Building Class Attendance Tool with Face Recognition of students

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Objective:

Taking attendance of students can take around 5-10 minutes daily of the class. Therefore, automating the process and recording daily information in a database can not only save instructor's time and effort but also will help in maintaining attendance information in more useful manner to perform different analysis.

Our goal is to take real-time input or pictures of the class and develop a face recognition system that identifies the present students thus helps in taking attendance.

This project mainly allows user to do face recognition on two modes which support different functionalities:

1. Camera mode (Online method)
2. Image mode (Offline method)

Both the camera mode and the image mode allow users to do face recognition based on current dataset and to input new users' faces into the existing dataset. The camera mode is implemented for real-time face recognition and the image mode is implemented for situations when the user cannot show up in front of the camera. However, if there is not enough number of images in the dataset, the camera mode may outperform the image mode. The detailed instruction can be found in Readme.

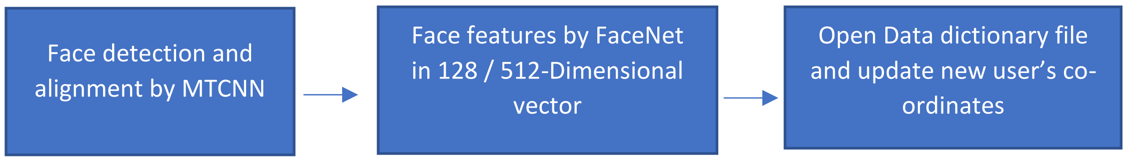
Approach:

While using the tool, the user needs to provide the input type to perform either of below tasks:

1. Enter a new user's face
2. Perform face recognition on existing users

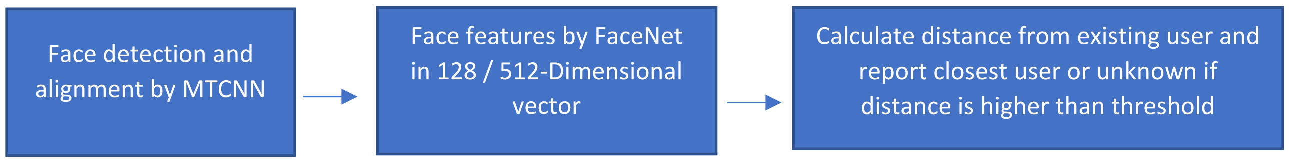
Both of these tasks are can be performed for camera and image mode.

1. <u>Enter a new user's face</u>


Face detection and alignment by MTCNN
Face features by FaceNet in 128 / 512-Dimensional vector
Open Data dictionary file and update new user's co-ordinates

In this way, embedding for new user will be generated and recorded in file maintained in JSON format.

2. Perform face recognition on existing users


Face detection and alignment by MTCNN
Face features by FaceNet in 128 / 512-Dimensional vector
Calculate distance from existing user and report closest user or unknown if distance is higher than threshold

The first two tasks are same as getting input. For all the faces detected, its features are generated using FaceNet and these embedding are used to calculate distance.

Steps:

Step 1: Face Detection

MTCNN uses three convolutional networks (RNet, ONet, PNet) to detect faces on both live camera and image. It outputs the bounding boxes to mark the face and generates facial landmarks to be used as input to do face alignment. There are three stages to be done in face detection with MTCNN.

In stage one, images/live camera inputs are passed in to the program which automatically creates multiple scaled copies of the image. The copies are then fed into P-Net which is the first convolutional network in MTCNN. At the end of stage one, P-Net outputs bounding boxes with high confidence after removing highly overlapped boxes.

In stage two, out-of-bound bounding boxes are padded and all the bounding boxes resulting from P-Net are passed to the second convolutional network (R-Net). Again, bounding boxes with low confidence are deleted and Non-Maximum Suppression is employed to remove highly overlapped bounding boxes.

Stage three is similar to stage two, except that stage three has a more complicated convolutional network (O-Net) whose output is more precise.

Step 2: Face Alignment

Align the face in a way that it is as closely centered as possible using landmarks from MTCNN in step 1.

In this step, we create a class to do face alignment after getting landmarks from MTCNN. The average positions of face points are extracted from Dlib open source code which is commonly used aspect ratio for 5 landmarks. This class is called when doing face recognition and inputting face features into the database for both camera mode and picture mode.

Step 3: Face Feature generation

Pre-trained models of FaceNet are used to generate Embedding in 128-Dimensional/512-Dimensional vector for each transformed image as the face feature. We tried three different model weights including one 128D and two 512D pre-trained weights. The two 512D weights are generated using FaceNet Inception Resnet V1 architecture on CASIA-WebFace and VGGFace2 training dataset. Details for the

128D model weights are missing, we only know it is trained on the FaceNet Inception Resnet V1 architecture.

