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FACE RECOGNITION BASED ON FRONTALIZATION OF MULTIPLE POSES USING G-GAN AND DWT

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Abstract

Face authentication is one of the embryonic issues for researches in modern days as it has many challenges and is used in several applications. The challenge of face recognition encounters large side angles in profile images as features between profile images and frontal images have large differences that lead to human identification. This is a reason much state-of-the-art facial recognition has reduced performance on human identification. In this research paper, we propose frontal face generation from profile face image before facial recognition using Global Generative Adversarial Networks (G-GAN). By using G-GAN along with unique error loss functions during training leads to good identity preservation and photo-realistic frontal face images. The Discrete Wavelet Transform (DWT) is used on generated frontal images from profile images and the frontal image stored in the database to extract features. The compressed low dimensional significant features from the low-frequency band are considered for face recognition. The Euclidean Distance (ED) between the ground true database frontal image and the frontal face images generated by G-GAN are computed for face recognition. The experimental results based on qualitative and quantitative analysis using available public datasets viz., Multi PIE, Bosporus, head pose-invariant, and Indian female are conducted and achieved good results. The experiment results of the projected scheme are related to the other existing approaches show the superiority of our method.

***Keywords*- Biometrics, DWT, Face Profile Images, Face Recognition, GAN.**

I. INTRODUCTION

Deep learning (DL) in the area of image processing due to its capability of an object, image, and human recognition attracted many researchers with exceptional accuracy than other normal shallow learning models. The Convolution Neural Networks (CNN) present in DL leads to successfully extract the distinctive and identical features of the images [1-2]. Later development of Deep Convolution Neural Networks (DCNN) achieved high success in Facial Recognition (FR). However, most solutions in FR still have less performance in the processing of various pose faces compared to frontal faces. There are two ways to resolve this issue. The first way is to capture the frontal face and different directions of side faces i.e., profile faces to train the model with all frontal and profile faces. One of the examples of this method is apple's Face ID in which the user needs to give a different pose face during registration. Nevertheless, many applications do not use side profile face images compared to frontal face images. It shows recognition faults occur while matching profile face images with other frontal face images. In addition, one can have to capture a greater number of directions and expressions of face images, which is unreasonable. The second way is to produce frontal face images from profile faces beforehand FR. The general awareness for this is 3D rebuilding [3], in this way first it calculates the projection angles from a 2D photo by marking the required features and it places a 3D face model to create a 2D frontal face using 2D projection and use any regular method to create a frontal face from profile face images. Other efforts [4-6] for face frontalization are 3D geometrical transformations to generate frontal face from various pose profile face. These ways are not replicate all features of the original human as it uses a general 3D model to generate 2D face and frontal images may not be accurate for large pose variations due to texture loss. The recent development of Generative Adversarial Networks (GANs), lead mature and emerging techniques to generate frontal faces [7]. However, the typical GAN [8] generates an image from noise, which includes both generator and discriminator. The frontal face from the profile face must be of the equivalent individual of profile image be ensured. The generator normally consists of encoder-decoder architecture, in the same way, the discriminator is consisting a model to direct the generator to create a photo-realistic frontal face along with good loss function and optimization techniques. The present methods of different GAN may not produce an excellent frontal image with various possess for FR.

Contribution: In this research paper, we proposed efficient G- GAN to convert tilt and pan angled profile face images into frontal face images. The face recognition to identify human beings from the generated frontal face images is executed using DWT. The G-GAN relatively performs well under large and different expression poses.

This research paper is scheduled as follows; section 2 delivers the literature study of GAN and face recognition. Section 3 provides the proposed approach. The result analysis is deliberated in Section 4. Conclusion and future work of the research is specified in Section 5.

