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Research Article

A Comprehensive Survey of Generative Adversarial Networks in Biometric Applications

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ABSTRACT

Being a sector of machine learning, deep learning aims to give robots abilities much like humans in learning, perception and intelligence. In the fields of image processing, GAN (Generative Adversarial Network) has become an important branch of deep learning. Now, deep learning generative networks allow for the generation of good quality synthetic data that still keep the same statistics as the original data. Keeping information secure in various important sectors like education, banking and others is very important as biometrics are adopted more and more for authenticity. During periods of large demand, synthetic biometric datasets come in very useful for checking and developing biometric systems. The amount of high-quality data, the training process's reliability and updates to the architecture are part of the evaluation too. Generative Adversarial Networks (GAN) is one of the most reliable frameworks for making realistic synthetic data. This study reviews several GAN architectures; the loss function they use and the common designs as well as fields of application and also looks at how they help in biometrics. Using unique characteristics from the body like fingerprints, face details and iris patterns, biometric systems now commonly use deep learning models. The research also looks at how GAN variations can be used in face, iris, fingerprint and palmprint identification. The purpose of this paper is to discuss the GAN-based methods in biometrics by systematically comparing these models and how they are used.

Keywords: Biometric traits, GAN, Image processing, GAN models.

1. INTRODUCTION

Machine learning means building models to carry out classification, regression, prediction and clustering tasks. They are generally applied in image processing, with the aim of enhancing image super-resolution. Even so, machine learning algorithms that depend on prior knowledge encounter difficulties like the need for humans to change and find the optimal settings. These problems are being tackled by developing deep learning approaches like CNNs. Deep learning relying on Deep Neural Networks (DNNs) improves both representation and reasoning, yet it has problems with image recognition, medical diagnosis and biometric authentication because data is not always plentiful. Traditional generative models, such as Gaussian Mixture, Restricted Boltzmann Machine, Naive Bayes, and Hidden Markov Model, rely on maximum likelihood estimates, which may not accurately capture the complexity of real data distributions. Deep generative models, such as generative adversarial networks (GANs), can automatically acquire all functions of any dataset and data type. GANs [1] are developed using maximum likelihood and parametrized models to handle the toughness of real data distribution through adversarial learning between a discriminator and a generator. They do well at making data look similar to real data and producing various types of information which helps computer vision with data synthesis. They have a wide range of uses in music, semi-supervised learning, art, missing data, unsupervised learning and drug discovery. They work to protect privacy by both defending against and dealing

with privacy concerns. Studies on GANs are broadening, with a focus on perfecting their training and using GANs for new applications. [2][3][4]
Because of GANs, building fake biometric data has become possible which is useful for testing and improving biometric systems in many situations. GANs save resources and can produce many different biometric samples [5] which helps them deal with problems caused by data distortion and corruption. They are also helpful in producing fake biometrics which reduces concerns about privacy with real ones. GANs [1] consist of two neural networks that compete with each other to produce real samples that look the same. They use the minmax approach, requiring the organizations to increase their particular strengths so that the results are equal for each side. With GANs, problems like creating images from text descriptions, getting high-quality photos, detecting objects and returning images matching a pattern have been successfully resolved. Generative adversarial networks, have an advantage over other generative models because they use parallel generation to build samples in Fully Visible Belief Networks. Unlike other models, GANs are not based on Markov chains and produce better samples. The survey seeks to place recent progress in GAN research within the context of various GAN models and how they resolve the main difficulties in training them. The study looks at the different structures of GAN and explains their uses, especially in biometrics.

2. GENERATIVE ADVERSARIAL NETWORK

GANs can create new data that looks similar to the training data [17]. Unsupervised ML techniques using GAN networks are based on using a generator and a discriminator network. A GAN is trained using two players (the discriminator and the generator) that each want to win at the expense of the other. Both methods try to create data that is difficult to distinguish from the original data in the datasets. The Generator, a neural network with hidden layers, activation and a loss function, follows unsupervised learning and produces fraudulent images based on probabilistic representation. Meanwhile, the discriminator which has supervised learning, classifies the images produced by the Generator as —not real and notifies whether the artificial images are genuine or not. In this scenario, the models are trained with data until their accuracy reaches the desired standard (Figure 1). Every time, the generator is made to produce clearer images and the discriminator is skilled at telling which images are real and which are from the generator. Once the generator makes the discriminator laugh, the training finishes and we can say that a generalized GAN model has been created.

