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Teaching Machine Learning to Middle and High School Students from a Low Socio-Economic Status Background

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Abstract. Knowledge about Machine Learning (ML) is becoming essential, yet it remains a restricted privilege that may not be available to students from a low socio-economic status background. Thus, in order to provide equal opportunities, we taught ML concepts and applications to 158 middle and high school students from a low socio-economic background in Brazil. Results show that these students can understand how ML works and execute the main steps of a human-centered process for developing an image classification model. No substantial differences regarding class periods, educational stage, and sex assigned at birth were observed. The course was perceived as fun and motivating, especially to girls. Despite the limitations in this context, the results show that they can be overcome. Mitigating solutions involve partnerships between social institutions and university, an adapted pedagogical approach as well as increased on-by-one assistance. These findings can be used to guide course designs for teaching ML in the context of underprivileged students from a low socio-economic status background and thus contribute to the inclusion of these students.

Keywords: Machine Learning, education, low socio-economic status, underprivileged, middle school, high school.

1. Introduction

Artificial Intelligence (AI) presents itself today in everyday applications such as image recognition (Li, 2022) motivating also the need to equip young people with the competencies needed to navigate today's world enabling them not only as consumers but also as creators of AI solutions (UNESCO, 2022; Touretzky *et al.*, 2019), especially as the demand for AI professionals is growing (World Economic Forum, 2020).

Some initiatives already aim at teaching AI to students from an early age on, such as the AI4K12 initiative and the Erasmus+ program, teaching basic ML concepts, such as fundamentals of neural networks and ethical issues (Touretzky *et al.*, 2022; UNESCO, 2022). First reports indicate that students from an early age can learn even complex ML concepts (Su and Zhong, 2022; Rodriguez-García *et al.*, 2021; Wan *et al.*, 2020).

Yet, students from low socio-economical status (SES) backgrounds seem not to be included in ML education as much as their more advantaged peers due to several limitations, such as a lack of infrastructure at home or at the schools they attend or a lack of prior basic computing competencies (Parker and Guzdial, 2015). This inequality in AI education is further magnified since many ML courses are paid (Hackr.io, 2023).

Focusing on this issue, some initiatives have begun to address AI/ML education in a way that increases student inclusion and diversity, including as AI4ALL (AI4ALL, 2023), The Coding School (TCS, 2023), and IBM SkillsBuild (IBM, 2023), by offering free educational programs to unleash students' potential. Yet, few courses specifically aim to make AI/ML education accessible to students with no prior basic computing competencies or experience with digital devices in middle and high school (Martins and Gresse von Wangenheim, 2023). These courses generally use unplugged activities, reinforce STEM content and computational thinking (CT), and adopt a slower pace of learning. However, findings point out the difficulty in working with students' lack of basic computer knowledge or mathematical concepts.

In this context, this article presents the application and analysis of the course "Machine Learning for All!" (a.k.a. ML4ALL) to 158 middle and high school students from a low SES background as part of a partnership between the initiative Computação na Escola and the program PodeCrer of the Vilson Groh Institute (IVG) aiming at the qualification in technology and innovation of young people from marginalized communities.

We expect that the results of this research can guide and facilitate the development of AI/ML courses for middle and high school students from low SES backgrounds by pointing out the main limitations proposing mitigation strategies to enable a larger involvement of these students in AI/ML education. By providing equality and inclusion opportunities, we aim to help them overcome adversities, to be more prepared for a competitive job market, and to ensure a more promising future for themselves and their families.

This paper is structured as follows: section 2 presents an overview on related work. Section 3 details the research methodology we adopted. In section 4 we describe the ML course that has been developed. The application of the course in a low socio-economic status is presented in section 5. The results of the evaluation of the course are detailed in section 6 and discussed in section 7. Conclusions are presented in section 8 summarizing the key findings and suggesting future research directions.

2. Related Work

As a result of a systematic literature review analyzing the teaching of AI/ML to middle and high school students from a low socio-economic status background, only very few courses were encountered (Table 1) (Martins and Gresse von Wangenheim, 2023).

In general, the concept of low socio-economic status varies from including students from low-income families, underprivileged conditions, living in marginalized communities, or studying at schools with a high level of vulnerability. The courses we encountered are typically aimed at novices with short durations ranging from 3 (Zhang *et al.*, 2022) to 6 weeks (Everson *et al.*, 2022). Courses are applied face-to-face (Araya *et al.*, 2021) or remotely (Zhang *et al.*, 2022; Everson *et al.*, 2022). In this context, various pedagogical approaches are adopted including collaborative learning (Araya *et al.*, 2021; Everson *et al.*, 2022), interactive and game-based learning (Zhang *et al.*, 2022). While Eguchi (2021) and Zhang *et al.* (2022) use Google Teachable Machine as a tool, Everson *et al.* (2022) used an AI chatbot created by the students themselves. Others due to limitations related to the technical infrastructure apply only unplugged activities (Araya *et al.*, 2021). Learning is assessed based on the students' performance (Everson *et al.*, 2022; Zhang *et al.*, 2022) or through tests (Araya *et al.*, 2021). The findings suggest that students in underprivileged contexts can comprehend computational models, reflect on their limitations, and understand AI/ML concepts, such as artificial neural networks and supervised learning, as well as even complex concepts, including Generative Adversarial Networks (GANs) (Martins and Gresse von Wangenheim, 2023).

Limitations reported in the context of low SES students include the lack of infrastructure in their schools and homes, creating a social and regional digital divide, affecting student activities and engagement. In some cases, unplugged activities have been used to mitigate this situation. Yet, this approach limits the learning objectives that can be achieved. In other cases, schools have received equipment through partnerships with universities or special funding projects. Another limitation reported is the lack of prior computing knowledge or basic digital skills, resulting in social segregation and digital exclusion. As a solution, STEM concepts were introduced focused on computing and CT at a slow, gentle learning pace.

However, a significant limitation of existing courses is the language barrier, as they are predominantly in English, posing a challenge for non-English speaking countries. Furthermore, the current performance-based assessments primarily focus on discussions (Everson *et al.*, 2022) and final presentations on topics such as ethical issues and AI bias (Zhang *et al.*, 2022). Existing assessment methods do not necessarily assess whether students have actually acquired the skills to develop an ML model. Our research seeks to address these gaps.

Table 1
Overview of courses that teach AI/ML competencies to low SES youth at the middle and high school level (Martins and Gresse von Wangenheim, 2023)

Reference	Brief description	AI/ML content	Main findings	Limitation and/or identified needs	Consequences	Mitigation action
(Araya *et al.*, 2021)	A framework for CT from the Inclusive Mathematics for Sustainability in a Digital Economy Project by the Asia-Pacific Economic Cooperation focusing on algorithmic thinking, computational modeling, and ML.	Computational modeling: Prediction; Basic ML algorithms: Classification; Decision tree; Measures, e.g., accuracy, correct and incorrect classification, graphic representation.	• Students accurately grasped the computational modeling example. • They successfully linked it to real-world problems, identified model limitations, and thoughtfully considered ways to enhance it to address those limitations.	• Lack of integration of CT and school curriculum • Lack of infrastructure in school	• Students had difficulties in understand real problems • Difficulty to teach CT and AI in vulnerable schools	• Teaching CT in integration with mathematics and science curricula • Instead of using a computer, students can work with a classmate playing their role, emulating training using paper and pencil
(Eguchi, 2021)	A project focused on developing an affordable open-source tool to address the need to promote AI literacy worldwide and especially support the urgent needs of developing countries and underprivileged communities.	Image classification; Ethics and societal impacts.	–	• Lack of infrastructure	• Social division (who has and who does not have access to education in AI) in underprivileged communities	• Using an AI educational tool that is accessible in any school in the world
(Everson *et al.*, 2022)	A co-constructed high school course for racially, ethnically, socioeconomically, and gender-diverse classrooms, framing the course as both a creative and critical introduction to computing, including AI.	Explore data, How AI works, and its sources of bias in creating a simple chatbot. Ethics and societal impacts.	• Students engaged in discussing topics of equity, justice, and marginalization in the AI context.	• Teaching online to low-income high school students in pandemic conditions while the students may not have access to computers	• Difficulty for low-income students to learn because they do not have digital devices	• University providing agnostic devices for students
(Zhang *et al.*, 2022)	A workshop that integrates ethics and career futures with technical learning to promote AI literacy for middle school students.	Introduction to AI; Logic Systems: Decision Trees; ML: Supervised learning, Neural Networks, Unsupervised learning, Generative Adversarial Networks, (GANs); Ethics and societal impacts; Career opportunities.	• Students gained a general understanding of AI/ML concepts, such as supervised learning and logic systems. • They learned to identify and mitigate bias in machine learning and consider AI's impact on their futures. • Students showed significant improvement in recognizing AI. understanding supervised learning and GANs.	• Gap in access to computing and AI education between students from minority groups and/or low-income families and their white, more affluent peers	• Difficulty in understanding IA concepts	• Design of a curriculum to teach AI, including technical concepts and processes • Using everyday context and interactive activities (e.g., hands-on, kinesthetic ones) to explain AI processes and implications and emphasize the relevance of AI to the students' live

3. Research Methodology

This research aims to apply and evaluate the ML4ALL course in the context of middle and high school students from a low socio-economic status background. To achieve this objective, an exploratory case study (Yin, 2017) is conducted that aims to understand these phenomena.

