**1. ResNet-56 Based ASL Classification - Christina Shatfor, Daniel Melesse.** Christina and Daniel’s project was centered on constructing a deep learning neural network to classify images of letters in the American Sign Language. The dataset they found included 24 static letters of the total 26, as letters ‘J’ and ‘Z’ involve motion in signing, which is unable to be captured in only an image. The ASL dataset was well-curated to include only grayscale images in which the signing hand is centered. This project set themselves apart from other ASL Deep Learning Networks through their exploration of a ResNet architecture. The ResNet-56 has 56 layers of identity and convolutional blocks. They achieved a baseline accuracy of 86.89% with this architecture. After expanding their dataset through a series of data augmentation (random flips, rotations, and changes in brightness), this ResNet-56 model achieved 96.29% accuracy. Misclassifications were on letters that are easily confused to the human eye. For example, ‘U’ and ‘R’ both involve what looks like how one would make a peace sign but if the pointer and middle fingers were to touch. The only difference is crossing these two fingers in the R. Next steps for this work would aim on training this network to be more precise about these subtleties.

**2. Predicting the String Being Played by a Cellist through Gaussian Filters, Hough Transforms, and k-Nearest Neighbors - Kenny Huang and Iroha Shirai.** In their project, Kenny and Iroha created a pipeline to predict the string played on a cello based on the cellist’s bow and fingerboard positions. This exploration involved curating a dataset of 132 images taken from YouTube. They split this dataset into an 80/20 train and test set. The dataset’s size was not only limited by 2-man annotation but also a specific angle of the cello that contains both the bow and finger board. They used a Gaussian filter and Hough transform to isolate the lines that trace out the bow and fingerboard. This extraction method achieved 82% accuracy to pinpoint the bow and fingerboard. Using these lines, they could find the theta values and use k-nearest neighbors (with a k = 11) to predict the strings played. This part achieved 73% accuracy on the test set. For future work, they are curious about addressing the limitations in curating the dataset with incorporating different camera angles and also running the procedure on real time videos.

**3. Pinpointing the Image Geolocation Problem across US States from a Different Angle - Hanna Xu, Jayson Wu.** This project aimed to explore image geolocation (predicting the location based on an image) within the United States. Using a pre-trained ResNet, Jayson and Hanna fine-tuned and used transfer learning on a dataset of Google Street View images. They built a model to classify images into a 50 state classification and a 10-split region based classification. The main focus of this research was that the 360º offered by Google Street View panoramas would offer features to improve the accuracy of geolocation models. They curated three total datasets: a baseline dataset with just the one view, a 4 view dataset with 4 views per baseline image, and an augmented dataset – the 4 view plus 3 views from the test. An interesting find was that Hawaii had the highest test accuracy of all the states. They hypothesized that this is because it is also the state with the least area and images were more concentrated spatially (the spread of images covered a higher percent of the land). Additionally, Hawaii has more distinct landscapes. Each of the different models focused on different areas. For example, model 3 tended to focus on roads and clouds. Adding panoramic views to do dataset and finetuning the model increased test accuracy by 16%, making this a helpful feature to add to image geolocation datasets.