II. LITERATURE SURVEY:

They are many approaches for face frontalization and present approaches are classified into three approaches: 3D-based approach, statistical approach, and deep-learning-based approaches. Zhai and Zhai [9] proposed a unique protective provisional GAN model. Introduced an encoder framework to compress an actual image into a covert image in the restrictive GAN and a restricted vector. A joint-loss to equilibrium the power of the uniqueness conserving loss against the discriminator when refinement the encoder is presented. The method proposed by Póka and Szemenyei [10] proposed a data augmentation technique in GAN for loss reduction. An effort to upsurge the excellence of few-shot knowledge FR using GAN with information expansion procedures. A method is offered to insert images into GAN's covert space and to use the improved forms for few-shot learning. Xia et al., [11] Proposed Local and Global Perception Generative Adversarial Network (LGP-GAN) with a two-stage cascaded assembly to excerpt and produce the particulars of the vital facial districts. The model exploits local networks to detention the local texture particulars of the crucial facial regions in facial expressions in stage 1. A global network to study the facial statistics in Stage 2 to produce the last facial expressions. Huang et al., [12] proposed TP-GAN in which the author used two paths to generate front face from profile face. One path to extract local features like eyes, noses, and mouth and other path is global way extract rough whole facial features. They assumed straight with the global method would not recall features of profile face image in the front face image. This was occurring due to the typical failure problem, which means for a provided exercise set; some parts of features can seem in the produced results. This deadly issue in producing front face images from profile face images. Lin et at., [13] proposed PacGAN, in this researcher modified the discriminator in such a way that it can judge the originality of more than one generated image at the same time and the damage was transmitted between all produced images. Therefore, the damage has high raise when the model collapse occurred. Yin et al., [14] dual attention GAN which used masked selected feature extraction before generating frontal face image to generate same person frontal face from profile face. The model uses an extra model to extract masked parts from the face, which consumes some time and memory to perform this extra task. As stated earlier, the work of frontal face generation is not only the produced frontal face is real but the same person of the profile image. The general present discriminators cannot perform these two tasks at the same time. Chen et al., [15] proposed a Cooperative Dual Evolution based Generative Adversarial Network (CDE-GAN). The method integrates dual progress concerning the generators and discriminators into an amalgamated adversarial outline to demeanor real adversarial multi-objective optimization. CDE-GAN decays the problem into two (i) generation and (ii) discrimination, and each one is resolved with detached E-Generators and E-Discriminators. A Soft Instrument is adapted to steadiness the trade-off among E-Generators and E-Discriminators to deportment stable exercise for CDE-GAN.

Statistical methods proposed by Sagonas et al., [16] used a statistical model for front face generation and landmark identification by cracking a little mark minimization problem. However, these approaches hurt while front image generation for large pose variation profile images. In deep learning methods researchers generally apply CCNs. Yim et al., [17] extract feature by using locally connected convolutional layers and synthesis front image by using a fully connected layer. This method performs well and gets high recognition rates, but it has blurred images under large pose variations. In recent years after developing GAN, many methods were proposed for the generation of front faces under large poses. Rong et al., [18] proposed GAN by enhancing features for face frontalization. An inborn plotting between the frontal and profile faces and their differences is estimated. The generator module has a compact module that supports plotting the features of the profile to the frontal faces. It yields a feature discriminator, which differentiates the features of profile faces and ground true frontal face images, to deliver satisfactory features of profile faces. Rao et al., [19] proposed DWT method for face recognition by extracting LL bands from the image. He also uses eigenvectors for the same under different illumination and expressions. Rangsee et al., [20] projected Nibble-based face recognition using the convolution of hybrids features for face recognition. Here authors proposed left side and right-side nibble bits for fast computational speed for face recognition. In Summary, for face frontalization GAN based approaches provide the best performance for frontal face generation and recognition under huge pose variations and expressions. In our paper, we use some of the methods of GAN-based models to generate frontal face images.

III PROPOSED APPROACH:

In this unit, we deliberate two items viz., conversion of angled profile face images into frontal images using G-GAN and recognition of face images using Discrete Wavelet Transform (DWT).

3.1 DATASETS:

The proposed method is tested with standard datasets such as Bosphorus dataset [21], Multi-PIE [22], head-pose rotation [23], and Indian female database [24] for training and testing purposes.

