DataBites: An embodied, co-creative museum exhibit to foster children's understanding of supervised machine learning

Hasti Darabipourshiraz
Hastidarabi@u.northwestern.edu
Northwestern University
Evanston, Illinois, United States

Dev Ambani
devambani2025@u.northwestern.edu
Northwestern University
Evanston, Illinois, United States

Duri Long
duri@northwestern.edu
Northwestern University
Evanston, Illinois, United States

Figure 1: DataBites museum exhibit, Pizza/Sandwich fixings constructed using ©Adobe Stock

ABSTRACT

It is essential to increase children's understanding of artificial intelligence and machine learning as they encounter it through their daily activities. We have developed *DataBites*, a museum exhibit aimed at fostering middle-school-age children's understanding of supervised machine learning. *DataBites* engages visitors in learning about the steps and practices of supervised machine learning, using three guiding design principles: embodied interaction, creativity, and collaboration. Our design allows learners to use tangible pieces to collaboratively create their own labeled examples of pizzas and sandwiches to include in a training dataset for an image-based machine-learning pizza/sandwich classification algorithm. The algorithm can classify sandwiches and pizzas by learning patterns from people's examples. Learners can view the results and self-evaluate how well their dataset did at enabling the algorithm to distinguish between the two items. This poster paper contributes a novel design and approach to engaging children in learning about AI in museum settings.

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CCS CONCEPTS

• **Human-centered computing** → **Interface design prototyping**; **Interactive systems and tools**; • **Social and professional topics** → **Informal education**; • **Applied computing** → *Collaborative learning*.

KEYWORDS

Museum exhibit, AI Literacy, AI education, ML education, tangible user interface, informal learning, supervised machine learning

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1 INTRODUCTION

Many kids around the world regularly use artificial intelligence and machine learning. Most interactive toys, games, mobile phones, and internet platforms made for children depend on AI and ML technology. Therefore, it is essential to increase children's comprehension of AI as they encounter it regularly through their daily activities. The earlier young learners are introduced to AI, the easier it will be for them to comprehend it, think critically about it, and learn how to use it to their advantage. We argue that it is important for every child to develop AI literacy, which refers to "a set of skills that enable individuals to evaluate AI critically, communicate and collaborate efficiently with AI, and use AI as a tool online, at home, and in the workplace" [24].

Research in education and design has only recently begun to explore how to introduce AI to kids through interactive demonstrations of AI technologies, kid-friendly AI coding platforms, and AI-focused curricula for K-12 classrooms (e.g., [14], [35], [12]). However, there has been comparatively little research on how to design tangible and co-creative AI education initiatives for informal learning spaces such as museums, which play an important role in public science education and can aid in increasing content knowledge and building connections between science and everyday life [29]. Moreover, creativity is an important part of children's education and tangible user interfaces (TUIs) provide exciting possibilities for creative, collaborative learning [22].

The purpose of this project is to investigate the following research question: *How can we leverage co-creation and tangible interaction to design a museum exhibit that engages middle school age (10-14 year old) children in learning about AI?*

In this paper, we present the design of *DataBites*, which is a creative, embodied, and collaborative museum exhibit aimed at fostering middle-school-age children's understanding of supervised machine learning, a type of artificial intelligence.

2 RELATED WORK AND BACKGROUND

2.1 AI Education in Museums

In recent years, AI museum exhibits have been limited because of the field's novelty and the cost and fragility of many AI systems/devices. It can also be difficult to illustrate the inner workings of AI in a museum setting since they are not easily observable or interactive [11]. Our prior work offers one of the only empirical studies of AI literacy in an informal learning space, exploring how learners engage with three at-home activities in which they can use tangible and interactive interfaces to explore some AI concepts like semantic networks, decision-making, supervised machine learning, and unsupervised machine learning [26]. In this project, we seek to build on these findings within a museum setting.

Other exhibits that have explored AI include Ars Electronica's *Understanding AI*, which featured installations where visitors could interactively explore how ML technologies work [3]; *Exploring AI: Making the Invisible Visible*, an exhibition in the Boston Museum of Science that showcases various examples of AI that we encounter in our daily lives [4]; and *Virtually Human*, an exhibit in The Lawrence Hall of Science Museum that teaches children how AI mimics human behavior [5].

