaningful to students (Brown, Collins, and Duguid 1989). This triad ensures that students not only know how to perform tasks but also understand why they are doing them and how these tasks fit into broader real-world scenarios and problem-solving situations. This leads to deeper learning and retention, as students can connect conceptual knowledge with practical application and contextual relevance (Davies and Seitamaa-Hakkarainen 2024).

Collaboration is a cornerstone of maker pedagogy activities in practice. Learners work together on projects, sharing ideas and learning from one another (Bevan et al. 2015). This collaborative environment mirrors real-world scenarios where teamwork and communication are crucial (Calabrese Barton and Tan 2018). In small groups, learners need to communicate actively, share their expertise and prior knowledge, make joint decisions, and negotiate roles and responsibilities for their collective work (Hennessy and Murphy 1999). Through collaborative design, they develop not only ideas and new artifacts, but also essential collaborative skills. They learn to make compromises, decide together, plan, and regulate their activities to achieve shared goals (Seitamaa-Hakkarainen et al. 2022).

Target age groups. Building on our earlier AI education platform—which has been tested with hundreds of children between grades 4 and 9 (Pope et al. 2024)—our robotics kit was designed to be adaptable across a broad age group. Similar AI education tools without robotics components have

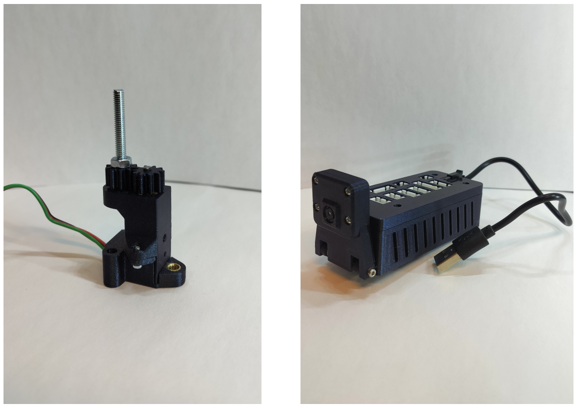


Figure 3: *Left*: The motor used to rotate the cleaning blade in our example desk cleaning robot (see Fig. 2). *Right*: Robot MCU and integrated camera

Component	**Price**
Raspberry Pi0	14,64€
32GB MicroSD flash memory	2,48€
Camera module	14,03€
Motor	8,55€
Custom PCB	0,80€
Connectors	2,40€
Rechargeable USB power bank and cable	3,90€
3D printing filament (37 g / 1.3 oz)	0,70€
Screws and misc.	1,00€
Total	**48,50€**

Table 2: Cost breakdown of parts involved in the examples.

also been tested with pre-kindergarten children aged 5-6 (Vartiainen, Tedre, and Valtonen 2020). Our robotics kit includes brackets to make the parts fit a variety of DIY materials, allowing learning interventions tailored to different age groups. In the future we will develop and pilot learning interventions for learners in pre-K (ages 5-6) using wooden construction kits appropriate for children aged 3-7, in lower primary school (ages 11-12) using plastic stackable blocks and cardboard creations, and in upper primary school (ages 14-15) using metallic construction kits designed for ages 8 and up.

AI concepts addressed. Our robotics kit supports a range of key AI concepts related to the ML workflow (see Table 1). These concepts are widely recognized in AI education, particularly in ML initiatives (Touretzky, Gardner-McCune, and Seehorn 2023; Carney et al. 2020). In addition to the items in Table 1, the tool also enables learners to explore common limitations of ML models, such as brittleness (even small changes in data can cause the model to dramatically fail), spoofability (models are often easy to trick and exploit), shallowness (models often struggle when applied to even slightly different scenarios), softness (models often provide a confidence level rather than a definitive answer), long tail (projects may learn to handle common cases well, but progress slows with a long tail of rare but important cases), and algorithmic bias (ML systems can reinforce or amplify systemic injustices or discrimination).

