Deep Learning based Human Recognition using Integration of GAN and Spatial Domain Techniques

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Abstract:
Real-time human recognition is a challenging task, as the images are captured in an unconstrained environment with different poses, makeups, and styles. This limitation is addressed by generating several facial images with poses, makeup, and styles with a single reference image of a person using Generative Adversarial Networks (GAN). In this paper, we propose deep learning-based human recognition using integration of GAN and Spatial Domain Techniques. A novel concept of human recognition based on face depiction approach by generating several dissimilar face images from single reference face image using Domain Transfer Generative Adversarial Networks (DT-GAN) combined with feature extraction techniques such as Local Binary Pattern (LBP) and Histogram is deliberated. The Euclidean Distance (ED) is used in the matching section for comparison of features to test the performance of the method. A database of millions of people with a single reference face image per person, instead of multiple reference face images, is created and saved on the centralized server, which helps to reduce memory load on the centralized server. It is noticed that the recognition accuracy is 100% for smaller size datasets and a little less accuracy for larger size datasets and also, results are compared with present methods to show the superiority of proposed method.

Key words: *Face recognition, GAN, Histogram, Human recognition, LBP.*

1. Introduction:

Human identification based on face images is an enthusiastic research area in the modern era of human endeavor blended with computer vision, which has been extensively used in numerous appliances such as security, video surveillance, image reconstruction, segmentation, detection, classification, and personal identification. Face-distinguishing techniques attain better accuracy when faces are captured in frontal poses and restricted scenes, however, precision declines when significant pose variations occur. The algorithms usually require an enormous amount of face image data for training to achieve great success and however, still get in trouble due to huge deviations of pose, low resolution, and expression in face images. In order to deal with pose variations and other problems, Goodfellow et al., [1] developed Generative Adversarial Network (GAN). GAN is a method for generative modelling using deep learning methods, and is an unsupervised learning task in machine learning that includes learning the patterns in input data to generate new output data.

A GAN constructs a model using two neural networks [2] viz., generator and a discriminator, where a discriminator discriminates face images from the real and created images from a generator, while a generator decreases its discriminativeness by creating a face of photorealistic quality. Their rivalry touches on when the discriminator is incapable of distinguishing between real and created face images [3]. The generator is like an organization that creates forged images and uses them without being noticed. The discriminator is like an investigator trying to detect a forged image. The generator generates data analogous to the training data. The discriminator recognizes whether the real or generated fake image from the generator. Finally, the generator and discriminators are trained until the discriminator model is confused, meaning the generator model is generating believable, real image.
GAN is an extremely incredible generative model in creating realistic samples once the GAN is trained on some information and used in image generation, video generation and voice generation. The advantages of GAN are used in dissimilar fields of computer vision and artificial intelligence. Numerous GAN applications in several fields, such as image, video, and speech. A few GANs are developed for dedicated tasks such as automatic photo editing is done by Gaussian Poisson GAN (GP- GAN) [4], Style GAN [5] has shaped in facial generation tasks, Big GAN [6] first generated images with high fidelity, Age-c GAN [7] and Progressive Face Aging GAN (PFA-GAN) [8] are very useful in cross-age face recognition etc. Face recognition with the help of GAN is very useful as side pose face-angled images are converted into frontal face images. Only one frontal face image per person is required to be saved in the server database in place of a larger number of face images with different pose angles per person leading to a minimum memory requirement in the server. The many face images with pose variations of a single person to be tested are converted into frontal face images using GAN and are likened with frontal face images already stored in the

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server dataset. The LBP is a simple and effective texture operator that labels the pixels of an image by thresholding the neighbourhood of each pixel [9]. The LBP technique is used to extract features of facial images for human identification in the spatial domain. The histogram is the distribution of number of pixels over intensity values in the spatial domain or it's a distribution of number of coefficients over the coefficient values in frequency domain. The histogram is used as a feature and helps in reducing the dimensionality of a number of features.

Contribution: Deep learning-based human recognition using integration of GAN and Spatial Domain Techniques is proposed in this paper. The DT-GAN is used to create several face images of an individual with dissimilar poses and styles to identify a person intending to dupe society to increase security level. LBP and histogram techniques are used to extract features.

