# Rider Posture-based Continuous Authentication with Few-Shot learning for Mobility Scooters

## Supplemental Material

### Model Implementation

Our authentication model leverages a series of graph convolutions before employing residual convolutional layers in producing an embedding. Figure 1 provides a detailed model diagram, with the four columns from left to right displaying the residual convolutional encoder for the upper torso, lower torso, left arm, and right arm, respectively. Each body segment is composed of three joints, with the exception of the lower torso being composed of two, and each convolutional layer has kernel 3.

The model intuition is facilitated by both body structure and the smaller dataset, which encouraged features such as the global averaging layers as a better alternative to fully connected layers. In performing frame-by-frame joint estimation as opposed to optical-flow algorithms or other algorithms that leverage prior joint positioning, we allow improved processing, as frames can be processed in parallel. Moreover, our model architecture enables improved parallelism through the separate convolutional encoders.

Although not shown in the diagram, a critical part of our model training is the choice of triplet mining and the Siamese structure. By leveraging a Siamese structure, we enable more efficient comparison of riders by simply comparing the embedding vectors, which only need to be computed once. Performing semi-hard triplet mining produces triplets containing anchor samples, close positive samples, and semi-hard negative samples, which have a greater effect on reducing training loss.

The model was trained in 30 minutes on an NVIDIA 3070Ti GPU with an Adam optimizer, a learning rate of 0.001 and 50 epochs.

### Data Collection Methods

The tasks that the 42 volunteers performed included many specific motions that we wanted to test. All participants performed a variant of the following:

1. Participants would ride the scooter along a designated track that includes gradual inclines, descents, gradual and sharp left and right turns, and backward movements. This track took most participants approximately 4 minutes.



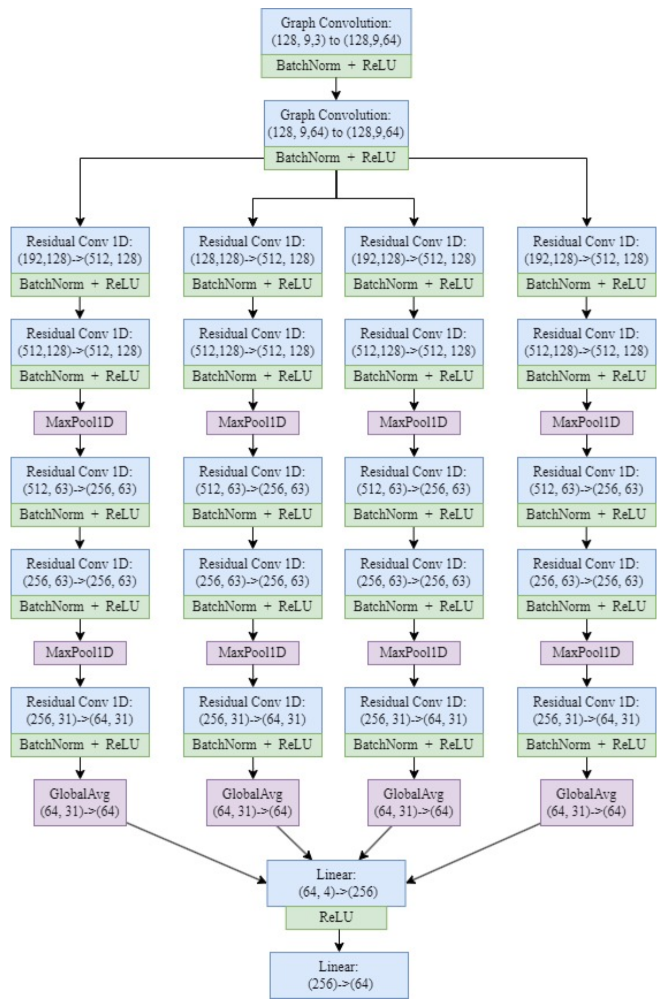


Figure 1: Detailed Model Parameters

2. The next task was less rigid to encourage realistic and individualistic usage of the scooter. We asked participants to drive for 5 minutes in any direction on designated paths, which intersected several times to allow riders to choose their own destination and route. We asked riders to perform left, right, and backward movements.

