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Deep Neural Network Framework for Hospital Queue Management

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***Abstract*: Recognition is the process of identification or checking the identity of a person who uses his face. Automatic face and gender recognition from facial images are used to expand its use in various programs and teams, notably through the development of online sites for human interaction and web-based media. In our proposed model the whole process is to develop a facial recognition. This model consists of several key steps which are developed using the most advanced techniques: Multi-task Cascaded Convolutional Networks for facial detection and Convolution Neural Network (CNN) for generating face embeddings. This proposed system is the practical application of these next generation deep learning approaches for facial recognition tasks. However, the performance of the existing system with the images of the physical world face, images, is not entirely excellent, especially when compared to the result of the face detection task. With the Deep Convolution of Neural Networks (DCNN) process, a development in grouping tasks according to gender classification that is a motivation behind the choice, a Proposed Convolution Neural Network Visual Geometry Group Network (VGGNet) architecture that can be used in extreme cases when the amount of training data used to learn DCNNs based on the VGGNet architecture is limited.**

***Keywords*: Convolution Neural Network, Deep Learning approach, Deep Convolution Neural Network, Face recognition, Face verification, Face identification, Gender recognition, Pretrained model, Transfer Learning, Visual Geometry Group Network.**

1. Introduction

Face recognition is an innovation of computer technology, used in various fields an application that recognizes human faces in digital images. The face recognition additionally alludes to the psychological system by means of which people locate and pay attention to in a visual scene. Identifying frontal human faces, it is no different from face recognition, in which the image of an individual is gradually co-ordinated. Any change to the face component in the information base invalidates the comparison process. Newest process is to recognizes the multiple simultaneous faces with their gender. The face recognition of two decades is extremely proven and fascinating, there are groups of scans for different applications like face recognition, face tracking and identity of human faces. Liveliness of the automated gender category is essential project in computer vision that has obtained enormous interest recently [1]-[7]. It plays a fundamental role in a variety of real-world applications such as targeted advertising, forensics, visual surveillance, search-based content and Human-Computer Interaction system. Gender classification based on various changes in viewpoints, facial expressions, pose, age, background and appearance of the face image. Infinite rendering conditions are more difficult. Automatic gender classification has been used in computer vision [6], [7], [12]. The writing reported that many discovered valuable calculations for gender classification, with geometric modelling methods being the most used.

The representation of the gender orientation in such cases depends strongly on the exact position of these parts of the face. Finding the landmarks on face is major challenge, whereas in the space and time-based strategy which is more likely to be done in real time, is carried out simultaneously, but a lot of time, data are required in both the tracking and the identification stage. There are two primary stages in the current face recognition strategies: recognize human faces as shown in Fig. 1. and identify the detected faces as shown in Fig. 2. To distinguish human faces, it is important to look for the face in the entire picture and it might be misinterpreted when different articles are like the face.

Fig. 1. Recognize human face

With the intention of co-ordinating the capability of human vision, visible area version and hypothesis on static pix or video frames have acquired large attention as of overdue. Specifically, surveillance frameworks depend increasingly more on multi view learning for the situation that the source space is not quite the same as the objective area in visual recognition. Ordinary face detection methods see faces by recognizing human faces, following the faces, catching a casing of the picture and a while later expelling highlights and

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planning appearances in inactive pictures. Nonlinear complex learning lastly coordinated with the synthetic picture.

Face detection is used to predict whether male or female a person is standing in a queue. Help of current technology which can find the person is based on the gender and age while standing in queue. It helps to find the person age more than 50, can give the first preference in hospital or some other government institution based on the age. It helps to predict person Gender as well as Age. Our approach is to predict the person gender with age from that allow the patient to join the queue prior.

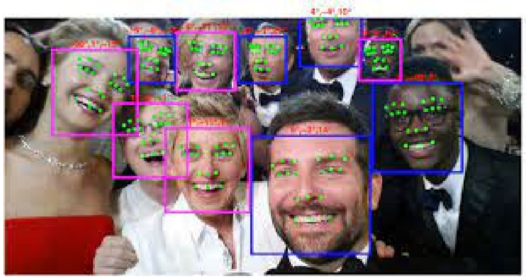

Fig. 2. Face detection

2. Literature Survey

Himanshu et al. [1] proposed that gender prediction is an essential challenge for human beings, as many social interactions are based on gender. In the context of biometrics, gender can be taken into consideration as clean biometric trait. Soft biometric trends such as sex, age and ethnicity may not be special for the individual, but it can be combined alongside number one biometric trends to improve recognition accuracy. Further, multi-classifier fusion is invoked for overall performance improvement.

