Machine Learning Engineer Nanodegree

Capstone Project

Gender Classification

I. Definition

Project Overview

Gender classification is to determine a person’s gender, e.g., male or female, based on his or her biometric cues. Usually facial images are used to extract features and then a classifier is applied to the extracted features to learn a gender recognizer. It is an active research topic in Computer Vision and Biometrics fields. The gender classification result is often a binary value, e.g., 1 or 0, representing either male or female. Gender recognition is essentially a two-class classification problem. Although other biometric traits could also be used for gender classification, such as gait, face-based approaches are still the most popular for gender discrimination [ref].

Problem Statement

The goal is to create a gender classification based on person face image so it’s a binary classification problem; the tasks involved are the following:

1. Download and preprocess the Adience Benchmark dataset
2. Explore the dataset distribution and make sure the data is balanced
3. Use a pre-trained CNN model to extract features from the images
4. Build a neural network to classify gender given image features
5. Train the network and try different network architecture and configuration
6. Evaluate each network and choose the best one

Evaluation Metrics

I’m working with the accuracy metric provided by keras for binary classification problems, it’s a good metric as I’m ensuring my data is balanced.

Here’s keras definition of binary accuracy: $\frac{\sum(y_{true} == y_{pred})}{n}$

II. Analysis

Data Exploration

The dataset used for training and testing for this project is the Adience Benchmark Dataset. It contains total 26,580 images of 2,284 unique subjects that are collected from Flickr. There are 2 possible gender labels: M, F and 8 possible age ranges: 0-2, 4-6, 8-13, 15-20, 25-32, 38-43, 48-53, 60+. Each image is labelled with the person’s gender and age-range.
I’m only interested in gender labels, there are 9372 images with label f and 8120 with label m.
The images are Face images, cropped and aligned, each of size (816, 816).
I’m only going to work on a subset of this data, since it’s a binary classification problem and I’m using a pre-trained model, I will use 6000 images for training, 2000 for validation and 2000 for testing, where I will sample each subset such that half of it with label f and the other half with label m.

