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# Exploring Student Self-Efficacy in AI Through Model Building Artifacts

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# Exploring Student Self-Efficacy in AI Through Model Building Artifacts

## Introduction

With the recent integration of Artificial Intelligence (AI) and Machine Learning (ML) within schools on the rise, students must get hands-on experiences with these technologies. New technologies require that we ask new questions in new ways, and so there is a need for research in AI and ML in the current educational contexts [1], [2]. AI is the theory and development of computer systems able to perform tasks normally requiring human intelligence which can include visual perception, speech recognition, learning, decision-making, and natural language processing [3]. ML is a subset of AI in that it has machines learn from currently available data to reach new conclusions [4]. In this study, a group of middle and high-school-aged Black scholars partook in a summer program for two weeks to learn about AI in science. Throughout the program, they explored how paleontologists utilize computer vision to classify images for scientific purposes. The children also identified potential issues with AI, such as biases in the datasets used to train ML models. Not only did the scholars learn about AI, but they also had hands-on experiences building models using Google Teachable Machine, a teacher and student-friendly tool for classifying data. For their project presentations, participants created posters that identified community-relevant issues to address via computer vision, the classification to perform, the data they used, and classification accuracy.

This study analyzed participants' project artifacts and self-efficacy for AI through the implementation of surveys taken before and after the two-week-long program. The surveys in this course were based on sources of self-efficacy identified in Bandura's social cognitive theory [5]. Additionally, this study was informed by the expectancy-value theory as identified by Wigfield and Eccles [6], hypothesizing that higher self-efficacy beliefs can be associated with better-designed and implemented projects, as scholars are more engaged and open to learning.

In this study, student self-efficacy was explored relative to how they completed their posters and projects in the camp. Investigating students' self-efficacy in relation to AI is crucial, as it influences their engagement and success in AI-integrated learning environments. Self-efficacy, or one's belief in their ability to succeed in specific tasks, affects motivation and learning outcomes. Research indicates that successes and challenges in AI-focused educational activities can indirectly enhance students' critical thinking by strengthening general self-efficacy and learning motivation [7]. The integration of AI in educational applications has a dual-edged impact on students' creativity and academic emotions. While AI can stimulate creativity and engagement, it may also lead to challenges such as creativity constraints and performance anxiety [8]. Additionally, studies suggest that frequent and satisfying interactions with AI tools can enhance students' self-efficacy and engagement [9]. Understanding how AI influences self-efficacy is essential for developing effective educational strategies that leverage AI's benefits while mitigating potential drawbacks. This knowledge can inform the design of AI-driven educational tools that support and enhance students' learning experiences. Therefore, researching students' self-efficacy concerning AI in education is vital for optimizing AI's role in fostering positive educational outcomes.

## Theoretical background

*Social Cognitive Theory*

This project is based on Bandura's theory of social cognitive theory which identifies learning as being influenced by three main factors: a person’s behavior, their external environment, and their personal factors [5]. The understanding of the interactions between these three factors can positively impact student retention and learning of information.

There is an interaction through the different things that people experience for them to believe that they are capable of something. Bandura [10] states that people “construct for themselves their own standards through reflective processing of multiple sources of direct and vicarious influence”[10, p. 254] Thus, students are subject to be influenced by a variety of perspectives. They will believe that they are capable of achieving based on what their environment supports, what their role models in their life are doing, and their personal beliefs.

*Self Efficacy*

Self-efficacy is a key component of Bandura’s social cognitive theory. Self-efficacy refers to “people's beliefs about their capabilities to produce designated levels of performance that exercise influence over events that affect their lives” [11, p. 1]. Thus, self-efficacy is crucial for students to be successful in future academia. If a student believes that they are not capable of completing a class or task, that can discourage them from pursuing higher education. According to [12], “if students believe they cannot succeed on specific tasks (low self-efficacy), they will superficially attempt them, give up quickly, or avoid or resist them” [12, p. 219]. This is a pertinent issue to instructors as it can lead to a snowball effect that hinders educational opportunities in the future. If someone struggles and is resisting higher-level STEM courses, because of their low self-efficacy, they can restrict their own access. In [13], the authors explain that “the access to science and mathematics courses in formal learning environments often directly affects a student’s interest in STEM” [13, p. 6]. The time to encourage students and support them is now.