Description of the Resource

Our robotics kit is built around a low-cost Raspberry Pi Zero (Pi0) board attached to a camera module and a custom designed PCB to form the main control unit (MCU) (see Fig. 3). The MCU is housed in a 3D-printed case with M4 threaded heat-set inserts for easy and reliable mounting. The MCU is lightweight and compact: it weighs only 70 grams (2.5 ounces) and fits in a 52mm(W) x 23mm(H) x 110mm(L) box (2”×0.9”×4.3”). The example kit includes a 2000mAh powerbank for power source and a PWM-controlled motor. The MCU connects to the power source via a USB-A connector, and the robotics components connect using JST-XH style connectors. Assembly is tool-free and requires no prior knowledge of electrical components. Table 2 presents a cost breakdown of the parts.

Unlike many educational robotics platforms like LEGO Mindstorms, which rely on standalone systems with limited real-time feedback of the robot’s internal states (e.g., LCD screen or LEDs), our kit synchronously connects to a mobile device, allowing real-time feedback and interaction. This synchronous connection enables immediate feedback of the model behavior, and it streamlines iterative workflows, allowing users to easily add training data and modify the robot’s actions without programming.

Setup and resources needed. The prototype system consists of two main components: The robotics kit and the development studio (which includes the control software). The robotics kit has a QR code for establishing a wireless connection between the robot and the user’s device. By scanning the QR code the user’s device establishes a WiFi connection and retrieves the development studio (Fig. 4) directly from the robot and launches it automatically. The entire system is self-contained and operates without Internet access.

To set up the kit, the electrical components (LEDs, motors, servos) are attached to the appropriate connectors on the MCU. The system is powered on by plugging the power source into the USB cable connected to the MCU, which boots up the Raspberry Pi. Once booted, the MCU hosts a wireless network, which can be joined by scanning a QR code. After connecting to the WiFi hotspot, a second QR code starts the development studio from the Raspberry Pi.

The studio automatically connects to the robot and the user is able to specify and name the classes the robot camera needs to recognize ①. The user can use the robot’s camera to populate the classes with examples ②. The user can curate the data by moving examples between classes or removing examples from the data set ②. New classes can be introduced as needed ③. After the data curation, user proceeds to train the classifier ④. The development studio retrieves all necessary files from the Raspberry Pi and trains the model locally on the user’s device. After training, the classifier can be tested and adjusted as necessary. The studio UI distinguishes between the trained classifier ⑤ and

