Frowning upon Bias: Exposing the Impact of Race on Emotion Classification

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https://github.com/Lu-David/frowning-bias

Outline and Deliverables

Uncompleted Deliverables

1. "Would like to accomplish #1": Compare the per-race accuracy results of our facial expression model with facial expression models of other popular facial expression models.

We chose to not pursue this objective as we shifted our project towards improving the fairness of our own model instead of comparing fairness to existing models. We started with a baseline model and then explored a variety of techniques to attempt to improve model fairness.

Completed Deliverables

1. "Must Accomplish #1": Determine the approximate race distribution of at least one popular facial expression dataset. See "Dataset" below.
2. "Must Accomplish #2": Perform hyperparameter search to tune model with high overall accuracy. See Results.
3. "Must Accomplish #3": Train an effective model for facial expression classification using a popular facial expression dataset without stratification by race. See Results.
4. "Must Accomplish #4": Compare overall model accuracy on the dataset with the model accuracy on subsets of the dataset broken down by race. See Results.
5. "Expect to accomplish #1" Re-train our facial expression model using a stratified train/test split (same distribution in train vs test set) by race and compare overall and per-race model accuracy. See Results.
6. "Expect to accomplish #2" Re-train our facial expression model using a stratified train/test split and stratified sampling within groups (same number of each category in each set) by race and compare overall and per-race model accuracy. See Results.
7. "Expect to accomplish #3" Perform analysis on model accuracy on the train/test set when broken down by race and facial expression to identify which facial expressions are most likely to be misclassified when considering the distribution of race. See Results.
8. "Would like to accomplish #3" Introduce additional dependent variables to compare accuracy across, such as gender or age. See Results.

9. "Must complete #1": We discuss our dataset pre-processing in "Dataset" below.

10. "Must complete #2": We discuss training our CNN baseline in Results.

Additional Deliverables

1. We introduced data augmentation to see if varying lighting conditions would make the model more agnostic to demographic characteristics. We discuss this in "Data Augmentation" section below.
2. We trained an "Attribute Aware" model that takes demographic information as an input to see if this would make the model more fair. We discuss this in "Attribute Aware Model" section below.

Preliminaries

Problem

Facial recognition systems are used ubiquitously in the real world. Law enforcement bodies use facial recognition algorithms to identify suspects in criminal investigations. Airport security often uses facial recognition algorithms to compare passenger faces in realtime against their passport/documentation photos. Employmers can use these algorithms as part of automated interview software to detect emotions or reactions during an interview.

Despite the serious ethical and practical implications of this problem, prior studies have found signficant bias on facial image-based algorithms. For example, in 2018, Buolamwini & Gebru published their study called "Gender Shades" in which they discovered most large-scale commercial APIs for gender classification had poorer accuracy on minority subgroups (i.e. darker-skinned females, and darker-skinned males). This project really inspired our study because it displays how hidden biases in facial recognition algorithms can create harmful effects when deployed in the real-world.

Our task is to train a convolutional neural network (CNN) to classify images of human facial expression into emotions accurately and fairly across race, gender, and age.

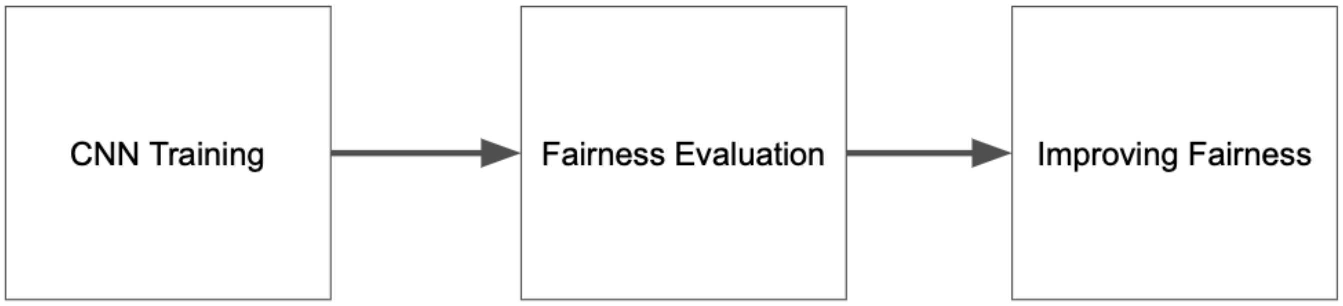
We chose to look at emotion recognition due to 1) the availability of quality data for this task, 2) how common emotion output is recorded from facial recognition APIs, and 3) the pratical implications of emotion recognition. We take a unique approach to this problem by looking to not just train a classification model, but then also quantify and improve upon classification fairness.

This problem is a multi-class computer vision problem. We studied these kinds of problems in the context of deep learning, and we explored in class how CNNs are popularly used for these problems.

Dataset

We used the Real-world Affective Faces Database (RAF-DB) dataset. This dataset consisted of roughly 30,000 images of center-cropped human faces. Each face was labeled with an expression (7 classes: angry, disgusted, fearful, happy, sad, surprised, neutral) along with three demographic attributes: race (Caucasian, African American, Asian), age (0-3, 4-19, 20-39, 40-69, 70+), and gender (Male, Female, Unsure (i.e. the gender is not discernable from the image)). Annotations were made by 40 independent human annotators.

The task we studied in this project was multi-class classification. The target label was the expression label, and the provided input was the image along with the race, age, and gender annotation.



In our project, we chose to use all three demographic attributes in our fairness analysis. Initially, our project was focused on race; however, as we will later display, our baseline CNN showed interesting biases when intersecting all three of these conditions.

Below, we provide code to setup a local environment.

In [1]:
```
# # Run this cell if using google colab
# from google.colab import drive
#
# %cd /content
# ! rm -rf frowning-bias
# ! git clone https://github.com/Lu-David/frowning-bias -b main
# %cd  frowning-bias
```

In [2]:
```
from download_data import download_raf

download_raf()
```

In [3]:
```
import os
import pandas as pd
from pathlib import Path
import matplotlib.pyplot as plt
import seaborn as sns
```

In [4]:
```
#       Gender
#       0: male         1: female       2: unsure
#    ----------------------------------------------------------------------
#       Race
# 0: Caucasian          1: African-American             2: Asian
# ----------------------------------------------------------------------
#       Age (5 ranges)
# 0: 0-3         1: 4-19                2: 20-39                3: 40-69
# NOTE: raw txt file has emotion labels 1-indexed, I am shifting to zero-indexing
emotion_lookup = {
    0: "Surprise",
    1: "Fear",
    2: "Disgust",
    3: "Happiness",
    4: "Sadness",
    5: "Anger",
    6: "Neutral"
}

race_lookup = {
    0: "Caucasian",
    1: "African-American",
    2: "Asian"
}

gender_lookup = {
    0: "Male",
    1: "Female",
    2: "Unsure"
}

age_lookup = {
    0: "0-3",
    1: "4-19",
    2: "20-39",
    3: "40-69",
    4: "70+"
}

# Construct dataframe for train/test data attributes
data_dir = Path("./data")
raf_dir = data_dir / "RAF"
train_dir = raf_dir / "aligned_train"
test_dir = raf_dir / "aligned_test"
annot_dir = raf_dir / "manual"
labels_file = raf_dir / "list_partition_label.txt"
df = pd.read_csv(labels_file, sep=" ", header=None)
df.columns = ["Name", "Emotion"]
df["Path"] = df["Name"].apply(lambda x: os.path.join(str(train_dir), x.replace(".jpg","_
df["Split"] = df["Name"].apply(lambda x: "Train" if ("train" in x) else "Test")
gender = []
race = []
age = []
for i,r in df.iterrows():
    annot_file = os.path.join(str(annot_dir), "{}_manu_attri.txt".format(r["Name"].repla
    with open(annot_file, "r") as f:
        lines = f.readlines()
        gender.append(int(lines[5]))
        race.append(int(lines[6]))
        age.append(int(lines[7]))
df["Gender"] = gender
df["Race"] = race
df["Age"] = age
# NOTE: raw txt file has emotion labels 1-indexed, I am shifting to zero-indexing
df["Emotion"] = df["Emotion"] - 1
df["EmotionLabel"] = df["Emotion"].apply(lambda x: emotion_lookup[x])
df["RaceLabel"] = df["Race"].apply(lambda x: race_lookup[x])
df["GenderLabel"] = df["Gender"].apply(lambda x: gender_lookup[x])
df["AgeLabel"] = df["Age"].apply(lambda x: age_lookup[x])
df_train = df[df["Split"]=="Train"]
df_test = df[df["Split"]=="Test"]
assert len(df) == len(df_train) + len(df_test)
```

In [5]:
```
from PIL import Image
from numpy.random import RandomState

random_state = RandomState(1)
samples = df.sample(2, random_state=random_state)
for i in range(len(samples)):
    sample = samples.iloc[i]
    img = Image.open(sample["Path"])
    print(sample["Path"])
    plt.imshow(img)
    plt.title(f"{sample['EmotionLabel']} - {sample['RaceLabel']} - {sample['GenderLabel'
    # hide the axes
    plt.axis('off')
    plt.show()
```

```
data/RAF/aligned_test/test_1396_aligned.jpg
```

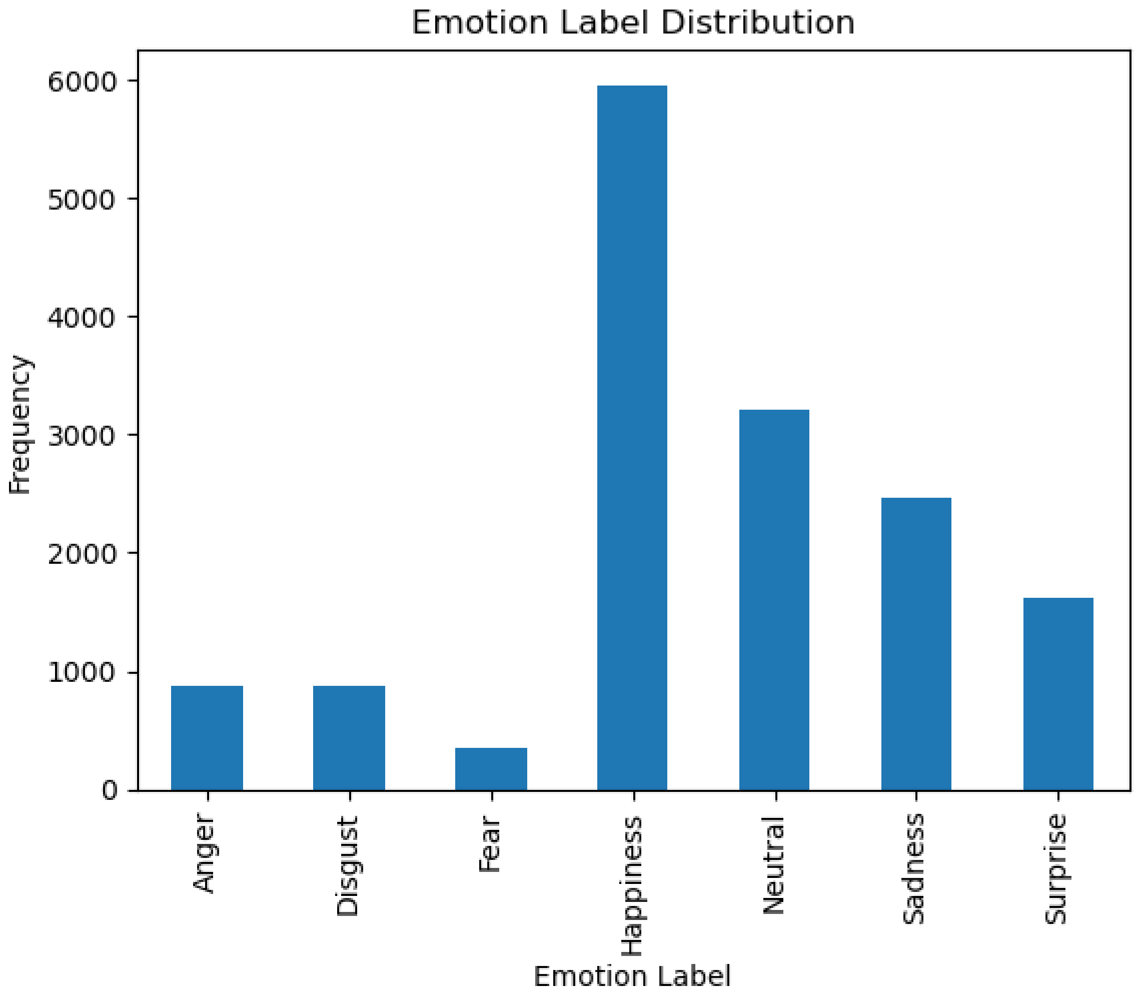
Sadness - Caucasian - Unsure - 0-3

```
data/RAF/aligned_train/train_08192_aligned.jpg
```

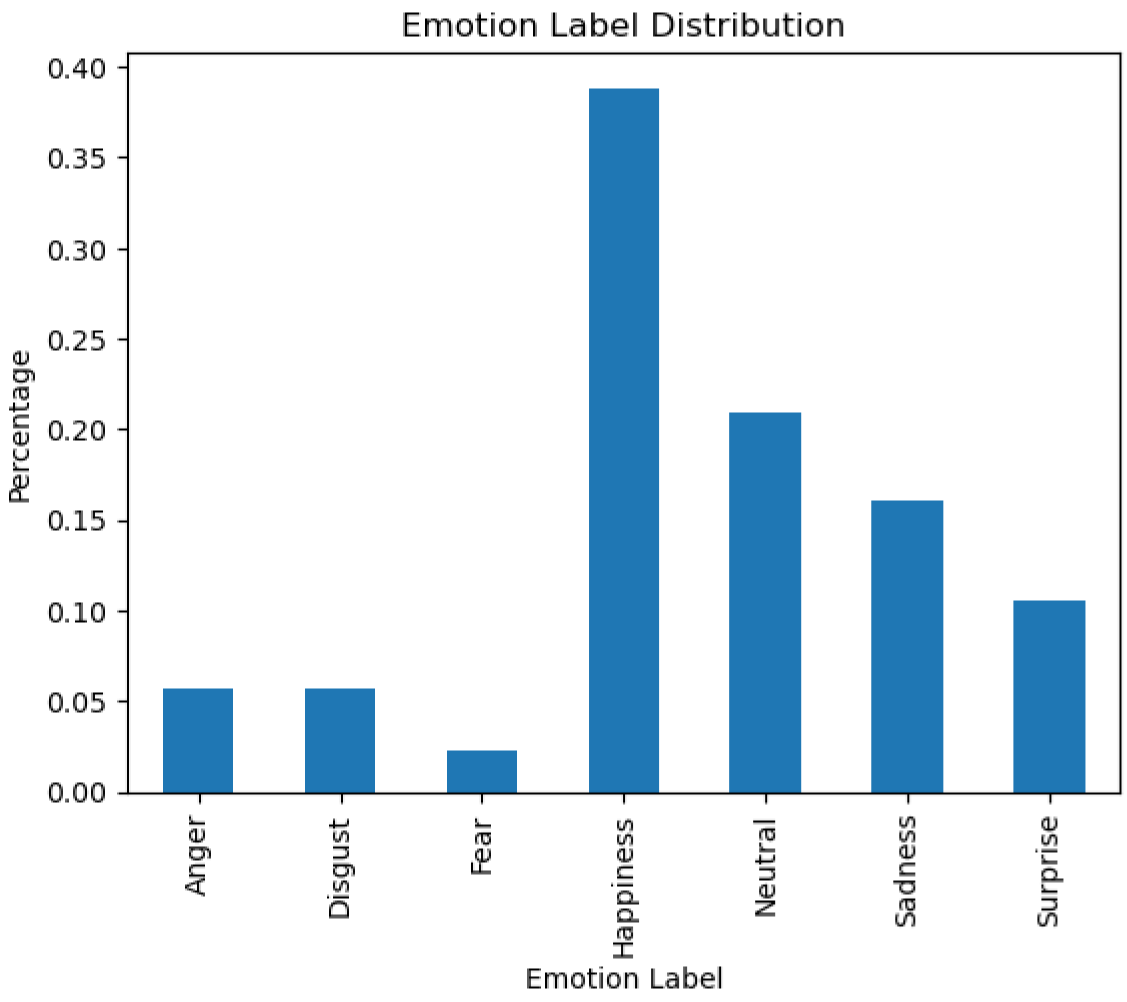
Surprise - Caucasian - Female - 20-39

We can see from these sample images that the RAF-DB dataset is diverse in terms of the lighting conditions, occlusions, head poses, and even post-processing routines applied onto the images.

