

Intentions and aims

My initial intention was to build a classifier for identifying models of skin colour from real images of people facing the camera lens. The aim is to create a classifier which is extremely accurate and allow for several different skin colours to be identified. This type of classifier was chosen as identify politics is a huge talking point and is being used throughout our political system.

Research into other related works

Research into similar work revealed several different Face recognition/ attribute classifiers. One work was created with the goal of Mitigating Bias and improving on existing Racial face datasets. They found that the numerous other datasets had a strong bias towards Caucasian faces, one study showed that some of the largest databases had a bias towards “lighter skin” faces (around 80%) compared to “darker” faces. They concluded that this bias needed to be removed so they created their Face Attribute Dataset known as FairFace. This was developed by UCLA using Python; it performed better in almost every aspect than the other datasets. They achieved this by carefully curating their dataset with an “emphasis on balanced race composition”. Meaning each of their 7 classes: White, Black, Indian, East Asian, Southeast Asian, Middle Eastern and Latino were well-balanced (**Figure 1.1**) and according to (Joo, J. (2021)) it is the largest of its kind. With this knowledge this project will attempt to maintain a well-balanced dataset to achieve better results.

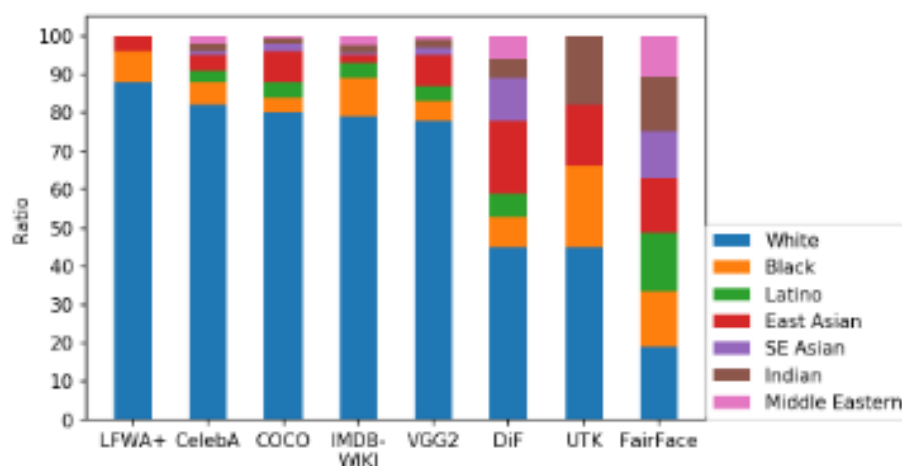


Figure 1.1: Ratio compositions in the different datasets. Joo, J. (2021)

As you can see (**Figure 1.1**) the FairFace dataset was not only well-balanced, but also has more classes than most of the other datasets. This was another step to remove the “white skin” bias and in turn “*performs better on novel data, not only on average, but also across racial groups, i.e more consistently*” they also explain that “*The inclusion of major racial groups, which have been missing in existing datasets, therefore significantly enlarges the applicability*” Joo, J. (2021). As this project wants to produce a similar application, it would be wise to include these different demographics to increase its overall applicability i.e., broaden its usability.

Another take away from this paper was the method in which to measure someone’s skin colour. It is measured using Individual Typology Angle (ITA). This objective classifier is based on the colorimetric parameters CIELAB.

The L^ parameter is the luminance or the level of grey, from black (value 0) to white (level 100). The b^* parameter is the yellow-blue component and the balance between yellow (positive value) and blue (negative value) that increases in relation to the intensity of pigmentation.*

Once the L^* and B^* have been determined the ITA can be ascertained in the following formula:

Figure 1.2. This allows for six different skin types to be classified:

- Very light $ITA^\circ > 55^\circ$
- Light $41^\circ < ITA^\circ < 55^\circ$
- Intermediate $28^\circ < ITA^\circ < 41^\circ$
- Tan $10^\circ < ITA^\circ < 28^\circ$
- Brown $-30^\circ < ITA^\circ < 10^\circ$
- Dark $ITA^\circ < -30^\circ$

