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DCGAN Beyond Generation: A Systematic Review of The Performance and Challenges of Forensic Face Models

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Abstract: Computer vision and deep learning techniques, especially deep convolutional generative adversarial networks (DCGAN), have enabled advanced mechanisms to address complex challenges in forensics, especially in reactivating cold case investigations. Cold cases present unresolved challenges due to deteriorating or scarce visual evidence. This paper provides a systematic review that analyzes, classifies, and evaluates the current status of DCGAN and related GAN structures in legitimate face modeling. The primary objectives are to evaluate reported methodologies, performance metrics, and limitations across key applications, including sketch-to-image conversion. The review identifies significant methodological gaps, particularly the absence of standardized assessment measures and the critical challenge of identity preservation. Furthermore, the research explores the ethical and legal considerations associated with computer-generated facial images, focusing on algorithmic bias, accountability, and legal admissibility in criminal investigations. The paper concludes by highlighting key research gaps and suggesting future directions and on DCGAN's role not only as a generative tool, but as a forensic decision support system designed to provide investigative leads by compiling visual evidence, while maintaining the primacy of human judicial expertise.

Keywords: Deep Learning, Generative Models, Face Image Reconstruction, Feature Extraction.

1. Introduction

In the context of law enforcement agencies and criminal investigations, resolving cold cases represents a unique challenge that requires innovative approaches, especially due to the scarcity of sufficient visual evidence in cases that require the identification of suspects or those involving missing persons and unknown remains. With recent advances in computer vision and deep learning, new methodologies have emerged to address these challenges. Among these methodologies, the use of advanced techniques such as deep convolutional generative adversarial networks (DCGAN) which gained significant momentum in recent years, contributing to the activation of cold cases and opening new horizons for investigators[1]. Although DCGAN has an exceptional ability to generate realistic visual representations of human faces[2]. Its application in the forensic field faces a critical research gap that requires stringent standards that go beyond mere "pictorial realism" to "biometric accuracy and identity preservation". This gap is concentrated in three main aspects: (1) Domain Gap:

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The large discrepancy between ideal datasets used in training and criminal reality characterized by distorted, low-resolution data, (2) Deficiencies of evaluation metrics: Current studies rely on metrics such as (FID) and (IS) that measure the statistical quality of an image but fail to ensure the structural accuracy of the features necessary for legal recognition. (3) Nature of the tool: The need to establish DCGAN's role as an "investigative decision support tool" aimed at assisting human experts and not replacing legal discretion or criminal expertise. Therefore, this review aims to bridge this gap by providing a comparative critical analysis of the performance, challenges, and future directions of DCGAN technology in generating legitimate facial models. This paper follows a systematic review methodology to achieve the following objectives:

a) Analysis of architectural and training developments in DCGAN relevant to the criminal context.
b) Evaluate the relative performance of DCGAN versus alternative generative GAN models.
c) Identify the key technical, practical, and ethical challenges facing the application.
d) Develop practical recommendations and suggest clear future research directions.

2. Systematic Review Methodology

This paper employs a systematic review methodology, strictly adhering to PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) standards to ensure transparency and repeatability. The study aims to investigate and evaluate the effectiveness of deep generative competitive networking (DCGAN) techniques in facial reconstruction for criminal purposes. The research was conducted in the scientific literature for the period from January 2014 to December 2023, encompassing five primary scientific databases: IEEE Xplore, ScienceDirect, SpringerLink, ACM Digital Library, and Google Scholar.

Search strategy and selection criteria: A logical search string (Boolean search) was used that included the following keywords: ("DCGAN" or "Deep Convolutional GAN"), ("forensic", "cold case", "crime investigation"), and ("face generation", "face reconstruction", or "sketch-to-photo").

- Inclusion Criteria: Studies focusing on applications of DCGAN or GANs in face generation or reconstruction, with explicit or implicit reference to forensic or cold case applications.
- Exclusion Criteria: Purely theoretical studies on GANs without applications not related to computer vision or faces, studies without measurable quantitative or qualitative results.

