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Deepgender: real-time gender classification using deep learning for smartphones

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Abstract Face recognition, expression identification, age determination, racial binding and gender classification are common examples of image processing computerization. Gender classification is very straightforward for us like we can tell by the person's hair, nose, eyes, mouth and skin whether that person is a male or female with a relatively high degree of confidence and accuracy; however, can we program a computer to perform just as well at gender classification? The very problem is the main focus of this research. The conventional sequence for recent real-time facial image processing consists of five steps: face detection, noise removal, face alignment, feature representation and classification. With the aim of human gender classification, face alignment and feature vector extraction stages have been re-examined keeping in view the application of the system on smartphones. Face alignment has been made by spotting out 83 facial landmarks and 3-D facial model with the purpose of applying affine transformation. Furthermore, 'feature representation' is prepared through proposed modification in multilayer deep neural network, and hence we name it Deepgender. This convolutional deep neural network consists of some locally connected hidden layers without common weights of kernels as previously followed in legacy layered architecture. This specific case study involves deep learning as four convolutional layers, three max-pool layers (for downsizing of unrelated data), two fully connected layers (connection of outcome to all inputs) and a single layer of 'multinomial logistic regression.' Training has been made using CAS-PEAL and FEI which contain 99,594 face images of 1040 people and 2800 face images of 200 individuals, respectively. These images are either in different poses or taken under uncontrolled conditions which are close to real-time input facial image for gender classification application. The proposed system 'Deepgender' has registered 98% accuracy by combined use of both databases with the specific preprocess procedure, i.e., exhibiting alignment before resizing. Experiments suggest that accuracy is nearly 100% with frontal and nonblurred facial images. State-of-the-art steps have been taken to overcome memory and battery constraints in mobiles.

Keywords Real-time systems · Machine learning · Image processing · Deep learning · Gender classification · Advanced mobile applications

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1 Introduction

Gender classification refers to the task of identification of human face in the image under consideration and then recognition of the person as male or female. Smart and interactive systems relating to the area of medical service, human–machine conversation, human-like actions, vending machines, security and surveillance are few examples where gender information is being used. In this era of smartphones where availability of photographs is immense and real-world acquisition has become an easy job with a handheld device, applications of image processing are becoming popular. Smartphones can do almost everything including but not limited to rapid networking, powerful and influential social networking attributes, innovative applications and real-time decision making. Smartphone has become a reliable resource designed for an always-on access to gather information, hook up with personal and social networks, etc. Gender classification not only is a vital machine learning tool but also can boost many other applications. Information is transferred to end users (e.g., using smartphone applications) of the application after processing of the data. The procedure of processing includes organization, sorting, formatting, transforming, summarizing and computing excessive data into useful real-world information [1].

The face recognition techniques which have been adopted for the identification of gender are invariant to many illumination andpose distortions because their algorithms possess distance measured attributes. Some other work in this regard includes crack finding, noise detection and articulations. Shapes can be represented in a range of forms like real-time moments, curving, shape signature, integral invariant and emblematic representations. These methods of 2-D shape matching and feature vector representation fall under the types of region based and contour based. Contour-based approach ignores pixels of shape under consideration and focuses on contour information, while in region-based approach, pixels play an integral part in obtaining shape descriptors [2]. Research interest in automatic unseen data classification has increased in recent years, especially in the areas of object detection, surveillance, medical photography including image enhancement, and financial data investigation. Unseen data classification depends upon the patterns composed in specified space [3].

The inspiration behind this work is ‘deep learning’ which happened to be the modern form of an older scheme of computing: neural networks. These thriving systems, loosely inspired by the densely interconnected neurons of the brain, imitate human learning by changing the strength of simulated neural connections based on experience. Human gender classification has also become linked to numerous automated systems, ever since the development of social media and networking. However, exhibition and performance of obtainable techniques on real-world raw images are still not up to the mark when it comes to the insightful process of face recognition. Although deep neural networks have gained popularity to enhance accuracy for different applications, when executed on a processor of smartphones it becomes unfeasible to attain end user’s satisfaction due to their rigorous computation requirements; however, this paper presents a client–server architecture for Deepgender model to be executed by caring memory and battery constraints.

This paper demonstrates that with exercising deep convolutional neural networks as presented here, noteworthy raise in performance can be attained. Making computer machines think like humans has always been a hot topic among artificial intelligence researchers. Contemporary consumers make use of smartphone software and applications in their daily life for listening, sorting, labeling and translating the multimedia content. Not only advance features but also affordable cost has raised the usage of smartphones over recent years. Keeping in view major constraints of smartphone, i.e., memory and battery, a novel deep learning gender classification approach ‘Deepgender’ is presented in this paper. The task becomes more difficult when we talk about real-time photographs comprising face images. This is because of diversity in the pose of a person, angle of camera and illumination conditions. However, deep neural networks have proved great.

Our presented system has been trained on two large-scale datasets which are CAS-PEAL and FEI. These big datasets possess versatility in pose and illumination. Its resemblance to the real-time environment of capturing and attaining images has made the presented model acceptable in terms of accuracy. Necessary dataset detail is provided in next section. ‘Deepgender’ is different from other contributions in this field; this study has used deep learning (DL) modeling by substituting well-governed features. Deep learning has emerged as a powerful tool when training data are very big [4]. Particularly in face image processing, the correctness of learned network is extremely reliant on 3-D facial alignment phase. The convolutional neural network architecture is standing on the postulation that after alignment and scaling (mostly reduced), localization of every facial section is permanent level pixel by pixel. It is, therefore, likely to use and learn from RGB pixel values with fewer layers of convolutions as compared to other networks [5].

Summing up, contributions of this study include:

1. Presentation of a successful deep neural network design controlling very large-scale datasets of face images.
2. Facial feature representation extendable to be applied to other similar datasets.
3. Practical alignment technique setup on 3-D facial modeling.
4. Boosting accuracy and reducing error rate.
5. Reducing memory and battery requirements in calculating feature vector of the test image for matching with already computed/trained classifiers.

