Bias in Facial Classification ML Models

Patrick Connelly Grace Cooper Bhavana Jonnalagadda Carl Klein
Piya (Leo) Ngamkam Dhairya Veera

2023-12-12

Table of contents

Abstract **3**

1 Introduction **4**

2 Data **5**

2.1 Exploration of Source Data . . . 5
2.2 Data Selection (UTK Dataset) . . . 6
2.2.1 Motivation for the Selection of UTKFace Dataset . . . 6
2.2.2 Data Collection Method . . . 6
2.2.3 Sources and Influences of Bias in the Dataset . . . 7
2.3 Selected Models . . . 7
2.3.1 FairFace . . . 7
2.3.2 DeepFace . . . 7
2.4 Dataset Features . . . 8
2.4.1 Input data set . . . 8
2.4.2 FairFace Outputs . . . 8
2.4.3 DeepFace Outputs . . . 9
2.5 Evaluating Permutations of Inputs and Models for Equitable Evaluation . . . 9
2.5.1 DeepFace Analysis Options . . . 10
2.5.2 FairFace Analysis Options . . . 10
2.5.3 Specific Permutations . . . 10
2.6 Model Evaluation Data . . . 11

3 Methods **13**

3.1 Data Cleaning: Standardizing Model Outputs . . . 13
3.1.1 FairFace Output Modifications . . . 13
3.1.2 DeepFace Output Modifications . . . 13
3.1.3 Source Data Modifications . . . 14
3.2 Exploratory Data Analysis (EDA) . . . 14
3.3 Research Questions . . . 14
3.4 Hypothesis Testing . . . 14
3.4.1 Demographics . . . 15
3.4.2 Demographics' Subgroups . . . 15
3.4.3 The General Proportion Tests . . . 15
3.4.4 Notation . . . 16
3.4.5 Proportion Testing of Subsets . . . 16
3.5 Performance Measurement . . . 17
3.5.1 Accuracy . . . 18
3.5.2 Precision . . . 18
3.5.3 Recall . . . 19
3.5.4 F1-Score . . . 19

4 Results **20**

4.1 Model Output . . . 20
4.2 Model Performance, Hypothesis Testing . . . 20
4.2.1 p-value Critical Values . . . 22

4.3 Meta-Analysis Plots . . . 23
4.4 Population Estmate Plots - UTK Face vs. Model . . . 24

5 Conclusions 27
5.1 Evaluation of Test Results . . . 27
5.2 Hypothesis Testing Results . . . 27
5.2.1 Age Prediction . . . 27
5.2.2 Race Prediction . . . 28
5.2.3 Gender Prediction . . . 28
5.3 Identifying Specific Biases with F1 and Accuracy Scores . . . 28
5.3.1 FairFace . . . 28
5.3.2 DeepFace . . . 28
5.4 Summary . . . 28
5.5 Age Prediction Conclusions . . . 28
5.6 Race Prediction Conclusions . . . 29
5.6.1 Race by itself . . . 29
5.6.2 Race given Age . . . 29
5.6.3 Race given Gender . . . 30
5.6.4 Verdict . . . 30
5.7 Gender Prediction Conclusions . . . 30

References 32

Abstract

Bias in how facial classification machine learning (ML) models label faces is a burgeoning problem; as the use of such models becomes widespread, it is more important than ever to identify the weaknesses in the models and how they could potentially discriminate against various class, like race, gender, or age. In this study, we run two widely used facial classification models (FairFace and DeepFace) on a popular face dataset (the UTKFace Dataset) and perform two sample proportion hypothesis tests – as well as evaluating model output using common ML performance metrics – in order to highlight and identify potential bias in the aforementioned classes. We found that DeepFace had significant bias in age and race, with white males being classified more accurately than other factor categories; FairFace performed significantly better with less detected bias, affirming the intended goal of FairFace being built specifically to be more "fair" (less biased) on various categories. The implications lead us to recommend more work to be done on improving facial classification ML models, in order for them to be equitable and fair to all humans they are run on.

Report PDF and Code Location

A link to download the PDF version of this report, and a link to the Github source code for this report, are both available as icons in the top bar of this website.

1 Introduction

The issue of algorithmic bias, especially concerning sensitive and personal data, is an ongoing problem in today's use of Artificial Intelligence (AI). Facial recognition is one field that is struggling with mitigating and minimizing the issue. According to a report by the National Institute of Standards and Technology, the rates of false positives, or misidentification, of African and East Asian faces were 10 to 100 times higher than those for White or European faces (NIST 2020). Numerous studies have found that many facial recognition algorithms, having been based and created in white-dominated spaces, often lack accuracy with darker faces, especially compared to their identification of white faces. This issue has caused numerous problems throughout the development of facial recognition. For instance, a Georgetown study found that African Americans were significantly misidentified in law enforcement databases, due to being overrepresented in mugshots (Georgetown Law 2016). That sort of misinterpretation could lead to unlawful arrests, accusations, or sentencings. A facial recognition algorithm has two main areas where these sorts of biases occur: the actual coding/iteration, and the data used to train it. The databases used to teach an algorithm how to make decisions and identify faces matter, from the balance of different races, genders, and ages, to how well those databases use facial markers to identify anything. As facial recognition becomes more widespread, this becomes a key question of data ethics and misuse (Lohr 2018).

Thus, it is necessary to examine existing algorithms for their accuracy in identifying faces properly. Two easily accessible algorithms that claim to do just that are FairFace, created by UCLA researchers (Karkkainen and Joo 2021), and DeepFace (Serengil and Ozpinar 2021), created by a team of researchers at Facebook. Both claim to accurately identify the race, gender, and age of any given photo. FairFace claims to have reduced bias compared to other common facial recognition algorithms. FairFace was trained on a balanced dataset, eqully stratified across race, including Middle Eastern Faces. The creators point out in their work that the majority of training datasets overwhelmingly represent white and male subjects, lending to algorithmic biases in any models leveraging such data for training (Karkkainen and Joo 2021). The DeepFace algorithm was developed by a team at Facebook, now Meta, and also aims to be an accessible and accurate open-source facial recognition system. In their paper on research and development of DeepFace, the creators claim 97% accuracy on gender prediction, but only 68% accuracy on race and ethnicity. There is a more complex discussion of age prediction, and the creators further state that a previous study produced more accurate results when compared to the current model. Furthermore, the current model was claimed to be less accurate than human-provided predictions (Serengil and Ozpinar 2021).

Our goal in this research is to test the strength of the models' claims and compare the algorithms' ability to predict age, gender, and race against a source dataset. Both will be tested against the UTKFace dataset, which consists of over 24,000 labeled faces that can be used for research purposes ("UTKFace" 2021). We will identify potential biases in the modelsl using two-sample proportion hypothesis testing, and by inspect specific instances of such bias using performance metrics such as F1 score and accuracy.

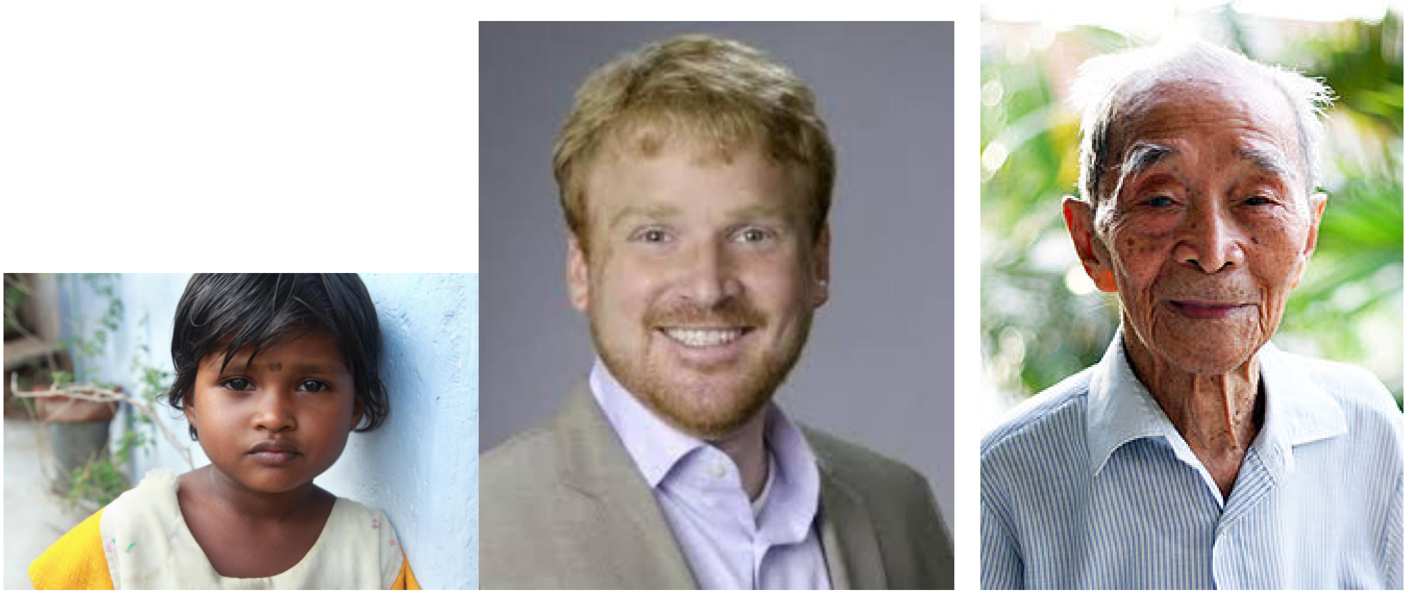
2 Data

Pursuant to the study, the team sought out multiple datasets on which we could evaluate the performance of two selected recognition models (Facebook's DeepFace and K. Karkkainen & J. Joo's Fair Face models) to generate performance data and perform statistical analysis on their ability to accurately identify race, age, and gender of a subject in a photograph.

Collectively, we landed on the UTK dataset to perform our evaluation: https://susanqq.github.io/UTKFace/

The dataset has three main sets available for download from the main page: A set of "in-the-wild" faces, which are the raw unprocessed images. The second set is the Aligned & Cropped Faces, which have been cut down to allow facial algorithms to read them more easily. The final file is the Landmarks (68 points) dataset, which contains the major facial landmark points that algorithms use and process to examine the images.

