values seen in Table 5, the smallest standard error in each metric is split between the two models. However, the standard error for precision is much smaller in the model with outlier exposure when compared to the model without.

Training Group	*Precision*	*Recall*	*Accuracy*	*F1*	*AUROC*
FairFace	0.59 ± 0.020	0.61 ± 0.007	0.55 ± 0.007	0.60 ± 0.009	0.57± 0.008
FairFace w/ OE	**0.62 ± 0.007**	**0.64±0.007**	**0.58±0.008**	**0.63±0.005**	**0.59±0.008**

Table 6: Averaged Results from testing on CelebA when classifying based on gender

Similarly to the LFW dataset, we set the weights for the male and female class to 1 and 1.15 respectively.

The model is also tested on the CelebA dataset to classify gender. The results shown in Table 6 are consistent with the ones seen in Table 5, where our improved model performs better in both fairness metrics and accuracy.

Due to averaging multiple trials, we also observe the standard error between both models. When comparing the values seen in Table 6, it can be seen that on average, the standard error of the precision of the model with outlier exposure is smaller than that of the model without. A lower standard error means that the results are less varied and more consistent.

Over the course of all experiments, we find that in general, our approach helps to reduce false negatives and false positives. This can be seen by observing the recall and precision in Table 5 and Table 6, in which both fairness metrics increase with our model. As such, this correlates to a lower false negative and false positive rate, which is very important as different applications suffer more from different false flagging. In contrast to the healthcare application mentioned prior, false positives can be particularly problematic in law enforcement applications, where a subject could be mislabeled as the culprit for a crime they did not commit. As such, being able to reduce both false positive and negative rates are important.

6. Conclusions. In this paper, we explore the concept of facial recognition classification. Specifically, we focus on how models struggle when confronted with data from different distributions during training and testing. Out-of-distribution data has been shown to significantly reduce the accuracy of facial recognition models. Throughout this paper, we document the results of a CNN model on different training and testing datasets. We also use KL distribution to identify outlier images from each dataset and incorporate Outlier Exposure into our model to see how it affected the model's accuracy and other metrics. We also attempt to weight the sampling of the different classes (male and female) and observe how the model's results change. Overall, we evaluate how facial recognition performs on out-of distribution data and conclude that outlier exposure can increase accuracy and other metrics of the model. We also conclude that utilizing weight sampling and outlier exposure can improve both the accuracy and the fairness of the model on out-of-distribution facial image sets. With the use of artificial intelligence and facial recognition in sectors such as law enforcement and healthcare, the lack of fairness and accurate classification of out-of-distribution data (often data & images of minority groups) has become an increasingly pressing issue. The methodologies we explore here can improve the metrics of these models, and we find that many techniques rely on having some knowledge about the dataset distributions, which requires a carefully considered

implementation of these different methods to maximize the metrics of concern.

For this paper, all experiments are performed in Python using the Pytorch package, with data analysis performed using Scikit-learn package. The hardware we use is a 16 GB RAM and a 6 core, 2.6 GHz CPU. Additionally, our code will be made available upon request.

6.1. Related & Future Work. While this paper is a good overview of current methods, there are alternate avenues that future researchers may want to explore to increase accuracy. One method is Geometric Sensitivity Decomposition, which works with feature norms of images after they have run through a neural network. Besides the importance weighting and outlier exposure perspectives we looked into, another region of focus is through bringing the distributions of the train and test datasets closer through the modification of the distributions. Working with this and incorporating geometric sensitivity decomposition would represent our next avenue to improve out-of-distribution images.

Along the same lines of fairness transfer, [25] develops a causal approach using conditional independence tests to characterize distribution shifts in healthcare machine learning, revealing that understanding such shifts can diagnose fairness discrepancies and suggesting potential mitigation strategies throughout the ML pipeline. Additional modifications to our CNN network could represent an area to improve the facial recognition of out-of-distribution images.

