Revitalizing Cold Cases Inquiries Through Deep Convolutional Generative Adversarial Networks (DCGAN) for Human Face Synthesis: A Survey

Conference Paper · July 2025

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Revitalizing Cold Cases Inquiries Through Deep Convolutional Generative Adversarial Networks (DCGAN) for Human Face Synthesis: A Survey

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KEYWORD

Deep Convolutional Generative Adversarial Network (DCGAN), Deep Learning, Cold Cases Investigation, Machine Learning, Forensic Face Reconstruction.

ABSTRACT

With the major advances in computer vision techniques and Deep Learning, especially the deep convolutional generative adversarial network (DCGAN) that have provided a lot of means to solve many outstanding cases such as invigorate cold case investigations. Cold cases have an unresolved, prolonged character that poses a major challenge to many criminal or law enforcement agencies. The thesis presents a model for reactivating cold cases in forensic investigations based on generating updated and more realistic representations of the suspects human faces using deep neural networks. The main aim of the proposed model is to build a DCGAN-based model with a new architecture that is capable of generating human faces where only outdated sketches or descriptions of suspects are available. The search reviews the ability to recreate reasonable representations of potential suspects or missing persons. Ethical considerations and privacy implications are also explored regarding the use of facial images created in the context of criminal investigations. This thesis contributes to bridge the gap between artificial intelligence, forensic science and law enforcement, and offers a new perspective for resolving unresolved issues by providing new facial image generation technology and achieving justice for victims and their families.

1. Introduction

In the field of law enforcement agencies or criminal investigations, solving cold cases presents a unique set of challenges that often require innovative approaches and methods. Due to the nature of the reopening of unresolved cases or the lack of sufficient visual evidence, especially in cases involving the identification of suspected persons or involving missing persons or unidentified remains. Because of recent advances in science and computer vision or deep learning, there are some methods to resolve such issues. One of these methods that has gained considerable momentum in recent years is the completeness of the latest technologies, specifically the use of Deep Convolutional Generative Adversarial Network (DCGAN) to activate cold issues that have contributed to opening up new possibilities for investigators(Nekamiche et al., 2022). The convergence between deep learning techniques and forensic science has paved a new methodology that holds promise to uncover those outstanding issues that have passed years or even decades(Toolin et al., 2022). In this thesis, we will explore the use of DCGAN in cold case investigations and its potential impact on law enforcement agencies. Enter DCGAN, revolutionary progress in deep learning and image processing the essence of this thesis can be the capability of generating vibrant human faces, a capability that can be harnessed in breathing life and activating cold case investigations. DCGAN is a kind of deep learning algorithm that uses two neural networks, a generator, and discriminator, to generate realistic images. These institutions operate based on the principle of hostile training, whereby a network of generators and a discriminatory network carry out a continuous dance for improvement, the network of generators creates images similar to training data, while the network of distinctions evaluates the created images and provides feedback to the generator network. This process continues until the generator network produces indistinguishable images from training data. The generator seeks to create realistic faces, while the characteristic learns to distinguish between real and artificial images(Salehi et al., n.d.). This dynamic interaction generates images that closely mimic real human faces, an advantage that carries enormous potential in the context of forensic reconstruction. One of the key advantages of employing DCGANs in cold case investigations is the ability to recreate facial vehicles for potential suspects or unknown victims. By inputting descriptions, graphics, or any visual data available in the network, investigators can create realistic images of individuals who may have played a role in the unresolved crime. This not only aids in refreshing public memory but also provides law enforcement with tangible leads to pursue. Moreover, DCGANs can be instrumental in age progression, a crucial aspect when dealing with cases where a significant amount of time has elapsed. The ability to predict and generate images of how a person might appear years after the commission of a crime enables investigators to adapt their search strategies and appeals to the public. This dynamic feature of DCGANs adds a temporal dimension to cold case investigations, allowing law enforcement to transcend the constraints imposed by the passage of time. In conclusion, the integration of DCGANs in cold case investigations represents a paradigm shift in the way we approach unsolved crimes(R. C. (Robert C. Davis et al., n.d.). The power of artificial intelligence to recreate human faces with remarkable accuracy opens up new frontiers in forensic science. As we stand at the crossroads of technology and justice, the application of DCGANs offers a glimmer of hope for those seeking answers in the shadows of the past(Creswell et al., 2018).