2.1 Exploration of Source Data

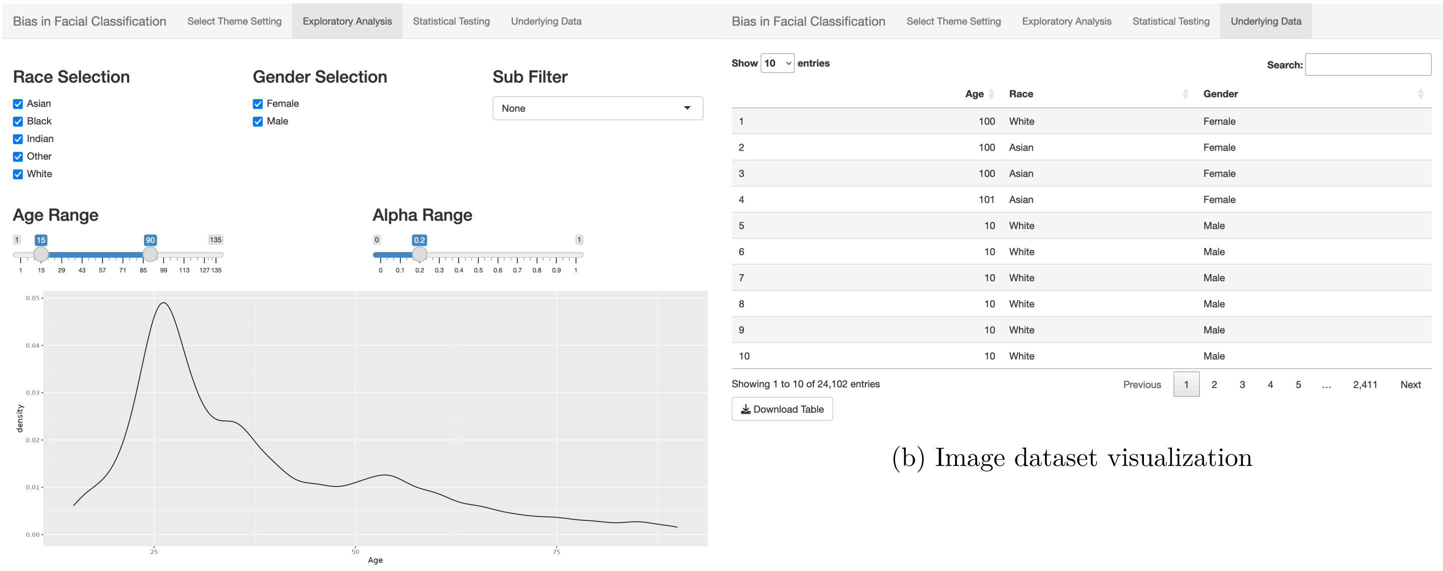


(a) Age=6, Gender=F, Race=Indian (b) Age=38, Gender=M, Race=White (c) Age=80, Gender=M, Race=Asian

Figure 2.1: Example face images from the UTK dataset ("UTKFace" 2021) with their associated given labels.

For initial exploration of the UTKFace dataset, we sought to determine the distribution of age, given other categorical variables. To support hypothesis testing, such as z-tests, t-tests, it is important for us to inspect our data for a normal distribution. In our case, we are only able to initially inspect age, as it is the only numerical variable from our data available.

Examining the data, we have a somewhat normal distribution of age with heavy tails, centered between the ages of 30 and 35. To examine distributions of race and gender, we will perform a bootstrapped sampling of proportions of these variables, and include them in our results section. Having such distributions will provide normal distributions and support us in evaluating our results.



Race Selection

- ☑ Asian
- ☑ Black
- ☑ Indian
- ☑ Other
- ☑ White

Gender Selection

- ☑ Female
- ☑ Male

Sub Filter: None

Age Range: 15 – 90 (1 – 135)

Alpha Range: 0.2 (0 – 1)

(a) Image data EDA

Show 10 entries   Search:

	Age	Race	Gender
1	100	White	Female
2	100	Asian	Female
3	100	Asian	Female
4	101	Asian	Female
5	10	White	Male
6	10	White	Male
7	10	White	Male
8	10	White	Male
9	10	White	Male
10	10	White	Male

Showing 1 to 10 of 24,102 entries   Previous 1 2 3 4 5 … 2,411 Next

(b) Image dataset visualization

Figure 2.2: Screenshots of the interactive figure showcasing the distributions of various data factors in the image dataset, and showcasing the underlying data. To see and interact with this figure, go to the website link

A note on sample independence. For each of the selected facial recognition models, we assume that each model's training dataset is independent of the content of the UTKFace dataset. Independence between each model's output and the source data is a requirement for performing our testing. We have no means or methods to verify whether or not any UTKFace images were used in the training of either model, and must make this assumption before moving forward in our methods and results.

2.2 Data Selection (UTK Dataset)

2.2.1 Motivation for the Selection of UTKFace Dataset

In 2018, Joy Buolamwini, a PhD candidate at MIT Media Lab, published a thesis on gender and racial biases in facial recognition in algorithms. In her paper, she tested facial recongition softwares from multiple large technology companies such as Microsoft, IBM, and Amazon on its effectiveness for different demographic groups. Her research led to a surprising conclusion that most AI algorithms offer a substantially less accurate prediction for feminine/female faces, particularly those with dark skin color.

To determine the degree in which bias is still present in modern facial recognition models, a dataset which comprise of face images with high diversity in regards to eethnicity is required. Upon searching, UTKFace came out as one of the largest datasets which fit our preferred qualifications.

2.2.2 Data Collection Method

The dataset utilized for this research is UTKFace dataset. It is a publicly available large scale face dataset non-commercial on Github. The dataset was created by Yang Song and Zhifei Zhang, researchers at Adobe and PhD candidates at The University of Tennessee, Knoxville. On its Github page, it is specified that the images were collected from the internet. They appear to be obtained through the application of technique such as web scrapping. The dataset contains more than 24,000 face images, representing a highly diversified demographics. However, face images vary in pose, facial expression, lighting, and resolution.

2.2.3 Sources and Influences of Bias in the Dataset

Facial datasets can be extremely hard to categorize correctly, never mind reducing bias overall. Facial features that are androgynous or defer from the average features of the set can often be misrepresented or reported incorrectly. Those with features that make them look younger or older than their actual age may also be difficult for a computer to accurately guess.

The datasets used for analysis contain solely male/masculine and female/feminine faces. As stated above, the faces are labelled either 0, for male, or 1, for female. There are no gender non-conforming/non-binary/trans faces or people reported in the datasets, which could introduce potential bias. This absence of an entire category of facial features could also result in inaccurate guesses should these faces be added to the data later.

The datasets do not report nationality or ethnicity. This can introduce inaccuracy in the part of the identification, and it also may identify the face in a racial group that the person identified would consider inaccurate. This is as much a matter of potentially inaccurate data as it is social labels. There is also a level of erasure associated with simply creating a “multi-racial” category, given that it would bin all multiracial faces together with no further consideration. That is to say, there is no ideal solution to the issue at this time. However, it is always worth pointing out potential biases in data, research, and analysis.

The data given in the UTK dataset is composed purely of people who have their faces on the internet. This introduces a potential sampling bias. Given the topic, it is also likely to come from populations well-versed in technology. This can often exclude rural populations. Thus, the facial data present can be skewed towards urban residents or other characteristics, which can potentially create “lurking variables” that we aren’t aware of within the data. This is a common problem that many Anthropological and Sociological studies face when collecting and analyzing data. Being aware of the possibility is often the first, and most crucial, step towards reducing it.

Our source dataset, and thus our results and conclusions, are dependent on the correctness of labeling of images within the UTK dataset. Given that the dataset was web-scraped, we do not know the degree of care placed on dataset labeling during web-scraping. Any incorrect labels present in the data can skew our results.

Overall, all the given potential biases listed above are simply the largest and most easily identified. It is possible that other sources of bias are present in the data that we haven’t noticed. And identifying these biases does not mean that the data is not sound, or that any conclusions drawn from it are invalid. It simply indicates that further research should be done and that this data is far from the most complete picture of human facial features and identification.

2.3 Selected Models

2.3.1 FairFace

Developed by researchers at University of California, Los Angeles, FairFace was specifically designed to mitigate gender and racial biases. The model was trained on 100K+ face images of people of various ethnicities with approximately equal stratification across all groups. Beside facial recognition model, FairFace also provided the dataset which it was trained on. The dataset is immensely popular among facial recognition algorithm developers. Owing to its reputation in bias mitigation, FairFace appears to be a valuable piece for the objective of this research.

2.3.2 DeepFace

DeepFace is a lightweight open-source model developed and used by Meta (Facebook). Being developed by one of the largest social media companies, it is widely known among developers. Therefore, its popularity prompts us to evaluate its performance. It should be noted that the DeepFace model we leverage in our evaluation is a free open source version. It is highly unlikely that this version is as advanced as any model Meta uses internally for proprietary purposes. We should not view the resulting output of this model as being representative of algorithms internal to Meta.

2.4 Dataset Features

Understanding and selecting the appropriate features for our data is key to success in analysis. Furthermore, understanding feature differences and planning standardization across datasets is key in making sound comparisons and analyses upon the dataset.

2.4.1 Input data set

The input dataset, being UTKFace, provided feature information natively in each filename without additional external data. The features contained therein include the following items for each image's subject. They are defined as follows in the UTKFace Readme:

- "[race] is an integer from 0 to 4, denoting White, Black, Asian, Indian, and Others (like Hispanic, Latino, Middle Eastern)."
- "[gender] is either 0 (male) or 1 (female)"
- "[age] is an integer from 0 to 116, indicating the age"

We processed each image to extract these features from each image and create a table of source information here.

As our work is focused in potential biases in protected classes such as race, gender, and age, the features of UTKFace are sufficient to meet the needs for an input dataset for category prediction in our selected models.

2.4.2 FairFace Outputs

FairFace outputs provided predictions age and race, and two different predictions for race - one based upon their "Fair4" model, and the other based upon their "Fair7" model. In addition to these predictions, the output included scores for each category. With the nature of our planned analyses, the scores are of less importance to us in our evaluation.

To examine more in detail on "Fair" and "Fair4" models, the latter provided predictions of race in the following categories: [White, Black, Asian, Indian]. Of note, the "Fair4" model omitted "Other" categories as listed in the race category for the UTK dataset. However, the "Fair7" model provides predictions across [White, Black, Latino_Hispanic, East Asian, Southeast Asian, Indian, Middle Eastern]. We elected to use the Fair7 model, and to refactor the output categories to match those of the UTK dataset. Namely, we refactored instances of Middle Eastern and Latino_Hispanic as "Other" and instances of "East Asian" and "Southeast Asian" as "Asian" to match the categories explicitly listed in UTKFace.

Additionally, FairFace only provides a predicted age range as opposed to a specific, single, predicted age as a string. To enable comparison of actual values to the predicted values, we maintained this column as a categorical variable, and split it into a lower and upper bound of predicted age as an integer in the event we require it for our analyses.

With the above considerations in mind, the following output features are of import to the team:

Table 2.1: FairFace Output Format

Column Name	Data Type	Significance	Valid Values
name_face_align	String	The name and path of the file upon which FairFace made predictions	[filepath]
race_preds_fair7	String	The predicted race of the image subject	[White|Black|Latino_Hispanic|East Asian|Southeast Asian|Middle Eastern|Indian]
gender_preds_fair	String	The predicted gender of the image subject	[Male|Female]
age_preds_fair	String	The predicted age range of the image subject	[‘0-2’|‘3-9’|‘10-19’|‘20-29’|‘30-39’|‘40-49’|‘50-59’|‘60-69’|‘70+’]

2.4.3 DeepFace Outputs

Default outputs provide a wide range of information for the user. In addition to providing its predictions, DeepFace also provides scores associated with each evaluation on a per-class basis (i.e. 92% for Race #1, 3% Race #2, 1% Race #3, and 4% Race #4). For our planned analyses, the score features are of less concern to us.