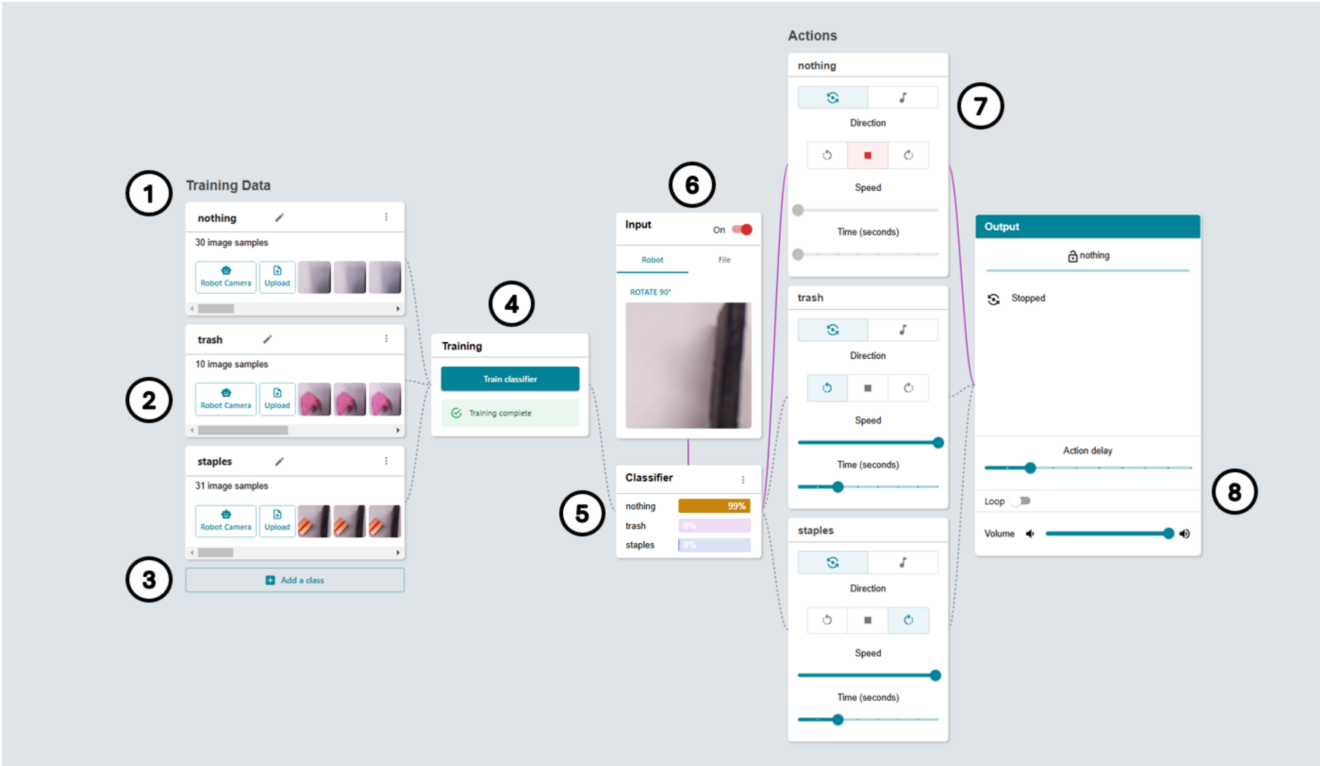


Figure 4: The development environment on a laptop, working on an app that can tell trash from office supplies, and then swings a blade one way to throw them off the table or the other way to push them back on the table. The circled numbers are added to denote the main interface elements.

the input mechanism ⑥, emphasizing the role of input as a separate concept (Touretzky, Gardner-McCune, and Seehorn 2023).

After the classifier has been trained and tested, user can set physical actions ⑦ to be triggered when a class is detected for a specified duration (1 to 10 seconds) ("action delay") ⑧. Looping can also be activated, enabling class actions to be repeatedly triggered for the same class at the specified action delay. Actions are configured using simple sliders and buttons, enabling easy control of electrical components without programming. The current prototype supports four types of electrical components for functional actions: A PWM-controlled motor, LED lights, servo, and sound output that can play uploaded sound clips or let user record his or her own. For demonstration purposes, the examples in Fig. 2 feature a single PWM motor (Fig. 4, left).

The robotics kit was designed for tinkering across various media, enhancing its adaptability for different classrooms. Figure 2 shows the same one-motor robot constructed using three different classroom-friendly materials: Cardboard (Fig. 2a), children's wooden builder kit (Fig. 2b), and children's metal builder kit (Fig. 2c). This malleability makes the kit versatile, allowing educators and students to use materials readily available in the classroom. It also enables learners to prototype and test ideas using inexpensive, easily manipulated materials before shifting to more complex manufacturing methods, such as 3D printing or laser cutting. This hands-on approach was adopted to facilitate creative exploration and engagement with AI concepts through physical prototyping and making.

Discussion

This paper presents a new AI education tool that combines physical, hands-on learning playground with a no-code, "Teachable Machine" style interface popular in K–12 education contexts (Carney et al. 2020). By embedding foundational pedagogical ideas into the tool's technological design, this paper presents a tool that can support interventions aimed to strengthen the still limited line of research on how to support the development of AI understanding and data-driven thinking through materially embodied design and making.

