Computer Vision
Homework #3

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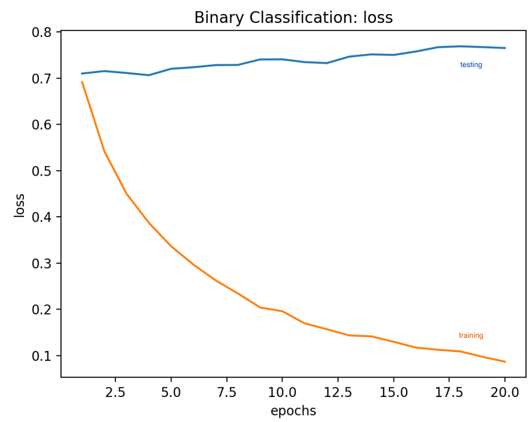
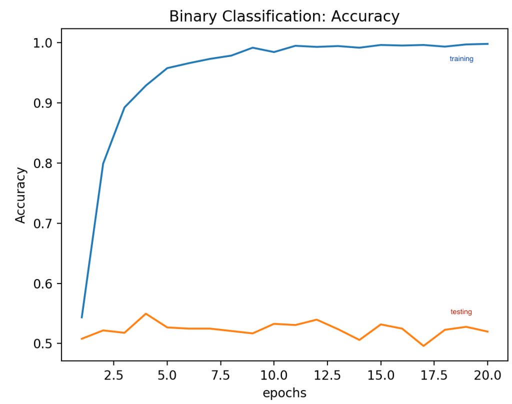
November 26, 2017

Deep Learning with Faces

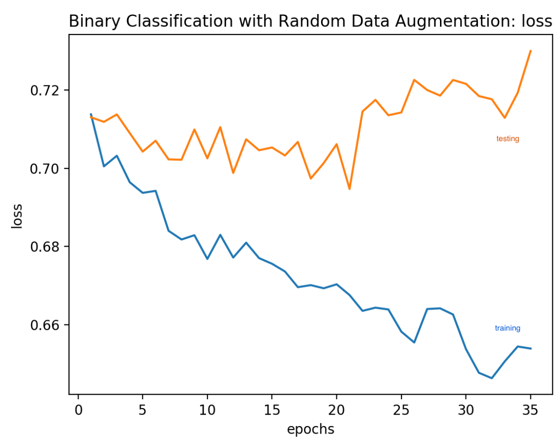
Part 1a: Binary Classification

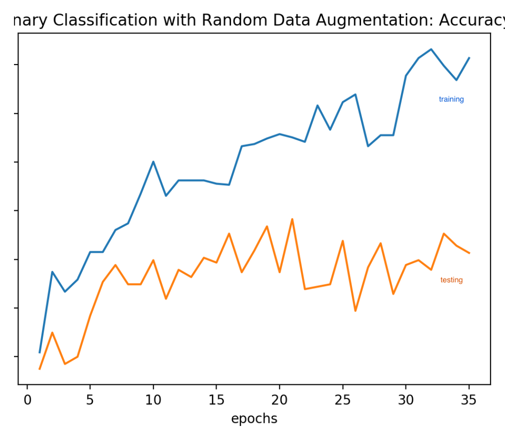
Without Random Data Augmentation





With Random Data Augmentation



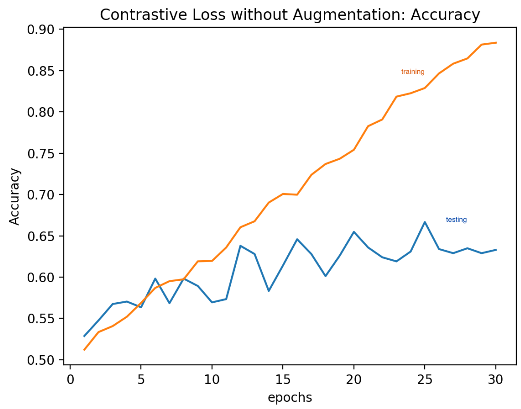


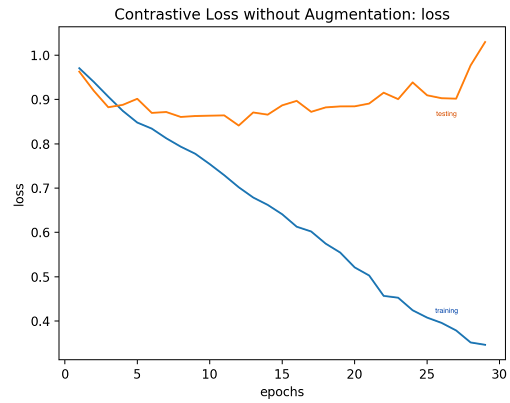
From the previous graphs we can see that the average train accuracy is higher for the model without random data augmentation and the test accuracy is higher for the model with random data augmentation compared to the test accuracy of the model without augmentation.

Part a without augmentation was memorizing the data so accuracy would increase and loss would decrease very fast; however, test accuracy and loss would not change that much since the model was not learning, just memorizing. Random data augmentation helped to prevent this from happening and it is evident that training accuracy increases slowly as it learns different transformations of the images. This helped the algorithm achieve a testing accuracy of 56%, which is higher than the testing accuracy of around 52% achieved without random data augmentation.

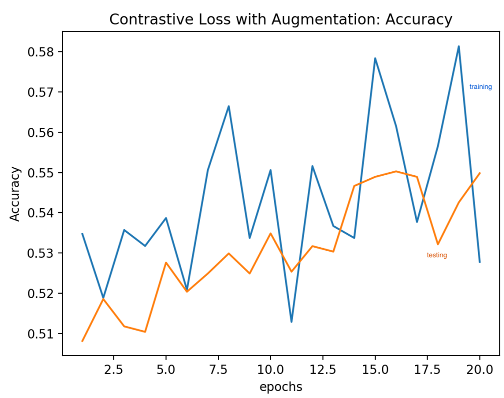
<u>Part 1b: Contrastive Loss</u>

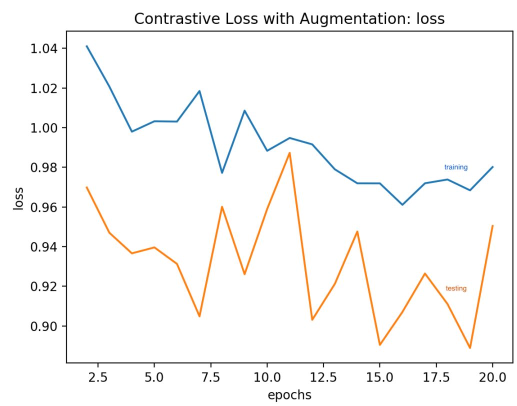
Without Random Data Augmentation





With Random Data Augmentation





The performance of contrastive loss was significantly better for the model without random data augmentation. We can see that the test accuracy goes up to 67%, which is higher than any other model in this assignment. The loss drops constantly for both the testing and the training. This is because contrastive loss tries to learn the difference between the features of different people. Therefore, without random transformations, it is not memorizing the data but learning from it and its features. For the model with random data augmentation, the best test accuracy achieved was of 56%. The transformations were not as beneficial as in the case of binary classification and resulted in a lower increase in accuracy and lower decrease in loss for both the training and the testing with random data augmentation.

With the results of this assignment, we can see that using a binary classification, some information that could help the model learn how to classify two images as being of the same person or not, gets lost. In the case of contrastive loss, comparing the distinctive features that are different between the two images had better results without needing the implementation of random data augmentation. We can also see how in the case of all models, it is important to know how many epochs are needed for the algorithm to learn without starting to memorize the data.