We focus on the following select features from DeepFace outputs to have the ability to cross-compare between UTKFace, FairFace, and DeepFace:

Table 2.2: DeepFace Output Format

Column Name	Data Type	Significance	Valid Values
Age	Integer	The predicted age of the image subject	Any Integer
Dominant Gender	String	The predicted gender of the iamge subject	[Man|Woman]
Dominant Race	String	The predicted race of the image subject	[middle eastern|asian|white|latino hispanic|black|indian]

2.5 Evaluating Permutations of Inputs and Models for Equitable Evaluation

Aside from the differences in the outputs of each model in terms of age, race, and gender, there are also substantial differences between FairFace and DeepFace in terms of their available settings when attempting to categorize and predict the features associated with an image.

The need for this permutation evaluation rose from some initial scripting and testing of these models on a small sample of images from another facial dataset. We immediately grew concerned with DeepFace’s performance using default settings (namely, enforcing requirement to detect a face prior to categorization/prediction, and using OpenCV as the default detection backend). Running these initial scripting tests, we encountered a face detection failure rate, and thus a prediction failure rate, in DeepFace of approximately 70%.

We performed further exploratory analysis on both models in light of these facts, and sought some specific permutations of settings to determine which may provide the most fair and equitable comparison of the models prior to proceeding to analysis.

The goal for us in performing this exploration was to identify the settings for each model that might best increase the likelihood that the model’s output would result in a failure to reject our null hypotheses. In layman’s terms, our tests sought out the combination of settings that give each model the benefit of the doubt, and for each to deliver the greatest accuracy in their predictions. For simplicity's sake, we leaned solely on the proportion of true positives across each category when compared with the source information to decide which settings to use.

2.5.1 DeepFace Analysis Options

DeepFace has a robust degree of available settings when performing facial categorization and recognition. These include enforcing facial detection prior to classification of an image, as well as 8 different facial detection models to detect a face prior to categorization. The default of these settings is OpenCV detection with detection enabled. Other detection backends include ssd, dlib, mtcnn, retinaface, mediapipe, yolov8, yunet, and fastmtcnn.

In a Python 3.8 environment, attempting to run detections using dlib, fastmtcnn, retinaface, mediapipe, yolov8, and yunet failed to run, or failed to install the appropriate models directly from source during execution. Repairing any challenges or issues with the core functionality of DeepFace and FairFace's code is outside the scope of our work, and as such, we have excluded any of these non-functioning models from our settings permutation evaluation.

2.5.2 FairFace Analysis Options

The default script from FairFace provided no options via its command line script to change runtime settings. It uses dlib/resnet34 models for facial detection and image preprocessing, and uses its own Fair4 and Fair7 models for categorization. There are no other options or flags that can be set by a user when processing a batch of images.

We converted the simple script to a class in Python without addressing any feature bugs or errors in the underlying code. This change provided us some additional options when performing the analysis of an input image using FairFace - namely, the ability to analyze and categorize an image with or without facial detection, like the functionality of DeepFace. FairFace remains limited in the fact that is only detection model backend is built in dlib, but this change from a script to a class object gave us more options when considering what type of images to use and what settings to use on both models before generating our final dataset for analysis.

2.5.3 Specific Permutations

With the above options in mind, we designed the following permutations for evaluation on a subset of the UTK dataset:

Table 2.3: List of Permutation Evaluations

Detection	Detection Model	Image Source
Enabled	FairFace=Dlib; DeepFace=OpenCV	Pre-cropped
Enabled	FairFace=Dlib; DeepFace=OpenCV	In-The-Wild
Enabled	FairFace=Dlib; DeepFace=mtcnn	Pre-cropped
Enabled	FairFace=Dlib; DeepFace=mtcnn	In-The-Wild
Disabled	FairFace,DeepFace=None	Pre-cropped
Disabled	FairFace,DeepFace=None	In-The-Wild

We processed each of the above setting permutations against approximately 9800 images, consisting of images from part 1 of 3 from the UTK dataset. Each of the cropped images (cropped_UTK_dataset.csv) and uncropped images (uncropped_UTK_dataset.csv) came from the same underlying subject in each image; the only difference between each image was whether or not it was pre-processed before evaluation by each model. Having the same underlying source subject enables us to perform a direct comparison of results between cropped vs. in-the-wild images, and better support a conclusion of which settings to use.

Table 2.4: Results of Permutation Evaluation

pred_model	detection_enabled	detection_model	image_type	all_rate	age_grp_rate	gender_rate	race_
DeepFace	False	None	cropped	0.0724949	0.1601227	0.6667689	0.6951
DeepFace	False	None	uncropped	0.0834356	0.1522495	0.7326176	0.6457
DeepFace	True	mtcnn	cropped	0.0889571	0.1534765	0.7249489	0.6807
DeepFace	True	mtcnn	uncropped	0.1023517	0.1615542	0.7834356	0.6665
DeepFace	True	opencv	cropped	0.0267894	0.0765849	0.1887526	0.1983
DeepFace	True	opencv	uncropped	0.0806748	0.1455010	0.6619632	0.5855
FairFace	False	None	cropped	0.4015337	0.6101227	0.8921268	0.7689
FairFace	False	None	uncropped	0.1031697	0.2671779	0.7599182	0.4477
FairFace	True	dlib	cropped	0.4015337	0.6101227	0.8921268	0.7689
FairFace	True	dlib	uncropped	0.4353783	0.6230061	0.9155419	0.7914

Examining the true positive ratios for each case, our team concluded that the settings that gave both models the best chance for success in correctly predicting the age, gender, and race of subject images are as follows:

- FairFace: enforce facial detection with dlib, and use uncropped images for evaluation
- DeepFace: enforce facial detection with MTCNN detection backend and use uncropped images for evaluation.

These settings are equitable and make a degree of sense. Using facial detection, specifically coded for each model, should give each model the ability to isolate the portions of a face necessary for them to make a prediction, as opposed to using a pre-cropped image that could include unneeded information, or exclude needed information.

Having decided on these settings, our team proceeded to run the entirety of the UTK dataset through both DeepFace and FairFace models using a custom coded script MasterScript.py that allowed us to apply multiprocessing across the list of images and evaluate all items in a reasonable amount of time. (cite FairFace here, may also need to reference that we rebuilt their script into a class format).

Due to the resource-intensive design of FairFace, our script enables multiprocessing of FairFace to allow for multiple simultaneous instances of the FairFace class as a pool of worker threads to iterate over the source data.

We attempted the same multiprocessing methodology for DeepFace, but encountered issues with silent errors and halting program execution when iterating over all images using DeepFace. To alleviate this challenge, we processed DeepFace in a single-threaded manner, and with smaller portions of the dataset vs. pursuing an all-in-one go execution. We proceeded to store the data for each of these smaller runs in multiple output files to combine once we completed all processing requirements.

2.6 Model Evaluation Data

The final listing of all inputs and outputs from each model, with standardization methods discussed in this section applied, are stored here: MasterDataFrame.csv

Table 2.5: Data Format for All Inputs and Outputs

Column Name	Definition
img_path	Relative path location of the file within the UTK dataset
file	The filename of each file within the UTK dataset
src_age	The age of the subject in each image from the UTK dataset
src_gender	The gender of the subject in each image from the UTK dataset
src_race	The race of the subject in each image from the UTK datset
src_timestamp	The time at which the image was submitted to the UTK dataset
src_age_grp	The age group (matching the predicted age ranges from the FairFace outputs) for each image in
pred_model	The model used to produce the predicted output (FairFace or DeepFace)
pred_race	The race of the subject in the image, predicted by the given prediction model under the pred_m
pred_gender	The gender of the subject in the image, predicted by the given prediction model under the pred_
pred_age_DF_only	The integer-predicted age by DeepFace of the subject in the image
pred_age_grp	The age group of the subject in the image, predicted by the given prediction model under the pr
pred_age_lower	The integer lower bound of the predicted age group
pred_age_upper	The integer upper bound of the predicted age group

3 Methods

As described in the previous section, the two selected models (DeepFace and FairFace) are run on the UTK face dataset in order to generate output of classification across 3 categories (age, race, and gender). We evaluate the performance of this classification, and perform hypothesis testing in order to answer the key research questions.

3.1 Data Cleaning: Standardizing Model Outputs

As can be seen in Chapter 2, there are some key differences between the outputs of both models as well as the source data that we needed to resolve to enable comparison of each dataset to one another. We'll focus on the primary features of age, gender, and race from each dataset.

3.1.1 FairFace Output Modifications

We'll discuss FairFace first, as it introduces a requirement for modification to both our input information as well as the outputs for DeepFace.

- **Age**: FairFace only provides a categorical predicted age range as opposed to a specific numeric age. We retain this age format and modify the last category of "70+" to "70-130" to ensure we can capture the gamut of all input and output ages in all datasets.
- **Gender**: No changes to predicted values; use "Male" and "Female"
- **Race**: the source data from UTKFace has 5 categories "White" "Black" "Asian" "Indian" and "Other". Using the definitions from UTKFace, we collapse the output categories of FairFace's Fair7 model as follows:

["Southeast Asian","East Asian"] => "Asian" ["Middle Eastern" , "Latino_Hispanic] =>"Other"

3.1.2 DeepFace Output Modifications

- **Age**: Cut the predicted age into bins based upon the same prediction ranges provided by FairFace. If the DeepFace predicted age falls into a range provided by FairFace, provide that as the predicted age range for DeepFace.
- **Gender**: we adjust the DeepFace gender prediction outputs to match that of the source and FairFace data with the following refactoring: "Man" => "Male" "Woman" => "Female"
- **Race**: we adjust the DeepFace race prediction outputs to match that of the source dataset with the following refactoring:
- "white" => "White"
- "black" => "Black"
- "indian" => "Indian"
- "asian" => "Asian"
- ["middle eastern", "latino hispanic"] => "Other"

3.1.3 Source Data Modifications

- **Age:** We cut the predicted age into bins based upon the same prediction ranges provided by FairFace. If the input / source data age falls into a range provided by FairFace, provide that is the source age range for the image subject.
- **Gender:** No changes.
- **Race:** No changes.

