Breakable Machine: A K–12 Classroom Game for Transformative AI Literacy Through Spoofing and eXplainable AI (XAI)

Olli Hilke[1], Nicolas Pope[1], Juho Kahila[2], Henriikka Vartiainen[2], Teemu Roos[3], Tuomo Parkki[4], Matti Tedre[1]

[1]School of Computing, University of Eastern Finland, Joensuu, Finland
[2]Applied Educational Science and Teacher Education, University of Eastern Finland, Joensuu, Finland
[3]Department of Computer Science, University of Helsinki, Helsinki, Finland
[4]Joensuu Lyseo School, Joensuu, Finland
{olli.hilke, npope, juho.kahila, henriikka.vartiainen}@uef.fi,
teemu.roos@helsinki.fi, tuomo.parkki@edu.joensuu.fi, matti.tedre@uef.fi

Abstract

This paper presents an eXplainable AI (XAI)-based classroom game “Breakable Machine” for teaching critical, transformative AI literacy through adversarial play and interrogation of AI systems. Designed for learners aged 10–15, the game invites students to spoof an image classifier by manipulating their appearance or environment in order to trigger high-confidence misclassifications. Rather than focusing on building AI models, this activity centers on breaking them—exposing their brittleness, bias, and vulnerability through hands-on, embodied experimentation. The game includes an XAI view to help students visualize feature saliency, revealing how models attend to specific visual cues. A shared classroom leaderboard fosters collaborative inquiry and comparison of strategies, turning the classroom into a site for collective sensemaking. This approach repositions AI education by treating model failure and misclassification not as problems to be debugged, but as pedagogically rich opportunities to interrogate AI as a sociotechnical system. In doing so, the game supports students in developing data agency, ethical awareness, and a critical stance toward AI systems increasingly embedded in everyday life.

App — https://spoof.gen-ai.fi/
Code — https://github.com/OH-BugHit/BM

Introduction

The rapid rise of artificial intelligence (AI) has fueled interest in bringing modern machine learning (ML) concepts into K–12 education, with the trend increasingly extending to pre- and in-service teacher training (Sanusi et al. 2022; Eguchi et al. 2025; 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 in AI education—focused not on how to use AI, but on understanding how AI systems work—reflects recognition of the influence of AI-driven technology on the future of work, societal structures, and everyday life (e.g., Grover 2024; Höper and Schulte 2023; Sentance and Waite 2022).

Current K–12 AI education efforts address AI concepts and techniques at different levels of abstraction—such as classifiers, pattern recognition, or neural networks—as well as broader themes, including AI ethics, curriculum integration, teacher professional development, and AI literacy (Heintz and Roos 2021; Grover 2024; Druga, Otero, and Ko 2022; Black et al. 2024; Lee et al. 2022). Some are focused on data—including topics such as data collection, curation, storage, and processing, with the overarching aim of cultivating students’ data awareness and fostering data agency (Olari and Romeike 2024; Höper and Schulte 2023; Vartiainen et al. 2024b; Morales-Navarro et al. 2024b; Fagerlund, Palsa, and Mertala 2025). Others are focused on AI techniques—including topics such as neural networks, classifiers, reinforcement learning, language models, word embeddings, and more (Touretzky et al. 2025; Jatzlau et al. 2019; Kahila et al. 2024b; Morales-Navarro, Noh, and Kafai 2025; Wiatrek, Verma, and Martin 2025). Many education efforts map their learning outcomes on one or more popular AI content frameworks, such as Long and Magerko’s (2020) competency framework, the AI4K12 “Five Big Ideas in AI” framework (Touretzky, Gardner-McCune, and Seehorn 2023), or UNESCO’s competency framework (Miao and Shiohira 2024).

Some AI education initiatives have advocated for transformative agency, which goes beyond awareness and literacy by focusing on the learners’ capacity to not just critically understand and challenge, but also reshape AI systems and the societal structures in which they are embedded (Iivari et al. 2024; Vartiainen and Tedre 2025; Veldhuis et al. 2025; Stetsenko 2019). Transformative agency emphasizes the development of ethical-political awareness, volition, and collective action to resist harmful data practices and reimagine more just alternatives—as well as individual and collective efforts to break away from existing practices, take initiative, and design new futures.

AI education interventions employ a wide range of modalities. Many tools allow students to explore AI techniques using a range of gadgets, apps, and games (Wiatrek, Verma, and Martin 2025; Touretzky et al. 2025; Kahila et al. 2024a; Cardenas, Molas, and Puertas 2023). AI auditing activities focus on interrogating existing systems (Morales-

(a) The game app

(b) A view of all students' profile pictures, shown on the classroom projector.

Figure 1: The game players work alone or in small groups, using a mobile phone with constant camera feed. (Fig. 1a). Players try to find props, backgrounds, clothing, and other means to increase the classifier confidence (on label "astronaut" in this case.) At the same time, all player profile pictures and names are shown on the classroom projector (Fig. 1b).

Navarro et al. 2024a), and unplugged activities do not require computers (Lindner, Seegerer, and Romeike 2019). One of the most popular approaches involves training one's own models—for instance, with Google Teachable Machine, Generation AI Teachable Machine, MIT's Personal Image Classifier, or IBM's Machine Learning for Kids (Carney et al. 2020; Pope et al. 2025; Tang et al. 2019; Lane 2021).

A key learning moment in model training arises when the system behaves unexpectedly: the user encounters an "expectation mismatch" between the model's output and their own expectation of what it should be (Dhanorkar et al. 2021). Such unexpected or incorrect predictions prompt the learner to dig deeper into the training data and process (Tedre, Denning, and Toivonen 2021; Olari and Romeike 2024). As Berland and Garcia (2024) forcefully argue in their book *The Left Hand of Data: designing Education Data for Justice*, educators should "find the surprising and creative; enable people to break the system." While most prior educational tools have focused on training AI systems, some classroom tools—such as "Erase Your Face"[1] (Abiodun et al. 2020)—have instead focused on how to break image classifiers.