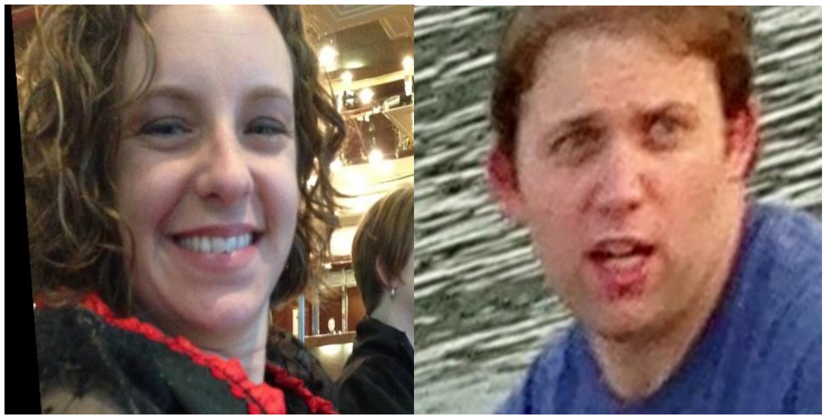
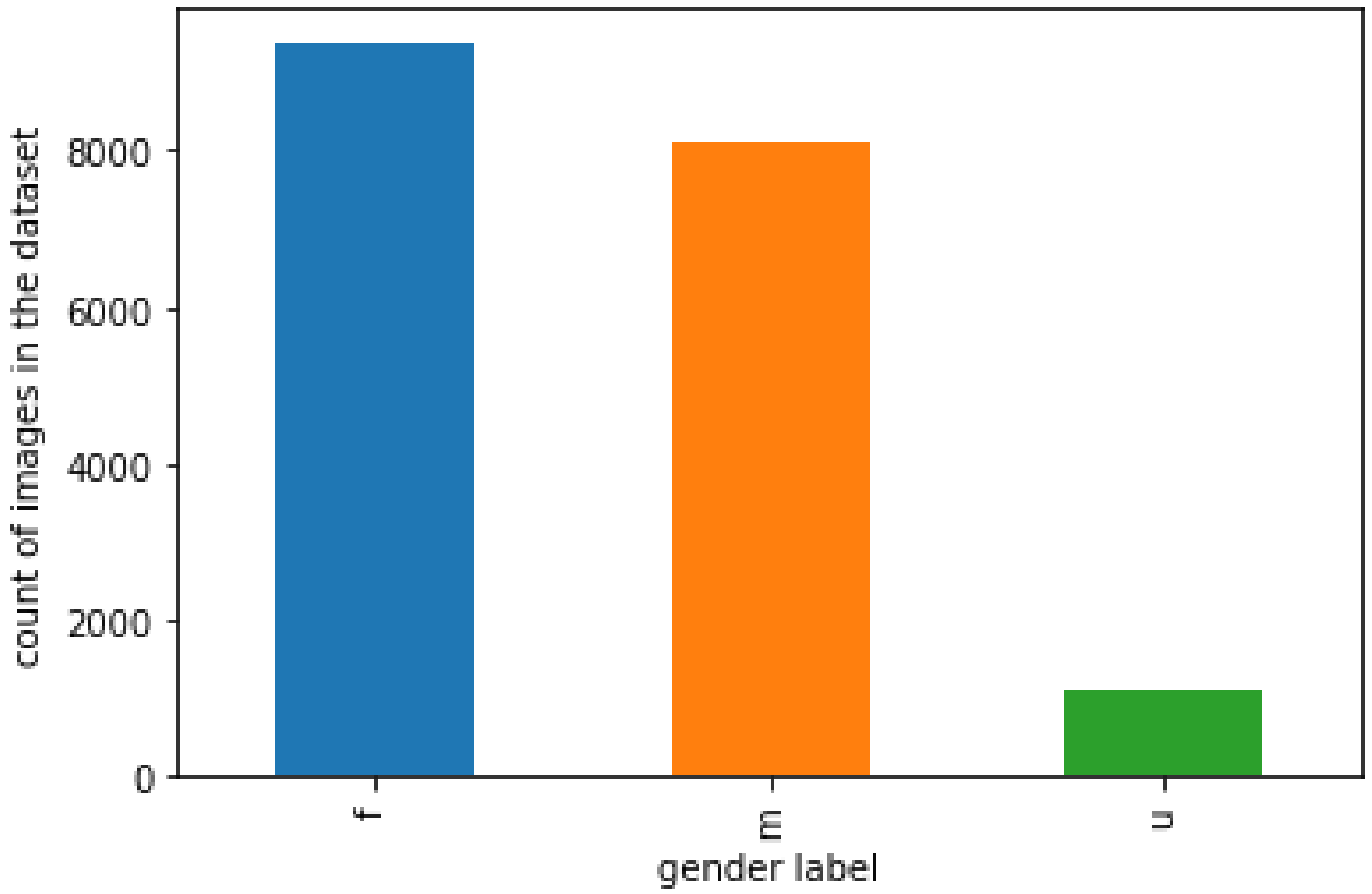


Figure 1 Images from the Adience Benchmark dataset

Exploratory Visualization

I’m only working to classify gender whether it’s male or female, so I’m only interested in gender distribution of the data.

This bar plot shows how many of the images are labeled m and which are labeled f and some are unknown.



As we can see in this bar plot, there are around 9000 images with label ‘f’, around 8000 images with label ‘m’ and around 1200 images with ‘unknown’ label.
We can see from this plot that our data is almost balanced, and there some images with no gender label that we need to handle before using this dataset, and since there are only around 1200 images with ‘unknown’ label I will just ignore them as we still have good number of images without them for our task.

Algorithms and Technique

For this task we are going to work with face images, so I will use convolutional neural network as its state of the art for most of the image processing tasks.

Core building block of convolutional neural network are the convolutional layer that apply a convolution operation to the input, passing the result to the next layer. The convolution emulates the response of an individual neuron to visual stimuli.

Max pooling layer is an important block in CNN, which reduces the dimensions.

A fully-connected layer usually comes as final layer/s and work as normal neural network.

