

# **Bias in Facial Classification ML Models**

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# Abstract

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## 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 right corner of this website.

Features of Quarto:

## How we should write this report

- See Karkkainen and Joo (2021) , that is an example on how to cite a bibliography.
- Sections/title headings are automatically numbered.
- Any changes you make, make sure to make a comment of your initials at the top of your work (INCLUDING written text) like so:

```
<!-- BJ !-->
Blah blah etc ....
```

```
OR
#BJ
r_var <- ...
```

- Make sure to add a unique name to all code cells, and to also enable the following (the quarto way) (In order for a figure to be cross-referenceable, its label must start with the fig- prefix):
- You can then refer to figures like this @fig-sec1-unique-name Figure 1
- Format tables doing the following [Link here](#)
- Do all your r work initially in your own custom .rmd file in this directory, so that it can be copy-pasted over later into the appropriate section (written descriptions/words can go straight into the .qmd files though). For example, Bhav's work is in 5000-final/BJ\_work.rmd.

## From the report requirements

A 3-5 summary of the paper. It should address the research question, the methods, and the conclusions of your analysis.

*"A good recipe for an abstract is: first sentence: specify the general area of the paper and encourage the reader;*

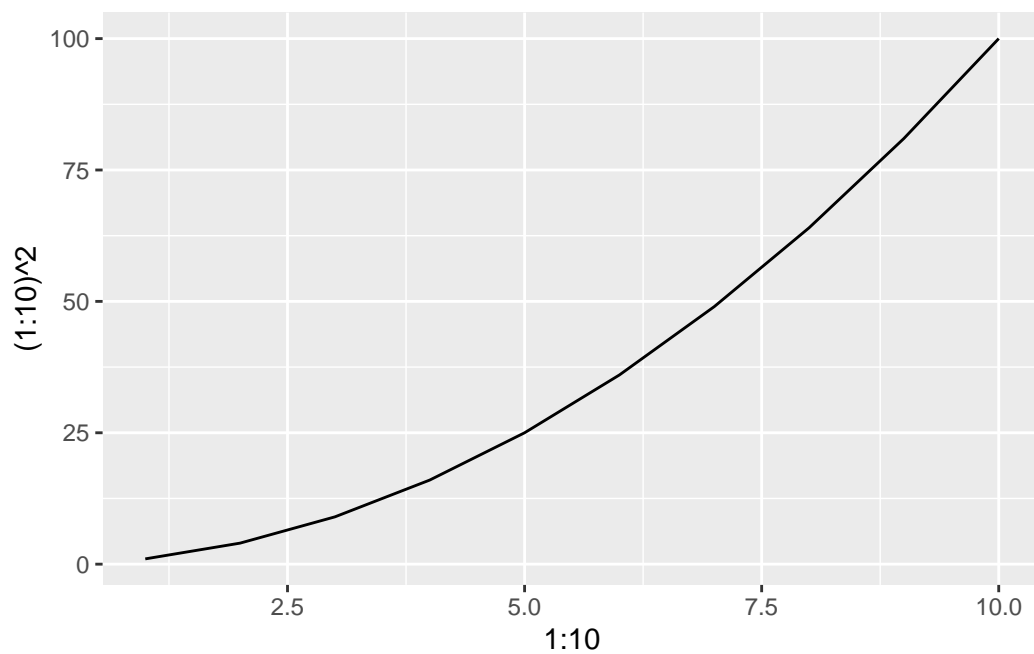


Figure 1: A caption for generated figure

*second sentence: specify the dataset and methods at a general level; third sentence: specify the headline result; and a fourth sentence about implications.”*

# 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. It was trained on a balanced dataset that featured equal numbers of different races, including Middle Eastern faces. The creators point out in their work that the majority of other training data is overwhelmingly white and male, lending those algorithms a bias ([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. The creators have shown an accuracy rate of up to 97% on at least one dataset, but replication is key when it comes to testing code ([Serengil and Ozpinar 2021](#)).