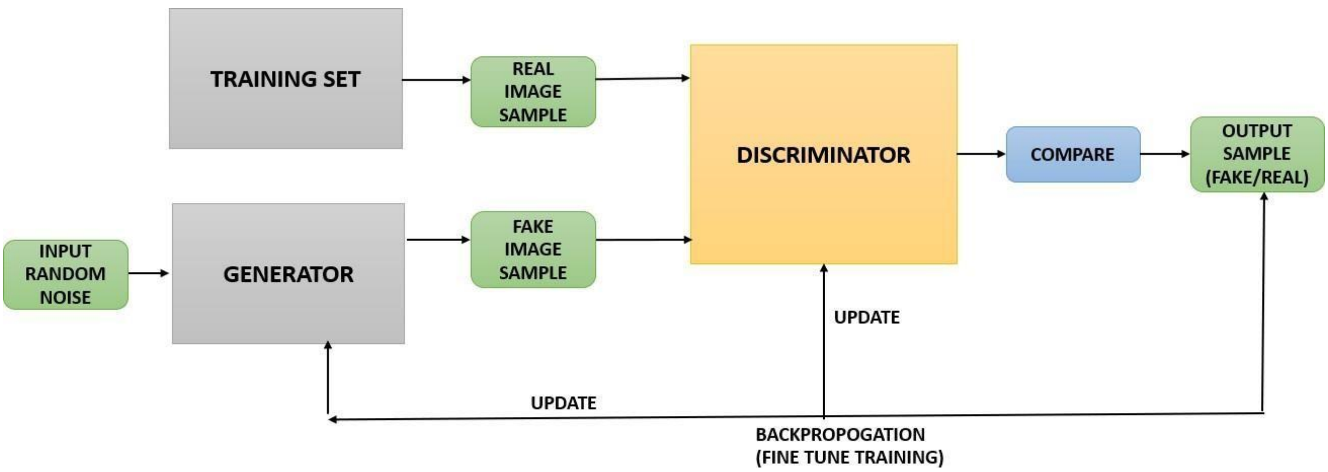

Figure 1: Architecture of Generative Adversarial Network

GAN Its goal is to identify samples created by the training data from those produced by the Generator model which uses a fixed-length random input. GANs are based on a minimax game and the Generator produces samples without any help. To give the generative process variation, a vector is randomly chosen from the Gaussian circulation. A latent space or hidden variables [2], is a way to present the main aspects of how information is organized. At first, it looked like GANs had only one solution, but if neither player can improve after losing, Nash Harmony (NE) is the result. Visually, there is a network that handles art and one that forges it. To generate realistic visuals, G (generator) in GAN literature creates forgeries. The discriminator, D, can tell apart both true and fake images. The generator improves by interacting with the discriminator, studying both real images and made-up images. Because the discriminator provides the ground truth, the generator is taught using the same error information which leads to better fake images.
If the picture is correctly organized, the Discriminator is paid, while the Generator is penalized and forced to rebalance its weight. If the data is erroneously categorised, the discriminator is penalized and forced to adjust its weights. The distribution of false photos starts to match that of actual images, and the Discriminator starts to categorize an image as fake or real with a probability of 0.5.
In this minimax game the generator (G) tries to maximise the loss of the discriminator (D) while the discriminator tries to minimise its reward V (D, G). While D is a function to separate Xfake and genuine data

Xreal, G is a function to operate a latent space z to make fake data that resembles real data, Xfake. Till D cannot tell the difference between Xfake and Xreal, G's training process is stopped. The following loss function is one that the generator and discriminator both attempt to reduce.

$$\min_{G} \max_{D} \mathbb{E}_{x \sim p_{data}}[\log D(x)] + \mathbb{E}_{z \sim p_z}[\log(1 - D(G(z)))], \quad (1)$$

The initial presentation of Generalized Artificial Networks (GANs) suggests a solitary solution, known as a Nash Harmony (NE) result, when neither player can recover from defeat. However, some studies suggest that achieving NE is unlikely in practice.[6] In the context of visual data, consider a network with one authority on art and another art forger. The generator, or forger, creates forgeries to create realistic visuals, while the discriminator, or master, accepts both real and falsified photographs. The generator learns through interaction with the discriminator, learning from both real-image samples and fictitious samples. The discriminator uses a binary classifier to accurately distinguish between the samples produced by the generator and the real samples. The generator tries to misrepresent the output's authenticity to increase the chances of the discriminator making a mistake. Knowing whether the picture originated from the real or the generator provides a ground truth that serves as the discriminator's error signal. This improves the two players and production quality, leading to higher-quality forgeries.

