Development of 7-Week Machine Learning-based Product Design Course

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Abstract: Developing the ability to design by interpreting and incorporating machine learning technology from a human perspective is important to define the role of product designers in the era of artificial intelligence. With this background, this study developed a 7-week product design course based on the design process and conducted a class with students on the subject of 'home camera' in the fall semester of 2023. The design process consisted of 1) user research and need definition based on machine learning understanding, and 2) machine learning-based interaction design development using NAVER ENTRY. The design course is expected to explore the role of designers who can implement human-centered design planning and design concepts considering the context of use using machine learning tools, and further provide a basis for suggesting the direction of design education methods.

Keywords: Design Education; Human-Centered Design; Product Design; Machine Learning; Designer Role

1 Introduction

As evidenced by the rapid surge in the use of AI image generation tools in 2023, interest in machine learning tools is on the rise (Marq's Blog, 2023). Many companies are exploring machine learning tools to inspire designers and enhance work efficiency. For instance, Audi employs its proprietary artificial intelligence software, FelGAN, to inspire vehicle wheel designs (Audi Media Center., 2022). IKEA has leveraged Stable Diffusion, using pictures from its 1970s and 1980s catalogs as data, to design furniture with a streamlined structure (Roettgers, J., 2023). With an increasing number of organizations incorporating machine learning tools into their design processes, a responsive trend in educational institutions has been observed. For instance, in 2022, Kookmin University inaugurated an AI Design department and the Royal College of Art (RCA) introduced a 9-week online course titled "Design Services & Products with Artificial Intelligence." In this context, this study aims to propose an educational approach to incorporate machine learning tools into product design.

2 Human-considered machine learning design approaches

There is a lot of research on how to use tools such as Midjourney (MJ) in the discovery or development stage, which is the divergent stage of the design process that inspires the design concept (Chiou et al., 2023, Turchi et al., 2023, Zhang, et al., 2023). However, due to the purpose-oriented nature of product design and the strong connection to human behavior, there is a limit to relying on interesting or unexpected accidental elements of the results generated by machine learning tools. Particularly in the field of interaction design, which has intricate connections to human physiology and behavior, solutions are required that go beyond what image-generating tools can typically offer (Tholander and Jonsson, 2023). In order to use the machine learning tool more actively in the product design process, it is necessary to consider the curriculum for creation that can understand human needs and behaviors, and solve problems.

Machine learning research often ignores human considerations such as usability, intuition, effort, and human learning and focuses only on the efficiency of algorithms. However, human intervention is important for application in real life. It is important to keep in mind that human values, goals, and social structures always play an important role in collecting training data, coordinating algorithms, and integrating machine learning into real-world systems. Human-centered machine learning is not a single approach, but a wide diversity of problems, methods, technologies, and theories (Gillies et al., 2016).

There is People + AI Research (PAIR), an initiative in Google, as an approach to designing machine learning centered on humans (Google, 2019). The aim of PAIR is, according to Google, "to explore the human side of AI by doing fundamental research, building tools, creating design frameworks, and working with various communities." This guidebook provides a series of articles outlining considerations for product development in AI: User Needs Defining Success, Data Collection Evaluation, Mental Models, Explainability Trust, Feedback Control, and Errors Graceful Failure. IDEO’s AI Ethics Cards are a tool to help guide an ethically responsible, culturally considerate, and humanistic approach to designing with data (Sampson and Chapman, 2019). The card set consists of four major design principles and ten activities, intended to be used in teams working on the development of data-driven products and services. They help designers to maintain a human-centered focus during the service or product development process.

Mathewson, K. W. (2019) conducted an anthropocentric approach to interactive machine learning design as follows: (1) Define the hypothesis State the investigated question of interest, (2) Loop in humans Define your values and principles, (3) Define the goal, (4) Define the data, (5) Build model, (6) Evaluate model, (7) Analyze trade-offs, and (8) Re-evaluate and iterate. von Wangenheim and von Wangenheim (2021) explained the approaches as follows: (1)Needs identification and characterization of the context, (2) Idea creation and specification of the intelligent system, (3) Requirements analysis of the ML model, (4) Data preparation, (5) Model training and evaluation, (6) Prediction, (7) Model export, (8) Model deployment, and (9) SW system test.