It is this paper's goal to test the accuracy of those claims and compare these algorithm's ability to guess the race, gender, and age of a given dataset, both with and without controlling for the race of the given faces. Both will be tested against the UTKFace dataset, which consists of over 20,000 labeled faces that can be used for purposes such as this ("[UTKFace](#)" 2021). We will examine the bias present in either tested model using hypothesis testing and by inspecting performance metrics such as F1 score and accuracy, and compare this bias against the baseline (aka, the bias inherently present in the UTK face dataset).

## 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.

#### **i** From the report requirements

This section should describe the data you’ll be using. Answer **at least all** of the following questions:

- How was the data collected?

The dataset used in this research is a publicly non-commercial available dataset on Github called “UTKFace”. The data was collected by the The University of Tennessee, Knoxville. It is specified on its Github page that the images were gathered from the internet. They are likely to be obtained through technique such as web scrapping. The dataset contains more than 20,000 images, representing a highly diversified demographic. However, face images are vary in pose, facial expression, lighting, and resolution.

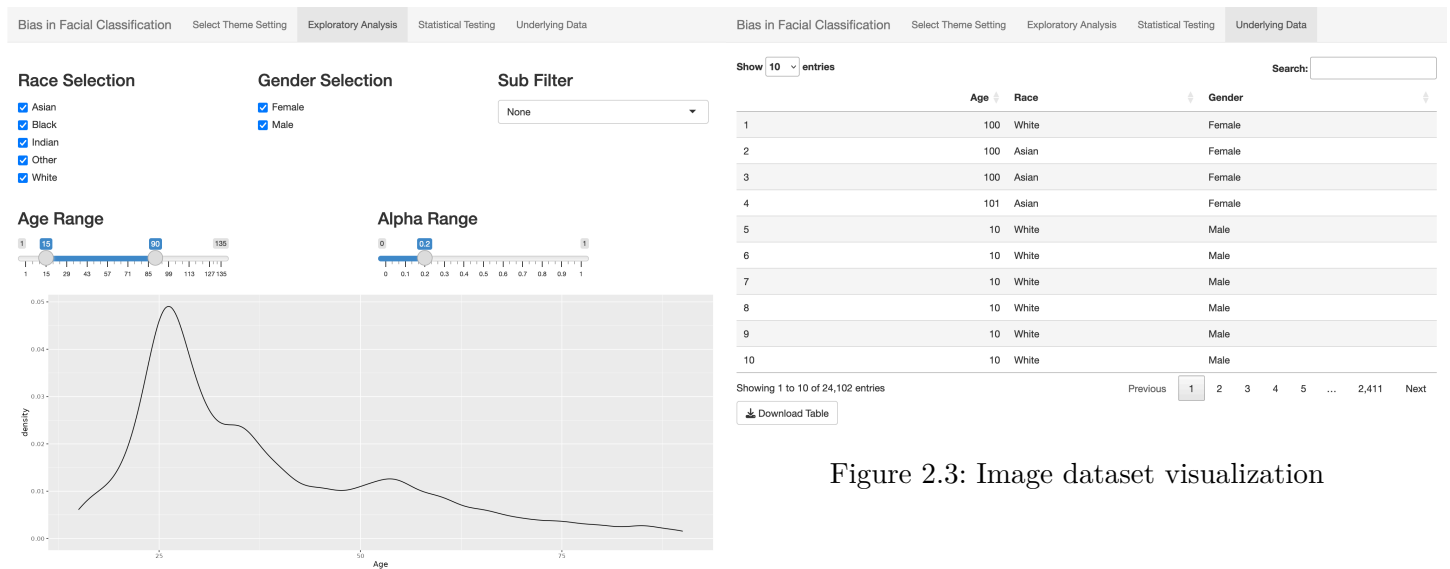


Figure 2.2: Image data EDA

Figure 2.3: Image dataset visualization

Figure 2.4: 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](#)

- What are the sources and influences of bias in the data?

The distribution of each demographic groups are not normally distributed. By plotting a distribution of each demographic group, it is evident that the dataset contains an uneven high volume of older White men. While a smaller porportion of female among ...(input race)... is present.

- What are the important features (=columns) that you are using in your analysis? What do they mean?