Study definition. The study is defined in terms of purpose and research design. From the objective, the research questions and measures are systematically derived using the Goal/Question/Metric (GQM) approach (Basili *et al.*, 1994). GQM is a structured method for measurement by establishing clear goals, deriving analysis questions related to the goals, and identifying appropriate metrics to assess progress toward those goals. The analysis questions and measures are based on the dETECT model (Gresse von Wangenheim *et al.*, 2017), aimed at evaluating the quality of instructional units for teaching computing in schools based on students' perceptions of learning and learning experience. The dETECT model demonstrated acceptable reliability (Cronbach's alpha $\alpha = 0.787$) and constructs validity (Gresse von Wangenheim *et al.*, 2017).

Additional analysis questions and metrics regarding the learning are analyzed through a performance-based assessment based on student-created artifacts using the scoring rubric proposed by Gresse von Wangenheim *et al.* (2022). The rubric has been shown reliable (coefficient Omega = 0.834/Cronbach's alpha $\alpha = 0.83$) and valid concerning internal consistency. The rubric has been automated as part of the online tool CodeMaster (Rauber *et al.*, 2023).

Study execution. The study is carried out by applying the course in practice to a specific target audience. Data was collected as defined, including ML artifacts created by students as learning outcomes as well as the perceptions of the students on learning and learning experience through questionnaires. The study was approved by the Ethics Committee of the Federal University of Santa Catarina (Approval No. 4.893.560).

Analysis and interpretation. Data collected with respect to the students' learning has been automatically assessed with the CodeMaster tool (Rauber *et al.*, 2023; Gresse von Wangenheim *et al.*, 2022). The assessment results and questionnaire responses have been documented in spreadsheets. The collected data were analyzed using descriptive statistics, including percentages, cumulative frequency, mean, median, and mode, as well as qualitative analysis of students' responses and observations.

4. Course ML4ALL

The ML4ALL course aims to popularize ML competencies to middle and high school students (Gresse von Wangenheim *et al.*, 2020). It is designed to teach basic ML concepts to students without prior knowledge of computing, programming, or AI/ML. This makes it particularly suitable also for students from a low socio-economic status background. The course objectives are aligned with the AI curriculum for K-12 (Big Idea 3) (AI4K12) (Touretzky *et al.*, 2019) as well as the guidelines on AI literacy proposed by

Table 2
Learning objectives of the course ML4ALL
(Martins *et al.*, 2023; Gresse von Wangenheim *et al.*, 2020)

ID	Learning objective
LO1	Know and identify examples of ML application
LO2	Describe basic ML concepts: what a neural network is, how it works and the ML process
LO3	Collect, clean and label data for the training of an ML model; understand how ML algorithms are influenced by data
LO4	Train an ML model
LO5	Evaluate the performance of an ML model
LO6	Discuss ethical concerns and the impact of ML on society

Long and Magerko, 2020) (Table 2). For the application of ML concepts, the course follows a human-centered ML development process outlined by Amershi *et al.* (2019).

The course also takes students to the application level, encouraging them to use the acquired knowledge, thus deepening learning and increasing the relevance of knowledge adopting a "computational action" strategy (Tissenbaum *et al.*, 2019), motivating them to create meaningful artifacts that directly impact their lives and communities. The course focuses on the "use" stage of the "Use-Modify-Create" (UMC) cycle (Lee *et al.*, 2011), on which students are guided step-by-step through the human-centered ML development process covering the basic steps of developing a pre-defined ML model, including data preparation, model training, evaluation of performance, and prediction (Martins *et al.*, 2023; Gresse von Wangenheim *et al.*, 2021a). The course also addresses ethical issues, social impacts, and career opportunities. The course syllabus is shown in Appendix A.

Content. The main focus of the course is to teach ML with a focus on computer vision, specifically on the task of classifying images. In class 1, students are introduced to the potential of AI, and learn to recognize ML applications in their daily lives. In class 2, the concepts of artificial neural networks are introduced. In classes 3 and 4, through hands-on activities, students are guided step-by-step in developing a predefined ML model for the classification of images of recycling thrash related to the United Nations' sustainable development goals (United Nations, 2015). In class 5, the entire ML process is reviewed, and in class 6, ethical issues, social impacts, and career opportunities are discussed.

Pedagogical approaches. Keeping expository lectures minimal, the course adopts mainly active methodologies in order to help students build their knowledge and engage them in higher-order tasks (Martins *et al.*, 2023; Sanusi and Oyelere, 2020). To support teaching, interactive slides, demonstrations (e.g., QuickDraw!(Google AI Experiments, 2022), MIT Moral Machine (MIT, 2017)) are provided (Fig. 1).

The instructional material is available in Brazilian Portuguese for free at:
`https://cursos.computacaonaescola.ufsc.br/cursos/curso-mlparatodos/`.

Technological tool. The course application has been supported by using the Moodle platform hosted at the university in order to provide the instructional materials. Stu-

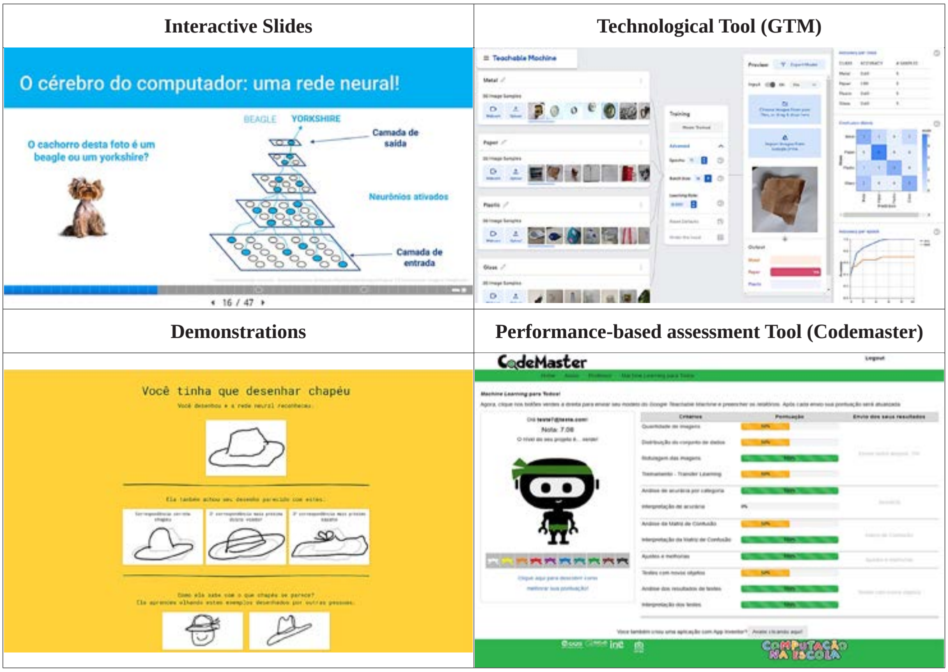


Fig. 1. Examples of instructional material and technological tools.

dents who are not directly affiliated with the university must create an external account to gain access. Communication with the remote instructor is facilitated through Google Meet accessible by students through their Google account. In order to support the training of the ML model Google Teachable Machine (GTM) (Google, 2023) was used, a free visual tool that allows training models without prior coding knowledge (Gresse von Wangenheim *et al.*, 2021b) available in Brazilian Portuguese, which also requires the login via Google account. For real-time feedback on the students' learning, the CodeMaster tool was adopted, accessible online by the students indicating their Gmail.

Learning assessment. Student learning is automatically assessed through using the CodeMaster tool based on a scoring rubric (Gresse von Wangenheim *et al.*, 2022; Rauber *et al.*, 2023). The rubric is detailed in Appendix B.

The course has already been applied successfully with students from other backgrounds (Martins *et al.*, 2023), achieving positive learning outcomes through a motivating and enjoyable learning experience.