3. Core of machine learning-based product design curriculum

3.1 Course Structure

Drawing from the studies above, the product design process for human-centered machine learning can be divided into problem definition and planning, model construction, and evaluation stages. In the problem definition and planning stage, the following steps are included: (1) defining user needs, (2) idea creation, and (3) creating an interaction flow to concretize ideas. The model construction stage encompasses (1) defining the necessary data, (2) data collection and preprocessing, and (3) model training. The model evaluation stage involves assessing the model's performance through a confusion matrix and exploring methods to address errors. The following two steps have been added to train the ability to design and implement a product from a human interaction perspective: emphasizing multimodal interaction and implementing interaction using Arduino. Multimodal interaction is a key element of user-centered machine learning design, addressing diverse user groups, natural interaction, information richness, and flexibility in responses. The course follows the flow as depicted in Figure 1.

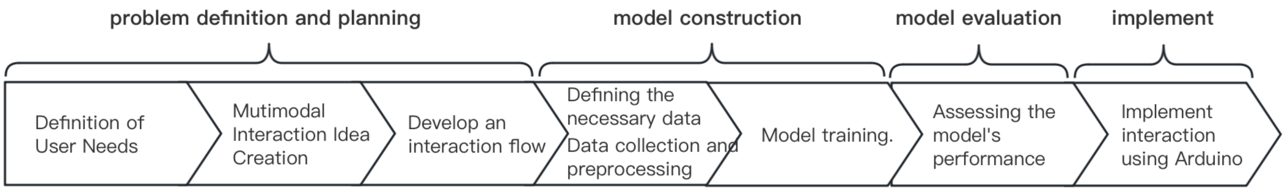

Figure 1. Product Design Course Structure based on Design Process

3.2 Phase 1: Definition of User Needs

The first phase is of the course focused on human-centered machine learning solutions, the emphasis is placed on equipping students with the necessary skills and insights to approach machine learning (ML) from a user-centric perspective. To effectively utilize machine learning to address real-world problems and create value, it is crucial to start from the user's perspective. Instead of asking whether machine learning can be used, designers should frame questions in terms of human-centered machine learning solutions. When designing user-centered machine learning solutions, it's essential to first explore machine learning concepts and elements from a UX perspective. Consider machine learning design within the context of user experience. Understand the process for structuring machine learning projects with UX in mind and explore when artificial intelligence (machine learning) can yield effective results and when it might not be the best fit.

The methodology for defining user needs involves 3 stages:

- Listing Existing Evidence: Collect existing data, research findings, and information related to the issues and needs that users have encountered. This establishes a foundation for comprehending user requirements.

- Detailed Description of User Needs: Utilize the gathered evidence to create a comprehensive and detailed description of user needs. This involves understanding what users desire, where they face difficulties, and the specific problems they aim to solve.

- Assessing the Potential Suitability of AI Solutions: Based on the existing evidence and the detailed description of user needs, evaluate whether machine learning-based solutions have the potential to effectively meet these needs.

In this phase, where students are tasked with defining user needs in the context of machine learning projects, the focus shifts towards practical application and engagement with real-world problems through a user-centric lens. Initiating from a user-centric standpoint and understanding user needs in this manner is fundamental to creating successful machine learning solutions that genuinely address user problems and enhance their experiences.