*Expectancy-Value Perspective on Self-Efficacy*

Expectancy-Value Theory (EVT), as articulated by Wigfield and Eccles [6], is another useful lens for understanding self-efficacy relative to achievement motivation. It posits that an individual's motivation to engage in a task is determined by two key factors: their expectancy for success and the value they place on the task. Expectancy for success refers to a person's belief about how well they will perform on an upcoming task. It is influenced by self-efficacy and perceptions of task difficulty. Subjective task value encompasses several components: a) intrinsic value (the inherent enjoyment or interest in the task), b) attainment value (the personal importance of doing well on the task, often linked to one's identity), c) utility value (the perceived usefulness of the task in achieving future goals), and d) cost (the perceived negative aspects of engaging in the task, such as effort, time, and potential loss of alternative activities).

EVT suggests that individuals are more likely to engage in tasks where they expect to succeed and that they value highly. Conversely, low expectancy and value can lead to task avoidance. This theory has been instrumental in educational psychology, providing insights into students' choices, persistence, and performance across various academic domains. It also informed the design of the summer camp program on computer vision, which is discussed in this study. Specifically, activities were designed to create high expectancy for success through the focus on community-relevant issues and computer vision model-building activities of interest to the teenage participants. Throughout the curriculum, the facilitators and activities reinforced subjective task value by highlighting the unique and important applications of AI in science and in the participants' daily lives. These curriculum design decisions were made to nurture participants' self-efficacy for AI and improve childrens' perception of the activities as interesting and relevant [14].

*Black Students in STEM*

Our program was conducted with Black children as program participants. This implementation was strategic because as seen throughout history, Black students have had more limited opportunities to engage in STEM activities in the classroom [15]. While society has improved over the years, some of these disparities are still being perpetuated by institutions. Thus, there is a lack of Black representation within STEM. Many factors impact a Black student's STEM identity, including cultural factors, environmental factors, and psychological factors [16]. To further identify the inequities that are perpetuated in STEM for Black students, an example of an external environment that impacts students can be seen through space exploration. According to Collins [16], "Without pronounced personal interest, if they never see astronauts that look like them nor understand how that career field will affect their innermost circle of friends and family, there is decreased value to that field of study for them" [16, p. 161]. Figure 1 further demonstrates how these aspects contribute to a STEM identity.

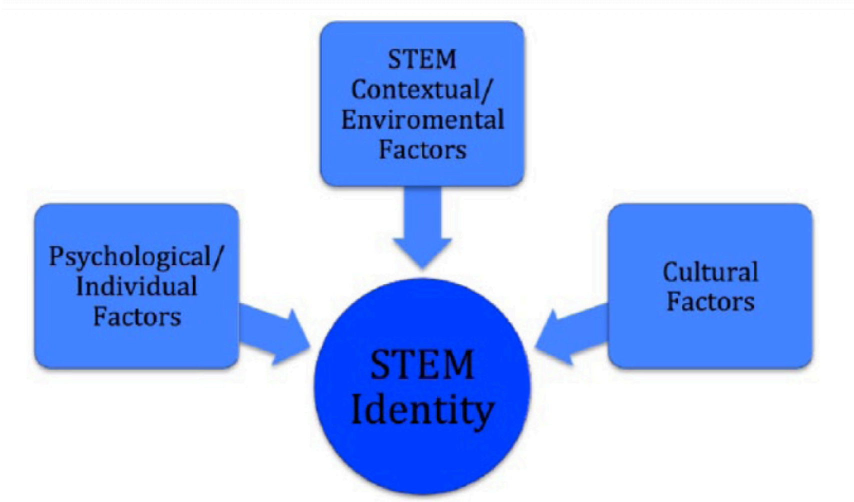


Figure 1. Black student STEM identity [16].