5. Course Application in a Low Socio-Economic Status Context

The ML4ALL! course was applied in 2022 as an extracurricular activity with middle and high school students from a low SES background as part of the Program PodeCrer at the Vilson Groh Institute (IVG)[1] in cooperation with the initiative Computação na Escola at the Federal University of Santa Catarina (UFSC). The IVG, a Brazilian nonprofit organization, supports a network of organizations promoting social justice through education. Focused on empowering marginalized communities, it offers comprehensive education and resources, enabling youth to access opportunities and dignified lives (IVG, 2022). The Pode Crer program assists young people aged 11–24, focusing on citizenship, technology, and socio-emotional skills. It aims to create an inclusive economy and combat poverty and violence by promoting leadership, creativity, and technological proficiency in marginalized communities to bring students closer to the innovation and technology ecosystem, supporting their insertion in the job market and universities (IVG, 2022). Students are provided with pedagogical, social, and psychological support within the program's scope. Additionally, the program ensures that students are served meals in the morning and afternoon. Furthermore, all enrolled students are awarded a scholarship and supplied with transportation vouchers.

As part of the program, the initiative Computação na Escola aiming at bringing computing education to all students, applied the ML4ALL! course in September 2022.

A total of 178 students from a low SES background were initially enrolled in the course. However, due to many factors, including dropouts, voluntary and institutional decisions, and other personal circumstances, 158 students completed the course. The student's ages range from 14 to 19 years old. Slightly over half of these students are from middle school, while the remaining students, who are over 15 years old, typically attend high school. Participation was also balanced concerning sex assigned at birth and the period in which the classes took place (Table 3).

The students participating in the PodeCrer program come from economically disadvantaged families, with many family members who have little or no higher education, and some of whom have not even completed high school. Many of these students face challenging family circumstances, including family conflicts/violence and/or food insecurity, causing many of these students to even partly rely on the program for daily food. Most live in violent and marginalized communities, facing problems such as crime and lack of basic infrastructure. The schools they attend also lack quality teaching, teacher training, and technical infrastructure. As a result of these circumstances, the student's prospects are limited, with little incentive to pursue higher education. Many see their only option as preparing for simple and poorly paid jobs. Furthermore, without ad-

Table 3
Demographic overview of the student distribution (number of students).

Sex assigned at birth		Educational stages		Class period	
Female	Male	Middle school (≤ 15 y)	High school (> 15 y)	Morning	Afternoon
77	81	63	95	82	76

[1] PodeCrer program at Instituto Pe. Vilson Groh `https://vilsongroh.org/`

equate support and encouragement, many of these students risk becoming involved in criminality and drug dealing.

The students are regularly enrolled in schools in the region and have basic knowledge in languages, mathematics, natural sciences, and humanities, following the Brazilian Common National Curricular Base (MEC, 2017). Students predominantly attend public schools (74%), while some receive scholarships to attend private schools. Most students are Brazilian and fluent in their native language (Brazilian Portuguese). Seven migrant students also participated, including 6 Spanish-speaking students and one French/Creole-speaking student, all of whom understand Brazilian Portuguese well.

At the time of enrollment, students undergo an initial assessment led by the IVG's social assistance and pedagogical coordination team. Despite this, it was only during their ongoing participation in activities that some students were identified as having a low reading, comprehension, and expression abilities. Additionally, some students exhibited potential signs of Attention Deficit Hyperactivity Disorder (ADHD) and cognitive challenges.

The students' pre-existing knowledge and skills in computer usage are limited. Despite the availability of computer equipment in their schools, they are unaccustomed to utilizing these resources. While certain laws advocate for and guide the use of computers, computer science is still not incorporated into the school curriculum in practice (FECAP, 2020; MEC, 2017). Most students do not have computers at home, and the only opportunity to use them is during the classes at the IVGs. However, many of these students have skills in using mobile devices, listening to music, using social networks, and playing games.

ML4ALL application. The ML4ALL course was applied as an extracurricular activity, with one 2-hours class per week. The classes took place in the computer laboratories of the IVG, with 25 students per class, with one notebook/headphones per student. An instructor of the initiative Computação na Escola provided instructions remotely (via Google Meet) during expository lectures, discussions, and explaining the practical activities. A teaching assistant from the PodeCrer Program helped to organize the classes. In addition, some students who had taken the course previously and stood out for their performance acted as peer tutors, also helping to answer questions from their classmates (Fig. 2).

6. Evaluation of the Course

6.1. *Definition of the Evaluation*

The objective of the evaluation is to analyze the students' learning and learning experience applying the ML4ALL course in the context of middle and high school students

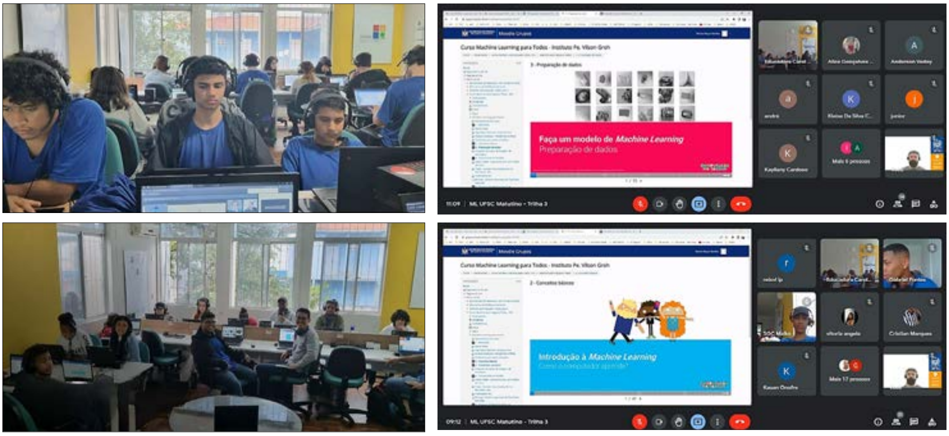


Fig. 2. Students during the application of the course.

from a low SES background through an exploratory case study. Based on this objective, the following analysis questions are derived:

- **AQ1.** Student Learning: Are learning objectives met, and are there differences with regard to the period of classes (morning vs. afternoon), educational stage, and sex assigned at birth?
- **AQ2.** Learning experience: Does the course promote a pleasant and enjoyable learning experience, and are there any differences regarding the period of classes (morning vs. afternoon), educational stage, and sex assigned at birth?
- **AQ3**. What limitations were observed due to the context of low SES students, what were the consequences, and what are possible mitigation actions?

6.2. *Data Collection*

Data was collected during the course through artifacts created by students using the Codemaster tool (Rauber *et al.*, 2023) and pre- and post-questionnaires on the students perception on learning and learning experience (Gresse von Wangenheim *et al.*, 2017) (Table 4).

6.3. *Results*

6.3.1. *Student Learning: Are Learning Objectives Met, and are there Differences with Regard to the Period of Classes, Educational Stage, and Sex Assigned at Birth?*

Student learning was assessed through a performance-based assessment using the scoring rubric developed by Gresse von Wangenheim *et al.* (2022) and Rauber *et al.* (2023).

Table 4
Quantity of collected data.

	Performance-based evaluation (n per criteria)												Questionnaire(n)	
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	pre	post
All students	**79**	**79**	**79**	**79**	**74**	**74**	**73**	**73**	**76**	**73**	**73**	**73**	**101**	**122**
Morning classes	36	36	36	36	32	32	32	32	34	32	32	32	46	59
Afternoon classes	43	43	43	43	42	42	41	41	42	41	41	41	55	63
Middle school	32	32	32	32	30	30	30	30	30	29	29	29	44	46
High school	47	47	47	47	44	44	43	43	46	44	44	44	57	76
Female	36	36	36	36	33	33	32	32	33	32	32	32	49	66
Male	43	43	43	43	41	41	41	41	43	41	41	41	52	56

The artifacts created by students in classes 3 and 4 were assessed based on the learning outcomes for developing an ML model to classify images assessing the achievement of learning objectives LO3–LO5 (Table 2). A total score was calculated on a scale of 0–10 as the sum of the student's scores in all criteria (C1–C12) to the possible total score (36 pts). As a result, the overall mean scores of the students were considered satisfactory (7,51 points). This score indicates that students were able to proceed through the main stages of an ML development process.

In general, students performed at the highest level for most criteria (Table 5). Exceptions are related to the criterion "C1:quantity of images" with a large number of students who used "less than 20 images per category". A possible reason could be the intention of these students to proceed quickly in this process, using the minimum quantity of images to advance to the next step of the process. Another exception is in the criterion "C7:analysis of the confusion matrix", in which many students demonstrated an "incorrect identification of classification errors (more than 2 errors)". A possible reason is that the matrix topic is a mathematical concept that some students may not yet have seen, depending on their educational stage. On the other hand, concerning C3 and C4, "labeling the images" and "training" items, all students demonstrated high levels of performance. Overall, most students scored on average at the highest level, between "acceptable" and "good" with respect to the other performance analysis and interpretation criteria.