Teddy Mantoro et al. [2] have a look at on more than one faces reputation the use of a hybrid approach of Haar Cascades and Eigenface. This have a look at objectives to enhance the overall performance of face reputation system the use of the Haar Cascades and Eigenface approach. OpenCV may be used as a face detector kind that works with the Haar cascade classifier. From an image, a face detector will test each part of the image and classify it as "face" or "not face". Non-frontal facial images can be reconstructed to frontal face images to increase the accuracy of the facial recognition. Another way to increase the accuracy of the face recognition can be through filtering techniques.

J. Kavitha and T. T. Mirnalinee [3] reconstruct the non-frontal cause face pictures to frontal face images to boost the face recognition accuracy. By estimating the amendment in pose with regard to yaw, pitch and roll angles supported the landmark points best viewed aspect of the pose is identified. The proposed algorithm is frontal face reconstruction which is fully automatic. Experimental results proved the effectiveness of the proposed algorithm which named as frontal face reconstruction, it works for both uncontrolled and controlled pose.

Gil Levi and Tal Hassner [4] use shallow CNN's for age and gender class. There are three convolutional layers that is absolutely related layers. They show a great development in the overall performance of the Audience benchmark for age and gender while the usage of deep function representations found out through the CNN. A multitask getting to know scheme the usage of CNN's for simultaneously appearing estimating pose, smile detection, and occlusions. When mixed with variations in age, hair, pores and skin color, and facial marks, it's miles clear that fashions skilled in this information want to be invariant to such modifications and generalize properly throughout facial characteristics.

A Rowley and Kanade [5] indicated that face popularity strategies can be characterised through function-primarily based totally and holistic approaches. The early invented techniques had been function primarily based totally. These strategies offer an example of a weak dimensional face totally based on ratios of angles, areas and distance. But in practical, this illustration is explicitly described and now no longer accurate.

Y. H. Kwon and N. da Vitoria Lobo [6] have developed the age classification model based on eyes, mouth, nose, mouth, wrinkles features. They focus on only three age groups which classified as babies, youth and senior-adults. The Experimental results shows the enough accuracy for finding the age correctly from the facial image.

Guo et al. [10] designed an automatic age estimation model from image which predict the age by using new learning method called manifold learning. Also, they designed locally adjusted robust regressor (LARR) for enhance overall performance of the age prediction.

Chen et al. [12] have proposed a novel approach for detecting the age from facial images. They take only normal age labels from the benchmark dataset, then they applied a novel ranking-CNN methods for predict the age. Finally experimental results acquire a slight approximation error when compared to previous approaches.

Fu et al. [13] used a contrasting part in the faces such as eye wrinkles for detecting the human age. However, they used a Bio inspired features for analyzing the parts of the face. Those features are important because which covers 30% of the parts in human face when compared other features and internal face.

Geng et al. [14] have been proposed method called aging pattern subspace which estimate the age automatically. First, they analyse the sequence of aging features because which holds unique characteristics. Here the algorithm learns the

Table 1
Summary of existing HQM approaches

Reference	Model	Method	Dataset
[27]	MTCNN	Multi-task cascaded CNN	MFD
[32]	GANs Map	Map and editing modules	CelebA
[33]	Pre-trained CNNs	CNNs	RMFRD
[34]	VGG-16, AlexNet, ResNet-50	Deep features of facial areas	RMFRD, SMFRD
[35]	VGG-16 and FaceNet	Learning cosine distance	Collected dataset
[36]	FaceMaskNet-21	Deep metric learning	Collected dataset
[17]	Attention-based	Face-eye-based multi-granularity	MFDD, RMFRD

pattern by subspace. For unseen human aging pattern can be recognized by reckoning in the subspace. While the position of the facial image in this aging model indicates its age.

Our proposed face detection with its gender classification is the recent methods based on deep Convolutional Neural Networks. Various methods which are based on deep Convolutional Neural Networks have achieved remarkable results for this face detection task. Table 1 summarizes the various models with dataset can be used in other research works.