2.2 AI Education focused on Machine Learning

Several games and platforms are designed to specifically teach ML concepts to novices. The *AI4K12* working group has developed a set of AI- and ML-related standards for K-12 grade bands, in collaboration with AI researchers and K-12 teachers [35]. Projects like *ML-Quest* and *LearnML* have explored how to teach ML concepts through games [30, 37]. Other projects like *Teachable Machine* and *MLM* have been developed in the form of graphical and tangible user interfaces to facilitate easier manipulation and training of ML models [12, 21]. *LearningML* is a platform that supports educators and students in the creation of hands-on AI projects, specifically based on machine learning techniques [32]. Some projects allow learners to program AI or train ML algorithms using novice-friendly coding platforms such as Scratch or MIT App Inventor [14, 36]. Also, *Scratch-NB* is an extension to Scratch to equip K-8 learners with foundational tools for developing a Naive-Bayes classifier, explicitly making its internal components transparent [31].

More studies are needed in this field, despite existing research. Sanusi et al. note that "[ML education] resources are more prevalent in high school than in kindergarten to middle school. It is also introduced more in formal school settings than in informal settings. The studies are mainly connected to computing skills which necessitate more research to be conducted on integrating ML into core subjects and domains" [33]. Consequently, there is a gap in interdisciplinary human-computer interaction and education research investigating how machine learning and artificial intelligence literacy are currently implemented in informal learning experiences like museums for young children.

3 *DATABITES* EXHIBIT OVERVIEW

DataBites engages visitors in learning about the steps and practices of supervised machine learning. *Supervised machine learning* is a type of AI that involves constructing algorithms that use provided instances to predict future outcomes. It is used in technologies like image and speech recognition and recommendation systems. In designing DataBites, we focused on introducing three competencies related to AI literacy [24]. These are: 1) understanding the steps and practices of machine learning; 2) understanding the role humans play in programming and training AI; and 3) understanding that computers learn from data.

In DataBites, we aim to demonstrate a few of the multiple steps involved in developing a ML application, including *dataset preparation*, *training*, and *testing*. Also, we want learners to recognize that the datasets that are used to train ML applications are created and curated by human programmers. DataBites shows how computers can learn patterns from a training dataset, providing children with an interactive learning experience. In this exhibit, children can teach the computer how to classify pizzas and sandwiches based on data points they create. Visitors can interact with tangible materials to create a dataset through a hands-on activity, feed it to the computer, and see the results of the image classification based on the dataset they create. Table 1 summarizes the mappings between learning outcomes and design elements in *DataBites*.

We chose pizzas and sandwiches as the classification topic because learners may have varying interpretations of these foods, making it a personally relevant topic that can spur conversation and debate (just Google "Is a hotdog a sandwich?" for a lively discussion). In addition, this topic is readily approachable, as it is in a non-technical area.

In order to create an engaging and educational museum exhibit with the DataBites installation, we focused on three key guiding principles–creativity, collaboration, and embodied interaction. By providing learners with opportunities to explore these areas, we aim to build effective and enjoyable learning experiences for children and their families. Below, we provide a definition of and motivation for each principle.

- *Creativity:* Boden defines creativity as the "ability to generate novel and valuable ideas" [8]. In informal learning spaces, creativity has been shown to encourage prolonged

engagement [20] in addition to facilitating visitor-led learning experiences that can lead to more personally relevant meaning-making [15]. Creative activities have also been shown to foster young learners' interest in computing [28], [10], which we hypothesize may transfer to AI.
- *Embodied interaction:* Dourish defines embodied interaction as "the creation, manipulation, and sharing of meaning through engaged interaction with artifacts'" [13]. In practice, this can take the form of both full-body interactions or engaging with tangible interfaces (e.g., [27], [23]). If implemented well, embodied and tangible interactions have the potential to make abstract concepts more concrete for learners [7], [19], [34] and reduce intimidation [18].
- *Collaboration:* We define collaboration as encompassing both shared dialogue and working together to achieve a shared goal [16]. Group activities have been shown to be motivating for learners in computer science education [38] and, more recently, AI education [25]. Also, it is especially important to provide opportunities for collaboration in museum settings since most visitors come in groups [17].

