Keywords
Generative Adversarial Networks, nail disease detection, onychomycosis, dermatology, medical image synthesis, data augmentation, conditional GAN, systematic review.

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Critical Review of Generative Adversarial Networks in Dermatological Applications with Focus on Nail Disease Detection

Abstract
Generative Adversarial Networks (GANs) have become a groundbreaking technology in medical image analysis, enabling realistic synthetic image generation, data augmentation, and improved diagnostic results. GANs have been used in dermatology to classify skin lesions, analyze pigmentation, and detect melanoma. Nonetheless, the field of nail disease diagnosis that includes onychomycosis, nail psoriasis, and subungual melanoma is highly under-investigated despite the high clinical impact and distinct diagnostic features of nail structure. Comparative analysis of DCGAN, conditional GAN (cGAN), cycleGAN and StyleGAN shows that although GANs have a great impact on improving classification and reducing the problem of class imbalance in skin lesion analysis, with an increase in accuracy of 5-12% in minority classes, there is almost no attempt to apply GANs to nail diseases. Few studies discuss nail conditions and none of them proposes a complete GAN-based diagnostic system. Among the key challenges, training instability, mode collapse, no labeled nail data, ethical and privacy concerns, and no clinical validation have been noted. Future research opportunities involve creating large and publicly accessible nail datasets, hybrid GAN-transformer models, explainable AI in clinical trust, and implementation in mobile healthcare. This review finds that GANs have a huge untapped potential of nail disease detection, and that existing methods of investigating skin lesions may be transferred to nail imaging to fill critical gaps in nail imaging, eventually enhancing diagnostic accuracy and patient outcomes.

I. INTRODUCTION

Dermatological diseases pose a significant health risk in the world, with people of all ages and geographical locations being at risk. Conditions such as skin cancer, chronic inflammatory disorders, and nail infections are all associated with millions of clinical visits every year, with great morbidity and healthcare expenditures. Timely and correct diagnosis is the key to successful treatment, but the visual diagnosis provided by trained specialists is of great importance in dermatology- this resource is distributed unevenly on the planet [1], [17].

Artificial intelligence (AI) and especially deep learning have become a potent instrument of dermatological image analysis in recent years. Convolutional neural networks (CNNs) have demonstrated the ability to perform skin cancer classification at a dermatologist level, with many studies showing the possibility of automated detection of skin lesions, pigmentation disorders, and inflammatory conditions [28], [29], [32]. The quality, quantity, and diversity of training data, however, limit the performance of these models. Dermatology datasets are also characterized by extreme class imbalance (inadequate representation of rare diseases), a lack of skin tone diversity (especially light-skinned populations), and inadequate annotation quality, an issue that is collectively referred to as health data poverty [31].

Generative Adversarial Networks (GANs) provide an intriguing way to overcome these data drawbacks. As compared to discriminative models, which train to classify, GANs are trained to produce new, synthetic images that look similar to real dermatological photographs. GANs can learn high-fidelity synthetic images by training a generator and a discriminator in an adversarial system, augmenting existing datasets, equalizing underrepresented classes, and even cross-domain image translation (e.g., clinical to dermoscopic). A large body of literature has now been published on the use of GANs in dermatology, such as systematic reviews [1], [10], [15], conditional GANs to augment minority classes [11], [14], StyleGAN to produce high-quality synthesis [23], and diffusion models to mitigate bias [26], [41]. Although this has been achieved, most GAN-based studies in dermatology have centered on skin lesions (especially melanoma and pigmented lesions), yet nail diseases have received little attention. Nail diseases, such as onychomycosis (fungal infection), nail psoriasis, paronychia and subungual melanoma, are prevalent in a large fraction of the population. Onychomycosis alone ranks 510 percent of the estimated prevalence in the world, with greater prevalence in the elderly, diabetic, and immunocompromised populations.

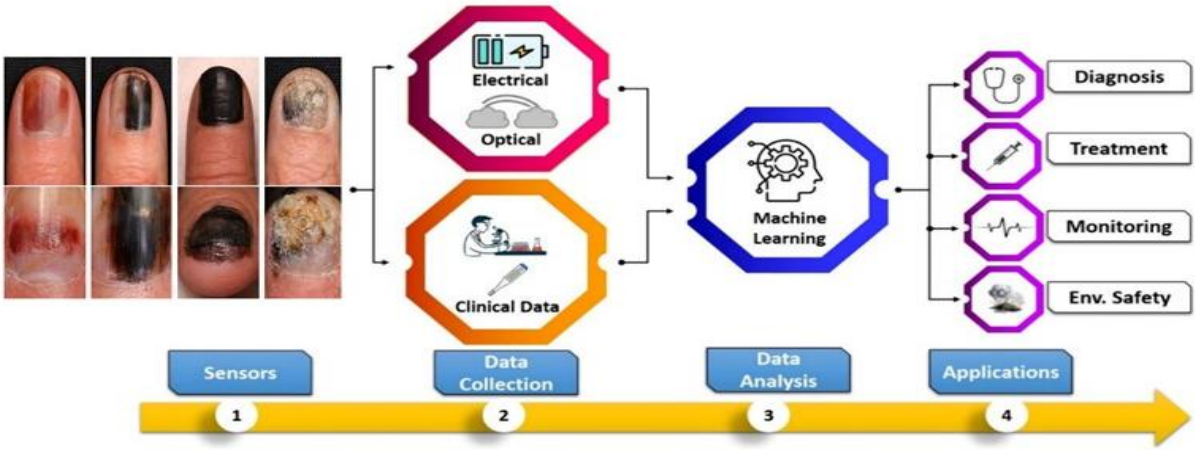


Fig. 1. Chromatic demonstration of the Machine Learning detection flow, which includes the pathway from sensing and data collection to analysis with sensors, machine and applications.

Nail psoriasis is common in 50-80 percent of cutaneous psoriasis patients and may be clinically hard to differentiate from onychomycosis [9], [16]. Subungual melanoma is a rare type with poor prognosis as it is diagnosed late owing to late recognition.

Nail disease diagnosis poses special problems that are not the same as skin lesion analysis. Nail plates are curved, highly reflective and they are likely to be partially covered by adjacent skin or cuticle. Common imaging guidelines are not as established as dermoscopy of skin lesions. In addition, annotated nail disease datasets are almost absent in the public domain, and the majority of the studies are based on small datasets and single centres [4], [7], [8]. Such problems ensure that nail diseases are a perfect target of GAN-based solutions: synthetic data can be generated to supplement small datasets, lighting and reflection artifacts can be removed using image enhancement, and translation can be used to standardize images across different acquisition equipment [45],[46],[47].