3. Methodology

The Proposed method consist of visual geometry group face, feature extraction and classification, pre-trained models and transfer learning modules. Object detection is to enhance the detect the person from the image. Face recognition is to detect the person face in image. In feature extraction module all the features are extracted using Deep face estimation technique. Classification module is to classify the gender and then finally predict the age as shown in Fig. 3.

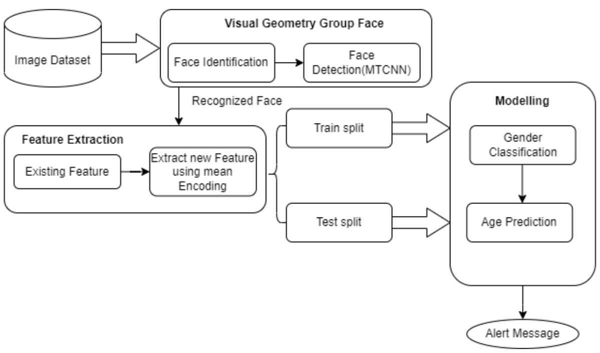

Fig. 3. Workflow for hospital queue management system

A. *Visual Geometry Group Face*

Face recognition is the overall task of recognizing and confirming individual's people from photos of their face using VGGFACE method as shown in Fig. 4. Face recognition depicts two primary modes for face recognition, as:

- Face Verification [2]. A one-to-one mapping for a given face against a known identity or not.
- Face Identification. A one-to-many mapping for a given face against a database of Known faces.

A face recognition frame is anticipated to fete faces present in screen and tape recordings accordingly. It can operate in either or two modes:

1. face verification (or authentication)
2. face identification (or recognition).

Face recognition is the overall undertaking of recognizing and checking individuals from photos of their face. Face recognition depicts two principle modes for face recognition [27].

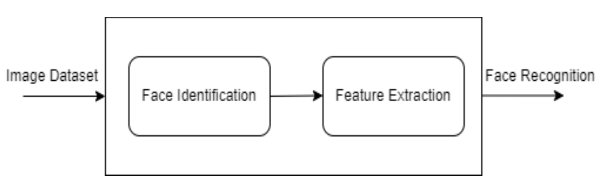

Fig. 4. Feature recognition and feature extraction

A VGGFace model can be made utilizing the VGGFace constructor and indicating the kind of model to make through the model contention. Face recognition is the computer vision errand of identifying and verifying an individual dependent on a photo of their face. As of late, Deep learning CNN have outperformed traditional strategies and accomplishing best in class results on standard face recognition datasets. Although the model can be challenging to implement and resource intensive to train, it is a very well may be handily utilized in standard deep learning libraries such as Keras using unreservedly accessible pre-prepared models and outsider open-source libraries. The keras-vggface library gives three pre-prepared VGGModels, a VGGFace1 model. Model ='vgg16' (the default), and VGGFace2 models 'resnet50'. Photographs of VIPs taken from Wikipedia. The model, for example, 'vgg16' and 'resnet50', at that point look at results. that the 'vgg16' is viable, yet the VGGFace2 models are most certainly not. The model could be used to identify new faces is shown in Fig. 5.

ResNet-50 is a convolutional neural network that is 50 layers deep. Its helps to stack a pretrained rendition of the network prepared on in excess of a million pictures from the ImageNet information database. The pretrained organization can arrange pictures into 1000 item classifications, for example, console, mouse, pencil, and numerous creatures. Subsequently, the organization has learned rich element portrayals for a wide scope of pictures.

Fig. 5. Sample image

B. *Feature Extraction and Classification*

Fig. 6. depicts the prediction of gender whether that human face is male or female based on the features. Convolution neural network can be used for predicting the gender before that need trained a CNN model [12] using lot of features. The gender prediction results are again fed into CNN model for predicting the ages [14] of individual human face shown in Fig. 7.