3.1.1 BOSPHORUS:

The dataset has both 2D and 3D images with angle labels, which includes 4666 images of 105 peoples. Each individual has nearly 45 images with dissimilar head postures of 13 yaws and pitch rotation, face occlusions, and 35 expressions. All images in png format and color texture images of dimension 1600*1200. The images are captured in a dark room using a 1000W halogen lamp. The sample images of the Bosphorus dataset with different expressions and face rotation angles are as shown in Figure1

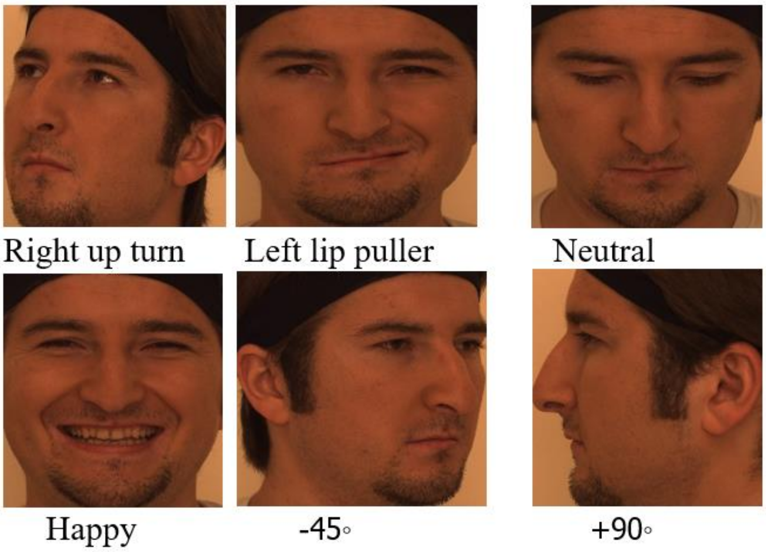

Fig 1 Sample images from Bosphorus dataset with different expression and pan angles [21]

3.1.2 MULTI-PIE:

Multi Pose, Illumination, Expressions (Multi-PIE) is one of the largest datasets with 755,370 images of 337 persons with dissimilar postures, illuminations, and expressions. These images were captured with different intensities and pose using 15 cameras and 18 flashes coupled to Linux computer systems. A total of 300 images were caught in 0.7 seconds each person has nearly 520 images. Each person has different expressions, neutral expressions, and different head pose rotations. Few sample images of the Multi-PIE dataset as shown in Figure 2 with the pan angle values on images.

Fig 2. Multi-PIE sample images with pan angles [22]

3.1.3 HEAD POSE IMAGE DATABASE (HPID)

The image dataset has 2790 face images with face tilt from -90 to +90 degrees. Two sessions were captured for each person, having 93 images in each session. The persons in the dataset wear glass and some without glass with different skin colors. The images were captured without any background to focus on the face image. Figure 3 shows sample images of the Head pose image dataset with the values of tilt and pan angles.

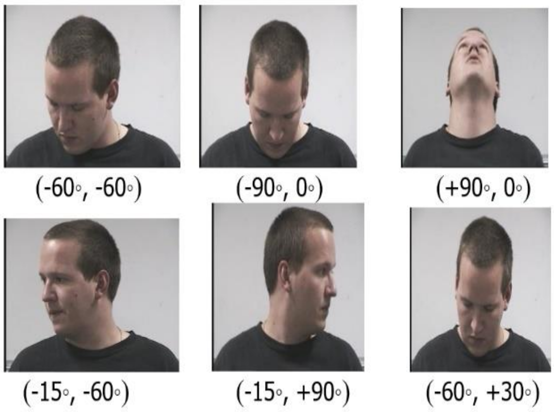

Fig 3 HPID Sample Images with vertical tilt and horizontal pan angles [23]

3.1.4 INDIAN FEMALE DATABASE:

The small dataset with 22 persons of each having 11 images with different expressions and face rotation captured randomly leads to 242 images. Figure 4 displays example images of the Indian female dataset.

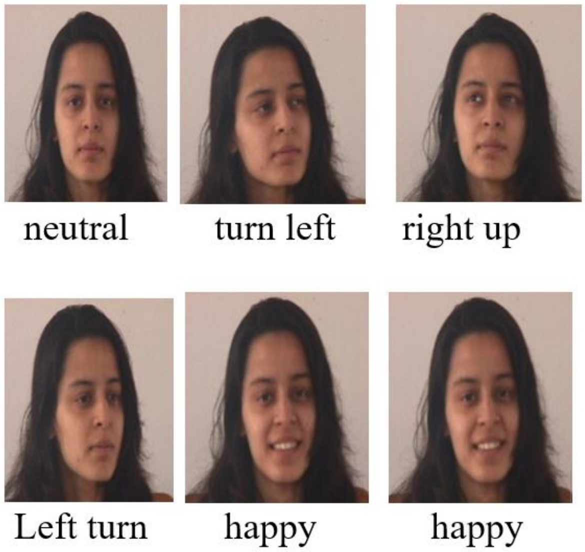

Fig 2. Sample images from Indian female dataset [24]

