Contrastive learning offers a unique approach to the traditional multi-class classification problem presented. The agricultural dataset provides a range of issues to address, and we strategized about the best way to the frame the problem, first and foremost, from the business perspective. For example, since the image set has 8 crop types and 1 weed type, is it simple enough to train a model on a 9 class methodology? Or should we force the model to only provide its probabilities for the 8 “in-classes”, and if all are below a threshold, classify the given image as an anomaly? Or, should we simplify even further to a binary classification problem (anomaly vs no anomaly)? Does it matter that much to classify the crop types? We explored each of these options, and the pros and cons of each can be argued extensively, but we reasoned it makes the most sense to make it a 8-class problem with thresholding. This way, anomalies can be generalized to images beyond the train and test datasets presented.

After applying hybrid approaches with traditional learning methodologies (CNN+VAE or CNN+AE), we wanted to see if more unique ML techniques can enhance the model, thus contrastive learning. Contrastive learning helps the model place data points of similarity closer together in its latent space while dissimilar images farther apart. To do this, we take an anchor image (reference image) and contrast it with two other data points (a positive and negative sample). We then find the contrastive (or triplet) loss between these 3 images. Ideally, we want to maximize the difference of distances between the reference and the positive and the reference and the negative samples. The larger this difference is, the more meaningful the separation is between the positive and negative samples ie the model is able to tell the images apart and classify them correctly. There are a series of losses (or hybrid losses) that can be used to fully functionalize this algorithm, but we still need to discuss/explore our options here.