The initial research resulted in a total of 87 studies. After applying inclusion and exclusion criteria and examining the abstracts, 32 directly relevant studies were selected for full review and analysis. Analysis framework: The selected studies were analyzed through three main axes:

- • Technical: Focuses on architecture, training mechanisms, and performance evaluation metrics such as FID and accuracy.
- • Applied: Focuses on the type of data set used, applied context (e.g., facial recognition, data augmentation), and practical results.
- • Critical: Focuses on the aforementioned challenges, limitations, and ethical considerations.

The results are documented in comparison tables to ensure transparency and traceability.

3. Cold Case Investigation: Traditional Challenges and Strategies

Investigations into cold cases are particularly constrained by the scarcity and deterioration of visual evidence. As a result, image-based forensic techniques, especially facial reconstruction, play a crucial role in generating investigative leads when traditional biometric evidence is not available[3]. The systematic convergence of deep learning techniques and forensic science has paved the way for a new methodology that promises to uncover outstanding issues that are years or even decades old. Despite ongoing challenges, rapid advances in forensic technologies and computational science provide a renewed path to solving ancient mysteries and achieving justice for victims and their families[4].

3.1. Cold Case Types and Forensic Techniques

Cold case investigations involve unsolved criminal cases and are characterized by limited, deteriorating, or outdated evidence, requiring the integration of multiple forensic methods. These cases typically include unsolved murders and missing persons investigations, where the absence of reliable biometric or physical evidence greatly complicates the identification process. Additional categories include sexual crimes and complex theft cases, which are often affected by late reporting or insufficient traceable information. Financial crimes and corruption-related crimes represent another category of cold cases, characterized by complex, long-term transaction records that require specialized forensic and analytical expertise. Furthermore, cases of historical significance can be reopened when advances in forensic science or analytical techniques allow for a re-evaluation of previously examined evidence. To address these challenges, law enforcement agencies use a combination of traditional and advanced investigative techniques. Forensic DNA analysis remains an essential tool for identifying a victim or suspect through biological evidence and reference databases. Facial recognition and image-based analysis are increasingly used to support the identification of unknown individuals from photographs or video footage, especially when conventional evidence is not available. Genotyping helps investigators analyze spatial crime patterns to prioritize suspected locations, while social media and digital content analysis provide complementary ways to identify witnesses, reconstruct timelines, and uncover unconventional forms of evidence. Together, these technologies form a multidisciplinary framework essential for revitalizing cold case investigations.

4. Generative Adversarial Network (GAN, DCGAN)

This section focuses on the architectural and training aspects of the GAN and DCGAN models that directly impact their applicability in forensics. In criminal investigations, especially cold case scenarios, issues such as training stability, identity preservation, robustness to degraded inputs, and resistance to situation collapse are far more important than mere visual realism. Therefore, only DCGAN components that affect forensic reliability and investigative validity are emphasized in the following discussion.

4.1. Generative Adversarial Network GAN

The generative Adversarial Network GAN is one of the designs of generative competitive networks GANs that has gained great popularity thanks to its innovative functions, and was developed by[5]. This model forms the basis of the unsupervised learning Unsupervised Learning model to be studied.

The DCGAN architecture consists of two main components: the generator G and the discriminator D, which are trained adversarially with minimal pretreatment as shown in Figure 1.

A. Generator (G)

The generator architecture consists of several successive layers, intended to convert a random noise vector into a realistic image. These layers include:

- Strided Deconvolutional Layers: Used to expand the spatial dimensions of data.
- Batch Normalization Layers: Applied to ensure the stability of the training process.
- Leaky ReLU Activation Function: Used as an activation function in most layers.

The generator gains knowledge by assigning samples from a random distribution to result matrices that form specific image models. The final product can be an RGB image with dimensions of 3x64x64[6].

B. Discriminator (D)

The discriminator acts as a binary classification network, and its architecture includes:

- Strided Convolutional Layers: used to reduce the spatial dimensions of data.
- Batch normalization layers.
- Leaky ReLU Activation Function: Used as an activation method, it is necessary to avoid the gradient dispersion problem, Gradient Vanishing.

