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Enhancing Face Recognition Dataset using Generative Artificial Intelligence: Review Study

Wrya Anwar Hayder

IT Department/College of Computer and IT,, University of Garmian, Iraq
wrya.anwar@garmian.edu.krd

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Abstract: Face recognition is a fast growing and crucial area of study due to its applicability in different life applications. Face recognition systems often face significant challenges due to poor-quality datasets, which can result from factors such as low illumination, low resolution, facial distortions, and varying environmental conditions. These limitations hinder the performance and reliability of face recognition technologies. Generative Adversarial Networks (GANs) have emerged as a powerful tool to address these issues by enhancing image quality and generating realistic facial representations under challenging conditions. This review paper explores various GAN-based models each designed to tackle specific face recognition challenges. These models demonstrate significant improvements in enhancement ratios, ranging from 75% to 97%, by leveraging advanced generative techniques to reconstruct and augment facial images. Beyond face recognition, the methodologies discussed in this research have broader implications for enhancing image datasets in other domains, such as medical imaging, surveillance, and autonomous driving, where poor data quality is a common issue. By improving dataset quality through generative AI, this research paves the way for more robust and accurate machine learning applications across diverse fields..

Keywords: Generative AI, Face Recognition, face Recognition enhancement, Generative Adversarial Network

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1. Introduction

Face recognition has seen a significant popularity over past years due to the importance of this field in many applications. This surge came with the widespread and availability of necessary technologies and applications. The new technologies increased the demand for more security measures and protections, such technologies such as smartphones, digital cameras and security surveillance devices. In addition, the advancement in computation technologies such as GPUs made the algorithms performance more efficient in machine learning and deep learning [1].

The importance of face recognition is considered to be a well-known biometric feature for personal identification which used for many daily life purposes. The collection of faces are stored within reference database to match and compare facial image for privacy purpose or for national identification. It is important to mention that face become one of the most widely used biometric features for identity recognition.

In many application, there are many advantages for using face as biometric characteristics. First face is most realistic biometric representative of human individuals, thus it is acknowledged as the foremost related identity proofed for authentication and personal identification. Faces are more accurate biometric security feature in compare with iris recognition or fingerprint which is provides more profound and accurate information. Secondly, facial image can by easily captured and accrued in contrast to iris or fingerprint images which done not required direct physical contact with the machine [2].

Significant advances has been made in the application of facial recognition after the emergent of artificial intelligence models. Machine learning and deep learning become an interesting motivation for researcher to produce a more accurate models under uncontrolled conditions where simple traditional algorithms cannot perform well. Deep learning can produce more accurate and robust face recognition models even under uncontrolled environment [3].

Despite the advances in face recognition technology and application, many challenges still present. In particular identifying faces captured in uncontrolled environment such as changing light, camera movement, bad posture or facial expression. Driven by the requirement of many devices and applications, face recognition has emerged as projecting field within image processing. However, there are still more studies required to overcome the performance limitation of face recognition in real word [4].

The main aim of this review study is to present the recent studies and publication on face recognition using the Generative Adversarial Network (GAN) deep learning models. GAN currently considered as the state of the art in the domain of facial recognition. It is important to review such domain to understand the researcher advances and also identifying challenges and new research opportunities.

2. Literature Review

Face recognition has seen many advances through past years until the improvement of deep learning models. This section review the main approaches have used for facial recognition systems. It covers the local and holistic approaches then elaborate in detail regarding deep learning approach. Finally, it represent the main challenges related to face recognition domain.

2.1 Local Approach

In this approach face recognition is applied based on the local facial features like mouth, nose and chin are extracted and fed to the classifier. The recognition processes are usually guided

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by local characteristics related to the facial parts. For example, nose or eyes has more distinctive patterns than forehead and cheeks Examples include Local Binary Patterns (LBP) and Scale-Invariant Feature Transform (SIFT). This approach is not used recently and replaced by holistic approach [5].

2.2 Holistic Approach

In this approach often consider the entire face as input data, to capture informative features and better handling variations in pose and illumination. The main methods have been used for this approach include, Principal component analysis (**PCA**) known as **eigenfacs**, linear discriminative analysis (**LDA**) known as **fisherfaces** and independent component analysis (**ICA**) all the three method considered as linear techniques.

PCA is a widely used technique in face recognition for reducing the dimensionality of facial images while retaining the essential information. PCA is a statistical method that transforms the original high-dimensional data into a new set of uncorrelated variables, known as principal components. In the context of face recognition, PCA is applied to images to extract a compact and discriminative representation of facial features. PCA is a linear technique, and while it has been successful in various face recognition applications, more advanced techniques, including non-linear dimensionality reduction methods and deep learning approaches, have also gained popularity in recent years. Nevertheless, PCA remains a foundational and widely used method in the field [6].

