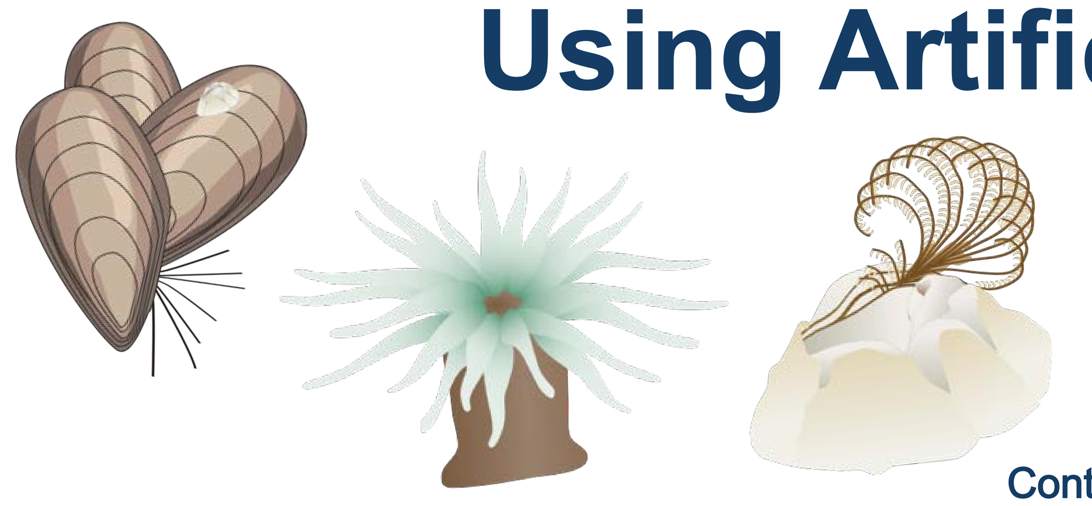

Using Artificial Intelligence to Detect Spatial and Depth-Related Variation in Biofouling Communities in the Patuxent River

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Background

- Biofouling communities, generated by marine sessile organisms, are important links in estuarine food chains.
- Biofouling succession begins with "microfouling," as microorganisms create a thin layer of biogenic material called "biofilm." This is followed by "macrofouling" by larger organisms which create three-dimensional structures that provide shelter to motile organisms.
- Artificial Intelligence (AI) can be a useful tool to efficiently assess biofouling organisms and system health. However, accuracy depends on data availability.
- This project sought to improve AI algorithms currently applied at APL through the observation of differences in biofouling communities due to depth and position of collection plates in a shallow, coastal marine environment.
- Samples were collected June 25 to July 22, 2025.

Methods

Lab Methods:

- Tested image quality of 4 camera models on pre-existing collection plates that had been submerged in the water for over a year, to ensure the presence of well-developed fouling communities.
- In situ (in water) and ex situ (in air) photos taken.

Field Methods:

- We deployed at three different sites on the shoreline of the Patuxent R. (Figure 1) that differed in substrate type and wave energy.
- Shallow plates were anchored at 3" depth and deep plates were placed approx. 25" below the surface of the water.

Figure 1: Deployment sites along the Patuxent River.

Figure 2: Shallow and deep PVC frames deployed at each site.

- PVC frames were created to hold 12 3x5" collection plates. We deployed two frames per site (Figure 2).
- Each week, photos were taken of each individual plate's top and bottom.
- YSI measurements were recorded twice a week.
- One-way ANOVA (Analysis of Variance) was run for all environmental factors with a p-value > 0.05.

Machine Learning Methods:

- All images of collection plates were processed through CLIP (Contrastive Language-Image Pre-training) AI, a learning model which pairs text and images based on similarity, to encode images.
- The image encoding step converts each image into a series of numbers that describe and represent the content of the image.
- A dimensionality reduction algorithm, t-SNE (t-distributed Stochastic Neighbor Embedding), is applied to the image encodings. The t-SNE algorithm reduces the image encoding from 512 dimensions to two dimensions while preserving the overall structure of the data set to analyze plate depth, side, site, and week accuracy (Figures: 5, 6, 7, 8).
- 100 images from week 2 were used to train the AI and 44 were used for testing accuracy.

Results

1) iPhone 11 camera had the best quality photos compared to GoPro Max, GoPro Hero 11, and Insta360.

Figure 3: In situ (underwater in the Patuxent River) pictures taken by each camera tested. From left to right: iPhone 11, GoPro Max, GoPro Hero 11, Insta360.

2) Out of water imaging was chosen for the remainder of the project as the best image taking method.