The tool presented in this paper elaborates the "breaking AI systems" theme by offering a playful, conceptually rich learning experience that highlights the concepts of trust, robustness, and accountability in AI. To better support students' transformative AI agency, we have developed an eXplainable AI (XAI)-driven classroom game that teaches children about the kinds of failures typical of many AI systems through engaging in spoofing an AI system; i.e., carrying out an adversarial attack against an image recognition system.

The *Breakable Machine* game aims to facilitate the development of a critical, transformative stance toward AI by enabling learners to take control over AI systems through hands-on experimentation, guided reflection, and collective sense-making. In the game, students are challenged to manipulate their appearance—such as what they wear or what is seen in the background—to "trick" an image recognition system into producing a high-confidence classification for a given label (e.g., "doctor"). All students in the class attempt the challenge in parallel, and the system displays each student's highest-confidence result on a shared leaderboard projected on the teacher's screen.

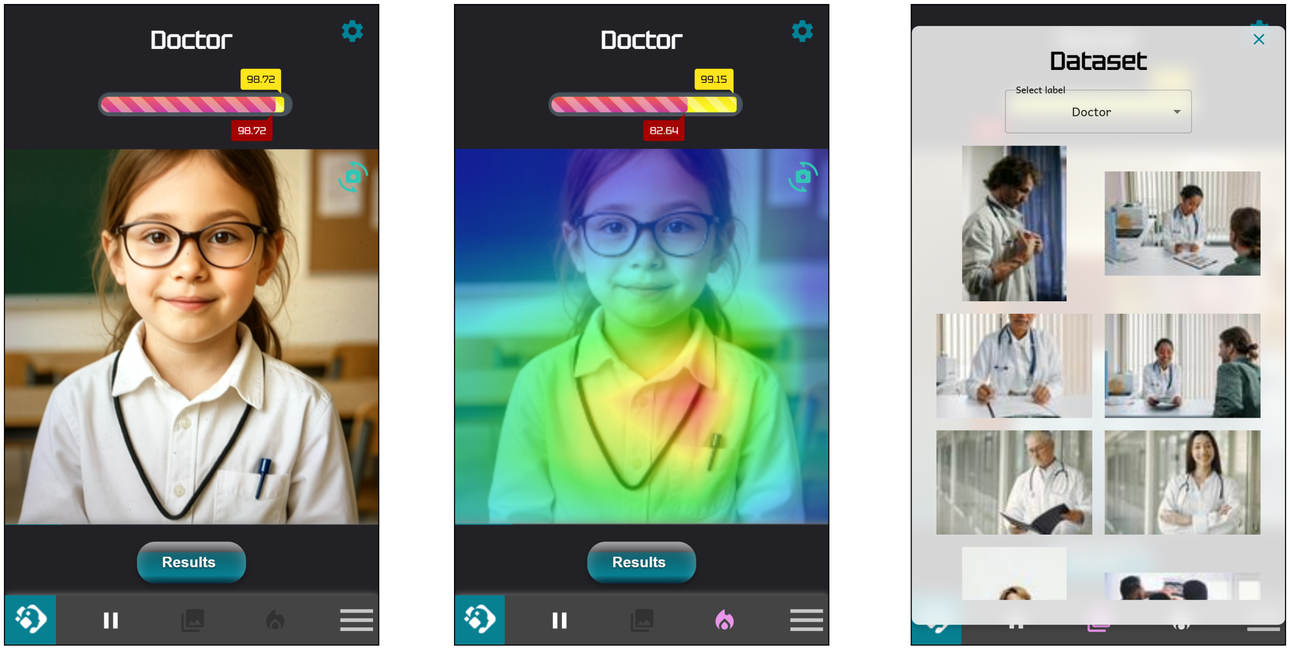
This paper describes the design and pedagogical foundations of the game, illustrated with screenshots and classroom use scenarios. As empirical evaluation of learning outcomes is scheduled for future work, this paper outlines the learning objectives and theoretical rationale for this approach to teaching critical AI literacy.

Description of the Resource

Gameplay. The teacher starts the classroom app, shown on the classroom projector, providing students with a QR code to join the game on their own devices. The teacher then selects a challenge for the students (e.g., "doctor", "bear"). Students try to modify their appearance or surroundings—such as by adding eyeglasses, changing the lighting, or holding up objects—in front of their webcam to try to make the system classify them with high confidence as the target label (Fig. 1a). A live leaderboard tracks each student's highest-confidence result, providing hints to other students, thus turning the classroom into a collaborative inquiry space for probing why the system responds as it does (Fig. 3).

Game Interfaces. The game consists of two browser apps: One running on the teacher's device, projected for the entire

[1] https://youthradio.github.io/erase-your-face/



(a) Spoofing app interface. (b) Heat map of salient image regions. (c) Examining the training data.

Figure 2: Three app views. The basic interface shows the camera feed and classification confidence for label "Doctor" (Fig. 2a). Users can examine an XAI heat map that highlights what image areas contribute the most to the classification result (in Fig. 2b white shirt, shoe string, and pen in pocket). Users can explore the training data set to get hints on spoofing the system (Fig. 2c).

classroom (Fig. 1b), and another running on students' mobile devices (Fig. 1a). The profile pictures here are replaced with AI-generated images for privacy. The teacher app has controls for pausing the game on all devices, changing the current challenge for all or for selected students, enabling heat map visualization on all devices, and unlocking access to the training data set on all devices. The teacher app also has views for showing all users, displaying the scoreboard and students' top-scoring images, and exploring the training dataset together. The student app can switch between live play, heat map exploration of the current camera feed, and browsing the training dataset.

Setup And Resources Required. The game is fully browser-based and works on browsers that support WebRTC data channels and ES11 (Chrome 56+, Firefox 44+, Safari 15.4+ and Edge 79+). It has been tested with devices ranging from laptops (Chromebooks, Windows, Mac and Linux) to mobile phones and tablets (Android, iOS). The classifier used is MobileNet V2, fine-tuned separately for each classification task.