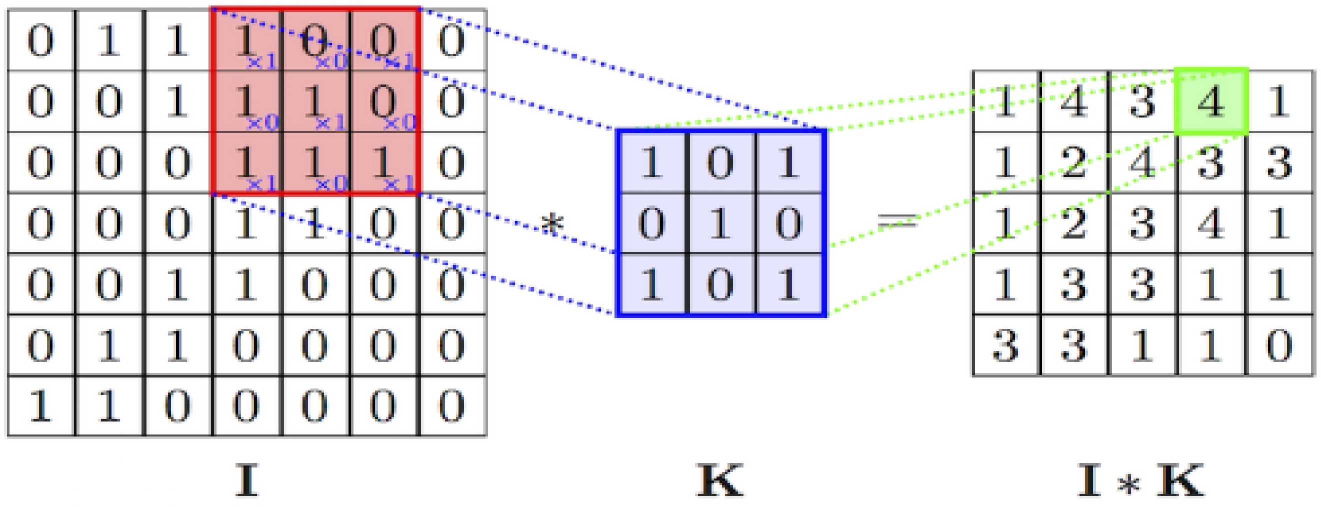


Figure 2 Convolutional layer

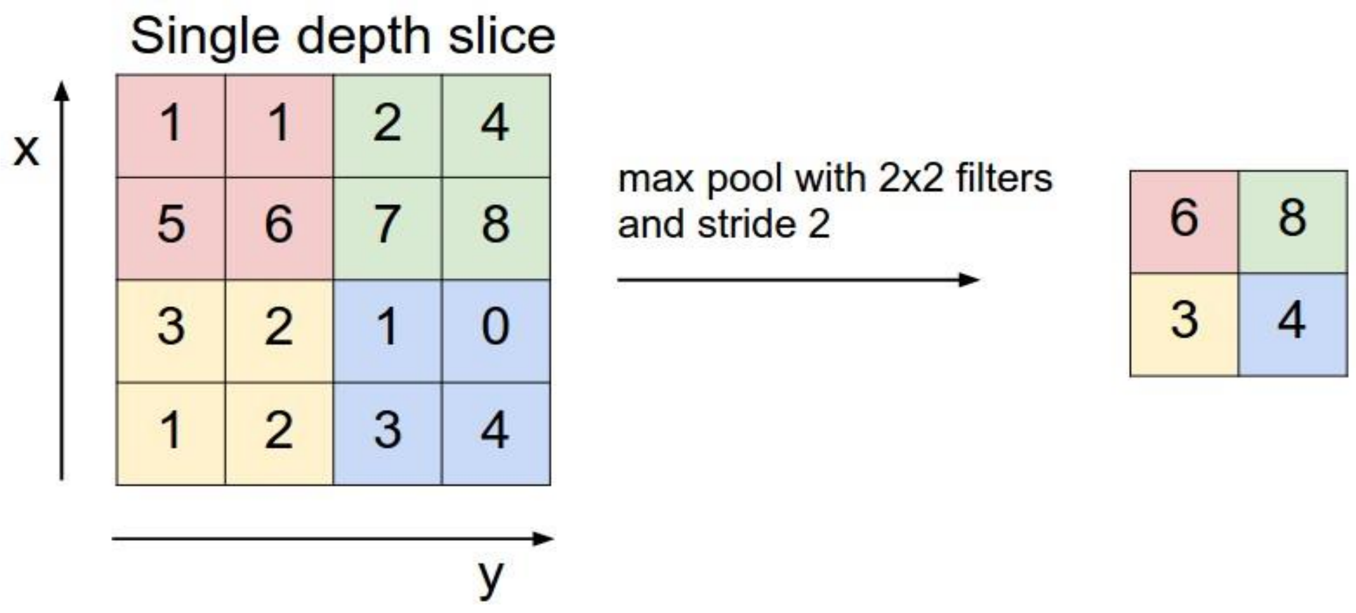
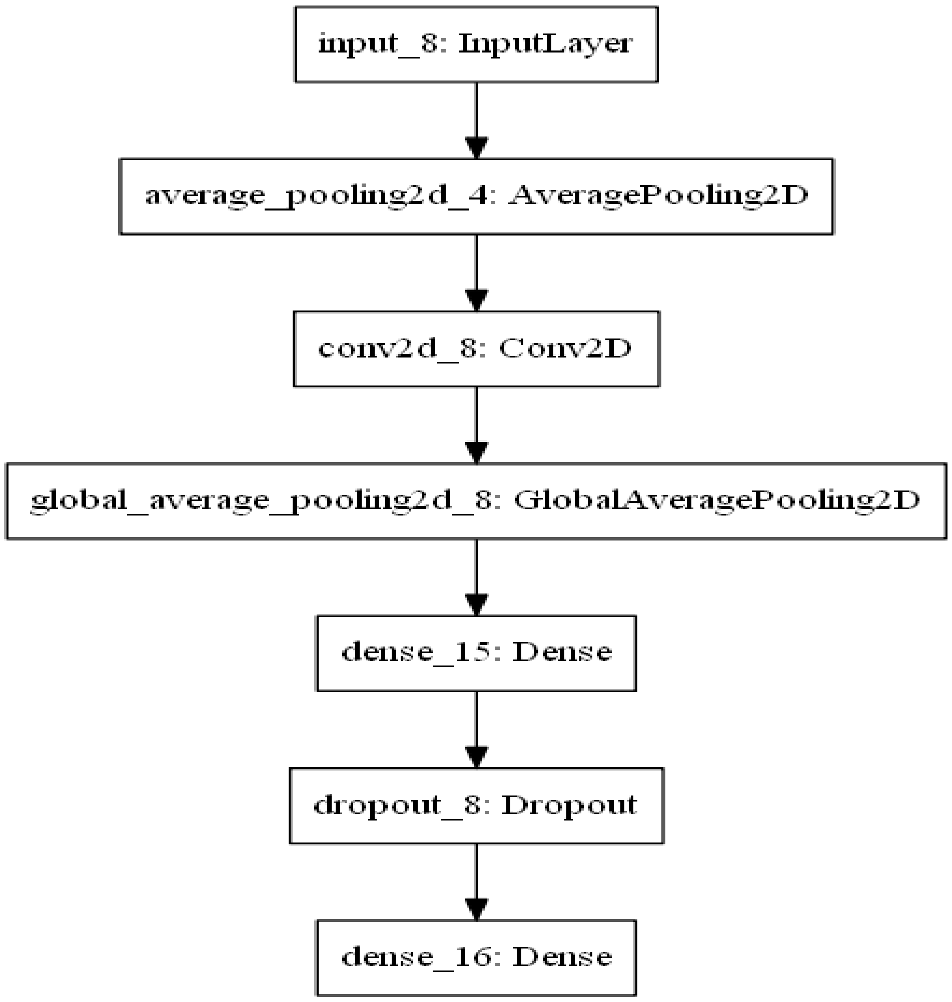


Figure 3 Max pooling layer

As this problem works with people face images I'm going to use a pre-trained CNN model for image classification (InceptionResNetV2) trained on imagenet dataset to extract useful features from images instead of training a new CNN that needs a lot of data and long time to train.

And then build a neural network that given the image features extracted from InceptionV3 can classify whether the person in this image is male or female, and will try to add Dropout layer with different rates to avoid over-fitting to the data and will be checking different rates for Dropout and different learning rates and optimizers based on the validation accuracy.

Benchmark Model


input_8: InputLayer
average_pooling2d_4: AveragePooling2D
conv2d_8: Conv2D
global_average_pooling2d_8: GlobalAveragePooling2D
dense_15: Dense
dropout_8: Dropout
dense_16: Dense

I used a simple CNN model with input (224,224,3) then decreasing size by using average pooling layer then using a convolution layer with 64 filters then a global average pooling layer then a dense layer with 32 neurons and a dropout layer then a dense layer with sigmoid activation.

