Face Recognition based on Frontalization of Multiple Poses and Expressions using GGAN and PCA

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Abstract

Face identification is an essential application in recent times as it has several applications like surveillance, criminal identification, etc. Many face recognition methods are still facing various challenges by researchers in real-time applications because of multiple rotational angles of faces and different expressions. To overcome this issue, we come up with the novel approach of Global Generative Adversarial Networks (G-GAN) to convert various expressions and side images into frontal images and Principal Component Analysis (PCA) to recognize the face in quick time with low cost, high accuracy and with use of less memory. The unique error loss algorithm is introduced in G-GAN during training which preserves identical features of profile images and photo-realistic good resolution front image. The single ground truth frontal image of an individual and G-GAN converted frontal pictures of individuals are considered, and PCA is applied to obtain features. The features are compared using Euclidean Distance (ED) to recognize an individual. The module used publicly available datasets like Indian male and female, ORL, and Multi PIE and achieved good results with a high recognition rate.

Keywords: *Biometrics, Face Recognition, GAN, Face Profile Images, PCA.*

1. Introduction

Deep learning (DL) is one of the trending and highly used methods by researchers in image processing and it has exceptional results in image classification and recognition compared to other traditional methods. Convolution Neural Networks (CNN) is one of the DL methods that produce good results in image classification and recognition [1]. After the emergence of Deep Convolution Neural Networks (DCNN) leads to exceptional image classification and recognition performance, however, Face Recognition (FR) faces many challenges when recognizing different side and expressions images compared to frontal face images. To overcome this issue, researchers have come up with two methods. The first method will capture many frontal, profile, and various expression images to train the model. Apple's Face ID method is one example of the first method in which it will catch many side images during registration. However, in a real-time situation, one cannot provide various side images and expressions at the time of registration as it depends on the

person's present situation. Training of multiple sides and expression images requires more time and memory. Hence the first method is not a fit method for FR. The second method first converts all various side and expression images into frontal images and then uses these images for FR. This method quite impressed researchers as it has many advantages over the first method. The traditional method for this is 3D rebuilding [2]; in the 3D method, first, it identifies required features, and it will make corresponding 2D projection angles and place these features in a 3D model to build a 2D frontal face using 2D projection. Another method to convert various side and expression images in 3D geometrical transformations [3-4] is to create frontal images from a different side and expression face images. These two methods were not produced a good frontal image when the angle of face rotation was high due to texture loss. The emergence of Generative Adversarial Networks (GANs) [5] has become a mature technique for front face creation. The ideal GAN [6] includes a generator and discriminator which will generate images from the noise. In GGAN, instead of noise, the profile images generate frontal face images with identity preservation of side or profile images.
There are various GANs that were available to convert front images but they might not create a good frontal image with identity preservation for significant pose variations and unique expression for FR. The features are extracted using various spatial, frequency, and hybrid domains from the converted frontal images, and ground truth images to classify the face images for FR.
Contribution: In *a* research paper, we came up with GGAN to produce multiple angled, expression, and tilt side face images into frontal face images. The FR of the generated front image of GAN is executed by using PCA. The combination of GGAN and PCA provides exceptional results in FR of various profile and expressions images.

This research paper includes a literature survey of FR, GAN, and PCA in section II. The proposed approach in section III. The result analysis of GGAN and PCA can be seen in section IV. Section V includes the conclusion and future work.

2. Literature Survey:

The existing techniques used in existing FR by various researchers are explained in this section. Most of the models used initially deal with where face images were used in both training and testing of the deep learning models [7-8]. Later developing CNN and DCNN [9-11] provide good results in FR in the wild, but it fails to deliver remarkable results to FR with different pose variations in face images. Zhu et al., [12] proposed the face identity preserving (FIP) features a method. This method will extract FIP, which will reduce intra-identity variances significantly. Also, it will maintain discriminative among identities which will help FR. Kan et al., [13] proposed the multi-view deep network (MvDN), extracting identical nonlinear features and viewing invariant features shared for multiple views. These features will help for better FR. The method proposed by Tran et al., [14] uses a typical encoder-decoder that creates a front face with an arbitrary face image up to an extreme profile image. Here decoder finds out the pose estimation, and the encoder will preserve identity features during front face image creation. Also, it will use learned coefficients to fuse multiple pose images into a single frontal face image. Wu et al., [15] proposed a match feature map operation in FR. This method enhances the FR in substantial-scale data and high noisy images. It uses a light CNN module to train deep face representation. Yi and Lill, [16] researchers have proposed a type of deep architecture based on new multilevel tasking learning. This method gives very high accuracy and performance in more considerable pose variation and different light illumination conditions.

Zhai and Zhai [17] proposed a distinctive protected GAN architecture. It used an encoder to compress authentic images and then convert them into restrictive GAN and a vector. By use of joint loss, it will calculate loss against the discriminator. This method used GAN to convert the front face image. Póka and Szemenyei [18] have proposed GAN, which will use the data augmentation method to reduce generator loss. In this method, GAN is used to convert profile images into frontal images. Xia et al., [19] Proposed Local and Global Perception Generative Adversarial Network. In local Perception, it extracted local identical features and produced some vital faces. Global Perception studies global statistics to preserve facial expressions. Cascading both local and international Perception leads to excellent front face creation from different rotational profile images. Huang et al., [20] proposed a Two Path Generative Adversarial Network, in this, the researcher's used two paths to generate a front face image from a side face. Here the first path is used to extract local features like noses, eyes, mouth, and skin texture; the second path is a global way to remove rough whole facial features with a front facial mask—the two paths were used because researchers assumed that the use of global features retains photo-realistic front face.