Rest of the paper is structured as follows: This study presents a summary of existing feature extraction and classification schemes for gender classification in Sect. 2. Real-time gender classification using deep learning is defined in Sect. 3. Two main steps (face alignment and feature representation) of the proposed work have been stated here along with explicitly defined training phase. Section 4 comprises of technical details of the proposed system. The system architecture involving smartphone in a client–server environment is presented in Sect. 5. Detail of datasets used in training and testing is documented in Sect. 6. Related detail of pseudo-code is presented in Sect. 7. Section 8 is composed of practical experimental setup detail along with statistical results and measures. Lastly, conclusion of this work is offered in Sect. 9.

2 Related work

Big data is a term that rapidly come into sight in past few years for a big number of photographs, movies and text crawled by Internet searching. Social networking has also made it possible to upload any kind of unconstrained objects in bulk. This research aims at the formulation of best gender identification scheme out of available modern work and then the mapping of this proposed method to the handheld smartphone application. As the data have grown, there is need to manipulate and compute these data with some powerful tools for cluttering and occlusion and to cope with lightning effects which are basic computer vision problems. In recent years, neural networks have gained researchers' interest. Image classification techniques have been employed to solve its specific area, i.e., gender classification as depicted by Krizhevsky et al. [5], e.g., using 'convolutional neural networks' on ImageNet dataset. Krizhevsky et al. also proved that training with bigger dataset leads to high accuracy when experimenting through back-propagation neural network.

Extended Cohn-Kanade Dataset (CK+) with smartphones which contain 593 images of 123 distinct subjects was used, and accuracy of 99.2% was attained [6]. Meseguer et al. [7] in 2013 also used CNN for users' driving styles on smartphones with 77% accuracy rate. Kim et al. [8] in 2015 compared CNN compression styles, and with their phenomenon, 89.40 was the accuracy rate. Human activity recognition using smartphones and utilizing CNN have been popular in recent years [9, 10]; their discussion will track us out of the problem under consideration, i.e., gender classification (Table 1).

Deep learning has been employed successfully for face finding [11], alignment [12] and recognition [13]. Gender classification has been accomplished using local binary patterns [14] to find face features. For this purpose, images are provided under uncontrolled environment for governing feature representation. Pose-aligned network [15] was proposed using deep attribute modeling over a bulky volume gender recognition dataset. Methodology presented here is based on a new architecture which outclasses previous usage of deep nets by indulging 3-D faces alignment, customized framework, and downscaling the neural network trained on large-scale human face datasets.

Summary of Table 2 is described in this section. Gender was predicted successfully with 90% accuracy by [16] in 2011 using regional localization as a feature. They further presented linear support vector machine fusion technique for classification. Their experimentation was done using web images acquired under uncontrolled environment. Rai and Khanna and Mousa-Pasandi et al. [17, 18] in 2014 also used SVM as a classification tool with 98.18 and 91.59%, respectively. Five numbers of datasets, i.e., FERET, FEI, AR, Indian Face and LFW, were used by [17]. Their acquisition environment and volume detail of these datasets are given in Table 2; likewise, Gabor filter 2DPCA was used for feature selection in horizontal and vertical directions separately by them. Gallagher's database has also been a choice for experimentation, while local binary pattern with radial basis function (RBF) kernel for feature selection [18]. Previously in 2008, Leng and Wang acquired accuracy up to 93% investigating three small-sized datasets, i.e., FERET, BUAA-IRIP and CAS-PEAL. Feature selection was made by Gabor filtering, and learning vector quantization (LVQ) and fuzzy SVM were presented for classification task [19].

The error rate in face recognition and similarly in gender classification has decreased over recent years when dealing with front-view face images under a controlled environment. Successful systems have achieved performance by using manually crafted mixed features. The method which is ahead in promising results has used thousands of facial descriptors [26]. On the contrary, here direct red, green and blue values at pixel level have been used yielding a compact descriptor.

In 2010, edge highlighting filters plus AdaBoost algorithm achieved an accuracy of 87.6% over Webimg dataset

Table 1 Remarkable accuracy rates using CNN on smartphones

References	Procedure	Dataset	Accuracy (%)
[6]	CNN	Extended Cohn-Kanade Dataset (CK+): 593 images of 123 subjects	99.2
[7]		Users' driving style database collected by different users	77
[8]		ImageNet CNN compression analysis on smartphone	89.40

consisting of 1199 face images with diverse pose and background [20]. Gaussian blurring method with progressive CNN was adopted to attain an accuracy of 97.95% upon mug shot [21]. Moreover, 90K photographs of mug shot and AR facial databases were considered for testing and training. Quaternion wavelet transform (QWT) along with principal component analysis (PCA) served classification requirement and temporal features for feature extraction by [22] utilizing medium-sized FERET dataset. Zhang in 2014 made use of neural networks as a tool for gender classification and computed features by the informative patch, poselet patch, task-aware facial crop and features through layers [15]. LFW yielded better results, i.e., 77.87% over Gallagher's database which achieved an accuracy of 72.83% [23]. Using poselet patch and CNN, Zhang et al. in 2014 managed to get 94.1% accuracy for correct male predictions [15], while task-aware face cropping technique along with CNN produced comparatively high correct prediction rate, i.e., 91.66% [24]. Utilizing 13,500 facial images of FERET and CAS-PEAL (LFW-a) and extracting features through layers by DNN in 2014, accurateness of 89.63% was posted [25]. Likewise, the proposed scheme of real-time gender classification is prepared and experimented using deep learning.

3 Real-time gender classification using deep learning

Descriptor engineering has become popular in the field of image processing. One way to apply these descriptors is the application of the single operator to all pixels onto an image containing a face. As more data are available, learning techniques perform better because of their ability to find best-matched features for the task under consideration which has become motivation for gender classification using deep neural network under uncontrolled real-time environment. In this regard, first step of facial alignment and a second one of feature vector representation are described under following subheadings.