In [6]:
```python
# Distribution of emotion labels
fig, ax = plt.subplots()
ax.set_title("Emotion Label Distribution")
ax.set_xlabel("Emotion Label")
ax.set_ylabel("Frequency")
df["EmotionLabel"].value_counts().sort_index().plot(ax=ax, kind='bar')
plt.show()
```



In [7]:
```
# Distribution of emotion labels
fig, ax = plt.subplots()
ax.set_title("Emotion Label Distribution")
ax.set_xlabel("Emotion Label")
ax.set_ylabel("Percentage")
df["EmotionLabel"].value_counts(normalize=True).sort_index().plot(ax=ax, kind='bar')
plt.show()
```



In [8]:
```
df["EmotionLabel"].value_counts()
```

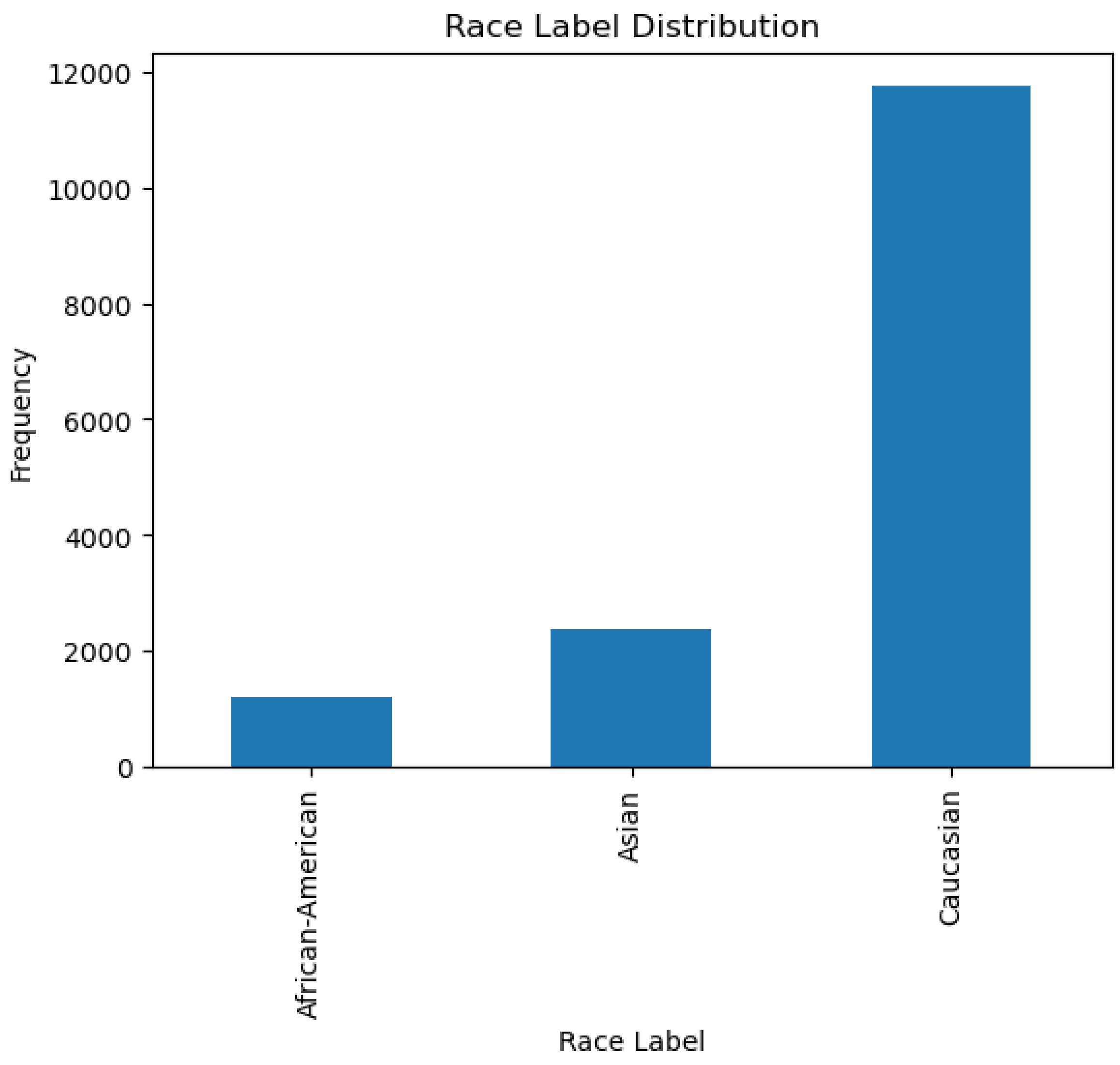
Out[8]:
```
Happiness    5957
Neutral      3204
Sadness      2460
Surprise     1619
Disgust       877
Anger         867
Fear          355
Name: EmotionLabel, dtype: int64
```

In [9]:
```
df["EmotionLabel"].value_counts(normalize=True).mul(100)
```

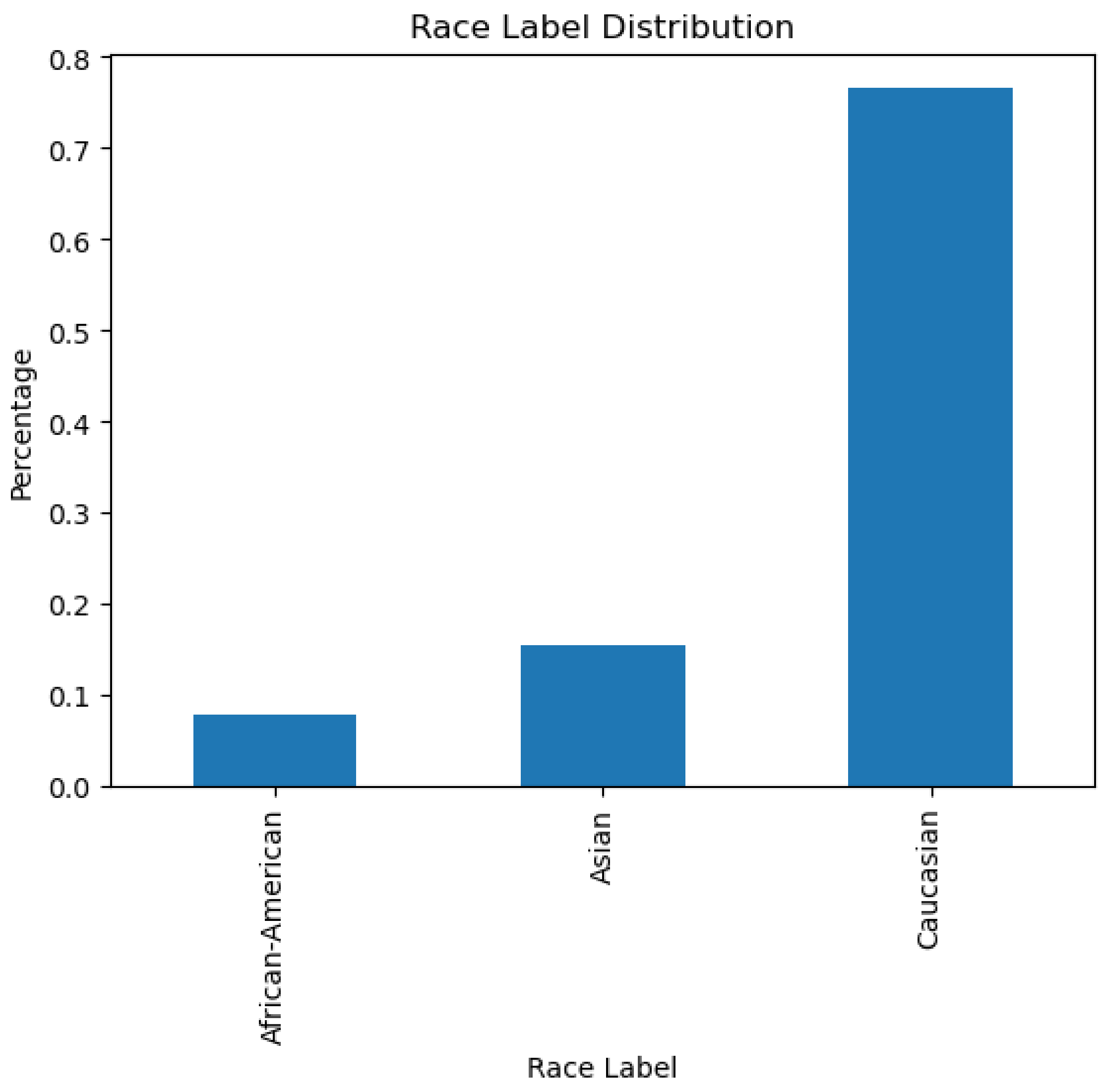
Out[9]:
```
Happiness    38.835648
Neutral      20.887933
Sadness      16.037551
Surprise     10.554795
Disgust       5.717452
Anger         5.652259
Fear          2.314362
Name: EmotionLabel, dtype: float64
```

Notice the dominant emotion labels are happiness, neutral, sadness, and surprise.

In [10]:
```
fig, ax = plt.subplots()
ax.set_title("Race Label Distribution")
ax.set_xlabel("Race Label")
ax.set_ylabel("Frequency")
df["RaceLabel"].value_counts().sort_index().plot(ax=ax, kind='bar')
plt.show()
```



In [11]:
```
fig, ax = plt.subplots()
ax.set_title("Race Label Distribution")
ax.set_xlabel("Race Label")
ax.set_ylabel("Percentage")
df["RaceLabel"].value_counts(normalize=True).sort_index().plot(ax=ax, kind='bar')
plt.show()
```



```
In [12]: df["RaceLabel"].value_counts()
```

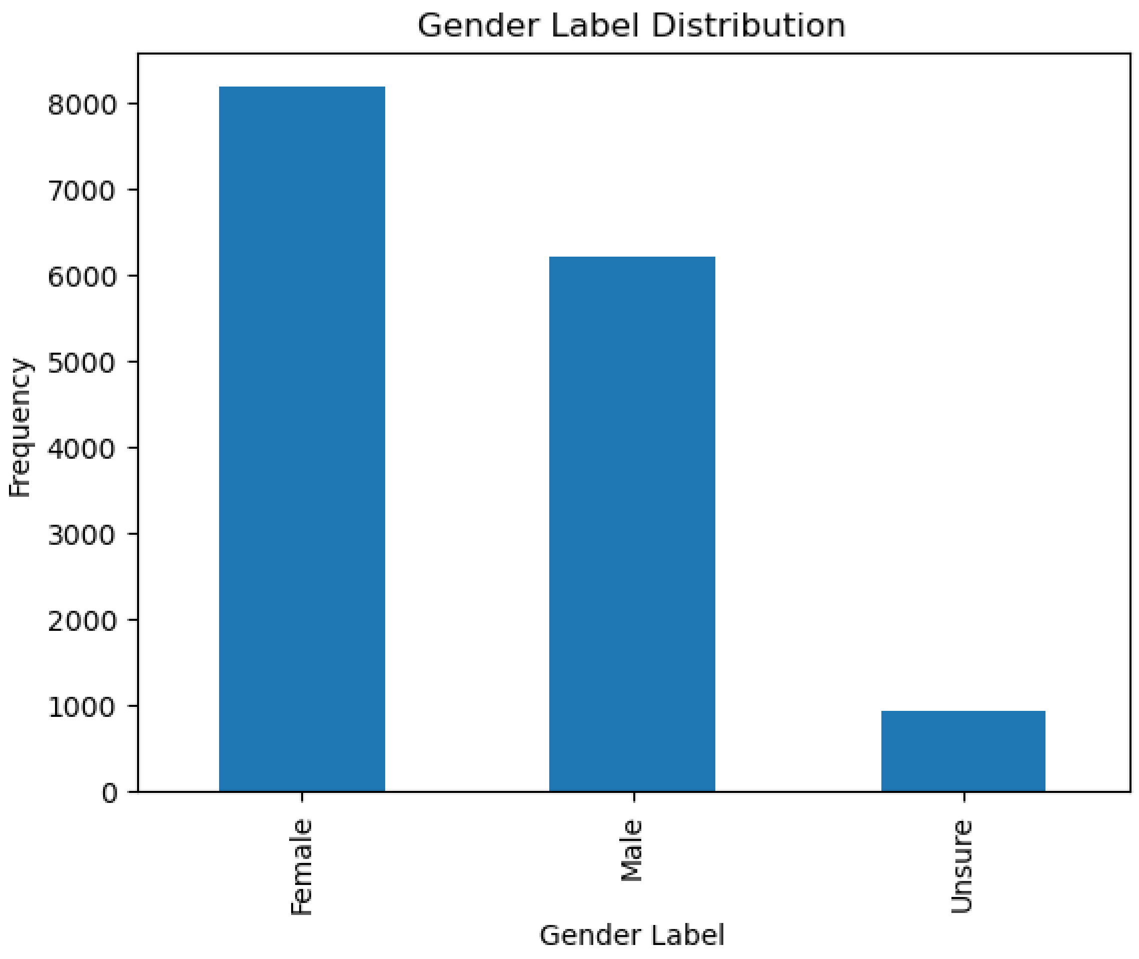
```
Out[12]: Caucasian           11742
         Asian                2395
         African-American     1202
         Name: RaceLabel, dtype: int64
```

```
In [13]: df["RaceLabel"].value_counts(normalize=True).mul(100)
```

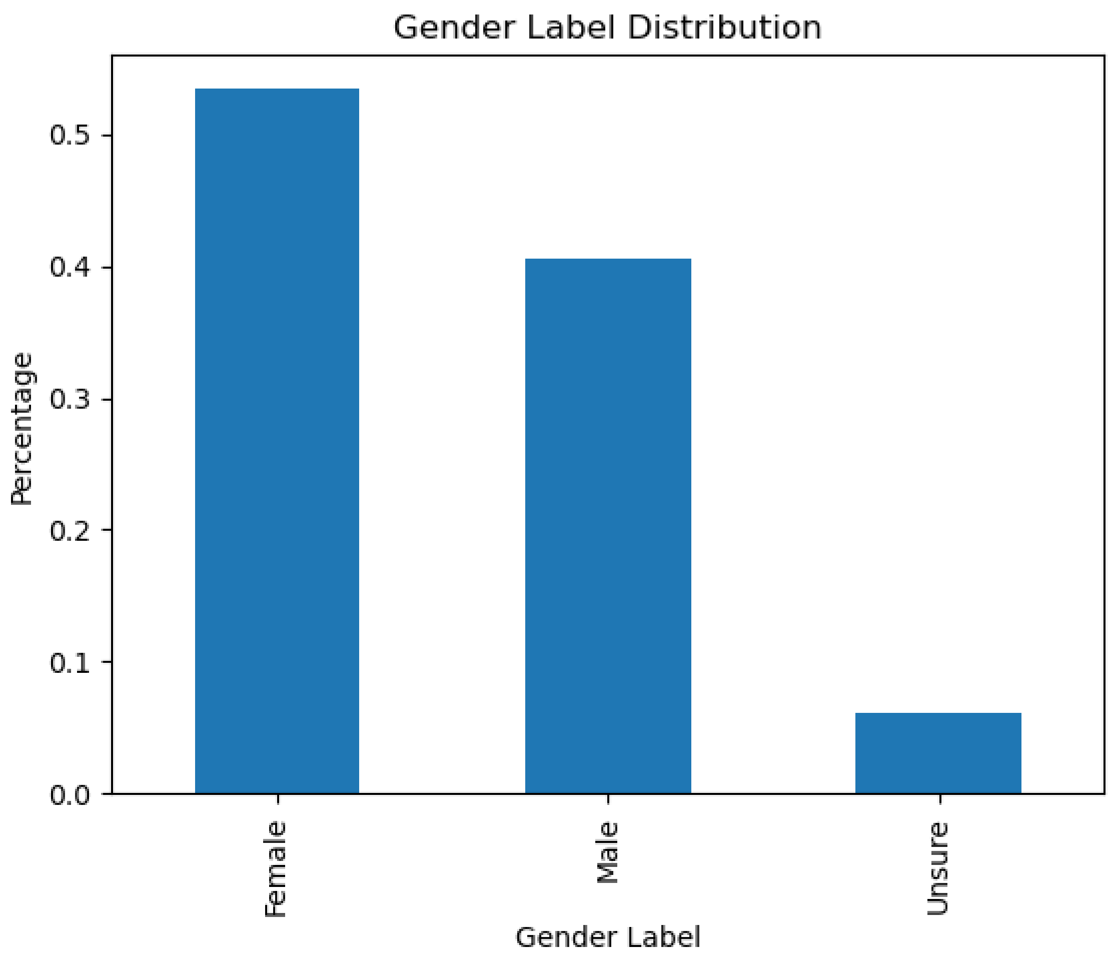
```
Out[13]: Caucasian           76.549971
         Asian               15.613795
         African-American     7.836234
         Name: RaceLabel, dtype: float64
```

