Gait Recognition

FINAL PRESENTATION - GROUP 5

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What to present

1. Background
2. Methodology
3. Results and discussion

Why gait?

- Everyone does not have the same body shape & style of walking -> a good candidate for biometrics

- An effective type of biometric *at a distance* ((such as at the airport, on the street) where other methods may not work

Challenges

- Unsupervised cross-domain gait recognition which aims to learn models on a labeled dataset to unlabeled dataset

- In gait recognition, some image sequences may not be available due to occlusion

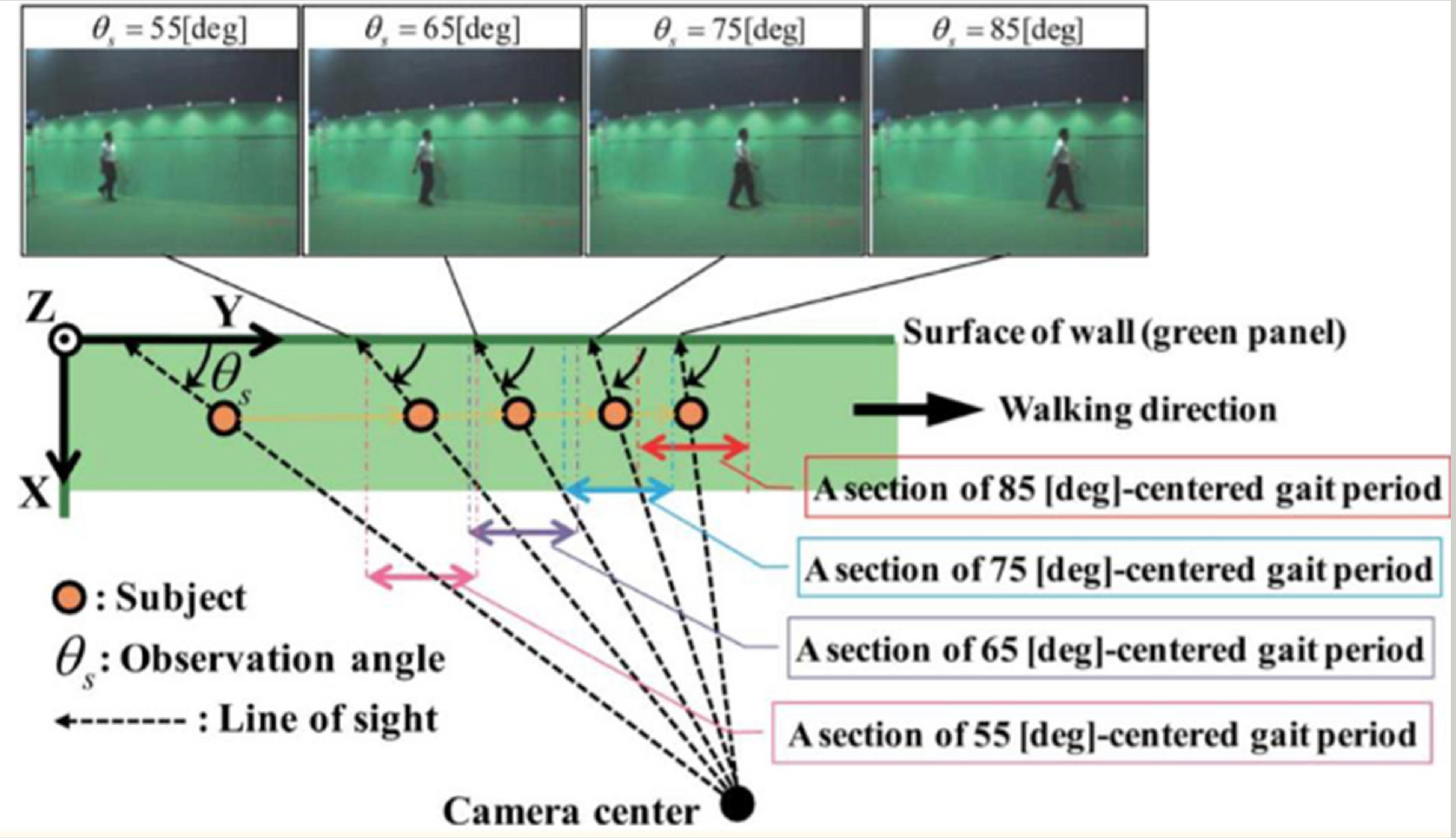
Usually very poor results

We explore 2 models - each focusing on one particular challenge

Problem statement

- **Problem**: Identifying or recognizing persons using their gait
- **Input**: A collection of images of a person’s walking
- **Output:** Identity of the person corresponding to input images
- **Dataset**: CASIA-B and OU-ISIR Biometric Database

Methodology



About the dataset

- 2D greyscale images of people's gait taken from CASIA-B and OU-ISIR Biometric Database
- Over 3000 subjects from a wide range of ages are included
- Consistent walking conditions & background mitigates noise from non-uniform conditions

Preprocessing

- Resize all images from 88x128 to 64x64
- Apply filters to reduce image noise from original image (be careful with tradeoffs)
- Convert to 1f-GEI, 3f-GEI, 5f-GEI...