Lin et at., [21] proposed PacGAN, in this author made changes in the typical architecture of discriminator in such a way that it checks real or fake images with more than one generated image at the same time; because of this advantage, distribute across all images leads less loss and quick training of generator. But the problem with this method is the damage is very high when the model collapse problem occurs.
Yin et al., [22] proposed dual attention GAN, in this method author, extracts all identical local features like eyes, noise, etc., from the profile image then these features merge into a mask front face to create a front face from the profile face. Here it consumes more time to create a masked front face image. Chen et al., [23] proposed a Cooperative Dual Evolution-based Generative Adversarial Network (CDE-GAN). This architecture merges the dual progress of the generators and discriminators into an amalgamated adversarial outline to demeanor real adversarial multi-objective optimization. CDE-GAN divides the problem into two, one is the generation, and the other is discrimination these problems solve by using detached E-Generators and E-Discriminators. A soft algorithm is used for a trade-off among E-Generators and E-Discriminators to develop a stable exercise for CDE-GAN. Sukanya and Pallavi [24] proposed principal component analysis (PCA) for FR. In this method, the authors created subspace or free space, which reduced the set of feature vectors. These feature vectors find eigenface with low errors in various illuminations but have a high error rate in high pose variation profile images.

Navya and Pnrl [25] proposed geometric-based PCA. This method it identifies different fiducial points in the face and compares them for effective face retravel. Later they used the PCA algorithm for fusion with a geometric approach for FR. Eyad et al., [26] proposed PCA with the Euclidean method, square Euclidean method, and city block distance method. Here PCA is used to extract the principal features and other three distance methods used for FR based on those distances. This method has good accuracy for different illumination faces and small rotational side images but not for high tilt profile faces. Maliha et al., [27] proposed projection self-space PCA. This paper mainly focuses on reducing ample storage space into small by selecting principal features. Here it uses a wide

1-D pixel vector from a 2-D face picture for FR using PCA. The correct space is determined by the use of covariance matrixes from their own vectors.

In summary, some good FR models for different illumination and expressions, are proposed by different researchers, but many modules fail to produce a good result in FR for various rotational profile face poses. Here in this paper, the novel approaches of GAN and PCA are used to address the existing problems for better architecture for FR.

3. Proposed Approach

In this paper, we combined two methods viz., one is the conversion of tilt, and different angle rotational side face images into frontal face images using GGAN and the second one is the PCA technique for features to develop an effective FR system as displayed in figure 1.