3.3 Phase 2: Multimodal Interaction Idea Creation

This phase is focusing on the practical application of combining machine learning with multimodal interaction to enhance user experience and facilitate seamless interaction between physical and digital environments. Karray et al. (2008) argue that the interaction between human-machine systems fundamentally occurs through the exchange of information via various input and output methods between computers and humans. Hinckley et al. (2014) further elucidate the nature of these exchanges, highlighting that inputs to a system constitute the information relayed by the user to the machine. Conversely, system outputs are essentially the feedback provided to the user, which aids in navigating and accomplishing tasks. This dynamic exchange effectively bridges the gap between the internal operations of the system and the tangible, physical world, thereby facilitating a seamless interaction that spans the digital and physical realms. The Multimodal human-Machine Interaction Model is depicted in Figure 2.

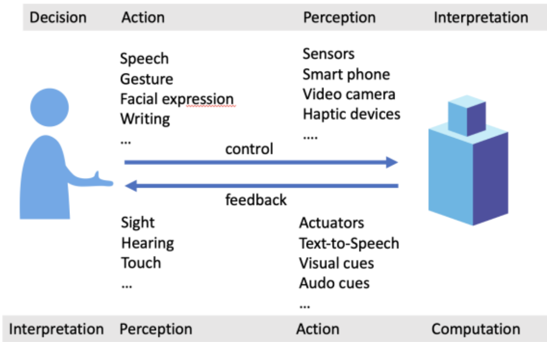

Figure 2. Multimodal Human-Machine Interaction Model

Humans naturally engage in multimodal interactions with the world, utilizing various sensory channels to perceive and respond to other people and the external environment. Several studies (Xiao et.al.,2003; Bolarinwa et.al.,2019; Mathewson, 2019) have demonstrated that implementing multimodal interaction systems is crucial for natural and realistic interactions between intelligent systems and users, as it enhances flexibility and facilitates the exchange of information. The combination of machine learning and multimodal interaction serves to improve the user experience and enables more effective handling of interactions between physical and digital environments.

In this phase, students are tasked with a critical examination of the dynamics between data input and output in the context of machine learning tools, guided by a human-centered perspective. This exploration is pivotal, as it requires students to consider how users interact with machine learning systems and how these systems, in turn, respond to and guide user actions. The emphasis on a human-centered approach encourages students to prioritize user needs, preferences, and behaviors in the design and development of machine learning applications.

3.4 Phase 3: Develop an interaction flow

In this phase, students are tasked with the critical challenge of developing interaction flows for machine learning-based interactive products or systems. This phase emphasizes the significance of understanding and designing for the dynamic relationship between humans and machine learning systems. Ghim (2021) highlights that interactive products possess two unique characteristics when compared to static products: human-machine interaction and temporal sequencing. For instance, users provide input to the product through physical actions and interpret the product's operation through mental processes.

Machine learning-based interactive products detect input through sensors, which can come from users or environmental changes, and respond through actuators or output components. The exchange of these actions and communications occurs sequentially over time to achieve the product's intended goals. Based on these two aspects, a framework can be established to help understand and design machine learning-based interactive products/systems, as shown in Figure 3.

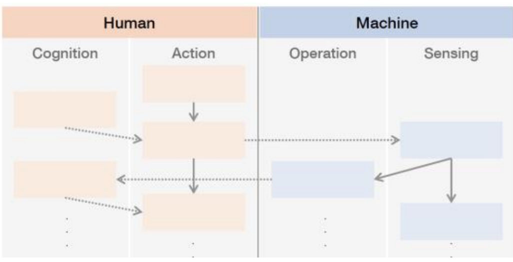

Figure 3. Human-machine interaction flow

In machine learning interactions, the role of humans varies in the relationship between human and machine, depending on user characteristics, user needs, and task requirements. It is essential to consider the points at which the roles of humans and machine learning interchange based on the user's usage context. As shown in Figure 4, when users have a high level of task performance capability, strong interest in the task, and engage in creative work or highly-sensitive domains, machine learning interactions should be designed to enhance the user's capabilities and creativity. In such cases, the machine learning system should act as a supportive tool rather than taking control. On the contrary, when users have low task performance capability, minimal interest in the task, and engage in repetitive tasks or work in low-sensitive domains, machine learning interactions should be designed to simplify and automate tasks. The system should require minimal user input and decision-making, focusing on efficiency and reducing the cognitive load for the user. The machine learning system should take on a more proactive role, providing assistance, guidance, and automation to make the user's tasks easier and more manageable.