Regarding the class period, students taking part in the afternoon classes achieved slightly higher scores. These students study at their regular schools in the morning, which may indicate a higher level of attention during subsequent daily activities. Although there are no substantial differences, the slightly higher scores of high school students may be linked to a greater previous exposure to basic competencies at this educational stage. Concerning sex assigned at birth, the total scores of males were slightly higher (Fig.3), although girls exceeded in two criteria (C1 and C7). In an exploratory data analysis, this can be initially explained as scores from female students having a greater variation than males, with (SD = 1.62), while scores from male students have a smaller variation (SD = 0.98).

Table 5

Frequencies and median performance level of all students by criterion

Criteria	Performance levels: Not submitted	Poor - 1 pt	Acceptable- 2 pt	Good - 3 pt	Median
Data management					
C1. Quantity of images	81	37	21	21	2
C2. Distribution of the dataset	81	4	45	30	2
C3. Labeling of the images	81	0	7	72	3
Model training					
C4. Training	81	0	77	2	2
Interpretation of performance					
C5. Analysis of accuracy per category	86	6	0	68	3
C6. Interpretation of the accuracy	86	7	0	67	3
C7. Analysis of the confusion matrix	87	38	15	20	1
C8. Interpretation of the confusion matrix	87	8	0	65	3
C9. Adjustments / Improvements made	84	13	35	28	2
C10. Tests with new objects	87	8	44	21	2
C11. Analysis of test results	87	29	0	44	3
C12. Interpretation of test results	87	19	0	54	3

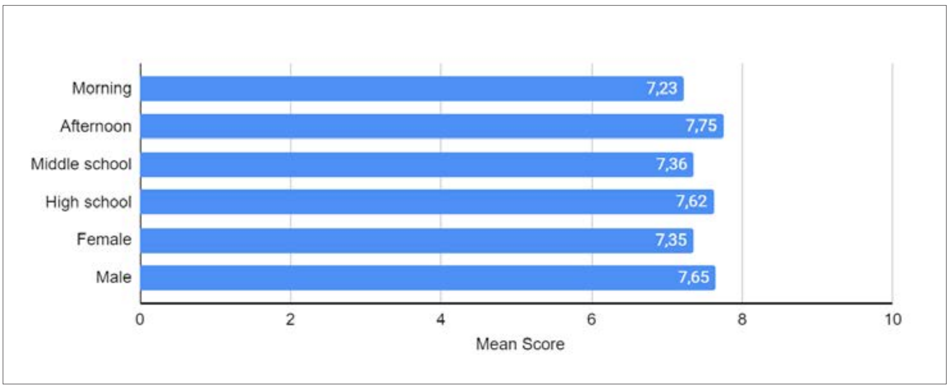


Fig. 3. Mean of total performance.

Comparing the medians of performance levels, no substantial differences across class periods were noted, although slight deviations are observed (Table 6). Students from the morning period achieved an “Acceptable” performance with respect to C1, as they used 21 to 35 images per category. On the other hand, students participating in morning classes achieved only a “Poor” performance with regard to C7 with respect to the confusion matrix analysis.

When comparing by educational stage, in general, there are no substantial differences. However, in relation to criteria C7, middle school students demonstrated acceptable performance in analyzing the confusion matrix, while high school students only achieved poor performance. This result contradicts the assumption that high school students, having already studied the topic of matrices, would achieve a higher score. On the other hand, high school students performed slightly better on criterion C1 by using more images per category.

Concerning sex assigned at birth, again there are no substantial differences. However, female students stood out by achieving higher scores on criteria C1 and C7 compared to male students. And although no general effect of the sex assigned at birth on learning performance could be identified, it points toward the idea that female students seem to take more care in separating the images and show more attention in analyzing the confusion matrix.

To complement the assessment of student learning, the student’s perception of their learning was analyzed. The vast majority of student respondents in the course indicated that they understood what ML is (Table 7). Based on the responses of the pre-questionnaire, students indicated an understanding of the learning potential of computers, and at the end of the course, there a 2% increase in this perception was observed. Only two students at the end of the course responded that computers with AI/ML could not learn. In addition, before the course, 13% of students thought that AI/ML could be dangerous or pose risks, while in the end, this increased to 35% of students, indicating that the course helped the students to recognize this risk. Also, a significant portion of the students answered that they felt able to develop an image classification model. Most students found the difficulty to develop an ML model as average, with only 2 considering it very difficult. On the other hand, only about 63% of the students think that they can explain what ML is.

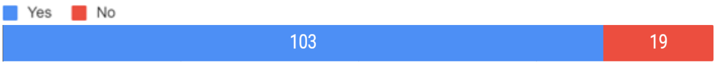
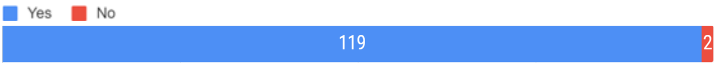
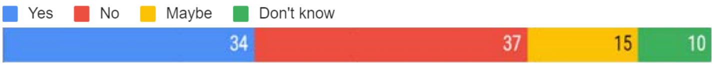
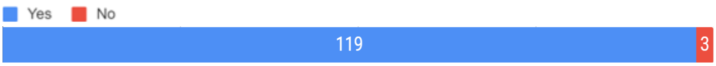
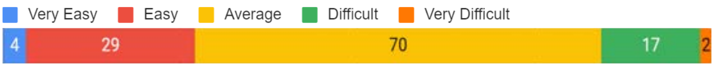
Table 6

Median scores per class period, educational stage, and sex assigned at birth

Comparison		Median scores (Poor (1 pt), Acceptable (2 pt), Good (3 pt))											
		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
Class period	Morning	**2**	2	3	2	3	3	1	3	2	2	3	3
	Afternoon	1	2	3	2	3	3	**2**	3	2	2	3	3
Educational stages	Middle school	1	2	3	2	3	3	**2**	3	2	2	3	3
	High school	**2**	2	3	2	3	3	1	3	2	2	3	3
Sex assigned at birth	Female	**2**	2	3	2	3	3	**2**	3	2	2	3	3
	Male	1	2	3	2	3	3	1	3	2	2	3	3

Table 7

Frequency of responses of the students' perception of learning

Data collection item	Frequencies of responses of all students
I understand what ML is	
Can computers or systems (with AI/ML) learn?	
Do you think AI/ML can be dangerous or does it carry any risk?	
Can I learn to make solutions with AI/ML?	
I can develop an ML model for image classification	
Developing an ML model is	
I can explain to a friend what ML is	

Considering the statistical mode and absolute frequency of responses of the perception of learning for all student respondents, no substantial differences were observed between class periods, educational stages and sex assigned at birth (Table 8).

Table 8

Comparison of mode and absolute frequency of responses per class period, educational stage, and sex assigned at birth

Data collection item	Statistical mode and absolute frequency of responses					
	Morning Period	Afternoon Period	Middle school	High school	Female	Male
	Mode and absolute frequency	Mode and absolute frequency	Mode and absolute frequency	Mode and absolute frequency	Mode and absolute frequency	Mode and absolute frequency
I understand what ML is	Yes (45)	Yes (58)	Yes (36)	Yes (67)	Yes (55)	Yes (48)
Can computers or systems (with AI/ML) learn?	Yes (57)	Yes (62)	Yes (43)	Yes (76)	Yes (65)	Yes (54)
Can I learn to make solutions with AI/ML?	Yes (56)	Yes (63)	Yes (43)	Yes (76)	Yes (64)	Yes (55)
I can develop an ML model for image classification	Yes (51)	Yes (59)	Yes (39)	Yes (71)	Yes (61)	Yes (49)
Developing an ML model is	Average (30)	Average (40)	Average (26)	Average (44)	Average (40)	Average (30)
I can explain to a friend what ML is	Yes (35)	Yes (42)	Yes (24)	Yes (53)	Yes (39)	Yes (38)

6.3.2. *Learning Experience: Does the Course Promote a Pleasant and Enjoyable Learning Experience, and Are there Any Differences Regarding the Period of Classes, Educational Stage, and Sex Assigned at Birth?*

The student's perception of the learning experience in the ML4ALL course was analyzed based on the post-questionnaire responses. In general, the responses of all students were positive (Table 9). The majority of the students pointed out that the course was "a lot of fun" or "fun". Also, 45% of students found the course "easy" or even "very easy". At the end of the course, most students indicated that they would like to learn more about ML.