## Methods

*Research Design*

This study used a mixed-method methodology to explore students' self-efficacy and performance based on quantitative data sources (pre- and post-implementation surveys and qualitative sources (quality of participants' final posters and computer vision models). Specifically, this study addressed the following research questions:

1. How does Black girls' and boys' self-efficacy for AI develop during a computer vision focused summer program?
2. To what extent are participants' self-reported self-efficacy related to their performance on the design of an AI-focused poster and building of a computer vision model? Are there gender differences?

*Study context and participants*

This study is part of an National Science Foundation-funded project to infuse computer vision and machine learning activities in formal and informal learning environments. The specific module that is the focus of this study was implemented in a summer camp conducted in the Southeastern region of the United States. This camp is a STEM summer camp that enrolled participants from the local area. This module ran for two weeks of the eight-week summer camp. The participants and instructors utilized Google Teachable Machine to give them a basic understanding of different scientific concepts such as computer vision, and artificial intelligence. Participants were not expected to have prior knowledge of this topic and were randomly enrolled.

*Participants*

The summer camp included 60 participants with varying attendance in two groups: boys (n=32) and girls (n=28). They were separated based on gender into two rooms. They participated in a seven-week STEM-themed summer camp that hosted our two-week program on AI in paleontology. Of these 60 participants, 33 provided all data, including GTM models, posters, and pre- and post-survey data. Survey data was received from 16 boys and 17 girls. Forty-one participants provided posters, and 42 provided GTM models. All of the participants identified as Black and were local to the area.

*Curriculum Overview*

The curriculum for this program took place over two weeks of the camp. The purpose was to familiarize teenagers with artificial intelligence (AI) and to teach them about different related concepts and terms to give exposure to a hot topic. This was taught through the utilization of Google Teachable Machine (GTM), an easy-to-use tool for creating computer vision models. This approach allowed for an entry-level hands-on experience with AI that allowed participants to have direct manipulation and feedback.

The program encouraged participants to have an active role in their learning, which follows a constructivist approach to teaching and facilitation. The summer program began with participants learning about datasets through the use of iNaturalist when visiting a garden anda  museum. They also completed teamwork and planning activities. After this, more scientific discussions began with the use of a peanut butter and jelly recipe writing activity, which served as a segue into a discussion about algorithms and the importance of data in training AI models. From there, GTM was introduced using the example of shark teeth and three classes: cutting teeth, grasping teeth, and crushing teeth. Computer vision was discussed as a type of AI that is often overlooked in K-12 AI education at the expense of increased emphasis on generative AI tools like ChatGPT. This then led to participants creating teams and negotiating their final project topics.

Thus, participants were encouraged throughout the program to not only participate in discussions but also engage with the materials. The teenagers were encouraged to be as creative as possible. After the models and posters were completed, the participants presented them in a showcase at the end of the two weeks. Children's parents and community members were invited to learn about AI, computer vision, and paleontology during the showcase and celebrate camp participants' accomplishments. This enabled them to not only participate but also to explain the importance of AI in science to their peers and community. This enabled scholars to feel a personal connection as their scientific project was envisioned within a real-world context.