The discriminator is provided with two inputs: either a generated sample from the G grid or a "real" sample from the original dataset, such as a 3x64x64 image. Its goal is to classify inputs as either real or generated correctly. The discriminator uses a cross-probability loss function, the Binary Cross-Entropy Loss Function, for training, which depends on the amount of input being correctly classified[7,8].

$$\min G \ \max D \ V(D, G) = E_{x \sim p_{data}(x)}[\log D \ (x)] + E_{z \sim p_z(z)}\left[\log\left(1 - D\big(G(z)\big)\right)\right] \quad (1)$$

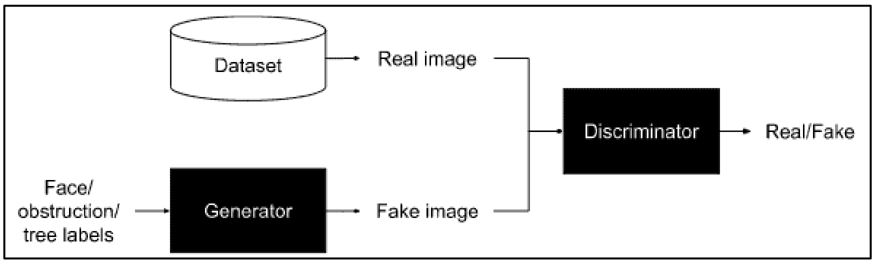

Figure 1. Basic structure of a generative adversarial network (GAN). The generator converts a random noise vector into an image, while the discriminator attempts to distinguish between the generated images and the real image. Both networks are improved through feedback.

4.2. Deep Convolutional Generative Adversarial Network DCGAN

The Deep Convolutional Generative Adversarial Network DCGAN is a fundamental improvement over traditional GANs, introducing the concept of convolutional processes into generative models of unsupervised learning training[9]. DCGAN is a specialized network architecture based on integrating convolutional layers and convolutional transfer layers into both the generator and discriminator. DCGANs are specifically designed to work with image data, giving them a clear superiority over regular GANs in this application. These networks are effectively used to create new images of personal characters or celebrities, for example. DCGAN offers significant advantages over GANs, including: improved quality of generated images, faster training, and optimal image data fit. DCGAN successfully addresses the problems faced by GANs; one of the fundamental drawbacks of deep learning applications is the scarcity of large datasets due to access constraints. Neural network performance can only be evaluated when sufficient data sets are available to effectively train the network model. DCGAN, as an advanced deep learning technique, is used to generate high-resolution synthetic data of an image that accurately resembles a real dataset to overcome the data shortage[10, 11]. In the DCGAN framework, generating real data and accurately classifying real and fake data are the tasks of the discriminator, while producing realistic fake data is the responsibility of the generator. The network discriminator will be able to distinguish between original and fraudulent data thanks to its architecture, and the generator will attempt to generate identical data in an attempt to deceive the discriminator. The architecture of DCGAN networks relies on the integration of a set of modern activation functions and the use of batch normalization to ensure the stability and effectiveness of the training process, as shown in Figure 2. A variety of activation functions are used in the layers of the generator model G to provide the necessary nonlinearity, most notably: the x-unit Sigmoid, the hyperbolic shadow Tanh, the corrected linear unit ReLU, the leaky corrected linear unit Leaky ReLU, the exponential linear units ELU, and the measured exponential linear unit SELU. Batch normalization[12] is used extensively in both generator and discriminator networks in DCGANs. A BN layer is applied after each convolutional layer except for the input and output layers in both networks, which helps solve training problems caused by poor parameter initialization and increases the speed of model convergence. In forensic contexts, architectural improvements such as batch normalization and stable activation functions are not just optimization techniques, but safeguards against misleading outputs. Instability in generative models may lead to repetitive or distorted facial hypotheses, which may negatively impact investigative thinking. Therefore, architectural simplicity and training robustness remain key advantages of DCGAN when deployed as an essential tool to support forensic decisions, especially in environments with limited computational resources.

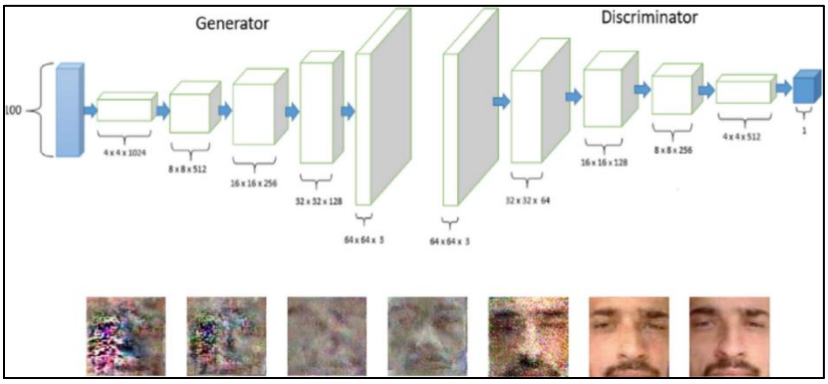

Figure 2. Architecture of DCGAN. Generator structure: Sequences of convolutional decomposition layers to convert noise into an image.