Privacy and Security. Designed with children's data privacy in mind, the game adheres to EU's GDPR regulations. It does not collect, send, or store any identifiable data outside the classroom. All data are kept local, shared only with the teacher's device for the duration of the session, and automatically deleted when the session ends. The only external data retrieved are the app itself and the image and label dataset. The tool uses WebRTC-based peer-to-peer communication, and requires only local network connectivity.

eXplainable AI. Similar to some recent educational XAI techniques (e.g., Wang and An 2021; Melsión et al. 2021), our approach uses Class Activation Maps (CAMs), which provide a visual heatmap indicating which areas of an input image contributed the most to the classification result (Zhou et al. 2016).

Intended Learning Outcomes

Target age groups and context of learning. The AI spoofing education game is designed for grade 4-9 classrooms (learners aged 10–15 years) but it is suitable for all novice learners. It is particularly suitable for classrooms that explore AI concepts through hands-on experimentation, play, and critical inquiry. The game requires each player to have a mobile device with a camera, an Internet browser, and Internet or local network connectivity. It includes a structured classroom activity to guide the learning process.

Prerequisites. Students should be familiar with the basic workings of image classification systems, including foundational concepts such as training data, classification, labels, prediction, and confidence. Tools such as Generation AI Teachable Machine[2], Personal Image Classifier[3], Machine Learning for Kids[4], or Google Teachable Machine[5] can serve as effective starting points.

[2]https://tm.gen-ai.fi/
[3]https://classifier.appinventor.mit.edu/
[4]https://machinelearningforkids.co.uk/
[5]https://teachablemachine.withgoogle.com/

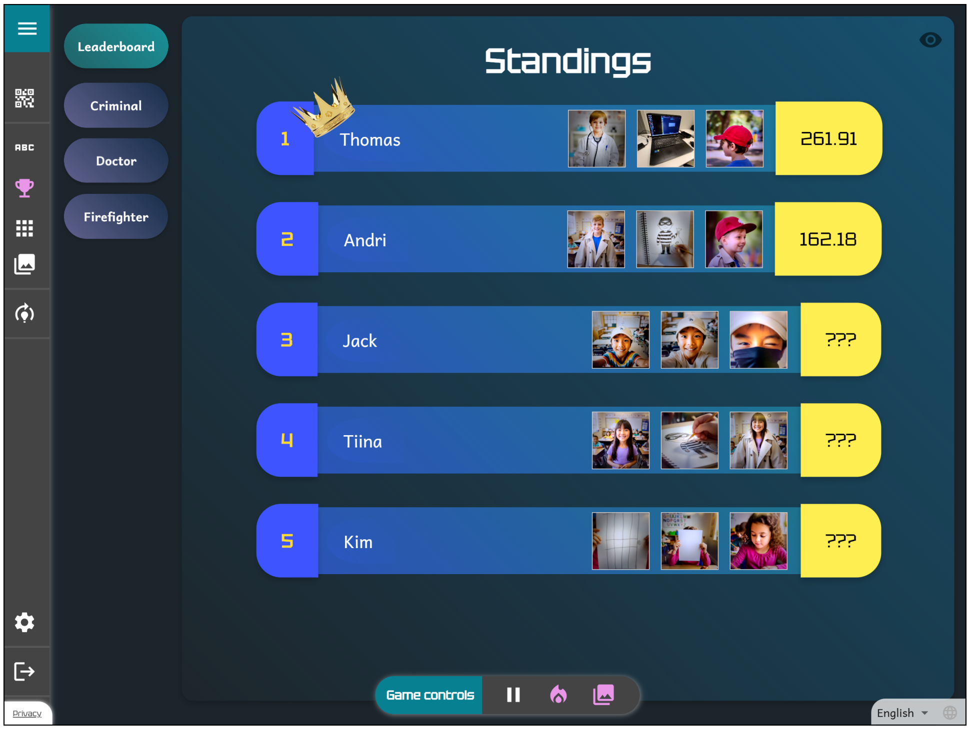


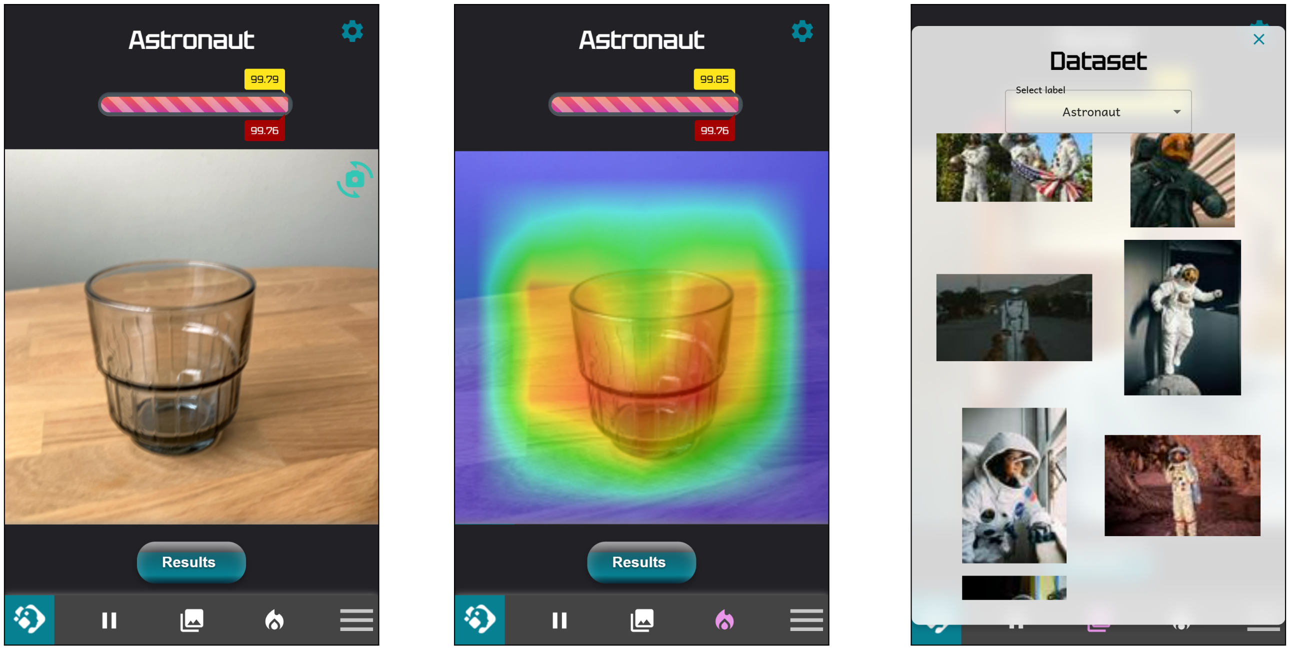
Figure 3: A view of top scoring players, with confidence score and a thumbnail of the image that scored it, shown on the classroom projector. The confidence scores can be completely hidden or shown only for the n highest scoring players (currently just two top players). This view is aimed at giving players hints from others' high scoring images.