There are three features in the dataset which are essential to our analysis. They are Race, Gender, and Age. Race is categorized into five groups; Asian, Black, Indian, White, and Other. It should be noted by Asian group in this dataset mostly refers to people from East and Southeast Asia. Whereas, Other includes ethnicities such as Hispanic, Latino, and Middle Eastern.

Gender is divided into two groups, either male or female.

Lastly, Age is represented with an integer. This dataset contains people of all ages ranging from 0 to 116.

Feel free to add anything else that you think is necessary for understanding the paper and the context of the problem.

## 2.2 Data Selection (UTK Dataset) - LN DV

### 2.2.1 Motivation for the Selection of UTKFace Dataset

In 2018, [Joy Buolamwini paper link](#), 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 Amazom 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 ethniicty is required. Upon searching, UTKFace came out as the



largest dataset which fit the 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 20,000 face images, representing a highly diversified demographic. However, face images are 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.

Overall, all of 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 (LN DV)

### 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). Since the model is used by one of the largest social media company, it is widely known among developers. Therefore, its popularity prompts us to evaluate its performance. It should be noted that this model of DeepFace is a [free open source version](#). It is highly likely that this version is less advanced than what Meta is actually utilizing. Thus, we should not view the result of this model as a representative of Meta's algorithm.

## 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 ([link to source data file 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 import 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 key 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:

Column Name	Data Type	Significance	Valid Values
name_face_string	String	The name and path of the file upon which FairFace made predictions	[filepath]
race_preds_string	String	The predicted race of the image subject	[White Black Latino_Hispanic East Asian Southeast Asian Middle Eastern Indian]
gender_preds_string	String	The predicted gender of the image subject	[Male Female]
age_preds_string	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 have 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 the purpose of our planned analyses, the score features are of less concern to us.

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

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 image subject	[Man Woman]
Dominant Race	String	The predicted race of the image subject	[middle eastern asian white latino hispanic black indian]

### 2.4.4 Standardizing model outputs

As can be seen above, 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.

#### 2.4.4.1 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”

## 2.4.5 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”

## 2.4.6 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 as the source age range for the image subject.

**Gender:** No changes.

**Race:** No changes.

## 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 - the Asian Face Age Dataset (**need citation here**). 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 what settings may provide the most fair and equitable comparison of the models prior to proceeding to further analysis.

The ultimate 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 lamens 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 avaialble 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 exeuction. 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 pre-processing, 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, similar to 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:

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.

Warning: package 'kableExtra' was built under R version 4.3.2

pred_model	detection_enabled	detection_model	image_type	all_rate	age_grp_rate	gender_rate	race_rate
DeepFace	False	None	cropped	0.0724949	0.1601227	0.6667689	0.6951111
DeepFace	False	None	uncropped	0.0834356	0.1522495	0.7326176	0.6457778
DeepFace	True	mtcnn	cropped	0.0889571	0.1534765	0.7249489	0.6807778
DeepFace	True	mtcnn	uncropped	0.1023517	0.1615542	0.7834356	0.6667778
DeepFace	True	opencv	cropped	0.0267894	0.0765849	0.1887526	0.1983333
DeepFace	True	opencv	uncropped	0.0806748	0.1455010	0.6619632	0.5855556
FairFace	False	None	cropped	0.4015337	0.6101227	0.8921268	0.7688889
FairFace	False	None	uncropped	0.1031697	0.2671779	0.7599182	0.4477778
FairFace	True	dlib	cropped	0.4015337	0.6101227	0.8921268	0.7688889
FairFace	True	dlib	uncropped	0.4353783	0.6230061	0.9155419	0.7911111

Examining the true positive ratios for each case, our team came to the conclusion 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 excluded 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 all of 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 Result Output Format

The following table outlines, after the input and output data modifications, the final format of our data for use in our analyses. This file is stored in the /data folder as [MasterDataFrame.csv](#)

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 dataset
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

Karkkainen and Joo (2021)

### 3.1 The Big Picture

- Is bias prevalent in facial recognition machine learning models?
- Can one model be shown to have statistically significant less bias than the other?
- Does one model outperform the other in a statistically significant manner, in all aspects?
- Does one model outperform the other in a statistically significant manner, in certain aspects?
  - This is where we can dive into “conventional” bias
- Are there disparate outcomes (i.e. lower chances of correct classification) for one racial group vs. another?