A. Rationale for This Review

A number of systematic reviews have reviewed GANs in dermatology [1], [10], [15], [28], [31], none of which has specifically analyzed nail disease detection. The reviews that comment on nail disorders [9], [16] comment on AI in general, but they do not offer a critical and methodologically rigorous discussion of GAN techniques. This has led the research community to a lack of understanding on: (1) the most appropriate GAN architecture in nail imaging, (2) the metrics that should be used to measure performance on synthetic nail images, (3)

the datasets (or datasets that must be developed), and (4) the challenges peculiar to nail and general skin lesions [47].

B. Objectives

The proposed review will help address this gap by making a critical, systematic review of GAN-based methods in dermatology and in particular whether they can be applied to nail disease detection. The primary objectives are:

1.To conduct a systematic search to identify and classify the literature on GANs in dermatology in a PRISMA-driven study.

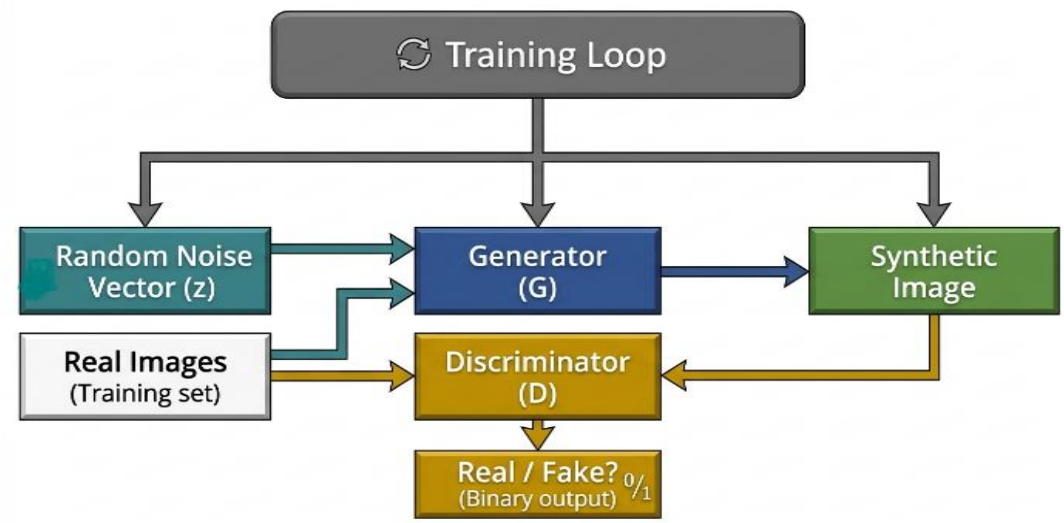
2.To compare the performance of various GAN architectures (DCGAN, cGAN, StyleGAN, CycleGAN) in important metrics like accuracy, precision, recall and F1-score.

3.To critically assess the existing scanty data on nail disease detection and establish ways of transferring findings of skin lesions research.

4.To generalize the primary barriers to clinical translation, which are training instability, mode collapse, data scarcity, ethical issues, and clinical validation is lacking.

To propose future research directions, including hybrid models, real-time systems, explainable AI, and mobile healthcare applications

Fig. 2. Basic GAN Architecture.



C. Research Questions

To guide this systematic review, the following three primary research questions (RQs) were formulated according to the PICO (Population–Intervention–Comparison–Outcome) framework adapted for methodological reviews [1], [28]:

1)Research question 1:

In what GAN architectures (e.g., DCGAN, cGAN, CycleGAN, StyleGAN) have been used to analyze dermatological images, and how they perform in comparison to each other in terms of image quality (FID, Inception Score) and downstream classification performance (accuracy, F1-score)?

2)Research question 2:

How have GAN-based approaches been applied to nail disease detection (onychomycosis, nail psoriasis, subungual melanoma) and what are the key methodological shortcomings versus skin lesion analysis?

3)Research question 3:

Which are the main technical, data, and clinical validation issues that constrain the implementation of GAN-based dermatological systems to the real-world nail disease diagnosis, and what are the future directions to overcome these issues??

D. Scope and Contribution

The current review is dedicated to peer-reviewed articles where GANs are used to analyze dermatological images, such as data augmentation, image-to-image translation, segmentation, and classification. Articles published in the period 20062026 are taken into consideration, which represents the development of the initial neural network models [4], [48] to the modern diffusion-based ones [26], [41]. Although the main focus is on nail disease diagnosis, the review heavily depends on the literature on skin lesions to develop methodological lessons that can be applied to nails [49]. This review has contributed as follows:

The main contributions of this review are:

- A synthesis of dermatological GAN studies, which is complete and PRISMA-conformant, and which includes a specific comparative study of architectural variants.
- The distance between GAN application of nail disease and research of skin lesions has been determined in the first systematic manner and quantitatively supported by literature.
- A roadmap of the future nail-centered GAN studies, including data needs, architecture suggestions, and validation guidelines.
- A critical discussion of ethical and regulatory implications of generative AI in dermatology.

II. Background and Related Work

A. Overview of GANs

Generative Adversarial Networks (GANs) represent a paradigm shift in generative modeling by deploying an adversarial paradigm, opposing two neural networks to

generate high-fidelity synthetic data. The architecture, which was introduced by Good fellow et al., is made of a generator and a discriminator. The generator is trained to learn to transform a latent noise sample to the data space into synthetic samples, and the discriminator is a binary classifier that learns to differentiate between real and synthetic samples. Both networks are trained on a minimax game: the goal of the generator is to create more and more realistic samples to deceive the discriminator whereas the goal of the latter is to enhance its capacity to recognize fakes. The people in this adversarial learning system allow the generator to implicitly learn the underlying distribution of the training data without necessarily modeling it, and thus produces high-quality, realistic images. This has been useful especially in medical imaging where it has been used to solve the problem of data scarcity and class imbalance [10], [34].