LDA is a dimensionality reduction and classification technique commonly used in pattern recognition, machine learning, and statistics. Unlike Principal Component Analysis (PCA), which focuses on maximizing the variance in the data, LDA aims to find the linear combinations of features that best separate different classes in the dataset. LDA assumes that the data is normally distributed and that the classes have the same covariance matrix. If these assumptions are not met, modifications or alternative techniques may be considered [7]. ICA is a computational technique used for separating a multivariate signal into additive, independent components. The goal of ICA is to find a linear transformation that maximizes the statistical independence between the resulting components. ICA is widely used in signal processing, blind source separation, and feature extraction in various fields, including image processing [8].

2.3 Deep Learning Approach

Deep learning based on artificial neural networks brought significant advancement to the field of image processing including face recognition. Deep learning models, especially **convolutional neural networks (CNNs)**, have significantly improved the accuracy of face recognition systems. These models can learn hierarchical features, capturing both low-level and high-level facial characteristics, leading to more robust and reliable recognition [9]. Deep learning models have been enhanced with domain adaptation techniques, allowing them to generalize well across different datasets and real-world scenarios. This addresses challenges related to variations in lighting, background, and imaging conditions [10].

CNN is considered the main deep learning architecture related to computer vision and image classification. They performed an excellent performance in classifying image based on feature extraction and learning. It organized in many hierarchical layers to represent and extract image features for classification purpose. CNN consists of some layers using convolutions and pooling which each layer performs specific functions as the following [11]:

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First: Convolutional Layer:

- Feature Extraction: This layer acts as a hierarchical feature extractor, capturing local patterns and spatial relationships within the input data. It employs a set of learnable filters, also known as kernels, to scan small, contiguous regions of the input, generating feature maps that highlight salient features.
- Shared Weights and Local Connectivity: The filters have shared weights, ensuring the ability to recognize features regardless of their position in the input image. Local connectivity, where each neuron connects to a limited region of the previous layer, reduces computational complexity and promotes the detection of localized patterns.
- Activation Function: Non-linear activation functions, such as ReLU, are applied to the feature maps, introducing non-linearity and enhancing the network's ability to model complex relationships [12].

Second: Pooling Layer:

- Spatial Dimension Reduction: This layer aims to reduce the spatial dimensions of the feature maps, leading to Computational efficiency: Fewer parameters to learn and process in subsequent layers. Translation invariance: Resilience to minor spatial translations of features. Overfitting prevention: Reduced risk of overfitting by introducing a degree of spatial invariance.
- Max pooling: Retains the maximum value within each pooling window.
- Average pooling: Calculates the average value within each pooling window [13].

***Third: Fully Connected Layer*:**

- High-Level Abstraction and Classification: This layer sits at the end of the CNN architecture and serves two primary purposes Integrates the extracted features from previous layers into a more abstract, high-level representation. Performs the final classification task, assigning probabilities to different classes based on the learned features.
- Dense Connectivity: Neurons in this layer are fully connected to all neurons in the previous layer, allowing for the fusion of information from across the feature maps [14].

In essence, these layers work in concert to achieve effective feature extraction, spatial invariance, and classification, forming the core building blocks of CNNs and their remarkable success in various computer vision and image recognition tasks.

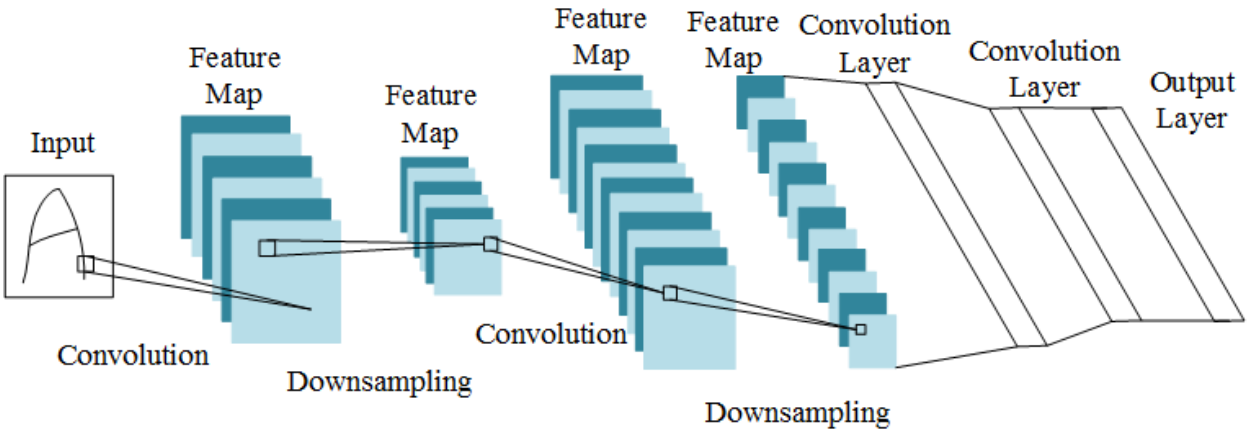

Fig 1: Convolutional Neural Network (CNN) Structure [5]

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2.4 Face Recognition Challenges