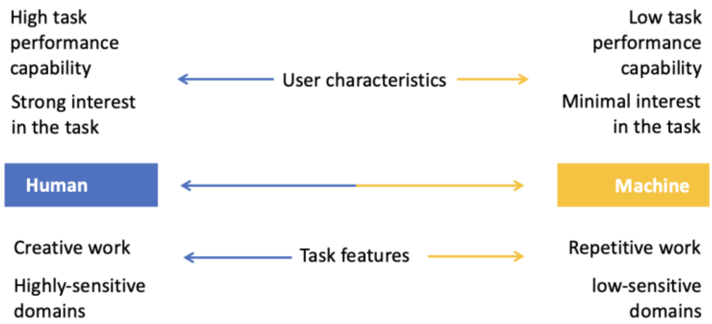

Figure 4. Changing Relationship Between Human and Machine Learning Based on User Characteristics and Task Features

Considering the fluid dynamics between humans and machine learning, as well as the intricate aspects of human-machine interaction and temporal sequencing, students are assigned the challenge of crafting interaction flows. These flows must be tailored to meet the unique requirements and characteristics of both the users and their projects. This task emphasizes the importance of understanding not just the technological capabilities of machine learning systems but also the human context in which these interactions occur.

3.5 Phase 4: Defining the necessary data and data preprocessing

In Phase 4, the emphasis is on the practical aspects of data handling for machine learning projects, specifically focusing on the collection, labeling and preprocessing of data to meet user requirements. The process starts with identifying the necessary dataset and then pinpointing the essential features and labels within this dataset that align with user needs. To enable machine learning products to make accurate predictions, it's essential for their underlying machine learning models to learn from patterns and correlations within the data. This data, known as training data, can encompass a diverse range including images, videos, text, and audio. Students can utilize existing data sources or may need to collect new data specifically for training their system.

The quality of the training data, including how it's sourced or collected and the way it's labeled, plays a pivotal role in determining the output of the system. It's not just about the quantity of data; the quality, relevance, and accuracy of this data are paramount. Properly labeled and well-structured data ensure that the machine learning model can learn effectively, leading to reliable and functional outputs. In addition to data collection, data preprocessing is an integral aspect of this phase. It involves cleaning the data, handling missing values, and standardizing or normalizing it for consistency. Preprocessing may also include transforming variables to make them more suitable for analysis. The goal of this step is to refine the data into a format that is conducive to training a high-performing machine learning model.

Through these tasks, students learn the critical role of high-quality, well-labeled, and properly processed data in building effective machine learning systems. This phase not only enhances their technical skills in handling data but also deepens their understanding of the foundational principles that govern the success of machine learning products, emphasizing the importance of meticulous preparation and analysis of data to meet user requirements.

3.6 Phase 5: Model training

In Phase 5, students use Naver Entry's AI Blocks to process data collected and build machine learning models based on that data. One of the key advantages of Naver Entry is its user-friendly interface, which is particularly accessible for design students with minimal programming background. The ease of use of Naver Entry means they can focus more on the application and implications of machine learning in their field, rather than being bogged down by the complexities of coding. Another key reason for choosing Naver Entry for model training in this phase is its adeptness in handling multimodal data, including images, audio, and text. This flexibility is crucial for a comprehensive learning experience and aligns well with the diverse nature of data typically encountered in real-world scenarios. It meets the course requirements and provides students with a practical, hands-on experience in model training.

