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CART451
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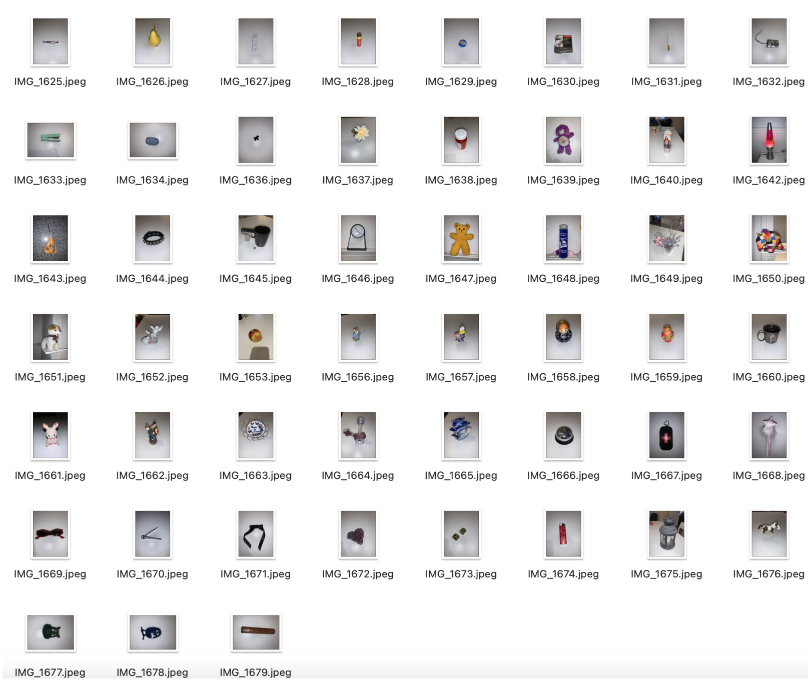
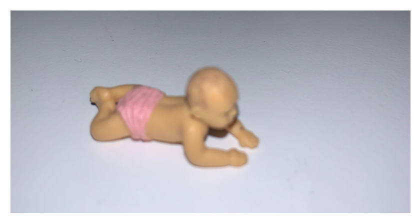
ML EXERCISE

<u>PART A</u>

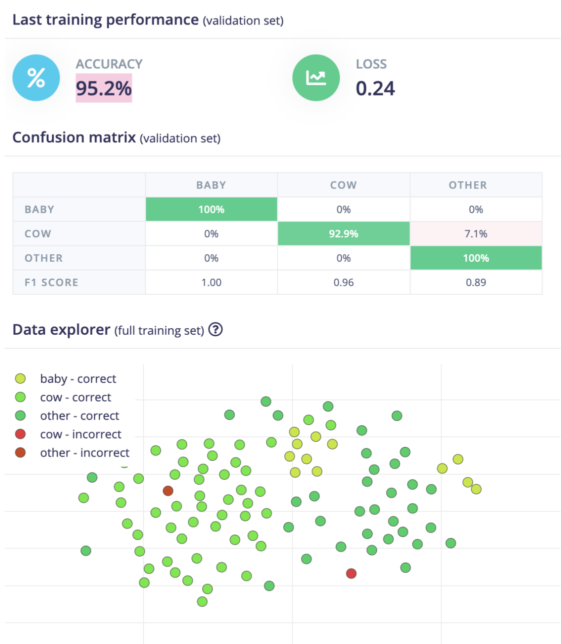
For the initial phase of the exercise, I selected two objects—a cow figurine and a tiny rubber baby. I chose these objects primarily for their small and amusing nature, making them convenient for bringing to class. In total, I collected a bit over 50 images for each object and an additional 50+ pictures of miscellaneous objects to provide noise to the dataset.



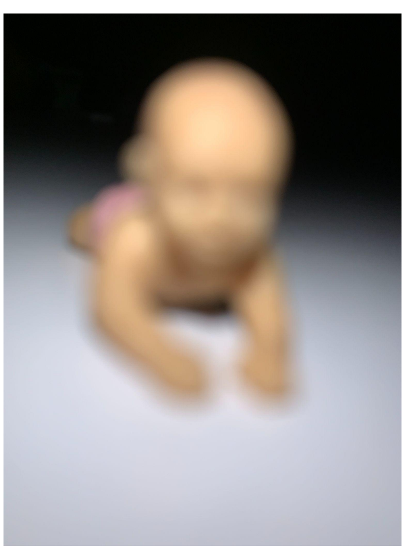


The primary objective was to train a model on a dataset of images, and subsequently utilizing this model for object identification. Using Impulse Design, the initial step involved uploading images the images of both the cow figurine and the baby, as well as pictures of miscellaneous objects unrelated to the cow or baby. Signal processing was applied to extract features from the raw image data—identifying patterns, shapes, textures, or other relevant characteristics within the pixels. Then we employed a learning block for classification. The model was then trained using the preprocessed and feature-extracted dataset. To assess its effectiveness, I tested the model using my webcam to recognize and identify the cow figurine.