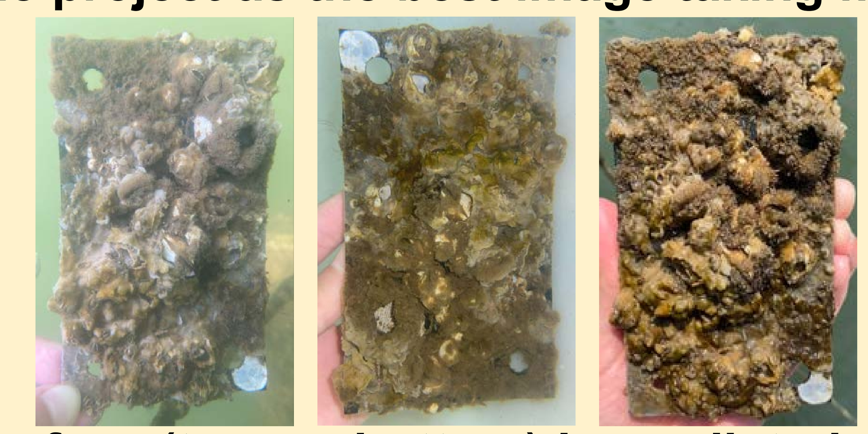

Figure 4: iPhone 11 images of plates in situ and ex situ, left to right.

3) Depth is predicted with 95% accuracy.

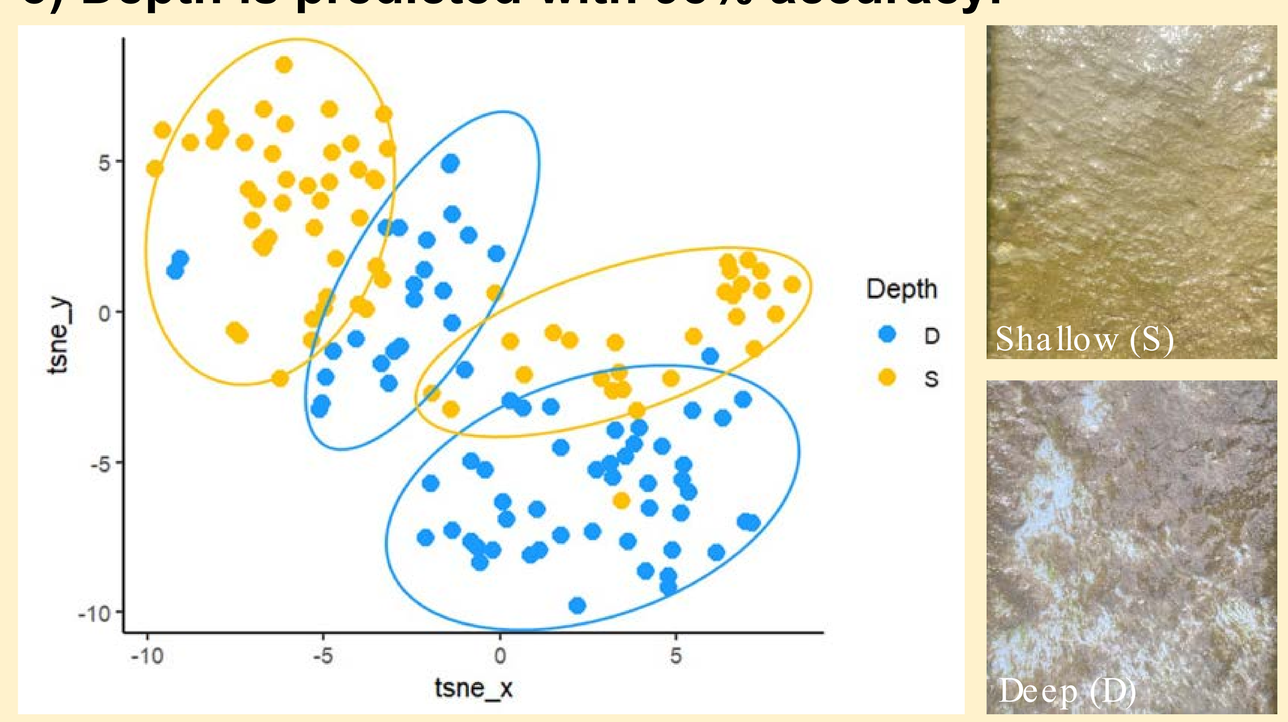

Figure 5: t-SNE plot of panel depth at week 2. images. from site 1 showing differences between depths. Top right: shallow (S), bottom right: deep (D).