5. Forensic Image Reconstruction

Forensic image reconstruction is fundamentally different from traditional image reconstruction tasks in computer vision. Unlike applications aimed at improving vision or aesthetic realism, forensic reconstruction prioritizes the preservation of identity-related features under conditions of incomplete, degraded, or biased evidence. Errors introduced during reconstruction may lead to widespread investigative bias or lead to misleading hypotheses, underscoring the need for controlled and interpretable reconstruction methodologies. Therefore, forensic image reconstruction must balance visual plausibility, biometric consistency, and the reliability of evidence[13]. This specialization aims to support or rebuild units that have been proven to have committed certain crimes. The primary goals of using computer forensics are to determine the purpose of the crime, when it was committed, and to identify the main perpetrator in each case. In addition, this specialty helps investigative institutions identify, review, and preserve crime-related documents for use as evidence in court[14]. A specialized branch within digital forensics known as forensic image analysis deals with the authenticity and substance of photographs and visual evidence. This app helps law enforcement use relevant data for prosecution in a range of illegal circumstances, including cybercrime. Forensic facial reconstruction is a field that combines creative ability with deep knowledge of anatomy, anthropology, and osteology. This technique is crucial for reconstructing a person's face from the skeletal remains they left behind. In criminal cases involving unidentified remains, facial approximation provides investigators and family members with a special alternative when all other identification methods have been exhausted. Approximate facial representations often provide the input required to identify remains positively[15].

6. Image Extraction Features

Image processing is defined as a method of digitally converting images, photographs, or video frames and applying various processors to them[16]. In forensic applications, feature extraction plays a very different role than traditional recognition or classification tasks. Rather than improving discriminatory performance alone, forensic feature extraction should preserve legally interpretable and relevant biometric features under adverse conditions such as aging, occlusion, stress effects, and variation across domains. Features that work well in controlled datasets may fail when applied to real-world forensic evidence, highlighting the importance of robustness and contextual validity. Figure 3 shows Feature Extraction. The type and longevity of available properties have a direct impact on how successful subsequent classification procedures are[17]. To ensure the success of the classification process, the extracted features must have the following positive qualities:

- **Power Robustness:** The feature works well in a variety of settings, including changes in ambient light and contrast.
- **Discriminability:** A feature is valuable for distinguishing between different interest groups.
- **Reliability:** Validates adaptive criteria for similar groups.
- **Independence:** The advantage is distinct within the specified category and does not exceed what is necessary in relation to other qualities.

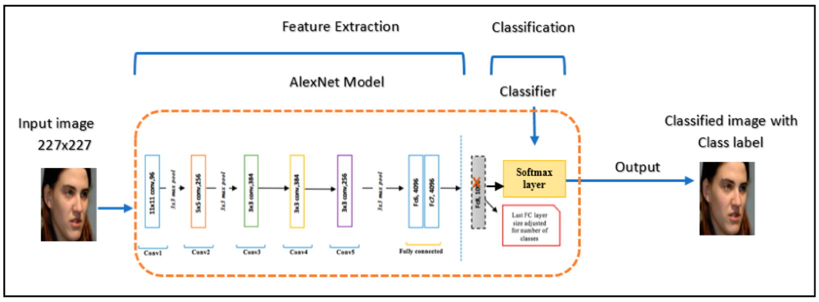

Figure 3. Features Extraction Process Overview.

6.1. Local features

Regional features Local Features are defined as a set of properties derived from certain visible areas known as "areas of interest". Regions of Interest - ROIs in an image[18]. These features adapt to different imaging conditions, such as changes in illumination, point of view, and measurement Scale, allowing a variety of visual aspects to be represented in the image. Regional features are frequently used in critical applications such as image matching and item identification Object Recognition. Its effectiveness is due to its reliance on a detector to determine the positions of key points and then characterize the surrounding area[19]. Local features are robust against a wide range of distortions and obstacles, including:

- Partial obstructions, Occlusions.
- Changes in volume and measurement Scale.
- Pressure-induced deformations: Compression.
- Changes in lighting and noise.