3.2 GLOBAL-GENERATIVE ADVERSARIAL NETWORKS (G-GAN)

The total block diagram of G-GAN is as displayed in Figure 5, that have generation module *G* and discriminator module *D*. The purpose of the generation module is to produce photorealistic, identity-preserving frontal face image from pose variant profile face images. Primarily it contains profile face image space, encoder, and decoder and at end generated frontal face image. The encoder uses Deep Convolution Neural Layers (DCNL) to transform profile face images into intermediate features. The yield of the encoder is given to the decoder, which has deep convolution neural layers. The decoder converts encoder intermediate features into the frontal image. The purpose of Discrimination module *D* is to advise generation module *G* to achieve excellent output effects. The inputs to Discrimination module *D* are a true real image and created image from a generator. Discriminator would differentiate among real true image and produced frontal image, which again guides generation module to generate photo-realistic frontal image outcomes. Similar to classical GAN's, in our model, *G* and *D* compete with each other to improve their performance. The generator *G* always tries to generate a real true image to fool *D* and *D* target to distinguish ground real image and generated fake image. We also introduced loss function to train our *D* and *G* modules in detail later in the following sub-section. The architectures of *G* and *D* with loss functions are discussed in the following subsections.

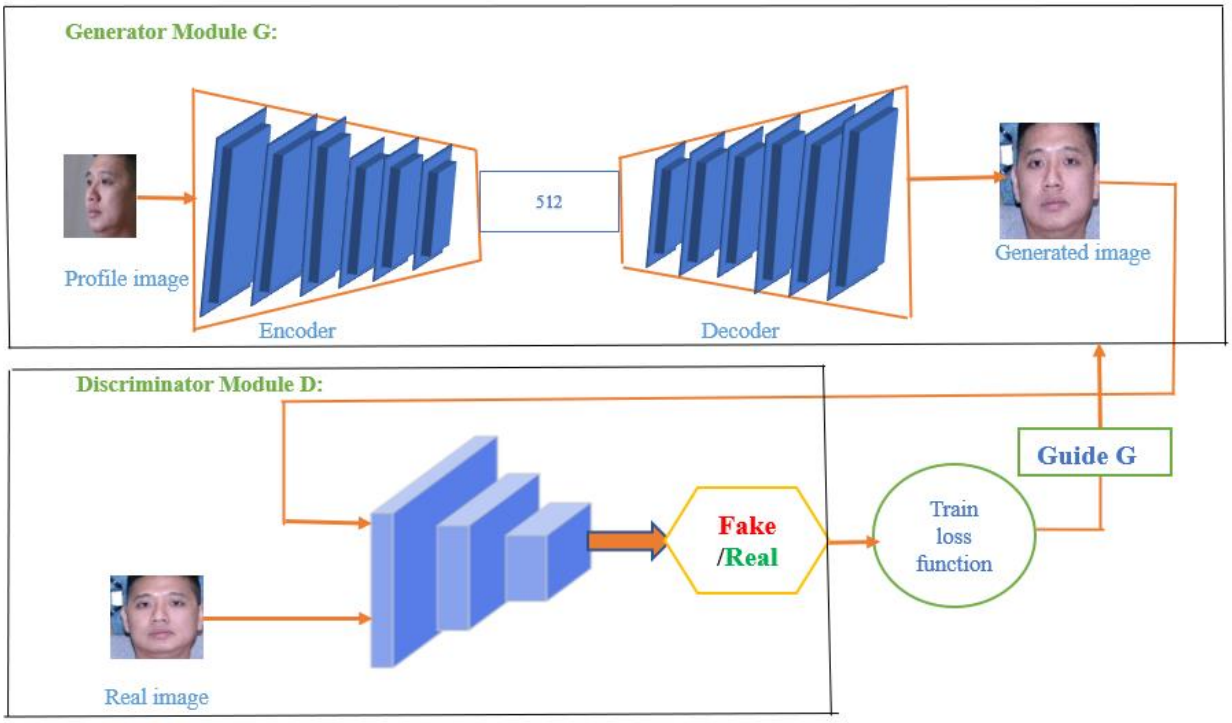

Fig 3. Projected G-GAN

3.2.1 ARCHITECTURE OF GENERATOR MODULE (G):

The generator module is divided into encoder and decoder. Generator encoder designed in a way to extract features from an input profile image, which has a classical 6-layer Convolutional Neural Network (CNN). The complete network stature of the generator encoder is revealed in table 1. The input profile image size is fixed to 128*128*3 that is 128 in width and 128 in height with 3 RGB channels.