3.2 Exploratory Data Analysis (EDA)

Our EDA performed on the source UTK dataset can be seen in the previous section in Figure 2.2. The EDA performed on the output from the models can be summarized as follows, and is presented in the Results section:

- Visualization of the histograms of distributions of predictions, per each category, per each model

We also perform some meta-analysis on the statistics and performance metrics calculated from the model outputs:

- Visualization of the p-values vs F1-score across all hypothesis tests across both models
- Confusion matrix of whether we reject or fail to reject the null hypothesis based on power and F1 score

3.3 Research Questions

We evaluate the output of the 2 models in order to answer the following questions:

- Is bias prevalent in facial recognition machine learning models?
- Can one model be shown to have a greater quantity of statistically significant biases than the other?
  - in all aspects?
  - In specific/certain aspects?
- Are there disparate outcomes (i.e. higher chance of incorrect predictions) for one racial group vs. another?

3.4 Hypothesis Testing

Our data consists of three main sets: the source input data, the Fairface output data, and the Deepface output data.

We'll be creating our hypothesis tests by running as two-sample proportion tests. The population is the set of all labels (of race, age, and gender as defined below) for a given image, for all face images. The first sample will be the source dataset "correct" labels of the images, and the 2nd sample will be the output of a given model between FairFace and DeepFace, respectively. The base null hypothesis will produce no difference in sample proportions. Gaining a statistically significant result would allow us to reject our *null hypothesis* in favor of the *alternative hypothesis*. In other words, rejecting the original assumption means there is a statistically large enough difference between the source data and output data, and could indicate that the source and predicted information originate from differing populations, which is a potential indicator of bias for or against the protected classes in question. We use a significance level of 99.7% to mitigate the risk of rejecting the the null hypothesis when it is true.

We'll be testing across different subsets contained within the data, as listed below:

3.4.1 Demographics

- Age Group
- Gender
- Race

3.4.2 Demographics' Subgroups

- Age Group (9 groups)
  - 0-2
  - 3-9
  - 10-19
  - 20-29
  - 30-39
  - 40-49
  - 50-59
  - 60-69
  - 70-130
- Gender (2 groups)
  - Female
  - Male
- Race (5 groups)
  - Asian
  - Black
  - Indian
  - Other
  - White

3.4.3 The General Proportion Tests

Our hypothesis tests will be testing different proportions within these subgroups between the source data and the output data.

The general format of our hypothesis tests will be:

$H_0 : p_1 = p_2$

$H_A : p_1 \neq p_2$

With the following test statistic:

$$\frac{(\hat{p}_1 - \hat{p}_2)}{\sqrt{\hat{p}(1-\hat{p})(\frac{1}{n_{p_1}} + \frac{1}{n_{p_2}})}}$$

With the p-value being calculated by:

$P(|Z| > z|H_0)$

$$= P(|Z| > \frac{(\hat{p}_1 - \hat{p}_2)}{\sqrt{\hat{p}(1-\hat{p})(\frac{1}{n_{p_1}} + \frac{1}{n_{p_2}})}},$$

Where:

- p_1 = the source dataset categories labels given and p_2 = the chosen model's labels given.
- $\hat{p}$ = the pooled proportion.
- n_{p_1}, n_{p_2} = the size of each sample.

We also calculate the power of each test performed, and use a power level threshold of 0.8 in order to assess the strength of the p-value calculated.

We believe that using two-sample proportion testing is an appropriate means by which we can evaluate the outputs of the two facial recognition models in comparison to the source data. In leveraging two-sample proportion tests, we can infer whether or not the proportions of age, gender, or race (or some combination thereof) from the UTKFace dataset (i.e. 1st sample) originate from the same population as the outputs from each facial recognition model (i.e. 2nd dataset).

In theory, similar proportions of protected classes between the two datasets could suggest that the source data and predicted data originate from the same population (pictures of people), and would thus indicate an absence of bias against the protected class in question. Vastly different proportions, however, could indicate that the source data and predicted data are from differing populations and indicate a bias against the protected classes in question.

Leveraging p-values and powers calculated on our samples for our protected classes of age, gender, and race, should enable us to provide a clear picture of any biases that may manifest from one or both models. Leveraging F1 scores (as described below) will help us identify the specific cases of bias, and whether it is in favor of or against a specific group.

3.4.4 Notation

We introduce notation for the specific tests we perform:

Let R be race, then $R \in \{Asian, Black, Indian, Other, White\} = \{A, B, I, O, W\}$

Let G be gender, then $G \in \{Female, Male\} = \{F, M\}$

Let A be age, then $A \in \{[0,2], [3,9], [10,19], [20,29], [30,39], [40,49], [50,59], [60,69], [70,130]\}$; or $A = \{1,2,3,4,5,6,7,8,9\}$

Let D be the dataset, then $D \in \{Source, Fairface, Deepface\} = \{D_0, D_f, D_d\}$

3.4.5 Proportion Testing of Subsets

Using this notation, we can simplify our nomenclature for testing a certain proportion of an overall demographic.

For example, we can test if the proportion of *Female* in the Fairface output is statistically different than the proportion of *Female* from the source.

Hypothesis Test:

$H_0 : p_{F,D_f} = p_{F,D_0}$

$H_A : p_{F,D_f} \neq p_{F,D_0}$

P-value Calculation:

$$P(|Z| > \frac{(\hat{p}_1 - \hat{p}_2)}{\sqrt{\hat{p}(1-\hat{p})(\frac{1}{n_{p_1}} + \frac{1}{n_{p_2}})}}),$$

where

- $\hat{p}_1 = p_{F,D_0}$: proportion of females from the source data
- $\hat{p_2} = p_{F,D_f}$: proportion of females from the FairFace output

Additionally, we could test for different combinations of subsets within demographics. For instance, if we wanted to test for a statistically significant difference between the proportion of those who *Female*, given that they were *Black*, as predicted by DeepFace, then we could write a hypothesis test like:

$H_0 : p_{D_d,F|B} = p_{D_0,F|B}$

$H_A : p_{D_d,F|B} \neq p_{D_0,F|B}$

These were two specific hypothesis tests, however, we'll be testing all combinations of these parameters and reporting back on any significant findings.

In the above, we've outlined our methods for examining a total of 432 hypothesis tests per recognition model on the totality of, and smaller samples of, our overall dataset. We have elected to sub-divide our source and predicted samples by these protected classes to inspect and investigate whether or not there may be bias against groupings of protected classes.

For instance, in the performance of our hypothesis tests, we may find an absence of bias when only examining proportions of gender between samples. However, by examining a subset of our samples, such as subject gender given the subject's membership in a specific racial category, we may find biases in predictions of subject gender given their membership in a specific racial group.

This could help us answer questions and draw conclusions about such groups. For example:

"Model X demonstrates bias in predicting the race of older subjects." Such a statement is not one of bias for or against the target group, but that a bias exists. A bias in either direction, if used in a decision-making process, could result in age discrimination.

"Model Y demonstrates bias in predicting gender, given the subject is Black, Asian, or Other." Such a statement is not one of bias for or against the target groups, but a statement that a bias exists. Such a bias, if used in a decision-making process, could result in gender or racial discrimination.

Structuring our tests in this manner will enable us to quickly analyze and report on the results of our tests.

3.5 Performance Measurement

We evaluate the performance of the models in order to choose which models to use (as described in the Data section), to ensure data integrity, and to evaluate the hypothesis testing in context of performance. These measures are not used in the calculation of the statistical/hypothesis testing.

There are four main measures of performance when evaluating a model:

- **Accuracy**
- **Precision**
- **Recall**
- **F1-Score**

Each of these performance measures has their own place in evaluating models; in order to explain the differences between these metrics, we start with concepts of positive and negative outcomes.

- **True Positive:** predicted positive, was actually positive (correct)
- **False Positive:** predicted positive, was actually negative (incorrect)
- **True Negative:** predicted negative, was actually negative (correct)
- **False Negative:** predicted negative, was actually positive (incorrect)

These outcomes can be visualized in a confusion matrix. In Figure 3.1, green are correct predictions while red are incorrect predictions.

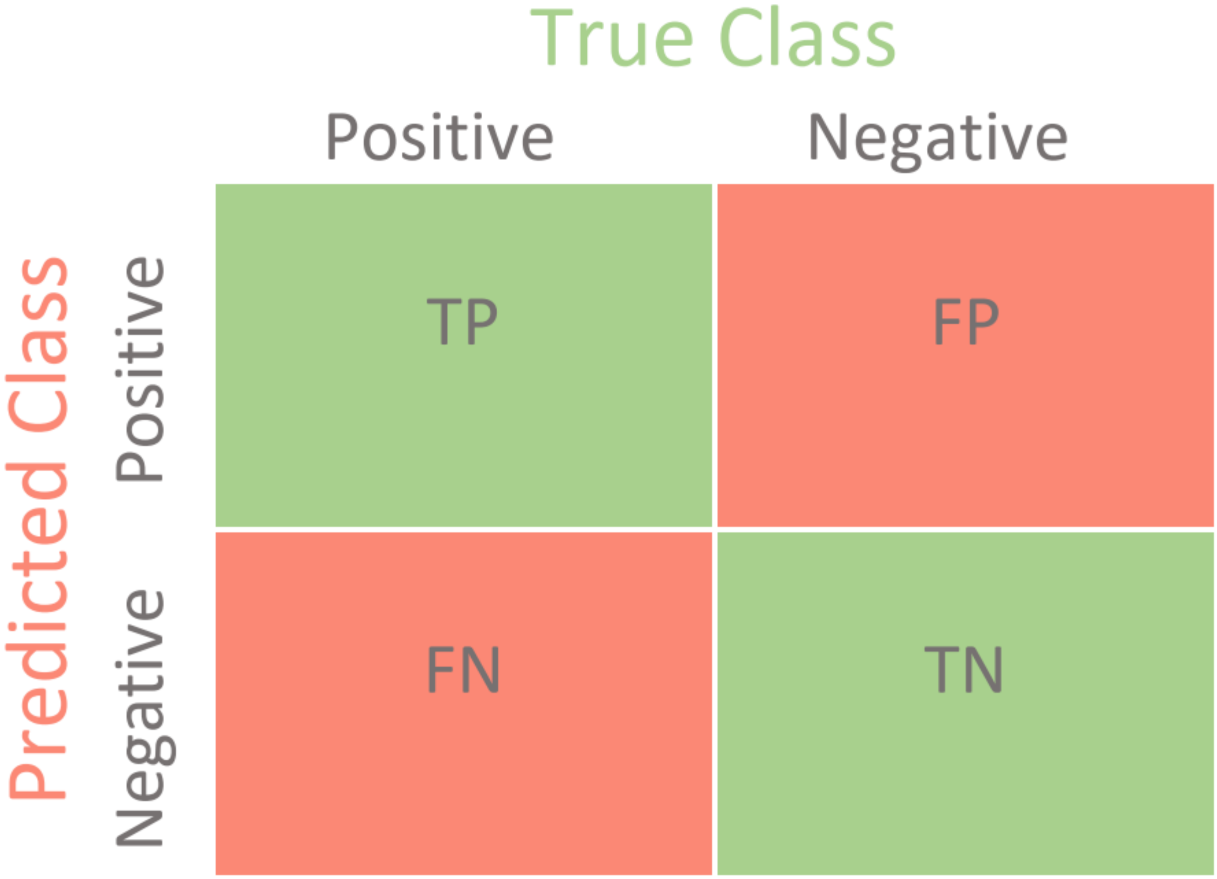


Figure 3.1: Confusion_matrix

3.5.1 Accuracy

Accuracy is the ratio of correct predictions to all predictions. In other words, the total of the green squares divided by the entire matrix. This is arguably the most common concept of measuring performance. It ranges from 0-1 with 1 being the best performance.