The CASIA-WebFace dataset consists of 453 453 images over 10 575 identities after face detection. According to the author of the models, the best performing model has been trained on the VGGFace2 dataset consisting of ~3.3M faces and ~9000 classes. Therefore, we implement all three pretrained weights for camera mode, but only implement weights trained on VGGFace2 for image mode.

Step 4: Face Feature comparison

Use camera mode/image mode to compare the face features with all face features existed in the dataset storing as a dictionary to find if there is a match or not. If there is a match, then the name will be presented; and if not, "Unknown" will be presented.

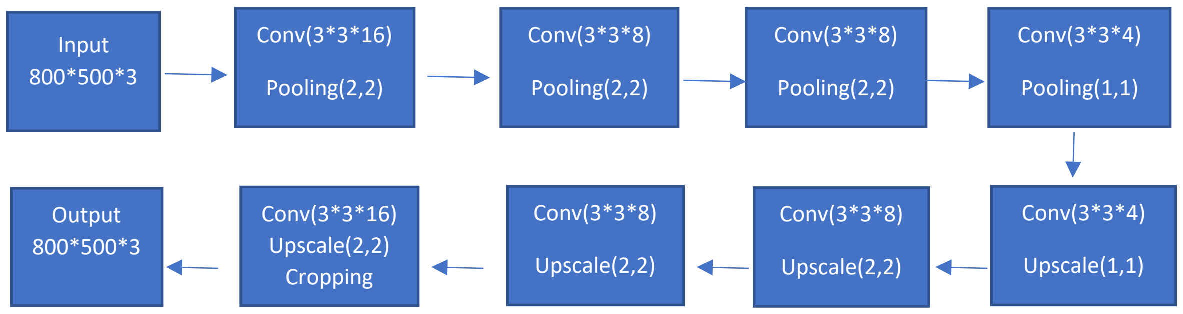
***Autoencoder:**

Moreover, since the image mode is not working as well as the camera mode, we also used autoencoder the generate extra images for the program to raise the accuracy.

The Autoencoder is trained on UTKFace dataset with following architecture.

The link to dataset: https://susanqq.github.io/UTKFace/

First all input are resized for shape 800*500*3 to have same dimension and output is saved to create deformed images.



Building Blocks:

1. <u>MTCNN</u>

Multi-task Cascaded Convolutional Networks (MTCNN) is used for face detection and alignment in the project. MTCNN applies a cascaded structure of deep convolutional networks with three stages and is able to achieve both face detection and alignment with multi-task learning where stochastic gradient descent is used for training CNNs in the networks.

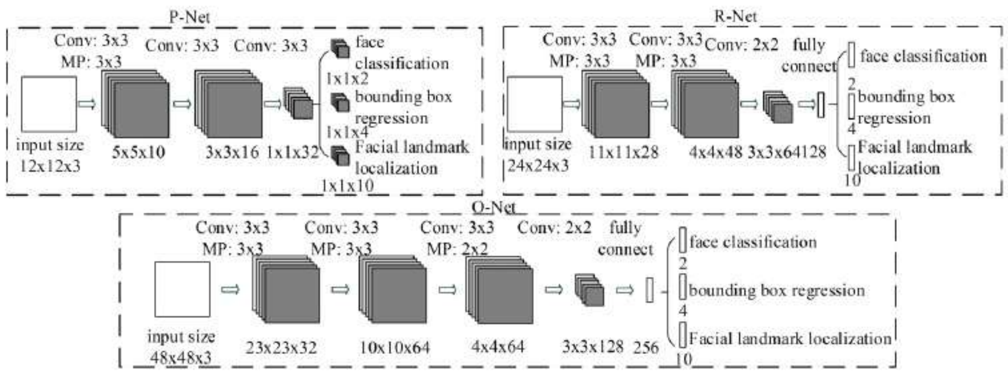
Stages:

i) P -Net
ii) R -Net
iii) O -Net

The first stage is a fully convolutional network (P-Net) to quickly produce candidate windows and their bounding box regression vectors which are used for adjusting the windows. Multiple scaled copies of the image are taken as input of P-Net. Then, non-maximum suppression (NMS) is applied to combine highly overlapped candidate windows by deleting candidate windows that have high overlap with the most confident candidates. The idea is capture small face in bigger windows and big face in small windows with fixed kernel size.

The second stage is a more complicated CNN (R-Net) which takes all the coordinates of candidate windows from P-Net as input to refine the candidate windows by using the bounding box regression and NMS.