Table 1: The network building of the encoder

Layers	Input	Kernel/ 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
BatchNorm 2d			
ReLU			

The stride size of two is used to move the filter’s 2 columns at a time to do convolution and padding used to fill zeros to the filter. These features pass it through CNN, which aims to decrease the width and height of the image and increase the number of dimensions as revealed in fourth column of table1. The height H and width W is calculated using formula H= ((Input image height-Kernel size+2*padding)/stride) +1. Similarly, width is calculated using W= ((Input image width-Kernel size+2*padding)/stride) +1. In our encoder, each convolution layer is followed by a batch normalization [25] and activated by Rectified Linear Unit (ReLU) [26]. At the end of the encoder, the max pool function is used, which has an output of 512-dimensional features. The dimensional reduction of the input image leads to preventing overfitting of the model.

The generator decoder, as the name, suggest its inverse work of generator encoder. It takes the low dimensional output of the encoder and recovers frontal-view face image with photo-realistic with preserving the identity of the original image. The decoder network arrangement is revealed in table 2. The decoder contains three parts viz., first part performs simple deconvolution layers to un-sampled the feature of the encoder. The second part is batch normalization stacked after each deconvolution layer to reconstruct the front image. The third part is Rectified Linear Unit (ReLU) as the activation layer for each deconvolution layer. At end of the sixth deconvolution layer, the network is actuated using hyperbolic tangent function (tanh).

Table 2: The network building of the decoder

Layer	Input	Kernel/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
BatchNorm2d			
ReLU			
Tanh			

3.2.2 ARCHITECTURE OF DISCRIMINATOR MODULE (D):

The Discriminator Module *D* advises *G* to yield photo-realistic and identity-preserving high-quality frontal face images. *D* consists of seven layers of CNN as shown in table 3. The discriminator model uses the LeakyReLU activation function for each CNN layer instead of ReLU as LeakyReLU to speed up the training process and it has zero-slope parts. Each CNN layer is stacked by batch normalization to standardize the inputs to a network and it also accelerates the training process. In the end, the Sigmoid function is used to map features between 0 and 1. If Sigmoid output is 1, then output is real image else the output of discriminator is fake or generated image. *D* will compete by *G,* which leads to producing excellent features in the decoder. *D* aims to differentiate the generated frontal image with the ground truth image. The generation module *G* and image discriminator *D* improve their performance on competing with each other that is generating a good realistic image by *G* and identifying fake/real image by *D*. If *D* is more powerful, then the generator will produce highly realistic images with all identity of a profile image. If *G* is more power full so that it can confuse *D* with that fake image as a real image and it improves the ability to distinguish between real and fake images that again train *G* in a better way to generate a good photo realistic identity preserving the image. In short, *D* and *G* enhance their performance by challenging each other.

Table 3: The network structure of the discriminator

Layers	Input	Kernel/Stride	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 TRAINING OF LOSS FUNCTION:

In this section, training of loss function is presented and consists of two-loss functions. The first one is a frontalization-training loss represented by Mean Square Error (MSE) loss function. This loss function makes sure that frontalization of the image is from the profile image. The second one is the Mean Absolute Error loss function. The main aim of this loss function is to make sure that the front image is of the same person image as the profile image person.