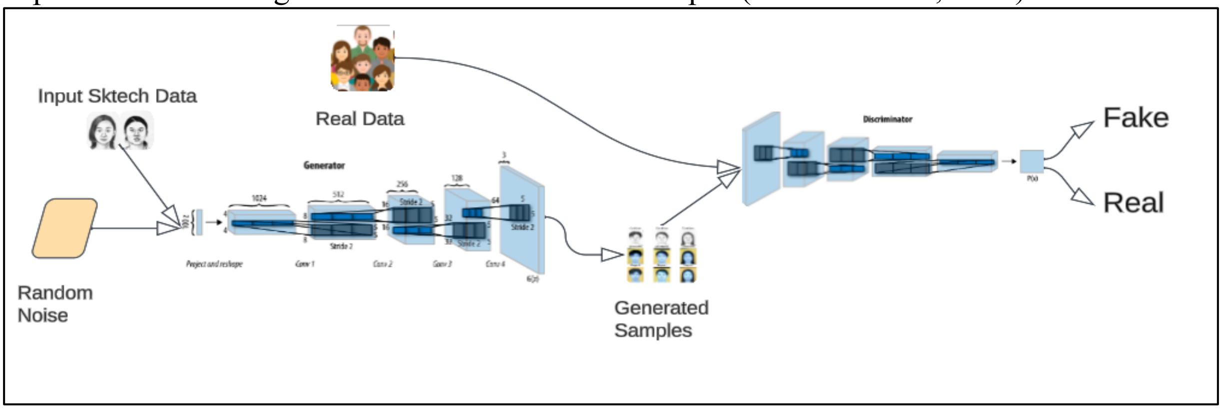

Figure 1. Generating Realistic Human face Image from Sketches Using DCGAN.

2. Cold Cases Investigation

Cold cases, which are unsolved over time, pose unique challenges for law enforcement agencies, including the gradual loss of resources and the psychological impact on victims' families. The use of fresh technologies and forensic techniques, such as DNA testing, facial recognition, and age progression, has the potential to shed light on these unresolved cases. Revisiting the crime scene, being persistent, leveraging forensic science and technology, recognizing relationship changes and the passage of time, and applying modern investigative methods are among the approaches used to solve cold cases. The integration of DCGAN in cold case investigations represents a paradigm shift, offering new frontiers in forensic science and providing hope for those seeking answers in unresolved cases. The convergence between deep learning techniques and forensic science has paved a new methodology that holds promise to uncover those outstanding issues that have passed years or even decades. Despite the challenges, advancements in forensic technologies and. science may provide a renewed path towards solving ancient mysteries and achieving justice for victims and their families(R. C. Davis et al., 2012).

2.1. Cold Cases Types

1. Homicides: Which is one of the most common cases where the killer does not leave or leave little resources or evidence behind.
2. Missing persons: It is another kind of cold case that causes a lot of pain or heartbreak to the missing people's families. Who may have little or no information about missing persons.
3. Sexual assault: It is one of the most difficult issues that organizations may face because it occurred in private or was not reported immediately upon occurrence.
4. Theft: One of the cold cases that is difficult because of the lack of evidence that the perpetrators may leave.
5. Financial crimes: cases involving complex financial transactions that are difficult to detect such as fraud or embezzlement.
6. Historical cases: refers to cases that have occurred over the past years or even centuries involving crimes that have been resolved but in which there is new evidence that must be re-investigated.

2.2. Technique used in Cold Cases

1. Forensic DNA analysis: One of the most essential procedures utilized in cold case investigations in which relevant institutions harvest DNA from crime scene materials and compare it to a database of offenders or missing individuals.
2. Face recognition technology: This technology compares photographs of suspected or missing people to existing databases in order to identify unknown people in images or videos.
3. Geographical profiling software: This application creates maps based on data obtained from crime sites and other sources to illustrate where culprits are likely to dwell or

operate. Cold case units can focus their search for suspects and boost the odds of resolving the case by analyzing these maps.

4. Social media networks: have proven quite important, and detectives can utilize them to contact witnesses who may have information about the case.