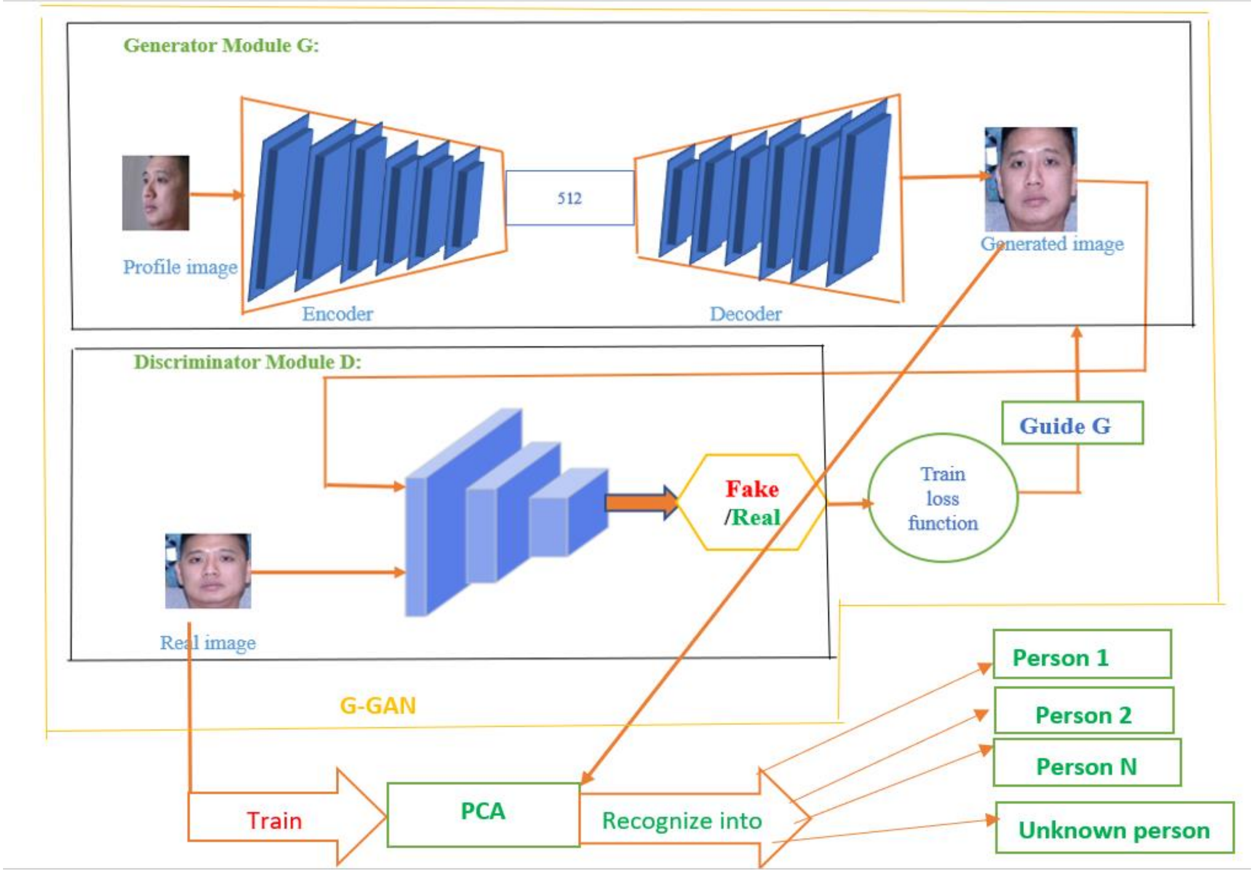

Figure 1. Projected FR with G-GAN and PCA

3.1 Face Datasets:

The proposed model is tested with public datasets such as Multi-PIE [28], ORL [29], and Indian male and female database [30] for both training and testing.

3.1.1 Multi-PIE face dataset:

The face database has a total of 750,000 images from 337 different persons who captured images during four sessions over a five-month period. Each image of a person was taken from 15 angles and 19 illumination conditions with a variety of facial expressions. In this chapter, only 100 different persons with 520 different images are used. Each face image in the dataset has a size of 128X128. Figure 2 shows the Multi-PIE dataset face image samples of four persons.

Figure 2 The Multi-PIE Dataset face images of four people [28]

3.1.2 ORL database:

It has 40 individuals with ten images of each with different facial expressions like open or closed eyes, smiling or neutral, sad or happy, etc., and facial rotation. All person's images were taken at different times with varying light intensities. All photos were in grey colour with 92x112 pixels and 256 gray levels per pixel as shown in figure 3.

Figure 3. The ORL dataset face images of 6 persons [29]

3.1.3 Indian Male database:

The Indian Male face database has a total of 220 images from approximately eleven distinct images of each of 20 different persons. Each image of one person has various facial orientations and expressions same as the Indian Female face database on the white background. Each face image in the database has a size of 480X640 pixels. Figure 4 shows the Indian Male dataset sample face images of four persons

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Figure 4. The Indian Male dataset face images of four people [30]

3.1.4 The Indian Female Face Database [30]

The Indian Female face database has a total of 242 images from approximately 12 distinct images of each of 20 different persons. Each image of one person has various facial orientations and expressions with smiles, laughter, sadness, disgust, and neutrality on the white background. Each face image in the database has a size of 480X640 pixels. Figure 5 shows the Indian Female dataset sample face images of four persons.

Figure 5. The Indian Female dataset face images of four people [30]

3.2 Proposed G-GAN Architecture:

The G-GAN has generation module *G* which generates photorealistic, identity preserving frontal face images from various multiple angle tilt pose variations face profile images and discriminator module *D* which is used to guide generator G to generate authentic images similar to ground truth images. Initially, train *D* with ground truth actual frontal images, later received output images by *G* module is connected to *D* to identify a created image is real or fake, based on discriminator observation on the generated image of *G* and ground truth actual frontal image. The generator module *G* always attempts to create a real ground truth image to fool *D* and *D* to distinguish between the ground truth real image and generated fake image.

3.2.1 Generator Module (G) Architecture:

The *G* module is having both an encoder and decoder similar to a classical generator. The objective of the generator encoder is to pull out the features from 128x128 input profile images ie., the height of (H), and width (W) of images, which have a 6-layer Deep Convolutional Neural Network (DCNN). The network architecture of the *G* encoder is shown in table 1.

Table 1: The network architecture of the *G* encoder

Layers	Input	Filter/ Stride/Pad	Output size
Conv0	128*128*3	4/2/1	64*64*16
Conv1	Conv0	4/2/1	32*32*32
Conv2	Conv1	4/2/1	16*16*64
Conv3	Conv2	4/2/1	8*8*128
Conv4	Conv3	4/2/1	4*4*256
Conv5	Conv4	4/2/1	2*2*512
BatchNorm2d			
ReLU			

In the encoder, 2-D convolution is used with a kernel size of 4 in order to do convolution and extract identical unique face features from the input profile image. The filter will move 2 columns and 2 rows while doing convolution for each kernel for the same reason, a stride size of 2 mentioned. In order to fit the feature extracted matrix with mentioned image size, a model used padding of zeros in columns and rows of feature matrix during each convolution. The height of the image (H) is based on the kernel, stride, and pad sizes, it is calculated using the formula H= ((Input image height-Kernel size+2*pad)/stride) +1. Same way width (W) of image is calculated using formula W= ((Input image width-Kernel size+2*padding)/stride) +1. After each convolution layer batch normalization [31] is in order to standardize inputs to the next convolution layer which leads to increased training speed and reducing generalization errors. The later proposed model is activated using Rectified Linear Unit (ReLU) [32] in order to reduce feature dimensions to eliminate features that have less importance. The extraction of identical photo-realistic features by reducing image size leads to preventing the overfitting of the encoder module.