The MSE, which calculate during training of both generator module *G* and discriminator module *D*. The general MSE function is given in Equation 1.

$$\ell(x, y)= L =\{\ell_1,\dots,\ell_N\}^T, \quad l_n= (x_n - y_n)^2 \quad \text{---------------------------(1)}$$

$$\ell(x, y)= \text{MSE}$$

L is the mean of $\ell_1, \ell_2, \ell_3 \dots \ell_N$

n= 1 to max image pixel value

N=Batch size (Total number of images)

$\ell_1, \ell_2, \ell_3, \ldots\ldots \ell_N$ = mean of 1st image, 2nd image…. Nth image

x_n= Number of Discriminator inputs

y_n= Number of Discriminator outputs

Here *N* is the batch size, which is 64. $\ell(x,y)$ is mean, it measures MSE between inputs to the discriminator and targeted values. Here two different targeted values are considered while training discriminator. When the input is a real image i.e., x_n while training discriminator, then, considers target value is *one* (y_n=1), it indicates that the discriminator targeted value is the real image this loss will consider as error1. While training discriminator with fake image, then the generated image from *G* is fake image i.e., x_n which is the input to the *D* and output value is zero (y_n=0). It indicates that the discriminator targeted is a fake image. This loss is considered as error 2. Add both error values of the discriminator and do back-propagation and optimize the parameters using Adam's optimizer to train D and guide G.

The MSE loss function for Generator module *G* is represented as, in equation 1, where x_n is the output generated by *G* and y_n is one to fool the *D* to consider the fake image as a real image. Discriminator output guides the generator module to generate an accurate frontal face image. Training the generator with the MSE loss error function is represented by the L1 loss function.

Also use the other two-loss functions that are Mean Absolute Loss represents as L2 loss, given in equation 2, and mean absolute square loss represents as L3 loss, given in equation 3. The use of the L2 and L3 loss function is to make sure that generated frontal image belongs to the same person of the profile image.

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

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

Here L2 will calculate absolute change in pixel values of real and fake image with mean. Similarly, L3 will calculate power alteration in pixel values of real and fake image with mean. The final error will be calculate using equation 4:

Error G = GAN_weight * L1 loss + L2_weight * L2_Loss + L3_weight * L3_Loss ---------------(4)

Where, GAN_weight = 0.001,

L2_weight =1,

L3_weight =1. The training loss function given in Table 4.

Table 4. Loss function of Training algorithm:

1. Assume batch size of 64, GAN_weight=0.001, L1_weight=1 and L2_weight=1
2. Assign y=1 while training real image for discriminator
3. Compute MSE between *y* and real image with mean =error_real
4. Assign y=0 while training fake image for discriminator
5. Compute MSE between *y* and fake image with mean=error_fake
6. Error_GAN=error_real + error_fake
7. Optimize Error_GAN for mentioned epochs
8. Assign y=1 while training generator
9. Compute MSE between *y* and generated image with mean=L1 loss
10. L2_loss = mean (abs (real – generated))
11. L3_loss = mean (pow ((real - generated), 2)
12. Error G = GAN_weight* L1_loss + L2_weight * L2_loss + L3_weight * L3_Loss

3.3 DISCRETE WAVELET TRANSFORM (DWT)

It is a powerful tool to convert spatial domain image into frequency domain [27] consisting of low and high-frequency coefficients using Low and High Pass Filters with decimation by 2. The frequency-domain has four bands of equal size corresponding to three high-frequency bands and one low-frequency band. The significant data of the original face image is present in the low-frequency band. The insignificant edge data of the original face image exists in three high-frequency bands corresponding to horizontal, vertical, and diagonal edges. In our method, the low-frequency band coefficients are considered by omitting high-frequency band coefficients as features for face recognition result in low dimensional final features for high-speed computation. The coefficients of low-frequency band Low- Low (LL), and high-frequency bands viz., Low- High (LH), High-Low (HL), and High-High (HH) are acquired based on equations 5- 9 for the image matrix of size 2X2.

$$X = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \quad \text{-------------------------------------(5)}$$

$$LL = \frac{a+b+c+d}{2} \quad \text{-------------------------------------(6)}$$

$$LH = \frac{a+b-c-d}{2} \quad \text{------------------------------------- (7)}$$

$$HL = \frac{a-b+c-d}{2} \quad \text{-------------------------------------(8)}$$

$$HH = \frac{a-b-c+d}{2} \quad \text{-----------------------------------(9)}$$

Where a, b, c, and d are the coefficients of the 2X2 matrix

IV RESULT ANALYSIS:

The exploration of the projected technique is based on two perceptions viz., (i) the side profile images of a person are converted into frontal face images using efficient G-GAN and (ii) the face recognition to identify a person using DWT for feature extraction and ED for matching.