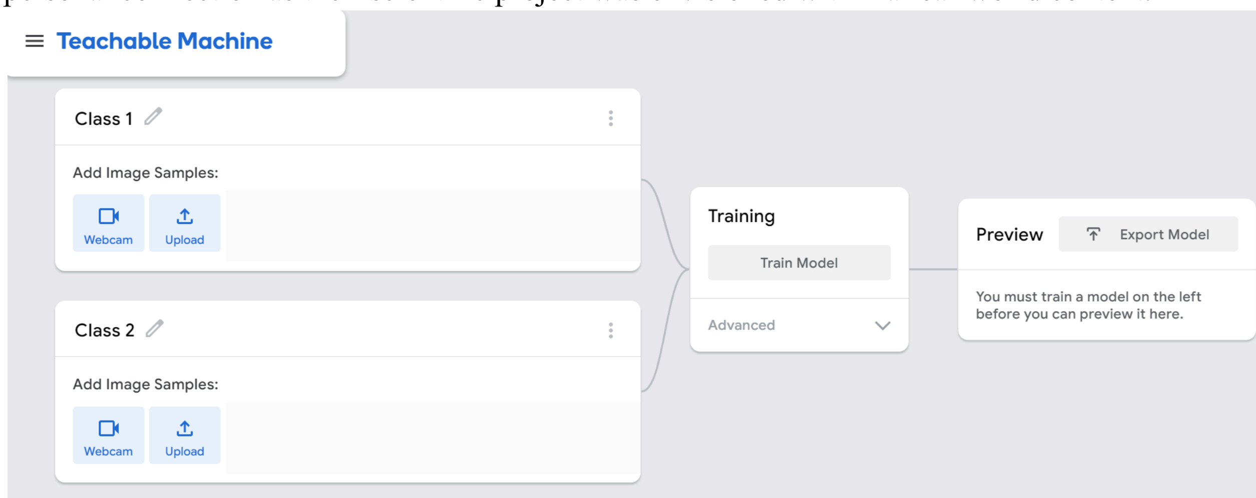


Figure 2. Google Teachable Machine [16].

*Measures and data sources*

The self-reports of the children's self-efficacy for AI were collected via a survey administered on Qualtrics before and after the Shark AI program. Self-efficacy for AI was assessed using an adapted version of the original Science subscale (9 items) and the Technology and Engineering subscale (9 items) of the widely used 37-item S-STEM questionnaire developed by North Carolina State University's Friday Institute [19]. Only the Science and Technology subscales were used for this study to assess a) self-efficacy for doing science with AI and b) self-efficacy for engaging with AI technologies. The verbiage was adapted to inquire about young people's beliefs regarding their self-efficacy for AI. In this study, "science" was appended with "and AI." For example, the original item for science attitude item one, "I am sure of myself when I do science," was adapted to "I am sure of myself when I do science and AI." Similarly, the Technology and Engineering subscale of the S-STEM instrument was modified to add "AI" before the word "technologies" in the scale. For example, the item "I believe I can be successful in a career in technologies" was changed to "I believe I can be successful in a career in AI technologies." The internal consistency of items in the original Science subscale was reported to be = .89. The internal consistency of the original Technology and Engineering subscale reached = .90. The original validation scale was conducted with 9,081 middle and high school students, which is consistent with the population explored in this study [19]. While there were sixty participants, not all were present for all days. Thus, data were only collected from thirty-three participants, leading to limitations in data analysis.

Students' computer vision models and posters were evaluated using authentic assessment rubrics (Appendices A and B). One of the team's model and poster are provided in Figures 3 and 4.