4 DATABITES DESIGN

4.1 DataBites Installation Design

Our design incorporates a table with six 11-inch x 11-inch segments and a kit of paper-laminated pizza toppings and sandwich fixings to allow learners to build their own pizzas and sandwiches as the labeled examples to include in their training dataset for an image-based machine-learning pizza/sandwich classification algorithm. The algorithm can differentiate between sandwiches and pizzas by learning patterns from people's examples. We use a stationary camera positioned above the table to capture images of the dataset, which are then fed into the computer. To improve the physical-to-digital workflow, we use high-contrast pizza toppings and sandwich fixings with bold strokes to produce a high-quality image of the training dataset as input for the algorithm.

There are three physical buttons available to the learner– the "Start" button to start the activity, the "Train" button to start the training process, and the "Refresh" button to refresh the activity. We utilize a large screen to display the results and provide feedback to the users (Figure 2).

4.2 DataBites System Design

4.2.1 User-Interface Design. We developed a web application that captures pictures of users' datasets as input and shows them the results based on the dataset they create (Figure 3). Once the user hits the "Start" button, the dataset creation starts, and the web application continuously captures frames from the camera stream. Learners can see their dataset-building process on the screen in real-time.

Once learners finish the dataset creation, they hit the "Train" button to start the training process and allow the model to classify the stored images of sandwiches and pizzas. While it is in training mode, the visual display shows a 15-second animation of the classification process due to the time needed for the training process and then displays the results to the users. Results are presented as 40 testing dataset images in a two-column table. One column is for displaying data items that are classified as sandwiches and one column is for displaying data items that are classified as pizzas. Each item has a confidence score indicating the algorithm's level of certainty in its classification. Also, images are arranged in descending order based on their confidence score. This means that the image with the highest confidence score will be at the top, followed by images with lower confidence scores. Learners can view this page and self-evaluate how well their dataset did at enabling the algorithm to distinguish between the two items.

To guide the learners, we include some instructions in the UI to tell them what to do throughout the activity and what is happening in each step. The following are the pop-ups for each step:

- *Start Page:* Welcome to DataBites! Explore the world of machine learning, where computers learn from examples to identify patterns, empowering them to make informed decisions. Tap the "Start" button to begin creating a dataset.
- *Dataset Preparation Page:* Create examples of what a sandwich or pizza looks like using the available ingredients and toppings. Tap the "Train" button once you feel ready to feed the created dataset into the computer.
- *Training Process Page:* The computer is learning from the images you chose for your dataset. It's figuring out how to classify sandwiches and pizzas.
- *Testing Page:* Based on your dataset, the computer has classified these images as sandwiches or pizzas. The confidence scores next to each item represent how sure the computer is that each item is a sandwich or a pizza. Tap the "Refresh" button to test out a new dataset.

4.2.2 CNN Image Classification Model. We created a CNN image classification system that classifies stored images of sandwiches and pizzas based on user-provided examples and labeling. To implement that, we collected a balanced dataset consisting of 3,000 images of pizzas and sandwiches sourced from the Food101 dataset, Food101 dataset (Kaggle version), and Food101-Enriched dataset (Hugging Face), built the CNN architecture for image classification, and finally trained the model using labeled images [1], [9], [2].

Then, we were poised to enhance the model's precision through transfer learning. This strategy involves incorporating a model already trained on a comprehensive dataset and adjusting it specifically for our classification challenge. The significant difference brought by transfer learning lies in its ability to adapt sophisticated models for our nuanced task, ensuring that the introduction of six new, visitor-generated images will be pivotal. These images are expected to profoundly influence the model's ability to accurately classify 40 predetermined images as either pizza or sandwich. The six learner-generated images could improve the model's performance or make it considerably worse, depending on what they put in their dataset.

5 DESIGN PRINCIPLES IN DATABITES

In this section, we describe how each guiding principle–creativity, collaboration, and embodied interaction– is realized in *DataBites* (Figure 4).

Table 1: Learning outcomes and their mappings in the design.