The Global-GAN can generate the frontal image of the equivalent person from its corresponding profile image. Its frontal image is photo-realistic and it also preserves the identity of a profile face image. Also, the method can recognize the generated frontal image using traditional DWT and ED methods.

4.1 EXPERIMENTAL TESTING APPROACHES:

The different standard face image datasets such as the Bosphorus dataset of 2D samples with different possess and expressions, Multi-PIE face image dataset, Head Pose Image Database, and Indian Female database are used for experimentation. In the pre-processing stage, all images are converted into a uniform fixed size of 128*128*3. While training G-GAN a batch size of 30 and learning rate of 0.0002 are used. The python programming for implementation run on google co-lab with PyTorch is used. For implementation, the Graphical Processing Unit (GPU) of NVIDIA GeForce Gtx and PyTorch data-loader are employed

4.2 VISUAL QUALITATIVE RESULT:

In this section, we compared the visual quality of frontal images of the proposed G-GAN with the existing method presented by Zhang et al., [28] based on Dual Discriminator GAN using Bosphorus dataset for training and testing. The images generated by the projected G-GAN have high visual quality compared to the existing technique as shown in Figure 6. The frontal face images in dual discriminator GAN have blurred images not clear compared to images produced by our model, result in the superiority of the proposed method.

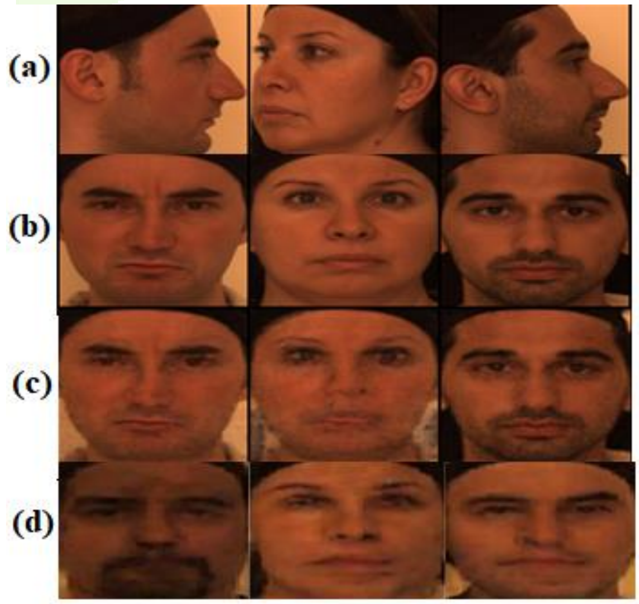

Fig 4. Comparison of proposed model results with Dual-discriminator-GAN model [28] results. (a) Profile Images (b) Ground Truth (c) Proposed model result (d) Dual-discriminator-GAN model result

4.3 QUANTITATIVE EVALUATION RESULT:

In this section, our method is assessed using Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM) between real image and generated frontal face image from the profile face image. The PSNR value is calculated using equations 10 and 11.

$$PSNR=20^{*} \log_{10}(MAX/\sqrt{MSE}) \text{-----------------}(10)$$

$$MSE = mean\ ((image\ A\text{-}image\ B)^{2}) \text{--------------}(11)$$

Where MAX is the maximum pixel intensity value, which is 255. To find SSIM a standard built-in program ie., available in skimage libraries are used. Figure 7 displays the comparison of image quality along with PSNR/SSIM values of the proposed model-generated images with existing models like PosXI-GAN [29], which, uses patch-wise loss function and Hybrid BEGAN [30] uses without patch-wise loss function. The first and second columns are related to [30], the third and fourth columns related to [29], fifth and sixth columns are related to the proposed method. The first, third, and fifth columns are profile images and the calculated PSNR/SSIM values between profile images result in 1/∞ as mentioned. The second, fourth, and sixth columns are generated frontal images and the calculated PSNR/SSIM values between profile and corresponding frontal images are mentioned. It is noticed that image quality and the parameters like PSNR/SSIM values are better from our G-GAN model compared to other existing models.