3.1 Face alignment

Face alignment in the uncontrolled real-time environment is considered difficult task because it must cope with versatility in the pose, change in expression and different illumination conditions.

Some reasonable alignment and normalization methods are:

- 3-D analytical modeling [27].
- Fiducial points construction [28].
- Similarity transformation [29].
- Template fitting [30].
- Regression based [31].

Out of above-mentioned methods, only 3-D modeling appeals more for the correct mapping with the actual 3-D shape of a face. This study presents a system 3-D analytical model using fiducial points for front alignment and accurate cropping. Alignment phase of the proposed system requires comparatively smooth fiducial points but with iterations based on local binary patterns histograms (Fig. 1).

Transformation is done by passing the image as an input and applying fiducial detection on new LBP feature space to improve formalization iteration. For this purpose, the proposed experimental setup applies 2-D image into 3-D model restoration formally adopted by [32] with the assumption that 3-D blend shape is achieved with 83 landmarks of eyes, nasal, lips and chin. Every subject to be aligned first passes through the process of landmark identification. A further process is described by Eq. 1:

$$M = C_r \times w_{id}^T \times w_{\exp}^T \quad (1)$$

where

- C_r is 3-D model with 83 landmark points,
- w_{id}^T and $w_{\exp}^T$ are vector weights for the respective tensor weights for those landmark points,

which gives basic blending, and any input image can easily be straightened by replacing their symmetrical counterparts.

3.2 Feature vector representation

Deepgender NN has been trained as a 2-class classification task as described in Fig. 2. In this figure, Deepgender architecture has been provided which depicts rectified/preprocessed input converted into 3-dimensional RGB (red, green and blue) portions. The input image is scaled down to 227 × 227 pixels, so the components. These three RGB vector components are used as an input to the convolutional network layers as CON1 → POOL1 →

Table 2 Some related work on gender classification as state of the art

References	Year	Feature extraction	Classification	Database	Acquisition environment	Database volume	%Age success
[16]	2011	Region localization	Linear SVM fusion	Yahoo!® Flicker®	Uncontrolled	13,383 males 13,383 females 26,766 photographs	90
[20]	2010	Edges based	AdaBoost	Webimg	Illumination, pose and background	210 males 259 females 1948 photographs	87.6
[17]	2014	Gabor filter 2DPCA for horizontal and vertical directions	SVM	FERET	Controlled	740 males 459 females 1199 photographs	98.18
				FEI	Smiling/not smiling	100 males 100 females 400 photographs	96.61
				AR	Illumination, expression, pose and background	70 males 56 females 4000 photographs	96.15
				Indian face	Uncontrolled	33 males 22 females 605 photographs	93.33
				LFW	Large variations/ uncontrolled	10,011 males 2999 females 13,010 photographs	88.34
[21]	2016	Gaussian blur	Progressive CNN	Mug shot	Frontal Occlusion Low resolution	Training set 90 K facial photographs	97.95 93.12 95.67
				AR	Occlusion expressions		85.62
[18]	2014	LBP RBF	SVM	Gallagher's database	Uncontrolled	28,231 faces, 5 folds of 2952 images	91.59
[22]	2014	Temporal features	DWT PCA	FERET	Controlled	740 males 459 females 1199 photographs	9.7% improved
[19]	2008	Gabor features	LVQ network Fuzzy SVM	FERET	Illumination, expression ages	160 males 140 females 300 photographs	96.5
				BUAA-IRIP	Controlled	150 males 150 females 135 individuals	93
				CAS-PEAL	Uncontrolled	400 males 400 females	89
[23]	2016	Informative patch extraction	Local DNN	LFW	Large variations/ uncontrolled	10,256 males 2977 females 13,233 photographs	77.87
				Gallagher's database	Uncontrolled	4 folds of training set 1 fold of test set 14,760 photographs	72.83

Table 2 continued

References	Year	Feature extraction	Classification	Database	Acquisition environment	Database volume	%Age success
[15]	2014	Poselet patches	Convolutional Neural Nets	Berkeley attributes	Pose, viewpoint occlusion	4013 training 4022 testing	91.7 male accuracy
				25 K test dataset	Pose, viewpoint occlusion	7489 testing 24,963 photographs	94.1 male accuracy
[24]	2016	Task-aware face crop	CNN	ChaLearn 16 FotW	–	Not known	91.66
[25]	2014	Features through layers	DNN	FERET, CAS-PEAL (LFW-a)	Mixed	6750 males 6750 females 13,500 photographs	89.63

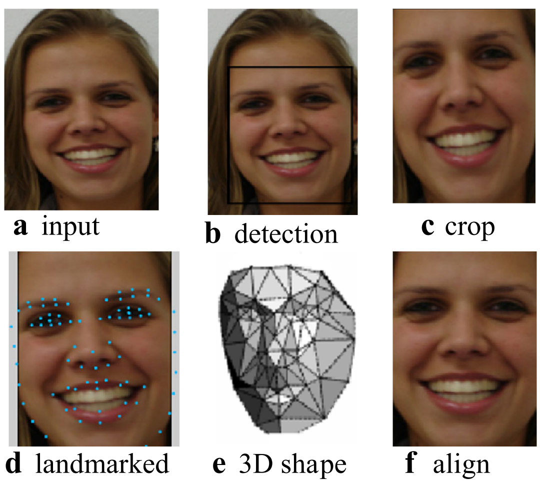

Fig. 1 Face alignment. **a** Input image, **b** detected face shown in a *box* which is also an area to be cropped, **c** cropped face, **d** 83 landmarks on 2-D crop, **e** reference 3-D shape for transformation with 2-D cropped image at corresponding landmarks. **f** Aligned and resized to 227 × 227 as a final image to be passed to CON1 layer