Learning Outcomes	Design Mappings
Supervised machine learning is a type of AI in which the computer learns patterns from many labeled examples.	Labeled examples are presented as pizzas and sandwiches created by visitors which the computer learns from.
Building a machine learning application involves multiple steps, including dataset preparation, training, and testing.	Each step is indicated by a badge in the user interface, to help visitors to understand them.
Human programmers decide what to include in the datasets that are used to train the machine learning applications.	Visitors have complete control over the dataset preparation, including what to include in the dataset.
Machine learning applications can be biased towards a certain outcome if their training dataset does not contain diverse examples.	Including various examples in the dataset helps visitors obtain well-classified results.

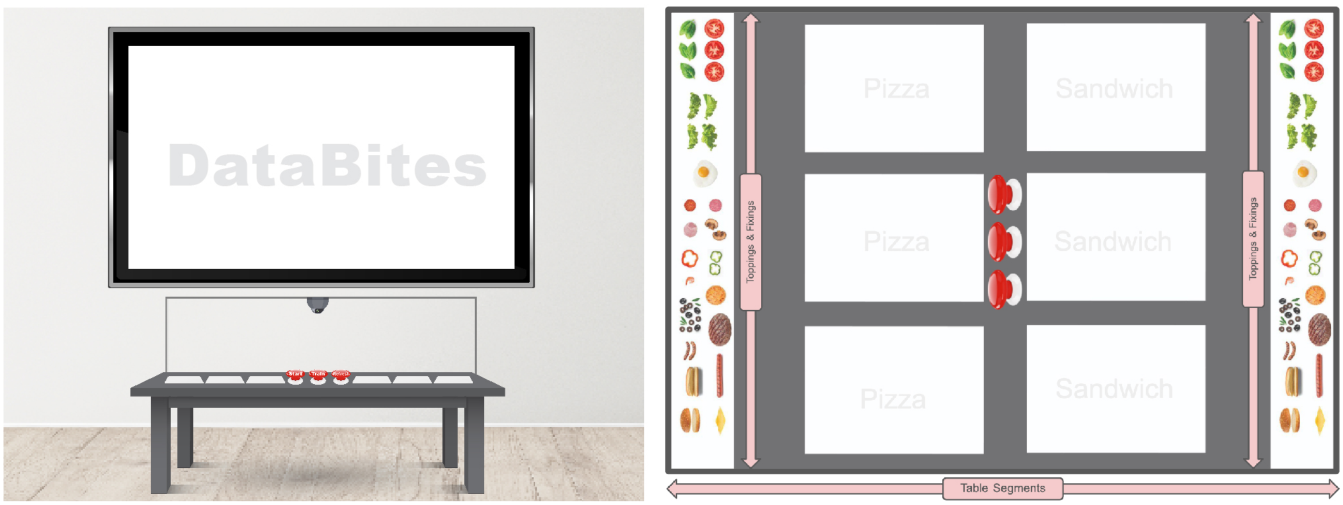

Figure 2: DataBites museum installation and table installation design. Assets constructed using ©Adobe Stock

5.1 Creativity

Visitors are able to use their creativity to craft the dataset by making their own data (sandwiches and pizzas) using the available materials and placing them on the table slots. Learners can creatively explore how to generate exemplar data as well as edge cases (e.g., sandwich toppings on a pizza) and interactively explore how different data items affect their output.

5.2 Embodied Interaction

The exhibit incorporates tangible interactives that allow learners to create their own labeled data items. In addition, designing the museum exhibit on a large scale enables visitors to interact with full-body interaction.

5.3 Collaboration

In DataBites, a group of people (at least two) collaborate to build a dataset and train the computer. Ideally, we aim to allow each person to create three examples of one type of data (one person creates the pizza dataset and one person creates the sandwiches dataset) and see each other's examples to discuss their whole dataset. The large size of the dataset creation space facilitates multiple people working together and tangible interactives have also been shown to foster collaboration [6]. A large visual display of the results allows onlookers to comment and engage in discussion.

6 FUTURE WORK

We aim to test the exhibit with children and their families at the Museum of Science and Industry, Chicago. We plan to collect both pre/post-interview data as well as audio/video data of learner interactions with the exhibit in order to understand whether/how the exhibit supports embodied interaction, creativity, collaboration, and learning. Our target audience is middle school students (and their families) who are visiting the museum. Our findings will inform future iterations of the exhibit design for an engaging and effective museum experience.