The last stage, which takes the result from R-Net as input, is to use an even more complicated CNN (O-Net) to refine the candidate windows and generate facial landmarks positions.



Loss Functions:

Loss function minimized in training includes three parts: face/non-face classification, bounding box regression and facial landmark localization.

Face classification: $L_i^{det} = -(y_i^{det}\log(p_i) + \left(1 - y_i^{det}\right)(1 - \log(p_i)))$ where p_i is the probability of recognizing x_i as face, and y_i is the label for x_i.

Bounding box regression: $L_i^{box} = ||\hat{y}_i^{box} - y_i^{box}||_2^2$

Facial landmark localization: $L_i^{landmark} = ||\hat{y}_i^{landmark} - y_i^{landmark}||_2^2$

Combined loss function: $min \sum_{i=1}^{N} \sum_{j \in \{det, box, landmark\}} \alpha_j \beta_i^j L_i^j$ where N is the number of training examples and α_j indicates the importance of the task.

Reference:

https://www.lao-wang.com/wp-content/uploads/2017/07/1604.02878.pdf

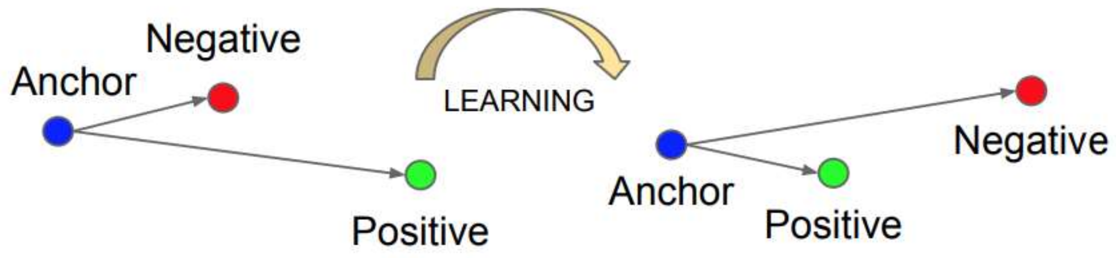
2. FaceNet

Reference: https://arxiv.org/pdf/1503.03832.pdf

As a one-shot learning problem, face recognition is usually done using so called Siamese network which indicates running the identical CNN on two different inputs and comparing the results.

FaceNet, introduced in 2015 by Google, uses a deep convolutional network to learn a Euclidean embedding for each face whose similarity is measured by the L2 distance in the embedding space. A triplet-based loss function is trained for the 128-D embedding representing the face feature. Capturing the similarities between faces, the 128-D embedding can be used for clustering faces. In other word, L2 distance in the embedding space will be closer for similar faces than for non-similar faces.

Triplet Loss:



Triplet Loss is a loss function where three types of inputs exist: anchor, positive and negative. While training, Triplet Loss minimizes the distance between a positive and an anchor and maximizes the distance between an anchor and a negative. Motivated by the nearest-neighbor classification, Triplet Loss want to ensure that an anchor face (x_i^a) is closer to all positive faces (x_i^p) than to any of the negative faces (x_i^n) with the constraint below for all set of triplets in the training dataset.

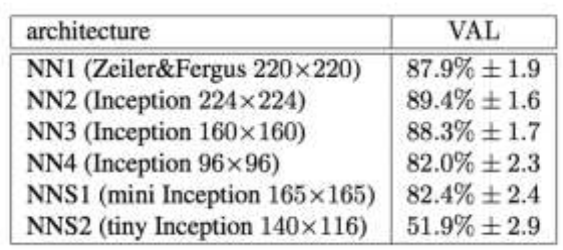
$$||f(x_i^a) - f\left(x_i^p\right)||_2^2 \ + \ \alpha < ||f(x_i^a) - f(x_i^n)||_2^2$$

where α is a margin that is enforced between positive and negative pairs.

