Bias in Facial Classification ML Models

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

Table of contents

Abstract

Here is where we will put the abstract.

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):

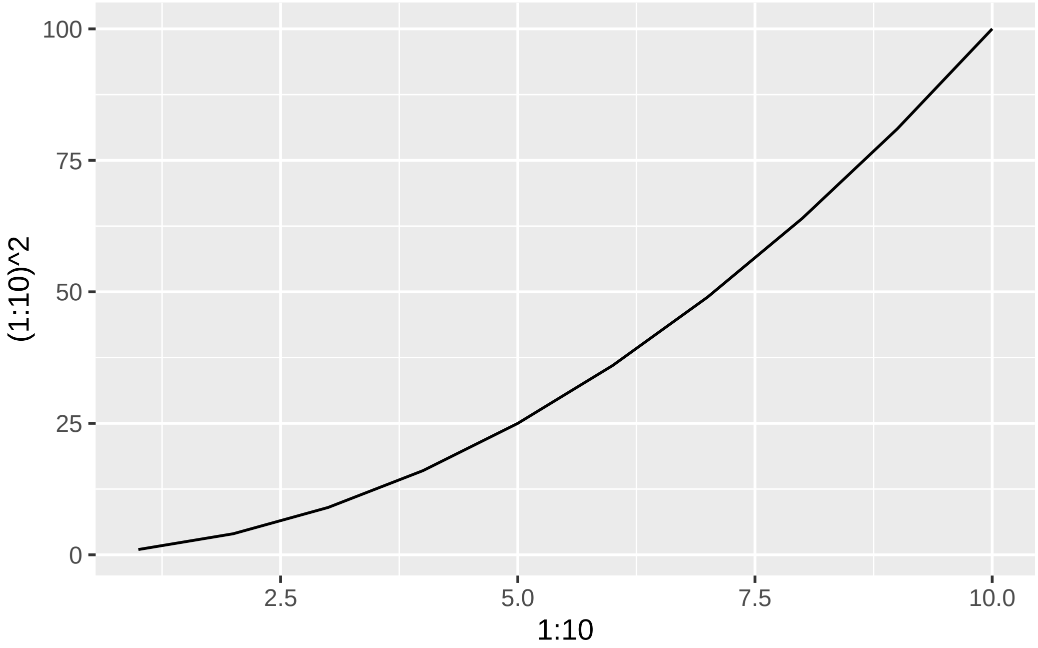


Figure 1: A caption for generated figure

- 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`.

ℹ 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; 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

From the report requirements

This section introduces your problem to a **non-expert** audience, describes the context and history of the problem.
For example, if your overall project topic is on Diabetes Prevention and Prediction, then you would use the Introduction to introduce what diabetes is, who it affects, why prevention is important, history on diabetes prevention, etc.
Some questions that you could answer in the introduction:

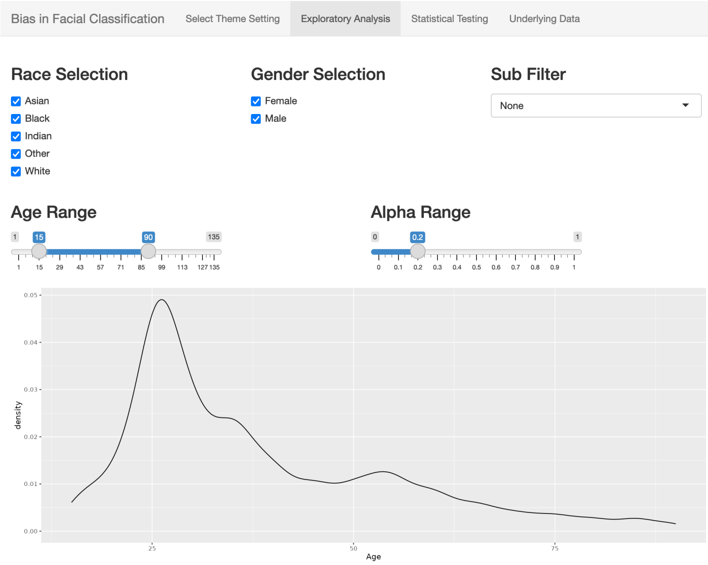
- What is the "research question"? why is it interesting or worth answering?
- What is the relevant background information for readers to understand your project? Assume that your audience
is not an expert in the application field.
- Is there any prior research on your topic that might be helpful for the audience?