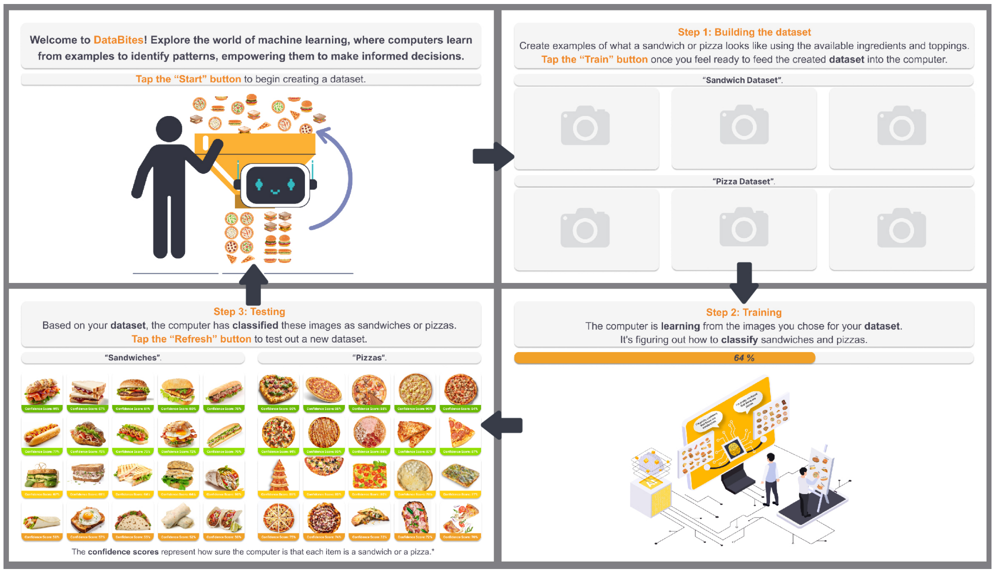

Figure 3: DataBites User-Interface Design. Some images constructed using ©Adobe Stock

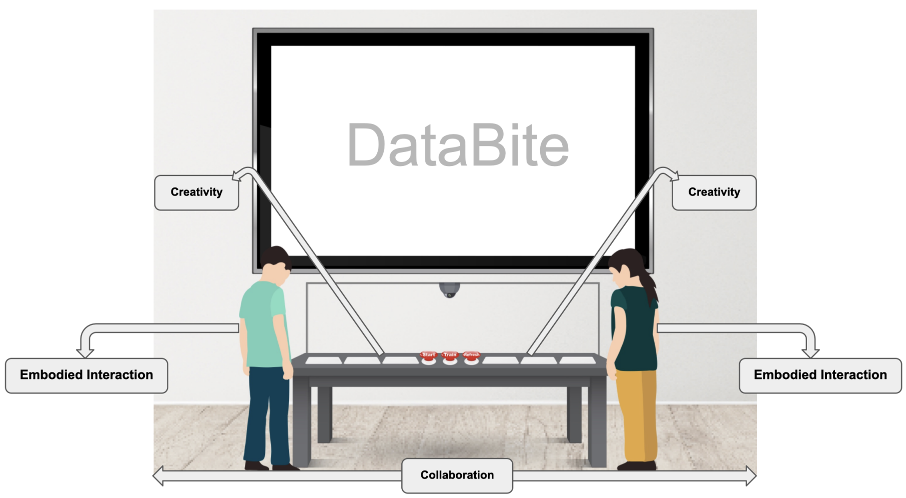

Figure 4: Design Principles in DataBites. Assets constructed using ©Adobe Stock

7 CONCLUSION

This paper presents the design and development of *DataBites*, a novel museum exhibit that aims to teach middle-school-age children about supervised machine learning. We aim to allow children to explore the steps and practices of supervised machine learning by interacting with the exhibit. Our design contributes to the field's understanding of how to teach young learners about AI and how embodiment, creativity, and collaboration can be leveraged to foster AI literacy in informal learning spaces.

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