- Pose Variations: Changes in head orientation, tilt, and rotation significantly alter facial appearance, often obscuring key features and creating mismatches between reference images and captured faces.
- Illumination Variations: Variations in lighting intensity and direction can dramatically alter shadows, highlights, and textures on the face, impacting feature detection and comparison.
- Facial Expressions: Dynamic facial expressions like smiling, frowning, or squinting introduce temporary deformations that can confuse recognition systems.
- Face Recognition and Occlusion: Facial occlusions by scarves, sunglasses, or even masks pose a significant obstacle for recognition systems.
- Single Sample Face Recognition: Traditional face recognition models require multiple training images per individual. However, scenarios like video surveillance often offer only a single image.
- Face Recognition in Video Surveillance: Real-world video surveillance footage presents challenges like low resolution, compression artifacts, and dynamic backgrounds.
- Face Recognition and Ageing: Facial features undergo significant changes over time, making recognition across age groups difficult.[15][16]

3. Methodology

This section represents the methodological approach followed in this review paper to study the link between GAN deep learning techniques and accurate face recognition system. It shows the data collection stages, analysis and the main research questions to achieve the research objectives.

3.1 Research Stages

The main sources for this article are the most famous article repository such as: Science direct, IEEE, springer, and MDPI. The data will be collected by extensive search within these digital repositories to select the high quality papers. The GAN algorithms and techniques regarding face recognition will be mentioned and summarized. The review study processes include four stage as shown in figure.

Stage 1: Data Collection

This stage involved an extensive search within reputable academic repositories, such as IEEE, Springer, ScienceDirect, and MDPI, to gather relevant research papers. The focus was to identify studies that apply GAN models to enhance face recognition techniques. High-quality peer-reviewed articles were prioritized to ensure that the review covers state-of-the-art advancements in the field.

Stage 2: GAN Models and Techniques Overview

Once the data was collected, the next step was to review and summarize the GAN models and techniques presented in the selected studies. This stage involved analyzing how GANs are applied to tackle different face recognition challenges, such as low-resolution images, pose variations, and facial expression recognition. Each GAN model was examined based on its architecture, performance, and the specific facial recognition problem it aimed to solve.

Stage 3: Challenges and GAN Solutions

In this stage, the challenges faced by traditional face recognition systems were categorized. This included issues like illumination variation, occlusion, and expression changes, which negatively affect the accuracy of face recognition. GAN-based solutions were then mapped to these

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challenges, showing how each model enhances face recognition performance in specific contexts.

Stage 4: Future Research Directions

The final stage focused on identifying gaps in the current literature and suggesting future research directions. Based on the review of existing models and their limitations, potential areas for further exploration were proposed, such as using GANs for real-time face recognition and enhancing single-sample recognition systems. This stage also highlighted emerging opportunities in leveraging GANs for more robust and adaptive face recognition systems.

3.2 Research Questions

The main research questions which this article aim to answer are:

RQ1: What are the main approaches used for face recognition in literature?

RQ2: How face recognition has been enhanced through GAN deep learning?

RQ3: What are the possible research opportunities for future works?

4. Generative Adversely Network

GAN is deep learning model to generate fake or unreal image that service as real image because of the low difference between both the generated and the real image [17]. The model consists of two deep neural network architecture first is a generator and the second is discriminator. The generator takes a noise vector as input then produce an image output that looks real. The generated image then will be given to the second architecture which called discriminator which works as classifier that receives image input both real and fake and label them accordingly.

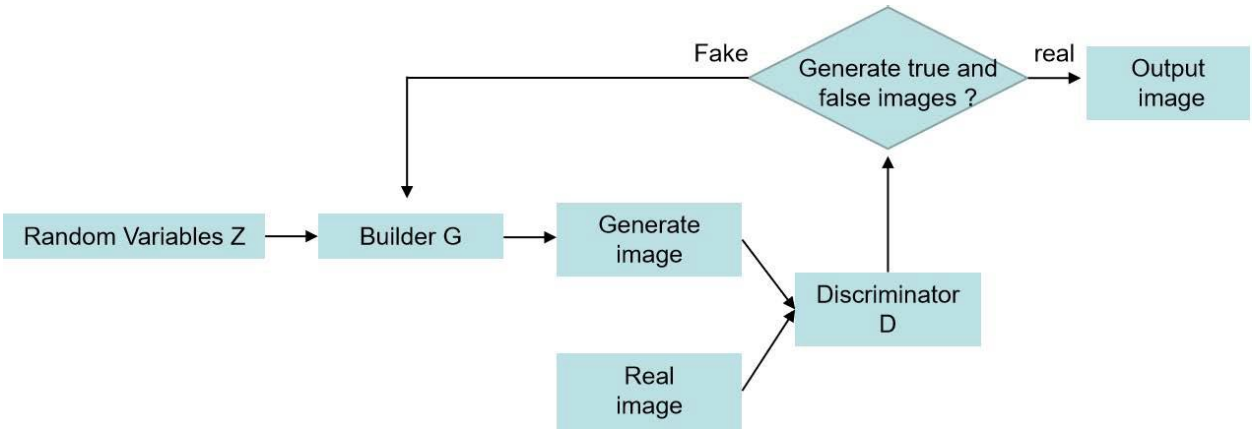

Fig 2: Generative Adversarial Network (GAN) Overview [18]

This process will continue through loss function and back propagation until the generator output will bypass the discriminator. Both the generator and discriminator use convolutional neural network (CNN) as basic architecture for their functions [18].