Naver Entry allows users to train the following models:

- Image Classification: Train a model that can classify images uploaded or captured via a webcam.
- Text Classification: Train a model capable of classifying text that you either write directly or upload as a file.
- Voice Classification: Train a model that can classify voices recorded from a microphone or uploaded as audio files.
- Numeric Classification: Train a model that classifies numeric data in tables into various classes based on the nearest neighbors (K-nearest neighbors) for each data point.

3.7 Phase 6: Assessing the model's performance

In the "Evaluation" phase, students delve into the critical process of assessing the performance of their machine learning models through the lens of a confusion matrix, a pivotal tool in understanding the nuances of model accuracy. The confusion matrix(Figure 5), also referred to as the error matrix, is a structured representation that showcases how well a classification model predicts outcomes across a set of test data, distinguishing between true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

		Predicted Condition	
		Positive	Negative
Actual Condition	Positive	True Positive(TP)	False Negative(FN)
	Negative	False Positive(FP)	True Negative(TN)

Figure 5. Confusion matrix (True positive (TP): Observation is predicted positive and is actually positive. False positive (FP): Observation is predicted positive and is actually negative. True negative (TN): Observation is predicted negative and is actually negative. False negative (FN): Observation is predicted negative and is actually positive.)

The effectiveness of a model is gauged by the magnitudes of TP and TN—indicating correct predictions, and the minimization of FP and FN, signifying errors. The strategic emphasis on either reducing FP and FN or maximizing TP and TN is a significant factor in tailoring the user experience, as noted by Davis and Goadrich (2006). This decision is not arbitrary but hinges on the specific goals of the machine learning application, the nature of the data, and the intended outcomes of the model.

When designing, the evaluation metrics to focus on vary based on the machine learning's purpose, data characteristics, and model objectives. For example, even for the same recommendation system, the important evaluation metrics can differ depending on the application. In product (advertisement) recommendations, high precision may be crucial because it increases the proportion of recommended products that the user is genuinely interested in. Precision is important when leading to purchase actions. On the other hand, in music recommendations, high recall can be important to help users explore and discover various types of music. Increasing recall can be important for music platforms to help users find diverse music and prevent churn.

Event	Match Rate	Prediction	Actual Condition	Confirmation	Feedback
	High (80~100%)	Positive	High probability of being Positive (TP)		
	Medium (50~80%) potential FP area		High probability of being Negative (FP)		
	Medium (20~50%) potential FN area		High probability of being Positive (FN)		
	Low (0~20%)	Negative	High probability of being Negative (TN)		

Figure 6. Assessing the model's performance and exploring methods to address errors.

In machine learning predictions, providing appropriate feedback to users when errors (FP/FN) occur is essential for maintaining user trust in the AI product. Feedback methods include clearly notifying users of errors, explaining why those errors occurred, apologizing to users, soliciting feedback from users to improve system performance and adjust based on user feedback, and providing options for AI intervention for more accurate results when necessary.

We first ask students to assess where the emphasis should be in this task. For instance, in safety-related issues, one should focus on reducing the likelihood of FN (false negatives). In other words, extra attention should be paid to cases where a problem genuinely occurred but was not predicted by the machine learning model. With a match rate of 20-50% (an area with a high likelihood of false negatives occurring), they need to consider how to provide feedback to users. We require them to outline how to request feedback from users and how to provide feedback to users in each situation as shown in the Figure 6.

In each situation, students must outline specific approaches for engaging with users, ensuring that the feedback loop is not only informative but also fosters trust and reliability in the machine learning application. By focusing on reducing false negatives or false positive and enhancing the dialogue between users and the system, students learn to create more resilient, responsive, and user-centric machine learning solutions.

3.8 Phase 7: Implement interaction using Arduino

In Phase 7, the application of machine learning extends beyond theoretical concepts, merging with the physical world and tangible products. The key objective in this phase is to bring machine learning into real-life application by employing Arduino. This phase reemphasizes the significance of multimodal interaction, focusing on the dynamic interplay between user input and system output, and integrates this with practical work using Arduino.