$Acccuracy = \frac{TP+TN}{TP+TN+FN}$

3.5.2 Precision

Precision is the ratio of true positives to the total number of positives (true positive + true negative).

3.5.3 Recall

Recall is the ratio of true positives to the number of total correct predictions (true positive + false negative).

3.5.4 F1-Score

F1-Score* is known as the harmonic mean between precision and recall. **Precision** and **Recall** are useful in their own rights, but the F1-Score is useful in the fact it's a balanced combination of both precision and recall. It ranges from 0-1 with 1 being the best performance.

F1-Score = $\frac{2*Precision*Recall}{Precision+Recall}$

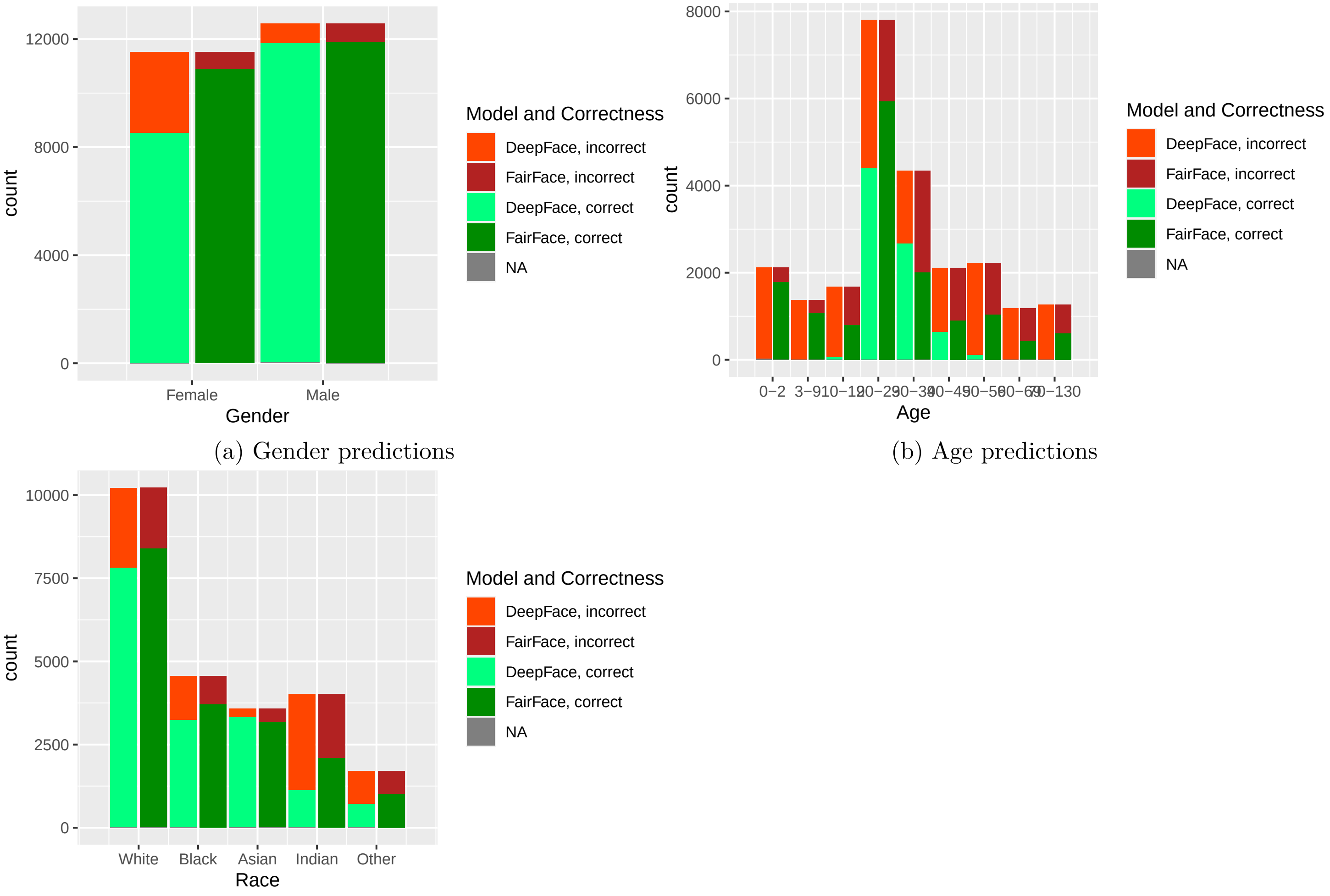
When considering the classification of a subject by protected classes of age, gender, and race, we believe that stronger penalties should be assigned in making an improper classification decision. Due to F1 being the harmonic mean of precision and recall, incorrect classification will more directly impact the score of each model in its prediction of protected classes, and do so more strongly than an accuracy calculation (Huilgol 2021).

We calculate F1 score as a measure of performance of our selected machine learning models. This was not used in the calculation or results of the hypothesis tests, but will be used for when we draw conclusions of our tests based upon p-value and statistical power. Namely, we do not plan to control for statistical power / Type-II error when running our 432 hypothesis tests, so statistical power may vary from test to test. Using F1 and Accuracy scores can support us in identifying specific cases of bias (and whether it is for or against) one or more protected classes. We elect to use an F1 score threshold of 0.9 to make this determination.

4 Results

4.1 Model Output

The two models, DeepFace and FairFace, were run on the dataset described previously. In Figure 4.1, one can see the results of the predictions done by each model, by each factor that was considered: age, gender, and race. Note that the total (across correct and incorrect) histogram distributions match the correct (source dataset) distributions of values in each category, so we can see exactly the difference between what was provided and what was predicted, along with how well each model did on each category within each factor.



(a) Gender predictions

(b) Age predictions

(c) Race predictions

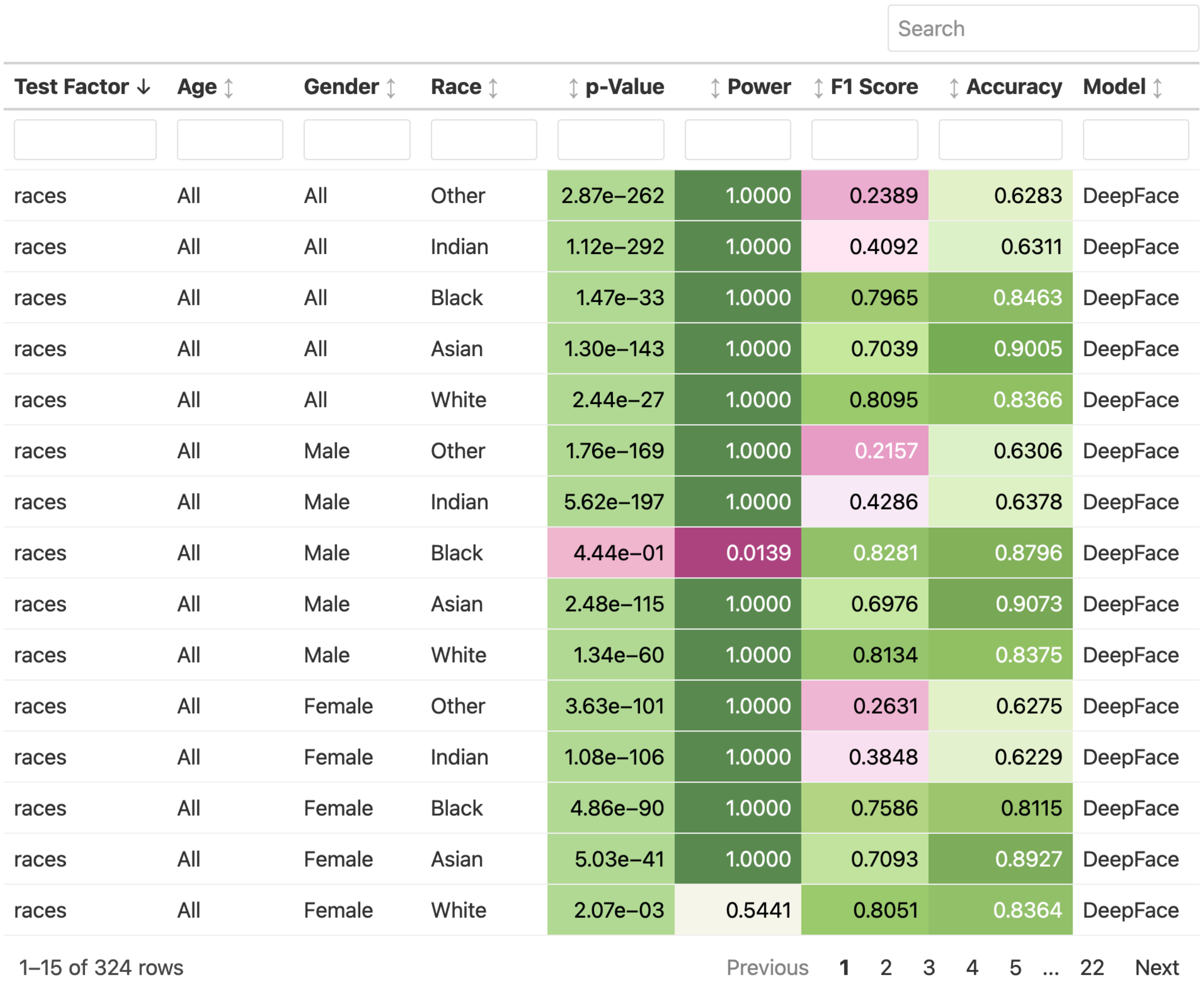
Figure 4.1: Histograms of the output from DeepFace and FairFace, with correct vs incorrect values colored. Note that the distributions match the correct (source dataset) distributions.

4.2 Model Performance, Hypothesis Testing

For each factor category and model, we calculate the F1 score, accuracy, p-value, and power, as described in section 3. Cell values are colored according to the strength of the metric; p-value is colored as to whether it crosses the significance value threshold of 0.003. We calculate these metrics and hypothesis tests across all categories of each factor, but also with conditional filtering on other factors; the value “All” indicates we did not filter/condition on that factor. The column `Test Factor` indicates which factor we are calculating the proportion for that hypothesis test. For example, the following column value subsets would indicate the given hypothesis test:

Test Factor	Age	Gender	Race	Model	Null Hypothesis	Description
gender	0-2	Female	All	FairFace	$p_{F,D_f\|A_1} = p_{F,D_0\|A_1}$	H_0 : The proportions of Female labels, given that the source age label is 0-2, are equal.
race	All	All	Black	DeepFace	$p_{R_B,D_d} = p_{R_B,D_0}$	H_0: The proportions of Black labels are equal.

