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Survey De-identification Generative Adversarial Network Based

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Abstract

There are several uses for the Generative Adver- sarial Network (GAN) technology. Anonymity, personal privacy, and protections for officials, managers, and powerful people are important legal concerns. These significant advancements, including facial recognition, are led by GAN-based technologies. This paper compares several Generative Adversarial Network types used in the de-identification field, depending on state of the art, such as privacy protection Generative Adversarial Net- work (PPGAN), conditional identity anonymization Generative Adversarial Network (CIAGAN), and semantic aware Genera- tive Adversarial Network (SAGAN), among others, to high-end products presented by researchers through multiple databases, including Celeb Face Attributes (CelebA), among others, to obtain the most accurate expressions and characteristics of real face images. Researchers used a range of techniques and strategies to present their findings and compare them to previous findings to obtain the best responses for de-identification. The strengths and weaknesses of developing new faces depend on the additions made to each proposed structure and the exploitation of raw resources into the basic system, which is reliant on the network's structure. After discussing each technique and the relevant technique for assessing the output—such as Siamese for true/face verification and Learned Perceptual Image Patch Similarity (LPIPS)—they were grouped in a table with the other techniques to clarify the differences. This research has produced several insightful findings, such as increased interest in the subject of identity concealment and developments in GAN technology, which provoked scholarly discussion.

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1. Introduction

Computer vision tasks in artificial intelligence include read- ing texts and recognizing faces, sizes, and objects. Numerous regions have invested in this crucial field. Our research in this article focuses on the processes of identification, classification, recognition of faces and people, and knowing their identities and information. It also addresses the attempt to safeguard people's identities from this automatic recognition, which is the topic of our study. These interconnected and sequential ideas and needs led to many applications. To achieve these outcomes, a variety of smart devices, technologies, equipment, and technical techniques are used. One such technology is GAN, which has made significant strides in most areas of artificial intelligence, particularly computer vision. , as shown in Figure (1).

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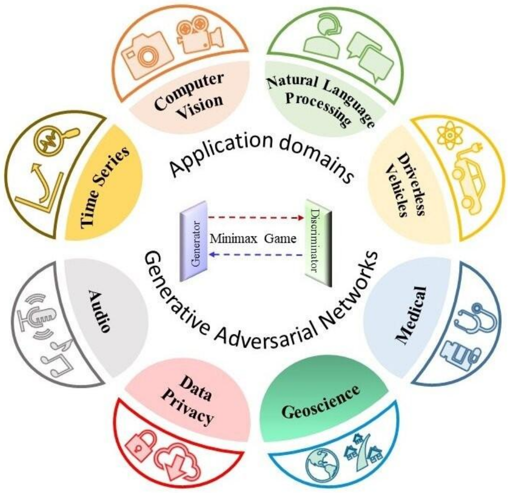

Figure 1. GANs applications levels [1]

GAN networks are considered one of the essential appli- cations that have entered many deep learning applications, especially in the field of computer vision, and provided results that convinced all researchers of their importance and accuracy compared to using previous traditional methods. There is a large number of smart electronic devices and technologies that contain cameras in the fields of multimedia, social networking sites, and others, as mentioned in [2] Automatic identification of individuals and their personal information is considered a violation of their rights, such as identification can expose important images for extortion and threats, such as heads of state, owners of companies, and others, as illustrated in [3], and [4]. Smart devices can identify people in photos, which has negative effects and positive effects in a few areas, such as [5]. Therefore, the issue of changing the facial features of persons captured in photographs is one of the important topics that fall within the field of computer vision [6]. Interventions to protect the personal rights of individuals, institutions, and important personalities with economic influence are by the General Data Protection Regulation (GDPR) that is in effect in Europe, which requires organizations to define policies based on user preferences as mentioned in [7]. All changes in facial expressions and attributes aim to develop privacy protections. Due to advancements in artificial intelligence, there are now many deep-learning techniques that deal with the issue of anonymization, as shown in [5], [8], [9] [10]. In this review, we will focus on literature that involves the process of anonymization or face de-identification using GAN techniques and its stages of technical development. This study aims to do several things, including:

1) highlighting how smart technologies may help protect individual privacy since this is a concern for cybersecurity

2) Highlighting the role of GAN networks, which have become of interest to researchers due to the impressive results they have found compared to other techniques.