Organization: The paper is prepared as follows. Section 2 offers a literature survey on face recognition using GAN and LBP. The projected method is given in Section 3. Section 4 explains the algorithm, the experimental results are given in section 5. Conclusion and future scope is provided in Section 6.

2. Literature Survey:

Face image generation using existing different GAN's are explained in this section along with spatial domain techniques for human recognition. Zhang et al., [10] proposed Pose-Weighted Generative Adversarial Network (PW-GAN) for photorealistic frontal face images. The pose angled images are converted into frontal face images through a 3D face model. They built a novel loss function that can manage the network to handle the large angles of face images. Zihao Zhang et al., [11] presented a multi-angle face identification using frontal face group, which substitutes the procedure of detection, alignment in the typical face identification scheme. The GAN with the facial landmark localization is used to solve the problem of face texture loss in large pose variation. Kawai et al., [12] presented a technique to generate static facial expression images from a natural face images using GAN.

He and Chen [13] proposed facial appearance based on improved LBP and HOSVD (Higher-Order Singular Value Decomposition). The temporary features are extracted by Local Directional Pattern and the determined features mined by Central Binary Pattern are combined to enhance the discernment of facial appearance features. Alpaslan and Hanbay [14] proposed hybrid LBP built on Hessian matrix and Attractive Centre-Symmetric LBP (ACS-LBP), termed Hess-ACS-LBP. The Hessian matrix offers the directional derivative material of dissimilar texture areas, whereas ACS-LBP divulges the local texture features proficiently. A cross-scale joint coding plan is used to concept Hess-ACS-LBP descriptor. The histograms are concatenated for final features. Xiao Luan et al.,[15] proposed a Geometry Structure Preserving based GAN for multi-pose face frontalization and recognition. GSP-GAN is a 3D free face model, which doesn't need any former idea of the type of pose. The discriminator model consists of a self-attention block, which helps to extract local and global attention and formation. This confirms better feedback for the generator to conserve the dimensions of the face structure. The proposed model generates high quality images of the face and also has increased performance when compared to other state-of-the-art models. Ming Liu.et.al.,[16] have proposed Patch-Attention Generative Adversarial Network (PA-GAN) model which is designed to gather all the prominent characteristics instead of collecting a large set of misleading frames. This significantly reduces computational costs and increases the accuracy of recognition. The proposed PA-GAN uses labelled faces to collect useful information from an input video.PA-GAN reduces time effectively as only a few images are passed through the feature extraction network.

Yu Yin et al., [17] proposed Dual-Attention Generative Adversarial Network (DA-GAN) for photo-realistic face frontalization. A self-attention-based generator is introduced to capture the long-range dependencies which help to produce improved feature representation. The facial attention discriminator is used to highlight the local aspects of facial regions and enhances the practicality of artificial frontal images. With the assistance of these two-attention block and discriminator and generator, the model can produce more accurate facial appearance and textures. Vishnu B Raj and Hareesh K et al.,[18] have discussed about the Generative Adversarial Network and its impact in the image processing and computer vision field. Earlier GAN was a strong contender for unsupervised learning whereas now GAN exhibits equal advantages for supervised and semi-supervised learning. Though GAN has some architectural constraints, it has many applications which help to produce better images with more detailed features. Soumya Shubhra Ghosh et al, [19] proposed a discriminative facial feature reestablishing GAN which is capable of recovering prominent features from low quality degraded images. A constraint angular metric learning method is used to learn and reconstruct discriminative features of the face. A weighted mixture of diverse losses is incorporated at different stages of the model to recuperate the feature, which enhances performance. The proposed model showed outstanding results on a data set of degraded face images.