Given that this application is attempting to remove as much bias as possible this formula will be used to objectively classify the project's dataset.

$$^\circ ITA = [\arctan(L^* - 50)/b^*] \cdot 90 \cdot 180/3.14159.$$

Figure 1.2: Individual Typology Angle formula. Joo, J. (2021)

Curating the dataset

The dataset was initially collated by browsing online search engines like Google and Bing. The results were mixed, so a criterion was created, it follows:

- No watermarks or text
- Lighting must remain consistent between the images (Not bright or too dark)
- Their face should be facing the camera
- Nothing covering their face
- Avoid group photos

To automate this process a Google Chrome web extension called Image Downloader Continued was used. This allows users to search and filter out images e.g., dimensions, sorting order. Once the filters have been selected just scroll and select the images you want. As soon as the user has all the images just press download and it'll begin downloading all the images. This is an efficient way of collating a dataset, rather than manually downloading images individually. The dataset comprised of a total of 400 images, these were split into 4 classes, Asian, Black, Brown and White. Each class had 100 images, and these were split into 3 folders/sets training, validation and testing 70-15-15 respectfully. Whilst the dataset was complete there was an oversight, personal bias was not considered when assigning the images. No objective method was used to organize the different classes. Therefore, the dataset was useless and needed to be curated again.



Figure 1.3: Imported image, red dot highlights where the LAB values are being obtained. Neal, E (2021)

Research was carried out to find a method (Refer back to research above) to objectively determine someone's skin colour. Once the method (ITA) was discovered, a python script was written in Google collab to speed up curating the new dataset. This script imported an image and plotted a dot onto the image Figure 1.3. At the dots position the L* and B* values were collected. This data was used in the ITA formula to categorize the image into the corresponding folder, Figure 1.4 demonstrates how they are grouped. While this allowed for the dataset to be curated, it was too laborious and was a suboptimal solution to create the new dataset. Due to the script being limited to reading one image at a time. Although there was consideration to adapt the script to sort through multiple images (folders), a far easier solution was uncovered. During the research phase a dataset with similar goals was retrieved, the FairFace dataset. This dataset split the different classes using a similar method which was used in the previously mentioned python script ITA.

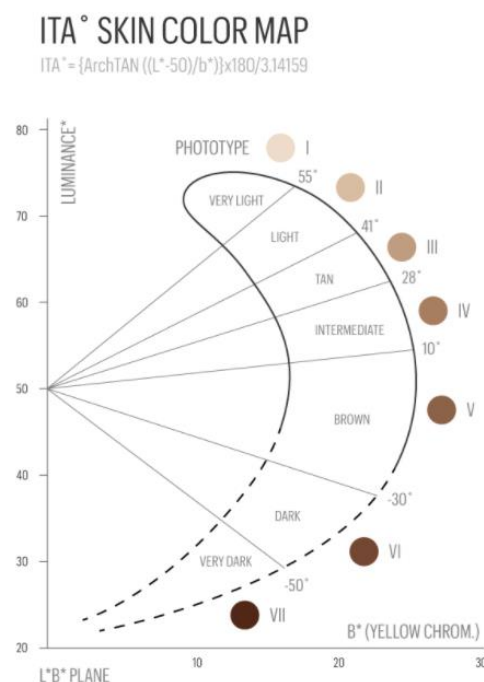


Figure 1.4: Individual Typology Angle (ITA) map. Hasarmi, D (2021)

Since the FairFace dataset had already categorised the data, it was decided to use the same categories to curate the dataset. Here is how the data was divided:

- Black
- East-Asian
- Indian
- Latino-Hispanic
- Middle Eastern
- Southeast-Asian
- White

Much like the initial dataset each class had 100 images, and these were split into 3 folders/sets training, validation and testing 70-15-15 respectfully.

Methods that were used

MLP

The model was initially trained using a Multi-Layer Perceptron network or MLP. This is a neural network where mapping between inputs and output is non-linear. They are composed of; input layers, output layers and one or more hidden layers.