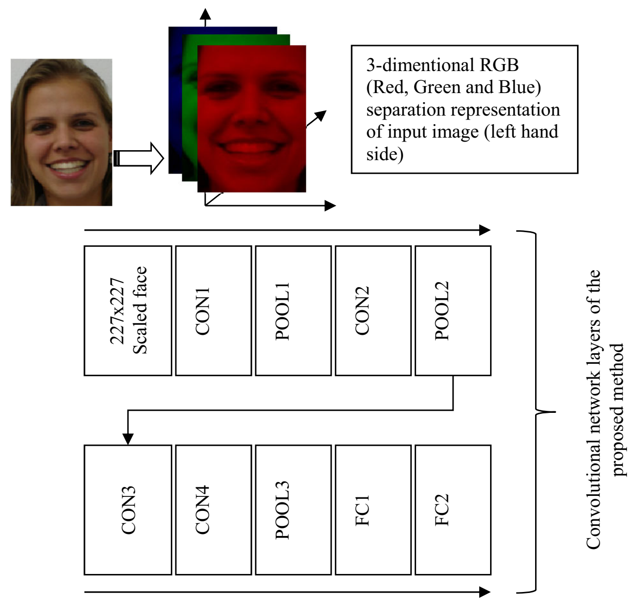

Fig. 2 Deepgender architecture. Rectified input for CON1 layer followed by POOL1, CON2, POOL2, CON3, CON4, POOL3, FC1 and FC2

CON2 → POOL2 → CON3 → CON4 → POOL3 → FC1 → FC2. Softmax (multinomial logistic regression) is applied further. The detail of the procedure is provided in Table 3, and technical explanation is produced in the next section.

Adopted sequence of work is Detect face → Crop → Align → Resize to the size 227 × 227 pixels. Deepgender layers with an individual set of weights and other details of size are summarized in Table 3.

The sequence of this deep network is:

1. This resized image becomes input to the first convolutional layer CON1.
2. CON1 is first convolution layer among four of them with 96 individual set of weights and kernel size 11 × 11 × 3 and stride 4. The number 3 represents the three RGB layers.
3. Next is max-pooling phenomenon whose function is downsizing with stride 2 and padding 0.
4. CON2 possesses 256 sets of weights with kernel 5 × 5 × 48, stride 1 and padding 0.
5. POOL2 is again for downsizings like POOL1 with size 3 × 3, stride 2 and padding 0.
6. CON3 and CON4 have individual sets of weights 384 and 256, kernel 3 × 3 × 256 and kernel 3 × 3 × 192, respectively. Stride and padding value for both is 1.
7. POOL3 is again max-pooling layer with kernel 3 × 3 × 192.
8. Next are two fully connected layers where FC1 has 512 output size and finally FC2 returns 2 labels/neurons.
9. Finally comes the softmax layer which does not pick highest or maximum value, but it is a probability

Table 3 Deepgender layers with an individual set of weights and other details of size, etc.

Layer name	Individual sets of weights	Convolutions	Stride	Padding
Input image reduced to size 227 × 227↓				
CON1	96	11 × 11 × 3	4	0
POOL1	–	3 × 3	2	0
CON2	256	5 × 5 × 48	1	2
POOL2	–	3 × 3	2	0
CON3	384	3 × 3 × 256	1	1
CON4	256	3 × 3 × 192	1	1
POOL3	–	3 × 3 × 192	1	1
FC1	512	1 × 512	–	–
FC2	2	1 × 512	–	–
→ Softmax (multinomial logistic regression)				

distribution formulating 0 or 1 to become more specific for loss and final class labeling. For all outcomes, $\exp(\text{coutcome} * k)$ is calculated and the result is divided by their sum for each outcome. A higher value of constant k means higher confidence on the trained network.

The objective of this deep network training is finding the accurate class (face representation/face vector) by means of probability maximization. CON1, CON2, CON3 and CON4 are filter repositories, and it is to be noted that every location under consideration in previous input plane learns dissimilar groups of filters. Different face regions in aligned and scaled image possess different heat/intensity values. More precisely, the portion between the eyes, mouth and nose regions and the cheek portion have obviously different manifestation. Over this truth, this proposed deep convolutional network has been tailored/customized. Fully connected layers exhibit the behavior of connection of outcome to all inputs because over a huge volume of training dataset can meet the expense of only two such layers, i.e., FC1 and FC2. Here (in FC1 and FC2), different parts of a face get associated with a common feature representation. Training procedure of this convolutional neural network has been explained in the next section.

3.3 Training

The way of using datasets by [33] is splitting the facial database into 5 sets for training and testing, and it does effect results when the image of the same person repeats in a different set with may be different posture. On the contrary, proposed experimentation first divides entire set of images into two folders named male and female. All male images were binned into a folder named male, and female images, into a folder named female, for both datasets. For the prediction of gender and the proposed deep neural network scheme, it was essential for constructing the better classifier. Now there are two ways to manage selected input: One is to crop the size as it is when a face image registers into the input pipeline, but it can lose important information while cropping, and the other is using size reduction technique, so the alignment is performed after face cropping and then produces the image to the required size 227 × 227.

Upon this setup following was achieved:

1. Construction of an optimized DNN scheme and overcoming the over-fitting problem which was achieved by minimizing fully connected layers only to two and the use of three max-pooling layers after convolutional layer.
2. Over-fitting was also reduced by separating the datasets for women and men in the process of training, for example, skin texture may contribute differently for both genders in a different race.

4 Technical details

Some more technical details are included in this section to discuss training procedure of proposed Deepface DNN.

4.1 Softmax

Top most layer in Deepface is softmax whose functionality is to compute loss for optimization and correct face feature vector representation by fine-tuned class probabilities. Some classification methods do not use softmax and treat the last connected layer as class labels, for example multi-class SVM training. Softmax is termed as 'multinomial logistic regression,' given in Eq. 2, and is used to fine adjustment of irregular probabilities:

$$f_j(U) = \frac{e^{uj}}{\sum_k e^{uj}} \tag{2}$$

where U_i is the class label of class i that is outcome of FC2. The aim is to maximize the chances of being correct class and minimization of −ve log likelihood, so

$$L_i = -\log \frac{e^{f_{yi}}}{\sum_j e^{fi}} \tag{3}$$

As softmax takes real values being output from f and normalization is done through exponential summation, the formula converges all scores to 1. Further this value is treated as true score in Deepgender. The loss computed here is entropy function loss. Precisely, this is the entropy between real distribution p and calculated distribution q termed in Eq. 4:

$$E(p,q) = -\sum_x p(x)\log q(x) \tag{4}$$

It can be understood that top softmax layer is suppressing the entropy between actual and calculated probability distribution. So, in learning 1 is being predicted as a real class and 0 for everything else.