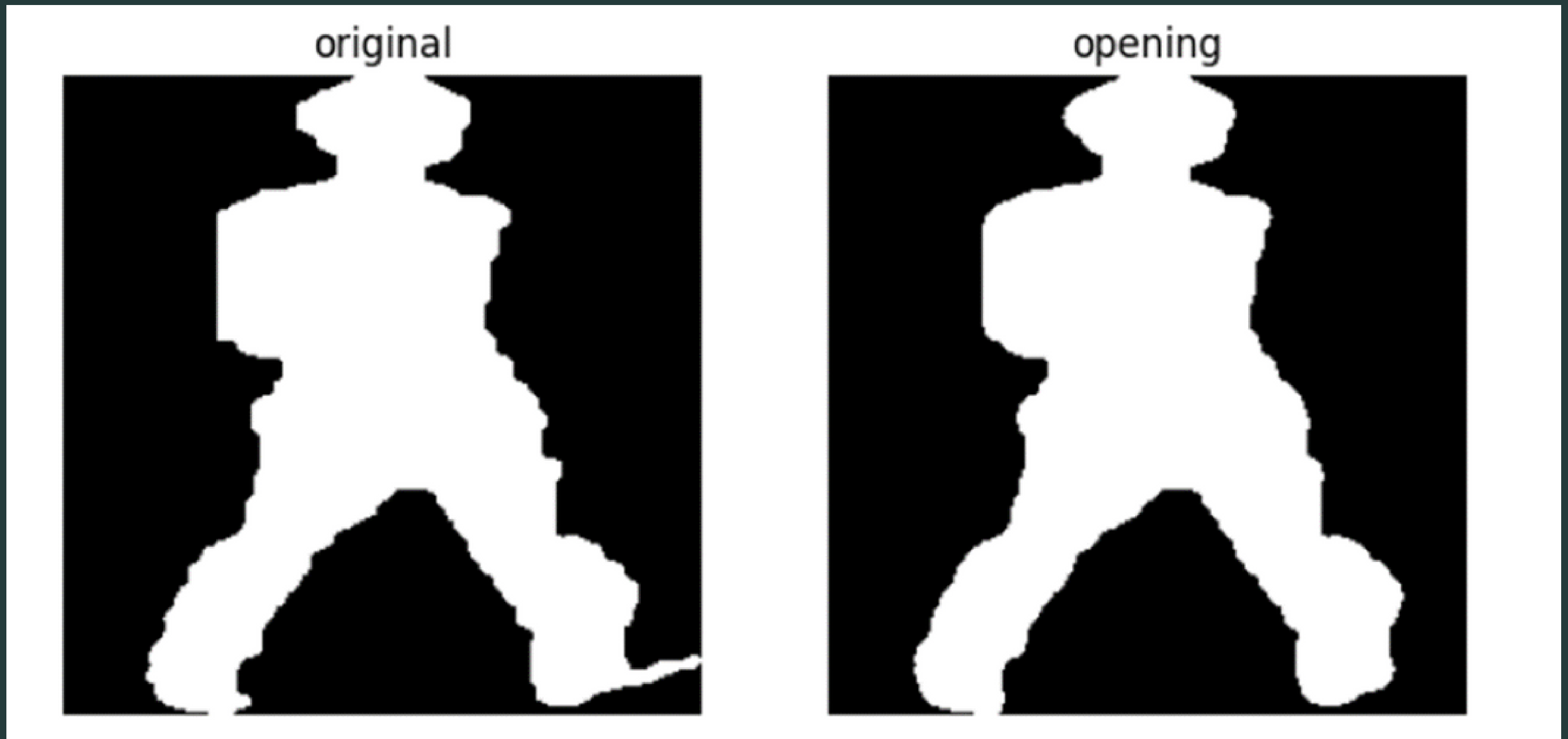


Figure 1: Comparison between original and morphological opening images

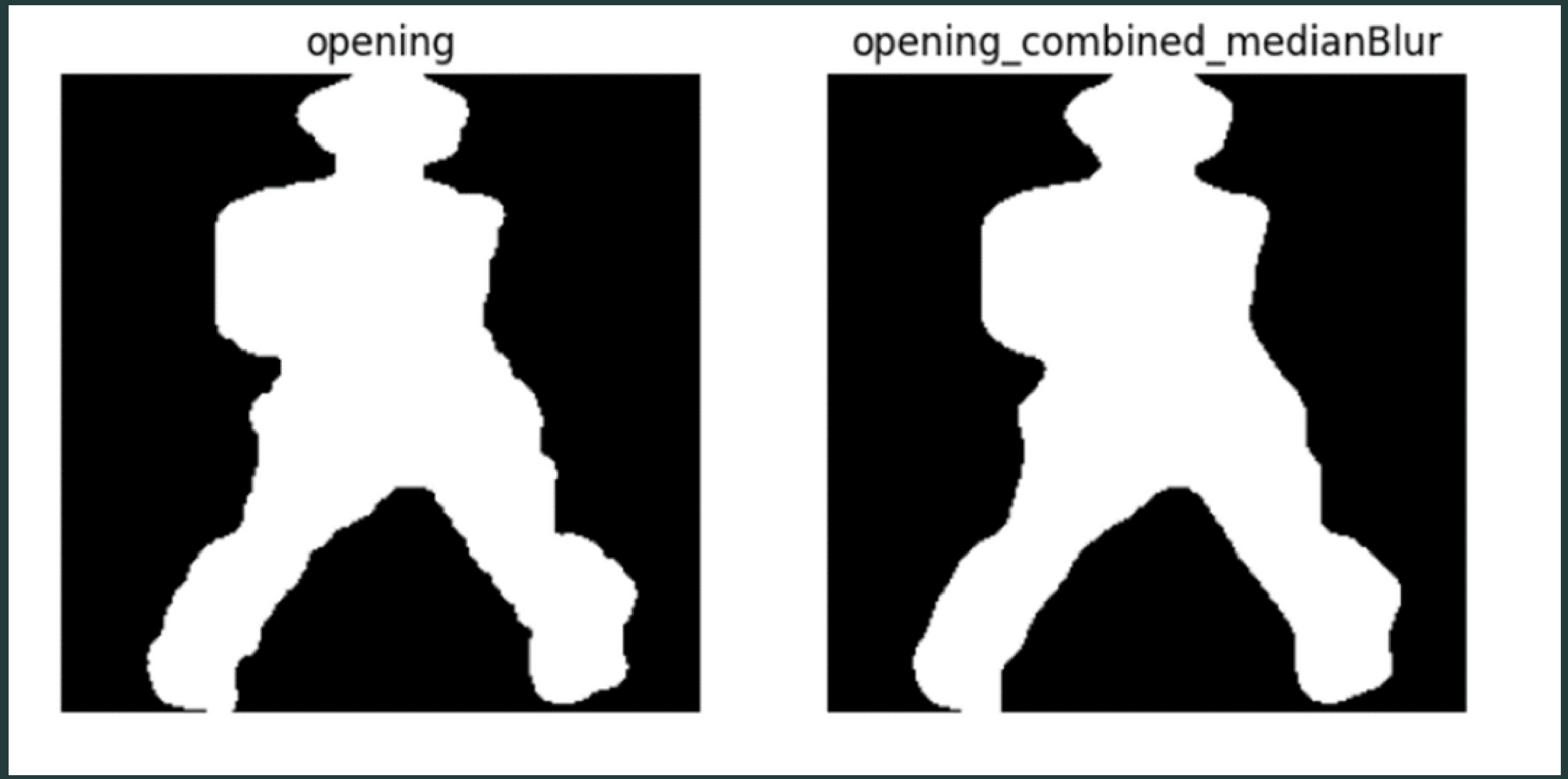
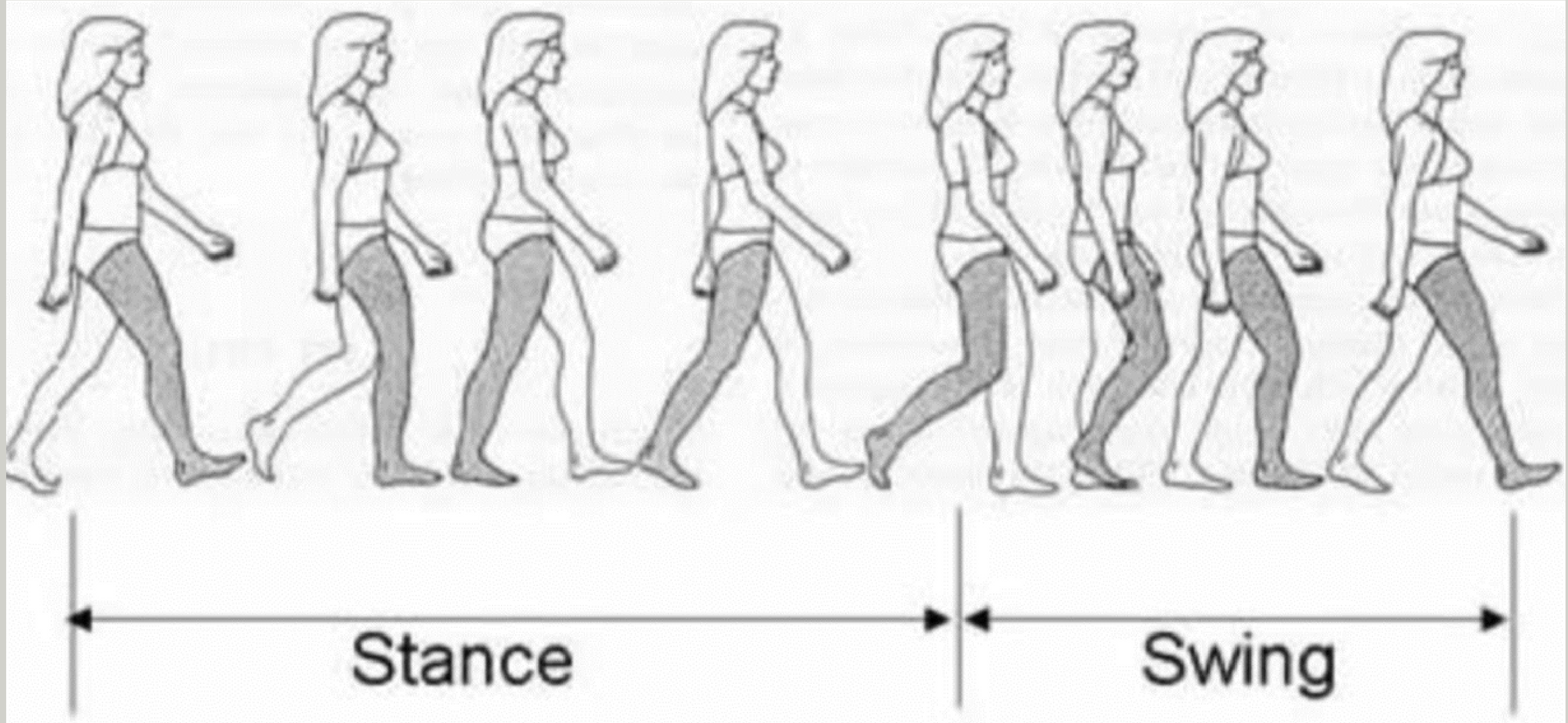


Figure 2: Comparison between morphological opening and morphological opening combined with median blur images

Feature Extraction

Gait cycle

- The time period between two instances of the same foot touching the ground
- Used for the purpose of normalizing silhouettes and computing gait templates



Gait Energy Image (GEI)

- A simple gait image representation, computed from the average of silhouette images of a walking person
- Dependent on the number of frames in 1 complete gait cycle (N)

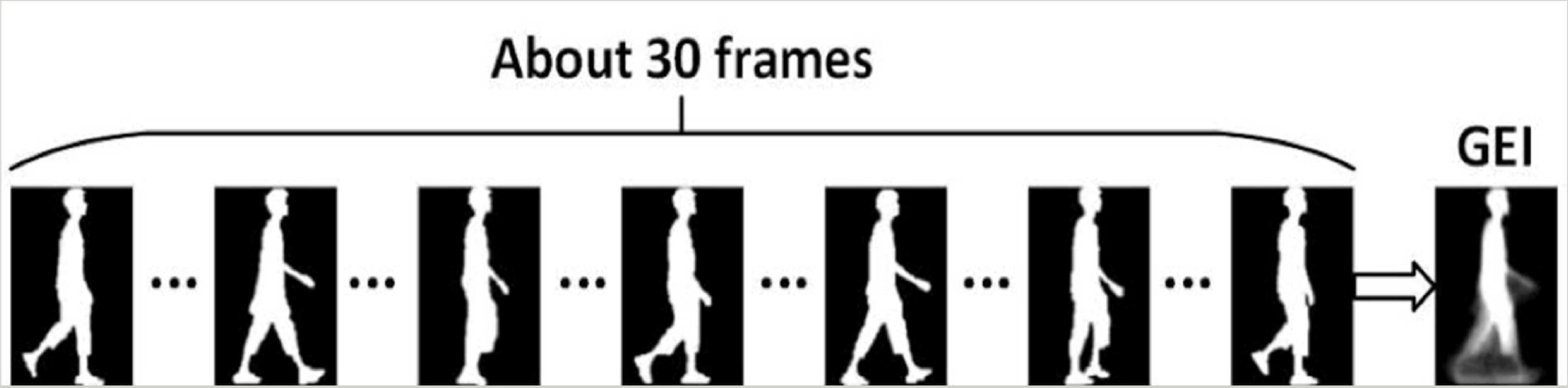
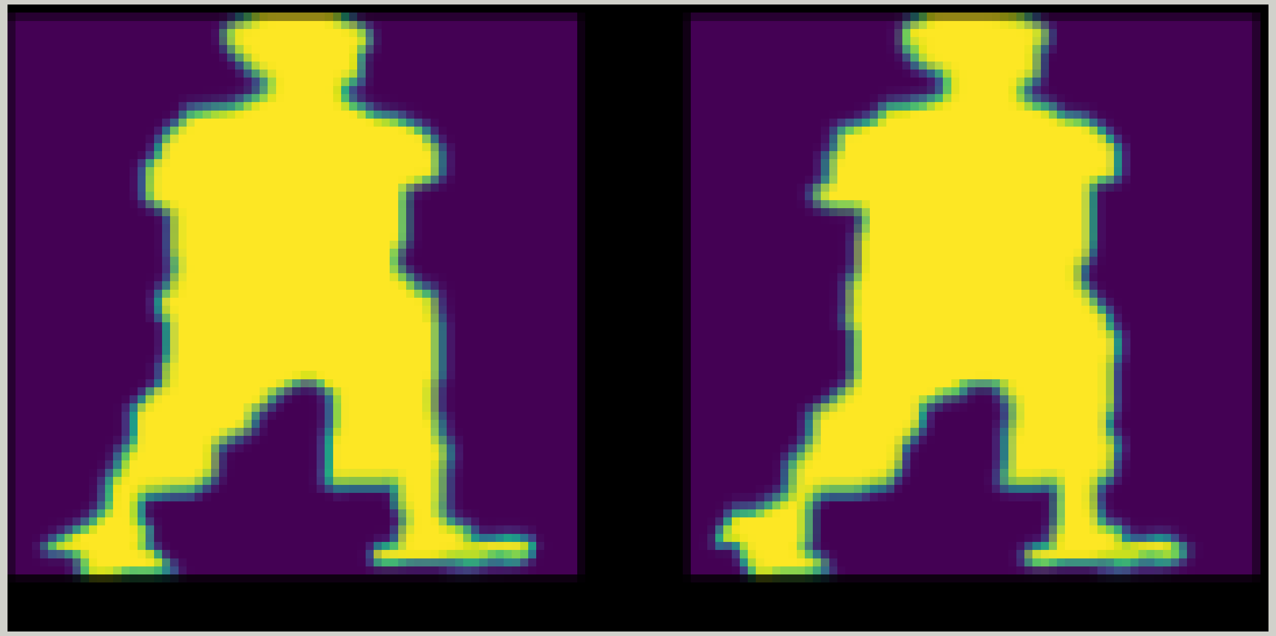


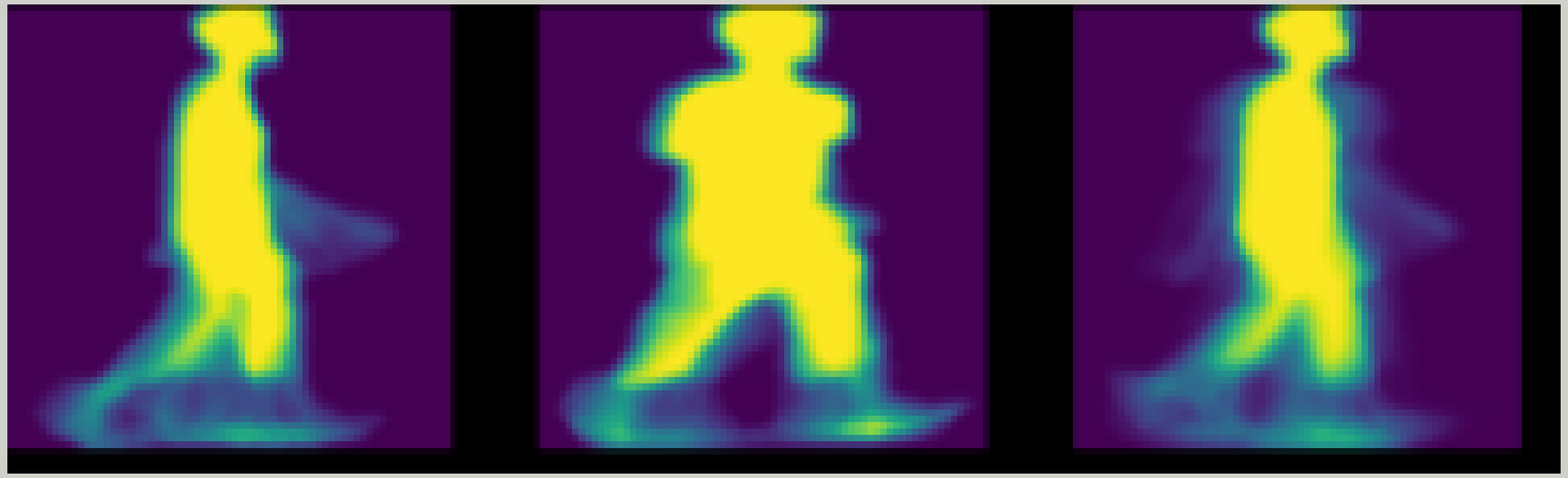
Figure 3: An example of a GEI with N ~ 30