The decoder of the *G* module has 5-layer deconvolution neural network which performs a reverse operation to the encoder of the *G* module. The output of the encoder which is a 512-dimensional vector is given to the decoder to recontact a frontal image with a photorealistic and preserve the identity of the real frontal face image. The decoder architecture is shown in table 2. Similar to the encoder the batch normalization function is used to standardize inputs during each deconvolution layer and Rectified Linear Unit (ReLU) to remove some of the less important features. In the end, the decoder is activated using a hyperbolic tangent function (tanh) which takes all real values and converts them from -1 to 1 similar to the sigmoid function.

Table 2: The network building of the decoder

Layer	Input	Filter/ Stride /Pad	Output size
Dconv0	Conv5	4/1/0	4*4*256
Dconv1	Dconv0	4/2/1	8*8*128
Dconv2	Dconv1	4/2/1	16*16*64
Dconv3	Dconv2	4/2/1	32*32*32
Dconv4	Dconv3	4/2/1	64*64*16
Dconv5	Dconv4	4/2/1	128*128*3
BatchNorm 2d			
ReLU			
Tanh			

3.2.2 Discriminator Module (D) Architecture:

It is a seven-layer DCNN network as reviled in table 3, it guides the generator *G* module in order to create a photo-realistic identity preserving the frontal image. By using ground truth real frontal images to train the *D* module initially to know what a real face looks like. As mentioned in table 3 convolution will use filter size of 3 to re-extract features using a stride of 2 and padding of 1. In the *D* module, the Leaky ReLU activation function is used after each CNN layer in order to increase the speed of the training process and maintain zero slop parts. Also, for each CNN layer, the batch normalization function is used to standardize inputs to the next CNN layer to accelerate the training process. The sigmoid function is used as a decision-maker in the discriminator. If the output of the Sigmoid function is 1 then it is a real image else Sigmoid is 0 then the discriminator output is a fake image. The aim of the classical discriminator is to differentiate the real image and fake images. In GAN's generator and discriminators compete with each other in order to produce good results. If the discriminator is more powerful then it identifies all generated images are fake images based on this it guides the generator to generate images similar to real images. If the generator is more powerful then it will fool the discriminator by making a fake image as a real image, also generator interim train the discriminator to identify fake images as fake. In this way, *G* and *D* challenge each other and guide each other to carte photorealistic identity preserving images.

Table 3: The network structure of the discriminator

Layers	Input	Kernel /Stride /pad	Output size
Conv0	128*128*3	3/2/1	64*64*16
Conv1	Conv0	3/2/1	32*32*32
Conv2	Conv1	3/2/1	16*16*64
Conv3	Conv2	3/2/1	8*8*128
Conv4	Conv3	3/2/1	4*4*256
Conv5	Conv4	3/2/1	2*2*512
Conv6	Conv5	3/2/1	1
BatchNorm2d			
LeakyReLU			
Sigmoid			

3.2.3 Loss Function:

The method uses two loss functions, one is Mean Square Error (MSE) and the other one is the Mean Absolute Error (MAE). The objective of MSE is to find image frontalization loss by optimizing this error generator to convert the profile image to the front image without identity preserving the profile image. In order to preserve the identity of the image, MAE is used. Training of this error leads to preserving identical parts of the profile image in the frontal image. So, a combination of these two images leads to the creation of a frontal image with the same photorealistic of the profile image. The formula for MSE is provided in equation 1.

$$M(a, b) = M = \{m_1, ..., m_N\}^T, \quad m_n = (a_n - b_n)^2 \qquad (1)$$

$M(a, b)$ = MSE

M is the mean of $m_1, m_2, m_3 .... m_N$

N=Batch size (Total number of images)

$m_1, m_2, m_3, ... m_N$ = mean of 1st image, 2nd image…. Nth image

a_n= Discriminator inputs

b_n= Discriminator outputs

n= 1 to max image pixel values

MSE will be trained during the training of both the generator and discriminator. While training the generator module a_n is the output of the generator and b_n is one to fool the discriminator to consider generated fake image as a real image. This loss will be *L1* loss.

During the training of MSE, the discriminator module will use two output values that are during training of real image will use output value as 1, and input values are ground truth real image features. Here targeted output value is one because the discriminator is trained for the real image and it has to identify as a real image that is the output of the discriminator as one. Similarly, while training fake images, the targeted output is zero as a discriminator to classify generated images as fake images, here input is profiled image features. Adams optimization algorithm is used to optimize the weights and errors during training *D* and *G*.