3. Generative Adversarial Networks (GAN)

A new type of artificial neural networks called GAN has been developed lately in 2014 by (Goodfellow et al., n.d.). The fundamental concept of GANs is the coexistence of two neural networks a discriminator and a generator that are simultaneously trained via adversarial training. The generators purpose is to produce artificial intelligence (AI) products that faithfully imitate actual data, including photographs. Using random noise as input, it produces samples that are distinct from actual data. In order to be successfully categorized, the discriminator must be able recognize differences between fake data produced by the generator and actual data. It is trained on both types of data. After receiving a vector of random noise, z, the generator (G) creates a sample, Xfake = G(z). Genuine data and samples generated by the generator are sent into the discriminator network D. It then generates a probability distribution that indicates the likelihood that the data came from the sources that it did. The idea of GAN training is summed up in equation (1). Differentiator D is taught to maximize the log-likelihood of assigning the right label, while generator (G) is trained to increase the chance that D will make a mistake(Iliyasu & Deng, 2020). It is well known that GANs are unstable and challenging to train. This frequently results in the generator producing unacceptable samples. As a result, the focus of numerous research studies was on enhancing training stability. One well-liked GAN design that yields innovative functionality is DCGAN(Radford et al., 2015). The unsupervised learning portion of the model we will study is the foundation of the deep convolutional generative adversarial network, or DCGAN. Its two constituent parts are generators and discriminators that must be trained against one another with the least amount of preparation. The generator consists of batch normalization layers, striped wrap layers, and LeakyRelu as the activation function. The feature includes batch normalization layers, striped wrap layers, and LeakyRelu as a method of activation. A picture of 3x64x64 can be utilized as an input. A 3x64x64 RGB picture will be the end product(Hariharan et al., 2022). By mapping samples from a random distribution into result matrices in a particular models form, the generator gains knowledge. Either an entry from a generator or a "real" sample of a dataset was used by the feature. Inputs are categorized as either real or generating by the discriminator. The feature employs an intersecting probability loss function for training, which is dependent on the quantity of inputs that are properly categorized as generators and as real.

Mathematical equations of GAN:

$$L = E\left[log\,P\ \left(Y = \frac{Real}{Xreal}\right)\right] + E\left[1 - log\,P\left(Y = \frac{Fake}{Xfake}\right)\right] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

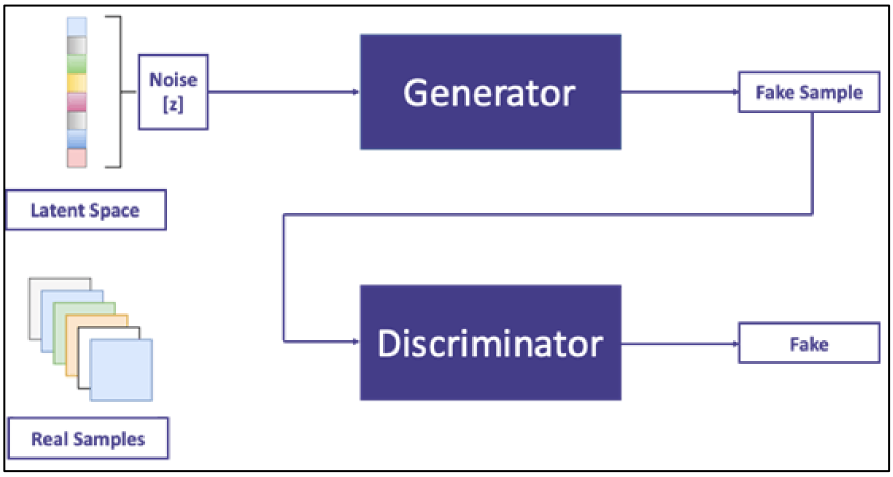

Figure 2. Overall GAN Architecture.