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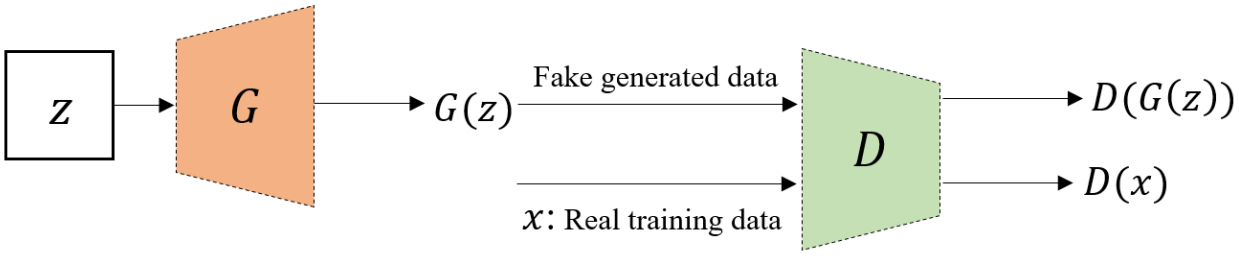

Fig 3: Generative Adversarial Network (GAN) Model [19]

Where z represent a noise vector, G(z) represent the image produced by the generator and X represent real images. The discriminator takes other the G(z) and X as input then acts as binary classifier to label the image as 1 real image or 0 as fake image [19].

5. Face Recognition Enhancement using GAN

This section covers the enhancement has been made to the field of face recognition by using GAN deep neural network.

5.1. Illumination-Invariant Face Recognition

Low illumination can significantly affect the quality of face in an image which leads to poor face recognition. The IL-GAN model proposed by [20] to enhance face recognition system to identify and recognize faces across different lighting conditions. The model consists of four steps:

- The first step by distinguishing the illumination level from the input image based on Singular Value Decomposition **(SVD).**
- The second is using encoder-decoder structure in the generative model aiming to extracting important features without the disturbing illumination included in the face image and generating new fake image.
- This third step is using another generator to reconstructing the original image from the generated fake image and the original illumination level coded from step one.
- The final step is using discriminator classification on identifying of generated fake image as well as the reconstructed image in third step.

The data set has been used is Yale B database which is publicly used in face recognition and contains 38 individuals with 9 poses under 64 different illumination conditions with accuracy by 89% which shows a significant improvement in compare with traditional approaches.

5.2. Deformation Invariant Face Recognition

Deformation refer to the effect of changes or distortions in the facial presence due to different environmental conditions. These deformation poses a huge challenges to the face recognition applications. Facial Augmentation GAN (**FA-GAN**) model proposed by [21] to overcome deformation constraint posed by different factors. The proposed model also a face augmentation approach by constructing face images with different desired deformation from original face image.

The model first preserve the identity information of the person, then extract distinguished information to generated different deformation attribute representations. This process achieves two goals one learning about the important face features, second augmenting face datasets with more customized deformation demand. Finally, the model obtain expanded new deformation

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samples to the data sets and improve the face recognition system invariant which deformation. The model improved the process by 75% accuracy when the face has 90 degree and 94% with 75degree angle.

Fig 4: Face Augmentation from 90 Degree Profile [21]

5.3. Multi-View Face Expression Recognition

Facial expression recognition considered one of the main application within face recognition domain. A Facial Expression GAN (**FE-GAN**) model proposed by [22] to better enhance the facial expression recognition.

This research proposes a lightweight, efficient system for recognizing facial expressions (FER) that excels even with tilted faces. It combines a compact FER model (DSC-DenseNet) with a posture-correcting GAN (LD-GAN) that preserves expression details. Compared to previous methods, their system achieves a high 92% FER accuracy with fewer parameters and handles facial angles better, making it ideal for real-world applications.