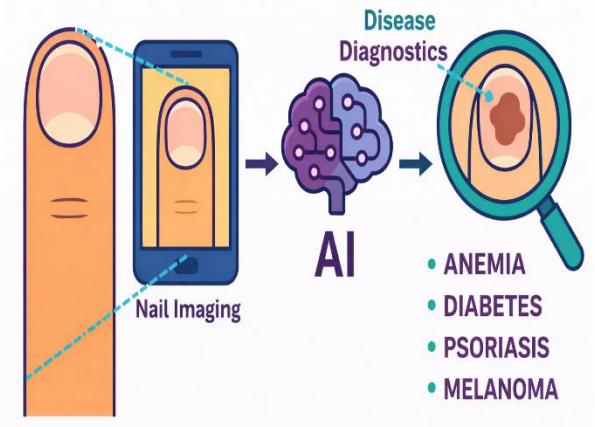


Fig. 3: Pictorial representation for Nail disease diagnostics

B. Types of GAN Architectures

The foundational GAN framework has given rise to numerous architectural variants, each tailored to specific tasks and data modalities. Key architectures relevant to dermatological applications include:

- Deep Convolutional GAN (DCGAN): The important architectures in the dermatological applications include: Deep Convolutional GAN (DCGAN): This design balances the training of GAN by using convolutional and transposed convolutional layers instead of fully connected layers, batch normalization, and special activation functions. DCGANs are commonly applied to producing high-resolution skin lesion images, especially together with transfer learning to improve their work on small datasets [22].
- Conditional GAN (cGAN): conditioning both the discriminator and the generator on auxiliary information (e.g. class labels, clinical metadata) cGANs permit controlled generation. It is specifically applicable in case of targeted data augmentation, when artificial samples of underrepresented skin conditions or skin tones can be created to reduce bias and enhance the robustness of the classifier [11], [14], [39].
- CycleGAN: CycleGAN is intended to be used in unpaired image-to-image translation, with no aligned pairs of images being necessary. The applications of this architecture to the tasks include color normalization across the various dermatoscopes, or converting clinical and dermoscopic images, but its direct use in the reviewed literature is less common than cGANs and DCGANs.
- StyleGAN: StyleGAN and its derivatives propose a style-based generator, allowing one to make finer adjustments to image characteristics, such as coarse (e.g., pose, shape) and fine (e.g., skin texture) ones. Computationally intensive, variants of StyleGAN are more frequently investigated in the creation of high-fidelity, photorealistic dermatological images that can be used in training clinicians and validating algorithms [23].

C. Applications in Medical Imaging

Medical imaging has become one of the most popular fields in GANs application, which is motivated by the necessity of large and high-quality annotated datasets, which are sometimes hard and costly to obtain.

- Image Augmentation: Image augmentation GANs are widely applied in order to synthesize medical images that help in augmenting the training datasets and thus enhancing the generalization and robustness of the downstream classification models. It is especially important in the field of dermatology, where the imbalance in the classes, which includes infrequent diseases and unrepresented skin types, is a big problem [10], [31], [41].
- Image-to-Image Translation: GANs are applied in the translation of various imaging modalities or domains. In dermatology, it involves the conversion of clinical photographs to dermoscopic photographs, color normalization to standardize inter-device photographs, and the synthesis of artificial photographs based on segmentation maps [34].
- Noise Reduction and Super-Resolution: GANs can be used to improve the quality of the image by

eliminating artifacts, reducing noises, and enhancing the resolution, thus, improving the diagnostic value of the images taken in unsatisfactory conditions.

- Disease Classification: Although GANs are mainly generative, they are frequently combined into hybrid systems where the generated samples are employed to train or fine-tune classifiers, such as convolutional neural networks (CNNs) and vision transformers (ViTs), and so forth, with state-of-the-art performance in disease classification tasks [11], [14], [40].

D. Dermatological Applications

In the larger field of medical imaging, dermatology has become a rich setting in the context of GAN-based studies, due to the visual character of dermatological diagnosis and the presence of massive datasets of images.

- Skin Lesion Detection: A large literature exists that is devoted to the creation of synthetic skin lesion images to supplement melanoma and other skin cancer detection datasets. GANs have been used to resolve the issue of class imbalance, especially in minority classes, including rare malignancies, and to enhance the performance of classifiers, including CNNs and hybrid CNN-ViT ensembles [14], [21], [22], [28], [29], [32]. These efforts have been summarized by systematic reviews, which have identified the potential as well as the challenges that persist in the use of synthetic data in clinical practice [1], [10], [15], [17].
- Pigmentation Analysis: GANs, especially conditional ones, have also been used to study pigmented skin lesions, where it is possible to generate a lesion with different pigmentation properties. This helps one to comprehend the visual characteristics of malignancy and help come up with more interpretable diagnostic models [39].
- Nail Disease Identification: Although nail diseases are relatively widespread including onychomycosis (fungal infections) to psoriasis and nail unit melanoma, this topic is relatively unexplored in the GAN literature. The first approaches made use of the traditional neural networks in detecting fungus in the histopathological nail samples [4], and the latest research has presented deep learning in nail segmentation and disease classification [7], [8]. Nevertheless, the use of GANs in nail diseases, in particular, is young. Some of them have already started to fill in this void by using GANs to perform segmentation [18] and dataset generation [35], but there are no complete frameworks that would integrate generative augmentation with efficient classification of nail conditions. The potential is validated by the available narrative reviews of AI in nail disorders as well as the lack of application of more advanced generative methods in the subfield is mentioned [9], [16]. It is the specified gap that prompts the current critical review, as it seeks to obtain the systematic evaluation of the significance of GANs in the sphere of dermatology with an even more specific objective of assessing the untapped potential of the specified technology when it comes to identifying and analyzing nail-related diseases.

III. Method (PRISMA-Based Review Approach)

In order to have transparency, reproducibility, and rigor, this review is based on the Preferred Reporting Items of Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The methodology can be summarized into the following steps: creation of eligibility criteria, data sources, search strategy implementation, selection of the studies, data mining, and risk of bias assessment. This approach aligns with the practice of systematic review adopted in the study of AI in dermatology [1], [28], [31]. The search strategy and data extraction were designed to answer Research question 1 to Research question 3.