It worked okay, with the model successfully recognizing the cow figure, although not consistently. However, it seemed unable to identifying the baby most of the time. Possible contributing factors include variations in lighting and environmental conditions between the classroom and the initial photo-taking setting. Additionally, the need to hold the object up to the webcam, partially obstructing it with my hand, may have affected the model's performance. Especially the baby, because it is so small. None of the training photos featured my hands, likely influencing the model's ability to identify.



Looking at some of the graphs provided by Impulse Design offers some insights. The training performance (left image), indicative of the machine learning model's accuracy during the training phase, produced a rate of 95.2%, which suggests that the model effectively learned the patterns in the training data. However, a look at the model testing (right image), which measures how well the trained model performs on new, unseen data that it hasn't encountered during the training phase, reveals an accuracy of 81.58%. Moderate performance for the Baby, with precision and recall at 63.6%, while the Cow class shows excellent performance with 100% precision and recall. This figure might indicate potential overfitting, where the model has become too specialized in the training data and struggles to generalize to new, diverse examples. This would make sense considering the photos I took, which were not diverse in lighting or environment, but I made sure to get every angle of the figures.



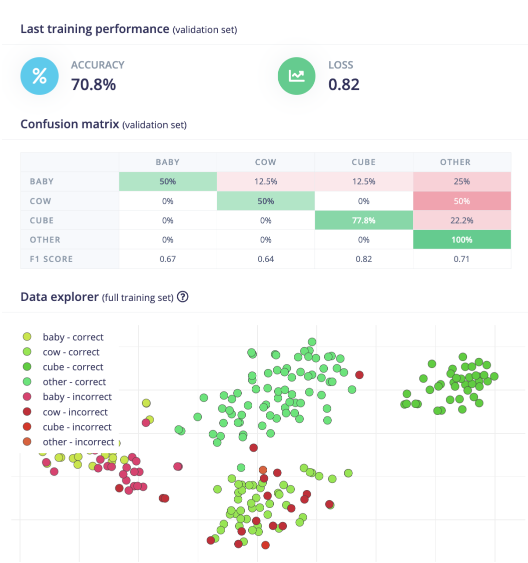
There are a few key factors that could improve this model. In hindsight, many of the images used in the training dataset were probably not optimal quality. They captured using a phone with flash, very different from the classroom lighting. The uniformity of the white table as the backdrop further impacted the model's ability to identify objects when presented with diverse backgrounds through the webcam. More diverse photos of the objects in different environments could improve the model. The size of the baby figurine posed challenges in capturing clear images. This difficulty in obtaining comprehensive visual data for the smaller object could have influenced the model's performance. If I had taken images of my hand holding the Baby, the model might have an easier time identifying the baby. Also providing images of my hand without a baby in the "other" category might be necessary. Probiving a more diverse set of images in theOther category would furtherimprove the model.

<u>PART B</u>

For Part B, I built on top of my previous model, including all of the the same images. I utilized the same images from Part A and introduced Pascal's cube as an additional object. I also provided more pictures of the cow figure, with different lighting and backgrounds, and pictures of me holding the cow in my hand. I also added more "other" images provided by classmates, this way the model has more lighting and environments to train with.\

The purpose of this task diverged from Part A, aiming to delve deeper into machine learning nuances and emphasize the significance of a diverse dataset. The dataset included more variations of the cow figurine, with diverse lighting and backgrounds, along with images of me holding the cow. The new dataset showcased notable improvements, particularly in the clustering performance of Pascal's cube. To optimize for a different testing environment, I changed the target device to a MacBook because I didnt intend on testing this with an Arduino.

In contrast to Part A, where the training performance achieved an accuracy of 95.2%, Part B exhibited a lower training accuracy of 70.8% (left image). Despite this decrease, the model testing accuracy for Part B (right image) is surprisingly much higher at 92.31%, surpassing the accuracy of Part A at 81.58%.The reduced training accuracy in Part B (70.8%) is probably due to it being a more generalized model, which could better adapt to diverse datasets. The higher testing accuracy in Part B (92.31%) supports the idea that the model is performing well on new, unseen data. Certain features could have been heavily weighted during training in Part A, which couldnt generalize well to new data, leading to the drop in testing accuracy.