4. Deep Convolutional Generative Adversarial Network (DCGAN)

DCGAN is a model improvement for generating adversarial networks, which introduces the idea of convolutional operations into generative models for unsupervised training(Shao, 2023). DCGAN is another type of generative adversarial network architecture in which the discriminator and generator utilize convolutional and convolutional-transpose layers as showing in the figure 3, as well. DCGANs are particularly built for picture data and outperform ordinary GANs in this application. They are used to generate fresh pictures of personal digits or celebrities, for example. DCGANs offer various advantages over GANs, including improved picture quality, quicker training, and image data appropriateness. The issues that GAN encounters are resolved by DCGAN. One of the primary drawbacks of deep learning implementation is the scarcity of large data sets as a result of data set access limitations. Only when sufficient data sets are available to train the network model effectively can neural network performance be assessed. Deep Convolutional Generative Advertising network (DCGAN), an advanced deep learning technique, is used to create synthetic data with high resolution for an image that precisely resembles a genuine dataset in order to overcome this shortage of data. genuine data generation and accurate classification of genuine and false data are the tasks of the discriminator, whereas realistic fake data production is the generators responsibility. The discriminator in the network will be able to discern between authentic and fraudulent data thanks to its architecture, and the generator will attempt to generate identical data in an attempt to trick the discriminator(Walia & Kumar, 2019). The sigmoid, hyperbolic tangent, rectified linear unit (ReLU), leakyReLU, exponential linear units (ELU), and scaled exponential linear unit (SELU) are among the activation functions that are frequently employed in the generator model of a DCGAN. Batch normalization (BN) is frequently used to the discriminator and generator networks in DCGANs. In the discriminator and generator, a Batch Normalization (BN) layer is used after each layer, which can help solve training problems caused by poor initialization and accelerate model training speed, so as to improve training stability. By normalizing a layers input characteristics to have a zero mean and unit variance, BN aids in stabilizing the GANs training process. It was shown to be crucial for handling issues brought on by inadequate parameter initialization and preventing mode collapse. BN is usually added to every layer, with the exception of the input and output layers of the discriminator and generator. This normalizing method helps DCGAN training be more stable and successful, especially when it comes to producing varied and high-quality pictures.

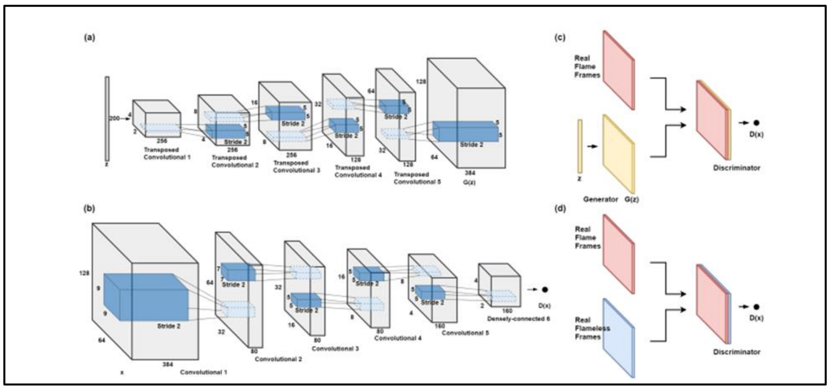

Figure 3. Overall DCGAN Architecture.

5. Forensic Image Reconstructing

forensic sciences these fields use scientific knowledge or methods to examine evidence from crime scenes and investigate crimes in order to speed up court cases. The field of research known as "digital forensic medicine" collects, evaluates, authenticates, and provides evidence that is derived from electronic resources in order to support or reconstruct units that have been found to have committed crimes. In addition to helping investigative organizations locate, review, and preserve crime-related documents for use as evidence in court, the primary goals of using computerized forensic evidence are to determine the purpose of the crime, when it was committed, and who the primary perpetrator is in each case. A branch of forensic medicine called "digital forensic medicine" deals with the authenticity and substance of photographs. This law enforcement, commonly referred to as criminal image analysis, assists in utilizing pertinent data to prosecute in a range of illegal circumstances, including cybercrime(Walia & Kumar, 2019). The technique of reconstructing someone face from the bones they left behind The field of forensic face reconstruction combines creative ability with knowledge of anatomy, anthropology, and osteology. or face approximation. In criminal situations involving unidentified remains, facial reconstruction offers investigators and family members a special alternative when all other identification methods have been exhausted. The inputs required to eventually positively identify remains are frequently provided via approximate facial representations.

6. Face Recognition

Face recognition is the process of identifying or verifying a person's identity based just on their face. It logs, examines, and contrasts patterns derived from an individual's facial characteristics(Syed Navaz et al., 2013). Two aspects of face recognition—identification and verification of faces are evaluated using metrics common to all face recognition systems.