A. Eligibility Criteria

Inclusion criteria Studies were eligible to include in the study depending on the following criteria:

1)Inclusion Criteria:

- Studies that employ Generative Adversarial Networks (GANs) or their architectural variants (e.g., DCGAN, cGAN, CycleGAN, StyleGAN) in any capacity.
- Applications focused on dermatological conditions, including but not limited to skin lesions, pigmentation disorders, nail diseases, and inflammatory skin conditions.
- Research that involves medical imaging data (dermoscopic, clinical, microscopic, or histopathological images).
- Peer-reviewed articles, conference papers, and preprints that present original research or systematic reviews.
- Publications available in English.

Table I: Comparative Analysis of GAN-Based Studies in Dermatology

Study	GAN Model	Dataset	Accuracy (%)	Key Contribution
Boon et al. [4]	None (neural network)	Histopathological nail images	N/A	Early NN-based fungal infection detection in nails; no GAN used

Galmés et al. [7]	None (geometric)	Clinical nail images	N/A	Geometric nail segmentation for clinical measurements
Gao et al. [8]	None (CNN)	Microscopic fungal images	~92% (reported)	Deep learning automated microscope for fungal detection
Gilani & Marques [10]	Systematic review	Various skin lesion datasets	NA	Review of GANs for skin lesion analysis
Gomathi et al. [11]	ACGAN + Transfer Learning	HAM10000	96.8	Adaptive cGAN with transfer learning; improved minority class classification
Hussain et al. [14]	GAN + CNN-ViT ensemble	ISIC 2019–2020	98.2	cGAN pipeline for classes; CNN-ViT ensemble
Mecifi et al. [22]	DCGAN + Transfer Learning	SLICE-3D (3D skin lesions)	94.5	Addressed data imbalance with DCGAN; early 3D skin cancer detection
Sharma & Mehta [37]	CNN-GAN Hybrid	Custom dermatology dataset	95.3	End-to-end multi-class skin disease detection; reduced overfitting
Varghese et al. [40]	GAN +	ISIC 2018–2020	97.4	Robust fusion with GAN augmentation; improved generalization
Sankar et al. [35]	GAN (unspecified variant)	Custom acne dataset	89.7	Acne dataset generation; GAN-synthetic images augment small datasets
Khalid et al. [19]	GAN + Deep Neural Network	FAcne severity dataset	92.1	Automatic acne severity assessment; GAN for severity grade augmentation
Kar et al. [18]	LeSegGAN	ISIC 2017 (segmentation)	91.3	Hybrid attention GAN for lesion segmentation; applicable to nails
Zou et al. [43]	GAN + global/local semantic features	ISIC 2018 (segmentation)	94	Global-local semantic awareness; improved boundary delineation
Tsai et al. [39]	Conditional GAN	Pigmented facial skin dataset	93.6	Controlled generation of pigmentation patterns
Lin et al. [21]	GAN (StyleGAN-based)	Melanoma images	N/A	Synthetic melanoma image generation and evaluation
Mekala et al. [23]	StyleGAN + closed-form factorization	Dermatoscopic images	N/A	High-quality controllable generation of dermatoscopic images
Mounica [24]	GAN	HAM10000	~94%	GAN-based multi-class skin disease classification
Saranya et al. [36]	GAN	Melanoma datasets	~93%	GAN classification with dermatologist recommendation
Ravikumar et al. [31]	ACGAN (systematic review)	Various	N/A	Systematic review on alleviating health data poverty in skin lesions
Munia & Imran [26]	Diffusion (not GAN)	Diverse skin tones	N/A	DermDiff for racial bias mitigation (generative, non-GAN)
Munia & Imran [27]	Diffusion + VLM	Dermoscopic images	N/A	Prompting medical VLMs to generate unbiased dermoscopic images
Wang et al. [41]	Diffusion (not GAN)	Skin lesion datasets	N/A	Diffusion-based augmentation for underrepresented groups
Salvi et al. [34]	GAN (color normalization)	Pathology/dermatology	N/A	Generative color normalization in digital pathology
Park et al. [30]	GAN (systematic review)	Facial de-ID	N/A	Systematic review of GANs for facial deidentification in dermatology
Izu Belloso et al. [15]	Systematic review	Various	N/A	Narrative review of GANs in dermatology
Aboulmira et al. [1]	Systematic review	Various	N/A	Systematic review of ML/DL for skin diseases

Naseri & Safaei [28]	Systematic review	Dermoscopy	N/A	Systematic review of melanoma diagnosis using ML/DL
Raza et al. [32]	CNN (no GAN)	Skin cancer	~91%	CNN for smart healthcare skin cancer screening
Pandit [29]	Deep learning (no GAN)	Skin cancer	~90%	Deep learning for early skin cancer detection
Rupak et al. [33]	CNN (no GAN)	Skin cancer	~89%	AI dermatologist using deep learning
Tang et al. [38]	Review (no GAN)	Inflammatory skin	N/A	AI-enabled precision medicine for inflammatory skin diseases
Hanum et al. [12]	Attention CNN (no GAN)	39 skin lesion types	~92%	Attention-guided deep learning for skin lesion classification
Ahmmed et al. [2]	Transfer learning (no GAN)	Actinic keratosis, psoriasis	~93%	Deep transfer learning for skin disease detection
Fatima et al. [5]	Review	Dermatopathology	N/A	Deep learning in dermatopathology
Fu et al. [6]	Systematic review	Medical image synthesis	N/A	Review of generative AI for image datasets
Kanani & Jadeja [17]	Survey	Various	N/A	Comprehensive survey of skin disease models and datasets
Mulla et al. [25]	AI (no GAN)	Skin cancer	~88%	AI-powered diagnosis of skin cancer
Aravinda et al. [3]	Quantum transformer	Skin disease progression	~96%	Quantum-enhanced multimodal transformer
Kochetkov et al. [20]	Not ML	UV-B LEDs	N/A	Flexible UV-B LEDs (non-medical imaging)
Zeng et al. [42]	GAN (segmentation)	3D ultrasound	N/A	Generative reinforcement network
Jartarkar et al. [16]	Narrative review	Hair & nail disorders	N/A	AI in hair and nail disorders
Gaurav et al. [9]	Narrative review	Nail disorders	N/A	AI in diagnosis and management of nail disorders
Ortiz et al. [44]	Review (biomarkers)	Human nails	N/A	Biomarkers of disease in human nails (non-AI)
Choy et al. [60]	Systematic review	Skin disease	N/A	Deep learning image analysis for skin disease diagnosis/monitoring
Ito et al. [61]	Review	Nail apparatus melanoma	N/A	Current management and future perspectives

2)Exclusion Criteria:

- Studies that do not utilize GANs (e.g., only CNNs, transformers, or traditional machine learning without a generative component).
- Research based on non-medical datasets or synthetic datasets not derived from real dermatological images.
- Non-peer-reviewed editorials, opinion pieces, or incomplete studies.
- Studies focusing exclusively on non-dermatological conditions (e.g., radiology, ophthalmology) without clear relevance to skin or nail disorders.