Mukhiddin et al., [20] have discussed the topics on GAN and its applications. GAN has appeared as a prominent family of unsupervised learning techniques, which has the ability to synthesis simple natural images. Along with the impressive performance of GAN in image processing and computer vision tasks there are some issues associated with such as manipulation of facial attributes and generating images which looks more realistic also become a public concern. Prabhat et al.,[21] compared the analytics of Deep Convolutional Generative Adversarial Network (DCGAN) and Conditional Generative Adversarial Network (CGAN). DCGAN has restrictions based on the neural network and hence, the discriminator used is quite significant. CGAN has supervised the learning process, which a multilayer perceptron structure unlike DCGAN which incorporates convolution neural networks-based limitations. The analysis showed that DCGAN generates images with increased pixel quality while seeking and producing images with the same pixel value. Zhe Li et al.,[22] proposed and orbital angular momentum demodulation method based on conditional generator adversarial network, to enhance the quality of convolutional neural networks-based demodulator. Previously, the accuracy of OAM in demodulation declined when the convolution neural network-based OAM demodulator was trained on a small sample set. In the proposed method, the discriminator in CGAN is fine-tuned as a new classifier for OAM demodulation. The experimental results depicted a significant improvement in recognition rate. Ruihao Yin [23] has proposed a Multi-Resolution Generative Adversarial Network (MR-GAN) that performs multi-resolution pedestrian identification while concurrently creating a high-resolution pedestrian image from a low-resolution image. The model will have multi-resolution generators and corresponding discriminators, which can create high eminence super- resolution images. It consists of unified end-to-end convolutional networks that can super-resolve and identify and classify the pedestrian at the same time. To direct the generator both classification loss and perceptual loss are considered. Hsu et al.,[24] have presented Disentangled Representation - learning Wasserstein GAN for face recognition and synthesis of face with a cross pose. The proposed approach consists of DR-WAN for unscrambled depiction learning and the nonlinear 3DMM-based face summarizing for data collection. In the test phase, cosine distance is employed as the metric for feature matching. Ma and Zhou [25] proposed Pose-Weighted Generative Adversarial Networks (PWGAN), which happens in a pre- trained pose guarantee unit to study face pose evidence. PWGAN blends fusion features with pose features for a single image. PWGAN also incorporates Pose and formation for several input images. PWGAN utilizes full information about the pose to generate better images by learning more about facial traits.

Ramakrishnan and Jay Kuo [26] have proposed Cycle-GAN which converts synthetic image to real world image. Domain adaptation and image translation are used to tackle any target domain task in a supervised manner through image generation and label transfer. The existing domain adaptation techniques have been analyzed and the advantages of the current Framework are discussed. Zhang et al.,[27] have presented Thermal-to-Visible Generative Adversarial Networks (TV-GAN) which is capable of converting thermal facial images into their respective VLD images while retaining adequate identifying information to perform recognition. To regularize discriminator network training, TV-GAN employs a clear locked set face recognition loss. Gradient loss will then be used to send this information to the generator or network.TV-GAN is able to maintain more identifying information while interpreting a thermal image of a person. Yang et al.,[28] have described identity- adaptive conditional generative adversarial network (IA-Gen) to overcome the subject differences by generating terminologies from any input images. Restricted generative replicas are trained to create six prototypical facial emotions from any inquiry facial images while maintaining identity information unaltered. For expression classification, a regular CNN (FER-Net) is fine-tuned, following the regeneration of the relevant prototypic facial terminologies from every facial image. The investigational results validate the efficacy of the projected method. Mudavathu et al.,[29] presented a modified auxiliary conditional adversarial neural network, which is a subset of GANs that use the labelled conditioning to produce images with global coherence. The input data which needs to be conditioned is fed to the generative model. the proposed network and hence the accuracy of the image classifier. Shen et al.,[30] have proposed Face ID-GAN which is capable of producing photo- realistic face images. Face ID-GAN is a 3 player GAN that adds an identity classifier C to the traditional GAN as an additional contender. C interacts with discriminator D to contend with generator G in two areas: Face identification and image quality. Face ID-GAN is designed with an information symmetry criterion that enhances stability and performance. Zhai and Zhai [31] proposed an identity- preserving conditional generator adversarial network (IPcGAN) for image-to-image conversion. The presented framework can learn the conversion purpose in two domains even if there is no corresponding image. It tries to map a real image into a covert space. In contrast to other techniques, the work describes a fine-tuning procedure and joint loss to reserve the original identity features. Huang et al.,[32] proposed two- pathway generative adversarial network (TP-GAN) which detects global structures and local facts along with the synthesis of photo-realistic frontal views. In addition to the typically used global encoder decoder, four landmark-located patch networks are used to address local textures. The combination of adversarial loss, symmetric loss and identity preservation loss are used to guide the preservation of identification. Deng et al.,[33] have proposed a framework for training Deep Convolutional Neural Network (DCNN) to fulfil the facial UV map extracted from in-the-wild images. The 3D Morphable Model (3DMM) is fitted with several multi-view images and video data sets to get detailed UV maps. A well-designed architecture is formulated that integrates local and global adversarial