The goal of the introduction it to capture the audience's interest in your paper. An introduction that starts with "Diabetes kills over 87 thousand people each year and in many cases may be preventable" is more engaging than "This paper is about diabetes prevention".
The introduction should be 2-4 paragraphs long.

2 Data Exploration

We describe the data here. Note that the default global setting for Quarto is set to NOT output the code into the rendered document, aka only including the results of any R code.

We should include a print of the head of the dataframe of our data, along with some sample images!!



Race Selection

☑ Asian
☑ Black
☑ Indian
☑ Other
☑ White

Gender Selection

☑ Female
☑ Male

Sub Filter

None

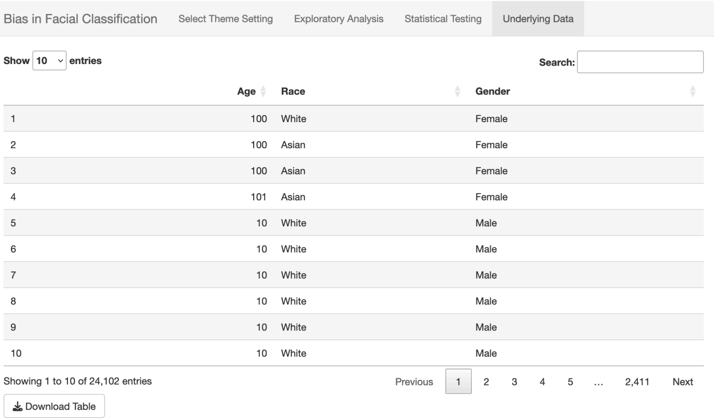
Age Range

1 15 90 135

Alpha Range

0 0.2 1

Figure 2.1: 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

Figure 2.2: Image dataset visualization

Figure 2.3: 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

> **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?
> - What are the sources and influences of bias in the data?
> - What are the important features (=columns) that you are using in your analysis? What do they mean?
>
> Feel free to add anything else that you think is necessary for understanding the paper and the context of the problem.

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

> 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.

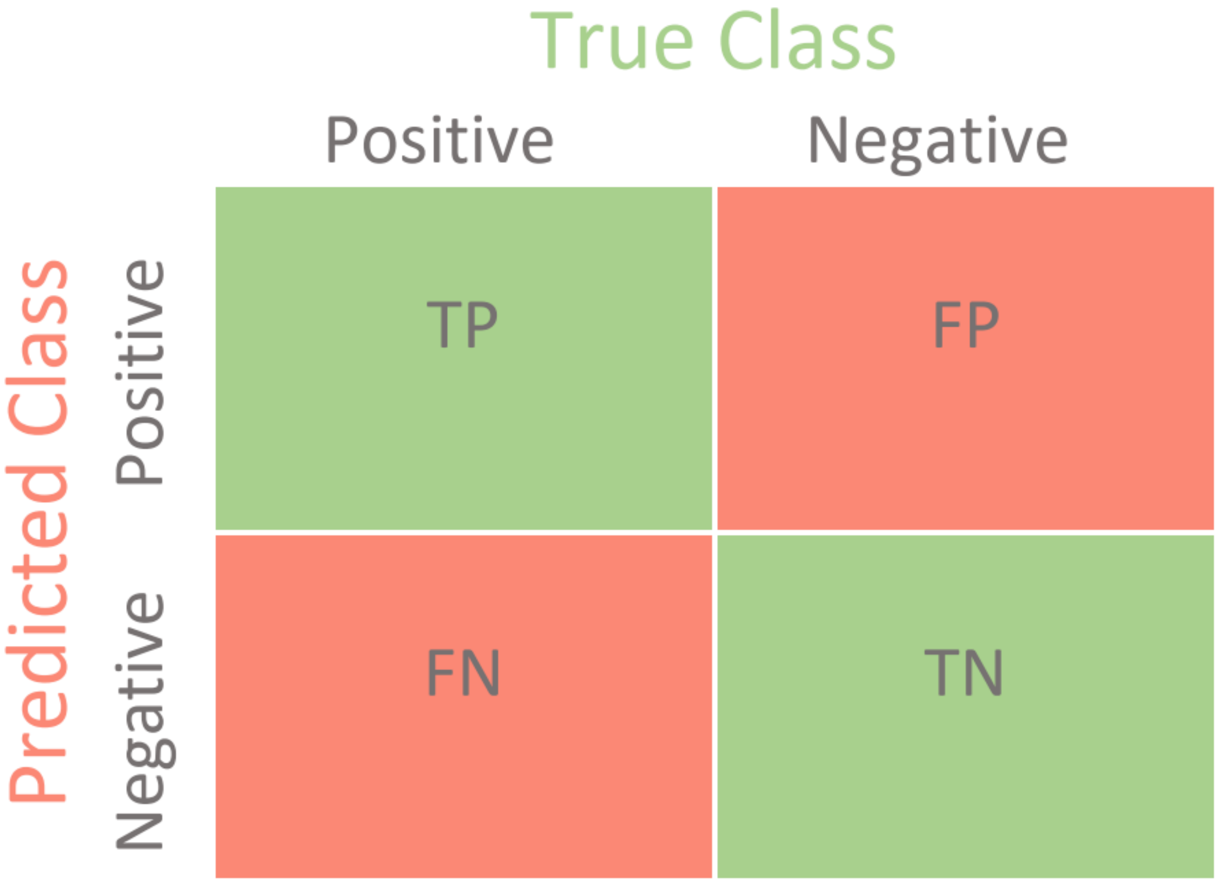
There are four main measures of performance when evaluating a model:

- **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.

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

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

3.3 Statistical Testing

Just as with the exploratory analysis on the data set prior to running either model, it's helpful to garner an understanding of what the results were using basic statistics and metrics. By calculating statistics in a cascading fashion, starting with the overall and then zeroing in on subgroups, we can get an idea if and where bias is worth investigating.

3.3.1 Overall

- Compare the mean age of the input to the mean age of the Deepface output
- Bin the input ages, compare bins between the input and the output of both models
- Bin the input ages, compare bins between the output of both models

Note: We can think of the binned data as categorical variables or as a small subset of discrete numerical data by ordering the bins.

3.3.2 Performance - Main Demographics

- Age Group
  - Fairface Results
  - Deepface Results
- Gender
  - Fairface Results
  - Deepface Results
- Race
  - Fairface Results
  - Deepface Results

3.3.3 Performance - Demographics' Subgroups

- Age Group (9 groups)
  - Fairface Results
  - Deepface Resultseepface Results
- Gender (2 groups)
  - Fairface Results
  - Deepface Results
- Race (5 groups)
  - Fairface Results
  - Deepface Results

3.4 Hypothesis Testing

Now that we have an idea how each of these models performed in general and across localized subsets, let's see if our models truly have statistically significant results and if bias is present.

Our tests will focus on proportions, and will discover if there is statistically significant differences between and within the models.

3.4.1 Difference in Means Test

The **Difference in Means Test** will be useful when measuring differences between the mean of ages. Whether that be the aggregate data means or means of demographic subsets.

Depending on the relationship between the data, there are different variants of this test.

3.4.1.1 Unpaired / Independent Samples: Unpooled Variances

This test is best for independent and separate groups.

The *hypothesis test* is:

- $H_0 : \mu_2 - \mu_1 = 0$
- $H_A : \mu_2 - \mu_1 \neq 0$

A look at the test statistic:

$T = \frac{\bar{x_2} - \bar{x_1} - \mu_o}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$

and has degrees of freedom, v, where

$v = \frac{(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2})^2}{(\frac{s_1^2}{n_1})^2/(n_1 - 1) + (\frac{s_2^2}{n_2})^2/(n_2 - 1)}$

3.4.1.2 Unpaired / Independent Samples: Pooled Variances

We can improve the precision of a test if we can assume the equivalence of variances.

A look at the different test statistic:

- $T = \frac{\bar{x_2} - \bar{x_1} - \mu_0}{\sqrt{s_p^2(\frac{1}{n_1} + \frac{1}{n_2})}}$,

with degrees of freedom $v = n_1 + n_2 - 2$,

and where $s_p^2 = \frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}$ is known as the *pooled estimate of variance.*

3.4.1.3 Paired/Dependent Samples

In the previous tests, we were considering independent samples. In this case, we'll be considering the samples have a dependency between them. This is a common test for "before" and "after" type testing.

We can simplify the *hypothesis test* for this kind of sampling relationship to:

- $H_0 : \mu_2 - \mu_1 = \mu_d = 0$
- $H_A : \mu_d \neq 0$

With the test statistic being:

$T = \frac{\bar{d} - \mu_0}{\frac{s_d}{\sqrt{n}}}$,

where $\bar{d}$ is the mean of the pairwise differences and s_d is the sample standard deviation of the pairwise differences.