Extracting this type of feature is performed using a variety of advanced algorithms, including:

- Local Binary Pattern LBP: An effective way to describe the texture of an image.
- Powerful Accelerated Features Speeded Up Robust Features - SURF.
- Scale-Invariant Feature Transform SIFT.

These methods enable the extraction of static properties independent of changes, enhancing the accuracy of computational applications.

6.2. Global features

Global features are a way of representing an image in which the image is understood as a single vector with multiple dimensions, covering the entire element, the image as a whole, as opposed to regional features that focus on specific parts[20]. Global feature vector values define multiple overall aspects of an image, which can be extracted after applying different filters. These aspects include:

- Color and Texture
- Edges and Shape
- Structural Layout
- Descriptive results Specific Descriptions

Global features are mainly used in classification, pattern detection, and image comparison applications. Although universal features are less memory-intensive and offer faster processing, they face significant challenges when applied in real-world scenarios, especially when:

- Blockages Occlusions: Blockage of part of the image affects the representation of the entire vector.
- Size Changes Scale Variations: Difficulty handling images of variable sizes.

- Compression-induced abnormalities, Compression Artifacts, are more likely to be affected by these changes.

Feature extraction plays a pivotal role in the process of revealing important information and achieving optimal visibility through complex data processing; The complexity of intrinsic data extraction requires the development of effective and appropriate methods, as feature extraction methods are classified, based on the characteristics of the current image and the nature of the processing, into two main groups: Traditional methods are rooted in established statistical and mathematical practices and rely on hand-designed algorithms to extract specific properties such as edges, and machine and deep learning methods that leverage cutting-edge technologies, intense neural networks, to extract hierarchical representations of features from data automatically. These methods enhance accuracy and adaptability to diverse and complex data sets. Collectively, these disparate approaches contribute to the comprehensive extraction of valuable ideas and valuable Insights from datasets, supporting progress in various fields, and this dynamic landscape emphasizes the synergy between the reliability of traditional approaches and the adaptability based on innovation in learning styles, ensuring continuous development in extracting information across diverse and complex datasets.[21], [22].

7. Discussion: Performance and Application Analysis: A Critical Literature Review

In this section, we review a critical analysis of the selected studies, focusing on the techniques used, data sets, results, and challenges. Table 1 summarizes the main findings.

Table 1. Survey of experiments and results in related DCGAN applications.

Author	Method	Dataset	Results	Critical Evaluation
Koc et al	Use DCGAN to generate industrial samples of scanned document images.	CelebA	The clarity of the generated images changes dramatically with increasing data size.	Strength: Study the effect of data size. Challenge: Not using standardized quantitative measures such as FID for evaluation.
Liu et al	Modify the value of super transactions (Hyperparameter) for the Adam Optimizer.	CelebA (200,000 images)	Balance the cost of time with the benefit of training after only four periods of Epochs.	Strength: Improve training efficiency. Challenge: May not apply to smaller or more complex datasets such as forensic scenes.
Yin et al	Add Patch Normalization, replace ReLU with SeLU, and integrate ResNet50 blocks into the architecture.	Private dataset	Increase classification accuracy to98.9% and stabilize the generator loss value at 0.15.	Strength: Noticeable improvement in stability and quality. Challenge: Increase the computational complexity of the architecture.
Jadil et al	Use DCGAN to generate industrial samples of scanned document images.	A collection of scanned documents	Increase the accuracy of aggregate classification to 89% in document classification.	Strength: Practical application of data augmentation in a different field. Challenge: Limited transfer to the field of forensic faces.
Ammar et al	Integrate DCGAN to generate realistic samples with SVM for classification.	LFW, VGGface2	Achieve accuracy rates of up to 94.5% in facial recognition.	Strength: An effective combination of generation and classification.