DCNNs to learn identity- preservation UV models of the face. By adding complete UV to the fitted mesh and producing instances of random poses, the framework showed increased performance.

3 Proposed Human Recognition Model:

In this research paper, we propose GAN-based human identification using LBP and histogram procedures for variations in pose angles in face images. In our method, only one facial image per person as a reference is essential to save in the server database. The real time/standard face images of a particular person captured by the camera are resized to uniform size of 70x70 and are fed to discriminator of GAN and random noise is connected as input to the generator of a GAN. The GAN model is used to generate dissimilar facial images of a particular person into a new dataset of facial images. These face images of a particular person can be related with the only one face image in the server dataset to identify a person. This procedure reduces the load/ memory on the server database to store only one face image in place a larger number of face images with variations in pose angles and styles of a single person which decrease the time consumption in identifying human beings. The technique of LBP is applied on generated face images to extract texture features and histogram on LBP features results in final reduced effective features.

3.1 Face image databases: The projected process is verified with slandered face dataset images such as Celebrities Dataset, JAFFE, ORL, and YALE.

3.1.1 Celebrities Dataset [34]: This dataset has 100k RGB face images with an image size of 128x128 and an image format of JPG.

3.1.2 Japanese Female Face Expression (JAFFE): This dataset has ten individuals with twenty typical pictures per person. Seven exciting facial feelings of every individual with an upright, frontal position are captured and measurement of each image is of 256 x 256 in grayscale and tiff image format [35].

3.1.3 Olivetti Research Laboratory (ORL) Dataset:
This image database was formed among 1992 to1994 and the dataset has forty individuals and ten face image samples per person with the image format of PGM and each image dimension of 92x112 [36]. The facial expressions such as open/shut eyes, laughing/not laughing, with/without glasses, changing the lightening conditions of single people were taken. A sheltered circumstantial with upright frontal and slight tilt of the head positions are considered while capturing every image.

3.1.4 YALE Dataset [37]:
This dataset has images of fifteen people with eleven image samples per individual. Face image samples of every individual were captured with different expressions over spectacles, without spectacles, centre-light, left-light, right-light, having moments of happy, sad, normal, sleepy, surprised, wink. The size of every face image is 320x243 with the GIF format.

3.2. Domain Transfer Generative Adversarial Networks (DT-GAN): The proposed model is encouraged by the power of GAN generated images with domain transfer and data augmentation [38]. The DT-GAN used in our model has two neural networks, in which one is skilled to create new images and the other is able to distinguish among the real and the fake images. It is unsupervised learning to overcome the problems of supervised learning. The model is an unpaired image transfer used to conduit the domain gap among the source domain and the target domain, which has the similar structure as that of Cycle GAN [39] with decline loss to measure the mapping among domains. The DT-GAN is mainly divided into two sections namely the generator section and the discriminator section. Where the generator generates new images with random noise as input, the discriminator plays a real or fake game. The input to the discriminator is the generator image and the image from the dataset, now the discriminator finds out the real and fake image among these two images. If the image is real the discriminator passes it else it sends it back to the generator for training.