Comparing the results, some variations in the perception of the learning experience were observed. Most of the students from the afternoon period found the course "easy"; in contrast, students from the morning period mostly found it "average" (Table 10). A possible reason may be the fact that these students have to get up early and have to take the bus, which may have influenced their perception.

When comparing the educational stage, the high school students perceived the classes to pass "quickly", whereas middle school students perceived the class time to have passed more slowly. This may be due to the fact that high school students are already more mature and experienced in basic competencies to the point that they learn the presented concepts more easily.

It is also noted that most female students perceived that the class time passed "quickly", while male students perceived it as passing more slowly. There are also indications that the female students have shown more interest and also pointing out that they could have learned more if they had more time.

However, most of the male students perceived the course as "excellent", while the female students rated it as "good". This may be due to a larger interest of male students in the subject of technology, while this interest in this subject is just emerging among female students.

Table 9

Frequencies of responses of all students

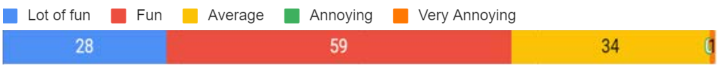
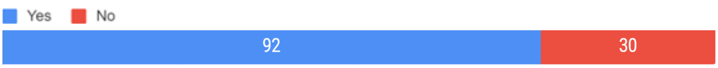
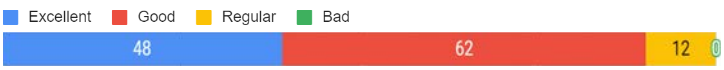
Data collection item	Frequencies of responses of all students
The course was?	
The course was?	
Class time has passed?	
I want to learn more about ML	
Overall the course was?	

Table 10
Mode and absolute frequency of responses per class period, educational stage, and sex assigned at birth

Data collection item	Statistical mode and absolute frequency of responses					
	Morning	Afternoon	Middle school	High school	Female	Male
	Mode and Absolute frequency	Mode and Absolute frequency	Mode and Absolute frequency	Mode and Absolute frequency	Mode and Absolute frequency	Mode and Absolute frequency
The course was?	**Average 33**	**Easy 27**	Average 25	Average 34	Average 33	Average 26
The course was?	Fun 27	Fun 32	Fun 18	Fun 41	Fun 34	Fun 25
Class time has passed?	**Quickly 21**	**Average 22**	**Average 15**	**Quickly 30**	**Quickly 26**	**Average 25**
I want to learn more about ML	Yes 47	Yes 45	Yes 31	Yes 61	Yes 47	Yes 45
Overall the course was?	Good 26	Good 36	Good 26	Good 36	**Good 38**	**Excellent 27**

General student feedback was positive (Appendix D). Many students commented that they enjoyed teaching a machine, classifying an image, creating an AI system, and learning more about technology. What they least liked was the fact that the class required students to perform sometimes more monotonous activities, such as separate images into recycling categories. Many students, especially girls, also recognize that learning ML helped them be prepared for the job market and emphasized their interest in technology.

6.3.3. *What Limitations were Observed Due to the Context of Students from a Low SES Background, what Were the Consequences, and what Are Possible Mitigation Actions?*

Applying the ML4ALL course to a public of middle and high school students from a low SES background faces a series of adverse situations, resulting in diverse consequences and requiring mitigation actions.

Technological needs. The course has been run in the IVG's computer lab, providing one notebook/headset per student as well as a robust Internet connection with sufficient bandwidth. This allowed the students to access the Learning Management System to execute the practical activities at their own pace. Yet, as the majority of the students do not have computers at home, the scope of the activities has to be limited to ones that could be completed during the classes due to the impossibility of any homework.

Basic computer competencies. The students are unfamiliar with email and various systems that require logins. When required to use the Learning Management System and their Google account (including Gmail, Google Meet, and GTM), we noticed that many students struggled to remember their passwords. This issue resulted in delays at the commencement of the initial classes. To mitigate this, we created cards for students to annotate their passwords, serving as a remembering aid.

Delays and absences. The start of morning classes often was delayed as the arrival of the IVG/PodeCrer instructors coincided with the beginning of the classes, postponing classroom preparation. To mitigate this, an additional instructor from the initiative Computação na Escola, who arrived earlier, took over this responsibility. Additionally, many students who live or study far from the IVG rely on public transportation, leading to further delays. This also impacted the start of afternoon classes, that had to be slightly postponed to allow for everyone's arrival. In addition, the end of the afternoon classes had to be anticipated to ensure students did not miss their public transportation.

Absences were frequent due to various factors associated with students from a low socio-economic status background due to family situations or illness. Other reasons encompassed issues with public transportation and even disruptions due to environmental and social events, such as road closures in the city due to heavy rain or protests. Instructors conducted a quick in-person review for students who missed classes or highlighted key points from the interactive slides to help them to catch up. Alternatively, absent students were encouraged to work collaboratively with a peer who had attended the class, enabling them to keep pace with the activities.

Mentoring needs. Since many students lack fundamental computer knowledge, we noticed that they struggled to follow the lessons step by step. For instance, a task like downloading a file was misunderstood by some students. To offer more support, particularly during practical activities, we assigned an additional instructor from the initiative Computação na Escola to be present in person. In this way, this instructor was able to personally assist the students, answering their questions and explaining basic computing concepts when necessary.

Some students were shy and felt uncomfortable asking the instructors for help, and/or experienced extreme difficulty (such as even typing on the computer). Therefore, some more advanced students were assigned as peer tutors to mitigate this situation. These peer tutors from middle and high school were selected for their maturity, interest, and performance in other IVG activities like web development and prototyping courses. The peer tutors are also IVG/PodreCrer students from a low SES context and had taken the ML4ALL course beforehand. Since they share age and classroom environment, students facing difficulties felt more at ease asking these peer tutors for help than the instructors. The performance of these peer tutors was commendable, also contributing in increasing their self-esteem as they were recognized as teachers in front of their fellow students before class. The tutors also exhibited proactivity, empathy, and concern for their peers. In the case of a student with significant learning difficulties, the peer tutors actively sought to assist this student during lessons, guiding her step by step. This enabled the student to tackle more complex activities within the course.

Adopting a learning strategy for hands-on activities, where students individually follow step-by-step online instructions, enabled them to learn at their own pace. However, this approach resulted in multiple students having questions on different topics simultaneously. Therefore, the presence of several teaching assistants at once was required, which was accomplished with the combined efforts of the instructors from the initiative Computação na Escola and the program PodeCrer/IVG, and the peer tutors.

Course planning. The course was conducted as part of the broader PodeCrer program, so the classes of the ML course were held only once a week. This led to a significant time gap between classes, causing students to struggle with recalling the content covered in previous classes. As a solution, instructors started doing quick reviews at the beginning of a new class to help students to remember the previous content before starting new content.

Student interest and motivation. During the classes, some students exhibited a lack of interest in the course, failing to engage in class activities and exhibiting apathy. Many of these attitudes can be attributed to the challenging social contexts and realities these students face. Many students are enrolled in the IVG/PodeCrer program by their families to provide opportunities and prevent them from engaging in criminal activities on the streets. However, this can result in a certain lack of interest among these students, as some feel obligated to be there. To mitigate this, in addition to the social assistance efforts of IVG/PodeCrer, instructors engaged these students in conversations to motivate them by highlighting the possibilities and opportunities that the course can offer, such as pursuing a career in the field or even developing their own marketable solutions. However, it should be noted that some students genuinely lack interest in technology and consequently prefer to engage in other activities within the classroom.

We also observed that the low participation and engagement in activities by some students may negatively impact the classroom environment and can demotivate other students. To mitigate this, instructors tried to identify the students' interests and connect them with the course content. For instance, if a student expressed an interest in cars, the instructors would share information about how machine learning is applied in autonomous vehicles. Making the technology more relevant to the student's interests helped increase their motivation to actively participate in the course. This was further enhanced through a visit to the University, where several research projects, including, e.g., an autonomous car project, were explained and demonstrated.

Older high school students exhibited larger interest, demonstrating concerns regarding their future prospects, such as pursuing higher education at a university and exploring job opportunities. One student even inquired about potentially including the ML4ALL course in their curriculum. At the same time, another expressed an eagerness to learn more about the technology courses offered at the university. To motivate these students, the university visit was also intended to showcase undergraduate courses in this area as well as ongoing AI/ML research projects. On the other hand, middle school students tend to prioritize their daily lives. Many of them would open online gaming tabs after completing the day's planned activities. Instructors seized these opportunities to briefly discuss AI/ML games and foster their enthusiasm for the subject. Engagement in these alternative activities was not discouraged, as the instructors recognized that even games outside the course could be beneficial, providing them with an opportunity to utilize and enhance their computing skills, especially considering that many students lacked computers at home.