In order to make sure identity preservation in the frontal image an absolute mean error *L2* loss is used given in equation 2 and absolute square loss that is *L3* loss in equation 3. These two *L2* and *L3* loss functions preserve the features of profile images in the frontal image.

L2 = mean (absolute (real face-fake face)) (2)

L3=mean (power ((real face-fake face),2)) (3)

Here *L2* will find out a change in pixel values of real and fake face images with mean. *L3* will find power changes in pixel values of the real and fake image with mean. The final error will be calculated using equation 4.

Error GAN = Weight1 * L1 + weight2 * L2 + weight3 * L3 (4)

Where, Initial values for weight1 = 0.001,

weight2 =1,

weight3 =1.

3.3 Principal Component Analysis [33]

It is an unsupervised learning algorithm with a statistical approach that is widely used in data analysis, as here it reduces dimensions in order to use data economically and select the principal values for making a predictive model [34]. The PCA uses the approach of eigenfaces, it first locates and tracks face images then it compares these features to unknown faces to classify faces.

3.3.1 PCA Algorithm

It is an orthogonal linear transformation that transforms the information to a new coordinate system such that the greatest variance by some scalar projection of the information comes to lie on the first coordinate called the first principal component, the second greatest variance on the second coordinate, and so on. It transforms a large set of variables into a smaller one that still contains most of the significant information of the large set.

It is used to find the vectors in the face image that have a one-dimensional eigenvector called eigenface and these eigenfaces are the principal components. The NxN image is converted into a column $1xN^2$ vector. If *P* images then each image is represented as Q_1, $Q_2 \dots Q_P$ vectors. All these *P* images will convert into $1xN^2$ column vectors and be placed in the PxN^2 matrix. After conversion, calculate the mean face as given in equation 5.

$$\mu = (1 \div \mathrm{P}) \sum_{i=1}^{p} Q\, i \quad (5)$$

Then calculate the mean-centered image by subtracting the mean value calculated in equation 5 with each column image vector as shown in equation 6.

$$\Theta i = Qi - \mu \quad (6)$$

Then matrix *X* will set all mean-centered images ie., the output matrix of the above calculation.

$$\mathrm{X} = [\Theta 1\ \Theta 2 \dots \dots . . \Theta p]$$

The covariance matrix using C= X X^T with N^2 x N^2 dimensions is computed, then eigenvalues and eigenvectors are computed. These eigenvectors are the main features extracted from the image and all features are not required, hence reducing dimensions up to fifteen percent ie., up to value *Y*, these features are the principal components that represent in subspace. In order to find principal components will add all eigenvalues and multiply these eigenvalues by 0.9 this value will store in *S*. Later will sum eigenvectors up to *S*. These summed eigenvectors up to *S* are the principal components this called eigenface of matrix *U* with the size of N^2 x Y. It means the dimensions of matrix reduced from N^2 x N^2 to N^2 x Y in matrix *U*. Now will find a new matrix which will have eigenface in column vector using equation 7.

$$\text{Subspace} = \Theta^T U \tag{7}$$

It will be a matrix of size P x Y where *P* is the number of images and *Y* is the principal components of those images and this is the subspace again will calculate the mean of each column in order to recognize the test image.

The following are the facial reorganization steps used using PCA in our proposed model.

1. Get frontal face images of the training set and give them to the discriminator during G-GAN frontalization. Only one frontal image of each person is used for training which leads to saving a lot of time and memory. Then compute the mean face image.
2. Find the deviation of each training image from the mean value calculated in step 1
3. Calculate eigenvalues and eigenvectors of the covariance matrix from that obtain face space by reducing dimensions.
4. Record projected mean of centered images in face space
5. For testing capture test images in this case test images were G-GAN generated images these are frontal images from profile side images. Repeat steps 1,2,3 and 4 for all test images.
6. Now calculate all mean differences of train face space and test face space.
7. The test image classifies to the minimum mean difference among the training images
8. Fix the threshold and compare it with the minimum mean difference among the training images, if the threshold exceeds then it will classify as an unknown person else known person.

4 Result Analysis:

The exploration of the proposed model is based on two methods viz., (i) the use of G-GAN to convert different angled profile test images into frontal face images and (ii) the face recognition is based on the PCA technique of G-GAN generated frontal images and frontal face images stored in the database.

4.1 Experimental Training and Testing Approaches:

The Multi-Pie, ORL, Indian male and female datasets are considered and observed many profile images with different illuminations, expressions, and face rotation. The G-GAN is trained and saves the model with all datasets of individuals with frontal face images without using profile side-angled test face mages. The proposed model is implemented using python programming in Google Co-lab with PyTorch. With Graphical Processing Unit (GPU) of NVIDIA GeForce Gtx and Pytorch data loader. Face recognition uses PCA on test and trained face images to obtain features. These recognition parts are implemented using python3, NumPy, and OpenCV.

4.2 Visual Qualitative Result:

In this section, the visual quality of the frontal images generated by G-GAN from different angled rotation profile images is discussed. The G-GAN is tested with Multi-PIE, ORL, Indian male, and Female datasets. The results of these datasets are revealed in figures 6, 7, 8, and 9. The profile images with various angled rotations are shown in Figure (a). The frontal images generated by G-GAN are shown in Figure (b). The ground truth frontal images are shown in Figure (c). It is observed that the visual quality of generated images is very good, and also these images are almost the same as ground truth images.