Notice that the dataset is heavily skewed towards Caucasian images.

```
In [14]: fig, ax = plt.subplots()
         ax.set_title("Gender Label Distribution")
         ax.set_xlabel("Gender Label")
         ax.set_ylabel("Frequency")
         df["GenderLabel"].value_counts().sort_index().plot(ax=ax, kind='bar')
         plt.show()
```



In [15]:
```
fig, ax = plt.subplots()
ax.set_title("Gender Label Distribution")
ax.set_xlabel("Gender Label")
ax.set_ylabel("Percentage")
df["GenderLabel"].value_counts(normalize=True).sort_index().plot(ax=ax, kind='bar')
plt.show()
```



In [16]:
```
df["GenderLabel"].value_counts()
```

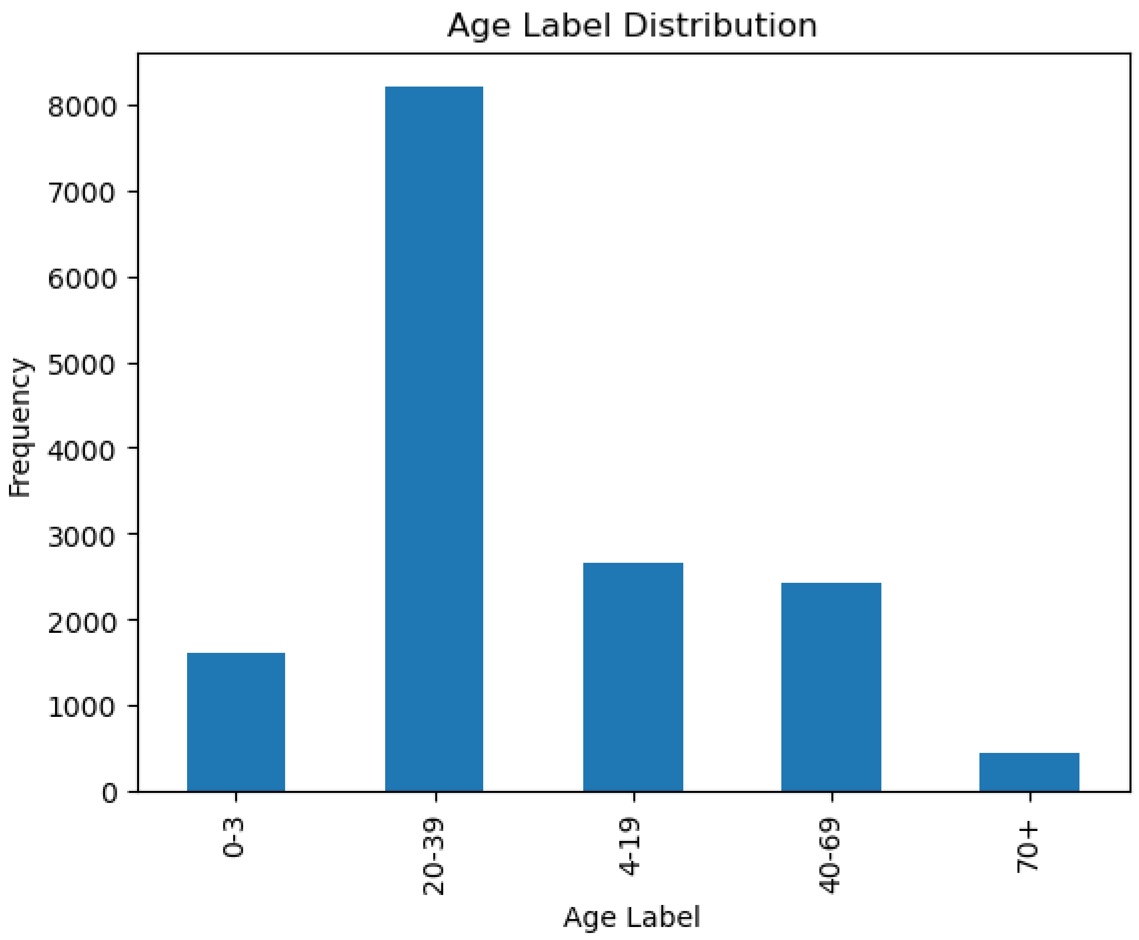
Out[16]:
```
Female     8182
Male       6206
Unsure      951
Name: GenderLabel, dtype: int64
```

In [17]:
```
df["GenderLabel"].value_counts(normalize=True).mul(100)
```

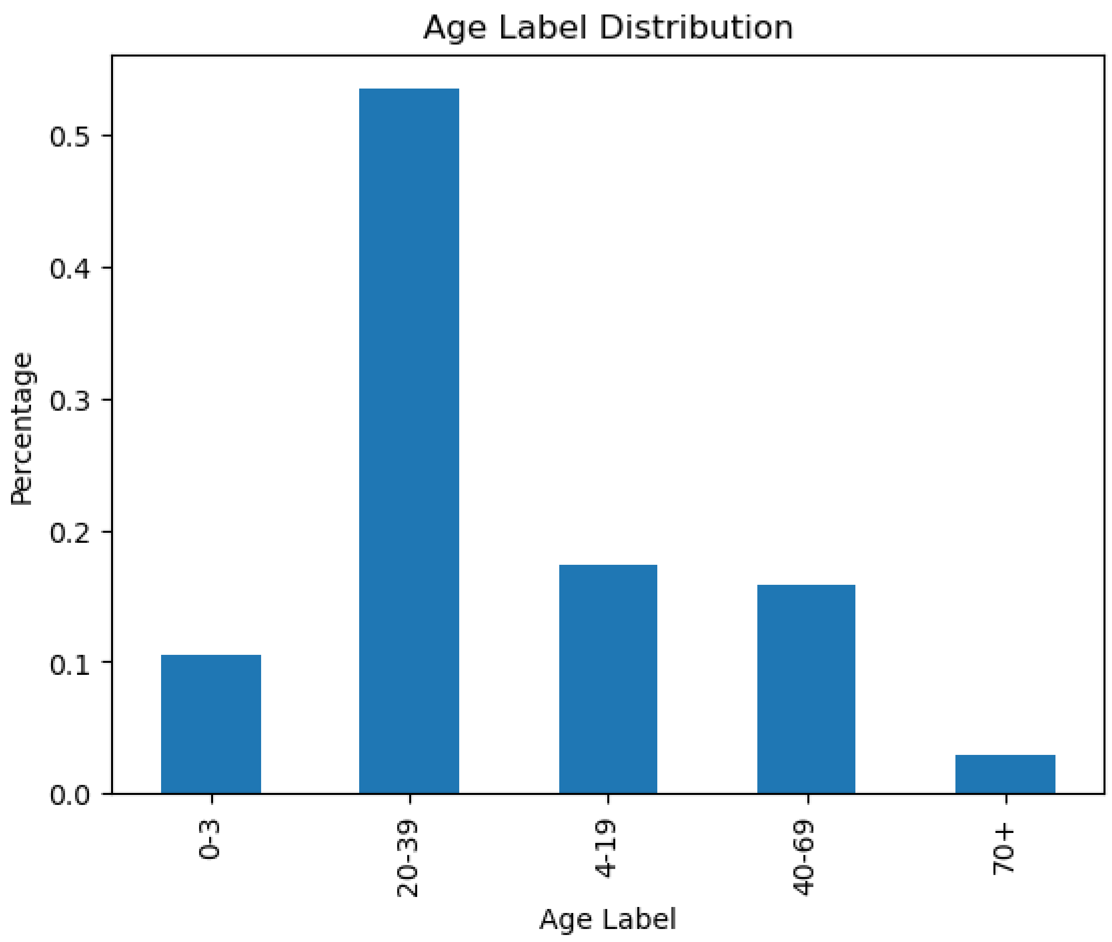
Out[17]:
```
Female     53.341157
Male       40.458961
Unsure      6.199883
Name: GenderLabel, dtype: float64
```

The dataset is slightly skewed towards female faces, but this not as signficant and somewhat exacerbated by the high frequency of "Unsure" annotations.

In [18]:
```
fig, ax = plt.subplots()
ax.set_title("Age Label Distribution")
ax.set_xlabel("Age Label")
ax.set_ylabel("Frequency")
df["AgeLabel"].value_counts().sort_index().plot(ax=ax, kind='bar')
plt.show()
```



```
In [19]: fig, ax = plt.subplots()
         ax.set_title("Age Label Distribution")
         ax.set_xlabel("Age Label")
         ax.set_ylabel("Percentage")
         df["AgeLabel"].value_counts(normalize=True).sort_index().plot(ax=ax, kind='bar')
         plt.show()
```



```
In [20]: df["AgeLabel"].value_counts()
```

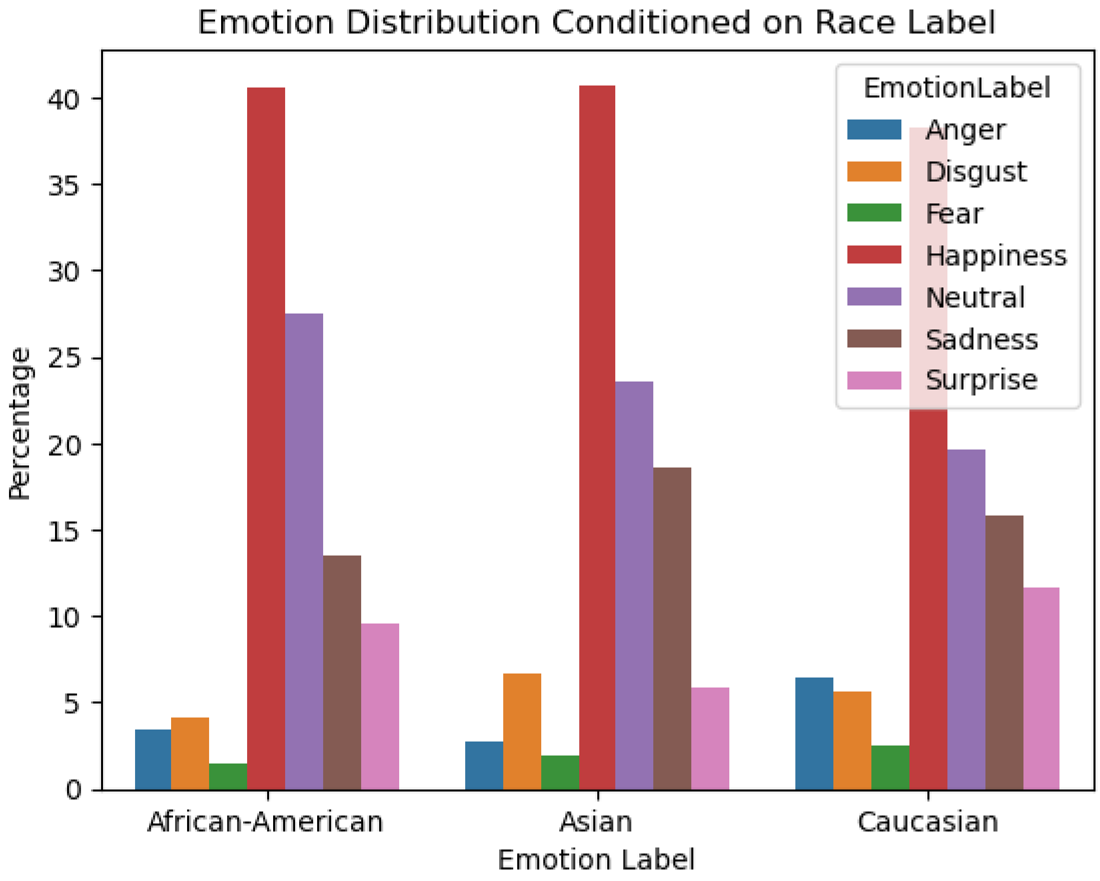
```
Out[20]: 20-39    8193
         4-19     2657
         40-69    2422
         0-3      1612
         70+       455
         Name: AgeLabel, dtype: int64
```

```
In [21]: df["AgeLabel"].value_counts(normalize=True).mul(100)
```

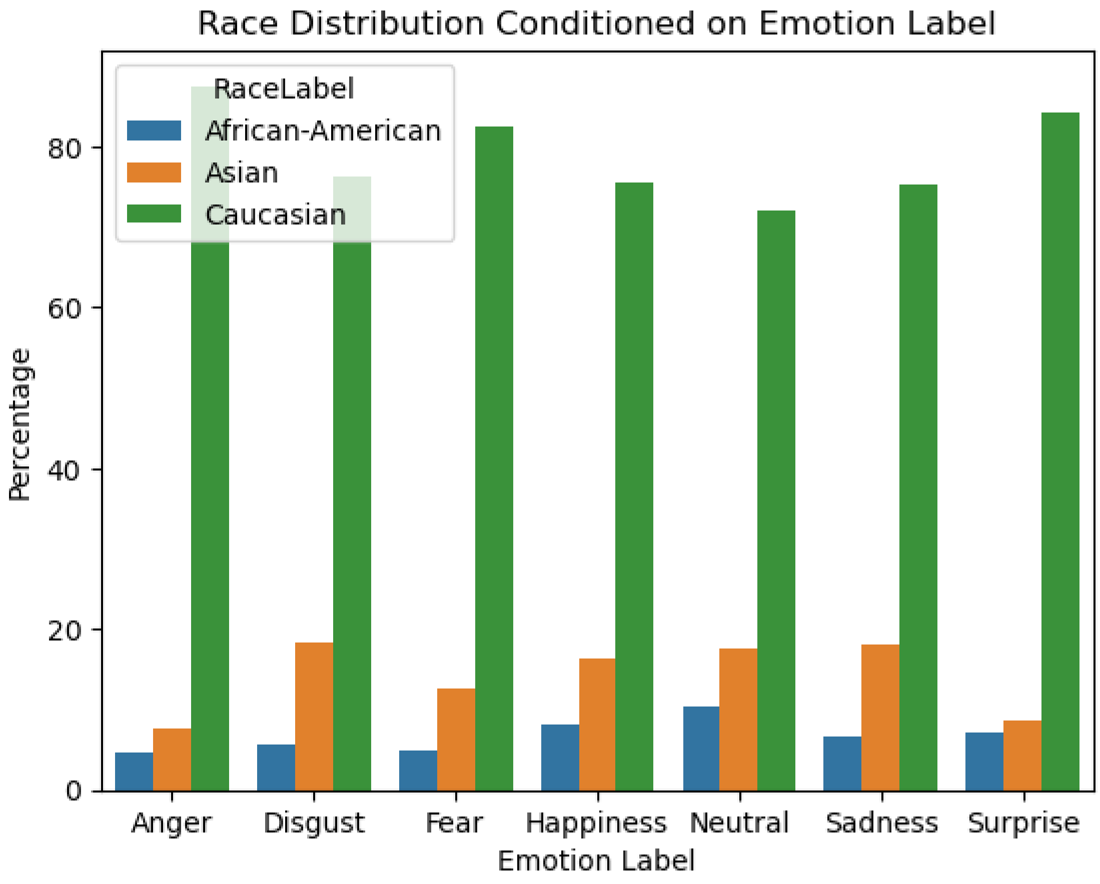
```
Out[21]: 20-39    53.412869
         4-19     17.321859
         40-69    15.789817
         0-3      10.509160
         70+       2.966295
         Name: AgeLabel, dtype: float64
```