I got accuracy 0.54 and val_acc 0.57 after 16 epoch when training on 5984 image and validation on 1984 with batch size 32

III. Methodology

Data Preprocessing

Data labels comes in 5 txt files (fold_0_data.txt - fold_4_data.txt), I merged all of them into one txt file called data.txt

Then the preprocessing as done in "pre_data" notebook consist of the following:

1. Loading the data and visualizing distribution of the labels of gender
2. There are some images with label 'unknown' we ignore them
3. View the distribution of the data labels
4. Define the path image from the data columns and explore some images
5. Sample 10000 images of the 17492 images such that 5000 are with label f and 5000 are label m and use 6000 as training set and 2000 as validation set and 2000 as test set
6. Save this cleaned data to try on different pretrained models

Implementation

After preparing the data and dividing it into training set, validation set and testing set.

Now we will choose a pretrained model offered by keras trained on imagenet dataset for image classification, we use it to extract features given the initial images.

I tried using VGG16, VGG19 and InceptionResNetV2 as pretrained models.

Then using the extracted features we train a simple dense layer to classify the gender, and also try to add some Dropout layer to avoid over-fitting.

Here are the process for the implementation:

1. Choose a model from the pretrained models offered by keras
2. Load the model from keras and remove the predication layer
3. Load the data we saved earlier
4. The images of the dataset are of different size, so we need to resize them to the default pretrained model input shape, keras offers this with the load_image function.
5. Also the images needs to normalized, but luckily keras also provide function called preprocess_input that take care of it.
6. After preprocess_input we just use the loaded model to get the features of the image
7. Now build a dense layer with dropout layer and train it to predict gender and choose a threshold to differentiate the two classes given the model predication probability.
8. Try different values of number of neurons on dense layer and dropout layer rate and choose best one based on the validation accuracy
9. Test the chosen best model on test data
10. Develop a function that given any image can extract it's feature and use the new trained model to predict the gender based on defined threshold

Steps 1-5 was the most harder steps, as there are couple of different pretrained models to try and test their performance on the dataset, and downloading each of them and using them for prediction took too much time as I'm working on a CPU and some of the models are very complex and take long time predicting..

Step 8 also took me a lot of trial and error, as the extracted features from the pretrained models tend to over-fit quickly, I tried many different dropout rates ranging from 0.3 – 0.9 and different number of neurons on the dense layer such as 128, 512, 1024 and choose the best architecture based on the validation performance.

As I was sampling 10000 images from the 17000 images only, I tried to sample the data three times and extracting features each time and training new model, to make sure that the data I sampled wasn't just an easy to learn data or something

Refinement

Here are some of the steps I went through:

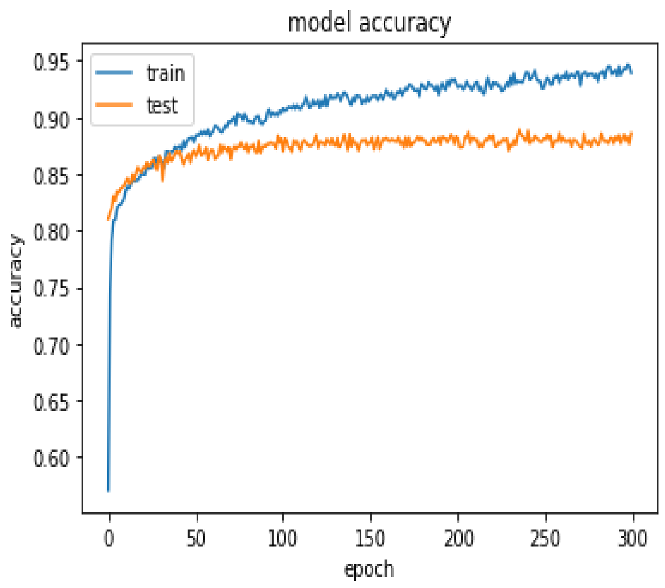
1. Using VGG16 to extract features then I used a dense layer with 512 neurons but the model over-fitted the training data very quickly. Adding a dropout layer with different rates, I started adding dropout rate with 0.3 but also the model over-fitted. Then started increasing the dropout from 0.3 up to 0.9 and trying different number of neurons such as 128,512 and 1024 with different dropout rate, the best rate I got was 0.9 and 128 epoch with 1024 neurons dense layer to get best validation accuracy of 0.862
2. Then tried using InceptionResNetV2 to extract features: I also used a different dropout rates and different number of neurons in dense layer, best result I got was with 1024 neurons in the dense layer and Dropout 0.8 after 300 epoch I got best validation accuracy of 0.889
3. Also for both VGG16 and InceptionResNetV2 I tried using two dense layers with 512 neurons and 128 neurons on the extracted features but it over-fitted very quickly, I added dropout to both dense layers with different values but the best result I got was worse than using just one layer, as this working on extracted features so it doesn't need all this neurons to learn.
4. Also when training I tried using different batch-size as this can effect learning, I tried using batch-size of 128 and 256 at first, then used 512 and it didn't make much different so finally I used 512.
5. I also tried using different optimizers, I used 'adam' at first, then tried using 'SGD' with default values, but it did horribly on this dataset, so I went back to use 'adam' with its default value as value of learning was quite reasonable on each epoch.