Figure 6. Results of G-GAN for Multi-PIE Dataset (a) Profile image, (b) Generated image (c) True images

Figure 7. Results of G-GAN for ORL Dataset (a) Profile images (b) Generated images (c) True images

Figure 8. Results of G-GAN for Indian male Dataset (a) Profile images, (b) Generated images (c) True images

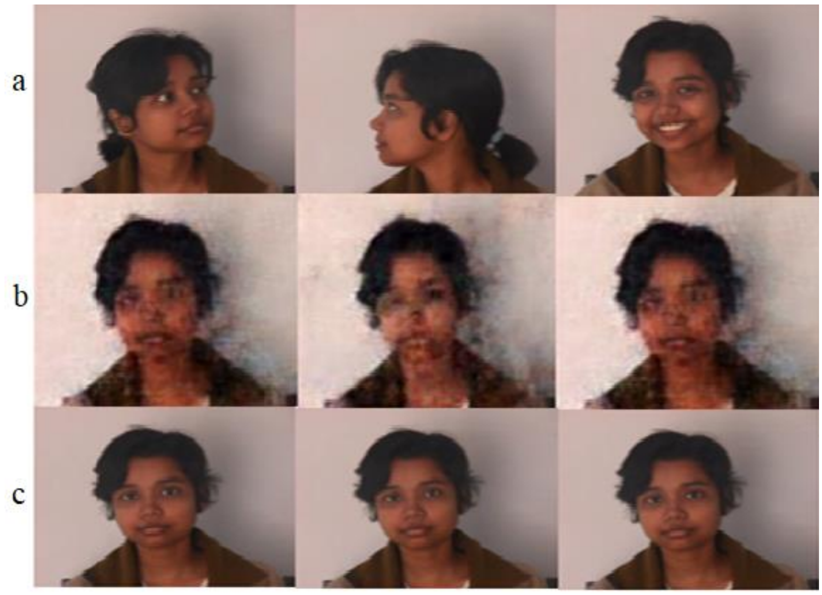

Figure 9. Results of G-GAN for Indian Female Dataset (a) Profile images, (b) Generated images (c) True images

4.3 Face Recognition Evaluation:

The process is a challenging task as images captured by the camera in real-time have multiple head rotations and tilt angles. The challenging part of classical algorithms is they need huge memory, hardware, and time in order to train a model with the number of variations in multiple head rotations and tilt angles leading to a costly system. Therefore, the proposed model that first converts all randomly captured images into frontal images using G-GAN and then will classify these images with corresponding true images that were used during the training of GAN. The main advantage of the proposed method is the training of GAN with ORL, the Indian male and female dataset will be completed in 10 minutes with exceptional photo-realistic images, and training of Multi-PIE will take nearly two hours as it has more images. The saved model was used in the testing of remaining profile images that were not used in training. The converted G-GAN frontal images are used in FR. For the FR part will make individual folders for all persons, the single ground truth frontal face is used during training of G-GAN by placing these images in the corresponding person folder to train PCA. Then will place all converted G-GAN frontal face images from profile faces into corresponding person folders along with some face images which will not be trained during the training of PCA. The proposed model recognizes all persons which used during training and it will classify other persons as unknown persons.

The sample result of the proposed model is shown in figure 10.

```
Total identical Person 19
Total Train Images 19
Total Test Images 59
Unknown Person i.e true rejection rate 3
Correctly matched persons are i.e True recognition rate 56
Wrong matched persons i.e false recognition rate  0
Accuracy 100.0
Total Time Taken for reco: 0.007049000000000305
Time Taken for one reco: 0.00011947457627119162
Training Time 1.380487
```

Figure 10. Sample ORL dataset FR results

Table 4 revealed the results of FR using various face datasets. It is seen that the accuracy is maximum and 100% with ORL, however, the accuracy is a little less in the cases of Indian males, females, and multi-PIE datasets since the angle variations are more. The time to train and FR are more with the multi-PIE dataset, since the large dataset.

Table 4: Sample results of FR in the proposed method

Dataset	% Accuracy	Time to train in seconds	Time for FR in seconds
ORL	100	1.3804	0.00704
Indian Male and female	99.23	1.1149	0.00098
Multi-PIE	99.12	1.768	0.00921

The accuracy result of FR is compared with other models using ORL dataset accuracy results are seen in table 5. Similarly, the accuracy of the proposed model for the multi-PIE dataset is compared and analyzed with other models as shown in table 6. It is observed that the accuracy of the proposed method is improved compared to the existing techniques with ORL and Multi-PIE datasets. The results are improved as the angled face images are transformed into frontal images using GAN and features are extracted.