Most faces were annotated in the 20-39 age strata.

```
In [22]: df_emotion_per_race_count = df.groupby(["EmotionLabel", "RaceLabel"]).size().reset_index
         df_emotion_per_race_count["Percentage"] = df_emotion_per_race_count.groupby("RaceLabel",
         df_emotion_per_race_count = df_emotion_per_race_count.sort_values(by=["EmotionLabel", "R

         fig, ax = plt.subplots()
         sns.barplot(x="RaceLabel", y="Percentage", hue="EmotionLabel", data=df_emotion_per_race_
         ax.set_title("Emotion Distribution Conditioned on Race Label")
         ax.set_xlabel("Emotion Label")
         ax.set_ylabel("Percentage")
         plt.show()
```

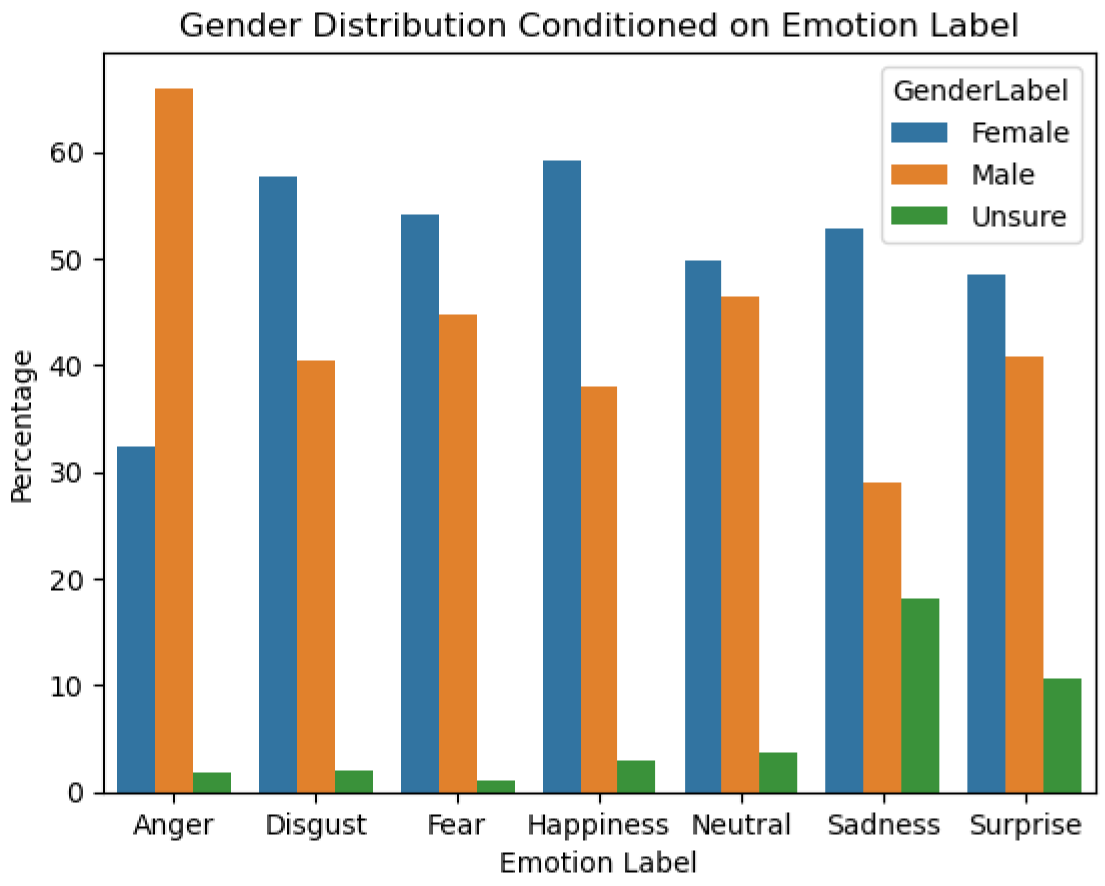


```
In [23]: df_race_per_emotion_count = df.groupby(["EmotionLabel", "RaceLabel"]).size().reset_index
         df_race_per_emotion_count["Percentage"] = df_race_per_emotion_count.groupby("EmotionLabe
         df_race_per_emotion_count = df_race_per_emotion_count.sort_values(by=["EmotionLabel", "R

         fig, ax = plt.subplots()
         sns.barplot(x="EmotionLabel", y="Percentage", hue="RaceLabel", data=df_race_per_emotion_
         ax.set_title("Race Distribution Conditioned on Emotion Label")
         ax.set_xlabel("Emotion Label")
         ax.set_ylabel("Percentage")
         plt.show()
```



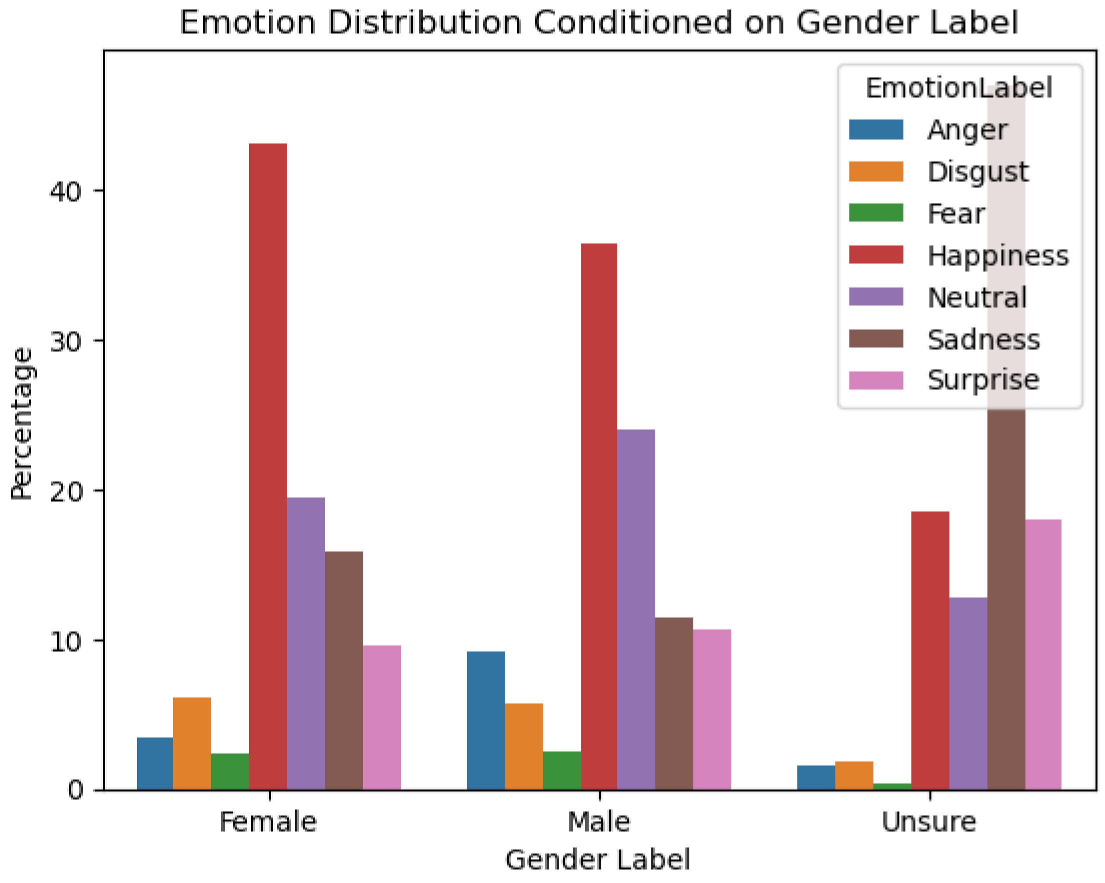
Emotion and race appear fairly independent of each other. That is, the distribution of either variable does not really depend on conditioning on the other.

```
In [24]: df_gender_per_emotion_count = df.groupby(["EmotionLabel", "GenderLabel"]).size().reset_i
         df_gender_per_emotion_count["Percentage"] = df_gender_per_emotion_count.groupby("Emotion
         df_gender_per_emotion_count = df_gender_per_emotion_count.sort_values(by=["EmotionLabel"

         fig, ax = plt.subplots()
         sns.barplot(x="EmotionLabel", y="Percentage", hue="GenderLabel", data=df_gender_per_emot
         ax.set_title("Gender Distribution Conditioned on Emotion Label")
         ax.set_xlabel("Emotion Label")
         ax.set_ylabel("Percentage")
         plt.show()
```



Notice that the anger emotion class has a signficantly different distribution of genders. While most emotions have more females than males, anger seems to be more frequently male. This might be an implicit bias in characterizing male faces as angry.

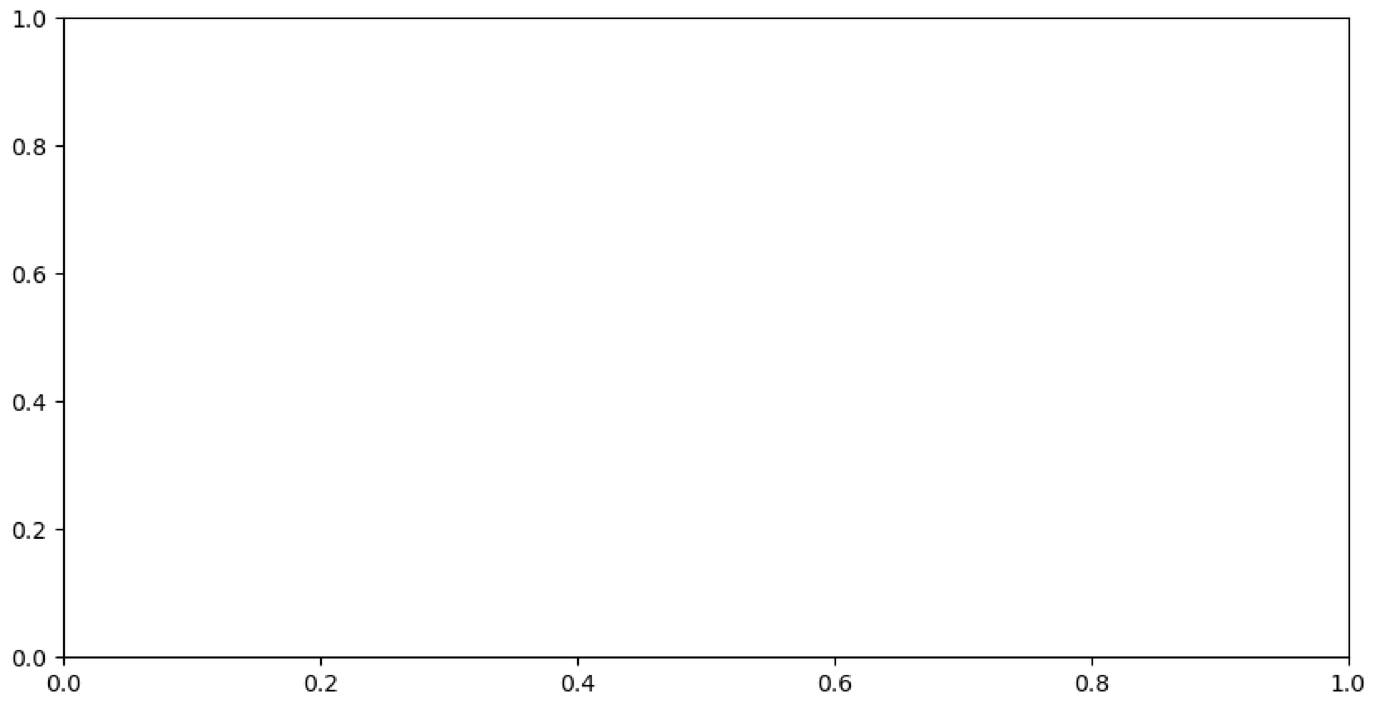
In [25]:
```
df_emotion_per_gender_count = df.groupby(["GenderLabel", "EmotionLabel"]).size().reset_i
df_emotion_per_gender_count["Percentage"] = df_emotion_per_gender_count.groupby("GenderL
df_emotion_per_gender_count = df_emotion_per_gender_count.sort_values(by=["GenderLabel",

fig, ax = plt.subplots()
sns.barplot(x="GenderLabel", y="Percentage", hue="EmotionLabel", data=df_emotion_per_gen
ax.set_title("Emotion Distribution Conditioned on Gender Label")
ax.set_xlabel("Gender Label")
ax.set_ylabel("Percentage")
plt.show()
```



Conditioning on gender (male vs female) does not seem to affect the distribution of emotions significantly.

In [26]:
```
df_age_per_emotion_count = df.groupby(["AgeLabel", "EmotionLabel"]).size().reset_index(n
df_age_per_emotion_count["Percentage"] = df_age_per_emotion_count.groupby("EmotionLabel"
df_age_per_emotion_count = df_age_per_emotion_count.sort_values(by=["AgeLabel", "Emotion

fig, ax = plt.subplots(figsize=(10, 5))
sns.barplot(x="EmotionLabel", y="Percentage", hue="AgeLabel", data=df_age_per_emotion_co
ax.set_title("Age Distribution Conditioned on Emotion Label")
ax.set_xlabel("Emotion Label")
ax.set_ylabel("Percentage")
plt.show()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Input In [26], in <cell line: 6>()
      3 df_age_per_emotion_count = df_age_per_emotion_count.sort_values(by=["AgeLabel", 
"EmotionLabel"])
      5 fig, ax = plt.subplots(figsize=(10, 5))
----> 6 sns.barplot(x="EmotionLabel", y="Percentage", hue="AgeLabel", data=df_age_per_em
otion_count, ax=ax, hue_order=age_label_order)
      7 ax.set_title("Age Distribution Conditioned on Emotion Label")
      8 ax.set_xlabel("Emotion Label")

NameError: name 'age_label_order' is not defined
```



Conditioning on emotion generally gives similar age distributions. This does not hold though for sadness, which is more uniform compared to other emotions.

In [ ]:
```
df_gender_per_age_count = df.groupby(["GenderLabel", "AgeLabel"]).size().reset_index(nam
df_gender_per_age_count["Percentage"] = df_gender_per_age_count.groupby("AgeLabel", grou
df_gender_per_age_count = df_gender_per_age_count.sort_values(by=["GenderLabel", "AgeLab

fig, ax = plt.subplots(figsize=(10, 5))
sns.barplot(x="AgeLabel", y="Percentage", hue="GenderLabel", data=df_gender_per_age_coun
ax.set_title("Gender Distribution Conditioned on Age Label")
ax.set_xlabel("Age Label")
ax.set_ylabel("Percentage")
plt.show()
```

Conditioning on age dramatically affects the gender distribution. Notice that ages 0-3, 40-69, and 70+ have more males, but 20-39 and 4-19 have more females.