The degrees of freedom for this test are $df = n - 1$.

3.4.2 Proportion Test

The **Proportion Test** will be useful when measuring differences of categories between models.

The *hypothesis test* we'll be using is:

- $H_0 : \pi_2 - \pi_1 = 0$
- $H_A : \pi_2 - \pi_1 \neq 0$

A look at the test statistic:

$Z = \frac{p_2 - p_1 - \pi_0}{\sqrt{p^*(1-p^*)(\frac{1}{n_1} + \frac{1}{n_2})}}$, where

the *pooled proportion*, p^* is calculated as

$p^* = \frac{x_1 + x_2}{n_1 + n_2}$

A look at the code:

- x: vector of successes and failures
- n: vector of counts of trials (can be ignored if x is a matrix or a table)
- alternative: we can change if we have a specific equality to test
- conf.level: 0.95 is the default (not pertinent to specify)

We can also build **confidence intervals**. We have 95% confidence that the true difference between the props lies within the following:

3.4.3 Chi-Squared Test

The **Chi-squared Test** will be useful when testing across k-levels of a categorical variable. For instance, this could be useful when testing proportion within a demographic for a singe model (i.e. accuracy across race in Fairface).

The *hypothesis test* we'll be using is:

Equivalent Proportions (test for uniformity):

- $H_0 : \pi_1 = \pi_2 = ... = \pi_n = \pi$
- $H_A : H_0$ is incorrect (at least one of the proportions is not equivalent)

A look at the test statistic:

$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i}$, where

O_i is the observed count, and

E_i is the expected count.

A look at the code:

Imagine using this test across the categories of race. A test which favored H_A could give credence to bias.

The standard is using the **Chi-squared Test** in testing for uniformity, however we can test specific proportions for each category. Here's a preview in R:

A possible use case of the non-uniform **Chi-Squared Test** could be to test if the proportion of inaccuracies follows the proportion of each demographic subcategory. For instance, does inaccuracy across race follow the proportions of race in the sample?

3.4.4 Non Parametric Cohort

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.

3.5 Standardizing output

The model outputs for both FairFace and DeepFace do not conform to the categories provided within the University of Tennessee - Knoxville (UTK) dataset. We elected to take the outputs from each model and modify them based upon the categories specified in the UTK dataset, namely:

- “[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”

3.5.1 From FairFace

- **Race**: The FairFace classification model had two options - one for “fair7” and one for “fair4.” The latter provided predictions of race in the following categories: [White, Black, Asian, Indian]. Of key note, the 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 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"

- **Age**: 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. This split will allow us to determine whether or not the prediction correctly binned the age (i.e. $lowerBound \leq actualAge \leq upperBound$), and if not - how far outside of those bounds the actual age lay.
- **Gender**: no change to outputs of "Male" and "Female."

3.5.2 From DeepFace

- **Race**: Racial categorical output from DeepFace includes the following categories ["middle eastern", "asian", "white", "latino hispanic", "black", "indian"]
- **Age**: DeepFace provides a prediction of a single, specific, predicted age. We elected to match the predicted age to be the same range as would be predicted by Fair Face. For example, if DeepFace predicts an age like "19," we assign it the same matching category as it would have in FairFace - "10-19." From there, we also split this category into an upper and lower bound. In spite of the fact that DeepFace does not provide any bounds or ranges on its age prediction outputs, to have a similar and fair comparison of both models, we give it those same upper and lower bounds for equitable comparison.
- **Gender**: DeepFace outputs are "Man" and "Woman", and we refactor those values to "Male" and "Female" respectively.

3.6 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 an image in each of these categories.

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, and using OpenCV as the default detection backend). Running these initial scripting tests, we encountered a failure rate in DeepFace of approximately 70% in identifying and categorizing an image of a face.

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.

3.6.1 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, 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 permutation evaluation.

3.6.2 FairFace Analysis Options

The default script from FairFace provided no options via its command line script to change 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 gives 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.