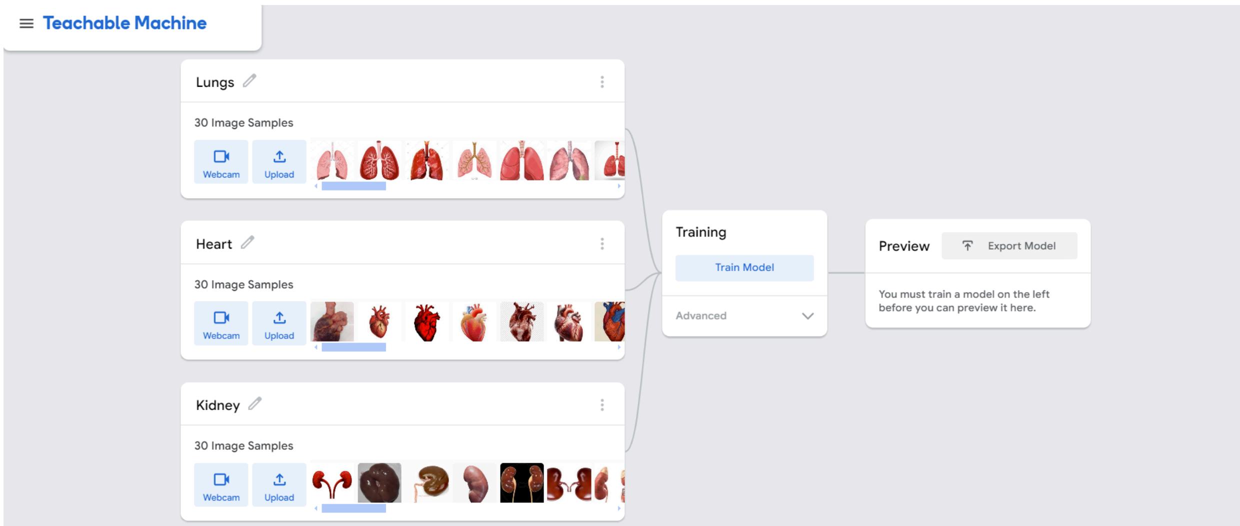


Figure 3. An example of one group's computer vision model.

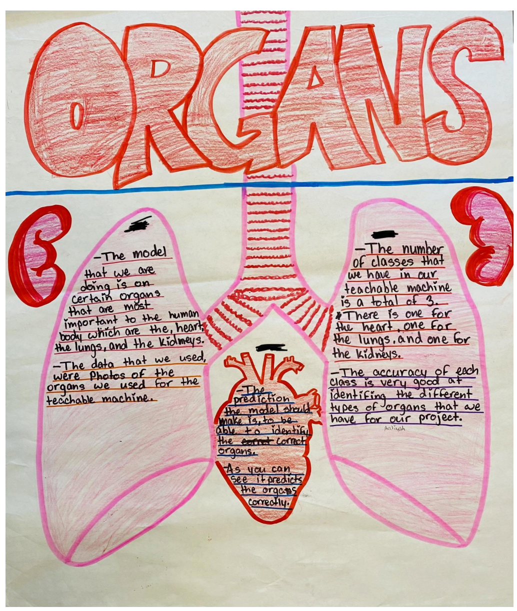


Figure 4. An example of one group's poster.

Posters and GTM models were evaluated using two different rubrics that evaluated questions like whether the topics were STEM-related, innovative, clear, and the quality of the work completed by children. These categories also evaluate the retention of information from the participants as well as how well they were able to create a model that works efficiently. The poster rubric had four different criteria that were assessed on a one-to-three scale. The model rubric had five different criteria that were evaluated on a one-to-three scale. To ensure the validity of the rubrics, they were developed by consulting current rubrics within the field and reviewed by an expert. Three different researchers utilized the rubrics to evaluate the posters. Percent agreement and standard deviations were calculated to ensure reliability among raters.

**Results and discussion**

The self-efficacy surveys were administered before the program began and then again on the final day of the program. Table I provides a summary of the relevant descriptive statistics. The data was analyzed for both groups of students and compared to their poster and model scores. When comparing the pre and post-self-efficacy surveys, improvements in the total SE for AI approached significance at $W_{32} = 316.5$, $SE = 48.49$, $p = .08$).

TABLE I
DESCRIPTIVE STATISTICS

| | **N** | **Minimum** | **Maximum** | **Mean** | **Std. Deviation** |
|---|---|---|---|---|---|
| Pre-AI For Science SE Score | 33 | 15 | 36 | 28.12 | 5.8 |
| Pre-AI For Tech SE Score | 33 | 21 | 38 | 31.61 | 4.53 |
| Pre-Total SE Score | 33 | 43 | 74 | 59.73 | 9.13 |
| Post-AI For Science SE Score | 33 | 17 | 40 | 29.09 | 5.47 |
| Post-AI For Tech SE Score | 33 | 22 | 43 | 33.48 | 5.13 |
| Post-Total SE Score | 33 | 44 | 81 | 62.58 | 9.63 |

Two types of artifacts were evaluated in this study: posters and GTM models. Both the posters and GTM models were created in groups of three to four people. After the completion of the study, the artifacts were rated by three different raters. Each rater has experience with the topic and was present throughout the Shark AI program. Tables II and III show the topics, average score, standard deviations, and agreement percent among the three raters.