A. The method of verifying someone's identification involves matching a given biometric to a predefined database template. The term "personal matching" describes this verification method.
B. Finding the identity of an individual through identification is the act of matching their live biometric samples to potentially many thousands of models that used to be kept in a systems database. A typical word used for describing this is one-to-many matching. The following stages are often followed by face recognition software:
   1. The face detection method is an essential step in locating and recognizing human faces in pictures and movies.
   2. The face analysis approach reads the geometry of the face. Important factors to take into account are the length of your cheekbones, the curve of your mouth, the size of the spaces between your eyes, the separation between your chin and forehead, the contour of your cheekbones, and the design of your ears. Finding facial traits that are necessary for face recognition is the goal.
   3. Based on a person's facial characteristics, the face capture technology transforms an analogue face into a collection of digital information or representations.
   4. Face matching establishes if two faces are those of the same person(Kortli et al., 2020).

Face recognition is the technique of comparing a given face picture to one in a face database. This is the second step in facial recognition; detection is the first step. Face recognition technologies have the potential to improve efficiency in security missions. Locate missing children and adults, recognize and track taken advantage of minors, track down offenders, and help and accelerate investigations(Almotiri, n.d.).

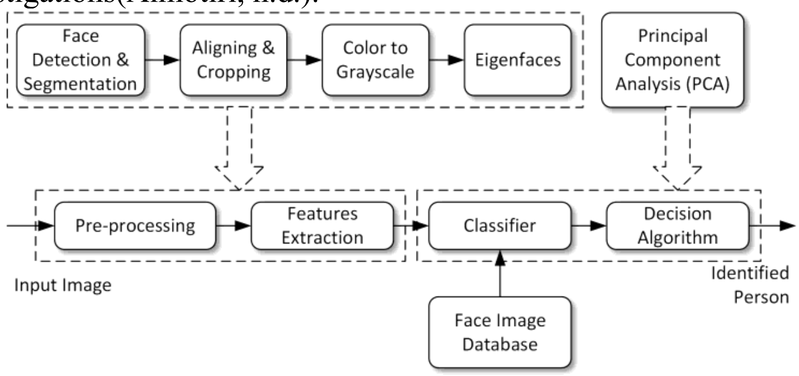

Figure 4. Face Recognition Architecture.

7. Image Extracting Features

It is a method of digitally transforming images, photos, or video frames and applying different processing to them. We refer to this procedure as picture processing. A photo is taken as the first step in the image processing process. Next comes image analysis and alterations, such as the extraction of features, which allows significant data to be handled without referring to the image utilizing the whole data image. Lastly, there is the final step, this enables for the generation of results according to image analysis. During the extraction process, the rich information contained in the images pixels is divided into a number of characteristics (expressed as statistical terms) which are difficult for people to identify, understands, or relate to. Those features extracted as a collection of vectors from the source images. The kind and longevity of characteristics that are easily available have a direct impact on how successful the categorization procedure is(Kumar et al., 2015). Among the positive attributes are: -

a) Powerful: The benefit performs well in a variety of settings, including ambient light, contrast, and lenses.
b) Feature: In order to differentiate across interest groups, the feature needs to be valuable.
c) Trustworthy: it validates the adaptable standards for comparable groups (items).
d) Independent: distinct within the given category and not beyond what is necessary in relation to other attributes.

In general terms, there are two categories of characteristics that may be retrieved from an image specific characteristics and global characteristics.

7.1. Local Features

Based on certain visible regions known as areas of interest that hold true under different conditions like lighting and viewpoint, a variety of aspects can be shown on the picture. Figure (2.10a) depicts the regional features. Local characteristics are frequently utilized for picture matching and item identification. Due to their employment of a detector to identify the positions of the key points and characterize the surrounding region, local features are effective against obstruction, size, compression, illumination, noise, and blurred. This kind of extract is carried out using a variety of approaches, including Local Binary Pattern (LBP), Strong Accelerated Features (SURF), and Fixed Feature Conversion for Scale (SIFT)(Hassaballah et al., 2016).

7.2. Global Features

When considering a particular element of the pixel picture, the picture is understood as a single vector with several dimensions of features that covers entire item. The values of the global feature vector quantify the many aspects of the picture, including color, texture, edges, form, textural chart, and outcomes (a specific description) that may be retrieved from the picture after filters have been applied(Wang et al., 2010). Global features can be used for classification, detection of patterns, and picture comparison. The general attributes shown in figure (2.10b). Although these features are less memory-intensive and speedier, they have difficulties with compression, size, and blockages.