This study focused on all types of GAN in the field of concealing personal identity and collected the data set with the methods used by all researchers to give a summary of ancient and modern studies in this important vital field.

2. Related Work

A. De-identification game

It is the process of changing facial features or hiding features and replacing them automatically or manually. Still, in this research, we will use advanced intelligent techniques to accomplish this change for the security goals mentioned in this paper. The face identity change game depends mainly on: First, face recognition methods designed on deep learning techniques as mentioned in [11]. To extract facial features and their borders, secondly, rely on facial generation techniques as illustrated in [9], and each method has advantages and disadvantages that we will discuss with what the researchers presented in this vital topic. We can define the process of identity change as that is the process of changing the identity of a character by manipulating facial features such as the eyes, nose, and chin, with the head remaining, And even wholly changing the features of the character, as mentioned in many of studies [5] [8] [9] [10], Each method to achieve these goals differs in a different technical way, which we will present in this study as shown in Fig.2.

Figure 2. Mix between two faces specifications [12]

B. Generative Adversarial Network GAN

GAN, also known as Generative Antagonistic Networks (GAN), is a technique that depends on a deep neural network (DNN). GAN consists of two DNN; the first one is called the Generator, which is used to generate fake images, and the second one is the Discriminator, which acts like a police officer to check between real and fake images as mentioned in [13] and [14] as illustrated in Fig.2. GAN has been active recently quickly and effectively because of its wide resonance and effective results, which were modified by [14] and entered many important vital fields and applications, especially in the field of

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computer vision, where it was of an initial version and then developed to modify it later to suit other applications In digital image processors as mention in [15] and [16] and in the field of Security, GAN technology has excelled in many aspects in its acceptance of many images [17] as well as the ability to produce images inspired by the input images, and the progress made in obtaining high image quality [16] approaching the truth by a very large percentage, and this is what It has been proven by the methods of standards and examinations approved by international research centers. Generative Adversarial Networks rely on the unsupervised artificial intelligence training techniques studied by [18] as shown in Fig.3.

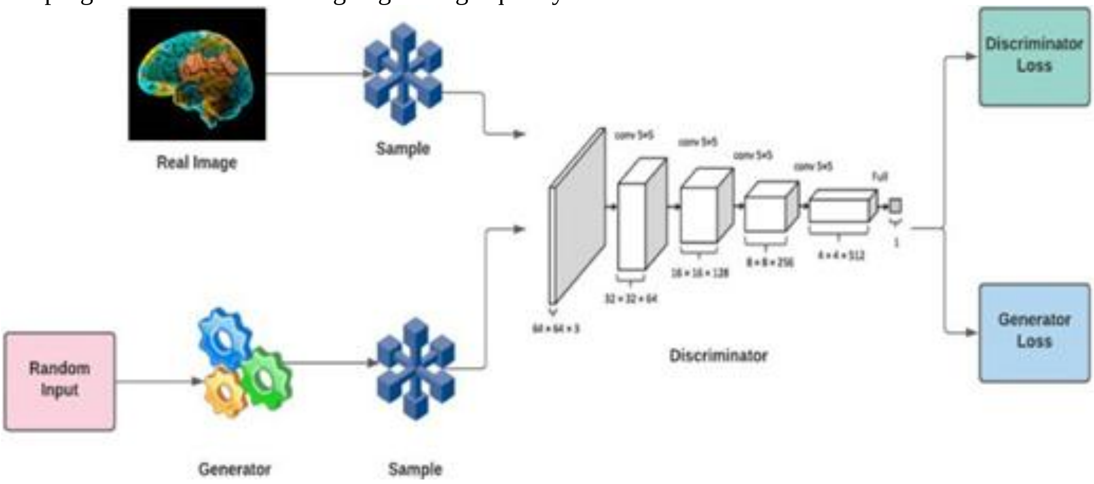

Figure 3. block diagram for GAN construction [19]

C. Mathematical description of GAN

To represent the GAN system with a mathematical equation, G is the Generative neural Network, and D is the discriminator Neural Network, Z is noise data, Y is the prediction data:

$P_x = P_X\,(log(1 - D(G(Z|Y))))$ (1)

(2) $[G][D]V\,(D, G) = [E_x] : [P_x]\,\log(1 - D(G(Z|Y)))$

3. De-Identification with Gan Technique

Many previous studies that dealt with the subject had been presented by researchers, such as anonymization, disguise,

Figure 4. Methods are used in De-identification [21]

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creating a new personality using a mask, blurring, pixelation, etc., as submitted in [20]. as shown in Figure (4) In this article, we will focus on research that dealt with changing facial identity based on GAN. We will discuss how these methods and techniques were developed, their impact on GAN in terms of technology, and the ability to absorb, shape, and overcome the defects present in the research of the predecessors.

4. Stages of Building Systems That Depend on Generative Adversarial Networks

The stages of face masking technology development are associated with the growth of the GAN network technology in terms of the volume of data entered, as well as the connections and additions that can improve the system designed to change identity. This will be addressed in this vital section of the study. A.

change Face Identity The studies that presented this type of face-based anonymization that uses generative adversarial networks, called Deep privacy, presented by [5], as in Figure 3 showed that it was interested in the process of personality protection and compared to the previously presented techniques, pre- sented by [22] [23] [24], which do not depend on deep learning techniques. This GAN architecture consists of a generator with a U-net architecture of 128 x 128. The model is trained with an incremental training technique as in [25] starting from a resolution of 8x8 and progressing to 128 x 128, which substantially improves the generated image quality and overall training time. While [6] present Privacy Preserving PPGANs based on the k-same framework, accept one input to generate a new face identity. While [11], the PriGAN model was presented to eliminate the blurring and distortion that occurred in the original face image generated due to the limitations of other methods While obtaining a change in the identity of the original image as shown in Figure 5.

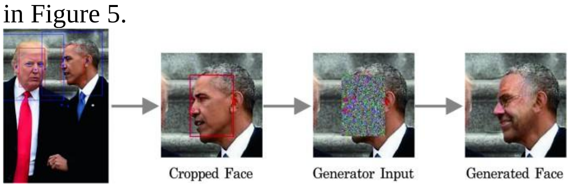

Figure 7. shown level De-identity process [21]

a new model using Facial Attribute Editing AttGAN, Star- GAN, and Selective Transfer Generative Adversarial Network STGAN, in which the ability to synthesize Facial expressions can be generated with real faces, but partial failure in de- identification can lead to the viewer recognizing the identity. While the Attribute-Aware Anonymization (A3GAN) model presented by [10] achieved excellent De-identification, it also generated a real face with a new facial expression.

5. Analysis and Discussion

Based on the studies discussed in this article, we will present a table (Table-1-) that contains data from the studies discussed in this article. There are several aspects to consider, including the method used, the volume of data that is dealt with, the type of data, and the method used to measure the percentage of identity change over the original identity as compared to the changed identity. On the other hand, by analyzing previous studies, it was shown that each method has capabilities that differ from the capabilities of the other method in terms of generating the real image, as well as in terms of the possibility of controlling facial expressions and methods of managing them, and on the other hand, complete concealment of the original identity in addition to complementary expressions of the face such as wearing glasses or a protective mask or headgear. These key features have been gathered in the table (Table-2-) and Evaluated By root mean square (RMS)to get the moment results for each method are submitted in state of the state- of-the-art study to distinguish the strengths and weaknesses for each method depending on the results are registered in (Table -1-).

6. Conclusion and Future Work

Through the study that we presented on the topic of Gener- ative Adversarial Networks, especially in the De-identification field, it became clear to us that this study gives us several things that we can summarize in the following paragraphs so that researchers in this field can benefit from them and how to develop the process in the future Generative Adversarial Networks is it suspended or continuous.

1) The competition does not stop in GAN to generate images in the future, but now the active and right choice is to make excellent De-identification by using the latest version from GAN.

2) All the methods have advantages and disadvantages from many viewpoints if the plans are perfect in the results, but the real-time response is the expensive time to achieve the mission examples. These obstacles push the researchers and developers to explore many methods and techniques to achieve de-identification in the best way, this challenges continuously also artificial intelligent market needs.