Pedagogical approach. Because the game requires familiarity with core concepts of image classification, it is pedagogically appropriate to embed it within a larger learning project rather than treating it as a short, standalone exercise. For example, it can be integrated into the CEDE pedagogical model (Vartiainen and Tedre 2025) that positions children as designers and knowledge creators in AI. In such projects, students develop their conceptual understanding, creative abilities, and critical thinking by designing and making their own ML-driven mobile phone apps using the Generation AI Teachable Machine (Kahila et al. 2024b; Pope et al. 2025). At the end of the GenAI project, the children reflect on the potential risks and harms of AI through their own app design process and are scaffolded to apply their evolving AI understanding to critical analysis and discussions of ethical and societal issues, such as algorithmic bias (Vartiainen et al. 2024a).

While tools like the Teachable Machine foster creative learning and collaborative inquiry, the spoofing game extends and deepens these knowledge-creative projects by adding new affordances for the *ethical and social reflection* phase that is central to CEDE-based learning projects (Vartiainen and Tedre 2025). It responds to recent calls for AI literacy education to go beyond technical understanding and foster critical thinking, ethical awareness, and an ability to interrogate AI systems as sociotechnical constructs (Morales-Navarro and Kafai 2023; Morales-Navarro et al. 2024b). Rather than presenting AI as a reliable or neutral decision-maker, the game positions AI as a fallible, human-made system, which can be intentionally probed, manipulated, and tricked.

In the game, advances in conceptual understanding through critical inquiry of image recognition systems are supported through hands-on learning experiences. Students are guided to test and construct their conceptions of image recognition by making observations and experiments, and by explaining their conclusions with systematic evidence (Aleknavičiūtė, Lehtinen, and Södervik 2023; Osterhaus et al. 2021). This approach makes abstract AI concepts more accessible, concrete and visible (Smetana and Bell 2012; Trundle and Bell 2010), and situates them in the context of real-world ethical issues (Vartiainen and Tedre 2025). Furthermore, the game allows students to challenge and test their prior beliefs and conceptions by visualizing objects and processes that are normally hidden and from perception and manipulation (Trundle and Bell 2010; Smetana and Bell 2012). Importantly, it also becomes a medium that externalizes learners' evolving ideas and lines of reasoning by making them tangible and shareable which, in turn, helps their collaborative and iterative advancement (Ackermann 2004).

This kind of exploration supports not only conceptual understanding but also what Freire (1970) termed as critical "re-reading" of the world. Learners are not just passive users or observers of AI systems, but active agents who investigate and challenge, and even "break", them. By learning to



(a) Spoofing app interface. (b) Heat map of salient image regions. (c) Examining the training data.

Figure 4: Example of spoofing the system with everyday items. Figures 4a and 4b show an empty glass classified as "astronaut" with high confidence. The training data view (Fig. 4c) hints that the reason might be the astronaut's round glass visor, found in all images in the training data set.

manipulate the results of AI systems, students begin to see AI not as a black box but as an engineered product shaped by human decisions, assumptions, and biases. This prepares them to grow as informed contributors in public debates and democratic decision-making about the use and governance of AI technologies. Understanding the limitations, brittleness, and fallibility of AI-driven systems is a critical component of AI literacy, particularly in an age where systems make high-stakes decisions and often convey a false sense of objectivity or certainty (Long and Magerko 2020; Tedre et al. 2021).

Critically re-reading the human-engineered mechanims and societal impacts of AI system may also cultivate learners' volition and capacity to become transformative agents capable of questioning, resisting, reimagining, and rewriting existing sociotechnical systems and data-driven practices in pursuit of a more just and equitable AI-driven world.

AI concepts addressed. The game introduces students to key aspects of how image recognition systems operate and, more importantly, how they can succumb to adversarial attacks and fail. It centers on four pedagogical activities: (1) analyzing how image recognition systems classify visual inputs, (2) exploring their fragility and failure modes, (3) experimenting with adversarial tactics to mislead an AI model, and (4) critically reflecting on the broader consequences of automated classification. These goals align with major AI education frameworks that emphasize the interplay of AI techniques, human-AI interaction, and societal impact (Miao and Shiohira 2024; Touretzky, Gardner-McCune, and Seehorn 2023; Long and Magerko 2020). The intended learning outcomes (ILOs) focus on four core concepts related to AI and data.

Confidence and Correctness. The tool displays a confidence score, which represents the model's estimated probability that a given input belongs to a particular class, based on its internal parameters. By allowing learners to experiment with ways to increase this score, the system helps them understand that a confident prediction is not necessarily a correct one (see Fig. 4). From the perspective of critical AI education, this emphasizes that machine "certainty" can be misleading, especially in manipulated situations.

Adversarial Attacks (Spoofing). Students engage in hands-on adversarial play by modifying their appearance or environment to induce misclassification by the model, with high confidence. Unlike synthetic adversarial attacks in the pixel space (see, e.g., (Papernot et al. 2017)), this game focuses on embodied, real-world spoofing that exposes vulnerabilities in the model's generalization. This introduces learners to foundational issues with AI robustness and adversarial attacks, providing a concrete entry point into broader questions about AI safety and system reliability.