Hybrid BEGAN [30] PosXI-GAN [29] Our G-GAN

Fig.7 Comparison of proposed method PSNR/SSIM values with other states of the art methods

Further, the projected technique is compared with other existing models viz., DR-GAN [31], RNN [32], and MTAN [33] with our model G-GAN as shown in Figure 8. The first row images are profile images, and the second-row images are generated frontal images by the proposed method. The generated frontal images in the third row are related to the models DR-GAN, RNN, and MTAN respectively. As indicated in the images the PSNR/SSIM values are poor in the existing models compared to our G-GAN.

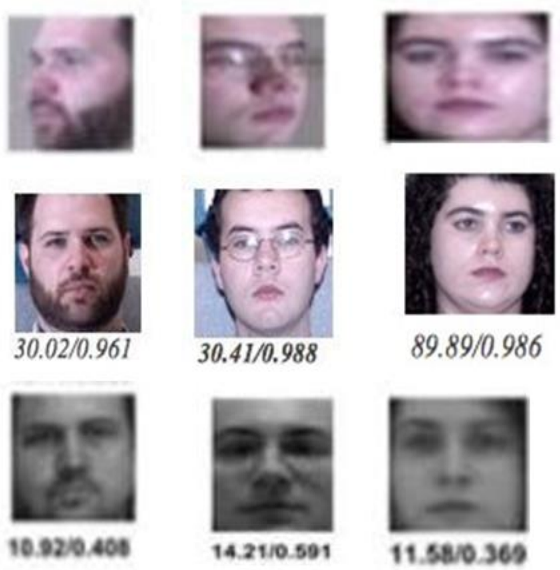

Fig.8: Comparison of PSNR/SSIM values (a) First-row profile images (b) Frontal images generated by our method (c) Frontal images generated by DR-GAN, RNN, and MTAN.

4.5 FACE RECOGNITION EVALUATION:

The process of face recognition with a solo frontal face image in the database stored in the server is an exciting task as the face images bagged by the cameras are of different face angles and tilts. This problem is resolved by converting captured face images of different angles and tilts into frontal face images and then compare with the single frontal face image in the database stored in the server. The face images of different angles and tilts captured by the cameras are converted into frontal face images using the proposed G-GAN. The DWT is applied on generated frontal images from G-GAN to obtain low and high-frequency band coefficients. The low-frequency band has significant information of face image with dominant coefficient values represented by LL band. The high-frequency bands have insignificant information of face image with low and negative coefficient values represented by three bands such as LH, HL, HH bands. The final features of face images are considered from LL band coefficients. The DWT is also applied on frontal images stored in the database server and considered only LL band coefficients as final features. Human beings are recognized based on the face images by comparing the images captured by a camera and the predefined images stored in the server database using ED. The coefficients of the LL band are one-fourth size compared to the initial image size, indicate 75% compression in final features, which leads to fast computation. The demonstration of face recognition is as shown in Figure 9 with a single image on the extreme left is ground true frontal image stored in the server database. The profile images with different pose angles of a person are given in the first row and the corresponding frontal images generated by our G-GAN are given in the second row. The calculated ED values between (i) ground true image and captured profile images and (ii) ground true image and generated frontal images using G-GAN are indicated. It is noticed that the calculated ED values between ground true image and captured profile images are high compared to ground true image and generated frontal images using G-GAN. The frontal images generated by G-GAN are visually almost the same as the ground truth image. Quantitatively, the profile angled image ED is more compared to generated frontal image leads to better recognition of a person with generated frontal images.

Fig 9. The single image is the ground truth image, the profile images with ED values in the first row, generated frontal face images along with ED values in the second row.

5. CONCLUSION:

The technique of face recognition to identify human beings is a tough task for several applications since the profile face images with different angles and tilts. The changes between effective features of the same person with diverse angles and frontal face images are very high, results in poor performance of face recognition. In this paper, we proposed a solution to the problem in profile images with angles using G-GAN to enhance the performance of face recognition. The G-GAN with a unique error loss function converts profile images into frontal images. The DWT is applied on generated frontal images to extract features by converting spatial domain images to the frequency domain. The compressed low dimensional significant features from the low-frequency band of DWT are used as features for comparison. The ED values are calculated among the features of the ground truth database frontal image and the frontal face images generated by G-GAN. The outcomes of the projected technique are compared with other current approaches to show the superiority of our method. In the future, the effective features are extracted based on the combination of spatial and frequency domains to recognize a person effectively.

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