In [ ]:
```
df_age_per_gender_count = df.groupby(["GenderLabel", "AgeLabel"]).size().reset_index(nam
df_age_per_gender_count["Percentage"] = df_age_per_gender_count.groupby("GenderLabel", g
df_age_per_gender_count = df_age_per_gender_count.sort_values(by=["GenderLabel", "AgeLab

fig, ax = plt.subplots(figsize=(10, 5))
sns.barplot(x="GenderLabel", y="Percentage", hue="AgeLabel", data=df_age_per_gender_coun
ax.set_title("Age Distribution Conditioned on Gender Label")
ax.set_xlabel("Gender Label")
ax.set_ylabel("Percentage")
plt.show()
```

Conditioning on gender (male vs female) leads to similar age distributions.

In [ ]:
```
df_gender_per_race_count = df.groupby(["RaceLabel", "GenderLabel"]).size().reset_index(n
df_gender_per_race_count["Percentage"] = df_gender_per_race_count.groupby("RaceLabel", g
df_gender_per_race_count = df_gender_per_race_count.sort_values(by=["RaceLabel", "Gender

fig, ax = plt.subplots(figsize=(10, 5))
sns.barplot(x="RaceLabel", y="Percentage", hue="GenderLabel", data=df_gender_per_race_co
ax.set_title("Gender Distribution Conditioned on Race Label")
ax.set_xlabel("Race Label")
```

```python
ax.set_ylabel("Percentage")
plt.show()
```

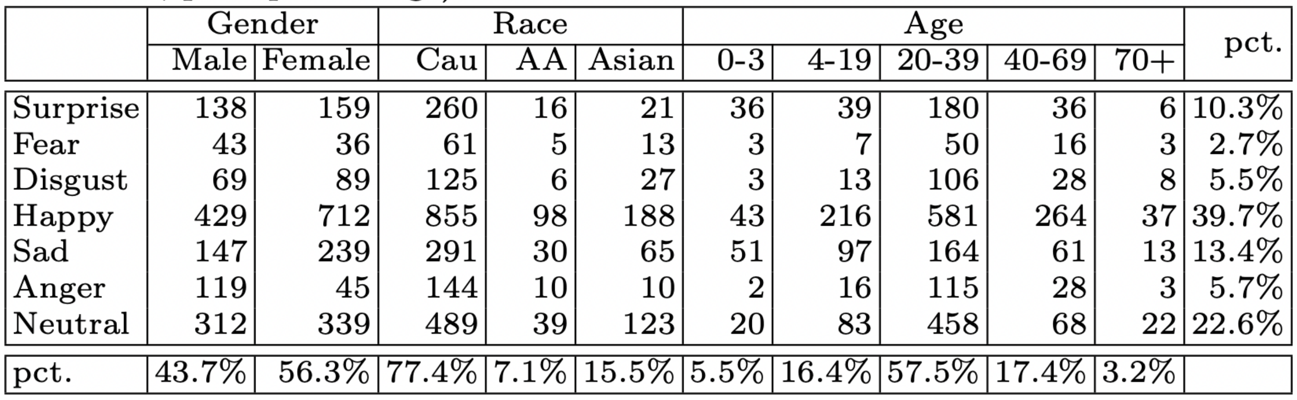
African-American faces tend to be more Male than Asian and Caucasian faces.

Adjusting Fairness Evaluation based on EDA

Based on our EDA, we chose to adjust how we evaluate fairness. In particular, we chose to first ignore the "Unsure" gender instances in the fairness metrics. This is because the "Unsure" annotation indicated that annotators could not discern the subject's gender from the image. Looking at the data statistics, this mostly applied to images of babies (0-3 age strata). Along a similar vein, we chose to ignore images coming from the 0-3 and 70+ age stratas in our fairness evaluation because these populations do not represent "important" subgroups in our practical applications of emotion recognition. Additionally, the frequency of examples in these groups are much less compared to other age strata.

Below is a summary table for the RAF-DB (original) test split, credit to Xu et al (2020).

Table 1: RAF-DB data distribution of the test set (Cau: Caucasian, AA: African-American, pct.: percentage).



	Gender		Race			Age					pct.
	Male	Female	Cau	AA	Asian	0-3	4-19	20-39	40-69	70+	
Surprise	138	159	260	16	21	36	39	180	36	6	10.3%
Fear	43	36	61	5	13	3	7	50	16	3	2.7%
Disgust	69	89	125	6	27	3	13	106	28	8	5.5%
Happy	429	712	855	98	188	43	216	581	264	37	39.7%
Sad	147	239	291	30	65	51	97	164	61	13	13.4%
Anger	119	45	144	10	10	2	16	115	28	3	5.7%
Neutral	312	339	489	39	123	20	83	458	68	22	22.6%
pct.	43.7%	56.3%	77.4%	7.1%	15.5%	5.5%	16.4%	57.5%	17.4%	3.2%	

Pre-processing

As mentioned previously, we chose to use both the image and all three demographic attributes in our analysis. Therefore, our dataset looked like:

$$D = \{\dots, ((x_i, a_i), y_i), \dots\}$$

The target label, emotion expression, was categorical and not balanced. The EDA revealed that the class labels were skewed towards happiness, sadness, and neutral. We handle this during model training by incorporating class weights into the loss function.

We did not have missing data, but we did notice that some "demographic subgroups" were not present in our dataset. See the output below.

In [ ]:
```python
for r in range(3):
    for g in range(3):
        for a in range(5):
            count = len(df[(df["Race"]==r) & (df["Gender"]==g) & (df["Age"]==a)])
            print(f"{race_lookup[r]}, {gender_lookup[g]}, {age_lookup[a]}: {count}")
```

We dealt with these missing subgroups by amending our fairness analysis. Specifically, when evaluating fairness

- we ignored images labeled "Unsure" since these were mostly images of babies that annotators apparently struggled to discern the gender of,
- we ignored images labeled "0-3" or "70+" since they were sparsely available in our dataset and did not reflect populations of interest for our project's broader goal/application.

We preprocessed all the data using standard ImageNet transforms. Each image was loaded to be in range [0,1] and normalized using the ImageNet mean and standard deviation. Images are resized from 100x100 to 224x224.

In [ ]:
```
import numpy as np
import torchvision
from torchvision.transforms import ToTensor, Resize, Normalize, RandomInvert

img_size = 224
transform = torchvision.transforms.Compose([ToTensor(), Resize(img_size), Normalize((0.4
```

In [ ]:
```
import matplotlib.pyplot as plt
sample_path = "data/RAF/aligned_test/test_1396_aligned.jpg"
sample_image = Image.open(sample_path).convert("RGB")
plt.imshow(sample_image)
```

In [ ]:
```
sample_image = transform(sample_image)
sample_image_np = sample_image.numpy().transpose((1,2,0))
plt.imshow(sample_image_np)
```

We show how this transform affected the mean pixel value per image and per image standard deviation distribution.

In [ ]:
```
pre_transform_means = []
pre_transform_stds = []
post_transform_means = []
post_transform_stds = []
for path in df["Path"]:
    im = Image.open(path).convert("RGB")
    pre_transform_means.append(np.mean(im))
    pre_transform_stds.append(np.std(im))
    post_im = transform(im)
    post_im = post_im.numpy()
    post_transform_means.append(np.mean(post_im))
    post_transform_stds.append(np.std(post_im))
```

In [ ]:
```
plt.hist(pre_transform_means)
plt.show()
```

In [ ]:
```
plt.hist(post_transform_means)
plt.show()
```

In [ ]:
```
plt.hist(pre_transform_stds)
plt.show()
```

In [ ]:
```
plt.hist(post_transform_stds)
plt.show()
```

Models and Evaluation

Experimental Setup

We evaluated the performance of our trained CNN emotion classifiers on two fronts. We first looked at pure scoring/accuracy metrics:

- accuracy
- AUROC
- F1 These metrics allowed us to sanity-check that our model was learning and make comparisons to performance statistics to state-of-the-art emotion classifiers on RAF-DB. Recall that AUROC is the area under the TPR vs FPR curve (we used a one-vs-all generalization for multiple classes), and F1 score is a metric that captures both the precision and recall of a model's predictions. Using F1 is particularly important for this problem due to the obvious class imbalances present in the dataset.

For fairness, we used equalized opportunity to capture differences in classification performance by demographics. Recall for a binary classifier, equalized opportunity requires that

$$P(R=1|Y=1, A=a_1) = P(R=1|Y=1, A=b).$$

We use the generalization presented by Xu et. al:

$$F = \frac{1}{\sum_{c=1}^{C} p(\hat{y}=c|y=c, s=d, x)} \min_k \sum_{c=1}^{C} p(\hat{y}=c|y=c, s=s_k, x).$$

We select d via

$$d = \text{argmax}_k \sum_{c=1}^{C} p(\hat{y}=c|y=c, s=s_k, x).$$

Equalized opportunity ensures that the probability of a positive prediction given that the true label is positive is the same across all demographic subgroups. The Xu et. al. equation works by assigning an opportunity score to each demographic group by summing the probability of a positive prediction given that the true label is positive across all classes. The demographic group with the highest opportunity score is then selected as the reference group, "d". The fairness score is then calculated by taking the minimum of the opportunity scores across all demographic groups and dividing by the opportunity score of the reference group. This results in a score ranging from zero to one, where higher is better. A score of one indicates that all demographic groups have the same opportunity score.

We used the cross-entropy loss function with class weights that account for class imbalance. We also modified this loss function in different methods we implemented/tried in order to improve fairness. This will be discussed subsequently in full detail.

We used the provided train/test split for model training and evaluation. For the hyperparameter search, we split our training set further, creating a validation set that we used for early stopping/performance comparisons. The validation split was made at the 80/20 level.

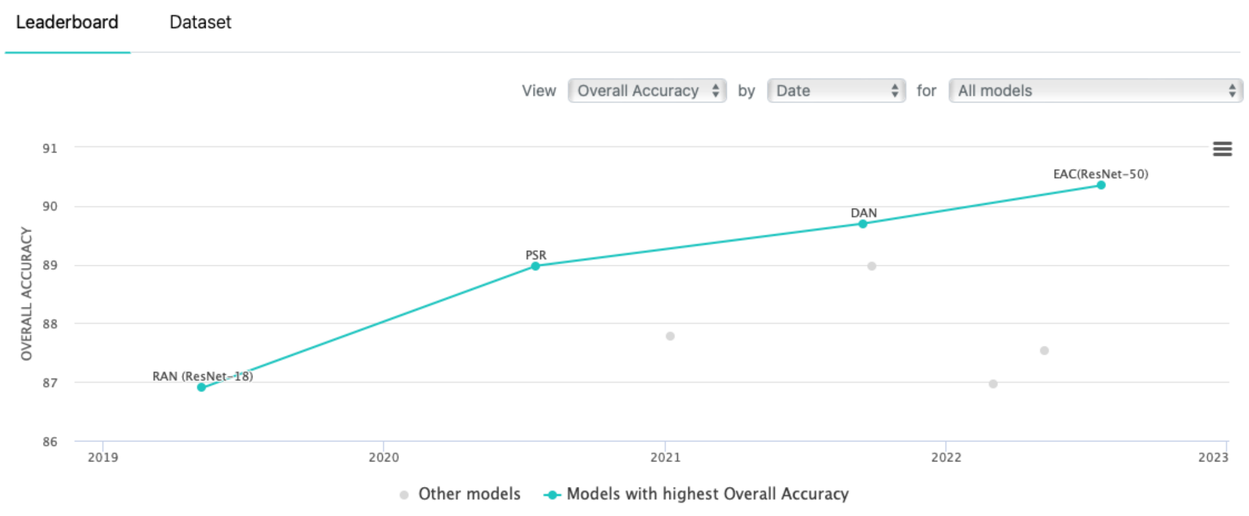
Code for loss functions: see lines 173-184 in train_all.py

Code for train/test split: see split.py

Baseline

We trained a baseline ResNet18 model to do emotion classification. We chose this model since it was popularly used for classification on RAF-DB and is a robust CNN architecture that is good at avoiding the vanishing gradient problem (due to residual blocks that create "highways" for gradient flow).

Below is the leaderboard for classification accuracy on RAF-DB.


Leaderboard Dataset

View Overall Accuracy by Date for All models

The loss function we used to train our baseline model was cross-entropy with inverse weighting per class. Mathematically,

$$L_{\text{batch}} = \frac{1}{B} \sum_{j=1}^{B} l(y_j, \hat{y}_j; w)$$

$$l(y, \hat{y}; w) = \sum_{k=1}^{K} = -w_{y_j} y_{j,k} \log \mathrm{Softmax}(\hat{y}_j)$$

$$w_k = \frac{1}{N_k^{\text{train}}}$$

Let's analyze in detail these equations. The first equation is the per-loss batch: we take the mean cross-entropy loss over the predictions in the batch. We call $l(y, \hat{y}; w)$ our per-example cross-entropy loss: this is a function of y and $\hat{y}$ and parameterized by the class weights w.

The next equation looks at the per-example cross-entropy loss. y_j is a one-hot vector, so the only contribution in this sum is from the correct class k' of the image. For this closs, we punish low probabilitiy predictions. We build the softmax function into our loss since the ResNet18 architecture we implemented outputs raw class scores (i.e. logits). In order to make it a probability distribution, we must use a Softmax.

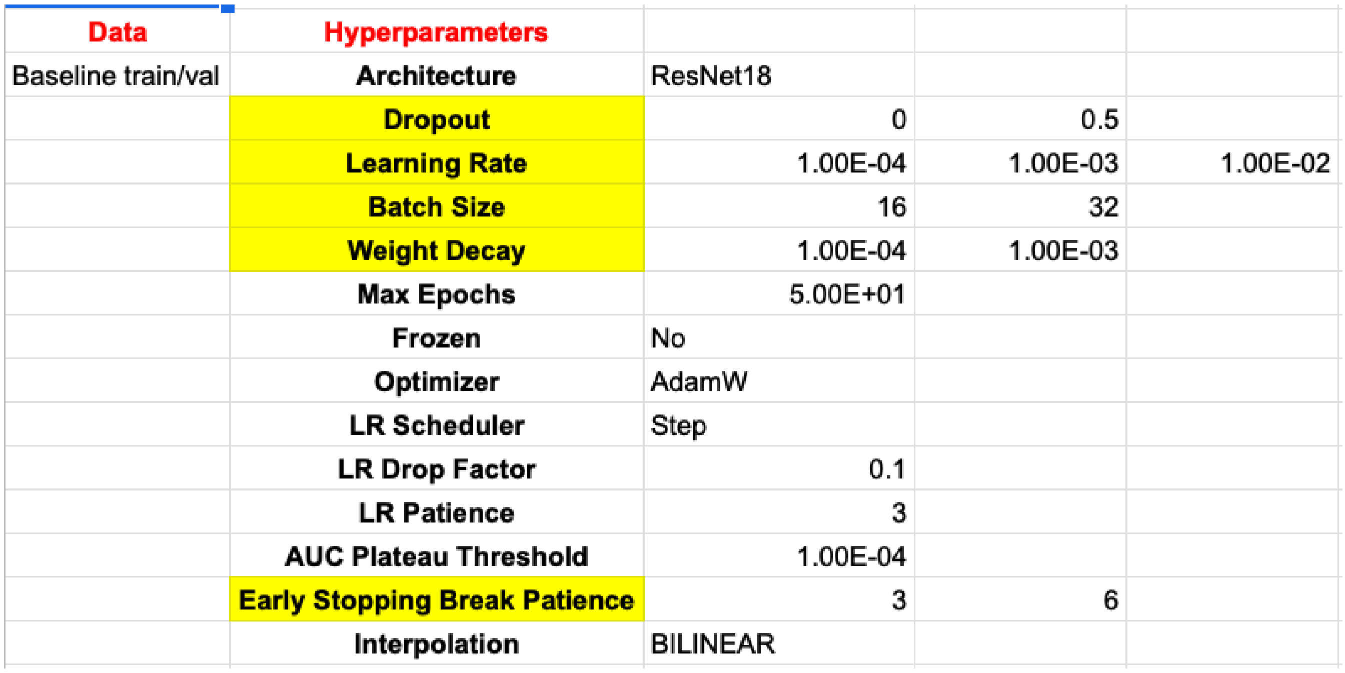
Finally, we have to account for class imbalance. To do so, we weight the per-example loss by a weight $w_{k'}$. The weight for a class k' is the inverse of the number of examples of class k' in the training set. By doing so, we accomplish two things:

- if two classes k_1 and k_2 have similar number of training examples, then the weights for these two classes will be similar.