The results are summarized in Figure 4.2.



Search

Test Factor ↓	Age ↕	Gender ↕	Race ↕	↕ p-Value	↕ Power	↕ F1 Score	↕ Accuracy	Model ↕
races	All	All	Other	2.87e−262	1.0000	0.2389	0.6283	DeepFace
races	All	All	Indian	1.12e−292	1.0000	0.4092	0.6311	DeepFace
races	All	All	Black	1.47e−33	1.0000	0.7965	0.8463	DeepFace
races	All	All	Asian	1.30e−143	1.0000	0.7039	0.9005	DeepFace
races	All	All	White	2.44e−27	1.0000	0.8095	0.8366	DeepFace
races	All	Male	Other	1.76e−169	1.0000	0.2157	0.6306	DeepFace
races	All	Male	Indian	5.62e−197	1.0000	0.4286	0.6378	DeepFace
races	All	Male	Black	4.44e−01	0.0139	0.8281	0.8796	DeepFace
races	All	Male	Asian	2.48e−115	1.0000	0.6976	0.9073	DeepFace
races	All	Male	White	1.34e−60	1.0000	0.8134	0.8375	DeepFace
races	All	Female	Other	3.63e−101	1.0000	0.2631	0.6275	DeepFace
races	All	Female	Indian	1.08e−106	1.0000	0.3848	0.6229	DeepFace
races	All	Female	Black	4.86e−90	1.0000	0.7586	0.8115	DeepFace
races	All	Female	Asian	5.03e−41	1.0000	0.7093	0.8927	DeepFace
races	All	Female	White	2.07e−03	0.5441	0.8051	0.8364	DeepFace

1–15 of 324 rows

Previous 1 2 3 4 5 … 22 Next

Figure 4.2: Screenshot of the interactive table showing F1 score, accuracy, p-value, and power, by each factor and category evaluated by the models, with a potential filtering condition. To see and interact with this table, go to the website link

4.2.1 p-value Critical Values

From the previous table, we extract and highlight key values; namely, where we reject the null hypothesis and where we do not, based on our criteria:

- Significance level of 99.7%
- Power threshold of 0.8
- F1-Score of 0.9

Which come from the rationale described in Chapter 3. We show the test values where there is no sub-filtering/conditions by another category; then, we also highlight the reverse null hypothesis decisions made with filtering for a sub-condition and for the specific rows as described in the table captions. The values are displayed in Table 4.2. There is only a Fairface table for not rejecting the null hypothesis (with no condition subfiltering) because no DeepFace values passed our given thresholds for not rejecting; the same reasoning is why there is no table for FairFace rejecting the null hypothesis with condition subfiltering.

Table 4.2: Highlighted statistics/metrics for DeepFace and FairFace, that pass the given significance level/power/F1-score thresholding.

	Category	p-Value	Power	F1 Score
age	70-130	$2.83e-43$	1.0000	0.6271
	3-9	$1.37e-05$	0.9198	0.7176
	10-19	$5.22e-05$	0.8640	0.5052
	0-2	$3.11e-06$	0.9568	0.8960
	20-29	$2.14e-08$	0.9959	0.7333
	40-49	$1.65e-08$	0.9965	0.3944
race	White	$5.83e-18$	1.0000	0.8610
	Black	$7.46e-12$	1.0000	0.8685
	Indian	$8.84e-94$	1.0000	0.6402
	Other	$0.00e00$	1.0000	0.3087

	Age	Gender	Race	p-Value	Power	F1 Score
age	0-2	Male	All	$4.94e-01$	0.0120	0.9190

	Category	p-Value	Power	F1 Score
age	70-130	$1.08e-283$	1.0000	NA
	3-9	$9.20e-293$	1.0000	NA
	10-19	$2.52e-148$	1.0000	0.0479
	0-2	$0.00e00$	1.0000	NA
	20-29	$2.00e-65$	1.0000	0.5054
	30-39	$0.00e00$	1.0000	0.3786
	40-49	$1.65e-91$	1.0000	0.2276
	50-59	$3.66e-202$	1.0000	0.0802
	60-69	$9.81e-229$	1.0000	0.0016
gender	Female	$1.18e-97$	1.0000	0.8198
	Male	$1.18e-97$	1.0000	0.8637
race	White	$2.70e-27$	1.0000	0.8095
	Asian	$1.75e-143$	1.0000	0.7039
	Black	$1.71e-33$	1.0000	0.7965
	Indian	$1.90e-292$	1.0000	0.4092
	Other	$4.64e-262$	1.0000	0.2389

	Age	Gender	Race	p-Value	Power	F1 Scor
gender	30-39	Male	All	$7.70e-02$	0.1185	0.922

	Category	p-Value	Power	F1 Score
gender	Female	$7.07e-01$	0.0053	0.9429
	Male	$7.07e-01$	0.0053	0.9476

4.3 Meta-Analysis Plots

In Figure 4.3, we show F1-score vs accuracy for all hypothesis tests that were performed. Note the relationship is not perfectly linear.

In Figure 4.4, we display confusion matrices of our null hypothesis rejections. We define the true/false positive/negative as follows:

- Reject null when we should reject null: p-value < 0.003, F1 < 0.9, power >= 0.8
- Reject null when we should fail to reject null: p-value < 0.003, F1 > 0.9, power >= 0.8
- Fail to reject null, when we should reject null: p-value >= 0.003, F1 < 0.9, power < 0.8

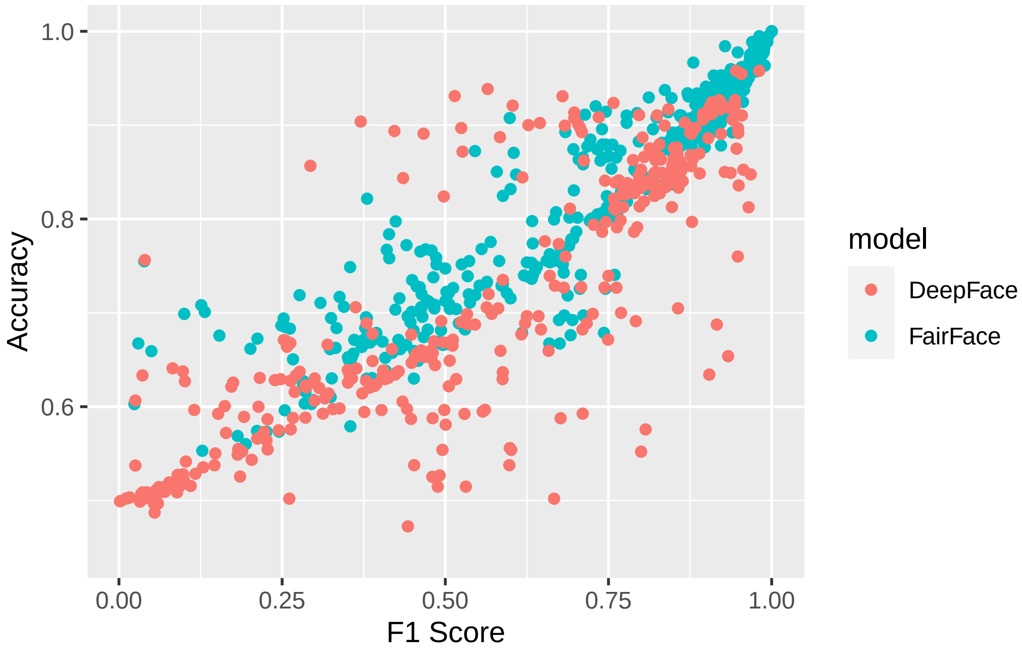
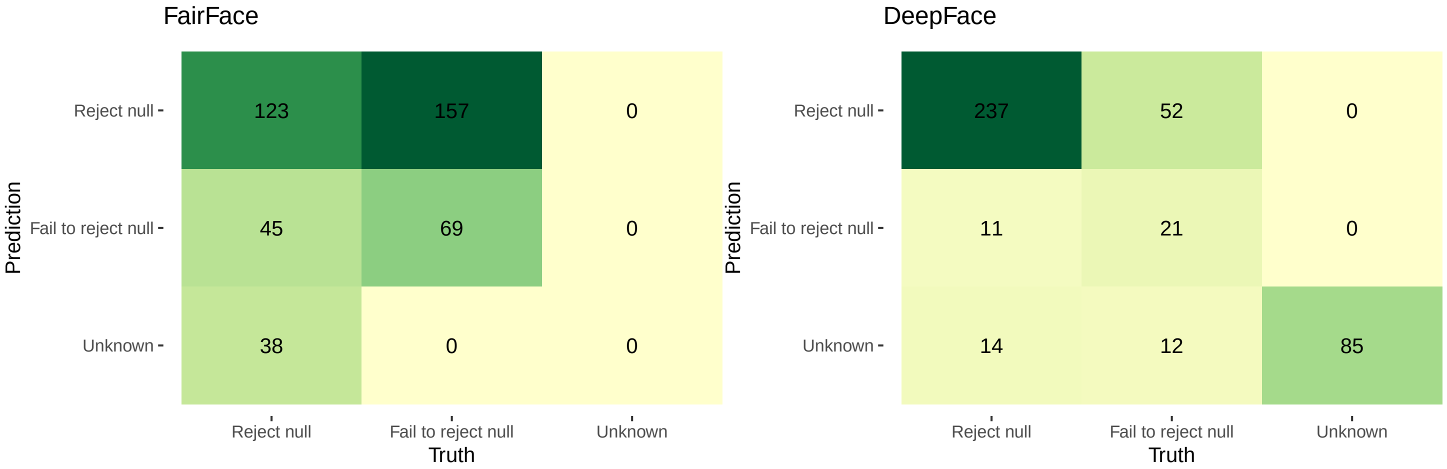


Figure 4.3: F1-Score vs Accuracy for all hypothesis tests performed.

- Fail to reject null, when we should fail to reject null: p-value >=0.003, F1 >= 0.9, power < 0.8
- Uknown: One of the values was NaN.