Approach 1: Classify objects

- **Main idea**: Generate the training, validation, and test set by choosing a number of consecutive original images (after preprocessing, the starting frame is chosen randomly) to create GEIs



Original images



n-f GEIs created by choosing a random starting frame
(n = 3,5,8,10,15,20,25,30)

Approach 1: Classify objects

- With the training set, number of images for each n-f GEI is 10.
- With the test and validation set, this number equals 3 and 4 respectively.

```
Found 201588 images belonging to 3844 classes.
Found 86059 images belonging to 3844 classes.
Found 76527 images belonging to 3844 classes.
```

From the top to the bottom: training, test and validation dataset

Approach 1: Classify objects

Model details:

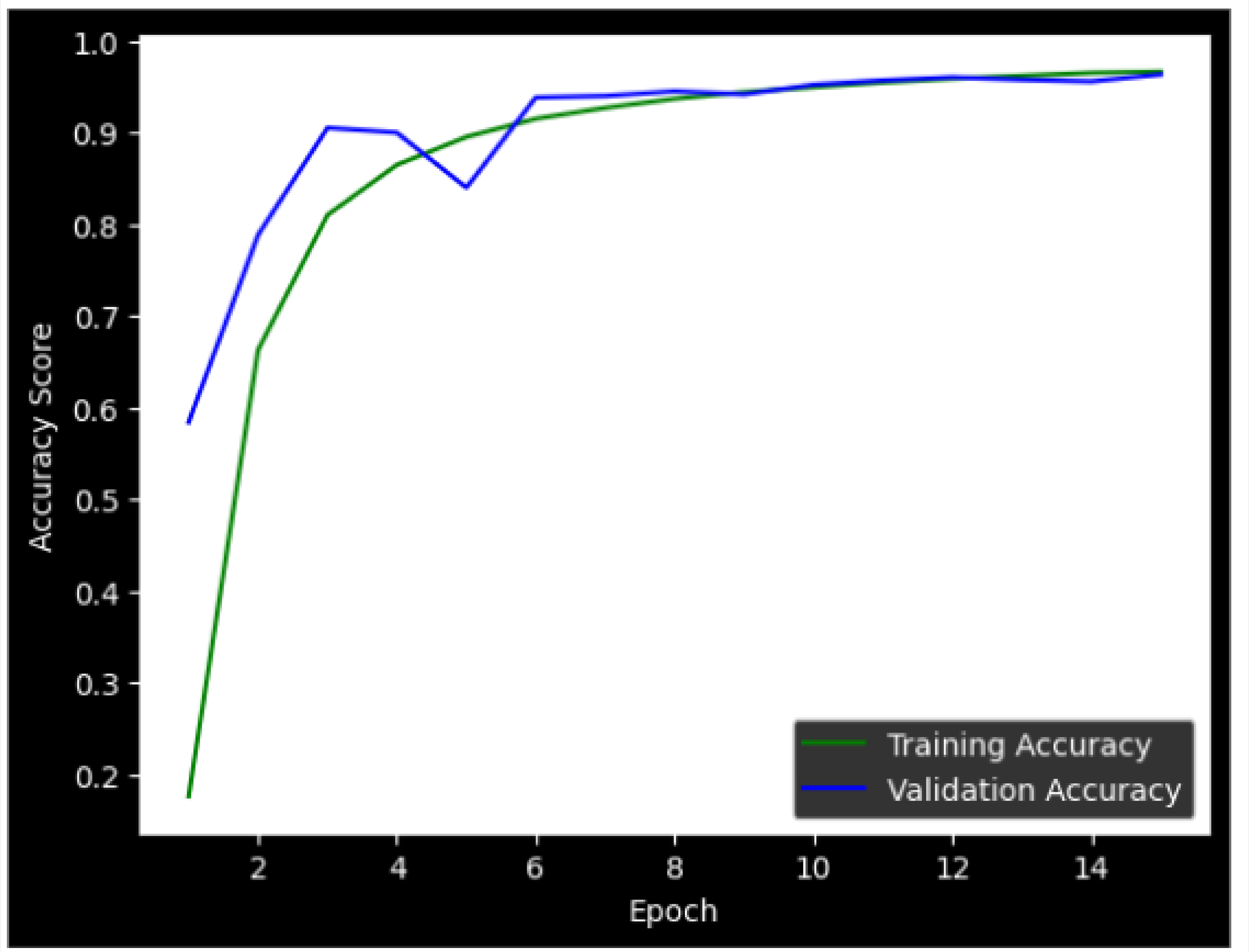
- Has 7 layers: the first 4 layers are convolutional layers, the next 2 layers are fully connected layers and the final layer is the output layer
- Activation function: ReLu
- Input size = 64x64 grayscale images (GEIs)
- The model takes the generated GEIs from the previous step as its input then learns to correctly classify them into 3844 classes.

```
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 64, 64, 32)        1600

 batch_normalization (Batch  (None, 64, 64, 32)        128
 Normalization)

 activation (Activation)     (None, 64, 64, 32)        0

 max_pooling2d (MaxPooling2  (None, 32, 32, 32)        0
 D)

 dropout (Dropout)           (None, 32, 32, 32)        0

 conv2d_1 (Conv2D)           (None, 32, 32, 128)       102528

 batch_normalization_1 (Bat  (None, 32, 32, 128)       512
 chNormalization)

 activation_1 (Activation)   (None, 32, 32, 128)       0

 max_pooling2d_1 (MaxPoolin  (None, 16, 16, 128)       0
 g2D)
...
Total params: 7263044 (27.71 MB)
Trainable params: 7259140 (27.69 MB)
Non-trainable params: 3904 (15.25 KB)
```

Approach 1: Classify objects

Evaluation

- After 15 epochs of training & validating with Adam optimizer (learning rate = 0.01), the model reached ~ 96% accuracy on both training and validation set.
- In some epochs, the validation accuracy is even higher than training!



Approach 1: Classify objects

Evaluation

- In the testing process, the model is asked to classify all GEIs in the test set to see if the predicted class is correct.
- Test accuracy is ~ 92%, which is good.

Classification Report

	precision	recall	f1-score	support
0000024	0.80	1.00	0.89	32
0000032	0.91	0.94	0.92	31
0000035	0.97	0.97	0.97	32
0000036	1.00	0.88	0.93	32
0000037	0.73	1.00	0.84	32
0000038	1.00	1.00	1.00	32
0000039	1.00	0.86	0.93	29
0000040	0.97	0.88	0.92	32
0000041	1.00	0.97	0.98	30
0000042	0.67	0.97	0.79	32
0000043	0.91	0.97	0.94	32
0000044	1.00	1.00	1.00	32
0000045	1.00	1.00	1.00	32
0000046	0.91	0.94	0.92	32
0000047	0.97	0.97	0.97	30
0000048	0.94	1.00	0.97	32
0000049	0.91	0.94	0.92	31
0000050	0.97	0.94	0.95	32
0000051	0.88	0.91	0.89	32
0000052	0.97	1.00	0.98	31
0000053	0.86	1.00	0.93	32
0000054	1.00	0.81	0.89	31
...				
accuracy			0.92	121456
macro avg	0.92	0.92	0.91	121456
weighted avg	0.93	0.92	0.91	121456

Approach 1: Classify objects

Evaluation

- We also calculate the confusion matrix based of the prediction of the model for the test set.
- In general, almost all of the off-diagonal elements are 0 in the confusion matrix.

```
Confusion Matrix
[[32  0  0 ...  0  0  0]
 [ 0 29  0 ...  0  0  0]
 [ 0  0 31 ...  0  0  0]
 ...
 [ 0  0  0 ... 16  0  0]
 [ 0  0  0 ...  0 32  0]
 [ 0  0  0 ...  0  0 31]]
```

Approach 1: Classify objects

Evaluation

Based on the confusion matrix, we calculated the False Acceptance Rate and False Rejection Rate as below:

```python
#calculate FRR,FAR
TP = np.diag(cm)
FP = np.sum(cm, axis=0) - TP
FN = np.sum(cm, axis=1) - TP
TN = np.sum(cm) - (FP + FN + TP)
# False Acceptance Rate (FAR)
FAR = FP / (FP + TN)

# False Rejection Rate (FRR)
FRR = FN / (TP + FN)
```

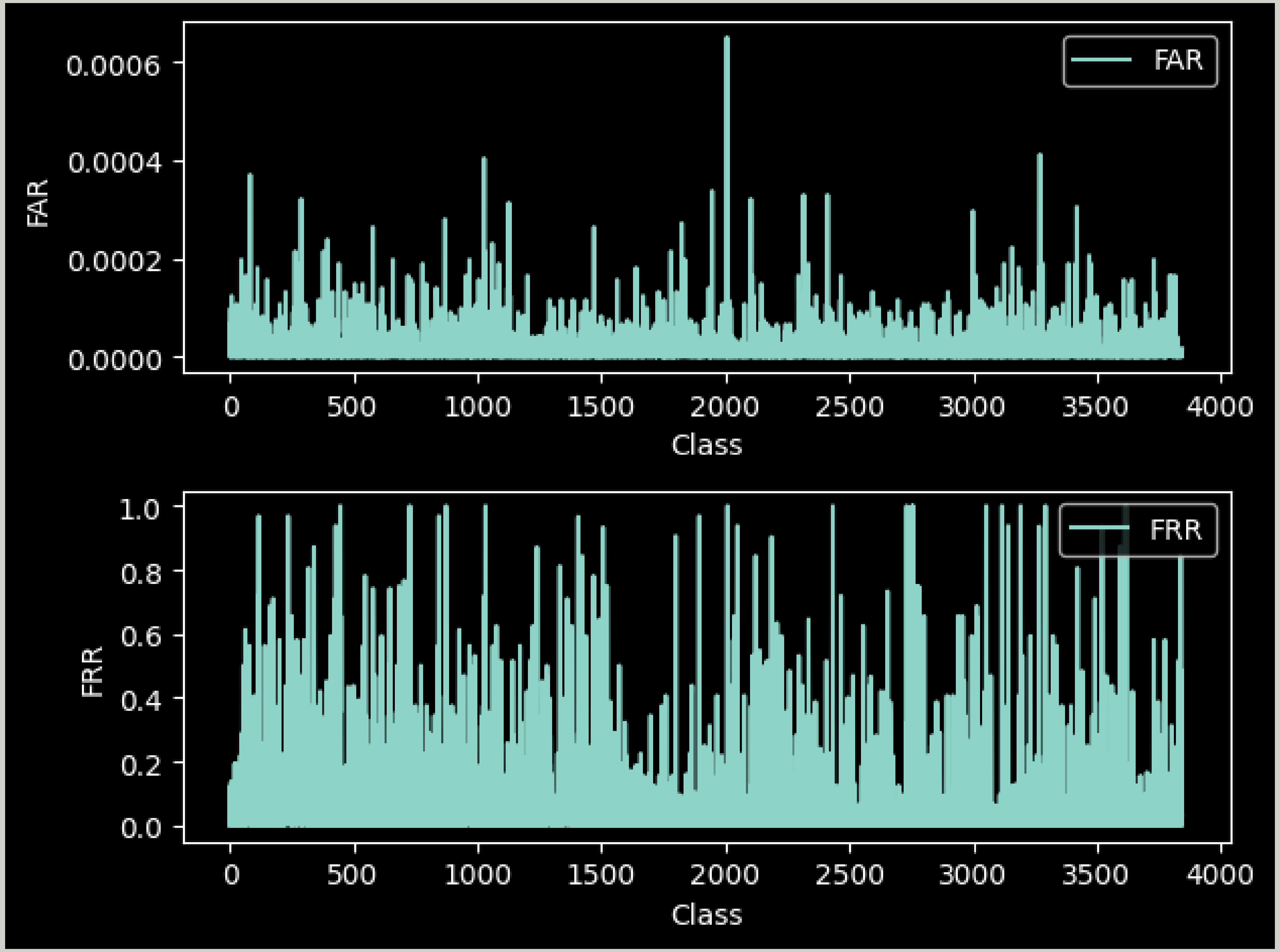
where:

- TP is True Positive
- FP is False Positive
- FN is False Negative
- TN is true negative
- cm is the confusion matrix

Approach 1: Classify objects

Evaluation

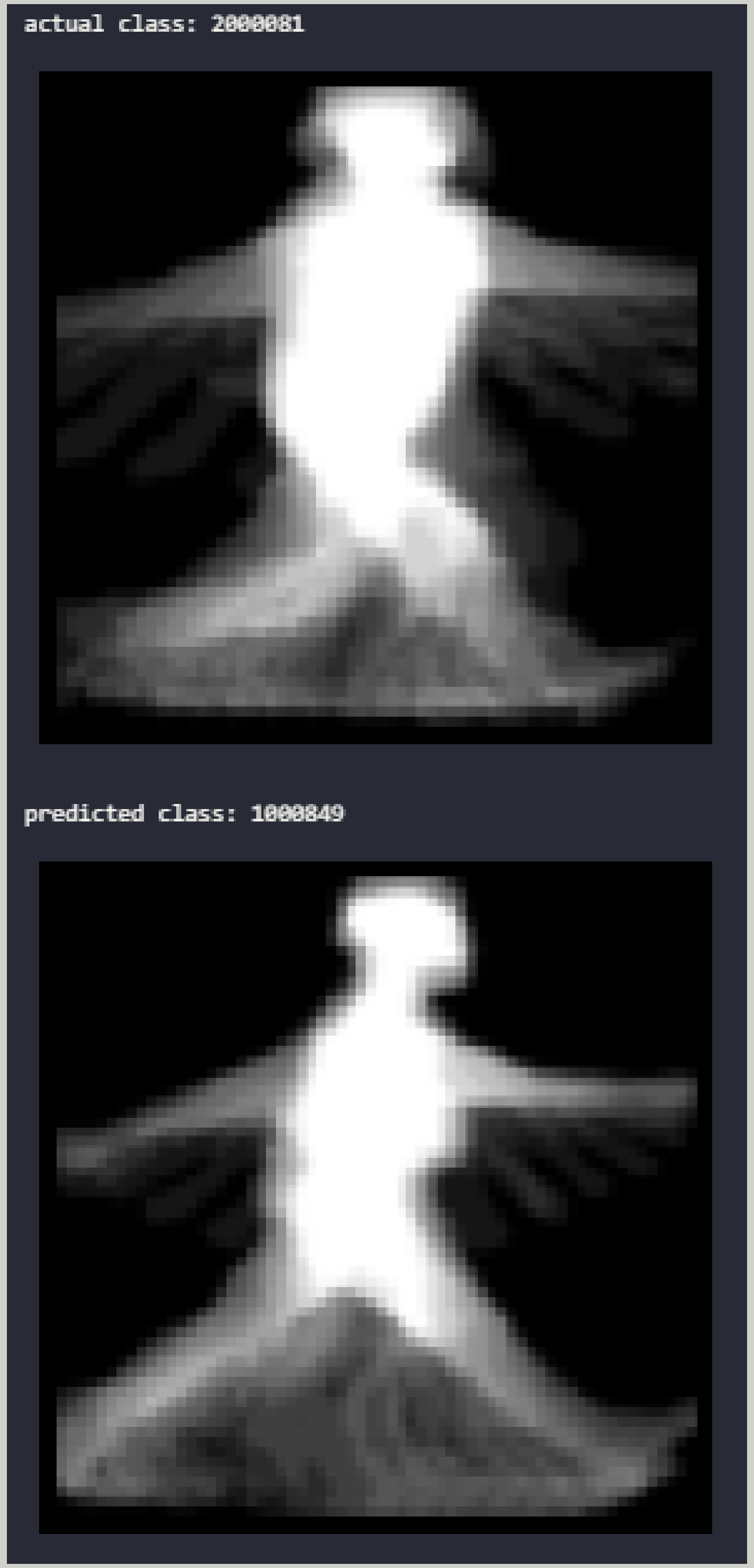
- Overall, FAR seems quite good since the maximum FAR value is ~ 0.00065.
- However, FRR of some classes is not on par with FAR - some even reach 1.0.



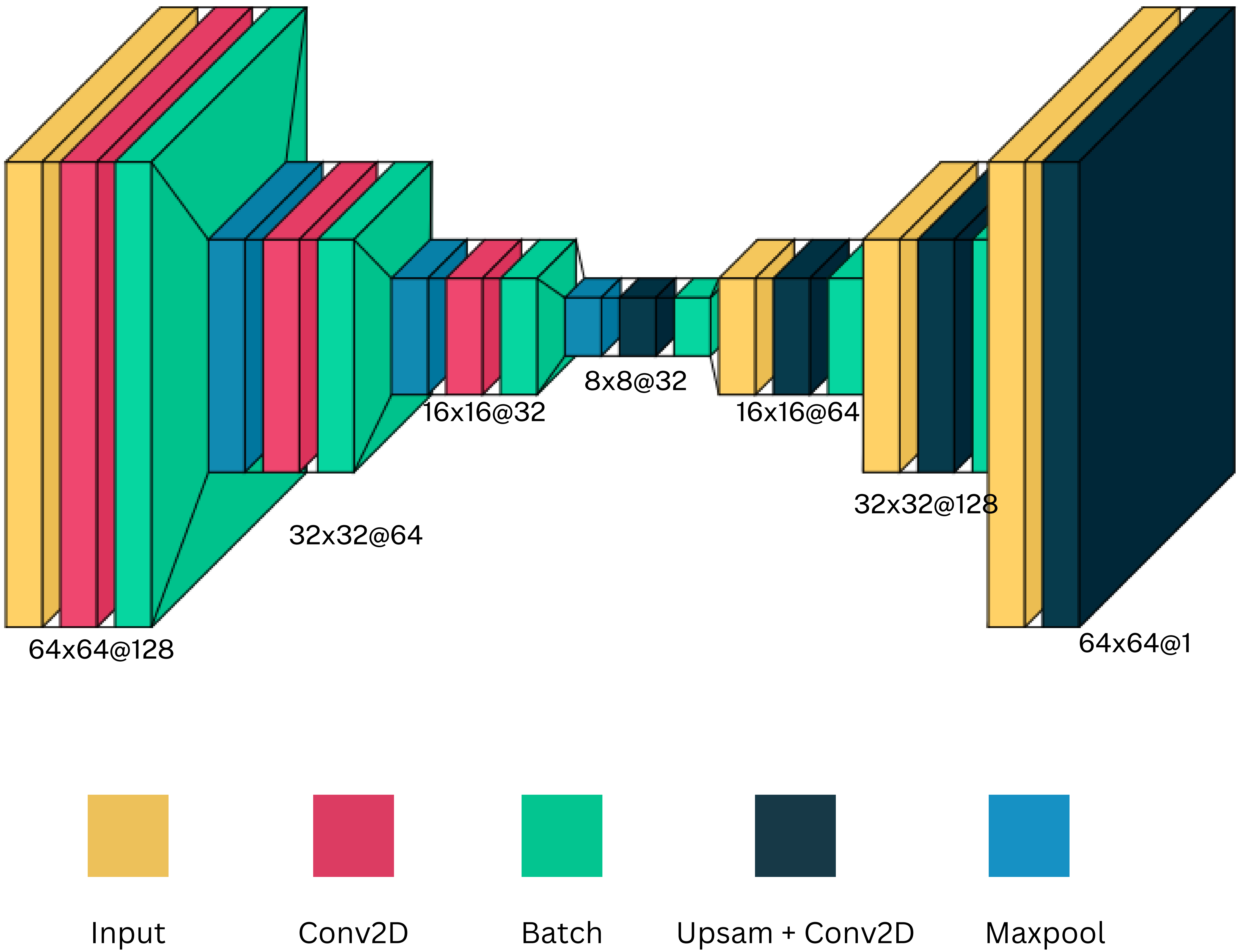
Approach 1: Classify objects

Evaluation

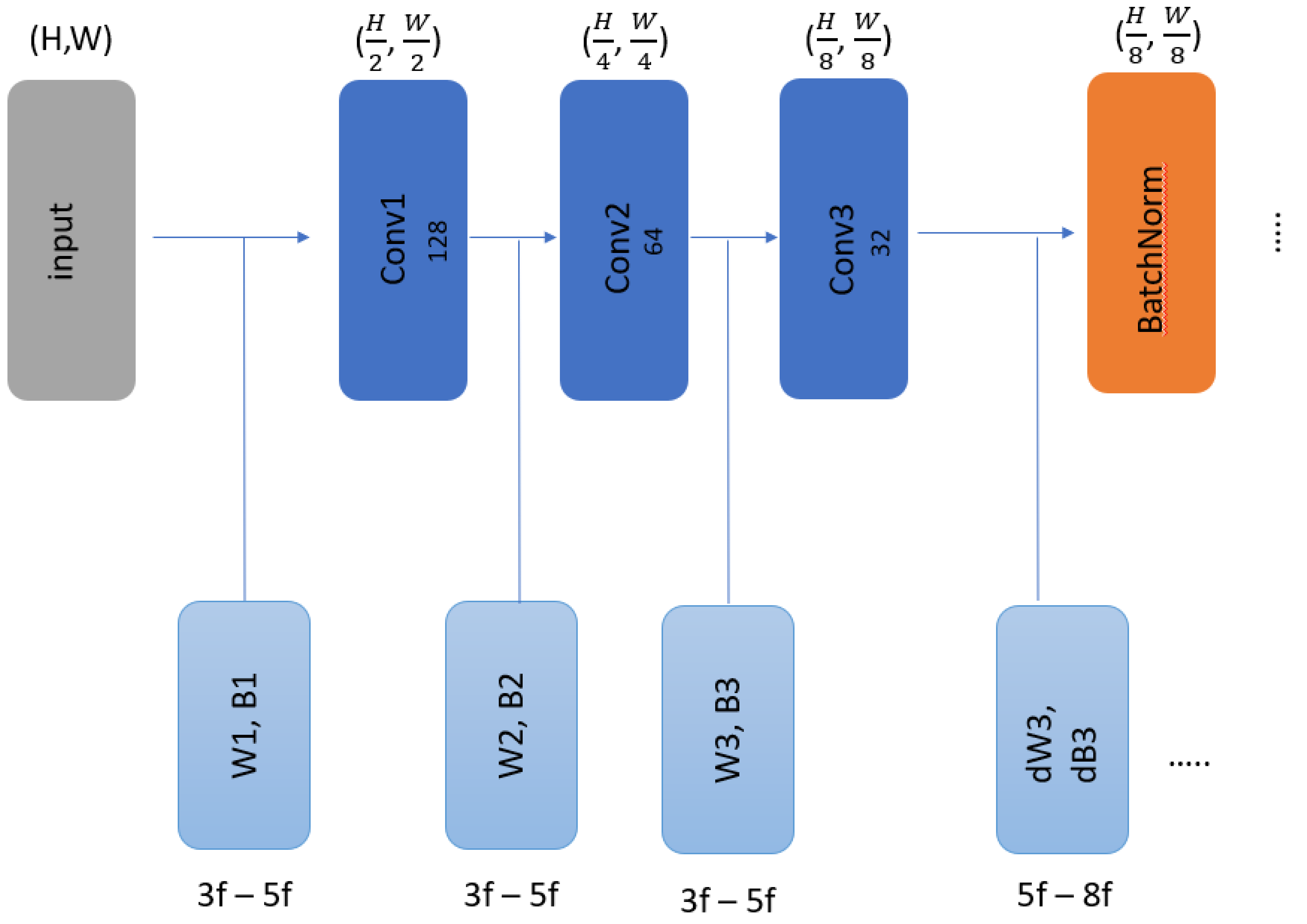
- In particular, there are 815/3844 classes that have FRR>0.1
- Their GEIs look very similar to other classes' GEIs.
- To solve that challenge, we attempted give more weight to these classes.