Feature Sensitivity and Saliency. Through iterative experimentation, students begin to recognize that image classifiers are highly sensitive to certain visual features—such as eyeglasses, headwear, skin tone, background objects, or lighting conditions—that may not be semantically meaningful. For example, why do automated job interview systems systematically give higher score to applicants with eyeglasses or with bookshelf in the background? (Narayanan and Kapoor 2024)

This introduces the concept of saliency: the system's strong weighting of certain input features in the classification outcome (e.g. the astronaut's visor in Fig. 4). By observing how seemingly insignificant visual changes can drastically shift outcomes, learners gain insight into how AI systems attend to data, and begin to ask not just what label is predicted, but what features the system is really responding to.

Brittleness and Failure. The activity facilitates understanding the vulnerability of AI based classification systems to sometimes unanticipated image features, challenging naïve conceptions of AI as smart, objective, stable, or infallible (Druga et al. 2017). Through playful experimentation—changing props, poses, lighting conditions, clothing, or background—students observe how seemingly minor, semantically irrelevant, or intuitively wrong changes can significantly influence model outputs. These interactions help to demystify AI and open space for critical discussions about generalization, robustness, reliability, and the limits of machine perception in real-world uses.

Misclassification and Its Real-World Consequences. The activity encourages learners to move beyond surface-level experimentation toward interrogating the socio-technical dimensions of AI systems. It raises questions like "Why does the model respond this way?", "Who decides how the system is trained?", (Gebru et al. 2021; Mitchell et al. 2019) and "What happens when AI systems misclassify people in real life?" (Buolamwini and Gebru 2018). By raising questions on misclassification, representational harm, and systemic bias, the game helps students recognize that AI systems are not neutral artifacts but products shaped by their design choices, training data, and cultural assumptions (Crawford 2021; Eubanks 2018; Birhane, Prabhu, and Kahembwe 2021). Learners are encouraged to critically reflect on who defines model objectives, whose data are included or excluded, and who are most affected by misclassification, as well as imagine more just and accountable AI futures.

From Conceptual Understanding to Critical Participation in AI. This game is designed not only to teach AI concepts but also to foster a mindset of inquiry, skepticism, and agency. By making visible the decision-making processes and vulnerabilities of image classifiers that are normally opaque to students it enables learners not only to become aware of these weaknesses but also to actively explore and manipulate them. By engaging with the fallibility of AI systems, students are positioned as critical investigators rather than passive users of technology—an important step toward critical participation in an AI-infused society. By that way, the game supports learners to develop a more critical understanding and attitude toward AI-driven systems, especially when embedded within purposeful pedagogical practices. Creative knowledge creation and critical inquiry mediated by this game can foster resistance and activism against the sociotechnical injustices that AI systems exacerbate, thereby providing essential scaffolding for cultivating transformative agency in the age of AI.

Discussion

While many existing AI education tools focus on training models and achieving functional outcomes (Carney et al. 2020; Pope et al. 2025), this paper's approach taps on failure and breakdown. By encouraging students to manipulate a model and induce misclassification, the *Breakable Machine* game creates opportunities for encountering and investigating expectation mismatches—moments when the system behaves in unexpected ways (Dhanorkar et al. 2021). These moments of cognitive dissonance invite deeper inquiry into the inner mechanisms of AI, including the role of training data, feature saliency, and generalization. Rather than treating misclassifications as problems to be corrected, the game treats them as a possibility for exploitation, critical exploration, and epistemic investigation. This aligns with recent shifts in AI literacy research that emphasize not only technical understanding, but also epistemic and ethical interrogation of how AI systems operate and where they fail (Morales-Navarro et al. 2024b; Long and Magerko 2020). The tool requires learners to have prior exposure to image classifiers at the (M)odel level of the SEAME framework, and enables activities at the framework's SE+A+M levels (Sentance and Waite 2022).

Central to our approach is the pedagogical reimagining of spoofing not as a glitch that can only hinder learning but as a tool for critical inquiry. By intentionally tricking the system, students are exposed to its brittleness and manipulability, revealing how AI systems can produce outputs that are not only wrong but confidently so. This hands-on adversarial play serves as an entry point into deeper questions about the sociotechnical complexity and fragility of ML systems, as well as safety and ethical accountability (Buolamwini and Gebru 2018; Crawford 2021).

This game repositions learners from passive users or consumers to active interrogators. Rather than mastering an AI tool or adapting their behavior to better fit an AI system, students learn to challenge and manipulate them—what Freire (1970) might describe as "re-reading the world." In that view, education is not about adapting to existing systems and oppressive practices, but about questioning the status quo, envisioning alternatives, and taking action for realizing that future. Similarly, it resonates with Stetsenko's (2019) notion of activist learning, which moves beyond reproduction and socialization into existing practices by positioning learners as active contributors and co-creators of social change. In this light, spoofing becomes a pedagogical act of resistance that cultivates understanding and transformative agency.

By engaging in collective experimentation and observing their peers' spoofing strategies on the leaderboard, students co-construct knowledge about machine perception and its limits. Students can observe, replicate, and refine each other's strategies, externalizing the reasoning and contributing to a shared understanding of AI behavior. This social learning environment reveals how classifiers respond to real-world variation, and fosters epistemic agency as students learn to question what counts as "correct" in image recognition systems, and why.

The game works with concepts that are less often addressed in K–12 contexts, such as adversarial attacks and feature saliency. While popular AI frameworks (Touretzky, Gardner-McCune, and Seehorn 2023; Miao and Shiohira 2024; Long and Magerko 2020) emphasize perception, learning, and societal impact, few current tools specifically encourage learners to directly probe the limits and vulnerabilities of AI systems. Our approach introduces learners to these limitations not as incidental glitches, but as core content for critical reflection. By emphasizing how AI systems can be manipulated or misled, the game challenges overly deterministic or instrumentalist views of AI systems as neutral or robust. This complements the growing body of AI literacy work that emphasizes data agency, algorithmic accountability, and participatory ethics (e.g., Vartiainen et al. 2024a; Morales-Navarro et al. 2024b; Babai et al. 2025). It expands the curricular space of AI literacy by integrating critical inquiry, hands-on spoofing, and sociotechnical reflection. Rather than shielding students from system flaws, we make them core content, preparing learners to navigate, critique, and shape AI-driven futures.