4.2 Stochastic gradient decline

Lets us discuss some technical detail of minimization of calculated loss for accurate training phase. Stochastic gradient decline has been used as optimization source here. The gradient is slope calculated by a derivative function. So, upon loss calculation is made through thousands of Deepface DNN system vector weights. Every time gradient is computed, we make little growth in a reverse direction in the iterative way of evaluation. So, this iterative process leads to decline in loss function and better classification modeling. It is explained in Eq. 5:

$$w = w - \eta \nabla_w L \tag{5}$$

Slope step or learning rate is denoted by η, $\nabla_w L$ is called loss gradient to calculate vector weight w. The problem with this technique is of heavy computation because it must update inflow weights at every iteration. One method of minimizing or even eliminating this burden is to use the technique of mini-batch gradient decent. In this course of work, this gradient is not applied over all span of the image instead of at some of its portion(s). It is very excellent in lowering the computation load. Another method is skipping some percentage of images in training when dealing with large dataset. It also shows better results in minimizing the computation. Keeping in mind, the dealing with smartphone devices where processor, memory and battery are big constraints, the training is performed separately by use of mini-batch stochastic gradient decline procedure which is fast, and at the time real-time smartphone application usage computing a single image forward (to determine loss) and backward (to compute gradient) through the overall network is extremely fast. This is because of the lower step size and distinct single image.

5 System architecture

Server and smartphone architecture are shown in Fig. 3. Tasks happening at server include:

1. It provides male and female images enrolment.
2. It performs preprocessing and training tasks.

Then, trained Deepgender model is sent to a smartphone as replica which is hereby converted into smartphone format, creating NetFile for:

1. Layers setup,
2. Execution mode,
3. Max mermory and

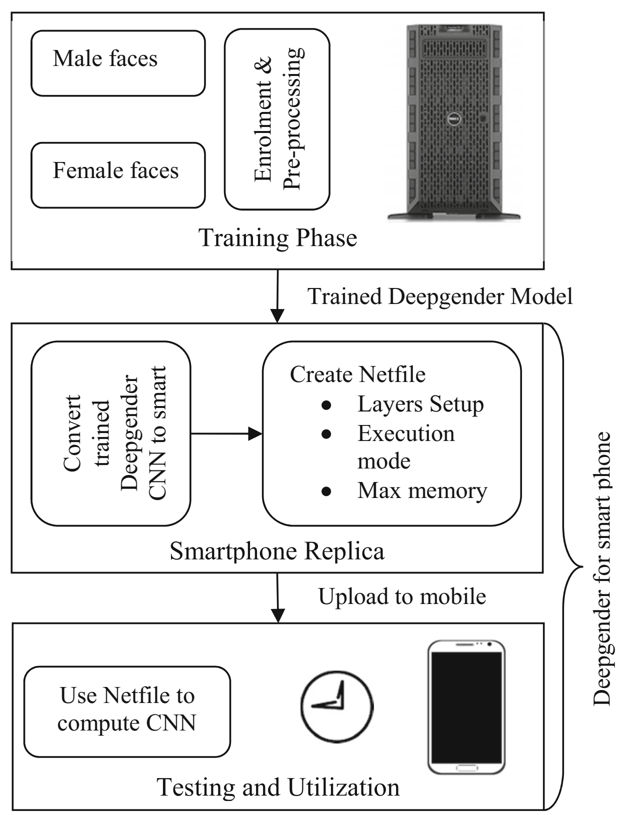

Fig. 3 Deepgender server and smartphone architecture. *Top* training phase occurs on server including male and female face enrolment (with labels) and preprocessing termed as Tier-3. *Middle* replication into smartphone format file, i.e., NetFile. It occurs in here Tier-2 which takes trained Deepgender as an input. *Bottom* Tier-1 is shown in the bottom rectangle which represents application layer. Here user interacts with the system. Utilization and testing happens over here

4. Auto-tuning.

Second and third layers in Fig. 3 are meant for a smartphone to embrace Deepgender. The executable NetFile is used for the desired CNN computation, hence becoming the backbone for application layer for testing and utilization. This executable NetFile also limits the smartphone application user as suggested by Hammoudeh et al. [34]; the attitude to bound end user's request scope to random subgroups of system results in significant energy savings, lower bandwidth utilization and better information. According to Abuarqoub et al. [35], reactive answering by the server is more efficient than proactive approach in terms of energy saving; the same has been implemented in creating NetFile as a replica to smartphone.

6 Datasets

Training and testing have been performed over two datasets as represented in Table 4. Some features of these datasets are described under their names as follows:

6.1 CAS-PEAL

CAS-PEAL [36], more precisely CAS-PEAL-R1, is an open-source face database for researchers. It was developed by Joint Research and Development Laboratory for Advanced Computer and Communication Technologies (JDL) of Chinese Academy of Sciences (CAS). It contains large-scale face images with different origins of dissimilarity, e.g., pose, expression, accessories and lighting (PEAL), hence the name CAS-PEAL. Its similarity with real-world images is due to PEAL factors. Each person undergoes nine photograph-capturing cameras, five types of expressions, three glasses and three caps; moreover, fifteen types of illumination tracks make it close to real-time photography. Dissimilar background, camera distance and age factor are some other additions in diversity. A male subject with different images with respect to camera positions is shown in Fig. 4.