Each sequence GEI type Model



Model for training End-to-End Network

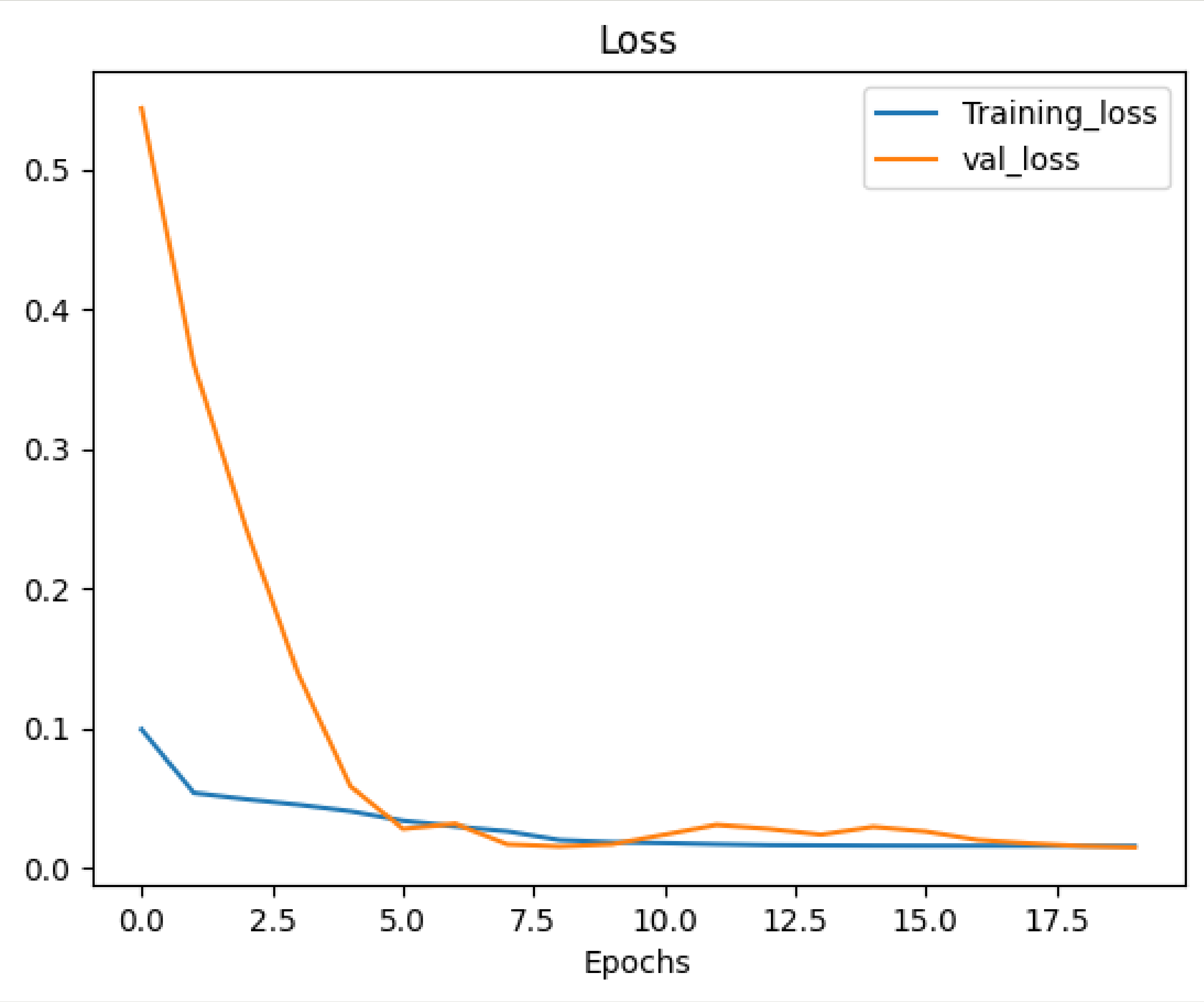


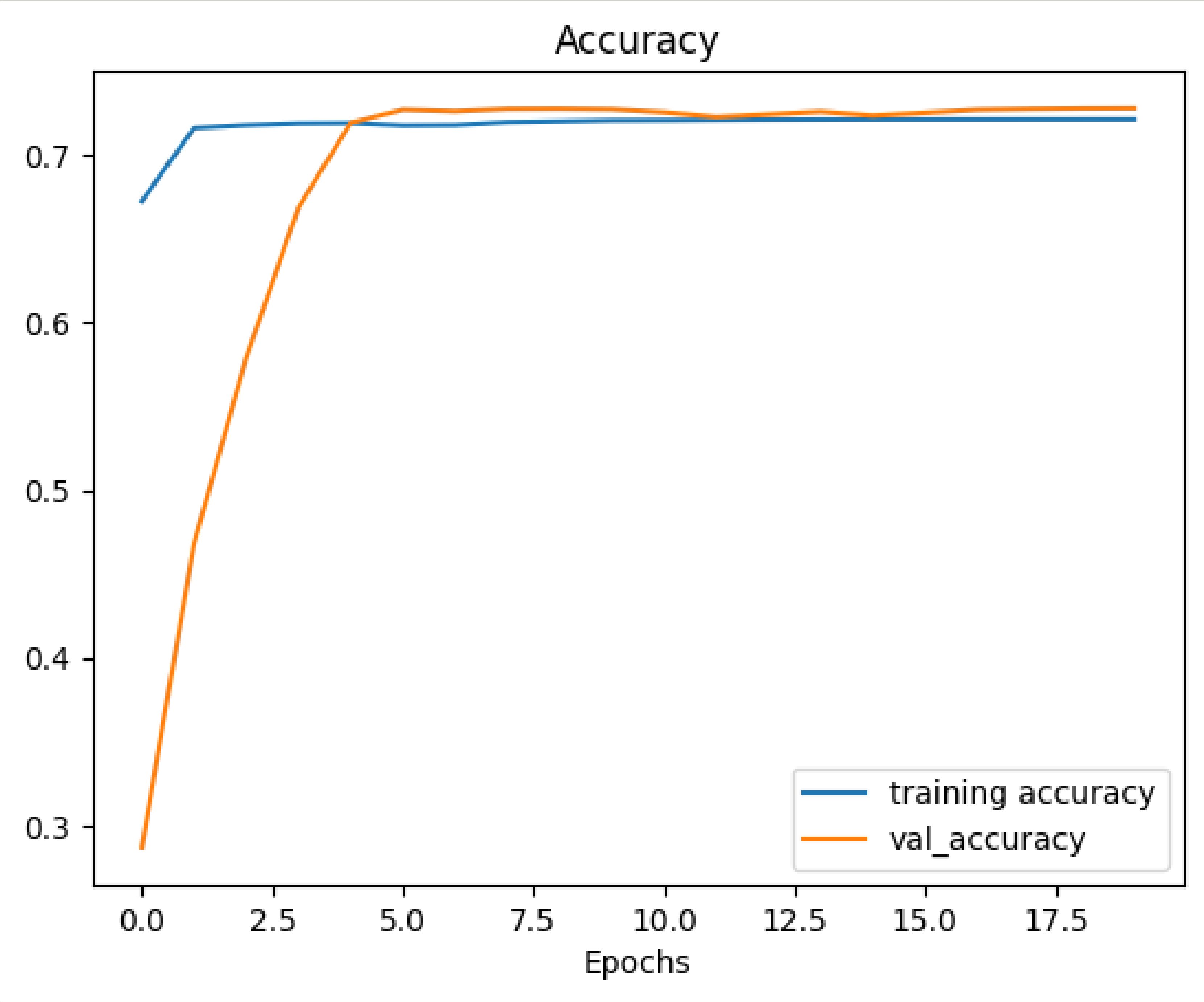
Evaluation

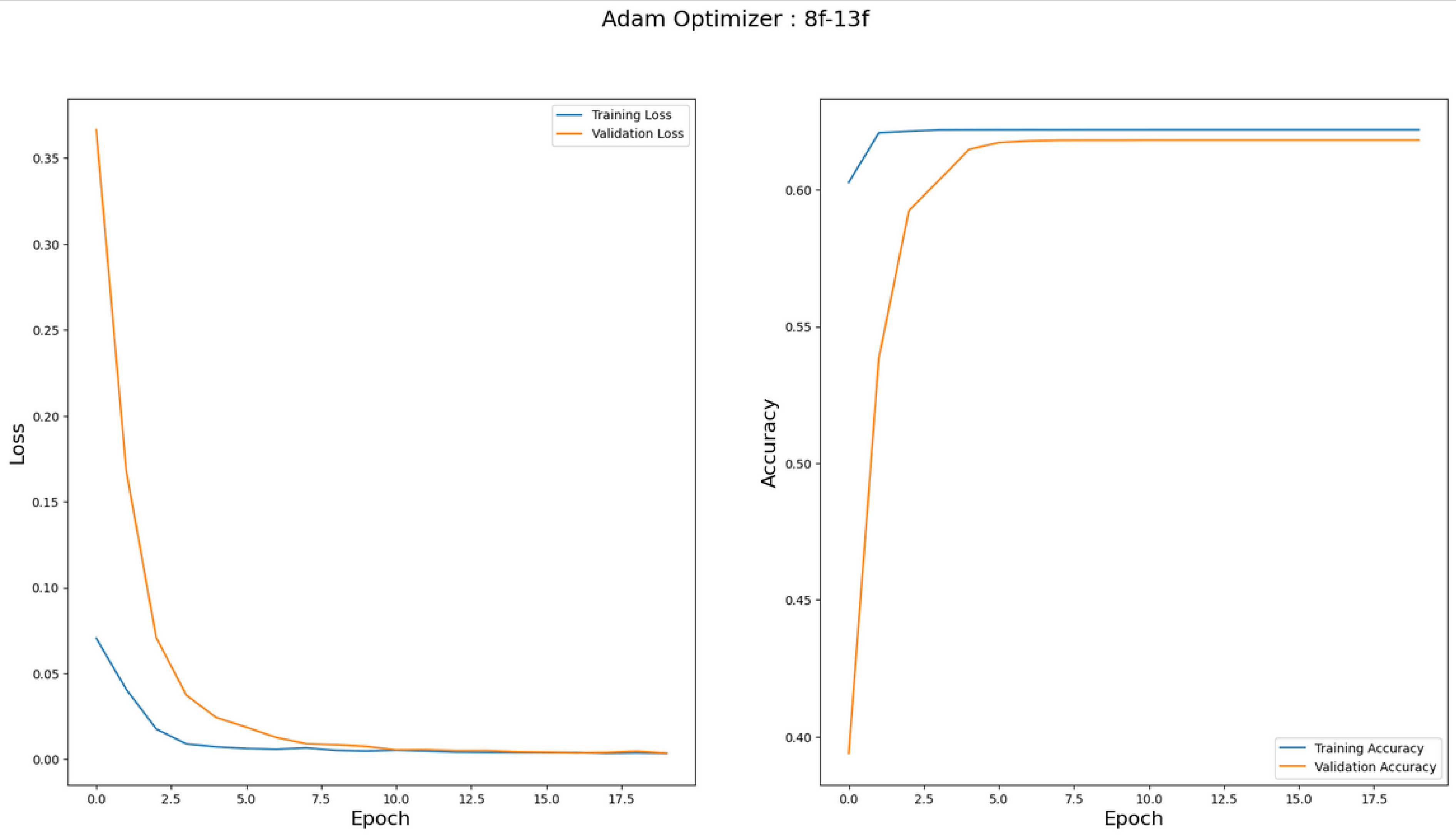
- Allthough we try different models for training such LSTM, CNN, the accuracy does not increase too much