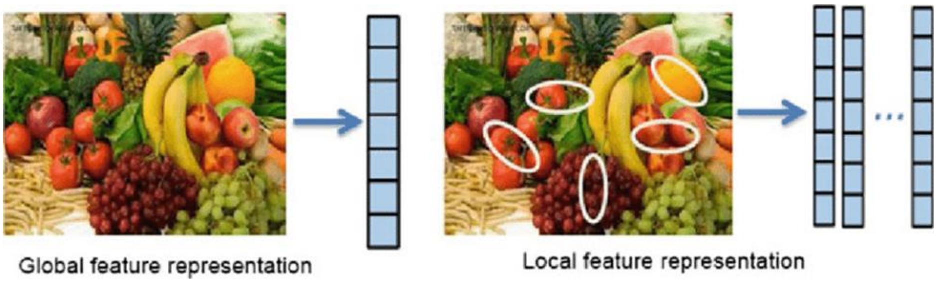

Figure 5. Image Features Representation.

The Extraction plays a pivotal role in unveiling crucial information with optimal visibility through intricate processes. The complexity of extracting significant data demands efficient approaches. The current image characteristics pave the way for categorizing extraction methods into two groups: traditional approaches, rooted in established practices, and learning methods, leveraging cutting-edge technologies for enhanced precision and adaptability. These diverse approaches collectively contribute to the comprehensive extraction of valuable insights from complex data sets, fostering advancements in various fields. This dynamic extraction landscape underscores the synergy between traditional methods' reliability and the innovation-driven adaptability of learning approaches, ensuring continual evolution in extracting insights across diverse and complex datasets.

8. Literature Survey

(Koç & Özyurt, 2023). suggested employing DCGAN, which consists of two boundaries networks that interfere with each other and where the network of generators applies the transposed layer of convolution when it attempts to generate the fake picture, as well as Batch Normalization, which uses simultaneously learning considering all of the layers on the network that are learning do not have to wait for their preceding layer to learn. This enables for faster training. ReLu and Tanh were also employed as activation functions by the researchers. The last layer is Sigmoid, which evaluates the real picture to the fake picture as a beginning class as well as in the middle of the picture. 10,000 mixed images, a combination of men's and women's photos, were taken from CelebA. The study's findings demonstrated that the phony image's clarity significantly changed as the amount of data increased.

(Liu et al., 2021). proposed a new hyperparameter value that may be employed in Adam's technique while performing data processing in DCGAN to get decent results when the number of epochs is limited. Furthermore, researchers employed 200,000 photos of famous people faces as a CelebA the data set, which was full of variety and diverse emotions. Researchers feel that extending the number of training times is neither necessary or significant since they have found a balance between the expense of time and the benefit of training after only four epochs. In addition to locating improved hyperparameters for the optimization technique. In order to avoid sequence collapsing and the gradual loss of the network gradients that the researchers will finally concentrate on the framework's effectiveness in training for a small amount of data and distribute it across various sorts of tasks.

(Jadli et al., 2020). used DCGAN to build a visual document classification model and produce images of scanned documents. CNN's use of documents is classified and the researchers' aim is to assess whether the fake images formed via the proposed model contain sufficient features and variations to effectively increase the training dataset. The researcher used concrete factual data such as bank cheques, receipts, handwritten invoices, electronic invoices, as well as photographs of those documents from different angles, certain lighting and others. The researcher came up with the production of counterfeit documents similar to the true documents well, and the researcher said that combining the two approaches brought the production accuracy of improving models to 89%. He also recommended that this approach be used in practice in the absence of labelled document classification data.

(S. Li, 2023). suggested comparing the optimal modernizing impact on the DCGAN model by employing DCGAN with three representative methods: smoothing the single label, the time scale update rule (TTUR), and the Earth engine distance (EMD). The Fashion MNIST dataset was used in each of the three methods in the researcher's article. The neural network was built with Tensorflow, and the researcher set the batch size to 100 to minimize runtime when experimenting with alternative tactics. In addition to employing Adam optimizers, the researcher reduced weight to force the value of a parameter to stay within a specific range. The study came to the conclusion that, although the first effect was more pronounced, both TTUR and unilateral smoothing of the label delayed the model's collapse. The researcher claims that if the data collection gets more complicated, the pictures produced can lose some of their detail when compared to samples from the data set. In order to enhance picture quality when adopting EMD, the researcher intends to employ spectral normalization or the gradient penalty in future work. Additionally, in order to increase the amount of empirical data available for analysis and comparison, more improvement methodologies and diverse data sets are required.