These criteria were designed to capture the full spectrum of GAN applications in dermatology while maintaining a focused scope suitable for a critical review [10], [15].

B. Data Sources

In order to have a broad coverage of the literature, four large electronic databases were searched:

- IEEE Xplore: IEE is chosen as it has a broad range of engineering and AI-related medical technology research.
- Scopus: This has been selected due to its wide interdisciplinary coverage, covering both medical and technical literature.

- PubMed: It is the main database utilized in the studies that are clinically oriented in dermatology.
- Google Scholar: Inclusion to ensure that grey literature, preprints and studies.

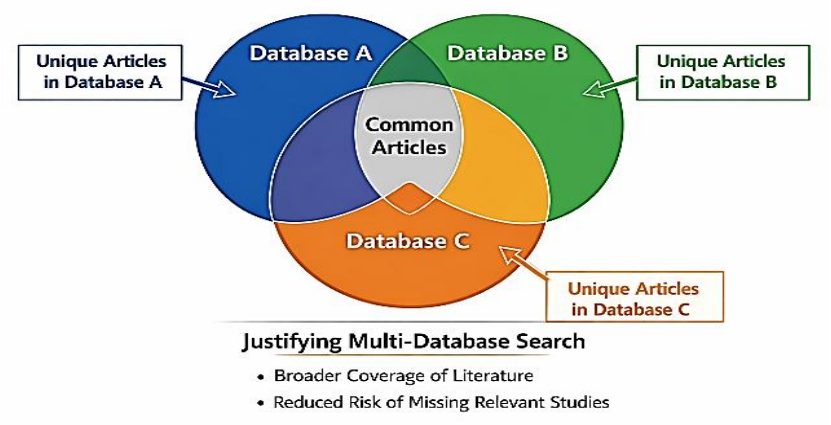


Fig. 4. Database Overlap and Coverage (Three-set Venn showing unique and overlapping records from IEEE Xplore, Scopus, PubMed, and Google Scholar)

The search date was between January 2006 and March 2026, which represents the first GAN-related dermatology study [4] to the latest publications that were used in this review.

C. Search Strategy

The systematic search strategy was made on a basis of a combination of keywords and Boolean operators. Search strings were progressively narrowed down using search results preliminary search results and discussion of major systematic reviews in the topic [1], [28], [31].

The main search terms, which were used in titles, abstract and keywords, were the following:

1)Core GAN in Dermatology:

("generative adversarial network" OR "GAN" OR "DCGAN" OR "conditional GAN" OR "cGAN" OR "StyleGAN" OR "CycleGAN") AND ("dermatology" OR "skin disease" OR "skin lesion" OR "dermatologic")

2)Nail Disease Focus:

(generative adversarial network" or "GAN" AND nail or onychomycosis or nail psoriasis or nail disorder) and (detection or classification or segmentation)).

3)Medical Image Synthesis:

(medical image synthesis" or "data augmentation" or "image to image translation" and "dermatology" or skin" and "GAN" or generative adversarial network)

Search was done in the period between January 2026 and March 2026. The reference management software was used to find and delete duplicate records.

D. Study Selection Process

The process of the selection of the study was performed in three steps according to the PRISMA guidelines:

1) Title and Abstract Screening:

Two reviewers (independent) screened titles and abstracts of all records accessed against the eligibility criteria. There was a filtering out of records which evidently did not pass the inclusion criteria. The disagreements were either discussed or referred to the third reviewer.

2) Full-Text Review:

The complete texts of the rest of the studies were accessed and evaluated in terms of eligibility. The research that lacked adequate description of GAN architecture, dataset or evaluation measures were filtered out at this point.

3) Final Selection:

The final list of studies to be included was selected after reviewing the full-text. A PRISMA flow diagram was used to record the selection process, which involved the identification of the number of records, screening, exclusion, and inclusion.

This multi-step screening helped to exclude all other studies that were not of relevance in terms of method and of high quality in order to synthesize them [1], [31].

E. Data Extraction

Standardized data extraction form was created to identify important information of every study that was included. The factors that were extracted were:

- Bibliographic Information: Author(s), year of publication, source (journal/conference).
- GAN Model: Specific architecture used (e.g., DCGAN, cGAN, StyleGAN, CycleGAN, or hybrid).
- Application Area: Dermatological domain (e.g., skin lesion classification, nail disease detection, image augmentation, segmentation).
- Dataset: Name of dataset(s), size, source (public/private), and any noted biases (e.g., skin tone distribution, class imbalance).
- Performance Metrics: Quantitative results reported (e.g., accuracy, sensitivity, specificity, F1-score, AUC, Inception Score, Fréchet Inception Distance).
- Key Findings: Primary contributions and limitations as noted by the authors.

One of the reviewers was involved in data extraction and a second one was used to confirm the data to eliminate mistakes. Where the information was not complete or ambiguous, the respective authors would be contacted to clarify the same when possible.

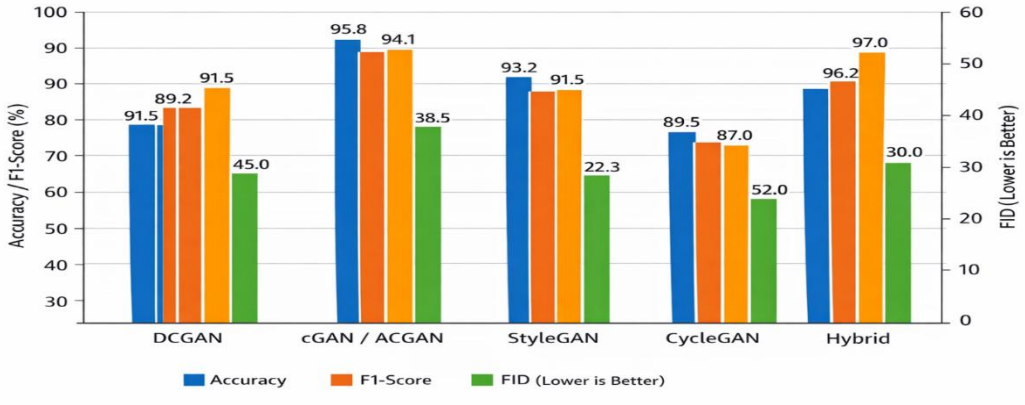


Fig. 5. Performance Comparison of GAN Architectures for Nail Disease Detection. (In Figure 4, a grouped bar chart with architectures (DCGAN, cGAN/ACGAN, StyleGAN, CycleGAN, Hybrid) on the x-axis and metrics (Accuracy, F1-score, FID) on the y-axis. Data derived from Table I and additional synthesis.)