				Challenge: Performance on "non-perfect" data (such as old graphics or images) is uncertain.
Mandal et al	It is proposed to use SSGAN as an add-on to the DCGAN architecture.	ETH Food-101	Consistently outperforms existing methods in food image classification.	Strength: Effective with partially labeled data. Challenge: Additional complexity in training.
S. Li	Investigate the impact of three optimization methods (Single Label Homogeneity, TTUR, EMD).	Fashion MNIST	Conclusion that TTUR and Unilateral Smoothing delay Model Collapse.	Strength: A comparative analysis of training stability techniques. Challenge: Apply to simple data (black and white, non-faces).
Arnob et al	Combine DCGAN with Bengali text encoding (Bangla FastText) to generate face images from a text description.	Bengali text description set	Best performance on FID (126.71) and IS (12.361) scale for generating facial images from text.	Strength: Processing for a specific language. Challenge: A relatively high FID value indicates room for improvement in realism.
Wan et al	Use DCGAN to create animations (Cartoon Illustrations) and anime images.	50,000 Images	Demonstrate the network's ability to learn complex visual patterns.	Strength: Demonstrate DCGAN flexibility. Challenge: Stay away from real and criminal applications.
Li et al	Improved DCGAN for Texture-like Image Clustering in Steganography.	DTD Dataset	The ability to embed a secret image within the fabric of the generator without the contrast being detectable by humans.	Strength: An innovative application in steganography. Challenge: The generated images may not be directly suitable as realistic faces, but they show texture control.

7.1. Analysis of Directions and Developments in DCGAN Methodologies

1. **Stability and acceleration:** Early studies, such as Liu et al, focused. [23]On improving training efficiency by modifying optimization coefficients, while later studies, such as Yin et al. [24] and S. Li [25] directly challenge stability using techniques such as Batch Normalization and multi-time scale update rules (TTUR). This demonstrates the shift from focusing on speed to focusing on stability and reliability, which is critical for forensic applications that require consistent results.
2. **Specialization and adaptation:** Research has shifted from using DCGAN as a general architecture, as in Koç et al. [26] To adapt it to specific tasks. We see this in the integration of ResNet blocks in Yin et al. [24]. To improve classification, use SSGAN in Mandal et al. [27]. To deal with data with partial labels, and to incorporate linguistic coding into Arnob et al. [28]. This suggests that DCGAN's future in the criminal field may lie in the development of hybrid and conditional models that accept qualitative inputs to the investigation (such as verbal descriptions).
3. **Quality assessment:** There has been a significant evolution in assessment scales, from relying on visual assessment or simple accuracy to adopting more complex standard scales such as the feature distance scale (FID) and the variance scale (IS), as in Arnob et al. [28]. This development is necessary for objective comparison between models and acceptance of their results in a rigorous scientific and legal context.

7.2. Evaluating The Suitability of Studies for Forensic Application

While all studies in Table 1 demonstrate the technical capabilities of DCGAN, its direct value for forensic applications varies:

1. **Highly directly relevant studies:** Considered the study of Ammar et al. [10] It is highly relevant because it combines face generation with the task of recognizing faces, which is the heart of the criminal scenario. S. Li [25] Study is important because it addresses training stability, which is a prerequisite for any practical model.
2. **Indirectly relevant studies:** Li et al[29] study in steganography, an advanced ability to control the properties of the generated image texture is demonstrated. This paves the way for research that allows the investigator to control specific facial features, such as scars, beards, and glasses, in the forensic model. Jadli et al[30] study DCGAN proves effective in increasing data for classification tasks even with imperfect data (scanned documents), which is similar to the input quality challenge in cold cases.
3. **Obvious gap:** A clear absence of studies that use real facial datasets from forensic or police environments, or that test models on the task of converting from a police drawing (forensic sketch) to a photograph. Most models are tested on celebrity faces or public images (CelebA, LFW), which limits the ability to extrapolate their performance in the real field.

7.3. Comparing DCGAN Performance with Alternative GAN Models

Recent years have seen the emergence of newer GAN models that outperform DCGAN in certain aspects, calling for a critical comparison:

- StyleGAN/StyleGAN2 [31]: Significantly outperforms in high-resolution image quality and precise control of stereotypical traits such as age, expression, and hairstyle. It is the perfect choice when hyperrealism is needed. Limitations: Higher training complexity, greater computational requirements.
- CycleGAN [32]: Excellent at translating a pattern between two fields (such as converting a sketch to an image). It can be a valuable complement to DCGAN in a pipeline that first processes drawing and then improves realism.