The generator synthesizes images similar to that of the original image with the help of the random noise function. These random noise functions are usually the Gaussian noise function generated using the inbuilt function of the Keras module. The generator consists of 8 layers and the Rectified Linear unit (ReLU) function is used as the activation function for all the layers except the output layer. The ReLU function gives the output as one for the positive input and gives zeros for the negative input. For the output layer, tanh activation function is used in the generator and an image will be created as the yield of the generator.
The celebrity dataset, which contains of 100k images and a new dataset which is a combination of JAFFE, ORL and Yale dataset, which consists of 208 are taken and is given to DT-GAN separately. These images are downscaled in order to resize the images, so that they can be given as input to the discriminator. The discriminator also consists of 8 layers and here the Leaky ReLU (leaky rectified linear unit) is used as the activation function for all the layers except the output layer. The function of the discriminator is to compare the generated images produced by the generator and the dataset image to determine whether the generated image is real or fake. Initially the discriminator is set as fake, and then it loads the input images from the generator and downscaled images from the dataset and gives the output. The discriminator only allows the generated image to pass only if it considers it real. In the output layer, sigmoid activation function is used and there is a dense 1 layer in the discriminator which gives the output as only 1 or 0, if the image is real then it is 1 or it is considered as 0.

The image accuracy is calculated based on two types of losses namely discriminator loss and generator loss, which is then fed back to the generator and discriminator respectively for the training purpose. These losses are back propagated to improve accuracy. The binary cross entropy loss function is used with the threshold set to 0.5. The performance parameters on which DT-GAN depends are

1. Discriminator loss: When the training of the discriminator takes place, the process of classifying the real image as fake and fake image as real is known as discriminator loss. The discriminator loss is given by the Equation 1.

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(x^{(i)}\right) + \log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right) \right] \quad \text{-------(1)}$$

Where the log (D(x)) is the probability that the generator is correctly classifying the real image and increasing the log (1-D (G (z))) value would help for the correct labelling of the fake image that comes from the generator block. *m* is the number of outputs and in this case, it is 2.

2. Generator loss: When the generator is trained, a random noise signal is given to the generator and the generator produces some images and is sent to discriminator for classification as real or fake. Generator loss is based on discriminator classification. The generator loss is given by the Equation 2.

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(z^{(i)}\right)\right)\right) \quad \text{--------------------(2)}$$

3. Accuracy: The ratio of the number of persons correctly recognized to the total number of persons to be tested is given in the Equation 3.

$$\text{Accuracy} = \frac{\textit{Number of persons correctly recognized}}{\textit{Total number of persons to be tested}} \quad \text{----- (3)}$$

3.3 Local Binary Pattern (LBP):

The method [40] being extensively used in two-dimensional texture examinations like identification of human beings in image processing applications. The 3×3 portion of an image is considered and the technique of LBP is used for neighbourhood geometry of an image. Each pixel intensity value of the image is replaced by a new value based on binary values of eight adjoining pixels. The pixel considered as centre pixel (Xc, Yc) surrounded by eight pixels is to be replaced by a new decimal values based on eight surrounding binary values obtained on comparison with initial centre pixel intensity value. The original centre pixel intensity value says *Zc* is to be replaced based on the surround pixel intensity values are represented by Z_{sp}, where *p* varies from 1 to 8. The binary *Bp* equivalents are based on surrounding pixel values using Equation 4. The binary equivalent values are converted into decimal values by assigning weights to each binary.

$$Bp = \begin{cases} 1 \text{ , } if \ldots \; Zsp \geq Zc \\ 0 \text{ , } if \ldots \; Zsp < Zc \end{cases} \quad \text{-------------------------------(4)}$$

3.4 Histogram: The LBP coefficients of face images of size 70x70=4900 are converted into 256 coefficients by applying Histogram. These 256 coefficients are considered the final features of each image lead reduced the number of features resulting in effective recognition of a person with less computation of time.

3.5 Matching:

The histogram features obtained from the training process and the histogram features of the original image features are compared using the normalized Euclidean distance given in equation 6.

$$d = \sqrt{\sum_{i=1}^{v} \left(\frac{(p_{1i} - p_{2i})^2}{v} \right)} \quad \text{--------------------------(6)}$$

Where, P_{1i} is the histogram feature of the input original image

P_{2i} is the histogram feature of the trained images.

v represents the number of dimensions and in this case is 256, each square of the difference is divided by the total number of the dimensions, in order to normalize the Euclidian distance.