TABLE II
POSTER DATA

| Topic | Score | Standard Deviation | Agreement Percent |
|---|---|---|---|
| Color identifier | 86.11 | 0 | 100 |
| Organ | 91.67 | 0.58 | 75 |
| Rocks | 77.78 | 0 | 100 |
| Color of Plants | 88.89 | 1.15 | 25 |
| Solar System | 86.11 | 0 | 100 |
| Mushrooms | 88.89 | 0 | 100 |
| Leopards & Jaguars | 55.56 | 0 | 100 |
| Bees & Hornets | 58.33 | 0.58 | 75 |
| Crocodile & Alligator | 47.22 | 0 | 100 |
| Dolphins & Sharks | 61.11 | 0.58 | 75 |
| Hives & Chicken Pox | 66.67 | 2 | 25 |
| Venomous & Non | 80.56 | 1.15 | 25 |
| Cheetah & Jaguar | 100.00 | 0 | 100 |
| Carnivores and Herbivores | 77.78 | 0.58 | 75 |
| Locs and Braids | 0.00 | 0 | 100 |

TABLE III
GOOGLE TEACHABLE MACHINE MODEL DATA

| Topic | Score | Standard Deviation | Agreement Percent |
|---|---|---|---|
| Color identifier | 86.67 | 0.58 | 80 |
| Organ | 88.89 | 0.58 | 80 |
| Rocks | 75.56 | 0.58 | 80 |
| Color of Plants | 86.67 | 0 | 100 |
| Solar System | 88.89 | 0 | 100 |
| Mushrooms | 97.78 | 0 | 100 |

| | | | |
|---|---|---|---|
| Leopards & Jaguars | 82.22 | 0.58 | 80 |
| Bees & Hornets | 66.67 | 1.53 | 60 |
| Crocodile & Alligator | 77.78 | 0.58 | 80 |
| Dolphins & Sharks | 73.33 | 0 | 100 |
| Hives & Chicken Pox | 75.56 | 3.06 | 20 |
| Venomous & Non | 88.89 | 0.58 | 80 |
| Cheetah & Jaguar | 93.33 | 0 | 60 |
| Carnivores and Herbivores | 80.00 | 0 | 100 |
| Locs and Braids | 57.78 | 0.58 | 80 |

According to a Spearman Rho correlation analysis, there was a strong positive correlation between poster scores and model scores ($r = .86$, $p < .001$). Girls' teams posters resulted in higher scores (mean rank of 11.25 for girls versus mean rank of 5.83 for boys) and a Mann-Whitney U analysis determined that this difference was significant ($U = 7.5$, $z = -2.30$, $p = .02$). Girls' GTM models were also better according to the raters than those of the boys (mean rank of 10.42 for girls versus mean rank of 6.39 for boys) but this difference did not reach statistical significance ($p = .08$).

Analyses were also performed to explore correlations between participants' poster scores, model scores, and self-efficacy for AI for science, self-efficacy for AI for technology, and total self-efficacy scores on the pre- and post-surveys. Scholars' poster scores and model scores were not correlated with their self-efficacy scores. One explanation for this finding could be the nature of the context. Summer programs are informal and do not have grades or other assessments that hold students accountable for the quality of their projects. Another explanation could be that the learners performed better due to the social expectations of working in groups and their feelings of individual accountability [18]. The participants could have been more enticed to produce better quality work as to not let their peers down which could be the reasoning for projects lacking correlation with self-efficacy.