Students are tasked with exploring and prototyping various methods of user sensing and feedback. Students use their machine learning models in conjunction with Arduino to develop intelligent system prototypes. This process involves the designing and building of Arduino circuits, gaining a deep understanding of how inputs and outputs operate within the Arduino ecosystem, and coding these interactions to function as intended. And this phase allows students to test and validate their designs against user needs and requirements. It provides an opportunity to assess whether the prototypes meet the intended purposes and to understand the practical role of machine learning in actual product development.

By culminating the learning process with the development of a functioning prototype, students gain valuable insights into the practical applications of machine learning, understanding its role and potential in enhancing user interaction and experience in the realm of physical products, thereby bridging the gap between theoretical knowledge and practical application.

4. Student Works

In the fall semester of 2023, we ran a course with seven students under the theme of ‘home camera.’ The students carried out various projects including smart camera for efficient study, Smile Boxes that help users maintain a positive mindset, pet-related products, and security-related products. The course aims to assess the effectiveness of the course proposal by examining the student outcomes, particularly focusing on the student who demonstrated the most fidelity to the machine learning-based product design process.

4.1 Student Project: Smart Home Camera for Pet Companionship

There is a growing trend of people considering their pets as part of their family. Users with such characteristics require more than simple observation; they need delicate care services. They want to provide appropriate support when they are alone, including observation, health monitoring, communication, providing treats, and guiding their pets to specific areas.

Based on the student's own experience of raising a pet and market research, she defined the design goals:

- Real-Time Monitoring: Design that allows users to monitor their pets' status and activities in real-time and respond effectively.

- Behavior Analysis: Functional design that uses machine learning to analyze pet behavior and notify the user.

- Enhanced Interaction: Design that enables bidirectional interaction between users and their pets through a smartphone app.

- User-Friendly: Design that considers elements to minimize pet stress.

And she checked that machine learning solutions can be helpful in providing personalized services to users and aligning with the potential suitability of user needs for machine learning solutions.

Base on the use needs, she created multimodal interaction ideas for providing an enhanced 'pet care service' experience Using Machine Learning:

- Utilize machine learning for providing personalized services to users (e.g., tracking pet activity).

- Process audio/video data based on learned patterns to send notifications only under specific conditions.

- Detect and respond to user-defined events using machine learning (e.g., entering specific areas, behaviors like scratching food bowls).

- Improve remote interaction between users and their pets (e.g., operating a speaker after tracking the pet).

Then the interaction flow, shown in Figure 7, has been created. The interaction flow design should consider both the user's and the pet's actions to create a comprehensive user experience. Since pets can also be users, the actions of pets are included in the flow.