2.1 ISSUES WITH GAN

Generative Adversarial Networks (GANs) are effective tools for producing synthetic data, but they also have drawbacks, such as mode collapse, delayed learning, and nonconvergence due to unstable discriminator-generator behavior. [7] Among the main issues are:

Mode Collapse Mode collapse means the generator often gives the same output regardless of the input in the latent space which limits the range of samples that are created.[8]. Even with many efforts to resolve it, this area remains unresolved. When the GAN creates the same output for every input, it is complete mode collapse, but when many of the results are similar, it is called partial mode collapse. Researchers have found that newer variants such as WGAN, help lessen mode collapse.[10] [11]

Stopping Problem GANs are unable to optimize the minimax game because traditional neural networks require a loss function that monotonically lowers as the cost function increases. Determining whether the models have achieved their maximum level of training optimization is challenging since the loss function lacks a clear pattern.[13][14]

Gradient Vanishing In rational learning, getting a GAN ready means keeping D and G in sync as they both change. An accurate D helps the model identify real data, so the gradients it produces for the G are very small. If the D does not work correctly, the G will not be able to tell real data from fake data.[12][8]

Instability Combining two trained models to enhance the overall loss function in a minimax game is known as GAN planning. The loss scenario, in which organizations battle to find their own layout, is taken into account in the model design. Network desynchronization timings are delicate, and major adjustments in one organization may lead to additional alterations. Training effectiveness may be impacted by unstable times. In order to enhance network performance, recent GAN designs emphasize stabilizing training; more stable training is incorporated in these advancements.[17] [2]

Evaluation Metrices There isn't a single standard way to judge the quality of data created by GANs because of their special features and many uses.[15]. Because each GAN application is unique, there is no general consensus in the research. Many ways are used to compare origin and synthesised distributions [16], though the most effective ones are still being discussed. What metrics are used depends on the application and gives a deeper understanding of how GANs perform.[9]

3. GAN MODELS

Among the limitations of GANs are mode collapse, back-and-forth oscillation between G and D and players becoming unstable as they get stronger. Should the samples be of poor quality, D can easily tell them apart, so the likelihood of generated samples being real is nearly zero. As a result, G will no longer update and will produce a tiny gradient. It is very important to select the right hyperparameters for GAN training to converge. GANs have been redesigned by researchers, who suggested modifications to the training process or the structure of G or D. In this section, we discuss the different GAN types and what they require to develop. (Ref. Table 1.)

DCGAN is a Deep Convolutional GAN [19] that doesn't use max pooling and instead relies on completely connected or convolution layers. It applies downsampling and upsampling through transposed convolution and convolutional stride and batch norm, strided convolution and LeakyReLU layers for the discrimination task. When standardization layers are applied, the noise level decreases and test results improve. Using the Redressed Straight Unit (LeakyReLU) leads to improved results from DCGAN when working with human faces and the LSUN dataset. These networks are great for image generation, unsupervised learning of features and improving the quality of images. They help provide sharp images, make training steadier and improve the way information is represented. Yet, they run into problems like being sensitive to the values of hyperparameters, collapsing into one mode and dealing poorly with non-image or non-structured data. In spite of these obstacles, DCGANs have become essential for generative modeling and have motivated many advanced types of GANs in image generation and restoration. The reason they are commonly used for tasks such as image synthesis, unsupervised learning, super-resolution, image inpainting and art generation is their skill at learning strong spatial hierarchies.

CycleGAN [4] is a GAN design that makes it possible to convert images from one type to another without requiring paired images for training. Two GANs are used to study the mapping between two types of images, taking features from the input and making new images with those features. CycleGAN trains each generator on its own, using the second GAN's discriminator to make a source image from a target image and the first GAN's generator to make a target image from a source image. CycleGAN includes two generator models, Generator-A and Generator-B which can be used for artistic style transfer, photo enhancement, object transfiguration, medical image translation and adapting synthetic images to the real world. It provides flexibility and saves important structural information, but may introduce artifacts, be sensitive to training changes and struggle with learning small distinctions.