Prior research on self-efficacy for STEM also shows that higher self-efficacy for science or STEM does not always lead to higher learning performance in these subjects. For example, [21] published a meta-analysis that examined the relationship between self-efficacy and academic performance. While there was a moderate overall correlation between self-efficacy and academic performance, the study found that in some subjects, such as science and mathematics, the relationship was weaker, suggesting that high self-efficacy in these subjects does not always translate into higher performance. A longitudinal study by [21] assessed the role of self-efficacy in science achievement. While self-efficacy initially predicted positive attitudes and motivation, the study found no consistent relationship between self-efficacy and actual academic performance in science. The authors emphasized that motivation, persistence, and study strategies could mediate or overshadow the effect of self-efficacy on learning outcomes.

## Significance

This study has useful implications for K-12 and informal educators working with middle and high-school-aged teenagers and for preparing the next generation of AI-skilled students. By exposing youth to different STEM topics with a support system such as the curriculum and summer program described here, they are more likely to feel positive self-efficacy. Additionally, this hands-on approach can motivate teenagers to pursue AI and science fields and increase their interest in STEM-related topics. This can lead to greater self-efficacy for AI and STEM and improved participation of individuals from traditionally underrepresented groups STEM degrees and careers.


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## Appendix A

This appendix includes the rubric for the Google Teachable Machine Models. They include the criteria, score options, and scoring guidelines for each artifact.

Google Teachable Machine Rubric

| Category | 3 | 2 | 1 |
|---|---|---|---|
| Model Training/ Sample Selection | The model is trained using multiple classes that each contain equal amounts of image samples. | The model is trained using multiple classes with sample sizes varying by <½ of the set images. | The model is trained using multiple classes with sample sizes varying by >½ of the set images. |
| Quality of Images | The images are high-resolution, well-lit, and properly focused to allow for the identification of | The images have noticeable quality issues which may not allow the model to train and learn | The images are of poor quality and have major issues demonstrating key features. |

| | | | |
|---|---|---|---|
| | key features. | effectively. Image composition may be inadequate for feature identification. | |
| Diversity of Images | The images are very diverse with varying backgrounds and angles. | The images have noticeable limits which can lead to biases. | The images are almost identical to one another with little to no variety which can lead to biases. |
| Model Accuracy and Performance | The model demonstrates high accuracy (above 90%) when identifying classes with minimal errors. | The model has moderate accuracy (75-90%) with frequent errors in identifying the classes. | The model has little to no accuracy (below 75%) and is unreliable in identifying classes. |
| Science Creativity | The model shows novel ideas that are original and executed in an intentional and thoughtful manner. | The model is limited in its topic and is functional but not very original. | The model lacks creativity and originality. The bare minimum was done. |

Appendix B

This appendix includes the rubric for the poster projects. They include the criteria, score options, and scoring guidelines for each artifact.

Poster Rubric

| Category | 3 | 2 | 1 |
|---|---|---|---|
| Clarity and Organization | The poster is well-organized with a clear flow of information. All sections are clearly labeled | The poster has some organization, but the flow may be confusing. Sections are inconsistently labeled. | The poster lacks organization making it difficult to understand. Labels are missing or confusing. |
| Content Justification and Understanding of Content | Shows a full understanding of the topic. Explains | Shows a general understanding of the topic. Is | Does not understand the topic and does not explain |

| | | | |
|---|---|---|---|
| | relevance and importance. Contains a proper table identifying a number of classes, sample sizes, and accuracy. | missing either relevance and importance or a proper table identifying most of the information about the number of classes, sample sizes, and accuracy. | importance or relevance. Does not contain a table with any information about the model. |
| Visual Appeal and Design | The poster is visually engaging, with a balance of images, color, and text that are relevant to the topic. | The poster is basic and does not enhance the topic. Visuals are cluttered or too simple. | The poster is unappealing or distracting and any elements used detract from the topic. |
| Spelling and Grammar | The presentation has no misspellings or grammatical errors. | The presentation has 1-2 grammatical errors but no misspellings. | The presentation has more than 2 grammatical and/or spelling errors. |