4) Surface (top vs. bottom) is predicted with 90% accuracy.

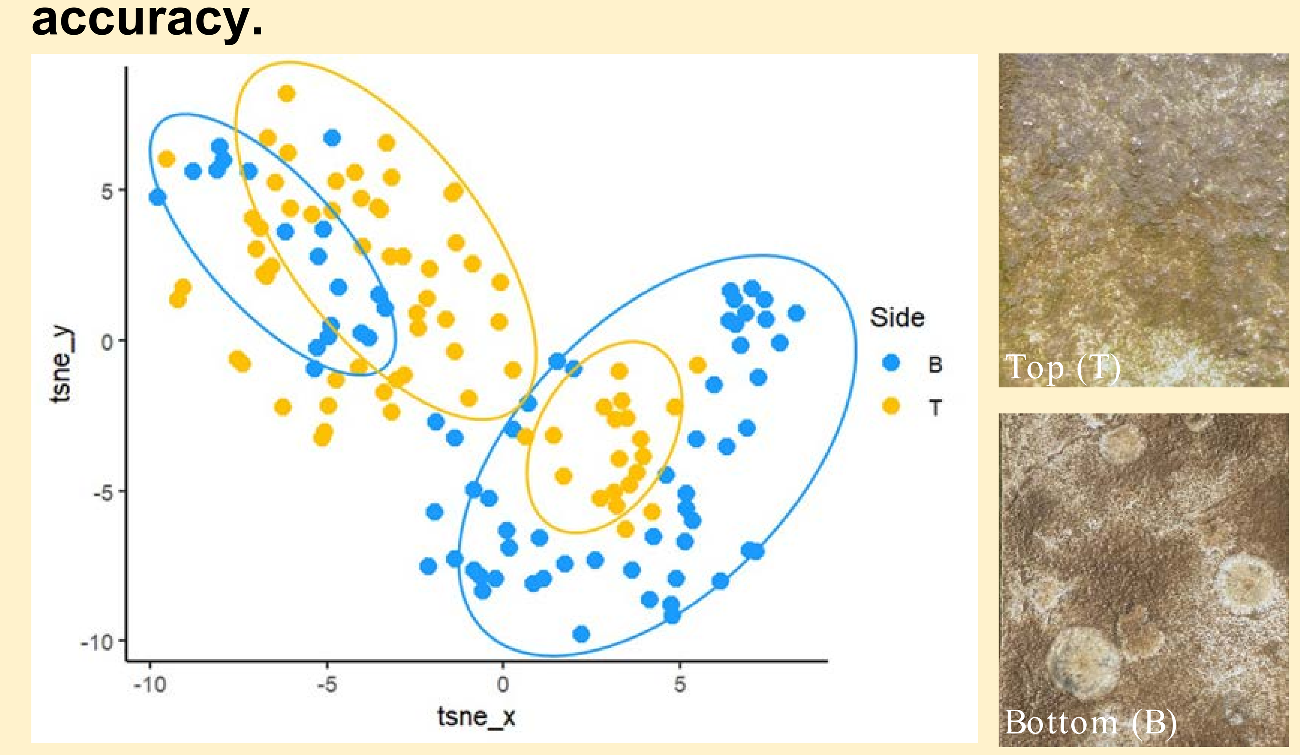

Figure 6: t-SNE plot of panel side at week 2. Images showing difference between sides. Top side (T) shown above bottom side (B) of the same plate.

5) Site is predicted with 86.3% accuracy.