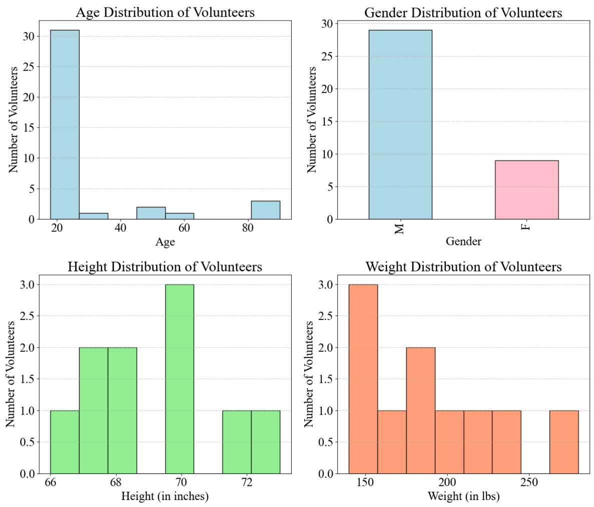


Figure 2: Volunteer Data

3. Similarly to the previous tasks, we next asked participants to ride off-road and on grassy and hilly terrain for 5 minutes for data in a dynamic environment with a less steady camera. We asked riders to perform left, right, and backward movements.
4. Our final task has users ride on a small track and perform several bouts of acceleration and sudden stopping. This task allows us to gather frequent stopping and acceleration data, which is largely not present in the other tasks.

The majority of volunteers completed all the above tasks, although several completed only tasks 1 and 2, and our hospital patients engaged in a longer routine that extended the above tasks. Most individuals spent in the range of $14 - 18$ minutes completing the $4$ tasks, with hospital patients spending $30 - 40$ minutes on their extended tasks. After filtering segments in which participants did not follow the tasks, there are $38$ different rides recorded, each with a unique rider. Keypoint, gender, and age data is shared for each ride and the corresponding participant, and some participants opted to include their height, weight, and mobility issues if present. Such data is summarized in Figure 2.

Of the volunteers, five were hospital patients and had medical conditions. Their data is represented below:

| ***Age*** | ***Sex*** | ***ht*** | ***wt(lb)*** | ***Condition*** | ***Impairment*** |
|---|---|---|---|---|---|
| 87 | F | 5’8” | 200 | Neuropathy | neck, trunk |
| 53 | M | 6’1” | 182 | Brain Injury | Lower extr. |
| 85 | F | 5’6” | 230 | Sciatica | Left lower extr. |
| 90 | F | 5’7” | 156 | Arthritis | Both hips |
| 62 | M | 5’7” | 180 | back&shoulder | Left upper extr. |

To take such measurements, we used a Drive Medical Phonix LT 4 Wheel Mobility Scooter among other brands. Figure 3 shows an image of the mobility scooters.

## Evaluation

To graphically illustrate an example from the table of ROC curves, we display the ROC curves with 40 embedding vectors and using MoveNet and MediaPipe in Figure 4 and Figure 5, respectively. The area under the first curve is 0.9897, and the second curve is 0.9479.

Figure 3: Mobility Scooter Image

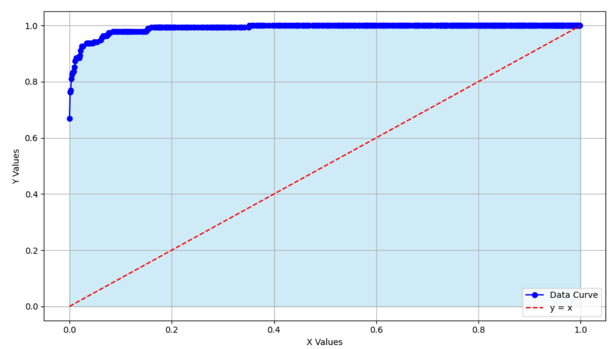


Figure 4: ROC Curve using MoveNet

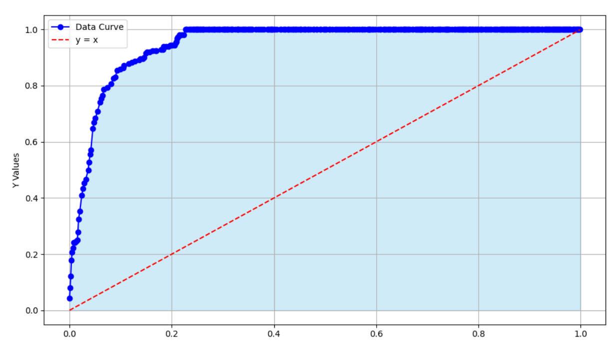


Figure 5: ROC Curve using MediaPipe