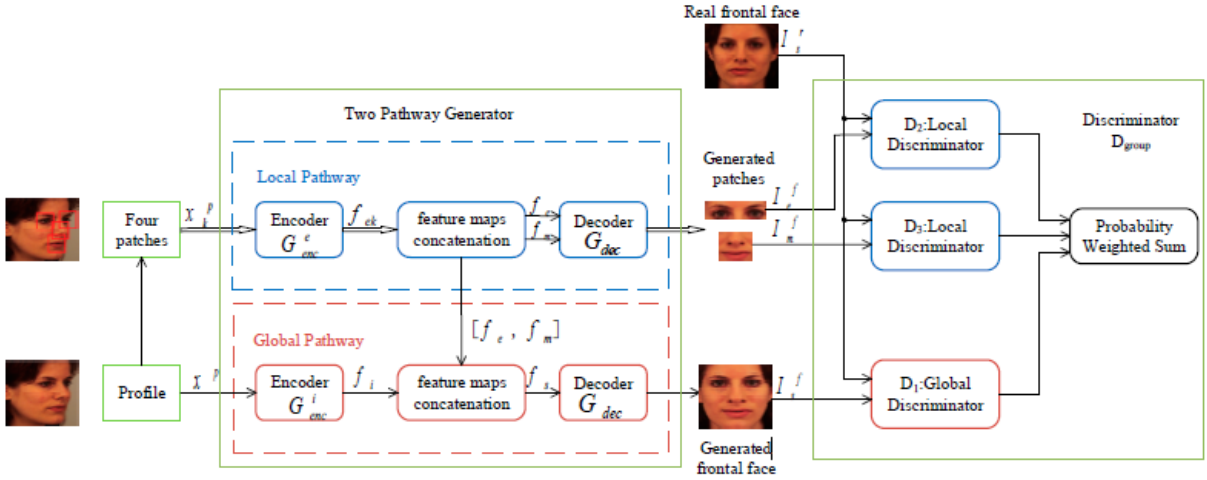

Fig. 5: Multi-View Face Recognition (FE-GAN) [22]

5.4. Degraded Face Recognition

Degraded face recognition refers to the process of detection and identifying facial images that affected by deterioration or degradation. There are many condition factors that leads to degradation such as low image quality, noise, blurriness and effects of some form of distortions.

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Recognizing face image in degraded conditions considered to be a huge challenging task for face recognition applications because of the low quality of input image.

A Low Resolution GAN (LR-GAN) model proposed by [23] to overcome this challenge. The prosed model generates more clearly constructed image by a generative model through adversarial training used for training the LR-GAN. The model then uses multi-scale structural similarity index (MS-SSIM) to measure the structural similarity index between the reconstructed image from the generator and the expected outputs (ground truth). This similarity process is to reduce the loss function outcome of the generator model and produce more realistic image. The model applied on different data set showing a good performance with 91% accuracy.

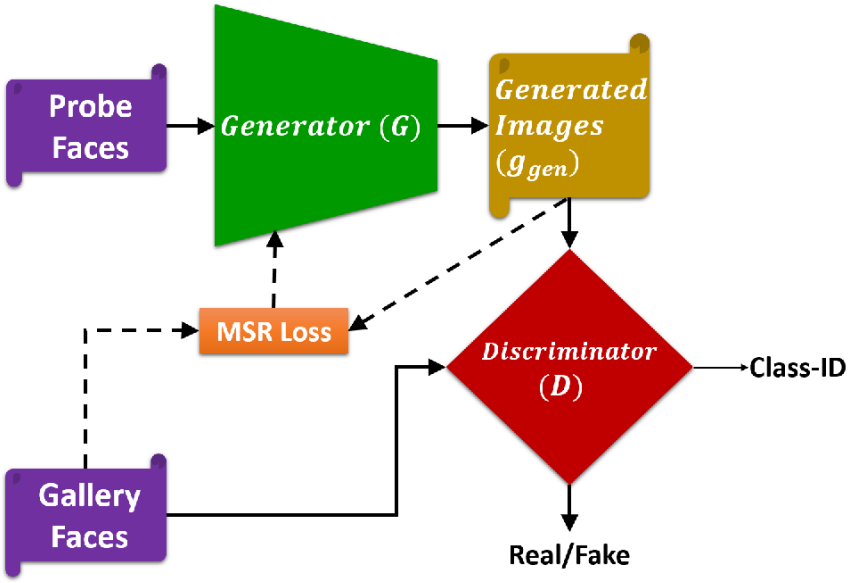

Fig 6: Degraded Face Recognition (LR-GAN) [23]

5.5. Pose Invariance Face Recognition

Facial recognition across different poses is challenging due to variation in appearance caused by changes in lighting, face details and the visibility of face features. Dealing with pose variation considered as challenge research concern in face recognition because of struggle to match faces captured under different orientation.

The Cross Posse GAN (CP-GAN) model is proposed by [24] as solution to the ill pose face recognition. The network architecture and training loss of the GAN has been enhanced under pair training procedure. The generator input is a set of different pose of a face to synthesis the frontal view face representation. Then the discriminator competes with the generator with shared weights that can take both the synthesized face and ground truth at the same time to minimize the distance and the loss between them. In this model a U-net architecture is used as generator because some detailed features may be missed or disappeared during low resolution or small size image. The model showed a 97% accuracy after training on both CASIA and IJB data sets.