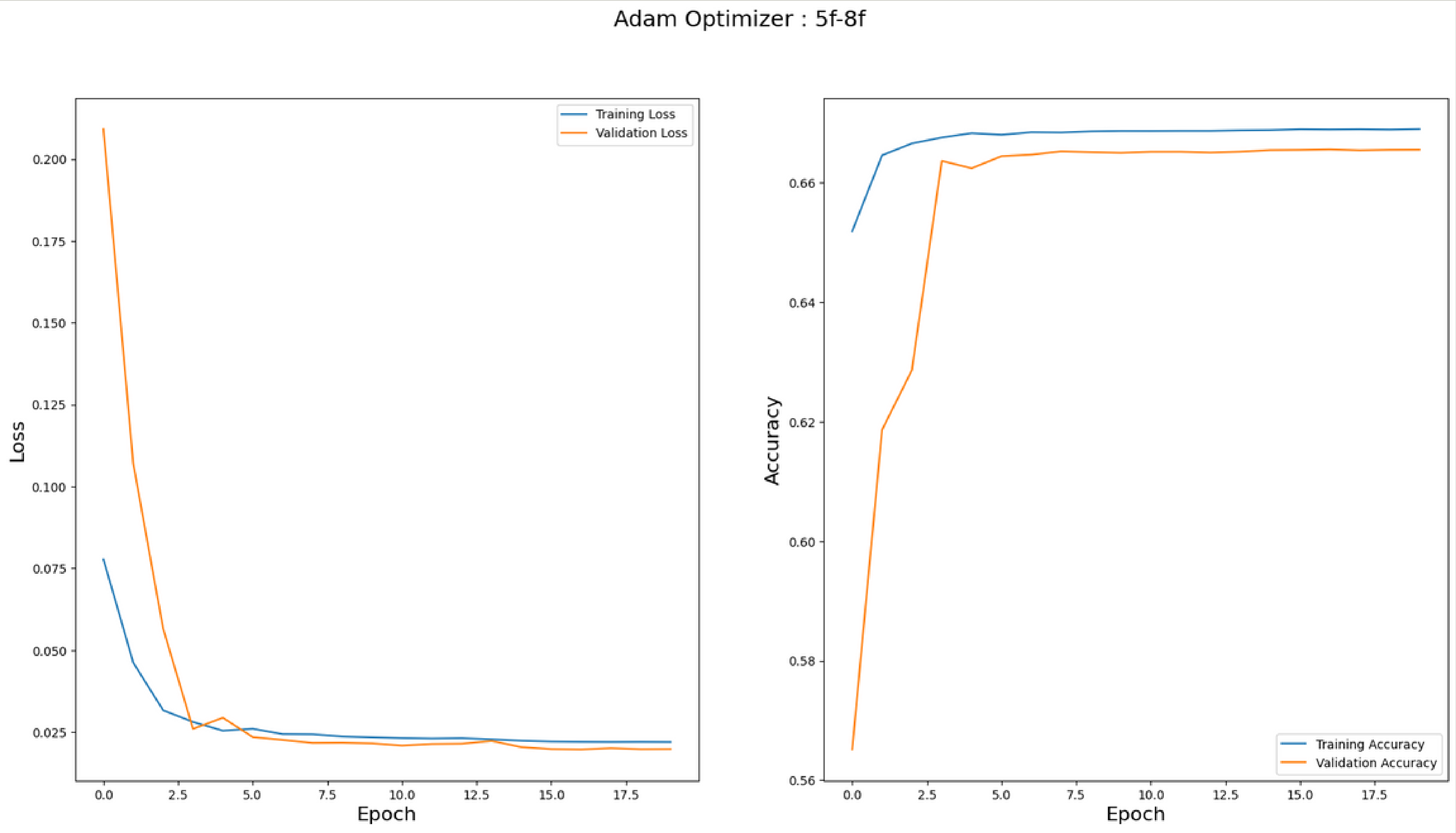
- It’s understandable since Gait Recognition is considered a “NP-hard” problem