Developed in collaboration between craft education and computer science researchers, the kit incorporates many principles of maker pedagogy. It provides an open problem space that supports creativity, collaborative learning, and open-ended problem solving (Resnick 2006). It encourages active engagement in making, experimenting, and messing about in science (Hawkins 1965), and aims to create a safe environment for trying out ideas and things, learning from constructive failure, and iterative development (Papert 1980). Through compatibility with a wide range of materials and tools, it allows learners to customize and personalize everyone's own maker learning process and paths (Vartiainen et al. 2020). This meta-design approach aims to create new AI affordances that allow learners to act as agentive innovators, designers, and makers (Fischer et al. 2004), rather than passive consumers of off-the-shelf products (Papert 1980). When learners are able to personalize their projects with the afforded tools and have the opportunity to affect their courses of actions with respect to meaningful problems and activities, they may also experience agency and ownership of their own learning.

This kit is not intended to replace traditional programming education platforms or serve as a conventional robotics education kit. It uses ML to handle messy real-world data that children collect, curate, and use to train ML models and control robots that interact with the physical world. By integrating ML into tangible, hands-on robotics projects, the kit encourages students to explore the relationships between data, ML models, and the consequences of using them in real-world systems. It lets learners experiment with AI outside of controlled, virtual environments, using real-world data to drive real-world actions, all defined and controlled in an all-in-one no-code development environment that runs on mobile devices.

Compared to the available AI and robotics education kits, this kit is limited in a number of ways. Its focus on data-driven design and thinking, rather than classical programming, may limit the intended learning outcomes and excludes the use of programmable logic from the process. The no-code environment helps focus on high-level AI concepts but may not challenge advanced learners who seek more control and command over the AI processes. Conversely, the opportunity to hybridize with materiality may push students already familiar with AI and programming to work at the edge of their existing competencies as they need to cross boundaries and to consider how to connect AI understandings into material making to develop products that are aesthetically pleasing, functionally effective, and ethically sustainable. Those skilled in material craftsmanship are challenged to engage in data-driven reasoning and to understand AI workflows to create new artifacts that address context-specific needs.

The kit uses robotics as a medium to teach AI and is not intended as a robotics education toolkit. This, together with the low-cost approach, limits the use of other sensors (such as touch, proximity, or light) and actuators. However, such technical additions are easy to to implement in future development of the kit. Instead, it currently relies on a single camera for input, which limits what children can build with the kit to help concentrate on AI approach. While design constraints like available tools and epistemic, material, and social structures may limit the freedom of what can be designed and created, the kit provides open-ended opportunities for new forms of inquiry, creativity, and collaboration at the intersection of digital and material worlds.

Currently in the prototype phase, the kit is not available as a prepackaged product for sale, but it requires 3D printing and manual assembly. Customizability to various DIY materials requires some assembly and preparing, which may pose a challenge to novice learners or educators seeking an out-of-the-box solution.

Future Work

This first paper on our AI education kit is planned to be followed by further development of technology and teacher material as well as research focused on evaluation, validation, and comparison with other approaches. The next planned steps involve exploring use cases through a co-design process across K–12 curricula with diverse groups of learners, iterative enhancement of hardware and software from a prototype to a stable test version, and empirical research on the kit's effectiveness in teaching AI concepts and data-driven thinking, both independently and in comparison with other AI education approaches. Integrating the kit into Finnish STEAM curricula will benefit from cross-disciplinary codesign that enhances its value and appeal across subject boundaries. For large-scale classroom testing, the kit requires teacher materials and educational resources—including lesson plans, project guides, teacher guides, ethical AI modules, and assessment guidelines, among others—that are in line with existing frameworks, such as those by AI4K12 and DSCF. We plan international collaboration to improve the adaptability, impact, and sensitivity of the kit to different contexts of learning.

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