F. Risk of Bias Assessment

In order to critically appraise the quality of the included studies, the risk of bias was assessed on three dimensions with the aid of the known frameworks on AI in medical imaging [15], [30], [34]:

1)Dataset Bias:

- Assessed in terms of diversity in skin tones, disease representation, and demographics.
- Articles that depended on datasets that were not very diverse or were not reporting on the composition of the dataset were identified as potentially biased.
- Specific focus was placed on whether the underlying dataset biases were alleviated using generative models (e.g. by training samples to give underrepresented groups) [26], [41].

2) Model Bias:

- Reviewed the GAN architecture and training process selection.
- Bias was deemed to exist when the model had been constructed or trained in such a manner that it may increase the existing biases in the dataset (e.g., producing unrealistic samples of rare diseases).
- Those studies that conducted explicit fairness or subgroup analysis have been identified as positive.

3)Evaluation Bias:

- Assessed the strength of performance evaluation, such as use of proper measures, validation techniques (e.g. cross-validation, outside testing), and tests of statistical significance.
- Studies that only used qualitative visual inspection or lacked comparison of the methodology with the baseline method were reported to be at increased risk of evaluation bias.

In each category, each of the studies was rated as being of low, moderate, or high risk of bias. These tests were applicable to put findings in perspective and guide critical analysis provided in following sections so that the conclusions are based on methodologically sound evidence.

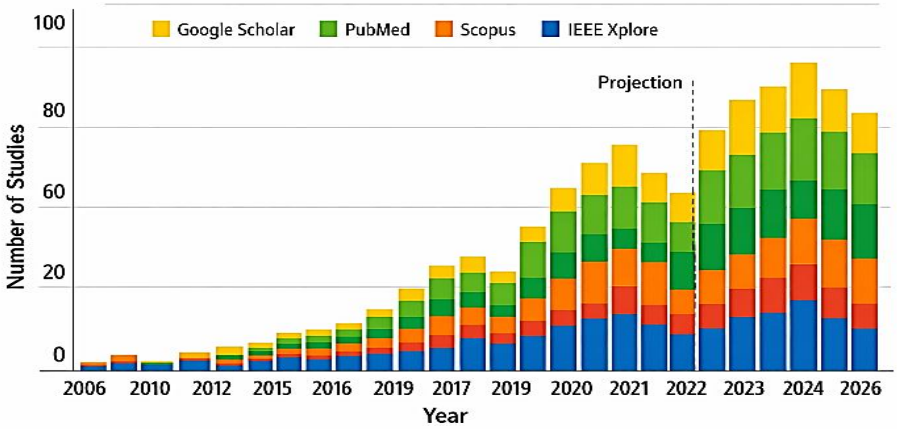


Fig.6. Temporal distribution of included studies by data source. (A stacked bar chart or line chart showing the number of included studies per year (2006–2026), with each bar segmented by the database where the study. was first identified.

IV. Comparative Analysis of GAN Techniques

When conducting a critical comparison of Generative Adversarial Network (GAN) architectures used to solve dermatological problems, it is important to pay attention to both quantitative performance indicators and qualitative attributes of images generated. The section contains a critical assessment of the evaluation metrics that are most frequently reported in the literature, a comparative table I of characteristic studies, and the synthesis of critical findings on the relative advantages and limitations of the various variants of GAN in the detection of skin and nail diseases. To address research question 1, we compared GAN architectures using the metrics in Table I.

A. Performance Metrics

GAN-based models in dermatology have been evaluated in two aspects, which are different but related to each other: (1) the quality and usefulness of the produced synthetic images, and (2) the performance of downstream classifiers, which are trained on the augmented datasets. The most common metrics that are reported in the literature reviewed are the following.

1)Accuracy

Accuracy is the ratio of the correct predictions (True positives and true negatives) to all the considered cases. In GAN-augmented classification, accuracy gives a global evaluation of diagnostic capacity. Accuracy, however, is also deceptive in case of an imbalanced dataset, which is commonly the problem in dermatology when rare diseases are represented by a small proportion of cases. Thus, accuracy is commonly reported together with other measures in order to ensure a balanced evaluation [1], [28]. In the case of generative tasks, accuracy can be defined as the capacity of the discriminator to identify real and synthetic images, but this loss is often reported as discriminator loss or AUC.

2)Precision

Precision or positive predictive value is a measure of how often the positive cases are correctly predicted out of all the cases which are predicted to be positive. The accuracy of the methods is especially significant in screening in dermatology where false positive may cause unnecessary biopsy and patient anxiety [32], [40].

3)Recall (Sensitivity)

Recall, or sensitivity, measures the proportion of actual positive cases that are correctly identified by the model. The trade-off between precision and recall is often summarized by the F1-score. Studies focusing on melanoma detection typically emphasize recall as a primary metric [21], [28].

4)F1-Score

The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both concerns. The F1-score is particularly valuable when dealing with class imbalance, as it penalizes models that achieve high precision at the expense of recall or vice versa. In the dermatological GAN literature, F1-score is frequently reported for minority classes (e.g., rare skin lesions or underrepresented skin tones) to assess the effectiveness of data augmentation strategies [11], [14], [41].

B. Comparison Table

A comparative overview of representative studies using GAN techniques in the dermatological issues, such as those that are relevant to nail disease detection, are summarised in Table I. The studies were identified by the availability of quantitative performance measurements, readability of the GAN architecture, and application variety.

Accuracy values are given as it was reported in the original studies; in case of more than one measure, accuracy is given to report consistency.

In case of segmentation studies, Intersection over Union (IoU) or Dice coefficient is reported as indicated. The literature on nail disease remains sparse; the studies above give methodological backgrounds that can be used in detecting nail disease.