“Multilayer perceptron’s are often applied to supervised learning problems: they train on a set of input-output pairs and learn to model the correlation (or dependencies) between those inputs and outputs.” Nicholson, C. (2020)

This differentiates itself from the single perceptron network, which only solves linear problems.

CNN

The second method that was used was a Convolutional neural network. This is another deep learning network designed for processing visual imagery. It learns patterns within in the image and understands what forms a shape of an object. CNN differentiates itself from other methods by utilising multiple layers. McGregor, M (2021) explains *“It processes data that has a grid-like arrangement then extracts important features”*

Typically, there will be up to 20 or 30 layers, however the most important layer is the convolutional layer. These layers are stacked up on top of each other, each subsequent layer can recognise more complex shapes. Wood, T (2019).

Data Augmentation

Data augmentation is a technique with dealing with a limited dataset or an imbalanced one. It achieves this by augmenting the data inside the dataset. This can include:

- Horizontally/ vertically flipping the image
- Rotating the image
- Resizing
- Cropping
- Adjusting the brightness
- Adding noise

These transformed images are added to the dataset increasing its size. The neural network will treat these new images as distinct images and therefore improve the accuracy of the classifier when dealing with images with these different variables. (Arun, K (2020))

Transfer Learning

Transfer learning is a method of using an existing trained model and transferring that into a new problem as a starting point. Dilmegani, C (2022) *"With transfer learning, we basically try to exploit what has been learned in one task to improve generalization in another. We transfer the weights that a network has learned at 'task A' to a new 'task B.'"* This method saves time and allows the model to improve as it has already identified the different patterns.

Technical implementation

This classifier is written in Python, utilises the Pytorch library and is run on Google Collab. The dataset is loaded from google drive and batch size is set to 32, as each class has around 100 images. The batch size was changed numerous times to check if it could perform better, but from testing it performed better on average than any other amount. Next all the images size and normalized values reflect the input of the pretrained network. Data augmentation then applies the various changes including:

- Random rotation
- CenterCrop
- RandomHorizontalFlip

This will improve the model's accuracy as it'll add variation to the input. Now the transfer learning will be used, more specifically the pretrained resnet18 model. Then the learning rate is set to a low value of 0.0001 as it performed better than if it were at a higher rate of 0.001. It also allows the model to learn correctly. The epochs were set relatively low at 20 because once it reached around 10 -15 it would start to drop off and continue to not improve.

Results

The results were better than the previous attempts, but the improvement was small. Of the 700 images in dataset only 38% were predicted correctly. The classes which performed best were Black (60%) and White (60%). The worst results were from Latino and Indian both with 13%. There are several factors that might have contributed to this poor performance.

Whilst there was an attempt to keep the dataset consistent and follow the criteria that was created, it was still very difficult. As the images would vary with, Lighting, Image quality and the Face/head orientation. With these issues the dataset was inconsistent and might be why the results were so poor. Many checks were made to see if there were any "patterns" occurring inside the dataset that could be removed or any other unsuitable images. Just to see if that could improve its performance, but unfortunately it would only make small improvements.

Application of creative task

This classifier could be used for security purposes where they filter through people's skin colour, so user could narrow down the person's identity. It could be also used in the dermatology field and be improved to recognise different skin diseases.

Conclusion

The project was average at best, the classifier was not accurate. The next step would be to do further research into other similar datasets and classifiers to achieve better results. A further step

would be to create dataset with professional help, and it keep it uniform/ consistent with zero variables. For example:

- Same lighting
- Neutral background
- Same expression being expressed by participant
- Zero glasses or any attire on head and face

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Figure 1.1

Joo, J. (2021) FairFace bar graph Available from:

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Figure 1.2

Joo, J. (2021) Individual topology angle equation Available from:

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Figure 1.3

Neal, E (2021) Image from dataset

Figure 1.4

Hasarmi, D (2021) Scarletred®Vision: A Scalable Digital Solution for Measurement of the Individual Typology Angle (ITA°) and Changes in the Skin Tone Available from:

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