Vein Finder
Data Collection & Training

이동기, **歐陽樂文, Semrah Odobašić,** 정어진

Data Collection

Given the nature of our veinfinding project to locate veins in people's arms, the data collection process requires us to take pictures and work on data processing without a ground truth. This complicates our process of data collection as there will be a manual segmentation step involved to pick the veins out of our images for projecting back onto the user's body. We started our data collection by taking a total of around 125 images of veins from 6 different people. From that we picked out the best images we had where you could see the veins clearly with the most contrast. That ended up giving us a total of 66 workable images which we then used to train our segmentation model. We ended up with a lot less photos than we initially took primarily because some veins were harder to find on certain people than others.

We then began to annotate our images for training the segmentation model. This was done by splitting the pictures we took between each team member and having each person essentially highlight the veins in Photoshop. This step is relatively trivial. We drew over what we thought were veins with white then added a black background. This gives us the segmented veins while removing everything else. By the end, we then had 66 original images taken from our IR camera, and a matching annotation of the veins representing our ground truth that we could use to train a segmentation machine learning model.

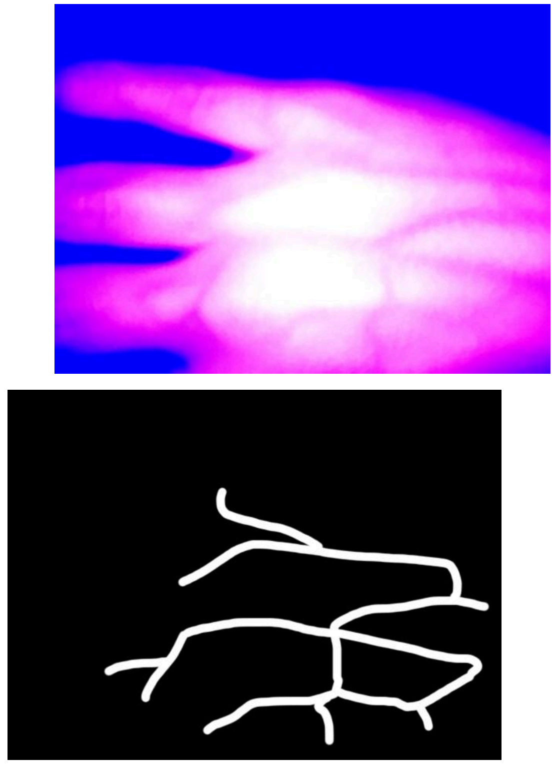

Fig 1: Original IR image (left) alongside the manual image annotations (right).

The segmentation model we used is a modified UNet provided by Rich Baird. We first tried to train the model using the original 66 images we took, but after trying different learning rates and number of epochs we found that the results were not good no matter what we tried. The determination was that this was due to not having a large enough sample size so we started work on augmentation so that we could rapidly expand our dataset.

Data Augmentation

For data augmentation, the goal was to produce as many images as possible from the original 66 while still creating images that were useful. In order to keep the aspect ratio the same for all of our images, we unfortunately can't do a rotation by 90 degrees since we're using landscape photos. However, we were still able to perform other translations to get a new and much larger dataset. The initial augmentations that we applied was a 180° Rotation, Vertical Flip, and Horizontal Flip.

After the first set of augmentations we got a total of 264 images. From training our model on these images on top of our original 66, we did have much better results than before, but they were still not good enough for what we wanted. Seeing as this was the primary barrier for accurate training, we decided to augment these photos even further. For additional permutations, we chose to crop into different sections of our full size images and export back to 640x480 pixels. This was done by scaling the image by 125% and then cropping into the top left, top right, center, bottom left, and bottom right. This gave us another 1,320 images to work with for a total of 1,584.

For now, this is definitely a much better sample size to get results we are genuinely happy with. Due to the fact we can get magnitudes more images without having to take too many original photos means that the training process becomes much simpler and more accurate for our final result.

Model Training

As we began training our UNet model, we logged the parameters we adjusted so we could determine which settings got us the best results. This would ensure that we could keep track of what was improving the quality and what was diminishing it. When we started training on the original dataset of 66 images the results were definitely not good. Usually it would result in weird coloring or a completely washed out gray image. This was consistent regardless of the learning rate or number of epochs we used.