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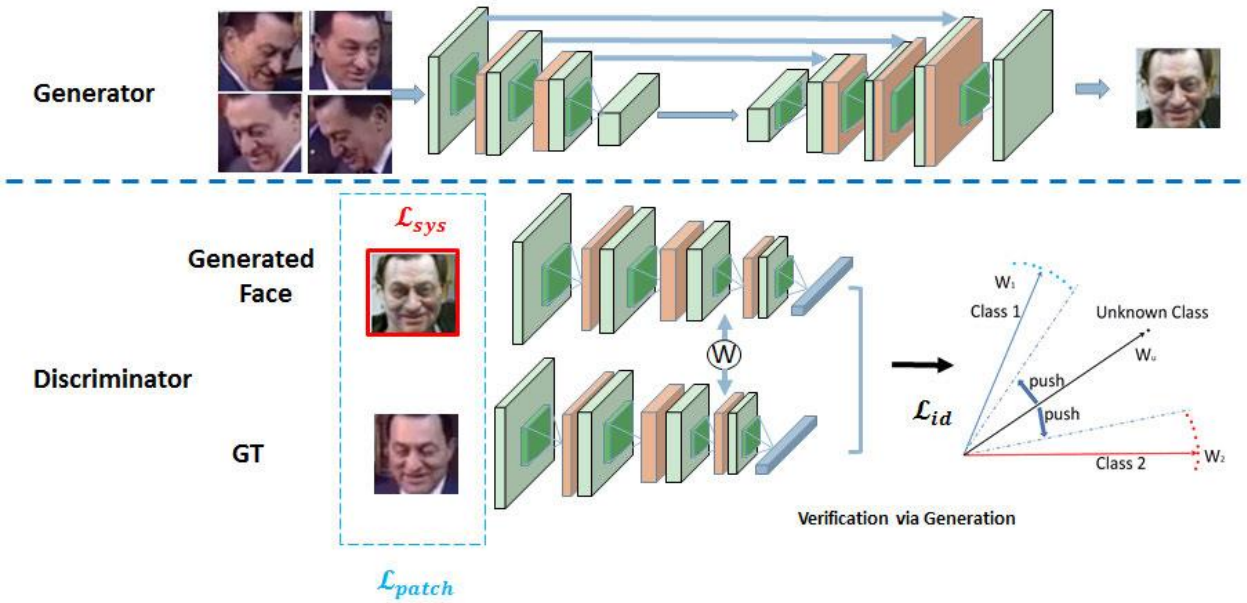

Fig. 7: Pose Invariance Face Recognition (CP-GAN) [24]

5.6. Face Hallucination and Recognition

Face hallucination refers to the process of generating high-resolution and realistic facial image from low resolution or degraded images. This process includes enhancement of the details and quality of facial image to produce higher resolution version. This task is challengeable because it requires generating a realistic natural looking facial features that is not available in the original low resolution image. Adversarial generative model can be used in face hallucination as this model can learn to generate realistic image features facilitating the reconstruction of high resolution facial image.

A face hallucination GAN (FH-GAN) model proposed by [25] to better enhance face recognition system. The proposed model focus on both local and holistic features using up sampling layers.as preprocessing phase the Local Binary Pattern (LBP) and Unsharp Masking (UM) is used on low resolution face images to extract the features edges. Using these techniques on input images helps the generator to produce more accurate facial images. The overall structure of the model uses a generator with 2X up sampling and residual self-attention block to extract holistic features and local features are extracted in the residual block. Finally, both the local and holistic features are combined followed by two rectifier linear unit (ReLU) activation function. The model showed accuracy of 79% on FERET data set of 990 face images, with better performance from many other traditional models.

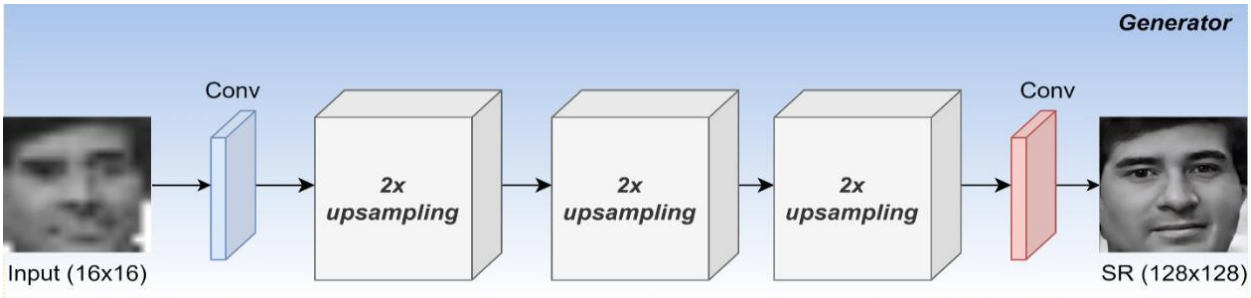

Fig 8: Face Hallucination and Recognition (FH-GAN) [25]

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5.7. Face and body recognition

Long distance image from surveillance cameras are difficult to obtain a front image of an individual. In addition face information can be distorted due to motion blur which requires face enhancement and deburring. By using GAN both the blur of face image can be restored and the body features can be recognized. The [26] research presents a novel Face and Body GAN (FB-GAN) approach for multimodal human recognition that tackles blurry images.