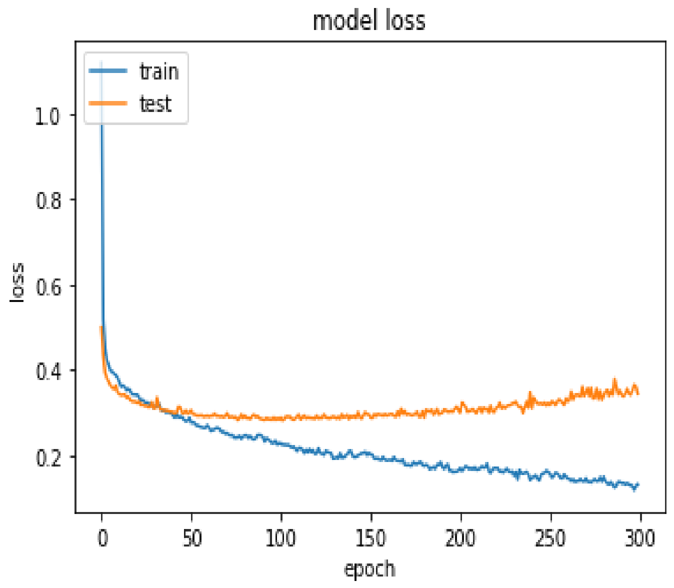
IV. Results

Model Evaluation and Validation

During development a validation set was used to choose the best model.

The best model validation accuracy was 0.889 and on the test set achieved 0.8855 accuracy.





Here's a complete description of the final approach chosen:

- Using InceptionResNetV2 as a pretrained model to extract features and using preprocess_input for this model to handle image before predicting.
- After extracting the features used a network with one dense layer of 1024 neurons and dropout layer of 0.8 and number of epochs was 300

To verify the robustness of the model I tested on the test set and also on couple of image from outside the dataset and it achieved pretty good results.

Justification

Given that our Benchmark model only achieved validation accuracy of 0.57 as described in the Benchmark section, and here we could achieve 0.889 validation accuracy so we make a big improvement

Also given that our dataset is only of faces images aligned but still I test it on general images of persons and it predict the right gender.

V. Conclusion

Free-Form Visualization

Here are 2 complete pictures of males that model can identify they are males even when that the trained model was trained on faces images only

Also two pictures of females the models could identify as females from the whole picture not just their faces

Reflection

The process for this project can be summarized using the following steps:

1. Think about interesting problem to solve, search about relevant work on this problem, find a good dataset to work on
2. Downloading the dataset and exploring it
3. Preprocessing the dataset and dividing it into training, validation and test set
4. Choosing a pretrained model to extract features and preprocessing the images for the model
5. Building a network that given the extracted features can classify whether it's male or female in the image and testing the model

I found step 1 to be somewhat difficult as it's hard to find good dataset to a problem you like.

Also step 2,3 depends on step 1 as there are some dataset that are not well organized and can be frustrated to work with and can cause the model training process to be hard or even impossible if there's a problem with the data that make the model can't learn

I liked step 5 as using features extracted from pretrained model increased the accuracy of the model by a big factor even on the first few epochs and even without training any layers on that model.

Improvement

To achieve a better accuracy we can try the following:

- We can fine-tune the last layers of the pretrained model we are using, but I couldn't do that as I'm working on CPU
- Increase the number of training images we are using, since I only used subset of the data
- Try different dataset
- For new images detect faces in them and align them before predicting