Table 5: FR Accuracy of different methods on ORL

Models	CNN [35]	LBPH [36]	I2-DPCA [37]	RCM-2DPCA [38]	Proposed G-GAN/PCA
% Accuracy	95.4	97	97.5	97.2	100

Table 6: FR Accuracy of different methods on Multi-PIE

Models	VS2VInetwork [39]	CDEF [40]	CCA [41]	AAMs [42]	Proposed G-GAN/PCA
% Accuracy	94.3	88.8	83.2	89.7	99.12

5. Conclusion:

The contemporary methods of face recognition are challenging as the real-time CCTV cameras capture images with multiple angles, tilts, and expressions leading to poor performance. Some FR models also used many diverse images to train a model to achieve the best performance but models consume huge time, memory, and hardware. In this paper, we come up with a solution to diverse profile image FR issues using G-GAN and PCA to increase the performance of FR with low time and memory. The PCA is applied on generated frontal images by GGAN and ground truth frontal real images to extract features. The ED is used to compare features to compute performance parameters. The experimental results are also compared with other present methods, and the proposed model shows superiority over other methods.

REFERENCES:

[1] *L. Tran, X. Yin, and X. Liu, "Disentangled Representation Learning GAN for Pose-Invariant Face Recognition," IEEE Conference on Computer Vision and Pattern Recognition (CVPR),* ***(2017)****, pp. 1283-1292.*

[2] *James Booth, Anastasios Roussos, Allan Ponniah, David Dunaway and Stefanos Zafeiriou, "Large Scale 3D Morphable Models" International Journal of Computer Vision,* ***(2018)****, pp 233–254.*

[3] *C. Ding and D. Tao, ''Pose-Invariant Face Recognition with Homograph-Based Normalization,'' Elsevier Journal of Pattern Recognition, vol. 66,* ***(2017)*** *pp. 144–152.*

[4] *T. Hassner, S. Harel, E. Paz, and R. Enbar, "Effective Face Frontalization in Unconstrained Images," IEEE Conference on Computer Vision and Pattern Recognition (CVPR),* ***(2015),*** *pp. 4295-4304.*

[5] *H. Tang, H. Liu, and N. Sebe, "Unified Generative Adversarial Networks for Controllable Image-to-Image Translation," IEEE Transactions on Image Processing, vol. 29,* ***(2020),*** *pp. 8916-8929.*

[6] *Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio, "Generative Adversarial Nets," ACM Twenty seventh International Conference on Neural*

*Information Processing Systems, vol 2, **(2014)**pp 2672–2680.*

[7] *Chen, M., Xu, Z., Weinberger, K., Sha, F, "Marginalized denoising autoencoders for domain adaptation". arXiv preprint arXiv:1206.4683, **(2012)**.*

[8] *Simonyan, K., Zisserman, A., "Very deep convolutional networks for large-scale image recognition". arXiv preprint arXiv:1409.1556, **(2014)**.*

[9] *Krizhevsky, A., Sutskever, I., Hinton, G.E, " Imagenet classification with deep convolutional neural networks". Advances in Neural Information Processing Systems (NIPS). **(2012),** pp. 1097– 1105.*

[10] *Taigman, Y., Yang, M., Ranzato, M., Wolf, L.: Deepface, "Closing the gap to human-level performance in face verification". IEEE Conference on Computer Vision and Pattern Recognition (CVPR). **(2014),** pp. 1701–1708.*

[11] *Chen, J.C., Zheng, J., Patel, V.M., Chellappa, R, "Fisher vector encoded deep convolutional features for unconstrained face verification". IEEE International Conference on Image Processing (ICIP). **(2016),** pp. 2981–2985.*

[12] *Zhu, Z., Luo, P., Wang, X., Tang, "Deep learning identity-preserving face space". Proceedings of the IEEE International Conference on Computer Vision (ICCV). **(2013)** pp. 113–12.*

[13] *Kan, M., Shan, S., Chen, X., "Multi-view deep network for cross-view classification". Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). **(2016),** pp. 4847–4855.*

[14] *Tran, L., Yin, X., Liu, X., "Disentangled representation learning gan for pose-invariant face recognition". Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). vol. 3, **(2017),** pp. 7.*

[15] *Wu, X., He, R., Sun, Z., Tan, T., "A light CNN for deep face representation with noisy labels". IEEE Transactions on Information Forensics and Security. vol 13(11), pp. 2884–2896.*

[16] *Yin, X., Liu, X. 2018: "Multi-task convolutional neural network for pose-invariant face recognition". IEEE Transactions on Image Processing. vol. 27, no. 2, **(2018),** pp. 964-975.*

[17] *Z. Zhai and J. Zhai, "Identity-Preserving Conditional Generative Adversarial Network," IEEE International Joint Conference on Neural Networks (IJCNN), **(2018)** pp. 1-5.*

[18] *K. B. Póka and M. Szemenyei, "Data Augmentation Powered by Generative Adversarial Networks," Twenty third IEEE International Symposium on Measurement and Control in Robotics (ISMCR), **(2020),** pp. 1-5.*

[19] *Y Xia, W Zheng, Y Wang, H Yu, J Dong, and F Y Wang, "Local and Global Perception Generative Adversarial Network for Facial Expression Synthesis," IEEE Transactions on Circuits and Systems for Video Technology, **(2021)**.*

[20] *R. Huang, S. Zhang, T. Li and R. He, "Beyond Face Rotation: Global and Local Perception GAN for Photorealistic and Identity Preserving Frontal View Synthesis," IEEE International Conference on Computer Vision (ICCV), **(2017),** pp. 2458-2467.*