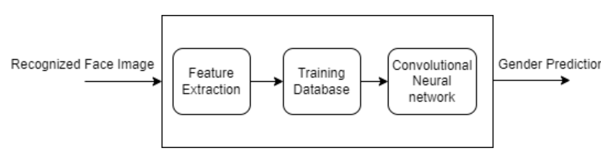

Fig. 6. Gender prediction

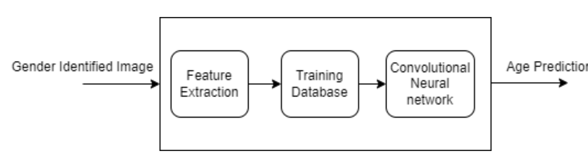

Fig. 7. Age prediction

Utilizing VGG blocks in models should to be normal since they are so basic and powerful. Exhibit a solitary model that has three VGG blocks, the initial two blocks have two convolutional layers with 64 and 128 channels separately, the third layer has four convolutional layers with 256 channels.

C. Pre-Trained and Transfer Learning

Deep convolutional neural network models [8],[33] may take days or even a long time to prepare on enormous datasets. An approach to alternate way this cycle is to reutilize the model loads from pre-prepared models that were produced for standard vision benchmark datasets, for example, the ImageNet picture recognition undertakings.

1) Useful learned features

The models have learned out how to recognize conventional features from photos, given that they were prepared on in excess of 1,000,000 pictures for 1,000 classifications.

2) State of the art performance

The models achieved state-of-the-art performance and stay successful on the picture acknowledgment task for which they were created.

3) Easily accessible

Deep convolutional neural network models may take days or even a long time to prepare on extremely enormous datasets [9]. An approach to alternate route this cycle is to re-utilize the model loads from pre-prepared models that were created for standard computer vision benchmark datasets.

D. Gender Recognition and Age Prediction with CNN

Gender orientation recognition utilizing OpenCV fisher faces execution is a few of you will have tried or recognized regarding it too. using another way of dealing with the perception of sex. [31] In the DNN bundle, OpenCV has given a class called Net which can be utilized to populate a neural network This is almost similar to the gender detection part except that the relating prototxt document and the Caffe model record are Caffe model prototxt deploy agenet. In addition, the CNN performance level (probability level) in this CNN includes 8 grades for 8 age groups 0-2, 4-6, 8-13, 15-20, 25-32, 38-43, 48-53,60). A Caffe model has 2 associated files, Prototxt This file defines the layers in the neural network, each layer's inputs, outputs and functionality. Caffe model contains the knowledge of the trained neural network. It caters to attention with its gender classification, although recent strategies have supported deep convolutional neural networks (CNNs). It achieved exceptional results for this face detection task. The tasks of face detection and gender classification usually are solved as distinct problems. The system is designed for Hospital queue management and controlling queue in hospital as well as gives the priorities to the patients. In general faces are detected and feature are extracted using deep face methods and stored in database, coaching image dataset used compare the feature between two Image and find same person are totally different person for classification CNN is employed gender imaginary place and Age prediction.

4. Experimental Results and Analysis

The implementation particulars of the proposed system are presented below. Hospital Queue Management using Deep Neural Network is done by using Anaconda, if you have a figure, simply paste it in the template and adjust the size of the figure as per the requirement.

A. Dataset

The image dataset is download from various platform like wider face [31] and imagenet [26], RMFRD, CelebA, LFW, CFP, Agedb; dataset is representative as people are standing in queue. Those dataset holds nearly 1000 cleaned image and requires fine tuning for face recognition task, age recognition task. The image taken as input for queue management system show in Fig. 8.

Fig. 8. Sample input image

B. Count Number of Person in Image

Count algorithm is used to total number of persons in image, is used identity the number of people is in image [5]. First human face can be recognized and extracted then only able to count easily by using counting algorithm.

1) Counting algorithm

1. Images is extracted from the input dataset and stored in a folder.
2. **for** each image in the folder **do**
3. Read images from folder
4. draw image with boxes(filename, faces)
5. print("Found {0} faces!".format(len(faces)))
6. end for

C. Face Detection

Various number of Deep learning techniques have been created and shown for face detection. Maybe one of the more mainstream approaches is known as the Multi-Task Cascaded Convolutional Neural Network or MTCNN [30]. The MTCNN is famous because it accomplished then state-of-the-art results on a range of benchmark datasets, and in light of the fact that it is prepared to do likewise perceiving other facial highlights, for example, eyes and mouth called milestone recognition. The MTCNN architecture is sensibly complex to implement. There are open-source executions of the design that can be prepared on new datasets, as well as preprepared models that can be utilized straightforwardly for face detection. The execution provided in the Caffe deep learning frameworks maybe the best-of-breed outsider Python-based MTCNN project. Face recognition is the overall undertaking of recognizing and confirming individuals from photos of their face.