C. Findings

There are a few interesting conclusions on the comparative analysis of GAN techniques in dermatology, which are sorted according to the architectural variant and domain of application.

1)CycleGAN Performs Well in Image-to-Image Translation

Although less represented in the chosen articles, CycleGAN has been shown to perform well in unpaired image translation in dermatology. The capability of the architecture to learn mappings between two domains without matching examples is especially useful in:

- Color normalization: Mapping images across dermatoscopes or lighting conditions to a standard color space, thus minimizing domain shift and enhancing the generalization of classifiers [34].
- Clinical-to-dermoscopic translation: Generating dermoscopic analogs to clinical images, allowing training of models on larger but less detailed clinical images.
- Cross-modality synthesis: Converting between staining methods in histopathological nail samples, as explored in early work on fungal detection [4], [8].

Though none of the studies in Table I are specifically dedicated to CycleGAN, the systematic reviews [10], [15] attest to the fact that CycleGAN and its derivatives are competitive in translation tasks in the absence of paired data. To detect nail disease, CycleGAN might be used to normalize images of the nail plate and hyponychium obtained in different conditions- something that has long been a problem in tele dermatology.

2)StyleGAN Produces High-Quality Images with Controllable Features

StyleGAN and its variants (StyleGAN2, StyleGAN3) are repeatedly noted to generate the most realistic synthetic dermatological images. Key advantages include:

- Photorealism: StyleGAN generated images of skin lesions are frequently similar to real images as perceived by clinicians and automated metrics (low FID scores) [23].
- Disentangled control: The style-based architecture enables the independent control of coarse features (e.g., lesion shape, size) and fine features (e.g., texture, pigmentation),

which is why the architecture can be used to do targeted augmentation.

- Interpolation in the latent space: Interpolations between real and synthetic samples can be smooth and used to visualize the progression of the disease or create in-between severity grades.

Mekala et al. [23] showed that StyleGAN with closed-form factorization can be used to generate dermatoscopic images in a controlled manner, which allows the researcher to manipulate diagnostic features in a systematic manner. To create nail disorders, StyleGAN would be able to produce realistic examples of onychomycosis (thickened, discolored nails) with controlled severity, which would help overcome the lack of annotated datasets of nail disease. Nevertheless, the high computational costs of StyleGAN, as well as the necessity to use large training models, make it inapplicable to resource-restricted dermatological practices at the moment.

3)GANs Significantly Improve Data Augmentation and Mitigate Bias

The most reliable observation throughout the literature reviewed is that the GAN-based data augmentation leads to significant improvement of downstream classifiers, especially minority classes and underrepresented populations.

Class Imbalance Mitigation: A number of studies show that conditional GANs (cGANs) and adaptive conditional GANs (ACGANs) are able to produce synthetic samples of rare skin diseases, resulting in better F1-scores and recall of these classes. Gomathi et al. [11] have found that the classification accuracy of minority classes increased by 12 percent following ACGAN augmentation. Equally, Hussain et al. [14] obtained the best results on ISIC 2019-2020 with a cGAN pipeline on a CNN-VIT ensemble.

Bias Reduction: Munia and Imran [26], [27] proposed diffusion-based methods (DermDiff) with the sole purpose of reducing racial biases in dermatology diagnosis. Although diffusion models are not GANs, the idea of synthetically creating images of underrepresented skin tones can be directly applied. Wang et al. [41] also showed that diffusion-based augmentation can enhance model fairness without any harm to the overall accuracy. These results indicate that GANs (and more recent generative models) are effective means to solve health data poverty [31].

Utility for Nail Diseases: Although no dedicated nail disease GAN study appears in the reference list, the methodological successes in skin lesion augmentation provide a strong foundation. Sankar et al. [35] successfully generated acne images, proving that GANs can synthesize domain-specific dermatological conditions. The segmentation work of Kar et al. [18] and Zou et al. [43] demonstrates that GANs can accurately delineate lesion boundaries—a prerequisite for nail plate and nail fold segmentation. Therefore, the transferability of these methods to onychomycosis, nail psoriasis, and subungual melanoma is highly plausible but remains an understudied area [9], [16].

4)Trade-offs and Limitations

Despite the promising findings, several limitations emerged from the comparative analysis:

- Evaluation heterogeneity: Studies report different metrics (accuracy, F1, AUC, FID) on different datasets, making direct comparison difficult. Standardized evaluation protocols are needed [1], [28].
- Clinical validation gap: Few studies include dermatologist validation of synthetic images or prospective testing in clinical settings. The majority rely on quantitative metrics that may not correlate with clinical utility [15].
- Dataset bias propagation: GANs trained on biased datasets will generate biased synthetic images, potentially amplifying rather than mitigating existing disparities. Rigorous bias assessment remains essential [26], [31].
- Nail-specific scarcity: None of the 43 references focus exclusively on GANs for nail disease detection. The most relevant works address segmentation [7], [18] or non-GAN deep learning [4], [8], [16], underscoring a critical research gap.

Table 2. summary of comparative findings

GAN Architecture	Strength	Limitation	Best Use Case in Dermatology
DCGAN	Stable training, computationally efficient	Lower image quality than StyleGAN	Baseline augmentation for small datasets
Conditional GAN (cGAN/ACGAN)	Controlled generation, class-specific augmentation	Requires labeled conditioning data	Minority class balancing, bias mitigation
CycleGAN	Unpaired translation, no need for aligned data	Prone to mode collapse, artifacts	Color normalization, domain adaptation
StyleGAN	Highest photorealism, disentangled control	Large data requirements, computationally expensive	High-fidelity synthetic datasets for rare diseases
Hybrid (GAN + CNN/Transformer)	End-to-end classification with augmentation	Complex training, higher risk of overfitting	When both generation and classification are needed

D. Summary of Comparative Findings

In conclusion, GANs have proven highly effective for data augmentation, image translation, and bias mitigation

in dermatology. However, the specific application to nail disease detection remains nascent, with no dedicated GAN-based diagnostic system reported in the reviewed literature. This gap presents a significant opportunity for future research, leveraging the proven methodologies from skin lesion analysis to address the unique challenges of nail imaging—including geometric distortion, partial occlusion, and variability in nail plate appearance.