CONDITIONAL GAN (cGAN) [18] is a type of generative model that uses extra information or a condition, in both its generator and discriminator. Thanks to this conditioning, cGANs are suitable for complex tasks such as turning images into other images, segmenting images, making them clearer and turning text into images. As a result, the generator and discriminator are pitted against each other in training, but there is still a rule that must be followed. Image-to-image translation, super-resolution, image inpainting, semantic segmentation and text-to-image synthesis all benefit from cGANs using conditioning to provide important context. Compared to other models, cGANs allow for better control of the output, are more relevant to the input and have more stable training when used in structured generation. Yet, there are issues too, including having more complex models, relying on good and consistent condition labels and sometimes needing datasets that match in some cases. Even with these limitations, cGANs are still a useful and flexible tool in today's generative modeling when precise results are needed.

WGAN [17] is a development of GAN that increases stability and better-quality images by reducing the Earth-Mover distance computation. The generator depends on its own probability distribution and the distribution found in real images (Pr) to create great results. We suggest using three techniques: Jensen-Shannon divergence, the Wasserstein distance and the Kullback-Leibler divergence. The Wasserstein distance makes WGAN training more stable and helps solve problems involving gradients. WGAN includes a generator for making fake data from random inputs and a critic for assigning real numbers to the inputs. Wasserstein distance is used as the loss function, making it easier to train the model and giving clearer gradients. WGAN is used for making realistic images, boosting image quality, synthesizing medical images and finding unusual patterns. Still, it comes with some problems, for example, being sensitive to hyperparameters, taking longer to train and having restrictions on weight clipping.

Pix2pix [21] GANs are a Conditional Generative Adversarial Network (cGAN) designed for paired image-to-image translation tasks. They use an encoder-decoder architecture with convolutional layers that are down-sampled and up-sampled to resize images. The generator network (U Net) maintains the image's dimensions and size using only one convolutional layer block before downsampling. The proposed discriminator design penalizes structure at the patch scale using a patch-wise approach. The final output of the patch GAN determines whether each patch in an image is authentic or forge. The patch GAN discriminator requires fewer training parameters, operates faster, and can be used with any image size. Pix2Pix has applications in medical imaging and graphics, converting sketches to photos, maps to satellite images, grayscale to color, and labels to scenes. However, it requires large amounts of paired training data, which can be difficult or expensive to obtain, and reduces generalization to unstructured tasks or unseen conditions.

SRGAN [22] is a deep learning model designed to make upscaled photos clearer and better quality and also to tell if the high-resolution images are real or produced. The approach uses a perception loss function to enhance the quality people see, with features learned from a deep neural network. SRGAN supports creative photo enhancement, image-resolution enhancement and video-resolution enhancement to improve the way we see visual content. Even though there are obstacles with generalization, model artifacts and training, it is an important advance in image super-resolution. The SRGAN model includes a generator, a discriminator and a perceptual loss function designed to produce photo-realistic images. The generator relies on residual blocks with skip connections to learn the identity mappings and the discriminator tells apart true high-resolution pictures from those made by the generator. With SRGAN, a perceptual loss is added, mixing mean squared error with loss calculated from upper-level feature maps, making the generated images both more realistic and similar to what humans can see.

StyleGAN [3] is an advanced GAN from NVIDIA that improves the generator by introducing noise, controlling style and mapping latent points to a middle latent space. With this model, you can get highly realistic and detailed images for both face synthesis and artistic image generation. Progressive GAN's generator architecture is followed and instead of using random latent variables, the model uses a predetermined tensor. StyleGAN also makes use of a technique called mixing regularization which merges two latent-variable styles during training. The generator architecture adds a mapping network and adaptive instance normalization (AdaIN) layers to control the style at various levels during image synthesis. StyleGAN is used to produce photorealistic faces, artwork, fashion designs, augment data sets and run simulations for forensic work. Despite some flaws, StyleGAN is still an important achievement in generative modeling and keeps affecting studies in AI-generated media.