- **Focus on blurs**: Unlike existing methods, they identify blurry images using a "focus score" before applying blur restoration with a Generative Adversarial Network (GAN). This reduces errors compared to simply applying GAN to all images.
- **Separate networks for efficiency**: They keep the blur restoration network (GAN) and the human recognition network (CNN) separate. This simplifies the overall structure and potentially speeds up processing.
- **Face and body differences**: Despite simultaneous processing being faster, they choose separate blur restoration for face and body images. This accounts for the distinct blurring tendencies and detailed information present in each.

Overall, this research improves multimodal human recognition by effectively addressing blurry images with separate restoration for face and body and a focus score-based GAN application. The model trained on a specific data set prepared by the researcher and showed 94% accuracy.

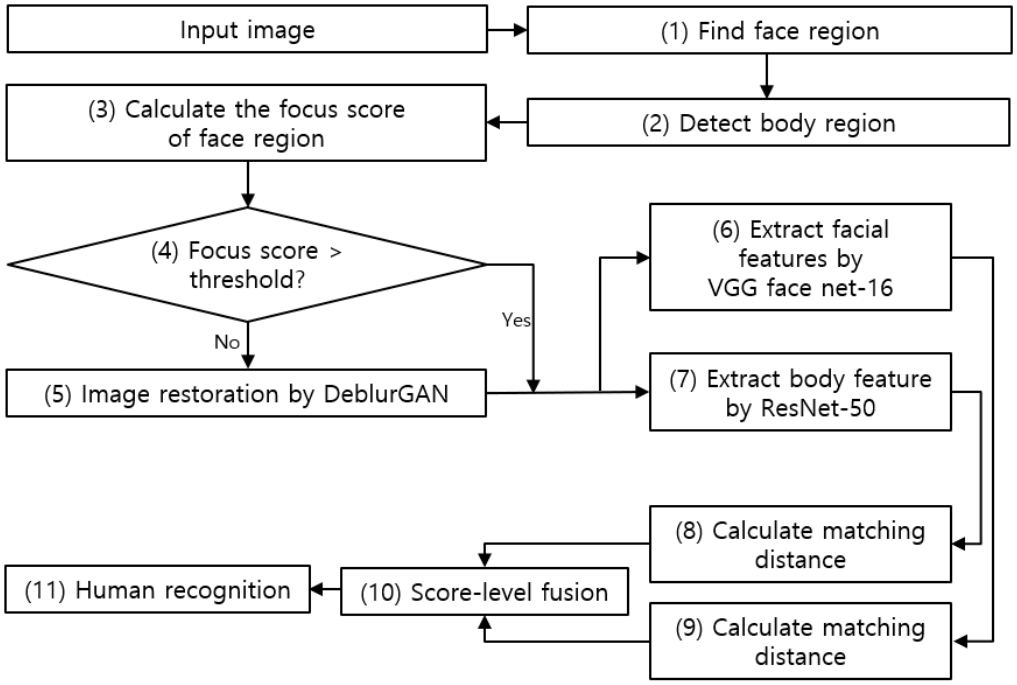

Fig. 9: Face and Body Recognition (FB-GAN) [26]

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6. Result and Discussion

This section is to answer the research questions has been defined at the methodology section. Based on the analysis of previous studies that has been mention in the above section the study shows the following:

***RQ1**: What are the main approaches used for face recognition in literature?*

There are various approaches for face recognition have been studied in literature. Starting from local feature-based methods which focus on extracting distinguishing facial features such as mouths, nose an eye, then utilizing these descriptors for recognition. Then holistic approach considers the entire face as a unified entity, capture global facial features, Eigenfaces and Fisherfaces are classic examples of holistic methods. They employ techniques like principal component analysis (PCA) and linear discriminant analysis (LDA). In recent years, deep learning approaches have gained significant popularity using convolutional neural network (CNN) and generative adversarial network (GAN) for face recognition.

***RQ2**: How face recognition has been enhanced through GAN deep learning?*

Generative Adversarial Networks (GANs) have significantly enhanced face recognition by adding a powerful tool to the arsenal of deep learning techniques. The following table summarizes how GANs are enhancing the field of face recognition:

RQ3: What are the possible research opportunities for future works?

Future research opportunities in face recognition using Generative Adversarial Networks (GANs) offer exciting prospects for addressing current challenges and expanding the capabilities of face recognition systems. Some potential opportunities are improving data augmentation for single sample, face recognition using more biometric information and emotion recognition using micro face expression.