Learning disorders. Some students exhibited significant challenges and a tendency to become distracted, raising concerns about the possibility of attention deficit hyperactivity disorder (ADHD). These students struggled to keep up with the activities and the learning process. Instructors and peer tutors collaborated closely to assist these students, providing step-by-step guidance more attentively. Additionally, the pedagogical coordination and social assistance teams of IVG/PodeCrer provided specific guidance to the individuals responsible for these students.

Difficulty in learning ML. On certain occasions, the course activities appeared overly complex for some students due to their lack of basic computer knowledge, causing them to give up rather quickly. Consequently, these students became easily distracted or engaged in other tasks. To mitigate this, instructors identified the students' closest friends or those with whom they felt most comfortable conversing in the classroom. They were then invited to work on activities in pairs or small groups. This collaborative approach proved to be successful as it encouraged discussion and collective problem-solving among the students in various activities. This arrangement also did not hinder the more advanced student's progress. Instead, the student assisting reinforced their understanding of the subject matter and seemed to feel valued.

Aware of the challenges in the context of students from a low SES background and their potentially stressful daily lives, the instructors provided constant support through positive feedback through words of motivation, praise, and encouragement upon completing activities. The instructor also looked to engage with topics that interested the students, such as anime, comics, and games, to establish a stronger connection between them, which fostered a sense of trust and created a more fluid teaching and learning environment in the classroom.

Heterogeneity of competencies. The students participating in the course come from various schools in the region, each with different levels of teaching quality, which consequently led to a range of competencies, experiences, and maturity levels. This diversity resulted in differing paces and interests within the course. As a mitigation strategy, the IVG attempted to separate classes primarily based on the school stage (middle and high school). At the same time, the instructors aimed to adopt a slower and more gentle approach to teaching to be as inclusive as possible.

Adaptation of the instructional material. The instructional materials for the ML4ALL course primarily consist of interactive slides. However, it was observed that students often skipped reading the instructions step by step, due to a lack of reading habits. This resulted in students incorrectly executing the activities. Recognizing that these students are accustomed to following short videos on social media platforms (such as Instagram stories or TikTok), we prepared short instructional videos to explain certain activities step by step, as well as to demonstrate the use of tools like GTM and CodeMaster (Appendix A). These videos have been shown to be crucial in elucidating the functionality of the tools, despite GTM being intuitive and suitable for students without prior coding knowledge.

A summary of these limitations, their consequences, and the mitigation strategies employed can be found in Table 11.

Table 11
Summary of limitations or identified needs, consequences, and solutions adopted in the application of the course in the context of low SES students

Limitations or identified needs	Consequences	Mitigation actions
Technological needs	• Lack of opportunity to learn.	• Running the course in a computer lab with notebooks (one per student). • No homework as part of the course.
Basic computer competencies	• Difficulty in learning. • Difficulty in following the classes. • Learning disadvantage.	• Face-to-face instructor to reinforce computing skills. • Cards to remember the password for the sw systems used in classes.
Delays and absences	• Difficulty in following the classes. • Delays in starting class. • Disturbances in the classroom. • Difficulty of follow-up by absent students.	• Instructors preparing classrooms and notebooks. • Starting classes a little later and finishing earlier. • Quick review and note-taking of the highlights in the material by the instructors in the beginning of classes.
Mentoring needs	• Difficulty in following the classes and activities. • Greater difficulty for students to learn the content. • Lower student engagement and motivation. • Instructors' overload.	• Need for instructors with experience in ML/AI (remote and face-to-face). • Instructors to help with basic computing. • Advanced class students acting as peer tutors.
Course planning	• Difficulty for students to remember previous classes and activities.	• Quick review by the instructors to remember previously presented content.
Student interest and motivation	• Low engagement and participation in activities and the classroom. • Poor performance in activities. • Dropping out of the course. • Negative impact on classroom climate and dynamics among students. • Demotivation of other student's.	• Personal conversations to motivate and engage students. • Support by social assistance to deal with sensitive social situations. • Alternative approaches to engage learners who are not interested in technology, linking course content to learners' interests. • Conducting a visit to the university presenting AI/ML research and potential.
Learning disorders	• Difficulty in learning. • Difficulty executing the practical activities.	• Orientation given to the students guardians provided by the pedagogical coordination and social assistance of the program PodeCrer/IVG.
Difficult in learning ML	• Dropout or dispersion in course activities. • Loss of learning opportunity. • Low self-esteem and insecurity regarding their ability and potential. • Lack of engagement in course activities.	• Working in pairs or small groups to encourage collaboration and knowledge sharing among students. • Linking course content to students' interests. • Creating an inclusive and welcoming learning environment for all learners. • Present course contents in various formats, such as interactive slides and videos to facilitate understanding.

Continued on next page

Table 11 – continued from previous page

Limitations or identified needs	Consequences	Mitigation actions
Heterogeneity of competencies	• Disinterests of some students. • Lack of student engagement and motivation in the course. • Very divergent performance results.	• Adoption of a slower and gentler learning pace. • Realization of practical activities individually or in pairs/small groups at their own pace. • Creating an inclusive and welcoming environment, recognizing individual differences in each student. • Peer tutors to help students with more difficulties.
Adaptation of the instructional material	• Difficulty understanding the content. • Difficulty following activities. • Difficulty in learning. • Student demotivation.	• Creation of short videos in addition to interactive slides.

7. Discussion

Considering the importance of making AI/ML knowledge available to everyone and making the popularization of this teaching more equal and inclusive for youth from a low SES background we applied the ML4ALL course in such a context. An exploratory analysis of learning outcomes and perceived learning experience, indicates that middle and high school students from such a background are capable of acquiring and building basic AI/ML knowledge. Learning outcomes reveal that these students are able to understand what ML is and how a neural network works and to develop a predefined ML model following a human-centered ML development process. Comparing the results by class period, educational stage, and sex assigned at birth, no substantial differences were observed. However, we observed that female students demonstrated greater attention and care in developing an ML model for image classification. They also seem to feel motivated to pursue a career in technology. Despite the fact that most of the students attend public schools demonstrating weaker mathematics foundations, middle and high school students achieved good learning performances. This provides a first indication that these learning objects can be achieved by middle and high school students equally, not affecting their understanding of the concepts addressed in the course.

Many of the students also perceived the course as a fun learning activity and generally thought the course was good. The vast majority of students indicated that they understood what ML is and became interested in learning more about ML.

Regarding the technological resources adopted in the course, the activities with GTM were mentioned as what the students liked most in the course. Many students also seemed motivated by the results of their real-time assessment through the CodeMaster tool, motivating some to even improve their trained ML model to obtain a higher grade and “ninja belt “ (a visual form of grade feedback).

The application of the course in a context of students from a low SES background faces several challenges, with direct consequences on the students’ learning. The way the course is taught with online course materials and technological tools requires an adequate infrastructure. Additionally, engaging effectively with these students requires social competencies and empathy. In this regard, the close partnership between the initiative Computação na Escola and the program PodeCrer/IVG played a crucial role in overcoming this challenge, bringing together people with different expertise within this context.

Other challenges, such as the lack of basic computer skills and the heterogeneity of competencies, caused consequences ranging from student demotivation to course dropout. Mitigation solutions included face-to-face support, a larger number of teaching assistants, e.g., peer tutors, in order to be able to provide help to a larger number of students in parallel, adaptations of pedagogical approaches, e.g., making connections with their interests, as well as adaptations to instructional material, e.g., creating short videos that are more understandable to students of this age.

In addition, the motivation and awakening students' interest was also challenging. Consequences of this ranged from dropping out of the course, the loss of self-esteem as they felt incapable, and perceiving a loss of an opportunity that could be significant for the student. In order to mitigate this issue, we motivated students to work collaboratively in pairs or small groups, and tried to link the course content more to their interests. In some cases in which demotivation was more related to their family context, social assistance was provided to them and their guardians.

Despite all the adversities due to the context of a low SES background, the findings indicate that middle and high school students from such a background are able to learn complex subjects such as AI/ML. Although there are no significant differences between the sex assigned at birth in learning this knowledge, the course was able to raise female students' interest in the IT area. Additionally, it showed that despite being complex, this content can be taught in a fun and motivating way.

These results demonstrate that young people from a low socio-economic status background just need the opportunity to learn technologies, to be enchanted with this topic and to be motivated to face the challenges of becoming creators of intelligent solutions, in order to take the opportunity to pursue a career in this area with the potential to change their lives.