While newer models excel in quality and control, DCGAN remains a balanced and robust choice in terms of relative simplicity, training speed, and computational efficiency. This makes it particularly suitable for:

a) Forensic laboratories with limited resources.

b) Applications that require rapid generation of prototypes.

c) As a starting point or basic standard (Baseline) for research and development.

7.4. Technical And Methodological Challenges

The application of DCGAN as a decision support tool in cold case criminal investigations represents an intertwined set of technical, practical, and ethical challenges that must be addressed in an integrated manner to ensure the effectiveness and ethics of this technology.

7.4.1 Training stability and output quality

DCGAN models face a fundamental challenge: Mode Collapse, where the generator produces a very limited variety of similar images regardless of the variety in the input. In a criminal context, this means that the model may generate only one or a few similar faces for all cases, losing the primary purpose of generating diverse investigative hypotheses. S.Li [25]. A study showed that using advanced optimization techniques like TTUR (Two Time-Scale Update Rule) and Unilateral Smoothing can effectively delay the emergence of this problem. Other studies have also indicated the effectiveness of using Wasserster loss with gradient penalty (WGAN-GP) in improving training stability [12]. These findings underscore the need to select and adapt appropriate optimization mechanisms to ensure that the forensic model generates a diverse and reasonable range of potential faces, rather than limited repetition that reduces its investigative value.

7.4.2 Data gap: between idealism and criminal reality

The development of DCGAN models for criminal context faces a fundamental problem of lack of high-quality, documented criminal data. Obtaining thousands of facial images of victims or suspects, along with their full criminal data, is nearly impossible for legal, ethical, and privacy reasons. The literature shows that most models are trained on generic datasets such as CelebA or LFW [10], [23], [26], which are radically different from the nature of data in cold criminal cases. To meet this challenge, several trends are emerging:

- **Transfer Learning:** Modifying pre-trained models on public data using a limited number of available forensic samples.
- **Integrative Data Generation:** Using DCGAN itself to generate industrial data that simulates specific criminal scenarios, such as degraded images or at imperfect angles.
- **Conditional Modeling:** Develop conditional DCGAN models that accept accurate descriptive inputs on the demographic and physical characteristics of what is required.

7.4.3 Algorithmic bias and the problem of generalization

The problem of bias in deep learning models is one of the most serious challenges in forensic applications. When a training group such as CelebA is racially or demographically unbalanced, the model inherits this bias and shows uneven and unfair performance across different populations. Antipov et al[19] She noted that models trained on unbalanced data can show a clear gender bias in facial recognition. In the global criminal context, this means that the model may be accurate in recognizing faces from categories overrepresented in training data, while failing with others. Overcoming this challenge requires international cooperation to build balanced and diverse criminal data sets and adopt techniques to detect and correct bias during the training process.

8. Conclusion And Future Direction

Based on this systematic review, DCGAN emerges as a promising tool in supporting cold case investigations via its ability to generate high-resolution facial images that can be used as complementary training data or as a tool to generate investigative hypotheses. However, effective application in the criminal field faces fundamental technical challenges that include training stability and the data gap between public groups and the real criminal environment, along with ethical and legal challenges related to algorithmic bias, privacy, and the issue of accountability. To realize the full potential of this technology, a participatory effort is required that includes the development of standardized and diverse forensic datasets by research communities, the adoption of an intelligent hybrid approach by developers that integrates the strengths of multiple models while ensuring transparency, and the development of clear legislative and ethical frameworks by legislators that define the auxiliary role of these tools without replacing traditional evidence or human experience.

Future research is directed towards developing multimedia DCGAN models capable of processing diverse inputs for cold cases, integrating anatomical and forensic knowledge into modeling processes, improving the interpretability of these complex models, and their full integration into investigative decision support systems. In short, while GAN technologies do not represent a comprehensive solution, they offer advanced tools that can, within a responsible and ethical framework, effectively contribute to reviving complex investigations and serving the course of justice .The future of DCGANs in forensics lies in their development as unified decision support platforms. They provide a strong synergy between machine learning and forensic science, provided they remain under strict oversight by legal and investigative professionals.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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