BEGAN [23] deals with image assessment by using boundary balance architectures. It measures the real loss between real and simulated reconstructions with the Wasserstein distance and BE-GAN ensures both high performance and a diverse dataset by using their 'boundary equilibrium GAN'. BEGAN is trained fast and consistently, ensuring both high quality and a good variety by using an equilibrium threshold. An autoencoder is also used to keep the training stable and create good quality samples. Images are produced from noise by the generator and the discriminator, trained on real images, tries to reconstruct them and check the loss experienced during this process. In BEGAN, the loss for the generator comes from the reconstruction error of the autoencoder and a balancing term guarantees that the generator and discriminator do not lose their equilibrium during training. BEGAN is especially helpful for high-quality image production, filling in damaged parts of images and cases where consistent GAN training matters. Even so, there are issues such as the small range of samples and the impact of adjusting the parameter γ which can modify how rapidly the models improve.

InfoGAN [20] produces generated data with clear and useful patterns of representation. The system includes a generator, a discriminator and an auxiliary network that predicts a latent code from what the generator has created. A structured latent code is fed into the generator to control the important changes in what is created. The discriminator separates genuine from fake data and the auxiliary network enhances the connection between the latent code and samples the generator produces. A combination of the GAN loss and mutual information regularization in the loss function helps the generator to include understandable features in its output. Researchers have successfully used InfoGAN for unsupervised learning of clearly separated features, for creating faces with custom attributes and for producing synthetic handwriting. Even so, it encounters problems such as having a hard time balancing the two types of losses, the risk of unstable training and sensitivity to how the latent code is arranged. InfoGANs alter what GANs do by connecting more common data across less information. They also support changing the output, making use of font tilt, thickness and illumination direction to affect the MNIST dataset.

Progressive Growing GAN (PROGAN) [2] uses multiple scales in its network and has proven to be more stable, have less variance and offer higher quality images than non-progressive GANs. It uses a few layers at once, has convergent first layers and only takes a short time to train. Yet, this method encounters the mode collapse problem which can make some training samples look exactly the same. As a result, it starts with basics and slowly adds details as the process goes on. Following this repeated process, the network is able to produce large, detailed images. ProGAN is designed to help improve stability and the quality of images created at high resolution. Both the generator and discriminator networks are trained gradually, beginning at low resolutions and advancing to high resolutions as more layers are added. The use of fading makes it easier to transition new layers at every step. ProGAN's advantages are that it produces images of very high quality, offers great smoothness in the training process and produces the fewest artifacts. Even so, it can be slower to use, more expensive in terms of resources and has only limited control over certain features of the images.

Table 1: Various GAN Models

S.No.	GAN MODELS	NETWORK ARCHITECTURE	LOSS FUNCTION	GAN APPLICATIONS
1.	DCGAN [19]	Convolution Network with constraint	representation hierarchy in D and G, from object to scenes.	Image Generation, Super Resolution Imaging, Image -Image Translation
2.	Cycle GAN [4]	Convolutional	Mix of adversarial loss, potentially identity loss and cycle-consistency loss.	style transfer, Unpaired image translation, domain adaptation.
3.	Conditional GAN [18]	Multilayer Perceptron	Minimize adversarial loss, provide realistic samples, and add task-specific conditioning objectives.	Image-Image Translation, Convolution Face Generation, Text - Image Generation
4.	WGAN [17]	Lipschitz continuity can be enforced using weight clipping or gradient penalties.	Using Wasserstein distance as the training aim leads to improved convergence properties.	Synthesis of higher-fidelity images
5.	PixtoPix [21]	PatchGAN discriminator, U-Net generators,	loss of pixel-wise similarity, directing paired image translation, Adversarial loss for realism	satellite images, colorization of grayscale photos

6.	SRGAN [22]	Deep residual network with perceptual and adversarial losses.	Reduce adversarial, perceptual, and content losses for realistic super-resolution images.	surveillance, medical imaging, artistic restoration and super resolution.
7.	Style GAN [3]	PG-GAN: style-based generator, mapping network, and stochastic variation.	Reduce perceptual loss, align feature statistics, and enforce disentangled latent space.	Synthesis of Photorealistic images, deepfake generations, artistical style transfer
8.	BEGAN [23]	encoder-decoder architecture, emphasizing balance in G and D training.	Use equilibrium to minimize generator and discriminator losses.	Synthesis of Facial expression, image-image translation
9.	InfoGAN [20]	Multilayered Perceptron	Maximum mutual information is used to generate a disentangled representation.	Disentangled representations, synthesis of facial expressions, artistical style transfer.
10.	PROGAN [2]	multi-resolution layers.	Adversarial Loss that is analogous to vanilla GANs	High-resolution image synthesis, realistic faces, progressive growing.