- if one class k has an over-abundance of training examples, then the weight for this class will be smaller, so the model does not overfit to this class.

Hyperparameter Search

We performed a hyperparameter search before training the baseline model. Due to constraints on GPU, we limited our hyperparameter search to a small subset of variables that we thought would have an important effect on model performance.



Data	Hyperparameters			
Baseline train/val	Architecture	ResNet18		
	Dropout	0	0.5	
	Learning Rate	1.00E-04	1.00E-03	1.00E-02
	Batch Size	16	32	
	Weight Decay	1.00E-04	1.00E-03	
	Max Epochs	5.00E+01		
	Frozen	No		
	Optimizer	AdamW		
	LR Scheduler	Step		
	LR Drop Factor	0.1		
	LR Patience	3		
	AUC Plateau Threshold	1.00E-04		
	Early Stopping Break Patience	3	6	
	Interpolation	BILINEAR		

For each hyperparameter setting, we trained the model on the training subset (i.e. the training set derived from a further train/val split on the original training set) and compared performance via one-v-all AUROC on the validation set. After selecting our best hyperparameters, we trained all models using these settings on the original training set. See https://docs.google.com/spreadsheets/d/1Pju7Ey7Nn2OvxeNtkLw6lVwhof0lohpiXrmB8bmw_EY/edit?usp=sharing for the complete results.

Hyperparameters	Best Value
Dropout	0
Learning Rate	0.001
Batch Size	32
Weight Decay	0.001
Early Stopping Patience	3

Methods

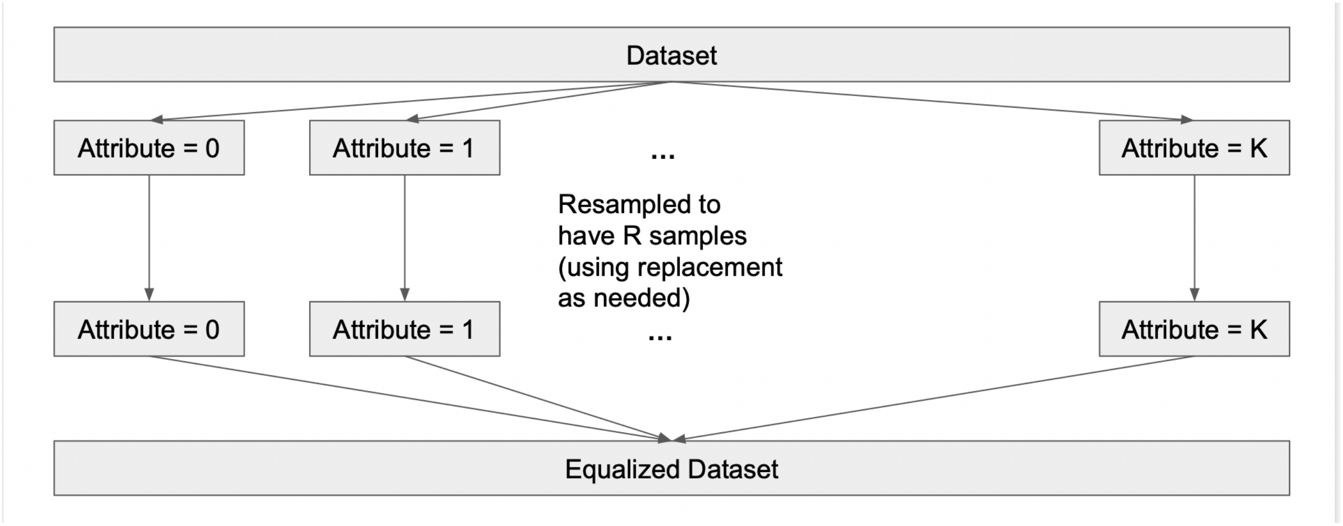
We implemented a variety of methods to attempt to improve model fairness. Recall that we defined fairness using F, our generalized equalized opportunity. We also looked at per-demographic accuracies to assess how consistent our model accuracy was across the demographics.

Remember all methods were trained using the original training set, with our searched hyperparameters, and evaluated for baseline performance and fairness on the original test set.

In our project, the key is not the actual implementation of these methods -- most of them are farily straightforward -- but rather finding a technique that could reasonably improve fairness. That latter part was difficult and took a lot of brainstorming and trail/error.

Method 1: Stratified Sampling

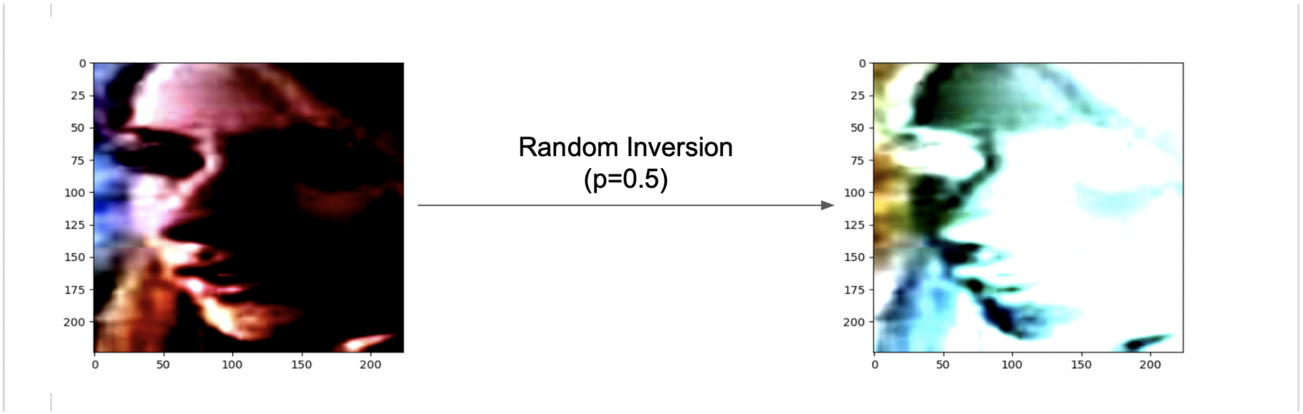
In our first approach, we posited that the model fairness could be improved by making our training dataset consistent across the demographic subgroups. We chose a single attribute (race, age, gender) and resampled our dataset such that each instance of these attributes had an equal number of training examples, R. We chose R using either the mean, maximum, or minimum number of examples for an instance of the attribute.



We implemented this using a PyTorch dataset, see the `RAFDataset` class in custom_modules.py. In all, we trained 9 models (3 attributes, 3 equalizing methods (mean, max, min)) and compared their fairness stats to our baseline.

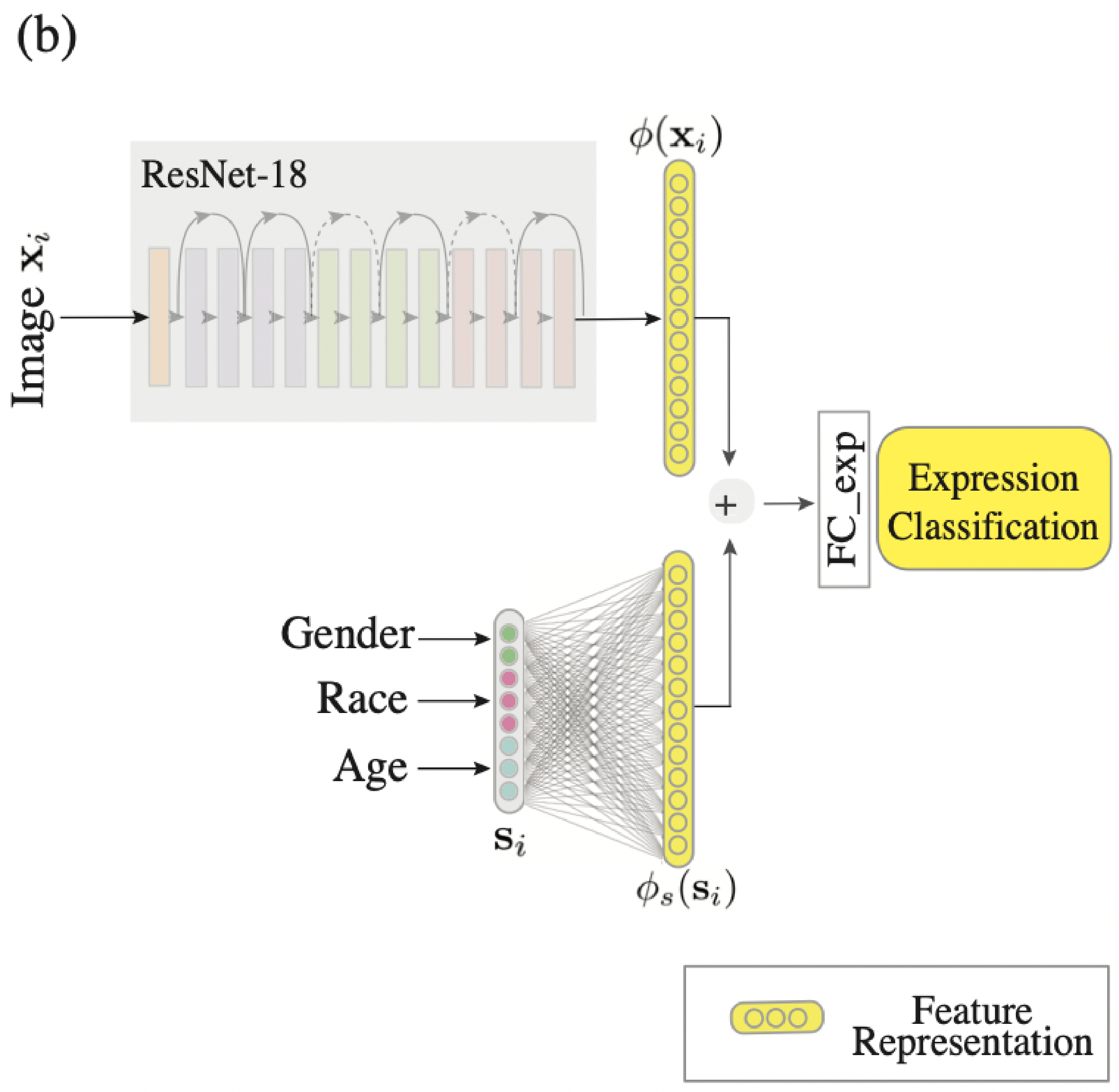
Method 2: Preprocessing via Pixel Inversion

Looking again at data-based techniques, we tried to artificially "steer" our CNN away from using demographics in decision making by obscuring the demographic attributes apparent in an image. We attempted to do this by inverting the pixels in the images at both training and test time. Below is an example of an inversion applied to an input image.



Method 3: Attribute-Aware Model

We implemented an attribute-aware approach as described by Xu et. al. The intuition behind this approach is, instead of implicitly using demographic information that can be inferred from an image, we might be able to improve fairness by just directly giving the model access to demographic attributes. The following figure provides the structure, taken from Xu et al.



Method 4: Affirmative Action Model

In this approach, we tried to make purposeful interventions in our model that overemphasize minority subgroups at train time. We accomplish this via modifications to our loss function. Recalling notation from above, our new "affirmative action" loss function is:

$$L_{\text{batch}} = \frac{1}{B} \sum_{j=1}^{B} l(y, \hat{y}; w) \alpha(r_j, g_j, e_j)$$

where $\alpha(r_j, g_j, e_j)$ is a kind of attention factor that we can design. For a proof of concept, we chose a simple structure for α, namely

$$\alpha(r_j, g_j, e_j) = 9\mathbb{I}(r_j = r', g_j = g', e_j = e') + 1.$$

Here, (r', g', e') represents the race, gender, and age triplet for the demographic subgroup we wish to overemphasize at train time. This function will assign our subgroup of interest a weight of 10 and all other groups a weight of 1. This scheme punishes a loss function more severely for making mistakes on examples in this "protected subgroup". We can also remember from our discussion in class about backpropogation that the gradients associated with examples in this subgroup will be larger, leading to more dramatic parameter updates. The natural question then is how do we choose (r', g', e'). In this project, we chose these subgroups based on accuracy using our baseline model. We looked at per-demographic accuracy using our baseline model, and we chose the two worst-performing subgroups to boost using affirmative action.

The code for our affirmative action model is available train_all_affraction.py. Note that the underlying model is the same as the baseline, only now we include a "attention" weight in the loss function.

In [ ]:
```
# Show plots of how these models performed during training.
#  For example, plot train loss and train accuracy (or other evaluation metric) on the y
#  with number of iterations or number of examples on the x-axis.
```

Results

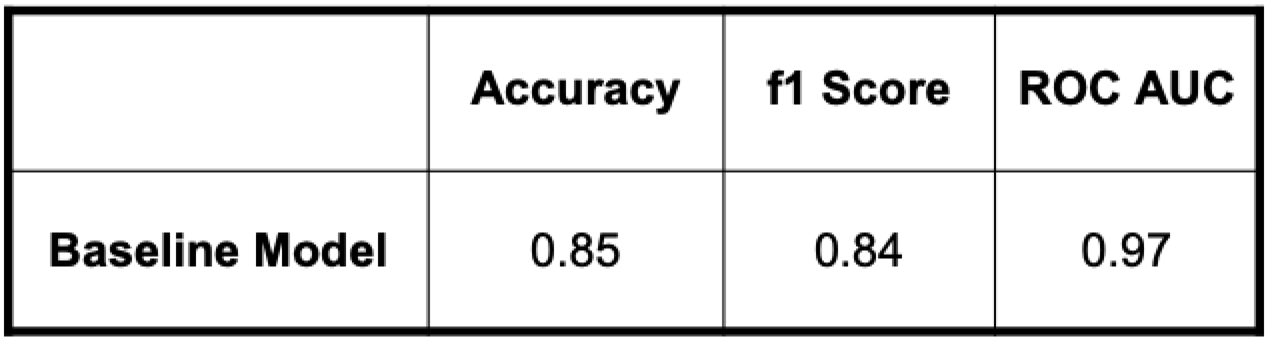
We first show results for our baseline model and then compare this performance (including fairness) against models trained via other approaches.

Baseline Model

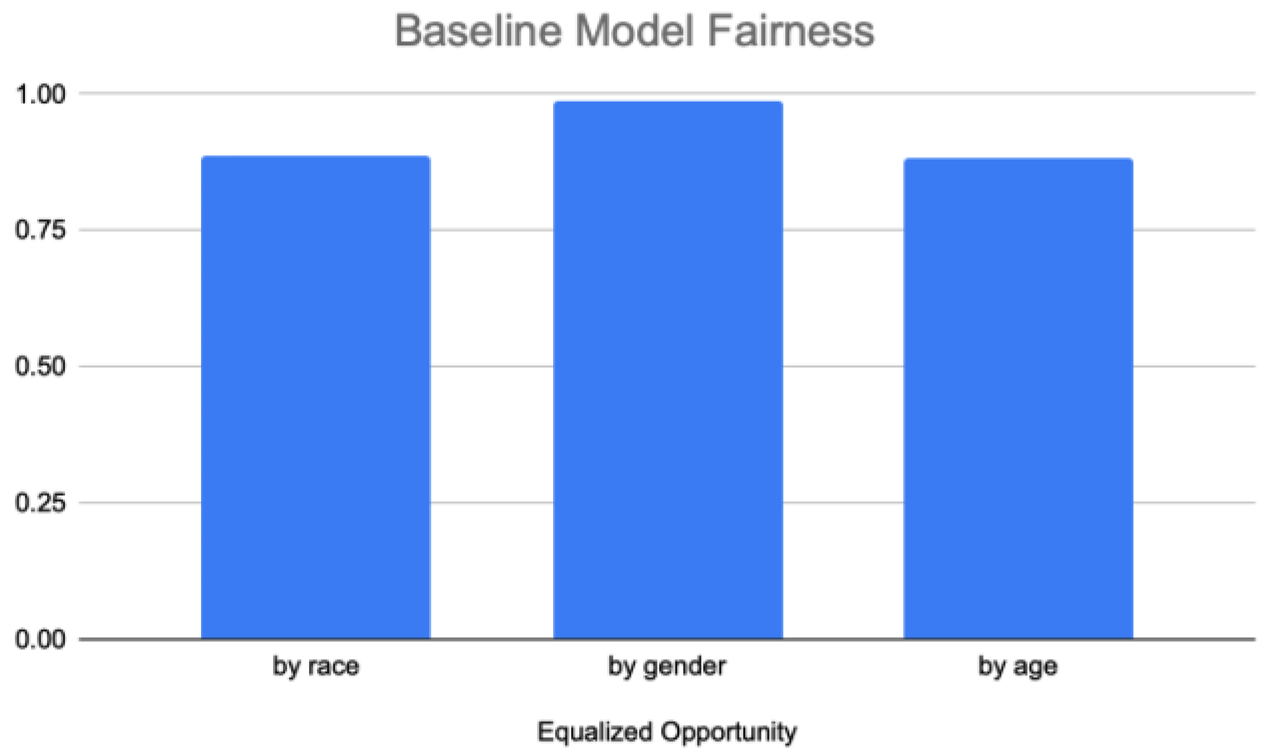
We first plot how the training & validation loss and accuracy changes over training iterations. These "debugging" curves show us that our model has not sufferred from overfitting and can be taken as a good baseline.