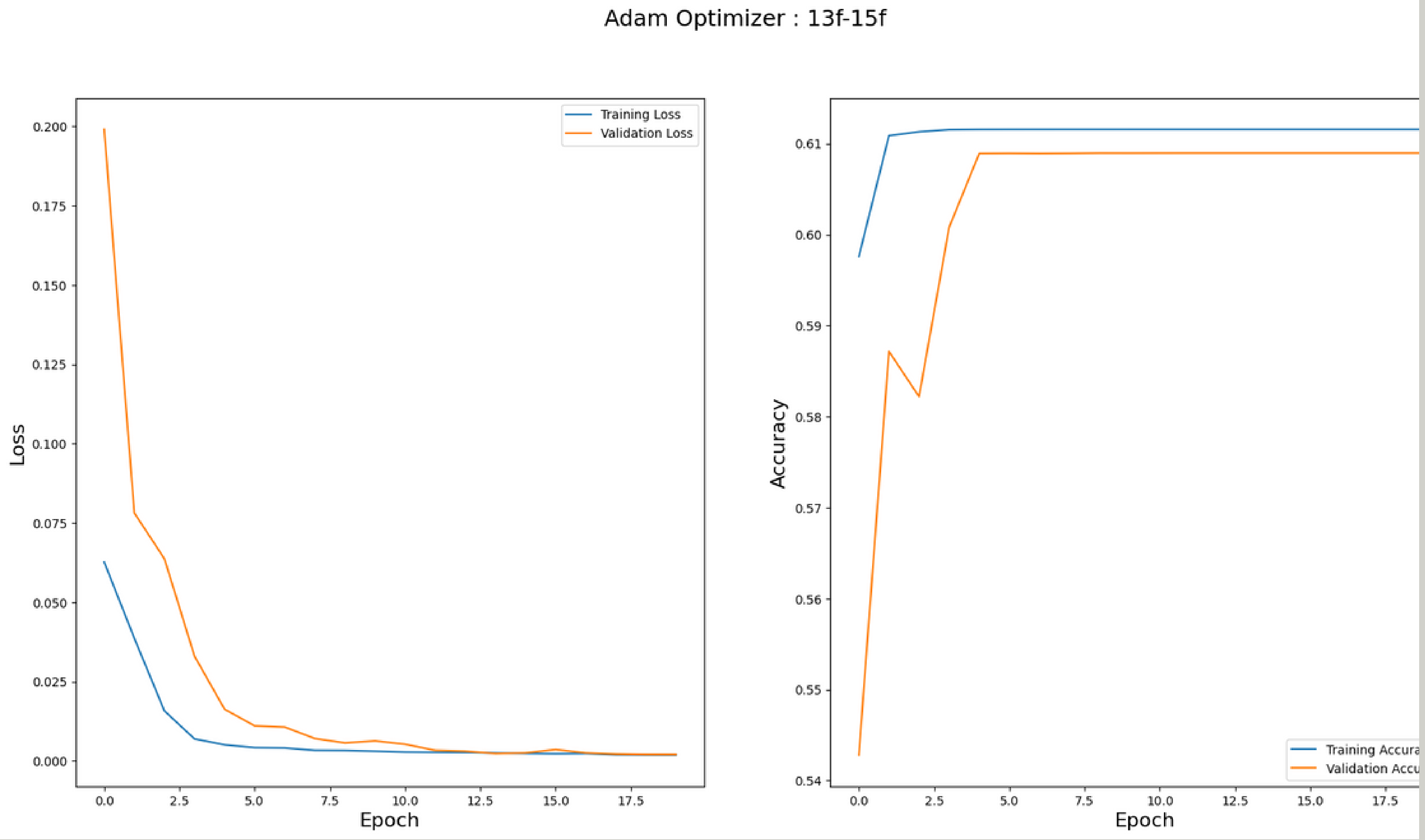
Accuracy and MSE for 3f - 5f

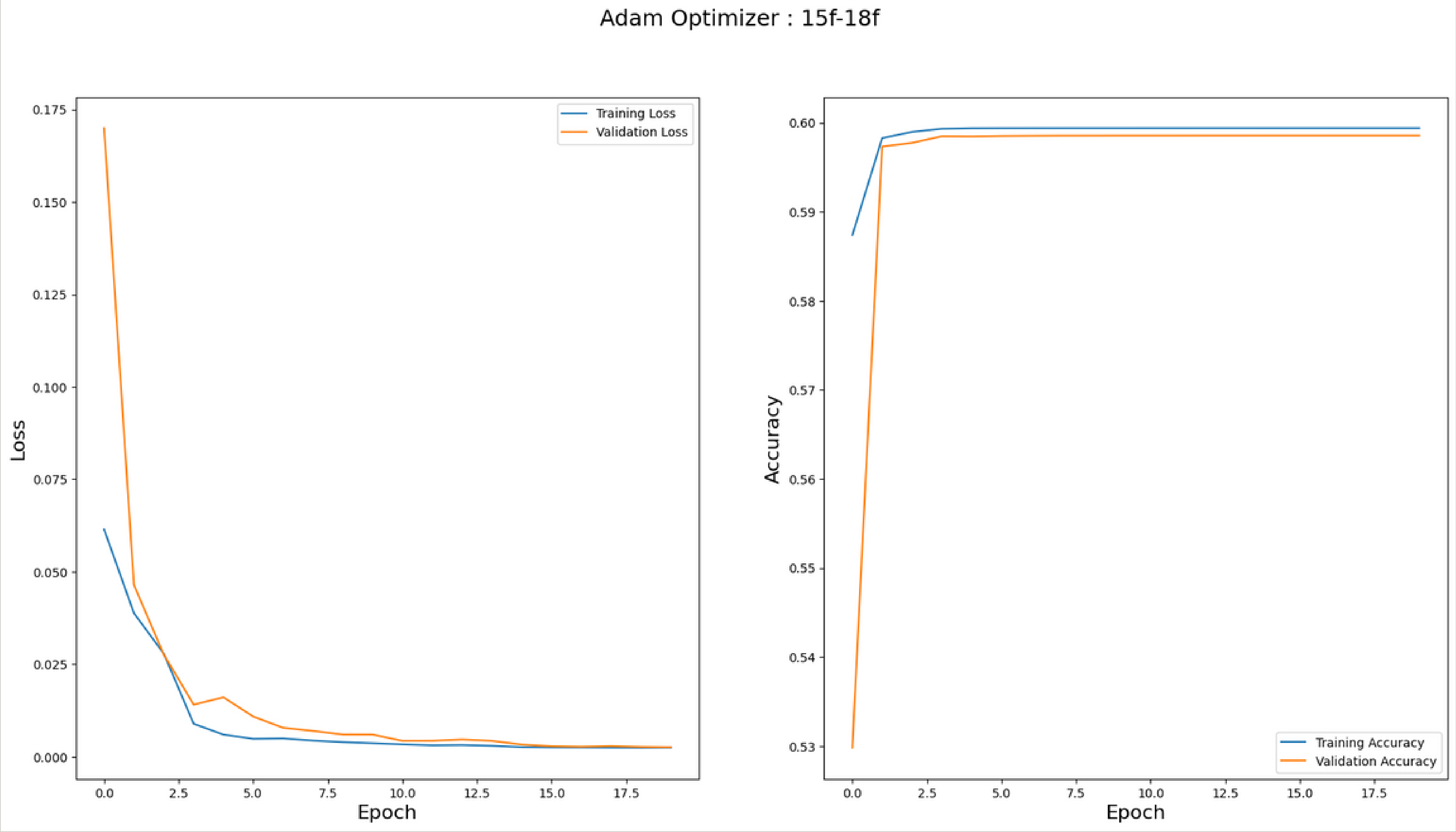




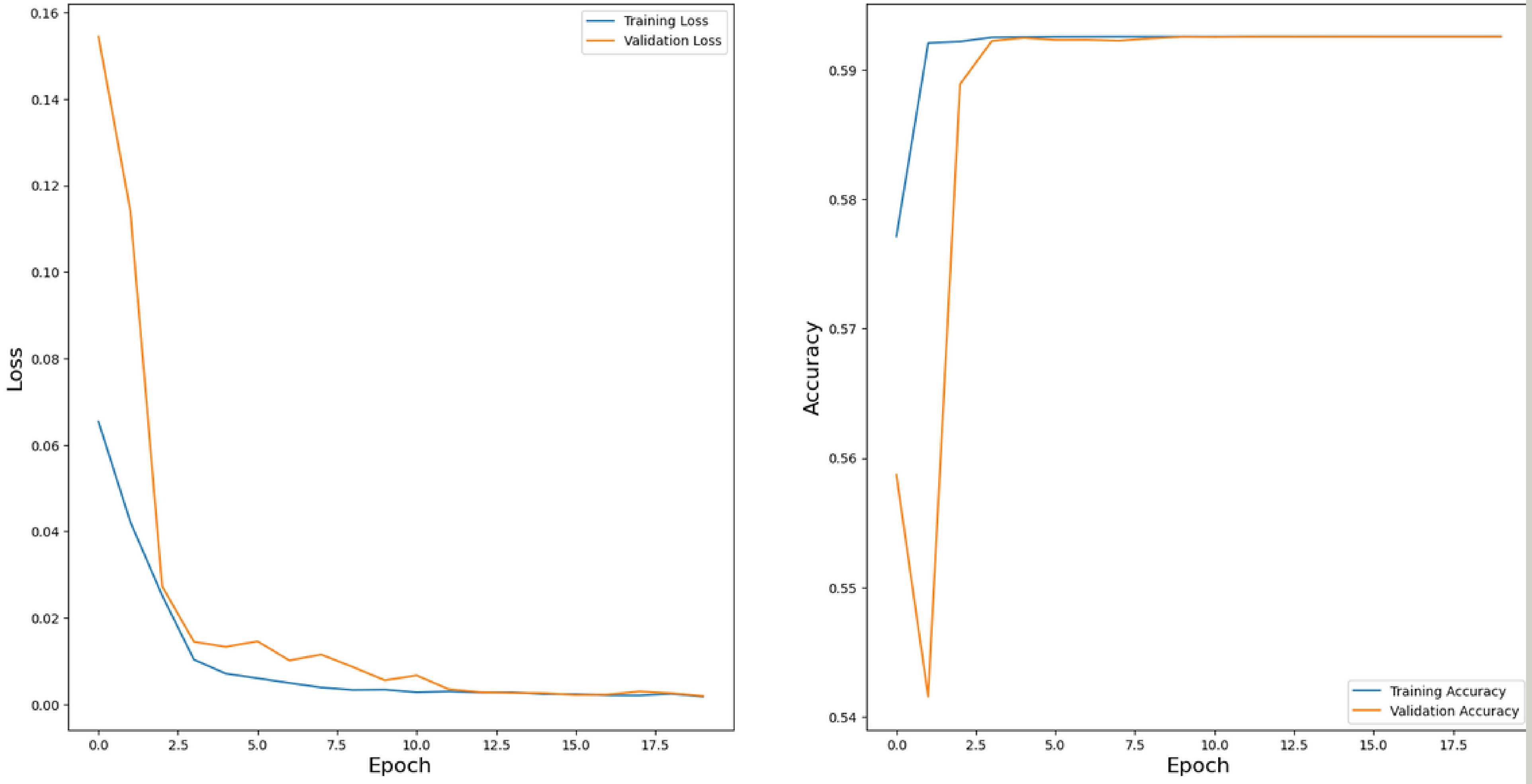

Adam Optimizer : 8f-13f
Training Loss
Validation Loss
Loss
Epoch
Training Accuracy
Validation Accuracy
Accuracy
Epoch


Adam Optimizer : 5f-8f
Training Loss
Validation Loss
Loss
Epoch
Training Accuracy
Validation Accuracy
Accuracy
Epoch

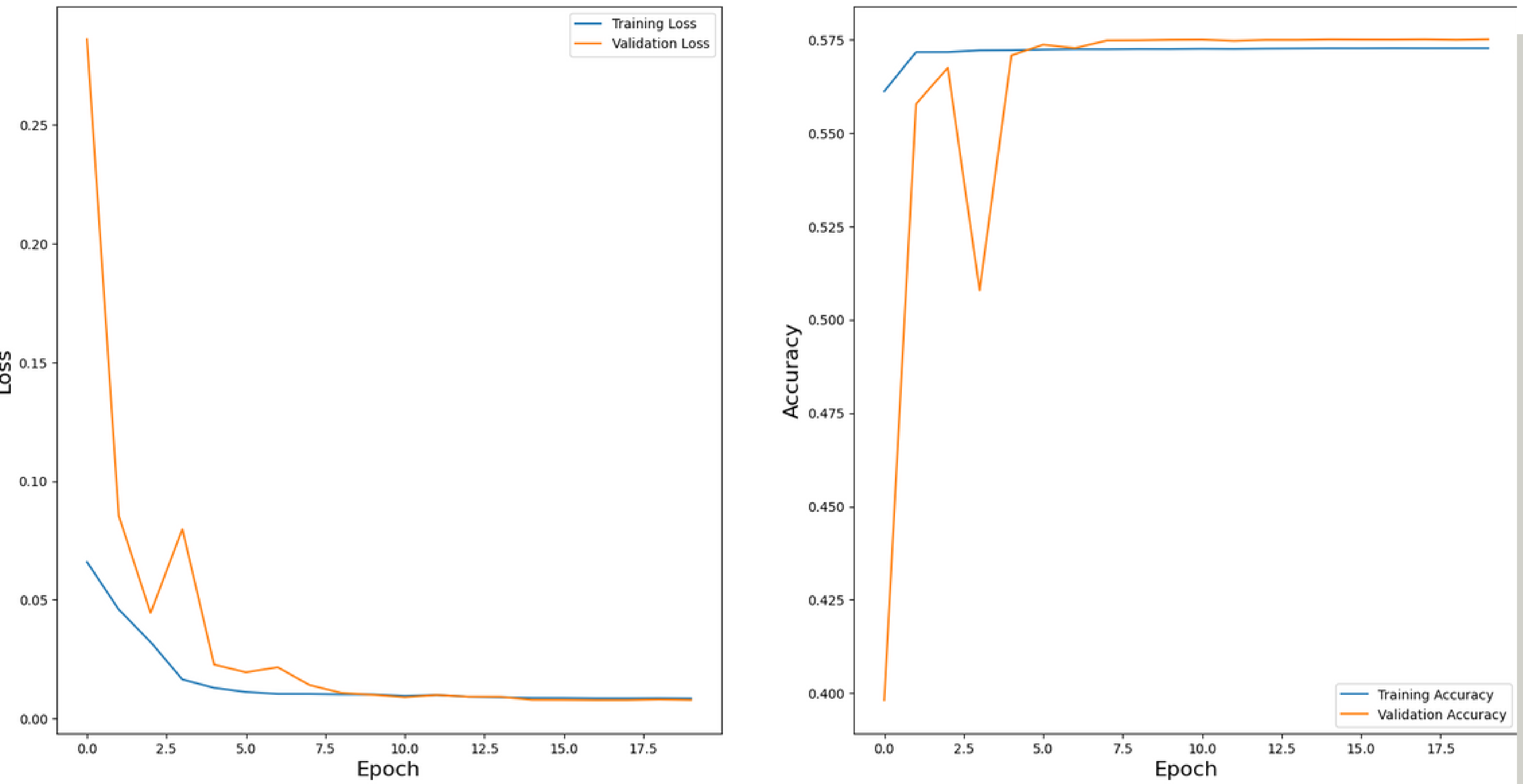

Adam Optimizer : 13f-15f
Training Loss
Validation Loss
Loss
Epoch
Accuracy
Epoch


Adam Optimizer : 15f-18f
Training Loss
Validation Loss
Loss
Epoch
Training Accuracy
Validation Accuracy
Accuracy
Epoch