4. Proposed Algorithm:

Problem Definition: Real-time effective human recognition based on DT-GAN generated augmented facial images combined with histogram features on LBP.

The algorithm is given in Table 1 for better recognition of human beings

Table 1. Projected human recognition algorithm

Input: Real time face images Output: Recognition of a person 1. Random Gaussian noise and real-time/dataset facial images are applied to the generator and discriminators of DT-GAN. 2. Face images of any size are converted into uniform size of 70x70 3. The images generated by the generator are connected to the discriminators input. 4. The discriminator classifies the generated image of the generator as real or fake. If the image is real, it passes the image from the discriminator output else it does not pass the image from the discriminator. This process is carried out several times till the real image is obtained. 5. The error functions generated will be back propagated into the generator and the discriminator for the training process to obtain better original facial images. 6. DT-GAN generates 24 augmented face images of a person with one face image sample as their input. 7. The spatial domain technique LBP is used in DT-GNN to generate 24 augmented grey scale face images and original face images in the server database to extract texture features of 70x70=4900 dimensions.

8. The histogram of LBP features is obtained to reduce the number of features from 4900 to 256 and these are considered as final features to identify human beings.
9. The ED is used to compare the final features of generating 24 augmented face images of each person with only one face image in the server dataset.

Objectives: Human identification based on face images captured with different pose angles, makeup and styles keeping only one face image per person in the server database. The DT-GAN is used to generate several face images with different styles of a single person. The objectives are as follows

(i)To reduce the memory load on the server by keeping only one face image per person in the server instead of many face images per person.

(ii)In real time, one face image of a person captured by a camera is converted into several face images with different panaches.

(iii)Effective identification of human beings with high accuracy for large databases

5 Results Analysis:

A novel human recognition based on face depiction approach to generate several dissimilar face images from only one face image of each person using DT-GAN combined with feature extraction techniques such as LBP and Histogram is projected. The Keras module, which works on the numerical library TensorFlow, the matrix form of the random noise is obtained with the help of the NumPy module and for displaying the matplotlib module of the Python language used. A random noise signal is fed into the generator of DT-GAN and it produces 24 identical images to that of the original image. The random noise fed to the generator is of the form of Gaussian noise.

5.1 Generation of face images of people with single face image:

5.1.1Generation of face images for different datasets with 1000 epochs: A dataset with many persons is considered and a single image of each person is applied to the discriminator to train the DT-GAN with 1000 epochs. The facial images will be generated with different poses, hairstyle, skin tone and gender as shown in Figures 1,2,3, and 4 for celebrity dataset, JAFFE dataset, YALE dataset and ORL dataset. The first image, labelled as (a) is the original image and the remaining twenty-four images are the DT-GAN generated images.

Fig 1. Generated celebrity dataset images in 1000th epoch

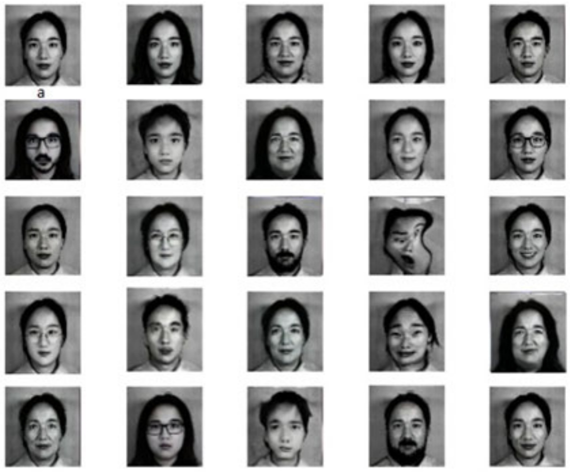

Fig 2. Generated JAFFE dataset images for 1000th epoch

Fig 3. Generated YALE dataset images at 1000th epoch

Fig 4. Generated ORL dataset images at 1000th epoch

5.1 Identification of persons:

The features of generated images by the DT-GAN and the server database images are extracted using spatial domain techniques viz., LBP and histograms to identify human beings. The LBP technique is applied to gray scale images of original and generated images and the corresponding LBP images are as shown in Figure 5. The total number of features of each image is 4900 for an image size of 70x70.