GAN variants differ depending on their goals and cGAN relies on labels to help with clearer separation and enhanced data production. InfoGAN works to maximize the relationship between labels and data generation. The authors use the Wasserstein distance to compute loss and avoid mode collapse. BEGAN relies on autoencoders for fair adversarial training, but DCGAN builds its architecture on deep CNNs to create top-quality images and videos. For global dependency, ProGAN gradually raises the depth of its drills to create more detailed images.

4. USE OF GAN IN BIOMETRICS

The application of GANs is altering biometric security by improving the accuracy of validating and recognizing human features. GANs are used in biometrics for image completion, image improvement, style transfer, random biometric sample generation, and image reconstruction using identification information (Refer Table 2.). The use of iris scans, fingerprinting, and facial recognition is critical in modern security. GANs used with biometrics may result in safer, more effective, and private systems. GANs are used to handle heterogeneous data, preserve privacy, and create reliable recognition models. It is easier for them to use dataset fragments to help build patterns that are difficult to create with models. Biometric traits use GANs to generate synthetic data, which is important for training and testing biometric recognition models. GANs may train models with less data by creating multiple combinations of biometric traits, allowing identification to operate effectively in a variety of contexts. They can copy biometric data in one modality using resources from another. Recently, some GANs and their modifications have been used in biometrics, for example, to generate fake handprints, fingerprints and irises. FingerGAN [26], PalmGAN [27] and IrisGAN [25], all have DCGAN as a base and FingerGAN and PalmGAN add total variation loss. Still, training these models takes a while and the outputs are not always clear. Shamsolmoali et al. [28] introduced G-GANISR which uses two generators to provide super-resolution data with improved quality. As a result, the system receives biometric data that is not very clear or well organized. A Conditional GAN is suitable for the synthesis of fingerprints with a given identity, through a little template and StyleGAN2, so that the identity is preserved and attributes are respected. GANs that have been improved can detect faces in any environment since they learn from one single photo. The method relies on a deep convolutional GAN to create irises from random data and it uses conditional GAN (pix2pix) for iris synthesis to boost the accuracy of recognizing the data.

FINGERPRINT

GANs help improve fingerprint recognition by making fingerprint images clearer, removing noisy parts, making ridges easier to see and better extracting important points. They are also applied in expanding fingerprint databases by making fake fingerprint pictures to improve the training data. A GAN model was suggested by DeepMasterPrint [33] for master fingerprint construction, but the images were not clear. Fahim and Jung [34] designed a new GAN Network, LGN-LSFG, that is lightweight and generates fingerprints at a large scale. To perform recognition, Takahashi et al. [36] resorted to applying CycleGAN to normalize the images. According to Pankaj Bamoriya et al., [38] generative networks from deep learning have greatly improved how synthetic biometric data is created, leading to fresh opportunities in training and developing biometric systems. According to Huang et al.,[35] they improved fingerprint images from crime scenes using

GAN, PatchGAN for identification and the NISTSD27 dataset for latent fingerprints. They used the same DC-GAN setup to make fingerprint images from the PolyU and FVC 2006 Fingerprint Databases. The fingerprint model, FDeblur-GAN [37], was accurate in matching deblurred and ground truth images.

IRIS

There are several ways researchers study false iris recognition, using 4DCycle-GAN, DCGAN, Super-resolution GAN. Kakani et al. [41] built a database of iris images using segmentation, identification and generative adversarial learning and Bhuiyan and Czajka [42] built a Conditional StyleGAN-based model for iris synthesis. Zou et al. produced fake iris images using 4DCycle-GAN [39], Minaee and Abdolrashidi made realistic images by using DCGAN [25], Kashihara [40] improved pictures using Super-resolution GAN.