Therefore, the loss is $\mathrm{L} = \sum_i^N [||f(x_i^a) - f\left(x_i^p\right)||_2^2 - ||f(x_i^a) - f(x_i^n)||_2^2 \ + \alpha]_+$

Inception Network:

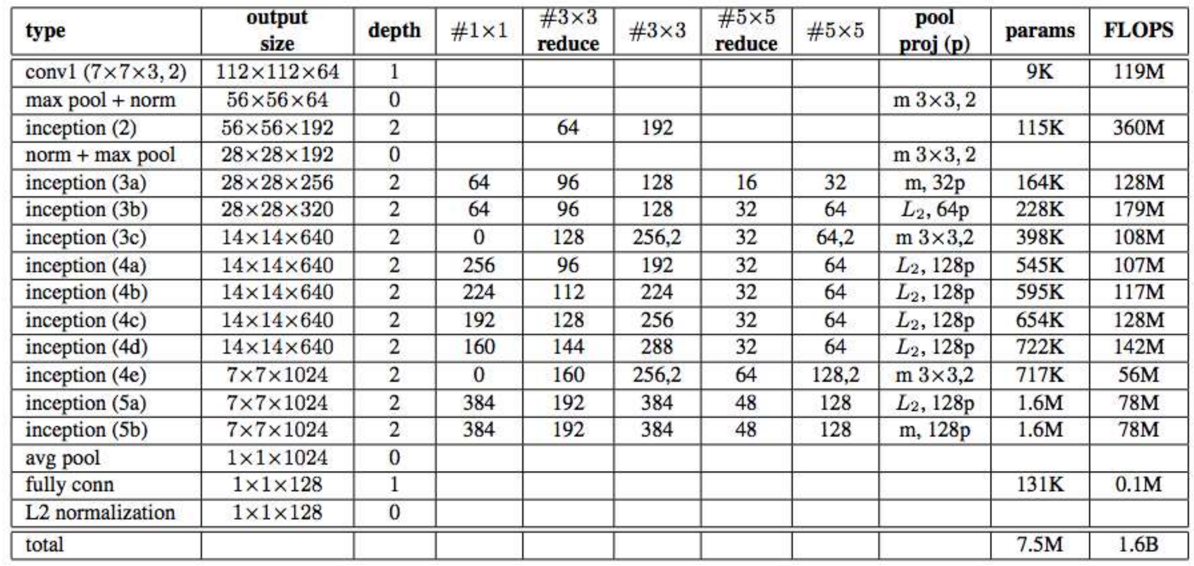
The original paper experiments on five different network architectures and tests the performance for each of them. The performance is shown in the picture below.



architecture	VAL
NN1 (Zeiler&Fergus 220×220)	87.9% ± 1.9
NN2 (Inception 224×224)	89.4% ± 1.6
NN3 (Inception 160×160)	88.3% ± 1.7
NN4 (Inception 96×96)	82.0% ± 2.3
NNS1 (mini Inception 165×165)	82.4% ± 2.4
NNS2 (tiny Inception 140×116)	51.9% ± 2.9

We chose pre-trained weights on NN2 model architecture which is the inception network because of the highest performance among all the model architectures tested by the authors.

Based on GoogLeNet style Inception models which have 20 × fewer parameters (6.6M – 7.5M), FaceNet Inception model is almost the same as the one discussed in the paper *Going deeper with convolutions.*



type	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj (p)	params	FLOPS
conv1 (7×7×3, 2)	112×112×64	1							9K	119M
max pool + norm	56×56×64	0						m 3×3, 2		
inception (2)	56×56×192	2		64	192				115K	360M
norm + max pool	28×28×192	0						m 3×3, 2		
inception (3a)	28×28×256	2	64	96	128	16	32	m, 32p	164K	128M
inception (3b)	28×28×320	2	64	96	128	32	64	L_2, 64p	228K	179M
inception (3c)	14×14×640	2	0	128	256,2	32	64,2	m 3×3,2	398K	108M
inception (4a)	14×14×640	2	256	96	192	32	64	L_2, 128p	545K	107M
inception (4b)	14×14×640	2	224	112	224	32	64	L_2, 128p	595K	117M
inception (4c)	14×14×640	2	192	128	256	32	64	L_2, 128p	654K	128M
inception (4d)	14×14×640	2	160	144	288	32	64	L_2, 128p	722K	142M
inception (4e)	7×7×1024	2	0	160	256,2	64	128,2	m 3×3,2	717K	56M
inception (5a)	7×7×1024	2	384	192	384	48	128	L_2, 128p	1.6M	78M
inception (5b)	7×7×1024	2	384	192	384	48	128	m, 128p	1.6M	78M
avg pool	1×1×1024	0								
fully conn	1×1×128	1							131K	0.1M
L2 normalization	1×1×128	0								
total									7.5M	1.6B

Conclusion:

The camera mode is working very well if face is trained by moving your it in different directions, model is able to capture face features efficiently. Faces are tested by putting on glasses, going far from camera, hiding part of face with hands etc.

Performance of image mode is highly dependent on variety of images provided in training. It also requires face to be in centering, left and right facing to work. Although, there is a good improvement in performance by image rotation and generating Autoencoder transformed images, there is scope for improvement in image mode.