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Table I. This Table Illustrate Gan Techniques with Evaluation Methods and Data Sets

Author	GAN type		Evaluation Meth- ods	Data Sets
[Wu et al,.2019] [6]	Privacy protection GAN		-DE- identification Error Rate - SSIM [26]	MORPH dataset: Single input Male white and male Black
[He et al.,2019] [11]	PriGAN depends on Conditional GAN		- Classifier type C -Cloud Server R	-CIFAR-10 Olivetti Faces
[Hukklelas al.,2019] [5]	et	Deep privacy de- pends on Condi- tional GANs	-Flicker Diverse Faces FDF YFCC-100M data set [27]	-WIDER-Face data set [4]
[Fang et al.,2020] [1]	Triple-GAN		- Cross-Age Celebrity Dataset (CACD) [28] - MORPH [29] CALFW [30]	- MTCNN [31]
[Maximov al.,2020] [9]	et	Conditional Iden- tity Anonymiza- tion GAN	-HoG [32], and SSH [33] for de- tection - Siamese for true/face ver- ification [34]	-Celeb-A [35]us- ing Resize image to 178 X 218
[Li et al.,2021] [36]	Star GAN		- Learned Perceptual Image Patch Similarity (LPIPS) Distance [37] -FID Distance [38]	-Celeb-A [35] - VGG-Face2 [39]
[Kuang al.,2021] [12]	et	Conditional GAN	-Top-k De- identification VGG16	-CelebA [35] VggFace2 [39]
[Jeong al.,2021] [21]	et	Facial Identity Controllable GAN	-FFHQ [40] - CelebA-HQ [41]	-(FID) [38] ArcFacee [42]
[Zhai et al.,2022] [10]	Attribute-aware anonymization GAN		- FaceNet [43] and Curricular Face [44] - BRISQUE [45] and FID [38] -SSH [33] and DSFD [46]	-Celeb-A [35] -WIDER FACE [4] -ExpW [37] -THU-DDD [47]
[Kim et al.,2023] [48]	Semantic-aware GAN		-Dlib [49] and SSH [33] - FaceNet [43] and FID [38] - SSIM [26] and PSNR [50]	-Celeb-A [35] -FG-NET-AD [51] -CALFW [28] and LFW [52]

3) Extracting all the modern methods used by researchers that specialize in methods of concealing identity, ex- plaining all the algorithms they used to measure the quality of the results they obtained by indexing them in a table and making a comparison with all the methods used for the same purpose. 4)

This study shows innovative modern methods for pre- serving identity or self-protection, which are key for researchers who want to develop or invent a new method based on deep learning so that it is less complex and more effective and can be used and injected into modern smart systems.

Table 2. This table illustrates the strengths and weaknesses of de-identification construction for each method.

Author	GAN structure	Anonymity	Real Face generate	Controllability
[Wu et al,.2019] [6]	Privacy protection GAN	0.60	0.65	0.40
[He et al.,2019] [11]	PriGAN depends on Conditional GANs	0.70	0.42	0.40

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[Hukklelas et al.,2019] [5]	Conditional GANs	0.82	0.43	0.63
[Fang et al.,2020] [1]	TriPle GAN	0.46	0.64	0.62
[Maximov et al.,2020] [9]	Conditional Iden- tity Anonymiza- tion GAN	0.78	0.48	0.65
[Li et al.,2021] [36]	Star GAN	0.65	0.66	0.80
[Kuang et al.,2021] [12]	Conditional GAN	0.64	0.40	0.75
[Jeong et al,2021] [21]	Facial Identity Controllable GAN	A0.59	0.81	0.47
[Zhai et al.,2022] [10]	Attribute-aware anonymization GAN	0.86	0.82	0.79
[Kim et al.,2023] [48]	Semantic-aware GAN	0.92	0.94	0.90

4) After testing the GAN technology and what researchers presented in the field of personal security Digital device production companies can adopt these high-end tech- nologies Through the speed of the available processors, which has enabled many applications that were impossible to inject into a chip, it will be a leading product in the digital market because of its bright future compared to current traditional systems.

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