3.6.3 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	Results Output
Enabled	FairFace=Dlib; DeepFace=OpenCV	Pre-cropped	new_ff_c_p.csv, crop_df_p_opencv.csv
Enabled	FairFace=Dlib; DeepFace=OpenCV	In-The-Wild	new_ff_uc_p.csv, uncropped_df_p_opencv.csv
Enabled	FairFace=Dlib; DeepFace=mtcnn	Pre-cropped	new_ff_c_p.csv, crop_df_p_mtcnn.csv
Enabled	FairFace=Dlib; DeepFace=mtcnn	In-The-Wild	new_ff_uc_p.csv, uncropped_df_p_mtcnn.csv
Disabled	FairFace,DeepFace=None	Pre-cropped	new_ff_c_np.csv, cropped_df_np.csv
Disabled	FairFace,DeepFace=None	In-The-Wild	new_ff_uc_np.csv, uncropped_df_np.csv

We processed each of the above setting permutations againnst approximately 9800 images, consisting of images from part 1 of 3 from the UTK datset. 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.

3.6.4 Permutation Sample Results (LN & DV)

(enforcement of facial detection, detection backend model, and cropped images vs. faces in-the-wild)

3.6.5 Setting Selection

Upon completion of our evaluation, we determined the settings that gave both models the best chance of success included enabling facial detection with mtcnn for DeepFace and Dlib for FairFace on uncropped images.

From there, we proceeded to process the entirety of the UTK dataset using these settings. The only exception are 4 images that did not conform to UTK's naming convention to identify age, gender, and race of the subject in the image.

We wrote a script, MasterScript.py, to enable us to perform batch iteration of images and generate output files. When processing, we generated both the non-normalized output content and normalized output content.

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 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.

The following table outlines the output files.

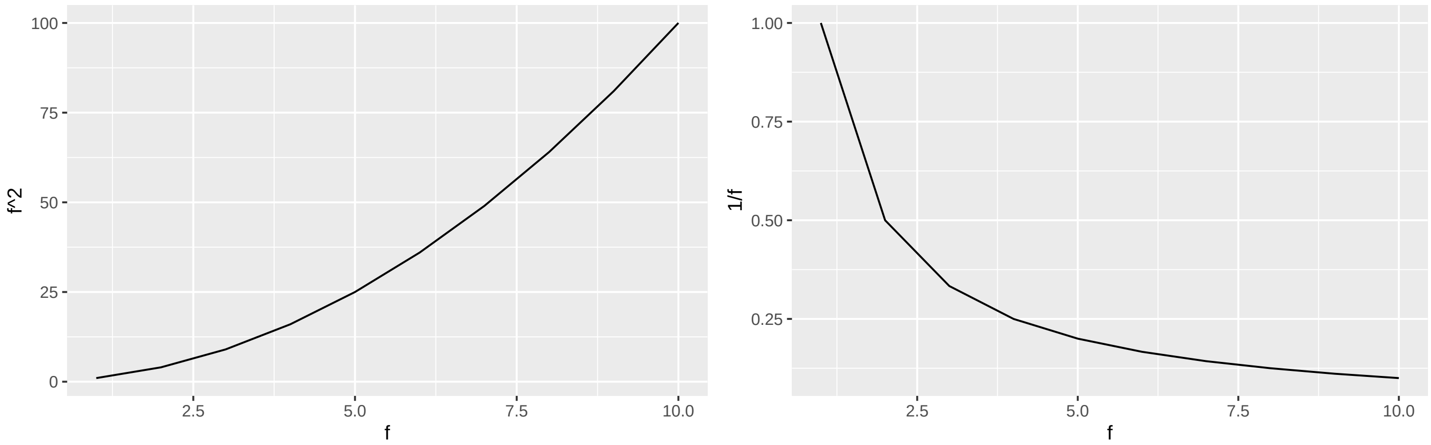
The last file, MasterDataFrame.csv, is the final output of our evaluation. This file is in the following format, with the following column definitions:

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 age ranges from the FairFace outputs) for each image in the UTK datas
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
pred_gender	The gender of the subject in the image predicted by the given prediction model
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
pred_age_lower	The integer lower bound of the predicted age group
pred_age_upper	The integer upper bound of the predicted age group

4 Results

This is where all the plots will go!!!! Here are some examples of plot layout:

4.1 Tabbed example output



(a) Subcap

(b) Subcap 2

Figure 4.1: ANother example caption

4.2 Example outout

```
[1]  1  2  3  4  5  6  7  8  9 10
```

From the report requirements

Describe the results of your analysis using visualizations, descriptive statistics, tables and similar.
Don’t focus too much on the implications in this section – that’s what the next section is for. Just present the numbers/graphs.

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

References

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.