1. Images is extracted from the input dataset and stored in a folder
2. Read image
3. Apply MTCNN model for detecting the face
4. extract the bounding box from the first face
5. extract the face
6. Resize image
7. end

The minimum box size for identifying a face can be indicated through the min face size contention, which defaults to 20 pixels. The constructor additionally gives a scale factor contention to determine the scale factor for the information picture, which defaults to 0.709. When the model is configured and loaded, it tends to be utilized straightforwardly to recognize faces in photos by calling the identify faces function. This returns a list of objects items, each giving various keys to the subtleties of each face identified, including: ‘box’: Providing the x, y of the bottom left of the bounding box, as well as the width and height of the box. ‘confidence’: The probability confidence of the prediction. ‘key points’: Providing a dict with dots for the ‘left eye’, ‘right eye’, ‘nose’, ‘mouth left’, and ‘mouth right’ that the library was installed correctly Python, Running the example will load the library, confirming it was installed correctly, now we can use it for face detection. An instance of the network can be created by calling the MTCNN constructor.

The version plots the image once more with bounding bins and facial crucial issues. That eyes, nose, and mouth are identified well on each face, even though the mouth on the correct face could be better recognized, with the focuses looking a little lower than the edges of the mouth. Fig. 9. shows a total number of faces in image.

Fig. 9. Face detection

Running the image creates a plot that shows each separate face detected in the photograph of the people standing in queue is shown Fig. 10. Separate face detected.

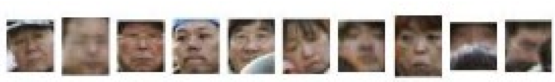

Fig. 10. Separate faces

D. Gender Recognition and Age Recognition

A convolutional neural network can be a deep neural community (DNN) [26] commonly used for reputation and image processing. Otherwise known as ConvNet, a CNN has unique recordings and performance levels and hidden levels, many of which can be convolutional. So, to speak, CNNs are daily collectors on many levels.

- Conv1: Beginning nodes holds 96 with kernel length 7.
- Conv2: next level holds 256 nodes plus kernel length 5.
- Conv3: Finally, the last level holds 384 nodes of kernel length 3.

The detection of a face has a head start this can be a protocol file and buffer protocol contains the definition of the graph and therefore the prepared version number. this can use it to run the expert version. Use argparse library to create opposition teardown, can get image argument from command prompt. Analyze the rivalry, keeping the image path reserved for gender and age orientation for face, age, and sex, present the help and conference version. Initialize the suggested version values and the older level and genre lists to categorize. Initialize the suggested version values and the older level and genre lists to categorize. Now, it uses the readNet method to load the networks. the number one parameter contains heavy weights and the second contains the following conveys the community design. Consider the video switcher on the occasion where you want to rate a webcam broadcast. Set the item to 20. Inside the occasion is something other than a video, with the help of then pause. We provide an option for Highlight Face paints with faceNet and packaging limitations, and what will benefit will be purchasing the names resultImg and faceBox produce a superficial replica of the body and reveal its top and width. Produce a blob from the surface replica. Set the Associate entry to Nursing and create a passage to the community. Face Boxes is now an empty list.

Gender prediction that wants to frame the gender prediction [27] as a type problem. The output level within the gender prediction community is of the SoftMax type with 2 nodes indicating the two categories “Male” and “Female”. Fig. 11. shows gender prediction in a picture.

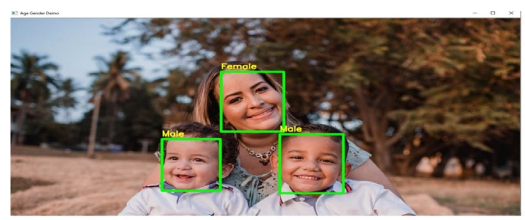

Fig. 11. Detecting male or female

E. Age Prediction

Deep Learning to precisely recognize the sexual orientation and age of an individual from a solitary picture of a face. The predicted sex might be one of 'Male' and 'Female', and the predicted age might be one of the accompanying reaches 0 to 2, 4 to 6, 8 to 12, 15 to 20, 25 to 32, 38 to 43, 48 to 53, 60 to 100. It is hard to precisely figure a careful age from a solitary picture due to factors like cosmetics, lighting, impediments, and outward appearances. Figure 12 shows as age prediction. Alert message is given when old people, people who need emergency treatment standing in the queue can serves first.