Acknowledgments

Funded by the Strategic Research Council (SRC) established within the Research Council of Finland (#352859, #352870, and #352876). TR acknowledges the research environment provided by ELLIS Institute Finland. We extend our heartfelt thanks to the teachers and children who actively participated in developing and testing this material.

References

Abiodun, X.; Araujo, V.; Balla, V.; Harwood, Z.; Ruberto, D.; Salgado, B.; and Tang, A. 2020. Erase Your Face.

Ackermann, E. K. 2004. Constructing Knowledge And Transforming the World. In Tokoro, M.; and Steels, L., eds., *A learning zone of one's own: Sharing representations and flow in collaborative learning environments*, 15–37. Amsterdam, The Netherlands: IOS Press.

Aleknavičiūtė, V.; Lehtinen, E.; and Södervik, I. 2023. Thirty years of conceptual change research in biology – A review and meta-analysis of intervention studies. *Educational Research Review*, 41: 100556.

Babai, N.; Gazulla, E. D.; Iivari, N.; and Kinnula, M. 2025. Navigating the Future of Data-Driven Systems: Children's perspectives on data and agency. In *Proceedings of the 24th Interaction Design and Children*, IDC '25, 124–139. New York, NY, USA: ACM. ISBN 9798400714733.

Berland, M.; and Garcia, A. 2024. *The Left Hand of Data: designing Education Data for Justice*. Cambridge, MA, USA: The MIT Press.

Birhane, A.; Prabhu, V. U.; and Kahembwe, E. 2021. Multimodal datasets: misogyny, pornography, and malignant stereotypes. *arXiv.org*, (2110.01963).

Black, N. B.; George, S.; Eguchi, A.; Dempsey, J. C.; Langran, E.; Fraga, L.; Brunvand, S.; and Howard, N. 2024. A Framework for Approaching AI Education in Educator Preparation Programs. *Proceedings of the AAAI Conference on Artificial Intelligence*, 38(21): 23069–23077.

Buolamwini, J.; and Gebru, T. 2018. Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification. In Friedler, S. A.; and Wilson, C., eds., *Proceedings of 1st Conference on Fairness, Accountability and Transparency*, 77–91.

Cardenas, M.-I.; Molas, L.; and Puertas, E. 2023. Artificial Intelligence with Micro:Bit in the Classroom. In Balogh, R.; Obdržálek, D.; and Christoforou, E., eds., *Robotics in Education*, 337–350. Cham: Springer Nature Switzerland. ISBN 978-3-031-38454-7.

Carney, M.; Webster, B.; Alvarado, I.; Phillips, K.; Howell, N.; Griffith, J.; Jongejan, J.; Pitaru, A.; and Chen, A. 2020. Teachable Machine: Approachable Web-Based Tool for Exploring Machine Learning Classification. In *The 2020 CHI Conference on Human Factors in Computing Systems*, CHI EA '20, 1–8. New York, NY, USA: ACM.

Crawford, K. 2021. *Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence*. New Haven, CT, USA: Yale University Press.

Dhanorkar, S.; Wolf, C. T.; Qian, K.; Xu, A.; Popa, L.; and Li, Y. 2021. Who needs to know what, when?: Broadening the Explainable AI (XAI) Design Space by Looking at Explanations Across the AI Lifecycle. In *Proceedings of the 2021 ACM Designing Interactive Systems Conference*, DIS '21, 1591–1602. New York, NY, USA: ACM. ISBN 9781450384766.

Druga, S.; Otero, N.; and Ko, A. J. 2022. The Landscape of Teaching Resources for AI Education. In *Proceedings of the 27th ACM Conference on on Innovation and Technology in Computer Science Education Vol. 1*, ITiCSE '22, 96–102. New York, NY, USA: ACM.

Druga, S.; Williams, R.; Breazeal, C.; and Resnick, M. 2017. "Hey Google is It OK If I Eat You?": Initial Explorations in Child-Agent Interaction. In *Proceedings of the 2017 Conference on Interaction Design and Children*, IDC'17, 595–600. New York, NY, USA: ACM.

Eguchi, A.; Cottrell, G.; Berg-Kirkpatrick, T.; and de Sa, V. 2025. Research Experience for Teachers in the Interdisciplinary AI – Report from the Summer AI Research Experience 2024. In Hartshorne, R.; and Cohen, J., eds., *Proceedings of Society for Information Technology & Teacher Education International Conference 2025*, 1446–1453. Orlando, FL, USA: AACE.

Eubanks, V. 2018. *Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor*. New York, NY, USA: St. Martin's Press.

Fagerlund, J.; Palsa, L.; and Mertala, P. 2025. Exploration of domains of educational purpose in K-12 data literacy education research. *Educational Research Review*, 46: 100663.

Freire, P. 1970. *Pedagogy of the Oppressed*. New York, NY, USA: Continuum Publishing Group.

Gebru, T.; Morgenstern, J.; Vecchione, B.; Vaughan, J. W.; Wallach, H.; III, H. D.; and Crawford, K. 2021. Datasheets for datasets. *Communications of the ACM*, 64(12): 86–92.

Grover, S. 2024. Teaching AI to K-12 Learners: Lessons, Issues, and Guidance. In *Proceedings of ACM Computer Science Education (SIGCSE) 2024 Conference*, 1–7. Portland, OR, USA: ACM.

Heintz, F.; and Roos, T. 2021. Elements Of AI - Teaching the Basics of AI to Everyone in Sweden. In *Proceedings of the 13th International Conference on Education and New Learning Technologies (EDULEARN21)*, 2568–2572. Online: IATED.