#### **i** Thoughts on Bias

We need to be careful how we define and use bias. Statistical bias is essentially error, and we could be crossing our definitions between statistical bias and conventional bias.

### 3.2 Measuring Performance

#### **i** Note

This performance section is important in choosing the correct models to ensure data integrity, however for the actual statistical tests, we'll focused on more common statistics like mean and proportion.

These are my recommendations on how we can look at the additional values:

For cases in which we reject the statistical null hypothesis, we plan to evaluate the below metrics for the same output category. Should we reject a null hypothesis for, let's say, the proportion of females, given that they are asian, we will examine the accuracy and F-1 scores for the same category. We will consider the following range of values:

- Accuracy < 70: poor/unacceptable performance
- 70 < Accuracy < 79: marginally acceptable performance
- 80 < Accuracy < 89: acceptable performance
- 90 < Accuracy < 99: excellent performance
- **Do we need anything else regarding precision or recall? and does this all need to be a table?**

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, however, to begin to explain the differences between these models we should 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 on a confusion matrix. In the image below, green are correct predictions while red are incorrect predictions.

		True Class	
		Positive	Negative
Predicted Class	Positive	TP	FP
	Negative	FN	TN

Figure 3.1: confusion\_matrix

### 3.2.1 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.

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

### 3.2.2 Precision

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

$$Precision = \frac{TP}{TP+FP}$$

### 3.2.3 Recall

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

$$Recall = \frac{TP}{TP+FN}$$

### 3.2.4 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.

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

## 3.3 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 treating the source data as the basis for the original assumptions (our *null hypotheses*), and then using the output from Fairface and Deepface to test for statistically significant differences. 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 a bias in model.

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

### 3.3.1 Demographics

- Age Group
- Gender
- Race

### 3.3.2 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

### 3.3.3 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:

$$H_0 : p = p_{\text{Source Data Subset}}$$

$$H_A : p \neq p_{\text{Source Data Subset}}$$

With the following test statistic:

$$\frac{\sqrt{n}(\hat{p}-p)}{\sqrt{p(1-p)}}$$

With the p-value being calculated by:

$$P(|Z| > \hat{p} | H_0) \\ = P(|Z| > \frac{\sqrt{n}(\hat{p}-p)}{\sqrt{p(1-p)}}),$$

where

- $n$ : output data subset size
- $\hat{p}$ : output data subset proportion
- $p$ : source data subset proportion

**NOTE** - may be worthwhile to state that we evaluated all cases here, but reduction to specific cases of controlling race and evaluating solely on gender or solely on race is of the most value to us. Performing tight filtering down to, for instance, the proportion of white people given they are 40-49 and female may be too restrictive.

Performing and analyzing calculations of  $P(\text{Age}|\text{Race})$  or  $P(\text{Gender}|\text{Race})$  are of more interest, as I think our research questions are looking at disparate impact to the outcomes for each racial group. ### Notation

Before we list the specific tests, we should introduce some notation.

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

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

### 3.3.4 More Specific Proportion Tests

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:

$$H_0 : p_F = p_{F|D_0}$$

$$H_A : p_F \neq p_{F|D_0}$$

P-value Calculation:

$$P(|Z| > \frac{\sqrt{n}(\hat{p}-p)}{\sqrt{p(1-p)}}),$$

where

- $p = p_{F|D_0}$ : proportion of females from the source data
- $\hat{p} = p_{F|D_f}$ : proportion of females from the fairface output
- $n = n_{F \cup M|D_f}$ : number of data points in the gender subset 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*, then we could write a hypothesis test like:

$$H_0 : p_{F|B} = p_{F|D_0 \cap B}$$

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

P-value Calculation:

$$P(|Z| > \frac{\sqrt{n}(\hat{p}-p)}{\sqrt{p(1-p)}}),$$

where

- $p = p_{F|D_0 \cap B}$ : proportion of females from the source data, given they were black
- $\hat{p} = p_{F|D_f \cap B}$ : proportion of females from the fairface output, given they were black
- $n = n_{F \cup M|D_f \cap B}$ : number of data points in the gender subset from the fairface output, given they were black.