(Mandal et al., 2018). suggest employing semi-supervised GAN (SSGAN) to implement modifications to GAN's deep bypass networks to make them reliable and efficient for categorizing food images, as well as additional enhancements to the unsupervised training structure suggested by Goodfellow et al. (2014), when the researcher seeks to come up with an efficient, deep-learning-driven method for CNN to gain insight into food to alleviate these limitations using training data partially separated on generative adversarial net. The study utilized an ETH food-101 dataset as well as a images of Indian food. The researcher employed DCGAN and Adam Mohsen, as well as Leaky ReLu (in all hidden layers) and Sigmoid (in the particular output layer). The results from the experiments demonstrate that, even with fully disaggregated data, CNN's suggested semi-supervisory generator technique to this task consistently beats the most recent existing approaches for all rankings for each of the data sets. GANs are challenging to stabilize and converge during, even though they have the ability to increase food identification accuracy with partially disaggregated data.

(Z. Li & Wan, 2021). It is suggested to use the GAN and DCGAN networks to generate cartoons illustrations that represent anime pictures. In addition to PyTourh technology, the researchers employed the DCGAN network. ReLu was employed in the generator, and the LeakyReLu activator was used in the functionality across all layers. The dataset for the learning process consisted of 50,000 images, and the results were obtained through a series of experiments conducted in covenants ranging from 600 to 18,400 covenants, where the images displayed prominent animated characters. Researchers have made suggestions for future algorithm improvements.

(Yin et al., 2022). It is proposed to improve the deep convolution neural network (DCGAN) to address the problems of model instability and poor quality during the training process by adding patch normalization for both generator and discriminator. The researcher replaced the ReLU activation guest with SeLU to give the image more details as well as insert ResNet50 blocks to improve the accuracy of the images. More than 1,692 images of different people's faces were collected as a data set for the proposed algorithm test. The researcher compared the original DCGAN algorithm with the improved algorithm and provided results at the 98.9% accuracy and recall rate based on the confusion matrix, and because the improved network offers the most stable remaining network structure ResNet50 depth, the value of the generator loss is more stable and fluctuates in very few cases, and the value of the loss eventually stabilized at around 0.15. The researcher evaluated image performance by Sum of Modulus of Gray Difference (SMD), Frichet Inception Distance score (FID) and structural similarity (SSIM). In addition to future work, the researcher recommends applying these algorithms to the most challenging data enhancement scenarios to verify the generalization capability of the model from multiple perspectives.

Ammar et al(Ammar et al., 2022). It proposes a technique which combines image data generation methods and basic processors with a support vector machine, or SVM, for facial recognition, where the sapsupport is produced by a deep convolutional generative adversarial network (DCGAN) to produce samples with realistic characteristics which are indistinguishable from those found in the original datasets. SVM was employed above embedding for classification where researchers utilized FaceNet as a model for recognizing fachu. In addition to the LFW and VGG photo databases, as well as the Chokepoint video database. To solve the problem of uncommon picture data, the researcher used a mix of DCGAN and simple image editing. In order he made the decision to supplement the original facial data with synthetic images. The methodology consisted of four steps: (1) applying MTCNN to identify faces; (2) using the MTCNN output as input from DCGAN to produce synthetic images; (3) applying fundamental manipulation to DCGAN-created images; and (4) adding images to the original data. where the accuracy ratios on the LFW and VGGFace2 datasets were 94.5% and 92.2%, respectively, for the researcher. The study outlined how DCGANs may be enhanced to provide more realistic and diverse face samples, which could increase the accuracy of the findings. These adjustments could be made to factors like batch size, progress, and learning rate. To enhance the quality of the pictures produced, future research may employ Wasserstein loss with a graded penalty.