Threats to validity. Several aspects of our study design could potentially impact the validity of our findings. A principal concern is the threat of low statistical power due to the limited sample size. However, given a sample size of 158 students, we assume that it is sufficient for an explorative study. We also selected analysis methods taking into consideration the sample size and research design. The conclusion validity of the results is reinforced by the reliability of the measurements used for data collection, including the rubric and the dETECT instrument, both of which have confirmed reliability (rubric $\alpha = 0.83$, dETECT $\alpha = 0.787$). The construct validity of dETECT and the internal consistency of the rubric have also been validated, further supporting the conclusion validity. In terms of internal validity, the dropout rate was notably low, especially when considering that the study participants were students from a low SES background. We, therefore, assume that this low rate of dropouts did not have a substantial influence on the results. The results presented here are based on data collected from the application of the ML course at the IVG in Brazil. Therefore, the possibility of generalization of the results may be limited. However, considering the lack of findings on teaching computing to underprivileged students in literature, we consider the results still a valuable contribution.

8. Conclusion

Aiming at teaching AI/ML to students from a low SES background in order to provide opportunities to these students we applied the ML4ALL course to middle and high school students from the program PodeCrer/IVG in Brazil. The results of this exploratory study revealed that the students from this background were able to achieve the course's learning objectives, understanding how ML works and executing the main steps of a human-centered ML development process. Furthermore, many students perceived the course as a fun and enjoyable learning experience and became interested in learning more about AI. No substantial differences were observed comparing class periods, educational stages, and sex assigned at birth. However, we observed a positive effect on female students discovering their interest in computing and realized that the subject is not exclusive to males.

During the application of the course, we faced several limitations and challenges, such as students' lack of basic computing skills, heterogeneity of competencies, and motivation and interest. However, adopting diverse mitigation strategies such as increased one-to-one support and adapted pedagogy and instructional materials enabled the achievement of the expected learning outcomes and created a positive learning experience.

These promising results are motivating us to continue the development of ML courses on the "create" level to allow these students to create their own ML model and solve problems they find relevant, and contribute to their communities.

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Appendix A
Course Syllabus

Class	Topics	Duration	Content	Learning objective(s)	Educational strategy			
					Pedagogical approach	Instructional method	Instructional material	Student Assessment
1	**General notions and importance**	2h	Motivation on AI and its application in daily life	LO1, LO6	Active learning; Game-based learning	Lecture, discussion, hands-on demonstrations	Interactive slides; demonstration: Object Detector and Classifier app, QuickDraw! game, video: Object detection and segmentation	Observation
2	**Basic concepts**	2h	Basic concepts of ML: what does it mean to "learn", ML process: data preparation (collection, cleaning, labeling), feature engineering, training	LO2, LO4	Active learning	Lecture	Interactive slides	Observation
3	**Make your first ML model**	1h	Classification of recyclables; data preparation (cleaning and labeling)	LO3–LO5	Active learning; Problem-based learning; Collaborative learning*	Lecture, hands-on activity	Interactive slides, dataset of recycling trash images (via Google drive), data preparation report (online form)	Performance-based assessment of the dataset (Rubric C1–C3)
4		1h	Training of the model and evaluation	LO4, LO5		Lecture, hands-on activity	Interactive slides; Google Teachable Machine, model training & performance evaluation report (online form); Video*	Performance-based assessment of the model training (Rubric C4) and evaluation (Rubric C5–C12)
5	**Review of content and ML process**	1h	Revision of the ML concepts and process	LO1–LO4	Active learning	Lecture, discussion	Interactive slides	Observation
6	**Ethical issues and societal impact**	1h	Ethical issues with respect to AI/ML, limitations, risks and job opportunities	LO1, LO6	Active learning; Game-based learning	Lecture, discussion, hands-on activity	Interactive slides, demonstration: MIT Moral Machine	Observation

*Adapted for teaching in the context of low SES.

Appendix B
Performance-Based Assessment: Rubric for Assessment of the Application of ML Concepts for Image Classification – Use Stage (Gresse von Wangenheim *et al.*, 2022; Rauber *et al.*, 2023)

Cri-teria	Item / Observable variables	Performance levels			
		Not submitted – 0 points	Poor – 1 point	Acceptable – 2 points	Good – 3 points
Data management					
C1	Quantity of images	No GTM file (.tm) submitted for assessment	Less than 20 images per category	21 to 35 images per category	More than 35 images per category
C2	Distribution of the dataset	No GTM file (.tm) submitted for assessment.	The number of images in each category varies greatly. More than 10% variation in at least one category (relative to the total)	The number of images bet-ween the categories varies between 3% and 10%	All categories have the same amount of images (less than 3% variation)
C3	Labeling of the images (Sampling 10% of images to test through hi-accuracy ML model)	No GTM file (.tm) submitted for assessment.	Less than 20% of the images were labeled correctly	20% and 95% of the images were labeled correctly	More than 95% of the images were labeled correctly
Model training					
C4	Training	No GTM file (.tm) submitted for assessment.	The model was not trained	The model was trained using the default parameters	The model was trained with adjusted parameters (epochs, batch size, learning rate)
Interpretation of performance					
C5	Analysis of accuracy per category	No information submitted about categories and/or interpretation.	Categories with low accuracy were not identified	--	All categories with low accura-cy were correctly identified

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Criteria	Item / Observable variables	Performance levels			
		Not submitted – 0 points	Poor – 1 point	Acceptable – 2 points	Good – 3 points
C7	Analysis of the confusion matrix	No information submitted about Confusion Matrix and/or interpretation.	Incorrect identification of classification errors (more than 2 errors)	Incorrect identification of one or two classification errors	Correct identification of all classification errors
C8	Interpretation of the confusion matrix	No information submitted about Confusion Matrix and/or interpretation.	Incorrect interpretation of the confusion matrix analysis of the model	--	Correct interpretation of the confusion matrix analysis of the model
C9	Adjustments / Improvements made	No information submitted about improvements.	No new development iterations were reported	A new iteration with changes in the dataset and/or training parameters was reported	Several iterations with changes in the dataset and/ or training parameters have been reported
C10	Tests with new objects	No information submitted about Tests and/or interpretation.	No new object tested	1–3 objects tested	More than 3 objects tested
C11	Analysis of test results	No information submitted about Tests and/or interpretation.	Incorrect indication of the number of errors in the tests	--	Correct indication of the amount of errors in the tests
C12	Interpretation of test results	No information submitted about tests and/or interpretation.	Wrong interpretation of test results	--	Correct interpretation of test results

Appendix C
Data Collection

Analysis question	Based on	Data collection instrument	Quality factor	Data collection items	Response scale
AQ1	Learning outcomes LO3 to LO5	Criteria C1–C12	Learning	Dataset Model .tm Test results Accuracy analysis Results interpretation Adjustments improvements	3-point ordinal scale
	Student's perception of learning	Feedback questionnaire	Learning	When I hear about AI/ML the first thing that comes to mind is:	Open text
				Do you think AI/ML can be dangerous or does it carry any risk? Can you cite an example?	Yes, no, maybe, don't know
				Can computers or systems (with AI/ML) learn?	Yes, no
			Learning/Self-confidence	Can I learn to make solutions with Artificial Intelligence/Machine Learning?	Yes, no
AQ1	Student's perception of learning	Feedback questionnaire	Learning	I understand what ML is	Yes, no
				Can computers or systems (with AI/ML) learn?	Yes, no
			Learning/Self-confidence	Can I learn to make solutions with AI/ML?	Yes, no
				I can develop an ML model for image classification	Yes, no
				Developing an ML model is?	5-point ordinal scale
				I can explain to a friend what ML is	Yes, no
AQ2	Student's perception of learning	Feedback questionnaire	Enjoyability	The course was?	5-point ordinal scale
				The course was?	5-point ordinal scale
				Class time has passed?	5-point ordinal scale
				I want to learn more about ML	Yes, no
			Overall quality of the course	Overall the course was?	5-point ordinal scale
				What did you like most about the ML course?	Open text
				What did you like least about the ML course?	Open text
				Any other comments?	Open text
			Motivating	What motivates you to study Artificial Intelligence/Machine Learning?	Open text

Appendix D
Student Feedback (in Open text and as Written) on what they Liked Most and Least about the Course

What did you like the most about the Machine Learning course? (x=Frequency of similar repetitions)*†