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

#### From the report requirements

Also can be called "Analyses"

This section might contain several subsections as needed.

- At least one subsection should describe the exploratory data analysis you did.
- What modifications were necessary to make the dataset ready for analysis? (e.g. dealing with missing values, removing certain rows, replacing/cleaning text values, binning, etc)
- Describe the analyses you did to answer the question of interest. **Explain why you believe these methods are appropriate.**
- At least one subsection should describe the exploratory data analysis you did.
- What modifications were necessary to make the dataset ready for analysis? (e.g. dealing with missing values, removing certain rows, replacing/cleaning text values, binning, etc)

- Describe the analyses you did to answer the question of interest. **Explain why you believe these methods are appropriate.**
- At least one subsection should describe the exploratory data analysis you did.
- What modifications were necessary to make the dataset ready for analysis? (e.g. dealing with missing values, removing certain rows, replacing/cleaning text values, binning, etc)
- Describe the analyses you did to answer the question of interest. **Explain why you believe these methods are appropriate.**

Some methods we learn in this class include distribution comparison, correlation analysis, and hypothesis testing. You are required to include hypothesis tests into the project, but feel free to use additional methods to tell a good story about the data.

# 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.

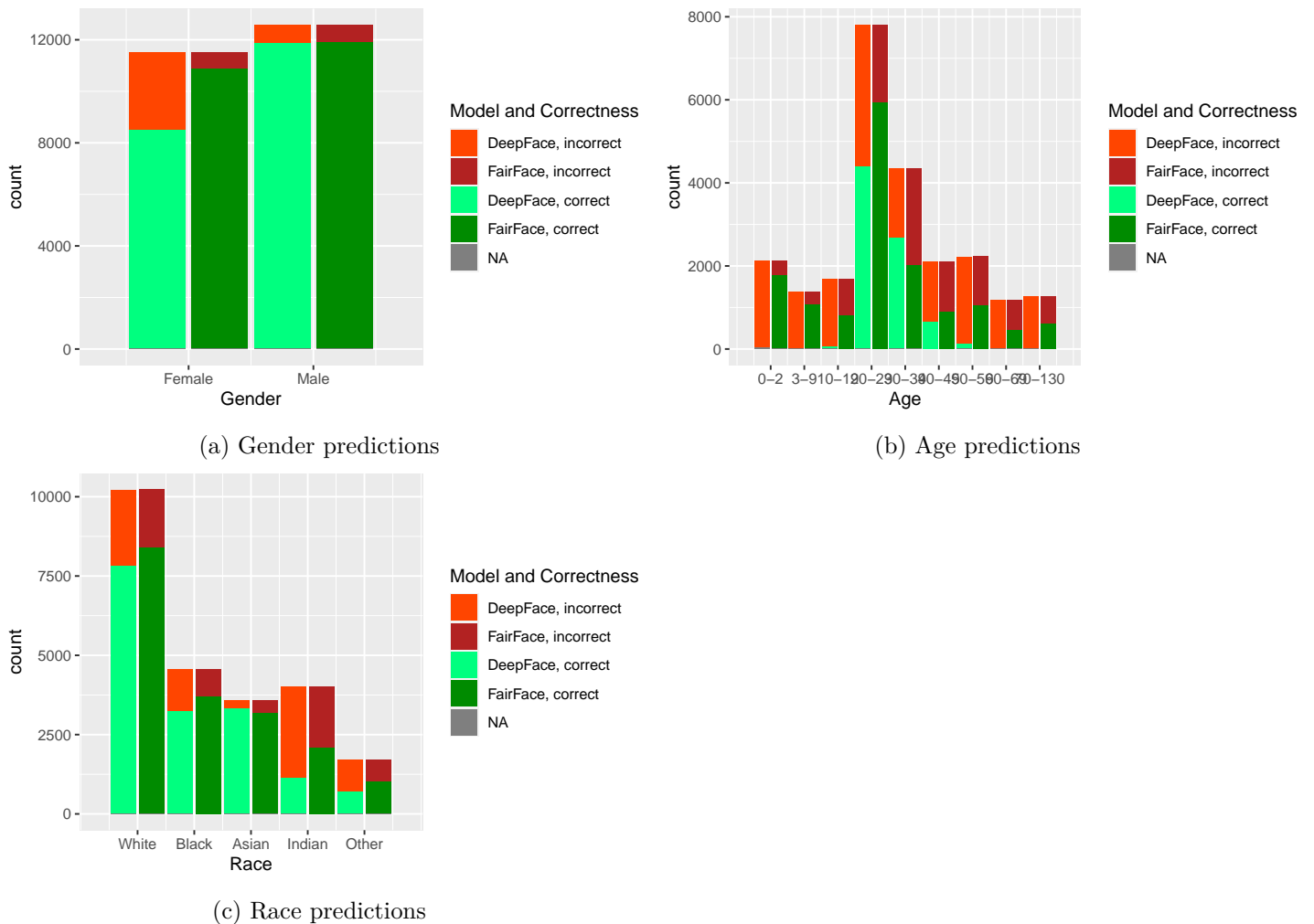


Figure 4.1: Histograms of the output from DeepFace and FairFace, with correct vs incorrect values colored. Note that the distributions match the correct (source dataset) distributions.

## 4.2 Model Performance

### 4.2.1 TODO: Remove

## 4.3 Hypothesis Testing

### 4.3.1 TODO: Remove

### 4.3.2 Updated Table Version with Data from Carl, Bhav

#### 4.3.2.1 TODO: Remove

## 4.4 Model Performance, Hypothesis Testing

For each category and model, we calculate the F1 score, accuracy, and p-value, as described in section 3. Cell values are colored according to the strength of the metric. We also specifically looked at the performance metrics of the models, when controlled for specific source categories; TODO

### 4.4.1 TODO

- Add color key
- Better description of signifiance of numerical values of Accuracy, F1 score, power

The results are summarized in Figure 4.2.

### 4.4.2 p-value Critical Values

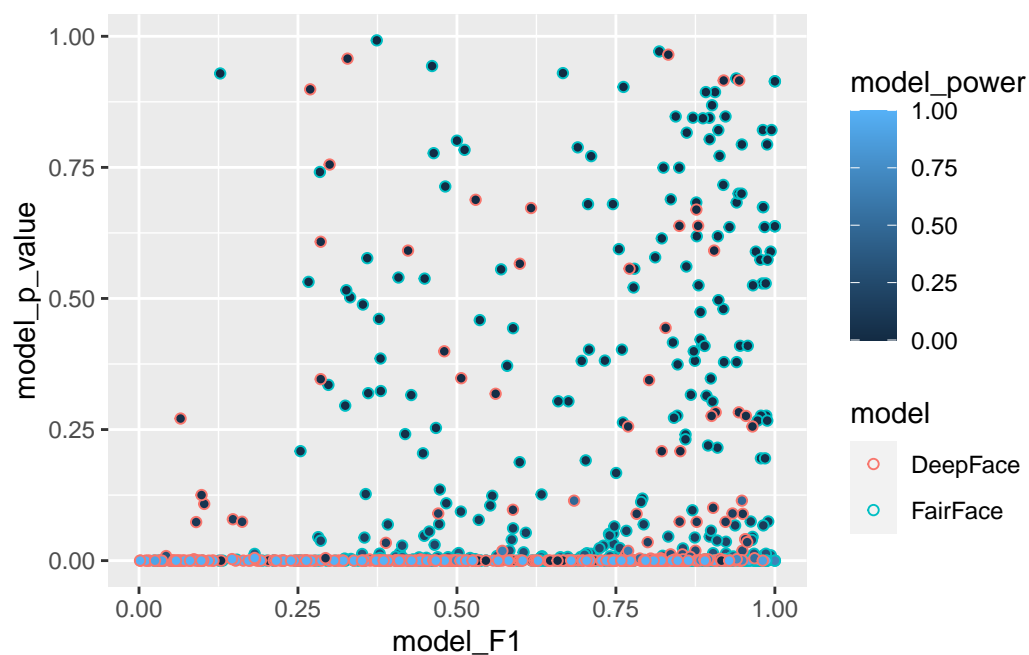
From the previous table, we extract and highlight key values; namely, the p-values where we reject the null hypothesis at a significance level of 99.7%, and where there is no conditional filtering based on another category. The values are displayed in Table 4.1.