TODO: plot of train AUC and accuracy over iterations. Comment on how we avoid over/under fitting, and what we did at train time to prevent that..

Next, we show the performance and fairness results for the baseline model.



	Accuracy	**f1 Score**	**ROC AUC**
Baseline Model	0.85	0.84	0.97



What jumps out immediately from these stats is how decently well the baseline model is able to classify emotions and its high equal opportunity by gender. This latter point can be explained by our EDA. Recall that our formulation of fairness does not take into account the unsure gender. If we look at the distribution of gender conditioned by emotion, we see that the Female and Male gender classes have roughly similar frequencies for each emotion. Therefore, we can rationalize why our model is able to make fair predictions by gender.

However, we notice then that the fairness scores for race and age are poor. We look next at the per-demographic accuracies.

Male:	**4-19**	**20-39**	**40-69**
Caucasian	0.85	0.81	0.84
African-American	0.85	0.88	0.67
Asian	0.79	0.84	0.80
Female:	**4-19**	**20-39**	**40-69**
Caucasian	0.86	0.84	0.86
African-American	0.84	0.95	0.92
Asian	0.89	0.86	0.76

From this plot,

we see more obvious disparaties in accuracy across demographic subgroups. Two populations that stick out are: 1) Male, African-Americans, 40-69 years old, and 2) Female, Asians, 40-69 years old.

On the other hand, a more suprising result is the strong accuracy for female African-Americans. Given the relative sparsity of African-American images in the dataset, this trend is interesting. To contrast this, notice the accuracy for Caucasian faces is $< 90\%$.

This heatmap also offers a nice visualization of fairness. In particular, looking at fairness as a single number, while mathematically rigorous, can hide some of the details (for example: which subgroup in a demographic is most unfair?). Therefore, looking at a heatmap of just accuracy alone can offer a new insight into what the predictions really look like "under the hood".

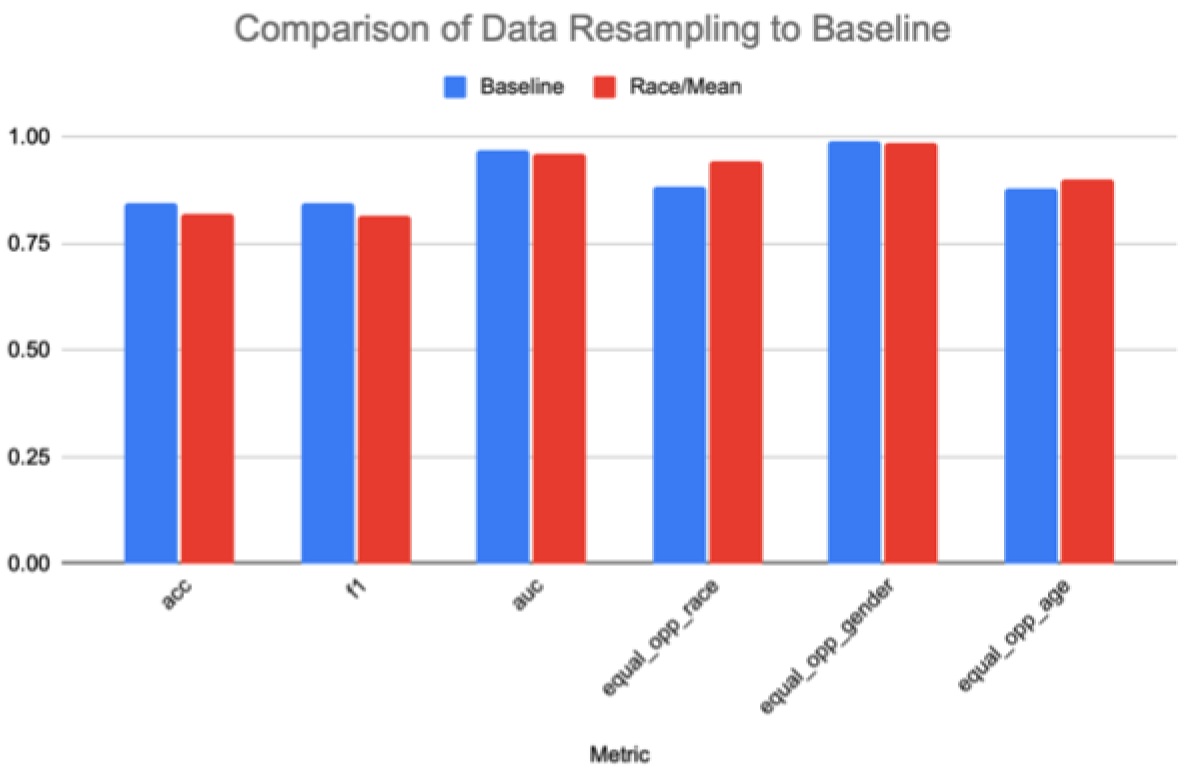
Resampling Data

We recorded fairness stats for each of the nine approaches (3 demographic attributes, 3 methods of equalizing). See https://docs.google.com/spreadsheets/d/1thmmfV8aJ9lB_GqUmet-8PoTkYaOso1ABum1zU6rCak/edit?usp=sharing (tab: equalize single attribute).

By fairness metrics, the best performing method was resampling the training data by race using equalizing by mean.

	baseline	**Race/Mean**
acc	0.85	0.82
f1	0.84	0.82
auc	0.97	0.96
equal_opp_race	0.89	0.94
equal_opp_gender	0.99	0.99
equal_opp_age	0.88	0.90
acc_race0	0.85	0.81
acc_race1	0.87	0.84
acc_race2	0.83	0.84
acc_gender0	0.83	0.80
acc_gender1	0.85	0.83
acc_gender2	0.89	0.86
acc_age0	0.91	0.88
acc_age1	0.85	0.86
acc_age2	0.84	0.80
acc_age3	0.84	0.82
acc_age4	0.79	0.72

We also plot the performance metrics as bars against the baseline.



These results are interesting because they seem to indicate a tradeoff between accuracy and fairness. Resampling the data to equalize race significantly boosted fairness by race, however both overall accuracy and per-race accuracy dropped. In fact, if we look at accuracy within each single attribute, compared to the baseline these accuracies are lower (for all except 4-19 age strata).

This offers an interesting takeaway: while simple data rebalancing might make our predictions more fair, we run the risk of reducing model accuracy across the board. This is a tradeoff that one will have to consider when deploying such algorithms in the "real world".

To drive home this point, here are the evaluation metrics for data resampling to equalize age by mean.

	baseline	**Age/Mean**
acc	0.85	0.81
f1	0.84	0.81
auc	0.97	0.96
equal_opp_race	0.89	0.84
equal_opp_gender	0.99	0.99
equal_opp_age	0.88	0.91
acc_race0	0.85	0.82
acc_race1	0.87	0.79
acc_race2	0.83	0.79
acc_gender0	0.83	0.79
acc_gender1	0.85	0.82
acc_gender2	0.89	0.87
acc_age0	0.91	0.89
acc_age1	0.85	0.83

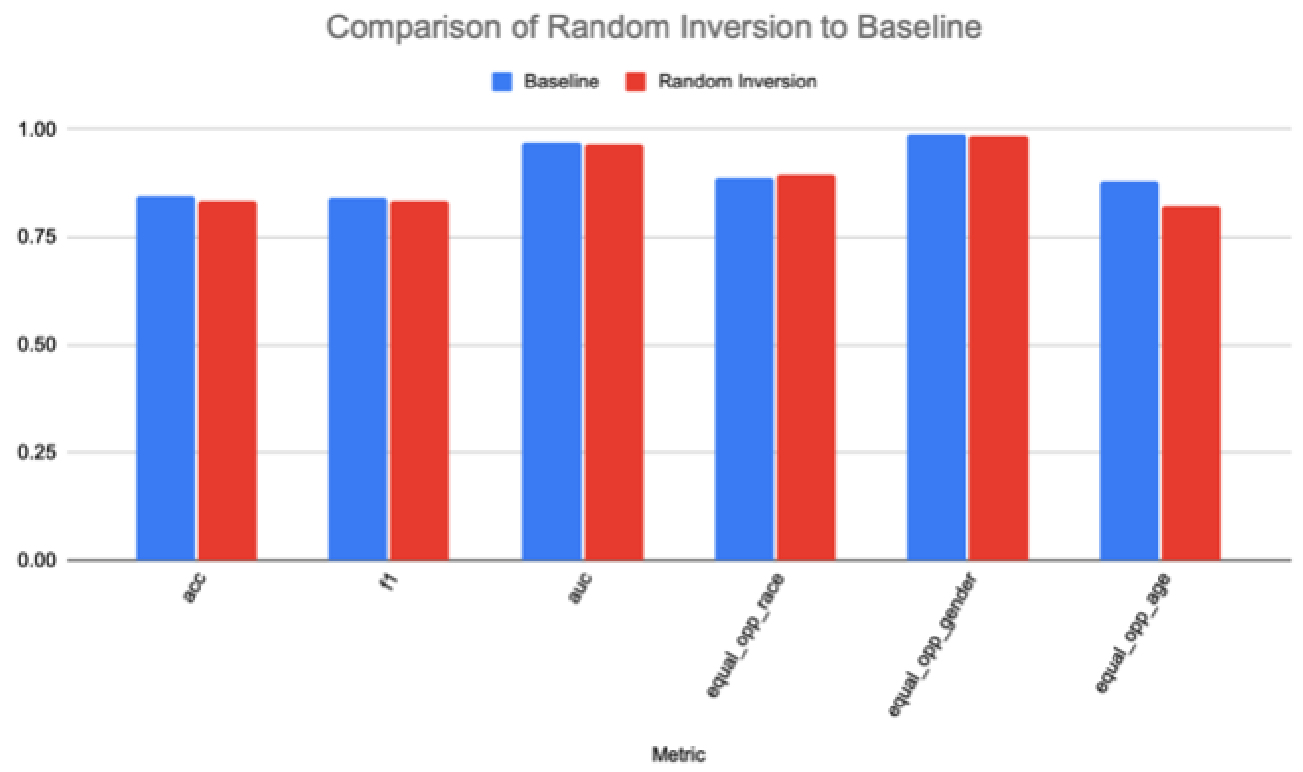
acc_age2	0.84	0.79
acc_age3	0.84	0.83
acc_age4	0.79	0.67

Again we see that while equalized opportunity by age increased, per-age accuracies fell, including significant losses for the middle aged folks (age strata 20-39).

Pixel Inversion

We implemented random pixel inversions during train time (with probability $1/2$). Evaluation metrics are reported below.

	baseline	**random invert (p = 0.5)**
acc	0.85	0.83
f1	0.84	0.83
auc	0.97	0.97
stat_parity_race	0.08	0.08
stat_parity_gender	0.10	0.10
stat_parity_age	0.16	0.16
equal_opp_race	0.89	0.89
equal_opp_gender	0.99	0.98
equal_opp_age	0.88	0.82
acc_race0	0.85	0.83
acc_race1	0.87	0.86
acc_race2	0.83	0.82
acc_gender0	0.83	0.81
acc_gender1	0.85	0.84
acc_gender2	0.89	0.88
acc_age0	0.91	0.89
acc_age1	0.85	0.83
acc_age2	0.84	0.82
acc_age3	0.84	0.86
acc_age4	0.79	0.75



We see this method simply did not improve fairness. It also resulted in poorer accuracies across the board. Overall, we conclude that inverting the pixels just created a more difficult learning problem, with no significant gains in terms of fairness.

Attribute Aware Model

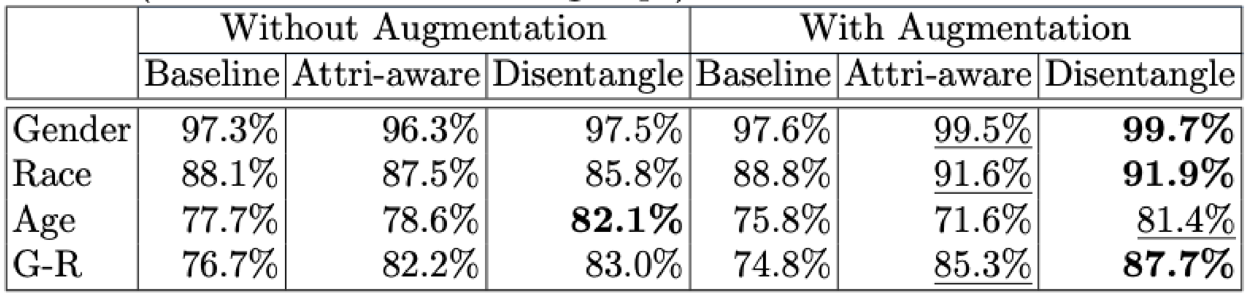
We report results for the attribute-aware model.

	baseline	attr aware
acc	0.85	0.86
f1	0.84	0.86
auc	0.97	0.97
equal_opp_race	0.89	0.87
equal_opp_gender	0.99	0.99
equal_opp_age	0.88	0.86
acc_race0	0.85	0.86
acc_race1	0.87	0.89
acc_race2	0.83	0.85
acc_gender0	0.83	0.84
acc_gender1	0.85	0.86
acc_gender2	0.89	0.92
acc_age0	0.91	0.94
acc_age1	0.85	0.87
acc_age2	0.84	0.84

acc_age3	0.84	0.86
acc_age4	0.79	0.73

In this situation, we see the opposite side of the accuracy-fairness tradeoff. While most per-demographic (and overall) accuracies increase, fairness for race and age drop. To get a handle on these results, we compared them to Xu et. al.

Table 4: Fairness measure of the models, broken down by attribute labels on RAF-DB (G-R: Joint Gender-Race groups).



	Without Augmentation			With Augmentation		
	Baseline	Attri-aware	Disentangle	Baseline	Attri-aware	Disentangle
Gender	97.3%	96.3%	97.5%	97.6%	99.5%	**99.7%**
Race	88.1%	87.5%	85.8%	88.8%	91.6%	**91.9%**
Age	77.7%	78.6%	**82.1%**	75.8%	71.6%	81.4%
G-R	76.7%	82.2%	83.0%	74.8%	85.3%	**87.7%**

While the baseline model has different fairness, we notice that in both cases fairness by race decreases when no data augmentations were used. On the RAF-DB dataset, it appears that Xu et. al. also had difficulties making consistent gains in fairness using the attribute-aware approach.