Table 1: Summary of Face recognition enhancement using GAN

References	Model	Challenge	Enhancement	Enhancement Ration
[20]	IL-GAN	Low illumination	using encoder-decoder structure in the generative model aiming to extracting important features without the disturbing illumination	89%
[21]	FA-GAN	Face augmentation distortions in the facial presence due to different environmental conditions.	augmentation approach by constructing face images with different desired deformation from original face image	75%
[22]	FE-GAN	Facial expression recognition	efficient system for recognizing a face with different expressions	92%
[23]	LR-GAN	Low resolution	generates more clearly constructed image	91%
[24]	CP-GAN	Multi pose invariance Face recognition	set of different pose of a face to synthesis the frontal view face representation	97%
[25]	FH-GAN	Face hallucination and recognition	the generator produces more accurate and higher resolution facial images	79%
[26]	FB-GAN	Face and body recognition	Long distance image from surveillance cameras recognition by both face and body image	94%

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Table 1 show how each model targets a unique issue, such as low illumination, facial distortions, expression recognition, low resolution, multi-pose invariance, face hallucination, and long-distance recognition. For instance, **IL-GAN** addresses low illumination by using an encoder-decoder structure to extract key features without illumination interference, achieving an 89% enhancement ratio. **FA-GAN** tackles face augmentation distortions caused by environmental conditions, with a 75% enhancement ratio. **FE-GAN** provides an efficient system for recognizing facial expressions, achieving a high enhancement ratio of 92%. **LR-GAN** improves low-resolution images, generating clearer outputs with a 91% enhancement ratio, while **CP-GAN** synthesizes frontal views from multiple poses, achieving the highest enhancement ratio of 97%. **FH-GAN** enhances face hallucination and recognition by producing higher-resolution and more accurate facial images, with a 79% enhancement ratio. Lastly, **FB-GAN** focuses on recognizing both faces and bodies from long-distance surveillance images, achieving a 94% enhancement ratio.

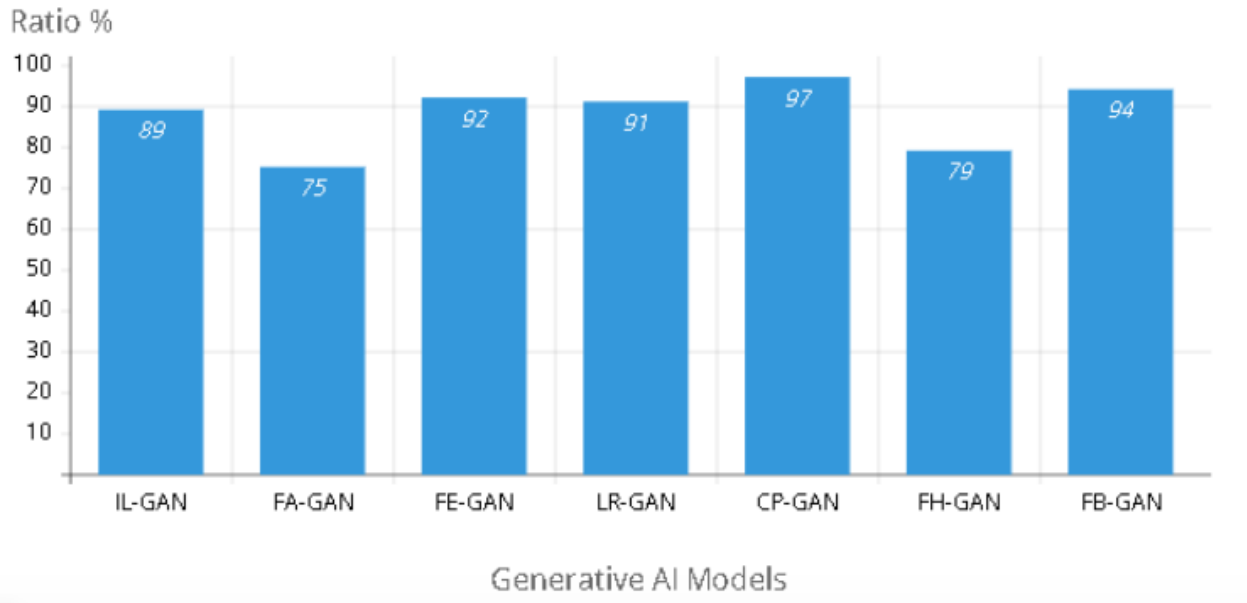

Fig. 10: Face Recognition Dataset Enhancement

Figure 10 presents represents the enhancement ratios of these models, highlighting **CP-GAN** as the most effective with a 97% enhancement ratio, followed by **FB-GAN** (94%) and **FE-GAN** (92%). These models collectively address a wide range of challenges in face recognition, from environmental distortions to resolution and pose variations.

7. Conclusion

In conclusion, this review paper highlights the transformative potential of GANs in addressing the challenges of poor-quality datasets in face recognition systems. By leveraging models such as IL-GAN, FA-GAN, FE-GAN, LR-GAN, CP-GAN, FH-GAN, and FB-GAN, researchers can effectively enhance facial images under various adverse conditions, achieving significant improvements in recognition accuracy and reliability. The success of these models, with enhancement ratios ranging from 75% to 97%, underscores the importance of generative AI in overcoming dataset limitations. Furthermore, the methodologies and insights presented in this research extend beyond face recognition, offering valuable tools for improving image datasets in

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other domains, such as healthcare, security, and robotics. As generative AI continues to evolve, its application in dataset enhancement will play a critical role in advancing machine learning technologies, enabling more accurate and robust systems across a wide range of applications. This research not only advances the field of face recognition but also contributes to the broader goal of improving data quality in AI-driven solutions.

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