Höper, L.; and Schulte, C. 2023. The data awareness framework as part of data literacies in K-12 education. *Information and Learning Sciences*.

Iivari, N.; Iversen, O. S.; Smith, R. C.; Schaper, M.-M.; Ventä-Olkkonen, L.; Hartikainen, H.; Sharma, S.; Kinnula, M.; Lehto, E.; Holappa, J.; and Molin-Juustila, T. 2024. Transformative agency – the next step towards children's computational empowerment. In *Proceedings of the 23rd Annual ACM Interaction Design and Children Conference*, IDC '24, 322–337. New York, NY, USA: ACM. ISBN 9798400704420.

Jatzlau, S.; Michaeli, T.; Seegerer, S.; and Romeike, R. 2019. It's not Magic After All – Machine Learning in Snap! using Reinforcement Learning. In *2019 IEEE Blocks and Beyond Workshop (B&B)*, 37–41. Memphis, TN, USA: IEEE.

Kahila, J.; Vartiainen, H.; Arkko, E.; Lin, A.; Pope, N.; and Tedre, M. 2024a. Enhancing Understanding of Data Traces and Profiling Among K–9 Students Through Interactive Classroom Game. In *Proceedings of The 19th WiPSCE Conference on Primary and Secondary Computing Education Research*, WiPSCE '24. New York, NY, USA: ACM.

Kahila, J.; Vartiainen, H.; Tedre, M.; Arkko, E.; Lin, A.; Pope, N.; Jormanainen, I.; and Valtonen, T. 2024b. Pedagogical framework for cultivating children's data agency and creative abilities in the age of AI. *Informatics in Education*, 23(2): 323–360.

Lane, D. 2021. *Machine Learning for Kids: A Project-Based Introduction to Artificial Intelligence*. San Francisco, CA, USA: No Starch Press.

Lee, I.; Zhang, H.; Moore, K.; Zhou, X.; Perret, B.; Cheng, Y.; Zheng, R.; and Pu, G. 2022. AI Book Club: An Innovative Professional Development Model for AI Education. In *Proceedings of the 53rd ACM Technical Symposium on Computer Science Education - Volume 1*, SIGCSE 2022, 202–208. New York, NY, USA: ACM. ISBN 9781450390705.

Lindner, A.; Seegerer, S.; and Romeike, R. 2019. Unplugged Activities in the Context of AI. In Pozdniakov, S. N.; and Dagienė, V., eds., *Informatics in Schools. New Ideas in School Informatics*, 123–135. Cham: Springer International Publishing. ISBN 978-3-030-33759-9.

Long, D.; and Magerko, B. 2020. What is AI Literacy? Competencies and Design Considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, CHI '20, 1–16. New York, NY, USA: ACM.

Long, D.; Roberts, J.; Magerko, B.; Holstein, K.; DiPaola, D.; and Martin, F. 2023. AI Literacy: Finding Common Threads between Education, Design, Policy, and Explainability. In *The 2023 CHI Conference on Human Factors in Computing Systems*, CHI EA '23. New York, NY, USA: ACM. ISBN 9781450394222.

Martins, R. M.; and Gresse Von Wangenheim, C. 2022. Findings on Teaching Machine Learning in High School: A Ten - Year Systematic Literature Review. *Informatics in Education*.

Melsión, G. I.; Torre, I.; Vidal, E.; and Leite, I. 2021. Using Explainability to Help Children Understand Gender Bias in AI. In *Proceedings of the 20th Annual ACM Interaction Design and Children Conference*, IDC '21, 87–99. New York, NY, USA: ACM. ISBN 9781450384520.

Miao, F.; and Shiohira, K. 2024. *AI Competency Framework for Students*. Paris, France: UNESCO.

Mitchell, M.; Wu, S.; Zaldivar, A.; Barnes, P.; Vasserman, L.; Hutchinson, B.; Spitzer, E.; Raji, I. D.; and Gebru, T. 2019. Model Cards for Model Reporting. In *Proceedings of the Conference on Fairness, Accountability, and Transparency*, FAT* '19, 220–229. New York, NY, USA: ACM. ISBN 9781450361255.

Morales-Navarro, L.; Kafai, Y.; Konda, V.; and Metaxa, D. 2024a. Youth as Peer Auditors: Engaging Teenagers with Algorithm Auditing of Machine Learning Applications. In *Proceedings of the 23rd Annual ACM Interaction Design and Children Conference*, IDC '24, 560–573. New York, NY, USA: ACM. ISBN 9798400704420.

Morales-Navarro, L.; and Kafai, Y. B. 2023. Conceptualizing Approaches to Critical Computing Education: Inquiry, Design, and Reimagination. In Apiola, M.; López-Pernas, S.; and Saqr, M., eds., *Past, Present and Future of Computing Education Research : A Global Perspective*, 521–538. Cham: Springer International Publishing.

Morales-Navarro, L.; Kafai, Y. B.; Nguyen, H.; DesPortes, K.; Vacca, R.; Matuk, C.; Silander, M.; Amato, A.; Woods, P.; Castro, F.; Shaw, M.; Akgun, S.; Greenhow, C.; and Garcia, A. 2024b. Learning about Data, Algorithms, and Algorithmic Justice on TikTok in Personally Meaningful Ways. In *Proceedings of the 18th International Conference of the Learning Sciences*, ICLS. International Society of the Learning Sciences.

Morales-Navarro, L.; Noh, D. J.; and Kafai, Y. 2025. Building babyGPTs: Youth engaging in data practices and ethical considerations through the construction of generative language models. In *Proceedings of the 24th Interaction Design and Children*, 1021–1026. New York, NY, USA: ACM. ISBN 9798400714733.

Narayanan, A.; and Kapoor, S. 2024. *AI Snake Oil: What Artificial Intelligence Can Do, What It Can't, And How to Tell the Difference*. Princeton, NJ, USA: Princeton University Press.

Olari, V.; and Romeike, R. 2024. Data-related concepts for artificial intelligence education in K–12. *Computers and Education Open*, 7: 100196.