[21] *Z. Lin, A. Khetan, G. Fanti and S. Oh, "PacGAN: The Power of Two Samples in Generative Adversarial Networks," IEEE Journal on Selected Areas in Information Theory, vol. 1, no. 1, **(2020),** pp. 324-335.*

[22] *Y. Yin, S. Jiang, J. P. Robinson and Y. Fu, "Dual-Attention GAN for Large-Pose Face Frontalization," Fifteenth IEEE International Conference on Automatic Face and Gesture Recognition (FG 2020), **(2020),** pp 249-256.*

[23] *Shiming Chen, Wenjie Wang, Beihao Xia, Xinge You, Qinmu Peng, Zehong Cao, and Weiping Ding, "CDE-GAN: Cooperative Dual Evolution Based Generative Adversarial Network," IEEE Transactions on Evolutionary Computation, **(2020)**.*

[24] *S. S. Meher and P. Maben, "Face recognition and facial expression identification using PCA," IEEE International Advance Computing Conference (IACC),* ***(2014),*** *pp. 1093-1098.*

[25] *N. S. Tummala and P. C. Sekhar, "Face recognition using geometric approach," International Conference on Computing Methodologies and Communication (ICCMC),* ***(2017),*** *pp. 562-565.*

[26] *E. I. Abbas, M. E. Safi, and K. S. Rijab, "Face recognition rate using different classifier methods based on PCA," International Conference on Current Research in Computer Science and Information Technology (ICCIT),* ***(2017),*** *pp. 37-40.*

[27] *M. Khan, S. Chakraborty, R. Astya, and S. Khepra, "Face Detection and Recognition Using OpenCV," 2019 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS),* ***(2019),*** *pp. 116-119.*

[28] *R. Gross, I. Matthews, J. Cohn, T. Kanade and S. Baker, "Multi-PIE," Eighth IEEE International Conference on Automatic Face & Gesture Recognition,* ***(2008),*** *pp. 1-8.*

[29] *I. Abbas,Eyad and Ehsan, Mohammed and Rijab, Khalida, "Face Recognition rate using different classifier methods based on PCA"* ***(2017),*** *pp.37-40.*

[30] *Indian Face Database; http://viswww.cs.umass.edu/~vidit/Indian Face Database.*

[31] *V. Thakkar, S. Tewary and C. Chakraborty, "Batch Normalization in Convolutional Neural Networks - A comparative Study with CIFAR-10 Data," Fifth IEEE International Conference on Emerging Applications of Information Technology (EAIT),* ***(2018),*** *pp. 1-5.*

[32] *V. Nair and G. E. Hinton, ''Rectified Linear Units Improve Restricted Boltz- Mann Machines,'' ACM Twenty seventh International Conference on Machine Learning (ICML),* ***(2010),*** *pp. 807–814.*

[33] *K. Pearson, "LIII. On lines and planes of closest fit to systems of points in space", The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science, vol. 2, no. 11, pp. 559-572.*

[34] *J. Shlens, "A tutorial on principal component analysis", arXiv preprint, arXiv:1404.1100,* ***(2014)****.*

[35] *Mengjia Yan, Mengao Zhao, Zining Xu, Qian Zhang. "VarGFaceNet: An Efficient Variable Group Convolution Neural Network for Lightweight Face Recognition", Horizon Robotics,* ***(2019)****.*

[36] *A. V. Sripriya, M. Geethika and V. Radhesyam, "Real Time Detection and Recognition of Human Faces," 4th International Conference on Intelligent Computing and Control Systems (ICICCS),* ***(2020)****, pp. 703-708.*

[37] *K. Woraratpanya, M. Sornnoi, S. Leelaburanapong, T. Titijaroonroj,R. Varakulsiripunth, Y. Kuroki, and Y. Kato, "An improved 2DPCA forface recognition under illumination effects," 7th International Conference on Information Technology and Electrical Engineering (ICITEE),* ***(2015),*** *pp. 448–452.*

[38] *T. Titijaroonroj, K. Hancherngchai and J. Rungrattanaubol, "Regional Covariance Matrix-Based Two-Dimensional PCA for Face Recognition," 12th International Conference on Knowledge and Smart Technology (KST),* ***(2020),*** *pp. 6-11.*

[39] *T. Zhang, Q. Dong and Z. Hu, "Pursuing face identity from view-specific representation to view-invariant representation," IEEE International Conference on Image Processing (ICIP),* ***(2016),*** *pp. 3244-3248.*

[40] *Dahua Lin and Xiaoou Tang, "Inter-modality face recognition," in ECCV,* ***(2006),*** *pp. 13–26.*

[41] *Annan Li, Shiguang Shan, Xilin Chen, and Wen Gao, "Maximizing intra-individual correlations for face recognition across pose differences," in CVPR,* ***(2009),*** *pp.*

605–611.

[42] *X. Chen, C. Wang, B. Xiao and X. Cai, "Learning associate appearance manifolds for cross-pose face recognition," IEEE International Conference on Image Processing (ICIP),* ***(2014)*** *pp. 1907-1911.*