6.2 FEI

FEI was used by [37] for face image analysis, and it is an open-source facial dataset available for researchers. It was developed at Artificial Intelligence Laboratory of FEI in São Bernardo do Campo, São Paulo, Brazil. Total individuals in this dataset are 200, and each person has fourteen different images. Pose, hairstyle, adorn, age cover main diversity factors.

Original images in both datasets were preprocessed and resized to 227×227 pixels. Three female subjects appeared in FEI database are shown in Fig. 5.

Table 4 Number of male and female images in the dataset

Dataset	Male	Female	# of images
CAS-PEAL-R1	595	445	30,871
FEI	100	100	2800
Total	695	545	33,671

7 Server and client pseudo-code

Building a client–server system is as much an art as a science. Smartphones when utilize a server infrastructure to provide services fall under the category of mobile cloud computing (MCC) [38]. Although there is no single traditional view of MCC in the field, mobile cloud computing can be presented in many ways. Pseudo-code for Deepface is presented for the computation and storage facilities at the server and downloadable as well as an executable file at smartphone side. Server–client connections, loops and computations are made light for a comparatively faster response, as shown in Fig. 6.

8 Experimental setup and some other results

The training and testing of this proposed work have been performed in Intel® Xeon® E5-2630 v4, 16 GB RAM, 2 TB. Smartphone application was run on 2 GB RAM, quad-core, 8-megapixel camera.

Deepgender was built from start, not including pre-trained stuff from some other development. Parameters for stochastic gradient decline (as shown in Fig. 7) were customized as: learning rate = le−3, decline factor = 10 after 10,000 cycles, mini-batch size = 100 images, total batches = 336, number of images not used in training/testing = 71. Seventy-one images were shed down arbitrarily from CAS-PEAL-R1.

The results were promising in terms of accuracy and speed. Actual and predicted numbers of male and female images as utilized in the experimentation are tabulated in Table 5.

Fig. 4 CAS-PEAL-R1, male subject with different images with respect to camera positions (gray-scaled)

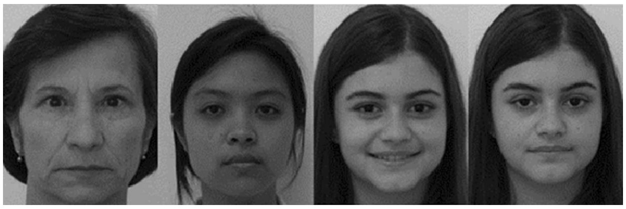

Fig. 5 Three female subjects appeared in FEI database (gray-scaled)

```
Pseudo-code 'deepface'
Training on server
InitializeWeights(DeepFace) after pre-processing
UNTIL reaching last convergence layer do
  FOR every input image do
    OutLabel ←ForwardPropagation Deepface(image)
    LossGradient ←ComputeError(OutLabel)
    Error ←BackPropagtion Deepface(LossGradient)
    UpdateWeight(Error)
    COMPUTE Activation ←dot product of weight vector
  and training image under consideration
    UPDATE ComputedActivation
  EXIT FOR
  IF (ComputedActivation>0)
    THEN OutPut = Female
  ELSE OutPut = Male
EXIT UNTIL
Testing/Utilization on smart phone
RECEIVE control from server
//∀Test images
  FOR every input image do Pre-processing
  TestDesign equals weight and test image
  COMPUTE Activation ← dot product of weight vector
  and testing image under consideration
    IF (ComputedActivation>0)
      THEN OutPut = Female
    ELSE OutPut = Male
  EXIT FOR
RETURN control back to server
```

Fig. 6 Pseudo-code 'Deepface' for training and utilization: Training procedure consists of weight initialization, label, loss gradient and error incorporation and computation of activation function. Testing and utilization code takes control from server and manipulates every image with preprocessing as in training phase. Computation of test design and activation occurs over here

8.1 Definitions

TP = True positive: Number of male images predicted as male.

FP = False positive: Number of female images predicted as male.

FN = False Negative: Number of male images predicted as female.

TN = True Negative: Number of female images predicted as female.

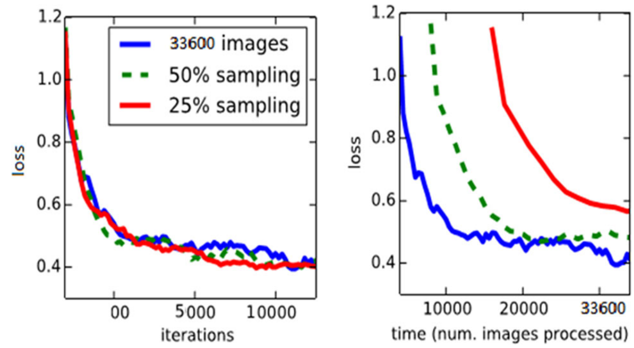

Fig. 7 In first graph, iterations with respective loss, and in second graph, time (milliseconds) in terms of images processed verses respective loss, are drawn. Both graphs are drawn with separate lines representing respective flow for all 33600 images, half sampling data, and 25% of sampling

8.2 Calculations

Formulas adopted for the results and calculation purposes are presented in Eqs. 4–9:

$$\text{precision} = \text{TP}/(\text{TP} + \text{FP}) \quad (4)$$

$$\text{recall} = \text{TP}/(\text{TP} + \text{FN}) \quad (5)$$

$$\text{fmeasure} = 2 \times (\text{precision} \times \text{recall}/(\text{precision} + \text{recall})) \quad (6)$$

$$\text{accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad (7)$$

$$\text{TP\_rate} = \text{TP} \times (\text{TP} + \text{FN}) \quad (8)$$

$$\text{FP\_rate} = 1 - \text{TN} \times (\text{TN} + \text{FP}) \quad (9)$$

Calculations according to above formulas for precision, recall, fmeasure, accuracy, tp rate and fp rate on CAS - PEAL - R1 + FEI, CAS - PEAL - R1 and FEI according to alignment before resizing, alignment after resizing and without preprocessing are summarized in Table 6.