After doing the first round of augmentations we tried to train again with a total of 264 images. This gave us predictions that were occasionally better and had slightly more definition on the veins, but other times we got the same results as before. We of course continued to tweak the epochs and learning rate to see what would happen and only got marginal improvements.

When we trained the model using the third set of augmentations with 1,320 photos however, the results were finally much better and more along the lines of what we were hoping to achieve. We finally ended up with correct coloring having a black background with the veins picked out in white. It also now properly identifies the veins with the only downside being that it prioritizes the largest ones. This is something we believe can definitely be improved on however by taking more images for the model to train with.

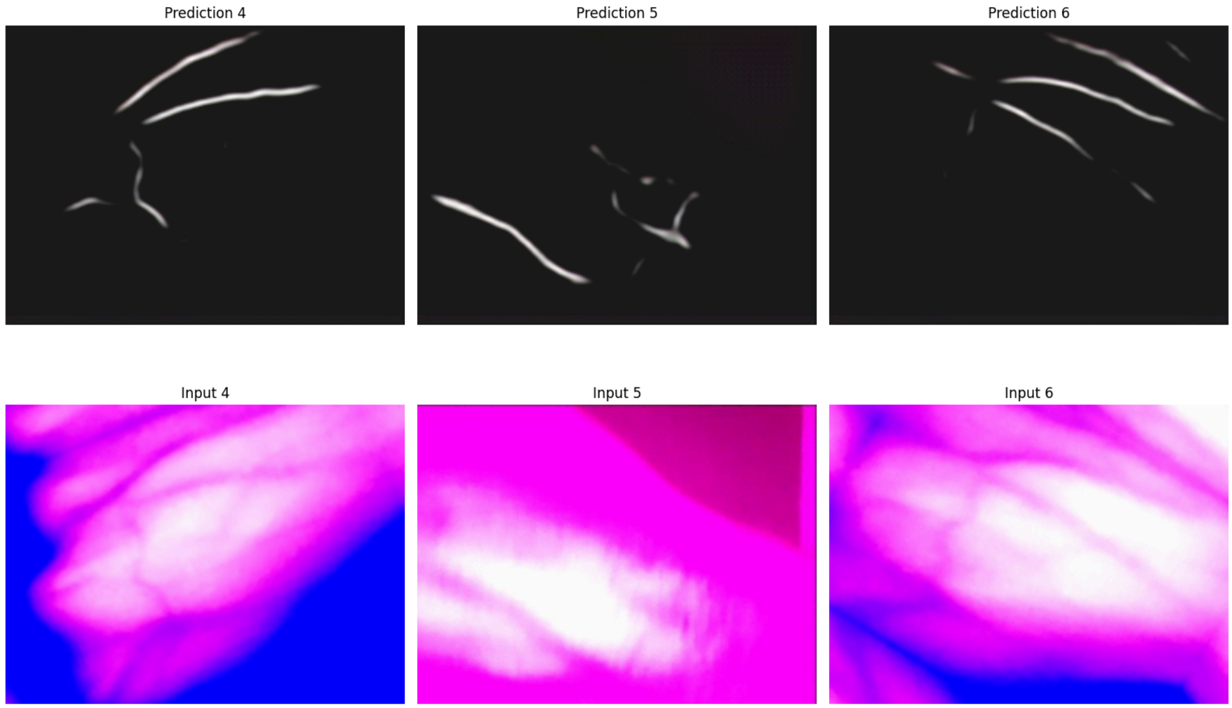

Fig 2: Image showcasing the current segmentation ability of our model.

Overall, we are very happy with the results we got from our final training run of the model but we believe that it can still be improved further. In addition to now fine tuning the learning rate and number of epochs for this dataset, we also hope to improve the quality of our input images to make the job easier on our model. Considering that we're currently going from color to black and white images, we want to try pre-processing our images to grayscale so the model only has to focus on segmentation rather than color grading as well. We'll also work on contrast and exposure adjustments so that as the images are being fed to our model, we'll have the highest contrast images possible which will all be aimed at simplifying the segmentation task for the machine learning. Lastly, we'll also continue to take more unique photos from new subjects so we can further diversify our dataset and provide even more data for the model to train on. Seeing as this has been the most effective at getting us to better results so far, we hope that this will provide the final push needed to have an effective vein finder by the completion of our project.