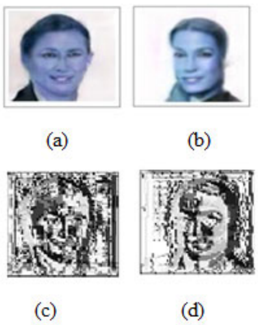

Fig 5. original and the generated gray scale images and the corresponding LBP images

The histograms of LBP images are obtained with dimensions of 256 and these are considered as final features. The ED is used in matching between the final features of original and generated images to identify human beings effectively. The percentage recognition accuracy of the proposed method is given in Table 2 for dissimilar face images. Note that the percentage recognition accuracy is 100 for JAFFE, ORL, and YALE face databases, as the number of images in the database is less in number. However, the percentage recognition accuracy is 95.5 since the number of images used are in large number.

Table 2. Percentage Recognition Accuracy of the proposed method

Dataset	Celebrity	JAFFE	ORL	YALE
Total number of images (One image per person)	200	10	40	15
Number of mages recognized correctly	195	10	40	15
Number of mages not recognized correctly	05	00	00	00
% Recognition Accuracy	97.5	100	100	100

Table 3: Proposed Method comparison with existing methods using ORL face database

Sl No.	Authors	Year	Technique	% Recognition Accuracy
1	Ying Wen [42]	2017	A discriminative common vector dictionary + sparse representation-based classification	96.54
2	Abuzneid and Mahmood [43]	2018	PCA+BPNN	96.90
3	Jun Fan et al., [44]	2017	Locality Preserving Projections + Maximum Margin Criterion for solving general eigenvalue	97.10
4	Jun Kong et al., [45]	2018	circular symmetrical Gabor filter and PCA neural networks	97.50
5	Rangsee et al., [46]	2019	Bit Endianness + DWT +HOG	98
6	Proposed method		DT-GAN and LBP with Histogram	100

The proposed method results are compared with existing methods using ORL and YALE face databases in Tables 3 and 4. The recognition accuracy is 100% in our method compared to lower accuracy values in the existing methods, this is due to generation of several face images from single reference face image by the concept of GAN.

Table 4: Proposed Method comparison with existing methods using YALE-B face database

Sl No	Authors	Year	Technique	% Recognition Accuracy
1	Abuzneid and Mahmood [43]	2018	PCA+BPNN	97
2	Jun Fan et al., [44]	2017	Locality Preserving Projections+ Maximum Margin Criterion for solving general eigenvalue	81.22
3	Jun Kong et al., [45]	2018	circular symmetrical Gabor filter and PCA neural networks	100
4	Santosh Kumar Jami et al., [47]	2017	Gabor Wavelets and Cross Local Binary Patterns	96.70
5	Guangyi Chen et al., [48]	2018	convolution between a face image and a set of low-pass and high-pass filters + LBP	97.3
6	Swarup Kumar Dandpatet al., [49]	2018	DFT+LBP	97.64
7	Proposed method		DT-GAN and LBP with Histogram	100

6. Conclusion:

The exciting task of human recognition through dissimilar makeup with single face image per person is strenuous, which leads to constraint in recognition. This restriction is addressed in our research by generating several face images using the GAN technique. In this paper, deep learning-based human recognition using integration of GAN and Spatial Domain Techniques is proposed. DT-GAN is used to generate 24 dissimilar facial images to be tested for recognition from a single reference face image. The features of face images are extracted using LBP – histogram and the features of face images to be tested are compared with face images stored in the server using ED to verify the accuracy of the algorithm. The performance of the proposed method is compared with the existing methods and observed the superiority of the proposed method. In the future, develop appropriate GANs to convert single face images into frontal face images with effective feature extraction techniques to recognize people for huge datasets.

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