Table 4.1: TODO

test_prop	test_subcat	model_p_value	model_power	model_F1	model_Accuracy	model
ages	70-130	2.047863e-43	1.0000000	0.627066116	0.7383514	FairFace
ages	3-9	1.252641e-05	0.9197828	0.717603501	0.8772778	FairFace
ages	10-19	4.824090e-05	0.8640459	0.505249761	0.7211461	FairFace
ages	0-2	2.872858e-06	0.9568115	0.895975702	0.9172888	FairFace
ages	20-29	2.022367e-08	0.9958932	0.733292156	0.8050592	FairFace
ages	40-49	1.507446e-08	0.9965034	0.394397023	0.6786302	FairFace
races	White	5.375419e-18	1.0000000	0.861039893	0.8788455	FairFace
races	Black	6.865360e-12	0.9999512	0.868485771	0.8997692	FairFace
races	Indian	6.718714e-94	1.0000000	0.640245776	0.7488102	FairFace
races	Other	0.000000e+00	1.0000000	0.308747333	0.7105889	FairFace
ages	70-130	3.873607e-284	1.0000000	NA	0.5000000	DeepFace
ages	3-9	3.289100e-293	1.0000000	NA	0.5000000	DeepFace
ages	10-19	1.425463e-148	1.0000000	0.047860101	0.5055825	DeepFace

ages	0-2	0.000000e+00	1.0000000	NA	0.5000000	DeepFace
ages	20-29	1.702327e-65	1.0000000	0.505432596	0.6217793	DeepFace
ages	30-39	0.000000e+00	1.0000000	0.378631811	0.6275447	DeepFace
ages	40-49	1.234331e-91	1.0000000	0.227627841	0.5866155	DeepFace
ages	50-59	2.041635e-202	1.0000000	0.080167306	0.5137145	DeepFace
ages	60-69	3.869853e-229	1.0000000	0.001612903	0.4991769	DeepFace
genders	Female	9.696988e-98	1.0000000	0.819770248	0.8402892	DeepFace
genders	Male	9.696988e-98	1.0000000	0.863662918	0.8402892	DeepFace
racess	White	2.438533e-27	1.0000000	0.809546093	0.8365916	DeepFace
racess	Asian	1.303250e-143	1.0000000	0.703897491	0.9005150	DeepFace
racess	Black	1.471038e-33	1.0000000	0.796499445	0.8462797	DeepFace
racess	Indian	1.123217e-292	1.0000000	0.409248134	0.6310597	DeepFace
racess	Other	2.869683e-262	1.0000000	0.238902067	0.6283106	DeepFace