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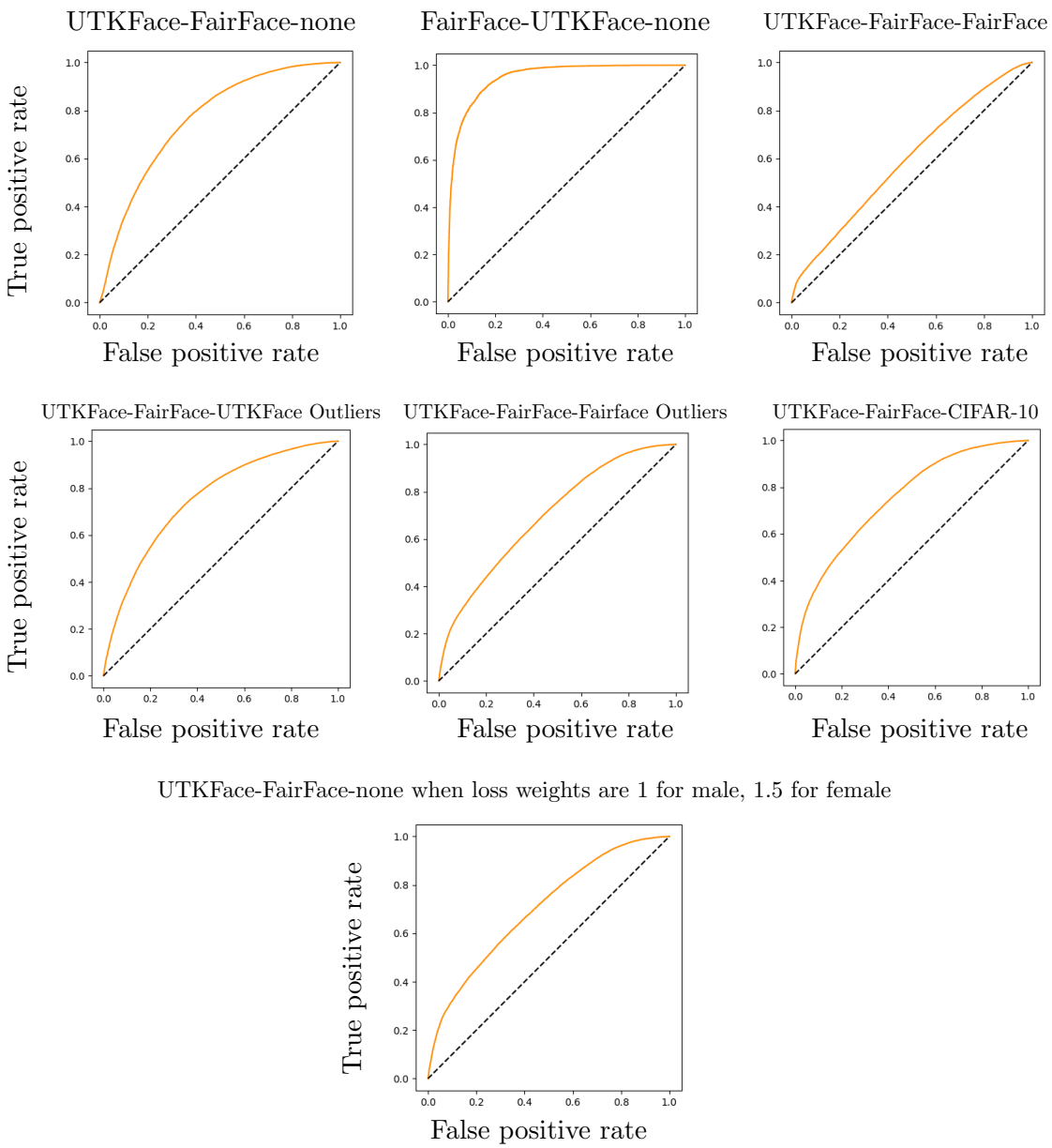
Appendix A. ROC Curves for Experiments.



UTKFace-FairFace-none when loss weights are 1 for male, 1.5 for female

Figure 6: ROC Curve from all experiments used, labelled in the order of "train set-test set-outlier set". Orange is the classifier performance and the dashed line is for 50% accuracy.

Appendix B. Confusion Matrix for Experiments.

Train-Test-Outlier	*Male-Male*	*Male-Female*	*Female-Male*	*Female-Female*
UTKFace-FairFace	33711	14274	12274	26484
FairFace-UTKFace	10818	1477	1573	9837
UTKFace-UTKFace	12079	226	312	11088
FairFace-FairFace	42657	3754	3328	37004
UTKFace-FairFace-UTKFace	36306	15304	9679	25454
UTKFace-FairFace-FairFace	26010	19041	19975	21717
UTKFace-FairFace-UTKFace Outliers	35693	16079	10292	24679
UTKFace-FairFace-FairFace Outliers	33636	16952	12349	23806
UTKFace-FairFace-CIFAR-10	36486	17144	9499	23614
UTKFace-FairFace (weights 1-1.5)	32003	15503	13982	25255

Table 7: Confusion Matrices from all experiments used. Columns labeled by "Predicted Label-Actual Label"

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