FACE

GANs have found many uses in face recognition, like producing synthetic faces, making recognition possible in any pose and changing facial features. CycleGAN is designed for image-to-image translation when data does not match and Zhang et al. [29] talk about using Conditional Adversarial Autoencoders to change ages in face images. According to Choi et al., [24] StarGAN makes it possible to change facial features from one domain to another. Progressive Growing GANs for high-resolution images are introduced by Karras et al. [2], while Wu et al. [31] introduce a PP-GAN model to solve de-identification privacy concerns. Even so, GANs confront problems like showing a wide range of images, handling attacks and making their choices transparent for people without expertise. Many advanced GAN models, including BigGAN, PG-GAN, StyleGAN and StyleGAN, have been built to make face images that appear real and show a wide range of characteristics. GAN inversion tools are now being used to connect real faces to their AI versions, making the images look even better. StyleGANs offer mixture of styles and improved image quality and the Alias-Free GAN [32] works on solving texture sticking and improving both Pseudonym Free GAN and StyleGAN blending.

PALMPRINT

Palmprint recognition, a biometric technique based on unique patterns in palm skin, has become a reliable method due to its stability and uniqueness. The use of Generative Artificial Neural Networks (GANs) has increased its popularity due to their ability to generate realistic and varied synthetic data. Previous studies have used DCGANs [27] to create realistic palm images, using the PolyU Palmprint Database. Wang et al.'s method,[43] however, required a large number of images, making it time-consuming.

Table 2: Various GAN models applied on Biometric Traits

Biometric Feature	Model Used	Year
Face	Conditional Adversarial Autoencoder [29]	2017
Face	StarGAN [24]	2018
Face	PROGAN [2]	2018
Face	Privacy Protective GAN [31]	2019
Face	Alias-free GAN [32]	2021
Fingerprint	WGAN [33]	2018
Fingerprint	Lightweight GAN [34]	2020
Fingerprint	PatchGAN [35]	2020
Fingerprint	Cycle GAN [36]	2019
Fingerprint	CGAN+Stack GAN [37]	2021
Fingerprint	DSBGAN [38]	2022
Iris	4D Cycle GAN [39]	2018
Iris	IrisGAN [25]	2018
Iris	SRGAN [40]	2020
Iris	GAN [41]	2023
Iris	Conditional Style Gan [42]	2023
Palmprint	DCGAN [27]	2020
Palmprint	DCGAN [42]	2020

5. DISCUSSION

Biometric identification systems are safe and reliable, but they can be attacked through direct or indirect attacks. Certain methods, such as face, iris, fingerprint, palmprint, ECG, and voice recognition, are vulnerable to attacks. Artificial intelligence (AI) can produce deepfakes that can be easily fooled by human sight. Countermeasures have been proposed to guard against gathered or fraudulent data entering biometric recognition systems.

Multimodal biometric systems improve user authentication accuracy, security, and dependability by fusing several biometric features. Implementing multimodal biometric authentication systems requires careful consideration of the right combination of biometric modalities, determining the number of traits to use, utilizing a fusion framework, effective recognition algorithms, device accuracy and reliability, real-time application-specific systems, and data acquisition tools. User acceptability is also crucial for successful implementation. StyleGAN is a realistic image generator used for training facial recognition systems, generating high-quality facial images and improving various facial aspects. However, it faces mode collapse problems. CycleGAN is used for age-progressed photos and rejuvenated facial biometric data, converting facial traits across age groups to create comprehensive datasets. BigGAN is a large-scale high-fidelity picture synthesis tool that can improve biometric identification systems training. StarGAN is a multidomain model that can produce multimodal biometric data like fingerprints, iris patterns, and facial features simultaneously. PRO-GAN's progressive training method can produce high-resolution biometric pictures by building complexity from lesser resolutions. However, scaling up may present challenges due to GPU resource limitations. Overall, these tools offer various solutions for training biometric systems, but they all have their limitations and limitations.

6. CONCLUSION

The paper discusses the advancements in Generalized Autonomous Networks (GANs). GANs, operating on the minimax game concept, have significantly advanced image processing and extended their influence to biometrics. The paper emphasizes the importance of understanding GANs' strengths and weaknesses, addressing challenges like gradient disappearance and mode collapse. To optimize GANs for various applications, the paper suggests exploring new objective functions and enhancing traditional network structures. The research suggests the need for a Universal GAN that works with all biometric datasets and features, facilitating the creation of multi-modal systems and facilitating cross-modal integration. This GAN can optimize computational resources, protect privacy, enhance adversarial robustness, and streamline research and development. It can also enhance the security of synthetic biometric data by providing protection against potential manipulations. It is seen that not much work is done on palmprint synthesis and restoration, further investigation will focus on the use of GANs in palmprint recognition, its challenges, achievements, and potential directions for improving precision, resilience and restoration

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