### 4.4.3 Comparison Plots



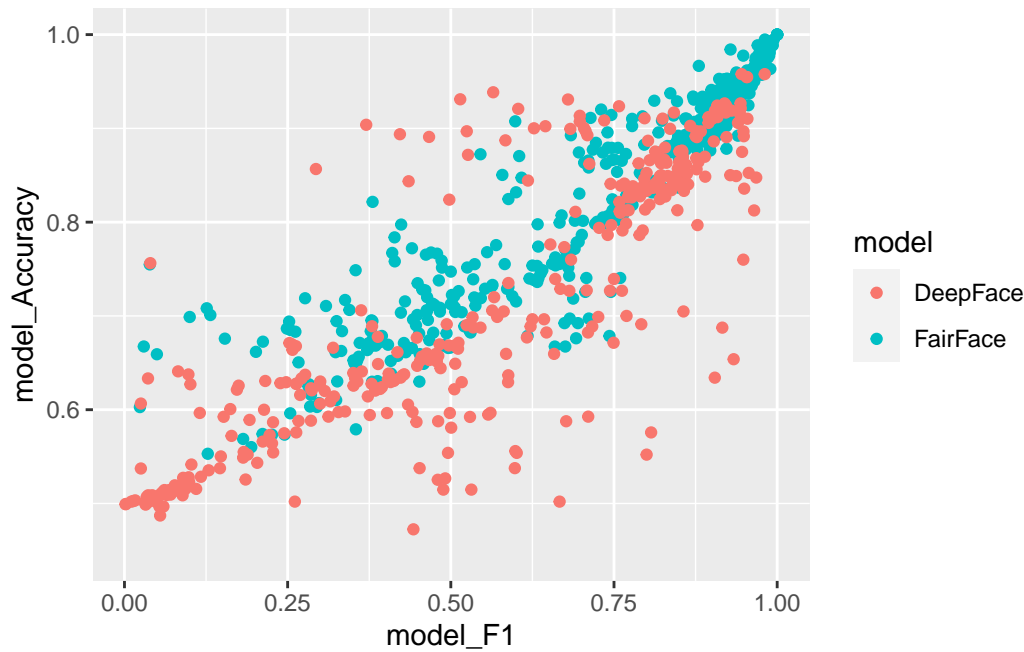


Test Factor ↓	Age ↕	Gender ↕	Race ↕	↕ p-Value	↕ Power	↕ F1 Score	↕ Accuracy	Model ↕
rac	All	All	Other	2.87e-262	1.0000	0.2389	0.6283	DeepFace
rac	All	All	Indian	1.12e-292	1.0000	0.4092	0.6311	DeepFace
rac	All	All	Black	1.47e-33	1.0000	0.7965	0.8463	DeepFace
rac	All	All	Asian	1.30e-143	1.0000	0.7039	0.9005	DeepFace
rac	All	All	White	2.44e-27	1.0000	0.8095	0.8366	DeepFace
rac	All	Male	Other	1.76e-169	1.0000	0.2157	0.6306	DeepFace
rac	All	Male	Indian	5.62e-197	1.0000	0.4286	0.6378	DeepFace
rac	All	Male	Black	4.44e-01	0.0139	0.8281	0.8796	DeepFace
rac	All	Male	Asian	2.48e-115	1.0000	0.6976	0.9073	DeepFace
rac	All	Male	White	1.34e-60	1.0000	0.8134	0.8375	DeepFace
rac	All	Female	Other	3.63e-101	1.0000	0.2631	0.6275	DeepFace
rac	All	Female	Indian	1.08e-106	1.0000	0.3848	0.6229	DeepFace
rac	All	Female	Black	4.86e-90	1.0000	0.7586	0.8115	DeepFace
rac	All	Female	Asian	5.03e-41	1.0000	0.7093	0.8927	DeepFace
rac	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 TODO. To see and interact with this table, go to [the website link](#)



#### 4.4.4 Statistical Power

$$\beta = P\left(\left|\frac{\sqrt{n} \cdot \hat{p} - p_a}{\sqrt{p_a(1-p_a)}}\right| \geq \frac{\sqrt{n} \cdot p_0 - p_a}{\sqrt{p_0(1-p_0)}}\right)$$

Our selected level of significance is 99.7% (3-sigma). Type-II error is denoted by  $\beta$  above, and Power will be  $1 - \beta$

With  $p_0$  being our *assumed* population proportion (from the source dataset and what we used in our tests),  $p_a$  being the *actual* population proportion (from one or more of the below methods),  $n$  being the number of predicted members of a racial group (i.e. “Indian”),

- For Gender - assume that sex at birth is a bernoulli trial, over time, the proportion for both genders should be 0.5
- For age groups - assume that age has a true normal distribution. Each race may have different means and standard deviations for their distribution of age, but still adhere to a normal distribution. The “population” proportions may be a bit more challenging to calculate, but under this framework, we may be able to get there.
  - May be able to get via bootstrapping the source dataset, average age by race - I think that’s what we did in our last project?
  - Could look at external data? May not have time to look through everything.

$$\frac{\sqrt{n_M} \cdot (\bar{p}_M - p_S)}{\sqrt{p_S \cdot (1 - p_S)}}$$

## 5 Conclusions

**i** 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 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

# References

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