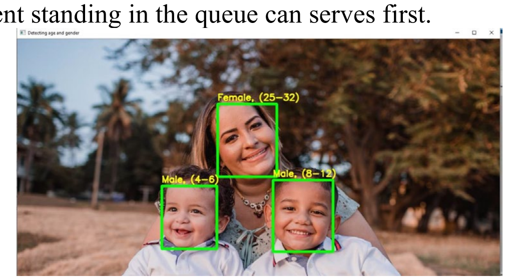

Fig. 12. Detecting male or female

F. Evaluation Metrics

1. *Accuracy:* one of the most widely used analysis metrics for recognition and classification problems. It

represents the quantitative relation between the proper range of predictions and therefore the total number of samples, which may be outlined as follows,

Accuracy = (TP + TN)/ (TP + TN + FP + FN) (1)

2. *Ranked accuracy:* Ranked accuracy metric is used to measure the performance of the model. Rank1 is used shows the correct accuracy for two labels. For Rank 5, Rank N can be used to classifying more than one labels with large dataset [37].
3. *Precision:* The ratio of efficiently labeled tremendous predictions defined as follows,

Precision = TP/(TP + FP) (2)

4. *Error rate (ERR):* ERR otherwise called misclassification rate, is that the complement of the accuracy metric. This metric describes the quantity of misclassified samples from each positive and negative classes. It is sensitive to unbalanced data, that is the same because the accuracy metric, calculated as follows,

ERR = 1-Accuracy (3)

5. *False discovery rate (FDR):* The ratio of the number of false-positive classifications to the total number of positive classifications. FDR formula is defined as follows,

FDR = FP/(FP + TP) (4)

6. *True positive rate (TPR):* Recall value shows the ratio of the classified positive to the total number of positive. Recall can be found by below formula.

TPR = TP/(FN + TP) (5)

7. False alarm rate (FAR): Its otherwise called as FPR, it shows the ratio allying the negative s that are inexact classified to the total number of the negative.

FAR = 1 - TNR = FP/(TN + FP) (6)

8. True negative rate (TNR) is the converse recall used to measure the ratio of the suitably classified negative to the total number of negative [38].

TNR = TN/(FP + TN) (7)

Table 2 summarizes the accuracy of performance of Hospital Queue Management methods (HQM) methods and Table 3 summarizes the ranked accuracy performance of HQM. Table 4 lists various types of performance metrics applied by the Hospital Queue Management methods.

Table 2
Comparison of accuracies achieved by different approaches

Work Ref.	Model	Value
[33]	CNN	69.18
[35]	VGG16+ FaceNet	97
[36]	Face Mask Net21	90.15
[17]	Attention	95
[27]	MTCNN	97.55
Proposed	VGGNet+CNN	98.50

Table 3
Comparison of ranked accuracy

Work Ref.	Model	Rank -1	Rank-5	Rank-10
[27]	MTCNN	93.46	-	-
[39]	CNN based PDSN	97	-	-
[32]	GAN	68.10	77.40	80.60
[34]	AlexNet	87.12	93.70	94.97
Proposed	VGGNet +CNN	96.52	-	-

Table 4
Comparison of evaluation measures

Work Ref.	Model	Metric	Value
[33]	CNN	Precision	62.17
[32]	GAN	ERR	1.36
[27]	MTCNN	TRP	87.25
[35]	FaceNet	TRP	89.33
Proposed	VGGNet + CNN	Precision	99.35

5. Conclusions

Despite various past techniques need to deal with the issue of gender recognition and age recognition through face image, that have set some standard that relies on state-of-the-art VGGNet network structures and attempts to show the determination of gender recognition and age recognition through face picture that can improve with VGGNet architecture of Deep Convolution Neural Network. It has utilized VGGNet for gender prediction and age predicition with Celebrity face dataset. That have utilized OpenCV, pytorch, tensorflow library with python language to actualized code with Graphical Processing unit (GPU) that has demonstrated an extraordinary outcome on such enormous number facial picture dataset. The future scope work in this is to involve using face, human expression classification to aid face recognition, facial disease detection, improve experiences with images and pictures of social media.

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