(a) Matrix for FairFace

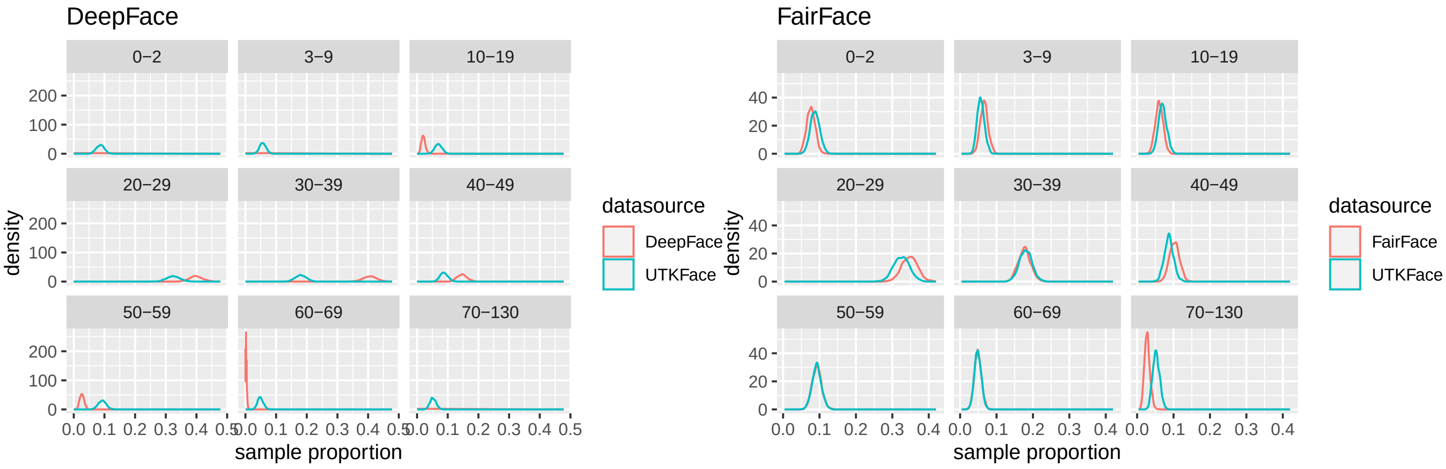
(b) Matrix for DeepFace

Figure 4.4: Confusion matrices of null rejection decisions.

4.4 Population Estmate Plots - UTK Face vs. Model

We used a resampling technique to produce estimated population proportion distributions for each sample. Each resampling included 2000 samples of 500 subjects under their respective test conditions.

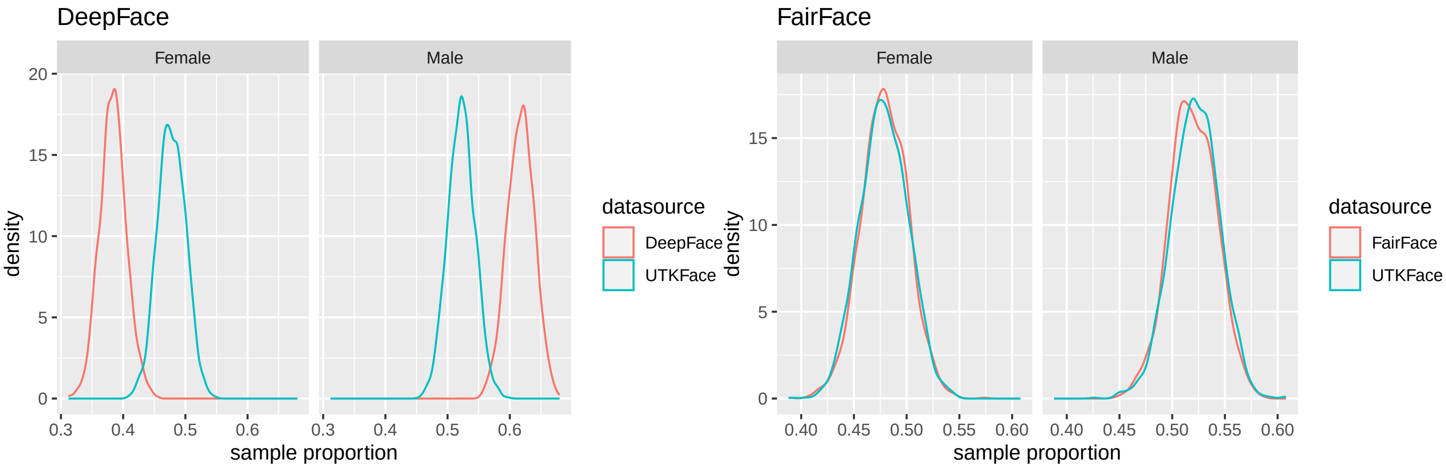
To support our analysis and conclusions, we leveraged a resampling technique (bootstrap sampling) to build approximations of each sample's parent population. The resampling took 2000 samples of 500 random subjects, with replacement, to build the estimated distribution of proportions in the population under specified test conditions. The plots can be seen in Figure 4.5 to Figure 4.7. We find that these plots coincide with our hypothesis testing results – namely, that higher p-values result in greater overlap between the predicted and actual distributions, and lower p-values result in less overlap between the distributions. As such, these distributions will support us in drawing our conclusions.



(a) DeepFace vs. UTKFace Age Distributions

(b) FairFace vs. UTKFace Age Distributions

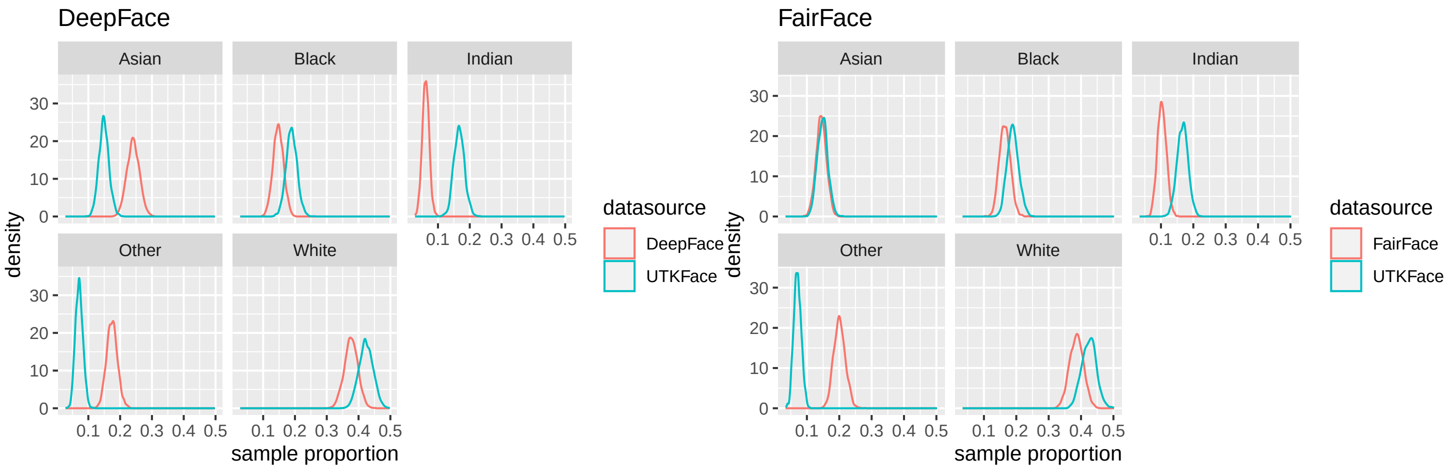
Figure 4.5: Distribution Plots of Age



(a) DeepFace vs. UTKFace Gender Distributions

(b) FairFace vs. UTKFace Gender Distributions

Figure 4.6: Distribution Plots of Gender



(a) DeepFace vs. UTKFace Race Distributions

(b) FairFace vs. UTKFace Race Distributions

Figure 4.7: Distribution Plots of Race

5 Conclusions

From the report requirements

- Summarize what the paper has done, and discuss the implications of your Results.
- Explicitly connect the results to the research question.
- Discuss how you would you extend this research

Like the introduction, this section should be written with a **non-expert** in mind. A person should be able to read Introduction+Conclusion and get a rough idea of the meaning and significance of your paper

5.1 Evaluation of Test Results

To evaluate our tests, we will first examine our hypothesis tests, and then move on to evaluate F1 and Accuracy scores. Our hypothesis testing can tell us where bias may exist, whereas F1 and Accuracy scores may tell us specific instances where bias exists in favor of, or against, specific protected classes.

5.2 Hypothesis Testing Results

The design of our hypothesis testing provides us with potential indicators of bias in each model. When the test result produces a value less than 0.003 and with test power greater than or equal to 0.8, the test can be indicative of bias. Inversely, a p-value greater than or equal to 0.003 will not provide sufficient evidence to indicate bias in the given test case. The p-value alone, however, cannot tell us whether the indicated bias is in favor of, or against, the protected class group(s) in question. This is because the the hypothesis tests only tell us the probability that the source and predicted results come from the same population.

Overall, for both models, our tests may are indicative of bias across the spectrum of age, gender, and race. Common threads between both FairFace and DeepFace include bias in predicting:

- Subject age (for specific groups)
- Subject race (for specific groups)

5.2.1 Age Prediction

5.2.1.1 FairFace

FairFace displays potential for bias in age prediciton with subjects in the age ranges 0-29, 40-49, and 70+. The age group 50-59 may also be included in this bias, but we do not have conclusive evidence from our tests alone to indicate such a bias.

For age proportions, given gender, potential biases manifest solely for Females in age ranges 0-19, solely for Males 40-49, and all subjects 70+. Additional biases arise for any subject from 20-29.

For age proportions, given race, potential biases are most prominent in the “ ” Category.

5.2.1.2 DeepFace

DeepFace displays extreme potential for bias in age prediction for young subjects (0-19) and old subjects (70+), failing to make a single prediction in any of these age ranges.

For age proportions, given gender, the biases are accentuated to all age ranges.

5.2.2 Race Prediction

5.2.2.1 FairFace

FairFace demonstrates biases in predicting race for Black, Indian, White, and Other categories.

5.2.2.2 DeepFace

DeepFace demonstrates biases in predicting

5.2.3 Gender Prediction

5.2.3.1 FairFace

We lack sufficient information to conclude that FairFace, absent other test conditions, holds a bias in correct prediction of subject gender.

5.2.3.2 DeepFace

DeepFace, abasent other test conditions, indicates bias in correct prediction of gender.