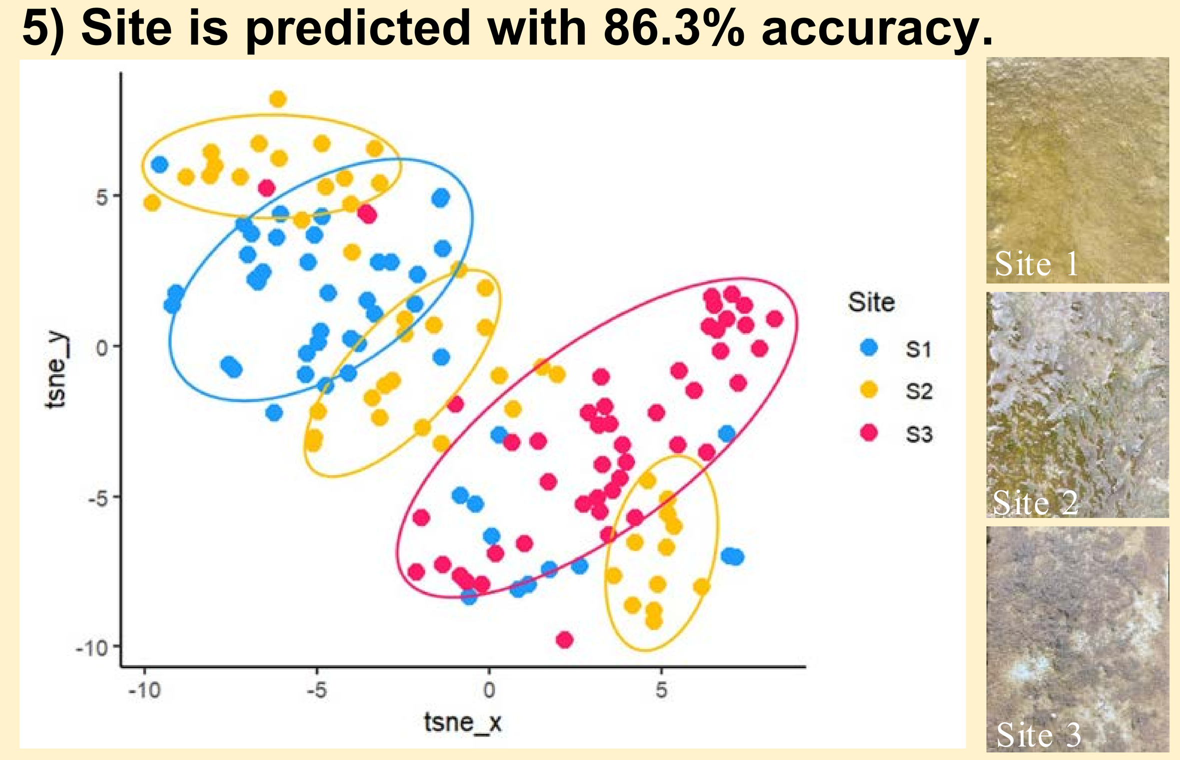

Figure 7: t-SNE plot of panel sites at week 2. Images (top side) showing differences between sites. In order of sites.

6) Exposure time is predicted with 85.7% accuracy.

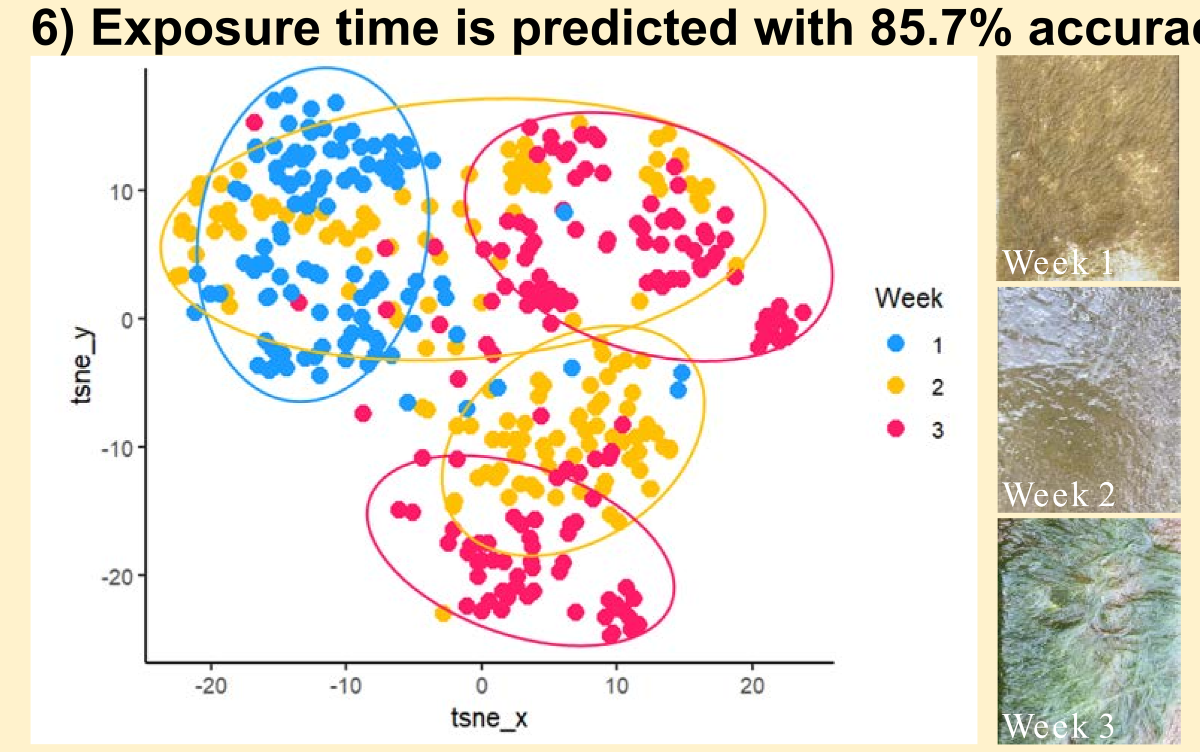

Figure 8: t-SNE plot of panels by week. Images showing succession of one plate (site 1) over three weeks. In order of weeks.