“Everything” (12x) / “I don’t know” (6x) / “Image classification” (2x) / “The part of separating the images” / “Identifying the objects” / “Learning haha” / “The images” / “From the learnings” / “Group work” / “Programming” / “Programming” / “I liked the fact that it showed how simple it is to create this artificial intelligence model” / “The classification of the images” / “The model we can create for recycling” / “I don’t know why I don’t remember!” / “The practical ease of doing the activities” / “Learning what Machine Learning means” / “A little of each thing” / “Learning to program the system” / “Training the machine” / “Separate the garbage” / “When training the robot” / “More or less” / “The part of teaching a machine” / “The idea of creating artificial intelligence” / “The issue of teaching a machine” / “I liked the part about how to recognize images” / “The activity of Separating the garbage” / “I think I liked everything” / “Separate the recycling images” / “Learning about computers and systems” / “Knowing how to select the images correctly and working with folders” / “I liked the machine’s classification of what is metal, plastic, etc...” / “I liked the way it teaches AI to learn about things.” / “I liked the selection of images, working with computer folders and doing image classification to fill the progress bar on the website.” / “I liked everything” / “I liked the identification of images” / “It makes things easier in everyday life, like basic garbage” / “Last Tuesday was my first time in this course and I’m really enjoying it, learning new things” / “What I liked the most was, how a robot can be intelligent, and how we can teach it to be intelligent” / “Programming” / “Only now do I know what it is and I believe that someday it will be useful for me to create a game or something” / “Many things” / “Separate metal from paper, plastic.”/ “The classes” / “Artificial Intelligence” / “I found everything interesting” / “I liked creating websites” / “I don’t know what I liked the most” / “Separating the images for the computer to try to guess” / “I would like to have more classes..” / “I liked it because I learned a lot that is very important for the work area” / “Separation of recyclables and knowledge” / “The way you pick the images and the machines say what it is” / “Almost everything”/ “The part of creating artificial intelligence” / “I didn’t like it, but I learned something more for the job market in case I needed it.” / “The practical activities” / “Learning about what Machine Learning is and how it works.” / “Learning about the machines and knowing that they learn” / “Seeing how intelligence works, how it learns, and so on” / “A little bit of everything... I liked learning everything.” / “I found it an incredible experience because it’s new learning” / “Separating the garbage” / “Assembling the neurons” / “Learning more about technology” / “The teacher” / “It was an interesting and educational experience” / “The ability to see the differences between objects” / “It’s about things that will happen in the future, it’s already happening” / “It was new content” / “I had some difficulties so I don’t have an opinion on it.” / “Some examples of what can help me” / “Yes” / “Being able to create an app to recognize what type of material it is” / “The theoretical part” / “I liked the part of creating an AI” / “Development” / “It was taught in a practical way.” / “It was the development of an AI in class” / “The activity of recognizing paper, plastic, metal, and glass” / “Separating the images” / “Learning and development in the area” / “Understanding how Artificial Intelligence learns things, how each neural network helps it identify things” / “Learning” / “The practical classes when we had the opportunity actually to train this artificial intelligence” / “So far none” / “The activities in general like the Codemaster” / “Making intelligence learn to identify images” / “The way we were treated” / “I liked everything in general” / “Learning more about things I didn’t even know”.

What did you like the least about the Machine Learning course? (x=Frequency of similar repetitions)* †

“Nothing” (8x) / “The explanation (4x)” / “I don’t know” (3x) / / “Program” / “I didn’t learn much” / “Most of the classes” / “Doing it on the computer” / “I don’t remember” / “Almost nothing” / “I had no disappointments” / “I liked everything” / “I don’t know either” / “It goes too fast haha” / “It’s kind of easy to learn” / “I don’t remember” / “I liked everything” / “From the first class” / “It could be in-person and not by call” / “I think it was the explanation” / “There was no such opinion” / “Choose things to prune in the garbage” / “More or less” / “It’s good” / “I liked everything” / “The issue of development” / “I liked everything” / “Separate the images by folder haha” / “The classes are a little boring” / “The brain part was a bit difficult” / “People who mess around” / “I liked everything, it was learning about what I didn’t know yet” / “Nothing, I liked everyone” / “It’s coming to an end” / “The duration of the classes, and the classes not being in-person.” / “I liked everything in the course.” / “I liked everything.” / “There’s nothing I liked less or more” / “I don’t have” / “That drawing app, where we draw and the robot tries to guess what it is” / “There’s nothing” / “Programming haha” / “The delay and quality of the classes, these online classes were not so good, not the teacher’s fault but Moodle’s, because even following the tutorial examples it didn’t work”.

*exactly as it was written. †only revealed comments with content.

Appendix E
Student Feedback (in Open Text and as Written) on What most Motivates them to Study AI/ML.

What motivates you to study Artificial Intelligence/Machine Learning? (x=Frequency of similar repetitions)* †
“Don’t know.” (3x) / “Learn.” (2x) / “Robots.” (2x) / “Nothing.” (3x) / “Learn.” (2x) / “I am interested in the subject.” (2x) / “Knowledge.” (2x) / “Learning new things.” (4x) / “Learn a little about artificial intelligence.” / “To learn more.” (3x) / “To make my own.” / “A lot of stuff.” / “The internet, the different experiences that can be used in the future too.” / “Programming.” / “Personal development.” / “Employment.” / “I feel that it is a way to be ahead in the society of the future.” / “I find it interesting and it can help me in the future with my knowledge.” / “Which is a very good field of study for the future.” / “The lack of people in the market causes overpricing of the service.” / “Knowing that I will have more to add to my resume.” / “My future.” / “The pursuit of new experiences.” / “Pretty cool.” / “Developing intelligent devices.” / “More or less.” / “Learning to build a machine.” / “Learning more about machines.” / “Cool.” / “Learning and helping with my creations.” / “This can help me in a future career.” / “Building a robot.” / “Interest in making machines.” / “It motivates me because it’s a means of work that I plan to pursue.” / “For the next evolution of the world.” / “To create an AI that accomplishes the objectives I desire.” / “It motivates me to improve myself more and more in the field of computing and to pursue this area for work in the future.” / “Later on, I will have a better understanding.” / “Learning and developing new knowledge.” / “Being able to facilitate basic things in everyday life.” / “My performance in the future.” / “It motivates me because there will be plenty of opportunities and such.” / “I think it’s cool how a robot can have so much knowledge.” / “The functioning.” / “Creating something that makes my daily life easier.” / “Maybe it will be useful later on.” / “The future.” / “To learn new things.” / “To be honest, almost nothing motivates me.” / “To know more about the subject.” / “Learning to work with artificial intelligence.” / “To help people, I don’t know what to say actually.” / “It’s interesting to learn new things.” / “The opportunities that this can bring me.” / “Curiosity and wanting to know more about machine learning.” / “I want to work in this field someday.” / “Working with computing.” / “Being able to do cool things.” / “I can create something that can help me and society.” / “I want to understand this area.” / “Nothing, except the job market.” / “The outcome.” / “To have knowledge for future jobs.” / “To have more knowledge.” / “Learning new things, having new experiences.” / “Curiosity.” / “People.”/ “I want to learn everything about technology” / “Wanting to learn more about artificial intelligence” / “Working with it” / “It is necessary to learn new things, because it will be useful in the future” / “The practice of working with technology” / “My future, because I want to work in computing” / “It’s useful” / “I think trying to change daily life, changing some professions” / “When I think about what I want to learn” / “In the programming part” / “Because I can develop any kind of artificial intelligence” / “It can be used in the future” / “To know more about how I can make my future more modern and autonomous” / “Gaining experience in the field” / “Because it is something very present in our reality and will be even more so in the future” / “The endless possibilities” / “I think it’s very interesting” / “I like it” / “The development of the classes made me more and more interested in the field” / “Knowing that it is a growing market and can generate income for me” / “To have a more cultured mind” / “The knowledge of new technology that is directly related to our lives” / “Actually, it’s more to know and understand what machine learning is, not necessarily a motivation.” / “To learn more about the potential of technology” / “I believe in developing a machine that can assist someone in their daily life.” / “To know more about it and be able to talk about it with a friend.” / “I like to study about everything in general” / “Learning about technology”.

*exactly as it was written. †only revealed comments with content.

Appendix F
Student Feedback (in Open Text and as Written) on Other Comments about the ML4ALL Course.

Any other comments?
“I really enjoyed everything.” / “Everything went well.” / “I liked the learning concept and the professionals.” / “The classes were very good, but I would prefer if they were in person because I can learn better that way.” / “No, thank you very much for the opportunity to learn machine learning, professor!” / “Thank you for this opportunity.” / “The classes were great, the professor teaches very well, no wonder he is a professor at UFSC.” / “No thank you for everything, bye.” / “Perfect classes! I thought the course, in general, was very cool.” / “Nothing else to add.” / “Gaining experience in the field will help me in my future.” / “I have enjoyed everything so far, and the teachers are very good too.”