Olari, V.; Zoppke, T.; Reger, M.; Samoilova, E.; Kandlhofer, M.; Dagiene, V.; Romeike, R.; Lieckfeld, A. S.; and Lucke, U. 2024. Introduction of Artificial Intelligence Literacy and Data Literacy in Computer Science Teacher Education. In *Proceedings of the 23rd Koli Calling International Conference on Computing Education Research*, Koli Calling '23. New York, NY, USA: ACM.

Osterhaus, C.; Brandone, A. C.; Vosniadou, S.; and Nicolopoulou, A. 2021. Editorial: The Emergence and Development of Scientific Thinking During the Early Years: Basic Processes and Supportive Contexts. *Frontiers in Psychology*, 12.

Papernot, N.; McDaniel, P.; Goodfellow, I.; Jha, S.; Celik, Z. B.; and Swami, A. 2017. Practical Black-Box Attacks against Machine Learning. In *Proceedings of the 2017 ACM on Asia Conference on Computer and Communications Security*, 506–519. New York, NY, USA: Association for Computing Machinery. ISBN 9781450349444.

Pope, N.; Kahila, J.; Vartiainen, H.; and Tedre, M. 2025. Children's AI Design Platform for Making and Deploying ML-Driven Apps: Design, Testing, and Development. *IEEE Transactions on Learning Technology*, 18: 130–144.

Rizvi, S.; Waite, J.; and Sentance, S. 2023. Artificial Intelligence teaching and learning in K-12 from 2019 to 2022: A systematic literature review. *Computers and Education: Artificial Intelligence*, 4: 100145.

Sanusi, I. T.; Oyelere, S. S.; Vartiainen, H.; Suhonen, J.; and Tukiainen, M. 2022. A systematic review of teaching and learning machine learning in K-12 education. *Education and Information Technologies*.

Sentance, S.; and Waite, J. 2022. Perspectives on AI and data science education. In *AI, data science, and young people. Understanding computing education*, volume 3, 2–9. Cambridge, UK: Raspberry Pi Foundation.

Shapiro, R. B.; and Fiebrink, R. 2019. Introduction to the Special Section: Launching an Agenda for Research on Learning Machine Learning. *ACM Transactions on Computing Education*, 19(4): 30:1–30:6.

Smetana, L. K.; and Bell, R. L. 2012. Computer Simulations to Support Science Instruction and Learning: A critical review of the literature. *International Journal of Science Education*, 34(9): 1337–1370.

Stetsenko, A. 2019. Radical-Transformative Agency: Continuities and Contrasts With Relational Agency and Implications for Education. *Frontiers in Education*, 4: 1–13.

Tang, D.; Utsumi, Y.; ; and Lao, N. 2019. PIC: A Personal Image Classification Webtool for High School Students. In *International Joint Conference on Artificial Intelligence, EduAI Workshop*.

Tedre, M.; Denning, P. J.; and Toivonen, T. 2021. CT 2.0. In *21st Koli Calling International Conference on Computing Education Research*, Koli Calling '21, 1–8. New York, NY, USA: ACM.

Tedre, M.; Toivonen, T.; Kahila, J.; Vartiainen, H.; Valtonen, T.; Jormanainen, I.; and Pears, A. 2021. Teaching Machine Learning in K–12 Classroom: Pedagogical and Technological Trajectories for Artificial Intelligence Education. *IEEE Access*, 9: 110558–110572.

Touretzky, D.; Gardner-McCune, C.; Hanna, W.; Chen, A.; and Pawar, N. 2025. Learning to Think like a Neuron in Middle School. *Proceedings of the AAAI Conference on Artificial Intelligence*, 39(28): 29212–29219.

Touretzky, D.; Gardner-McCune, C.; and Seehorn, D. 2023. Machine Learning and the Five Big Ideas in AI. *International Journal of Artificial Intelligence in Education*, 33(2): 233–266.

Trundle, K. C.; and Bell, R. L. 2010. The use of a computer simulation to promote conceptual change: A quasi-experimental study. *Computers & Education*, 54(4): 1078–1088.

Vartiainen, H.; Kahila, J.; Tedre, M.; López-Pernas, S.; and Pope, N. 2024a. Enhancing children's understanding of algorithmic biases in and with text-to-image generative AI. *New Media & Society*, 14614448241252820.

Vartiainen, H.; Pellas, L.; Kahila, J.; Valtonen, T.; and Tedre, M. 2024b. Pre-Service Teachers' Insights on Data Agency. *New Media & Society*, 26(4): 1871–1890.

Vartiainen, H.; and Tedre, M. 2025. The CEDE Model: A Learning-Sciences Based Approach for Critical and Transformative K-12 AI Education.

Veldhuis, A.; Lo, P. Y.; Kenny, S.; and Antle, A. N. 2025. Critical Artificial Intelligence literacy: A scoping review and framework synthesis. *International Journal of Child-Computer Interaction*, 43: 100708.

Wang, C.; and An, P. 2021. Explainability via Interactivity? Supporting Nonexperts' Sensemaking of pre-trained CNN by Interacting with Their Daily Surroundings. In *Extended Abstracts of the 2021 Annual Symposium on Computer-Human Interaction in Play*, CHI PLAY '21, 274–279. New York, NY, USA: ACM. ISBN 9781450383561.

Wiatrek, N.; Verma, Y.; and Martin, F. 2025. Word2Vec4Kids: Interactive Challenges to Introduce Middle School Students to Word Embeddings. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 39, 29228–29235.

Zhang, H.; Lee, I.; and Moore, K. 2023. Preparing Teachers to Teach Artificial Intelligence in Classrooms: An Exploratory Study. In *Proceedings of 17th International Conference of the Learning Sciences (ICLS) 2023*, 974–977.

Zhou, B.; Khosla, A.; Lapedriza, A.; Oliva, A.; and Torralba, A. 2016. Learning Deep Features for Discriminative Localization . In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2921–2929. Los Alamitos, CA, USA: IEEE Computer Society.