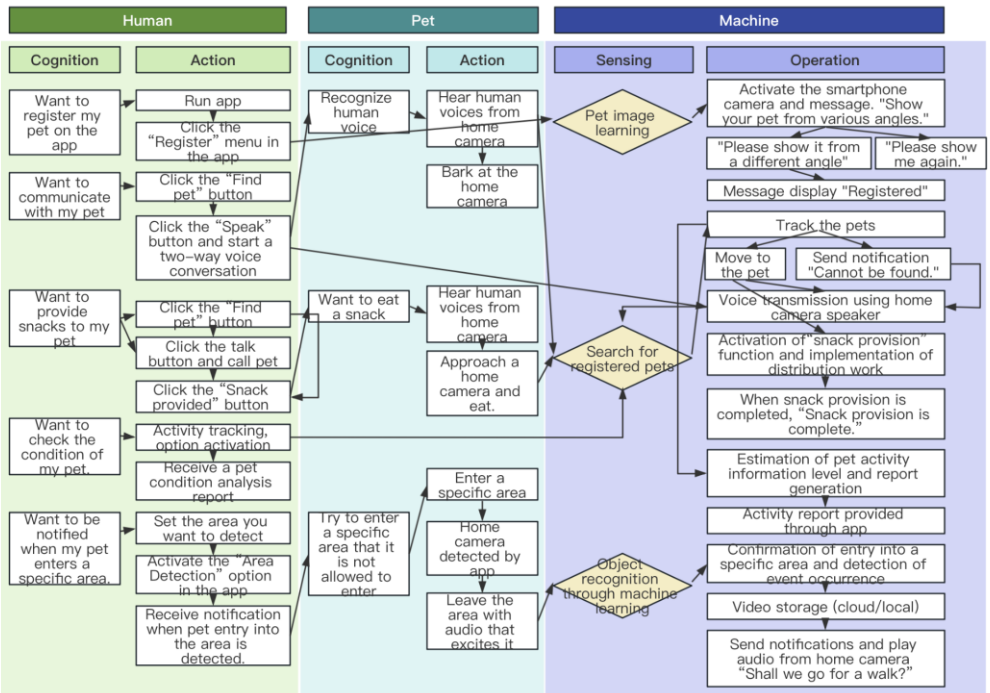

Figure 7 Interaction flow of Smart Home Camera for Pet Companionship.

Then she defined the data needed to train the machine learning model:

- User and pet basic information data: User profiles, pet species, age, health status, behavior patterns, preference data, and audio/video data.
- Pet behavior data: Data related to a pet's entry into specific areas or specific behaviors.
- User feedback and interaction data: Data on interactions between users and pets, user feedback, and service usage records.

This student's work considered various user needs, including real-time monitoring, behavior analysis, enhanced interaction, and user-friendliness. The strengths of the project lie in the systematic process and the thorough consideration of the user's perspective, including that of pets.

5. Conclusion

During the 7-week class held in the fall semester of 2023 with seven students, we saw meaningful advancements in understanding user needs for machine learning-based product design. The students learned to reflect these needs consistently throughout the design process. Additionally, they gained insights into the design methods that utilize machine learning technologies appropriate for their selected project topics, with the aid of "Entry," a block coding tool, which simplified the implementation of machine learning programs.

According to student evaluations, the class was beneficial as it provided them with opportunities to handle various AI-powered programs and apply machine learning to unfamiliar areas. However, they noted some challenges with remote delivery, including difficulties in performing practical exercises due to the limitations of virtual instruction. From the instructor's perspective, the class faced certain constraints. Primarily, the focus was on supervised learning due to time limitations and the restrictions of the coding tools used, which narrowed the scope of AI applications. Additionally, there was a noted deficiency in students' understanding of data; the collected data often did not adequately reflect the users' actual situations and needs. Moreover, time constraints prevented the inclusion of product appearance and interface design in the curriculum.

For future iterations of the course, it is essential to incorporate a broader array of machine learning technologies, including unsupervised learning techniques such as clustering models and reinforcement learning. This expansion will enable students to apply their design skills in more diverse real-world contexts. Additionally, there is a clear need to enhance the curriculum with more extensive data utilization, ensuring students can extract and model meaningful information effectively. These improvements will not only deepen students' understanding of machine learning applications in design but also enhance their ability to use machine learning to address real user needs.

In addition to the limitations of operation, it is necessary to continue to improve the module proposed in the proposed machine learning design education method. The essence of design education isn't merely about efficiency; it's about nurturing designers' ability to think critically and use tools to cultivate innovation. Historically, photography was approached primarily from a technical perspective, aiming to capture subjects effectively. However, photography soon transitioned into an esteemed art form. The transformative power of new technology on human life and culture is evident, especially when considering how modern photography practices significantly influence our society and daily lives. As designers increasingly incorporate machine learning tools into their repertoire, introspection about their evolving role becomes essential. This means machine learning tools should be harnessed not just for efficiency but for fostering human-centric innovation. It's about anticipating the shifts in human consciousness that these tools might bring about. Furthermore, subsequent research is warranted to mold this approach into a comprehensive design education methodology—one that can foresee and understand the ensuing changes in consciousness, societal norms, cultural shifts, economic transitions, and the broader life evolutions they instigate.

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