This result is quite surprising, because plain intuition would suggest that allowing the model to directly "see" the demographics would make it more fair. Prior literature, for example Guo & Mu 2010 IEEE, would also support this. However, we find that we were not able to backup these conclusions.

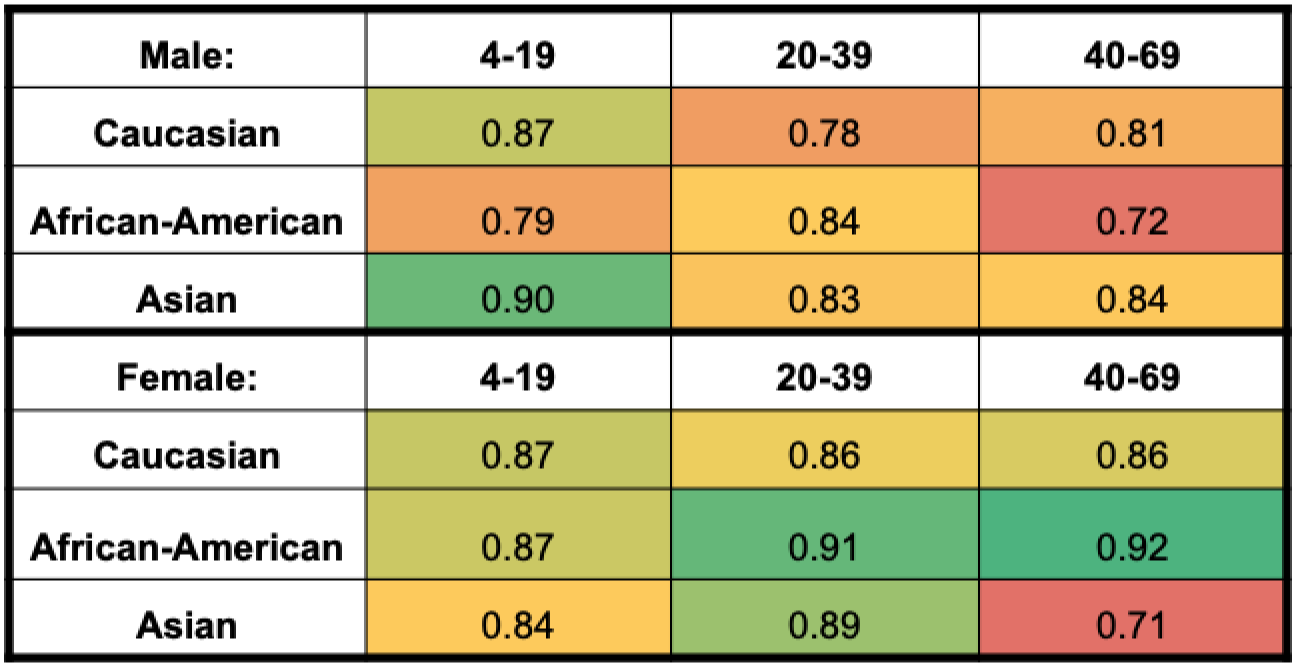
Affirmative Action

We implemented affirmative action on two protected groups: Male, African Americans, 40-69 years old, and Female, Asians, 40-69 years old. We chose these two groups due to worst per-subgroup accuracy with the baseline model.

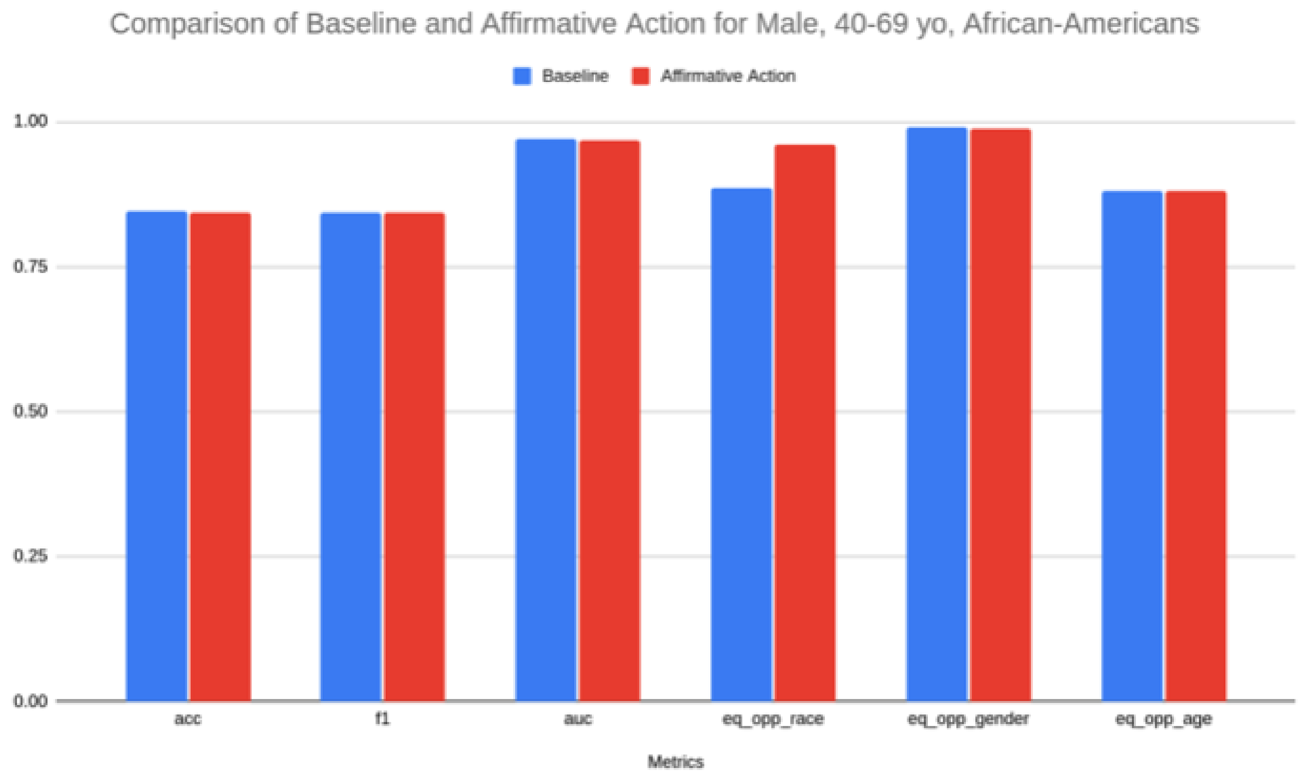
Results are reported below.

	baseline	**Affirmative Action on African-American Male 40-69 yo**
acc	0.85	0.84
f1	0.84	0.84
auc	0.97	0.97
equal_opp_race	0.89	0.96
equal_opp_gender	0.99	0.99
equal_opp_age	0.88	0.88
acc_race0	0.85	0.84
acc_race1	0.87	0.85
acc_race2	0.83	0.85
acc_gender0	0.83	0.81
acc_gender1	0.85	0.86
acc_gender2	0.89	0.89

acc_age0	0.91	0.91
acc_age1	0.85	0.86
acc_age2	0.84	0.84
acc_age3	0.84	0.83
acc_age4	0.79	0.74

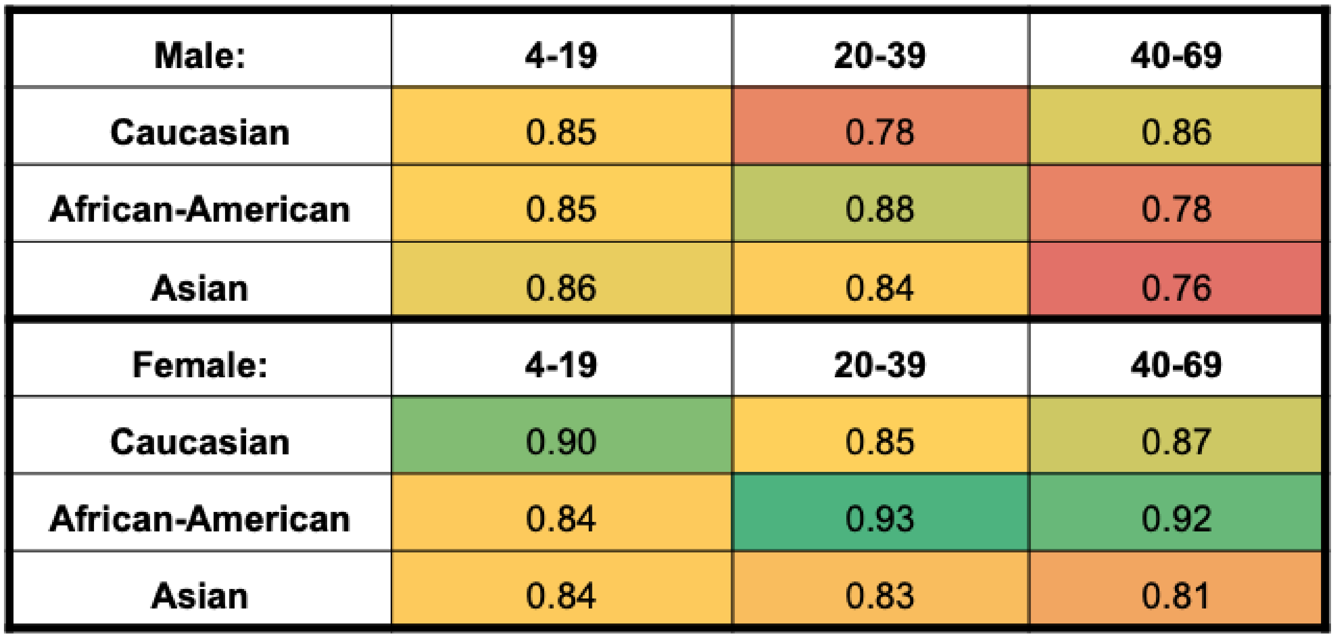


Male:	4-19	20-39	40-69
Caucasian	0.87	0.78	0.81
African-American	0.79	0.84	0.72
Asian	0.90	0.83	0.84
Female:	**4-19**	**20-39**	**40-69**
Caucasian	0.87	0.86	0.86
African-American	0.87	0.91	0.92
Asian	0.84	0.89	0.71

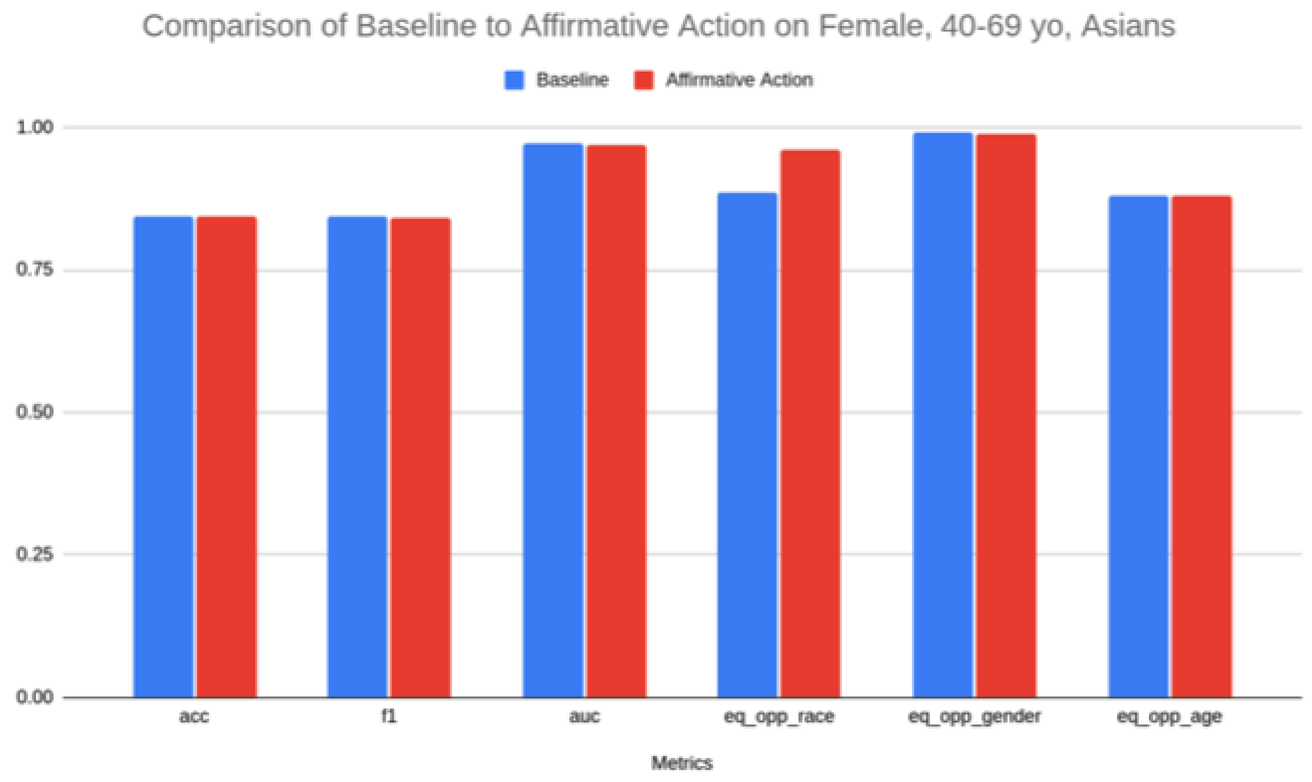


In this first case, affirmative action was able to boost per-subgroup accuracy by 5% compared to the baseline. We notice significant gains in equalized opportunity by race, while maintaining fairly consistent overall accuracy (and F1/AUROC). Looking at accuracy for each single attribute, we see a fairly even change relative to the baseline. In other words, a few attributes (for example, Caucaisan race, Male gender) suffer on accuracy, other groups maintain or slightly increase in accuracy. We conclude that this approach does better on the fairness-accuracy tradeoff than data resampling.

	baseline	Affirmative Action on Asian Female 40-69 yo
acc	0.85	0.85
f1	0.84	0.84
auc	0.97	0.97
equal_opp_race	0.89	0.93
equal_opp_gender	0.99	0.99
equal_opp_age	0.88	0.92
acc_race0	0.85	0.85
acc_race1	0.87	0.88
acc_race2	0.83	0.83
acc_gender0	0.83	0.83
acc_gender1	0.85	0.86
acc_gender2	0.89	0.88
acc_age0	0.91	0.91
acc_age1	0.85	0.86
acc_age2	0.84	0.83
acc_age3	0.84	0.86
acc_age4	0.79	0.75



Male:	4-19	20-39	40-69
Caucasian	0.85	0.78	0.86
African-American	0.85	0.88	0.78
Asian	0.86	0.84	0.76
Female:	**4-19**	**20-39**	**40-69**
Caucasian	0.90	0.85	0.87
African-American	0.84	0.93	0.92
Asian	0.84	0.83	0.81



Similarly, the second affirmatve-action approach shows a 5% increase in protected subgroup accuracy, significant gains on equalized opportunity, and an overall balanced impact on per-attribute accuracies.

On the other hand, we also notice that affirmative action has some "unwanted" effects. In other words, the impact of over-emphasizing one subgroup in the loss function had a reverberating effect that also impacted the performance on unrelated subgroups. We can see that from the accuracy-by-demographic heatmap. This is a point of interest for potential future projects: can we make our human interventions more controlled so that accuracy only boosts for the demographic attributes of interest?

Taking these results together, we propose two key takeaways:

- there appears to be a fairness-accuracy tradeoff,
- affirmative action is the best at improving fairness while minimizing the impact on accuracy.

Discussion

What you've learned

Note: you don't have to answer all of these, and you can answer other questions if you'd like. We just want you to demonstrate what you've learned from the project.

What concepts from lecture/breakout were most relevant to your project? How so?

What aspects of your project did you find most surprising?

What lessons did you take from this project that you want to remember for the next ML project you work on? Do you think those lessons would transfer to other datasets and/or models? Why or why not?

What was the most helpful feedback you received during your presentation? Why?

If you had two more weeks to work on this project, what would you do next? Why?

TODO: copy in stuff from the google doc.