Chart representation of the results is provided in this section. Figures 8, 9 and 10 represent (1) alignment before resizing, (2) alignment after resizing and (3) without preprocessing for precision, recall, fmeasure, accuracy, tp rate and fp rate have ranged from 0 to 1; vertical scale is taken according to that.

Figure 8 contains both datasets. Results show that FP rate for this is very high for without preprocessing settings. Obviously, processing and response speed gets high, but tp rate is sacrificed. Figure 9 also shows promising results for precision, i.e., 0.974258 and 0.954557 for alignment before resizing and alignment after resizing, respectively. It must also be noted that processing and response time remains same even if we move alignment step. FEI yields best results for the presented procedure as depicted in Fig. 10, so it could be inferred that if proposed system is only used

Table 5 Actual and predicted number of male and female images for CAS-PEAL-R1 + FEI, CAS-PEAL-R1 and FEI in three different situations, i.e., alignment before resizing, alignment after resizing and without preprocessing

Actual								
Alignment before resizing			Alignment after resizing			Without preprocessing		
	Male	Female		Male	Female		Male	Female
Predicted								
CAS-PEAL-R1 + FEI								
Male	16,251	428	Male	16,002	700	Male	15,101	14,181
Female	549	16,372	Female	798	16,100	Female	1699	2619
CAS-PEAL-R1								
Male	15,101	399	Male	14,599	695	Male	13,500	13,303
Female	299	15,001	Female	801	14,705	Female	1900	2097
FEI								
Male	1381	16	Male	1352	38	Male	999	612
Female	19	1384	Female	48	1362	Female	401	788

Table 6 Calculations for precision, recall, fmeasure, accuracy, tp rate and fp rate on CAS-PEAL-R1 + FEI, CAS-PEAL-R1 and FEI per alignment before resizing, alignment after resizing and without preprocessing

	Alignment before resizing	Alignment after resizing	Without preprocessing
CAS-PEAL-R1 + FEI			
Precision	0.974339	0.958089	0.515709
Recall	0.967321	0.9525	0.898869
fmeasure	0.970818	0.955286	0.655397
Accuracy	0.970923	0.955417	0.527381
tp Rate	0.967321	0.9525	0.898869
fp Rate	0.025476	0.041667	0.844107
CAS-PEAL-R1			
Precision	0.974258	0.954557	0.503675
Recall	0.980584	0.947987	0.876623
fmeasure	0.977411	0.951261	0.639765
Accuracy	0.977338	0.951429	0.506396
tp Rate	0.980584	0.947987	0.876623
fp Rate	0.025909	0.04513	0.863831
FEI			
Precision	0.988547	0.972662	0.620112
Recall	0.986429	0.965714	0.713571
fmeasure	0.987487	0.969176	0.663567
Accuracy	0.9875	0.969286	0.638214
tp Rate	0.986429	0.965714	0.713571
fp Rate	0.011429	0.027143	0.437143

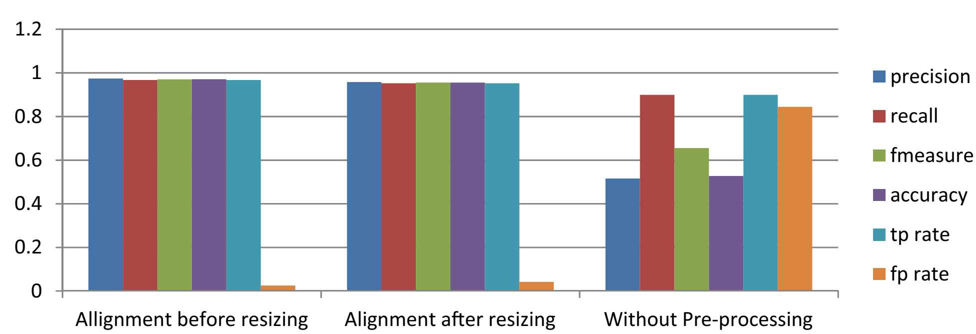

Fig. 8 Precision, recall, fmeasure, accuracy, tp rate and fp rate for combined CAS-PEAL-R1 + FEI datasets on the scale 0–1

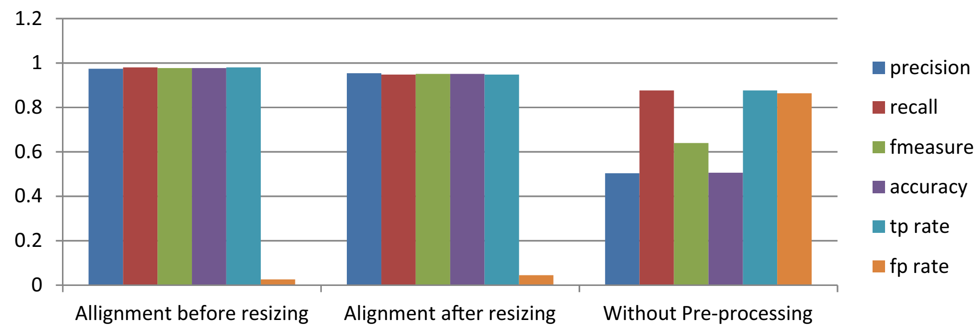

Fig. 9 Precision, recall, fmeasure, accuracy, tp rate and fp rate for CAS-PEAL-R1 dataset on the scale 0–1

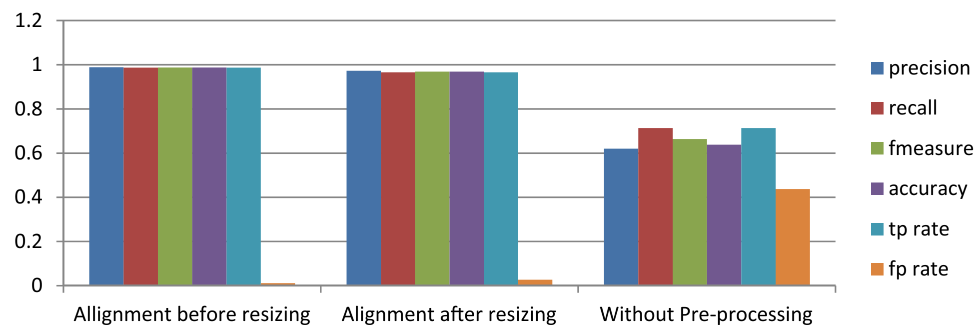

Fig. 10 Precision, recall, fmeasure, accuracy, tp rate and fp rate for FEI dataset on the scale 0–1

for fun purposes in a smartphone, preprocessing step may be excluded, but when used for real-time surveillance and security-related systems preprocessing must be done with alignment before resizing.