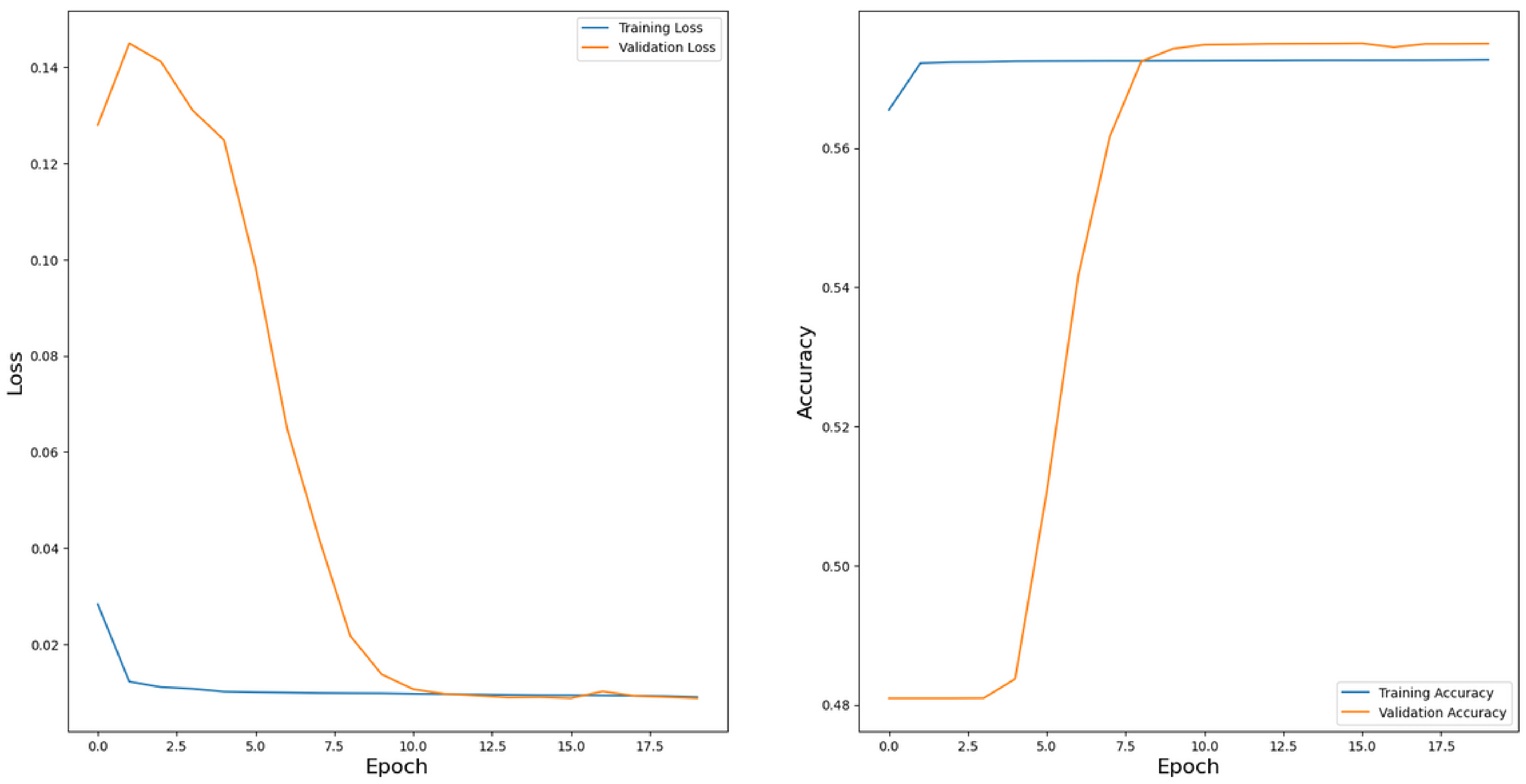
Adam Optimizer : 18f-20f



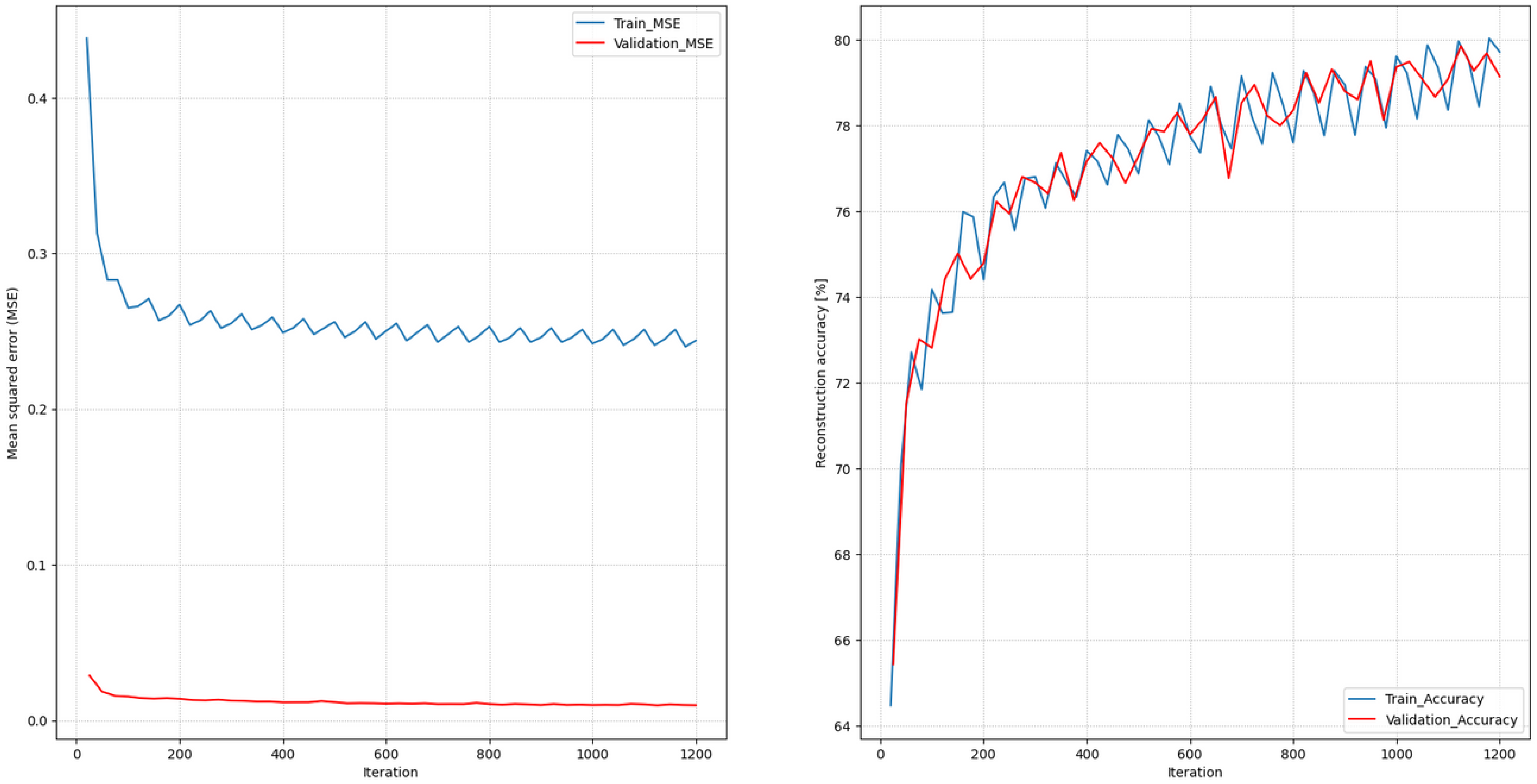
Adam Optimizer : 20f-full

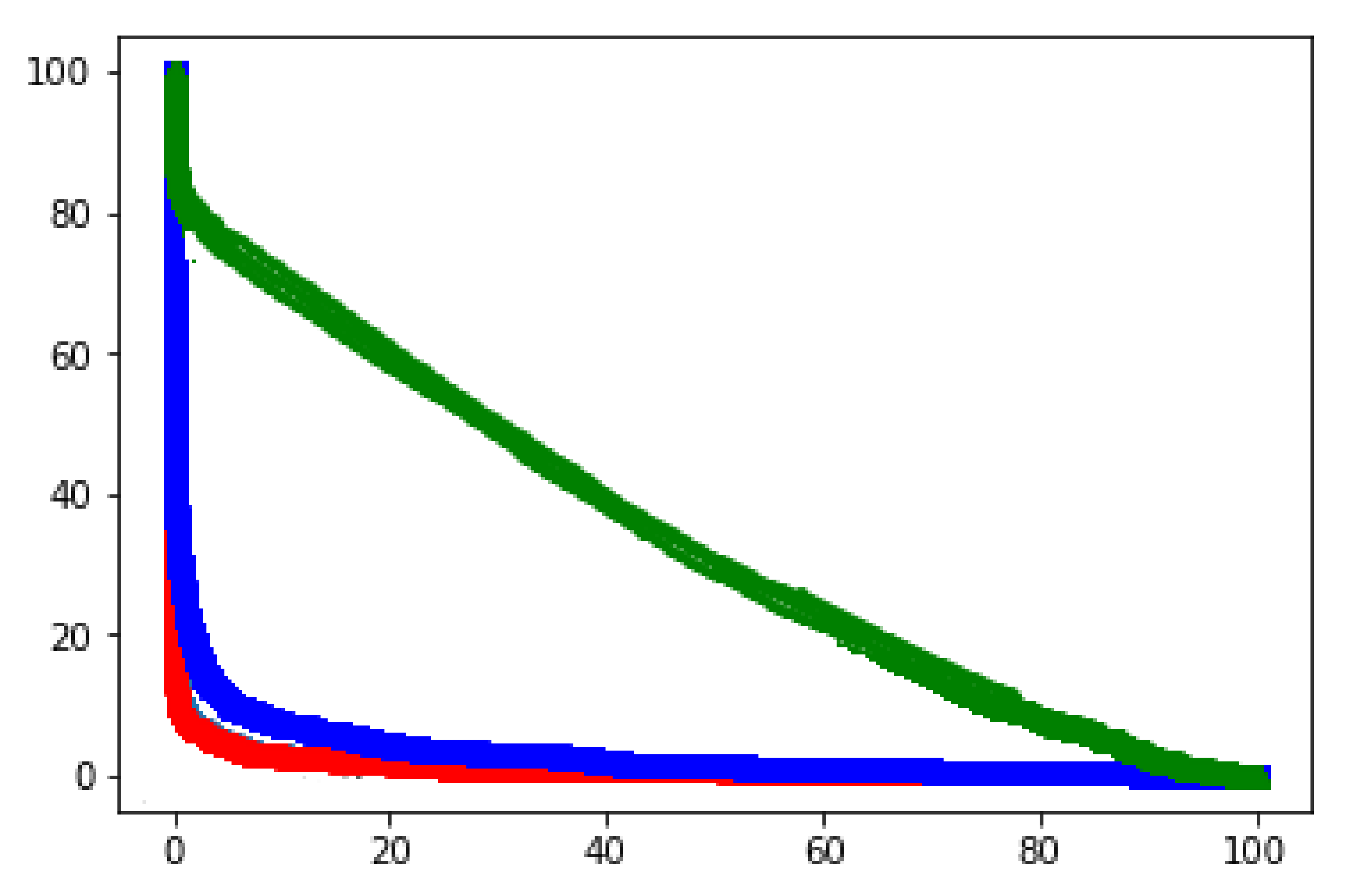


Adam Optimizer : 3f-full Single Auto-Encoder

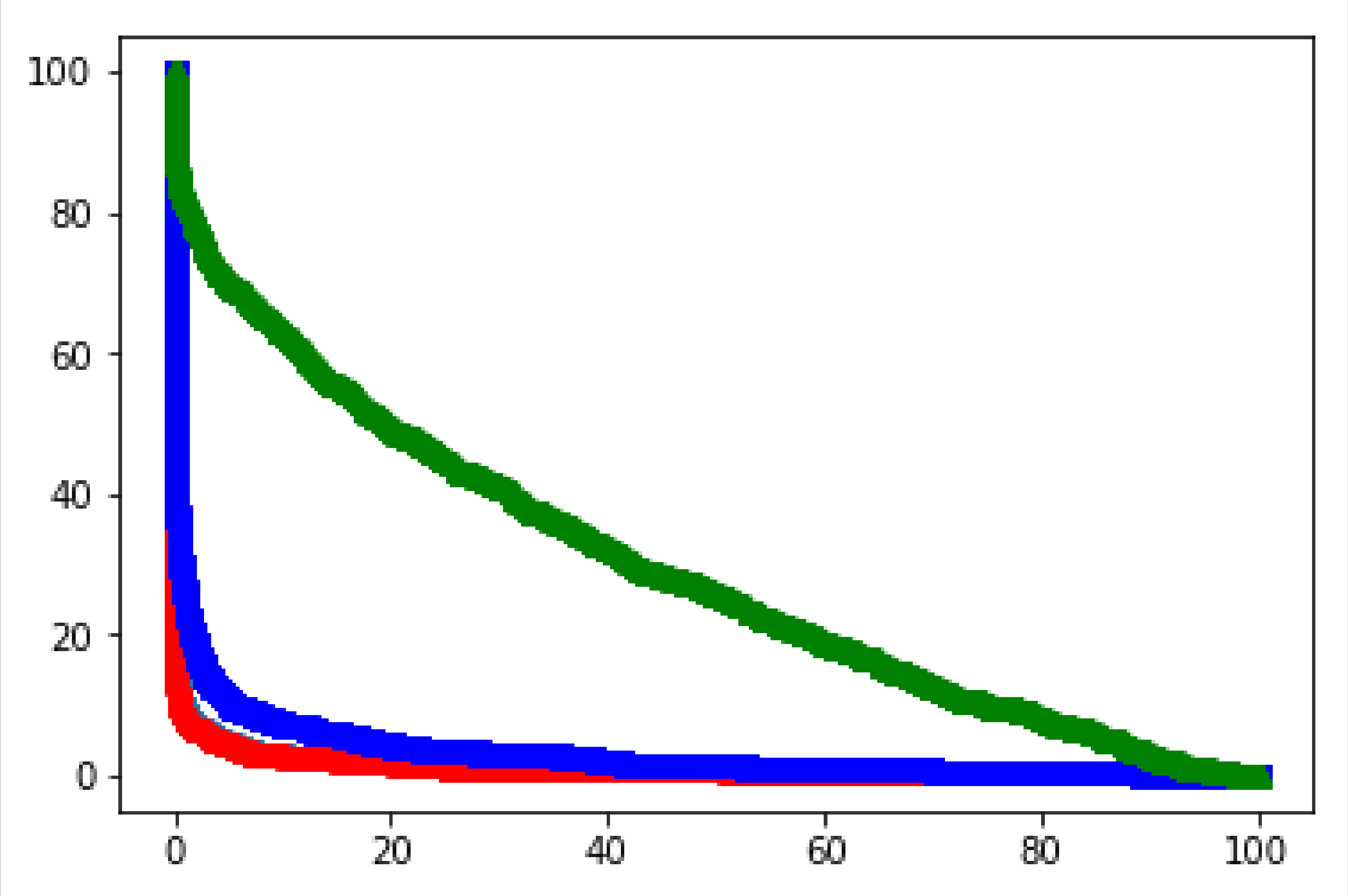


Adam Optimizer : 3f-full using Fully Convolution Neural Network with hidden layers





3f



5f

Verification results on the OULP test data. The ROCs of the reconstructed GEIs (blue), incomplete GEIs (red), and true GEIs (green). Vertical line corresponds to False Rejection Rate while horizontal line corresponds to False Acceptance Rate.

Conclusion

- Gait recognition is a flexible recognition solution without requiring active human interaction and will gain in popularity in the future.

- Despite our exploration outcome leaves a lot of room for improvements, this was a good endevor for us to do some research on a hard biometric problem.

Thank you