(Mairukh Khan Arnob et al., n.d.). The researcher proposes a system that uses descriptions of Bengali text to generate facial photographs. The model includes two primary parts: text encryption and a deep convolutional generative adversarial network (DCGAN). For this work, CelebA Bangla was utilized in addition to the CelebA dataset to create the suggested method. CelebA Bangla presents celebrity pictures together with the Bengali face traits that explain them. Over 200,000 128 × 128-pixel photos make up this collection. The researcher attained a score of 126,708 on the Frichet Inception Distance (FID), 12,361 on the Beginning Grade (IS), and 20.23 on the Indicative Facial Distance (FSD). This study's approach of integrating the additional material is better than earlier efforts. The thorough qualitative and quantitative study demonstrates how much better the system performs than other pilot systems. The study conducted a comparative analysis by assessing generated face pictures using five different performance metrics: FID, IS, LPIPS, FSS, and FSD. According to the study, out of all the models that were evaluated, the suggested model (DCGAN + Bangla FastText) performed the best, scoring 126.71, 12.361, and 20.23 for FID, IS, and FSD, respectively.

(C. Li et al., 2018). Using an improved deep convolutional generative adversarial network (DCGAN), it suggests a method for assembling a complicated texture-like image of any size. It then shows that it is possible to include another image inside the generator texture such that the variance between the two images is essentially undetectable to the human eye. The researcher's suggested network structure comes in two distinct designs that correspond to two distinct application scenarios. In order to construct the initial architecture, the secret image inclusion method and texture image production are separated. A deep convolutional generative adversarial network produces the texture-like picture, which is subsequently used as an input image by the concealment network to mask the image. The second approach combines the deep-diversion generating network and the concealing network. In this manner, one picture may be included into the process while the entire network creates a fabric image. The DTD dataset uses 4,135 resized training photos from the dataset in addition to a variety of texture image types. Even though SSIM is more practical and the training era of the generation network varies based on the texture pictures, the researcher trained the concealment network 230 times by lowering the average square error of pixels between the original image and the hidden image. The researcher has produced high-quality photos and proposes that more intricate and advanced network designs, such as those for the building and surviving network, may be used to better accomplish the feature extraction procedure. It is possible to generate more realistic-looking pictures and a lower detection rate by integrating the texture image generating process with the image embedding process.

No	Authors	Methodology	Datasets
1	(Koç & Özyurt, 2023)	Suggested employing DCGAN, which consists of two boundaries networks that interfere with each other.	CelebA dataset
2	(Liu et al., 2021)	Proposed a new hyperparameter value that may be employed in Adam's technique while performing data processing in DCGAN to get decent results when the number of epochs is limited.	CelebA dataset
3	(Jadli et al., 2020)	Used DCGAN to build a visual document classification model and produce images of scanned documents.	photographs documents from different angles

4	(S. Li, 2023)	Suggested comparing the optimal modernizing impact on the DCGAN model by employing DCGAN with three representative methods	LFW and VGG photo databases
5	(Mandal et al., 2018)	Suggest employing semi-supervised GAN (SSGAN) to implement modifications to GAN's deep bypass networks to make them reliable and efficient for categorizing food images.	ETH food-101 dataset
6	(Z. Li & Wan, 2021)	Suggested to use the GAN and DCGAN networks to generate cartoons illustrations that represent anime pictures.	50,000 images
7	(Yin et al., 2022)	Proposed to improve the deep convolution neural network (DCGAN) to address the problems of model instability and poor quality during the training process by adding patch normalization for both generator and discriminator	1,692 images of different people's faces.
8	(Ammar et al., 2022)	Proposes a technique which combines image data generation methods and basic processors with a support vector machine, or SVM, for facial recognition.	LFW and VGG photo datasets
9	(Mairukh Khan Arnob et al., n.d.)	Proposes a system that uses descriptions of Bengali text to generate facial photographs. The model includes two primary parts: text encryption and a deep convolutional generative adversarial network (DCGAN).	CelebA dataset
10	(C. Li et al., 2018)	It suggests a method for assembling a complicated texture-like image of any size. It then shows that it is possible to include another image inside the generator texture such that the variance between the two images is essentially undetectable to the human eye.	DTD dataset contain 4,135 resized training photos

9. Conclusions

Based on the survey, there are plenty of ways to recognize the human face through DCGAN. This is to produce industrial images that are more like realism than forensic sketches. These methods are compared to the models and methods available to analyze the performance of each model separately. There is a significant difference between these studies in terms of the accuracy of the productive images and performance. Not all these lessons can be mentioned in this paper because they are broad. In the future, more flexible GAN neural networks can be used in performance to increase the efficiency of images produced for human facial detection and recognition systems through images produced by DCGAN where they are realistic for images entered graphics. It is not possible to differentiate between original images and images produced due to the high precision created by DCGAN.

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