Precision is the degree of refinement in being accurate in gender prediction. For CAS-PEAL-R1 + FEI with alignment before resizing, this measure comes out to be 0.9743. The recall is statistical information retrieval measure. This fraction is the relevant outcome in the prediction of gender. Its value is found out to be 0.9673. Moreover, precision and recall can produce fmeasure (0.9708 as stamped), which is weighted measure (here 2) of the harmonic mean of precision and recall computed earlier. Accuracy comes out to be 0.9709 over this big and diverse dataset. Comparison of the results of state-of-the-art methods is listed in Table 1; Rai and Khanna [17] achieved an accuracy of 98.18, but it was over comparatively small and controlled captured dataset, i.e., FERET. Juefei-Xu et al. [21] in 2016 managed to produce 97.95% accurate results, but they only considered frontal face images in mug shot dataset. Song et al. achieved an accuracy of 99.2%, but over a smaller dataset [6]. In perspective of this discussion, it is claimed that the proposed method achieves high accuracy if images are frontal and not blur as compared to others present today (Fig. 11).

ROC curve has been plotted as a fundamental tool for test evaluation on the databases as:

- CAS-PEAL-R1 with preprocessing.
- FEI with preprocessing.
- CAS-PEAL-R1 + FEI with preprocessing.
- CAS-PEAL-R1 + FEI without preprocessing.

TP rate (sensitivity) plotted against fp rate (100-specificity) of above four cases is represented in Fig. 8. Here, *area under curve* corresponds to total accuracy coverage over time. It is intuitive from the curve that preprocessing has a high impact upon accuracy in gender prediction. FEI

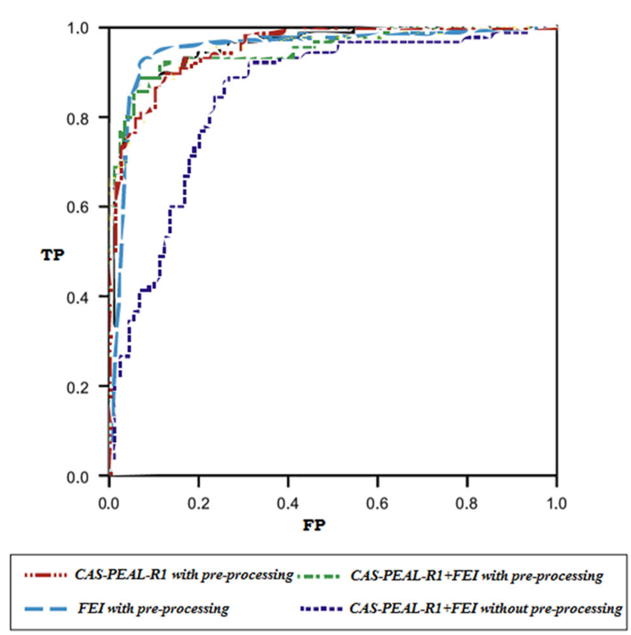

Fig. 11 ROC curves for **a** CAS-PEAL-R1 with preprocessing, **b** FEI with preprocessing (highest accuracy), **c** CAS-PEAL-R1 + FEI with preprocessing and **d** CAS-PEAL-R1 + FEI without preprocessing (lowest accuracy)

with preprocessing has the highest accuracy, while CAS-PEAL-R1 + FEI without preprocessing achieved less area under the curve, hence lowest accuracy measure. The performance of the proposed system becomes worse by combining both CAS-PEAL-R1 and FEI without preprocessing. Based on the findings of above results, few guiding principles are recommended to perform similar procedures. It will help other researchers working on facial image processing with smartphones.

I. Pick only publically available datasets or at least one to facilitate other researchers for comparisons of their work.
II. Use dataset(s) which is/are large enough for statistical comparisons with other methods.
III. Use more than one dataset in the experimentation, some for good quality like FEI and some for varying quality like CAS-PEAL-R1as used in this work. CAS-PEAL-R1 is utilized as varying quality; thus, the correctness of proposed method is claimed for real-time facial images.
IV. If you have used CNN, mention size of convolutions, stride and padding at each layer. Others can help for evaluation of their results precisely.
V. Be prepared to offer additional information to fellow researchers. Inevitably, no matter how precise you are when describing the outcomes, there will remain something unclear or forgotten.
VI. Furthermore, it is to everyone's advantage that the methods employed and results established are comparable.

9 Conclusion

Deepgender is a case which has made CNN prosperous in the two-class modern classification of gender identification, broadening the conventional scheme to segmentation and improving the layered architecture for smartphones which leads to improving state of the art as well as making it run faster. Meanwhile, the closeness of dataset used for learning diverse photograph background, facial pose and expression, and different lighting conditions has made it precisely adaptable for real-time capturing of images with smartphones at resource-constrained environment. Proposed work includes 3-D-model-based alignment phase and improvement in gender classification by use of generic features and representation of Deepface client–server architecture for smartphones. A novel training Deepface architecture and respective pseudo-code have made possible achieving an accuracy of up to 97.09% which is promising in terms of diverse and large dataset compared to the state-of-the-art procedures. For better result elaboration and inferential purposes, statistical charts have also been employed.

Moreover, in future gender classification for real-time face images in smartphone application, we plan to improvise the results when these systems are exposed to same skin color and race, e.g., Chinese and Japanese people.

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