5.3 Identifying Specific Biases with F1 and Accuracy Scores

5.3.1 FairFace

5.3.2 DeepFace

5.4 Summary

5.5 Age Prediction Conclusions

Based on the results of evaluating both models for age prediction accuracy, given age, gender, or no particular category, there is a definite bias in both models towards differing demographics. Overall, DeepFace displayed a significantly lower accuracy rate in classifying the ages of given faces and was unable to produce predictions for faces between the ages of 0-9 and 70-130, indicating that it is unable to predict younger and older faces. However, it did display consistent test scores to evaluate the accuracy and efficacy of its results, indicating that the null hypothesis should be rejected here. FairFace, on the other hand, showed higher accuracy results, especially in Figure 4.1.b, where the only age bracket which DeepFace performed better for was 30-39. There is the possibility that a testing error resulted from our efforts with FairFace, but it is unlikely for the overall results. Things get more complicated when we include gender and/or race as given statistics for evaluating age. While DeepFace was consistent with gender overall, its results for race given no other variables were less accurate. There were noticeable discrepancies in identifying non-white faces, particularly Indian, Black, and Other faces. When specified for race and gender together, a trend of male faces being identified more accurately was observed, particularly white and Asian faces. For FairFace, there was still a higher accuracy rate of identification, but error test scores were higher overall. While DeepFace struggled to identify very young and old faces, FairFace generally struggled with faces in the range of 20-69. While the actual results show a higher rate of identification for all faces, FairFace has higher error test rates for nearly all races, save white faces. FairFace also mirrors DeepFace in a trend of lower error scores for lighter faces, although FairFace seems to have more of a bias towards female faces instead of male ones. Using the above results, as well as the tables from earlier, we can conclude that there is bias present in both the FairFace and DeepFace models when predicting age given gender or race. There is a definite trend towards white faces in both models in terms of predictive accuracy. That being said, based on the accuracy scores of FairFace, it is more likely that FairFace is less biased than DeepFace, especially given that DeepFace is unable to predict the ages of very young and very old faces with any degree of accuracy. That being said, the high error scores (p-values and power scores) indicate that perhaps FairFace requires further testing, in case the tests we created are wrong, and we should not reject the null hypothesis. Given the nature of the results, combined with the test scores, it is difficult to say whether or not one model completely outperforms the other. DeepFace is technically more accurate and less prone to rejection errors, but FairFace produces better results, even though it is less accurate over a wide age range. Overall, FairFace does seem to be the better predictor, given its accuracy rating and better age range, as it includes younger and older faces far better than DeepFace. In terms of disparate outcomes, both FairFace and DeepFace are more likely to correctly predict the race of white or Asian faces, while races with typically darker skin tones, Black, Indian, or Other, have far lower accuracy ratings across the board. In terms of what should be done in future research, further testing is required. It would be ideal to cross-reference either the models, the testing data, or both, with other predictive models and datasets to determine if any possible errors are present due to the match. The ideal goal would be to minimize any potential error scores while evaluating a multitude of models and using the results to craft better predictive models that display less disparity due to age. In the future, datasets should strive to account for a diverse range of faces from all possible races, genders, and ages.

5.6 Race Prediction Conclusions

5.6.1 Race by itself

Both FairFace and DeepFace demonstrate potential racial bias. We filter the data across five races (Asian, Black, Indian, White, and Other) and perform statistical hypothesis testing. From the test results, there presents strong evidence suggesting potential bias for all tests but one, the FairFace's Asian test. Upon reviewing the result data, it is highly possible that there is an error in the testing. Therefore, we cannot draw a solid conclusion for this particular test. There are multiple reasons which might lead to errors such as too small sample size. Further investigation and testing will be necessary to re-evaluate FairFace's Asian test.

(Note: CK and PC mentioned that they will ask the professor about the usage of power. So there might be some adjustment to the section above.)

Next, we examine the models' performance in how often they make correct predictions and not give out wrong positive outputs. Surprisingly, our results go against the trend that facial recognition models offer a poorer performance for dark-skinned faces compared to light skin. Both models perform the best with Asian face images. Black comes in second and then White with a slightly less performance score. Nonetheless, Indian and Other receive substantially less accurate predictions. In regards to race, a better prediction model is FairFace with a higher performance score across the board.

5.6.2 Race given Age

In most tests, FairFace and DeepFace showcase a strong potential for bias in the context of race and age group. In some cases that the tests do not imply potential bias, there presents a hypothesis testing error. This prevents us from reaching the conclusion that the models have mitigated bias. In regards to models' performance, FairFace offers a higher score for all age groups of all races. For both models, Asian, Black, and White receive similar high test scores. Whereas, scores for Indian and Other are noticeably lower.

Using FairFace, not a single test across all combinations of race and age group has shown to alleviate bias. In addition, there are numerous tests with error output. For each race, there are up to 3 testing errors with the exception of the Asian dataset. Beside the age range of 30 - 39, errors are present in all other Asian age groups. Among the errors, there does not appear to be a pattern in which age group occurs the most error.

Its counterpart, DeepFace, also does not offer a better test result as most tests still signify potential bias. There are only two instances in which the model has successfully mitigated bias. Those are Indian and Black in the age range of 60 - 69. Furthermore, DeepFace is simply unable to predict face images that are younger than 9 years old and older than 70 years old. This proves that DeepFace is strongly biased against young and old people across all races.

5.6.3 Race given Gender

With the context of race and gender, both FairFace and DeepFace also exhibit a high potential for bias. Among all tests, there are only four cases which might not showcase bias. Nevertheless, those results follow a common pattern of having hypothesis testing errors. Similarly, both models' performance go hand-in-hand with the pattern of higher scores for Asian, Black, and White and lower for Indian and Other.

With FairFace, most tests indicate a bias potential. There are three cases which come with errors. Those are White and Asian females and Asian male. As for DeepFace, there is only one error case which is Black male. In terms of performance, there is no discrepancy between male and female for any races for both models. Hence, there does not seem to be a commonly-believed pattern of bias against females.

5.6.4 Verdict

FairFace and DeepFace display potential racial bias. Despite that, our test result goes against the widely believed notion that models are discriminatory towards darker-skinned faces and females. We found that Indian and Other always score the lowest in regards to both models' performance. There also does not appear to be a difference in performance for both genders. Nevertheless, there is solid evidence that DeepFace is biased against those who are very young and very old.

Overall, there are a significant number of errors in this study. This is quite detrimental to our finding as we can not draw a firm conclusion from those tests. Further study or change of methodology might be essential to reduce those errors. This would allow us to arrive at a stronger conclusion.

5.7 Gender Prediction Conclusions

###Gender by itself

When examining gender classification in isolation, a clear disparity emerges between DeepFace and FairFace. This distinction becomes evident when scrutinizing key metrics such as the p-value, statistical power, and F1 score. Our chosen threshold for the face model's acceptability necessitates a p-value below 0.003, a power exceeding 0.8, and an F1 score surpassing 0.9.

Remarkably, FairFace consistently meets these stringent criteria, showcasing its robust performance. This conclusion is not only supported by numerical metrics but is also visually reinforced through meticulously crafted graphs. The juxtaposition of the actual model and the UTK Face dataset reveals an almost complete overlap, affirming the reliability of FairFace.

Conversely, DeepFace falls short of these benchmarks. A closer examination of the statistical measures exposes a significant deviation. The p-value, power, and F1 score collectively fail to meet the established thresholds, signifying a subpar performance. This inadequacy is further illustrated through visual representations, where the plots exhibit only a partial overlap with the UTK Face dataset.

###Gender given Age

When examining gender classification across different age groups, a shared challenge becomes apparent for both models: the struggle to accurately detect toddlers in the 0 to 2 age bin. However, a stark contrast emerges when we closely analyze DeepFace's performance within specific age cohorts. Notably, DeepFace encounters difficulties not only in identifying the youngest individuals (0 to 2 years) but also in recognizing those in the age groups of 3 to 9 and 70 to 130. It's worth emphasizing that DeepFace consistently falls short of meeting the established threshold criteria across all these age brackets.

An intriguing observation arises when considering the instances where DeepFace fails to meet the threshold criteria—most of these instances involve females. This hints at a potential bias of underperformance towards females in the DeepFace model, raising important questions about the model's robustness and inclusivity. On the other hand, the performance of FairFace stands out as consistently strong and well-distributed between males and females. Notably, FairFace does not exhibit any prominent bias, offering reliable results across gender categories and age groups. This conclusion is substantiated not only through numerical calculations but also by insightful visualizations.

A compelling aspect is revealed when examining the graphs comparing FairFace to the UTK Face distributions. In stark contrast to FairFace, DeepFace shows minimal overlap in these plots, with the most significant disparity occurring in the age bins of 40 to 49 and 50 to 59. This visual representation accentuates the challenges DeepFace encounters, particularly in these age ranges. Conversely, the graphs comparing FairFace to UTK Face distributions tell a different story. While there is a slight underperformance in the age group of 70 to 130, the overall graphs showcase nearly complete overlap. This suggests superior performance by FairFace, reinforcing its effectiveness across various age groups.

###Gender given Race

When examining gender in relation to race, a striking initial observation is that most permutations for DeepFace do not align with the established thresholds for P-value, power, and F1 score.

However, a nuanced perspective emerges when scrutinizing both DeepFace and FairFace, revealing shared struggles in accurately classifying the "other" race. Notably, DeepFace exhibits suboptimal performance with the "black" race, hinting at potential bias.

A deeper dive into the graph distributions for the models against the UTK face dataset unveils distinctive patterns. DeepFace demonstrates minimal overlap in most graphs, with the highest convergence observed for the "white" race. In contrast, FairFace showcases substantial overlap, particularly with the "Asian" and "white" races.

Upon considering both numerical values and graphical representations, an additional noteworthy observation surfaces: females exhibit a slightly lower F1 score than males, potentially indicating bias in both models. Furthermore, there appears to be a trend of better performance towards the "white" race in both models, raising questions about potential biases in these gender and race classifications.

###verdict

While both models exhibit a bias towards females, DeepFace displays a more substantial inclination compared to FairFace. This bias is evident in instances where our calculations indicate a failure to reject the null hypothesis, particularly more frequently in DeepFace. Despite this, FairFace outshines DeepFace in overall performance, excelling in both gender given the age and gender given the race scenarios. Additionally, a discernible trend suggests a potential bias towards the white race in both models, with this tendency being more pronounced in DeepFace. These insights underscore the need for ongoing scrutiny and refinement to address biases and enhance the inclusivity of these models.

References

Georgetown Law. 2016. "The Perpetual Line-Up: Unregulated Police Face Recognition in America." *Center on Privacy & Technology*. https://www.perpetuallineup.org.

Huilgol, Purva. 2021. "Accuracy vs. F1-Score - Analytics Vidhya - Medium." *Medium*, December. https://medium.com/analytics-vidhya/accuracy-vs-f1-score-6258237beca2.

Karkkainen, Kimmo, and Jungseock Joo. 2021. "FairFace: Face Attribute Dataset for Balanced Race, Gender, and Age for Bias Measurement and Mitigation." In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, 1548–58.

Lohr, Steve. 2018. "Facial Recognition Is Accurate, if You're a White Guy." *N.Y. Times*, February. https://www.nytimes.com/2018/02/09/technology/facial-recognition-race-artificial-intelligence.html.

NIST. 2020. "NIST Study Evaluates Effects of Race, Age, Sex on Face Recognition Software | NIST." *NIST*. https://www.nist.gov/news-events/news/2019/12/nist-study-evaluates-effects-race-age-sex-face-recognition-software.

Serengil, Sefik Ilkin, and Alper Ozpinar. 2021. "HyperExtended LightFace: A Facial Attribute Analysis Framework." In *2021 International Conference on Engineering and Emerging Technologies (ICEET)*, 1–4. IEEE. https://doi.org/10.1109/ICEET53442.2021.9659697.

"UTKFace." 2021. *UTKFace*. https://susanqq.github.io/UTKFace.