Last training performance (validation set)

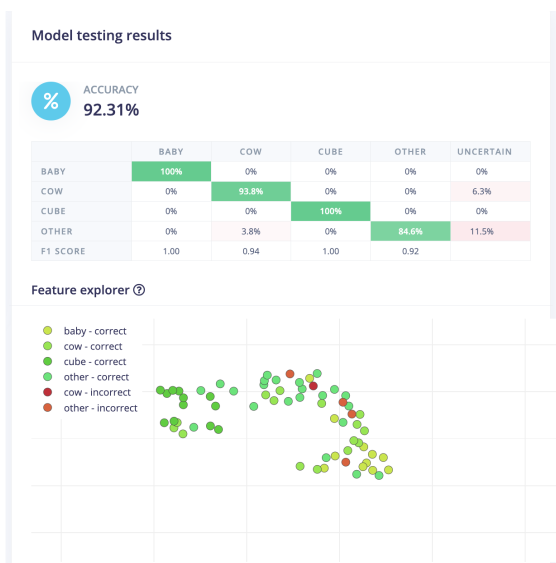
ACCURACY 70.8%

LOSS 0.82

Confusion matrix (validation set)

	BABY	COW	CUBE	OTHER
BABY	50%	12.5%	12.5%	25%
COW	0%	50%	0%	50%
CUBE	0%	0%	77.8%	22.2%
OTHER	0%	0%	0%	100%
F1 SCORE	0.67	0.64	0.82	0.71

Data explorer (full training set)



Model testing results

ACCURACY 92.31%

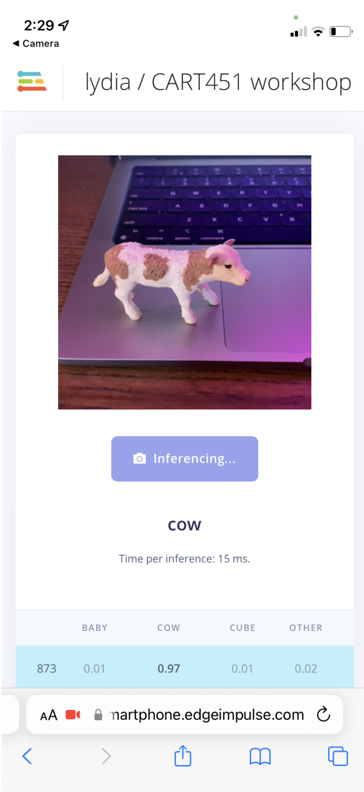
	BABY	COW	CUBE	OTHER	UNCERTAIN
BABY	100%	0%	0%	0%	0%
COW	0%	93.8%	0%	0%	6.3%
CUBE	0%	0%	100%	0%	0%
OTHER	0%	3.8%	0%	84.6%	11.5%
F1 SCORE	1.00	0.94	1.00	0.92	

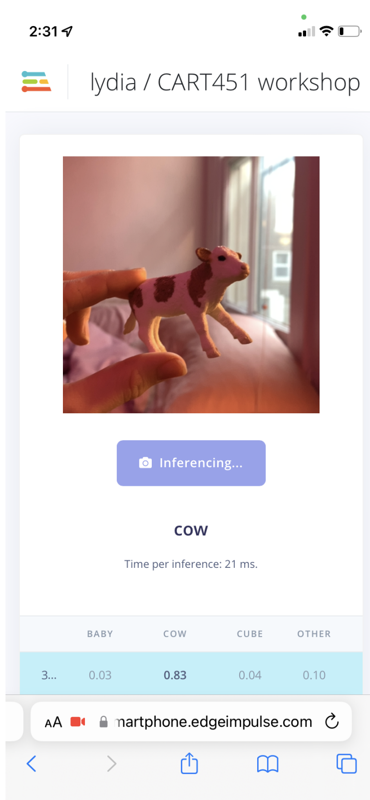
Feature explorer

The model in Part B demonstrates excellent precision and recall for the "CUBE" and "BABY" classes, achieving perfect scores. For the "COW" class, the model demonstrates high precision (93.8%) and recall (100%)indicating strong performance. The uncertainty within the cow class is possible due to the newly provided cow images, suggesting a more diverse dataset that contributes to enhanced overall performance across different environments.

The performance improvement, especially in identifying the "BABY" class, despite no new data provided for it, could be attributed to the inclusion of more noise, enabling the model to better discern the unique features of the "BABY" class. Unfortunately, I seem to have lost or misplaced the tiny rubber baby. It was just too tiny to keep track of. Although I couldn't test the model's accuracy on the baby due to its unavailability, I suspect that this model may not perform significantly better than Part A in recognizing the baby. The lack of new could present challenges for the model in the webcam scenario. Without additional variations in the dataset, such as different lighting conditions or images featuring my hand holding the baby, the model might encounter similar difficulties in accurately identifying the baby, despite the supposed increase in overall accuracy.

Testing with the webcam, It could identify my cow pretty much immediately and very accurately. This success is likely enhanced by the consistent lighting environment shared between the my current webcam and some of the provided dataset photos.





<u>PART C</u>

Object Detection integration inspired Shazam, an app that can identify music based on a short sample played using the microphone on the device. In this scenario, I suggest Shazam-for-object, allowing users to point their cameras at objects, instantly recognizing and providing information about them.
Imagine you notice and admires a friend's stylish pair of pants while hanging out. You discreetly points her pants, the app recognizes the material, brand, and provides links to online stores where you can buy it. This innovative solution not only spares you from engaging in human interactions but also brings you a step closer to making that desired purchase and spending your money.