7) Environmental differences between sites was not significant.

- Temperature, salinity, and DO is do not vary enough between sites to indicate a difference in biofouling structure on collection plates.

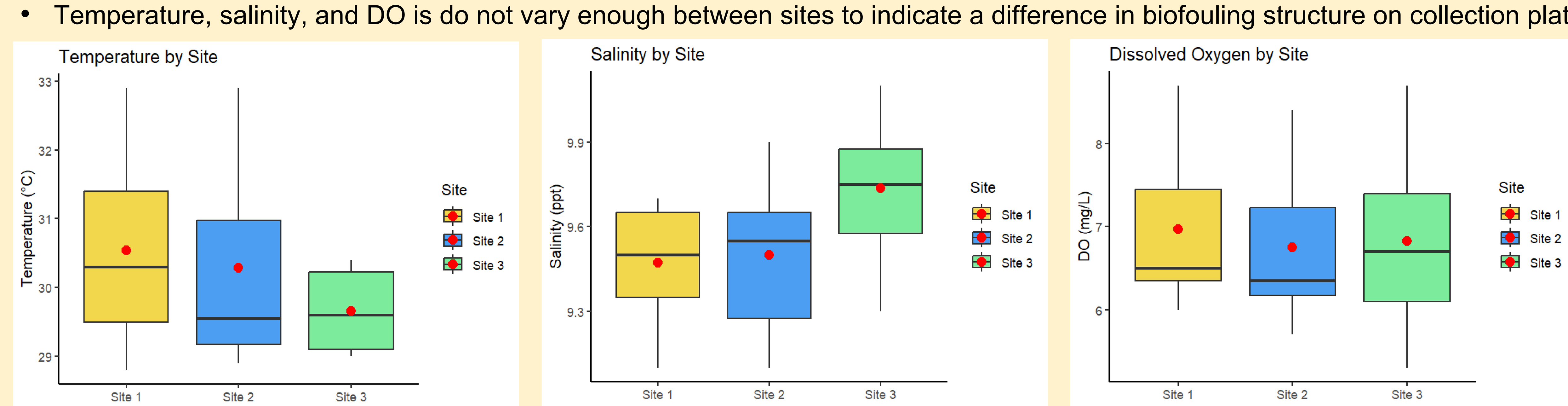

Figure 9: Comparison of dissolved oxygen, salinity, and temperature between three sites.

Main Takeaways

- AI predicted depth, side, site, and week with high accuracy using images collected in week 2 (Figures: 5, 6, 7, 8).
- Week 3 results are similar, with accuracy of depth, side, and site being 95%, 97.7%, 79.5% respectively.
- Site 2 had overlap with sites 1 and 3, which may reflect more substantial differences between sites 1 and 3, such as wave energy or bottom substrate type.
- iPhone 11 camera with a waterproof case was used to take photos throughout the project due to its image clarity and user-friendly design, compared to images taken in situ and ex situ with a GoPro Max, GoPro Hero 11, and Insta360 (Figure 3).
- Best method for taking photos was when plates were exposed to air (Figure 4). This method is also compatible with pervious data collected, allowing for a larger dataset to be used in future machine learning tasks.
- Numerous unanticipated differences in community structure were observed:
  - Encrusting bryozoans present in high quantities at site 2 compared to other sites.
  - Increased presence of bryozoans on deep plate bottoms compared to deep plate tops.
  - From site 1 to site 3, green algae growth decreased on top plates.
  - Environmental factors at site 3 differ most from sites 1 and 2.

Next Steps

- Explore possible factors attributable to unexpected observations, e.g., higher bryozoan presence.
  - Ho1: UV availability
  - Ho2: Wave energy
  - Ho3: Bottom substrate type
  - Ho4: Community interactions
  - Ho5: Increased human traffic at site 3
- Continue improvement of machine learning by supplying AI with more images of collection plates to increase the number of training images.

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