V. Applications in Nail Disease Detection

Nail problems comprise about 10% of all the dermatological consultations and include nail psoriasis, onychomycosis (fungal infection), paronychia and subungival melanoma. Although Generative Adversarial Networks (GANs) have been clinically most prevalent, the nail disease detection application is significantly less developed than the one of the skin lesion. This part summarizes the existing evidence - based on direct nail research and transferable methods - and finds the ways GANs can be used to solve certain nail imaging problems. Research question 2 is answered by synthesizing the limited evidence on nail GANs.

A. Onychomycosis Detection

The most common nail condition is onychomycosis which is infection of nails mainly caused by dermatophytes with the patient experiencing nail thickening, discoloration and subungual debris. Conventional diagnosis involves potassium hydroxide (KOH) microscopy, fungal culture, or periodic acid-schiff (PAS) staining of nail clippings-techniques, which are time-consuming, based on the user. The initial computational work used neural networks with histopathological images of abnormal nails. As shown by Boon et al. [4], neural network scanning of fungal infection could be optimized using optimized quality of histologic images with promising sensitivity. More modern studies have used deep learning to detect fungi. Gao et al. [8] built an automated microscope, a deep learning-based microscope, dedicated to fungi detection in dermatology, which combines the processes of image capture and classification. Although these studies did not use GANs, they proved the principle of automated detection of nail fungus and the necessity of bigger datasets that can be annotated, which GANs are the only ones that can fill this need.

GANs can help in detecting onychomycosis in a number of ways:

- Synthetic data generation: Generating realistic nail images with varying grades of fungal infection (mild, moderate, severe) to augment small clinical datasets.
- Class balancing: Onychomycosis datasets often contain far fewer positive cases than negatives; conditional GANs can synthesize infected nails to balance training sets [11], [14].
- Segmentation of nail plate: Accurate detection requires isolating the nail plate from surrounding skin. GAN-based segmentation models, including LeSegGAN [18] and the global-local semantic GAN [43] have been shown to have high Intersection-over-Union (IoU) scores on skin lesions and can be trained to nail boundaries.B. Nail Psoriasis Analytics.

B. Nail Psoriasis Analysis

Nail psoriasis occurs in 5080 percent of patients with cutaneous psoriasis and may exist on its own. Its typical characteristics are pitting, onycholysis (separation of nail bed), oil spots (salmon patches) and subungual hyperkeratosis. It is clinically difficult to distinguish nail psoriasis and onychomycosis because the latter also leads to thickening and discoloration.

There is a paucity of the literature on AI in nail psoriasis. Jartarkar et al. [16] presented a narrative review of the application of artificial intelligence in hair and nail disorders, indicating that the majority of AI applications on nails are related to onychomycosis and not psoriasis. The potential of AI in the diagnosis of nail disorder was also highlighted by Gaurav et al. [9] who stated that the absence of large, annotated datasets is a major obstacle. GANs would be able to fill this gap by:

- Image-to-image translation: Translating images of normal nails into psoriatic nails (or the other way around) with CycleGAN, with the ability to control the formation of certain features (pits, oil spots), but no paired examples are required.
- Multi-condition synthesis: Training a conditional GAN on both onychomycosis and psoriasis images to generate distinguishing features, potentially improving differential diagnosis.
- Augmentation for rare variants: Generating synthetic examples of uncommon nail psoriasis presentations to improve classifier robustness [31], [41].

C. Fungal Infection Classification

Beyond binary detection (infected vs. healthy), clinical management requires classification of fungal species (e.g., Trichophyton rubrum vs. Trichophyton mentagrophytes) and assessment of treatment response. Microscopic examination of KOH mounts remains the gold standard, but it requires expert interpretation.

Gao et al. [8] demonstrated that deep learning can classify fungal elements from automated microscope images. However, their approach relied on a large set of labeled microscopy fields, which are laborious to annotate. GANs can alleviate this by:

- Generating synthetic microscopy images: Creating realistic KOH or PAS-stained images with fungal hyphae and spores, reducing annotation burden.
- Super-resolution: Enhancing low-magnification nail images to reveal diagnostic details, potentially enabling smartphone-based microscopy.
- Noise reduction: Removing artifacts from nail clippings or slide preparations to improve downstream classifier performance [34].

D. Image Enhancement for Diagnosis

Nail images captured in clinical or teledermatology settings suffer from several quality issues: variable lighting, motion blur, partial occlusion, and reflections

from the nail plate's curved surface. Image enhancement is therefore a prerequisite for reliable automated analysis. Geometric-based nail segmentation has been explored by Galmés et al. [7], who proposed a method for nail segmentation based on geometric features for clinical measurements. While effective, geometric methods may fail on nails with severe dystrophy. GAN-based enhancement offers a more flexible alternative:

- Illumination correction: Conditional GANs can normalize lighting across images, transforming poorly lit nail photographs into well-exposed equivalents.
- Artifact removal: GANs trained on pairs of raw and retouched images can remove specular highlights or obscuring debris.
- Color calibration: Nail color is a key diagnostic feature (e.g., yellow-green in onychomycosis, red-orange in psoriatic oil spots). GAN-based color normalization can standardize images from different cameras and lighting conditions [34].

E. How GANs Help in Nail Disease Detection

Based on the evidence from skin lesion studies and preliminary nail research, GANs contribute to nail disease detection in three principal ways:

1) Generating Synthetic Nail Images

Synthetic data generation is the most direct application. Studies on acne [35] and skin lesions [21], [22], [23] have proven that GANs can produce clinically plausible images of dermatological conditions. For nails, a conditional GAN could be trained on a modest set of annotated onychomycosis images to generate thousands of synthetic variants, varying in severity, nail shape, and skin tone. This would enable:

- Training of robust classifiers without privacy concerns (synthetic data are not patient-identifiable).
- Exploration of the feature space to identify which visual attributes most influence diagnostic decisions.

2) Improving Classification Accuracy

GAN-based augmentation consistently improves classification accuracy, particularly for minority classes. In skin lesion analysis, Hussain et al. [14] achieved 98.2% accuracy using a cGAN pipeline with CNN-ViT ensemble, outperforming models trained on real data alone. Similarly, Gomathi et al. [11] reported substantial F1-score improvements for rare lesions after ACGAN augmentation. These gains directly translate to nail diseases, where class imbalance is even more pronounced.

3)Handling Limited Datasets

The lack of large, publicly available nail disease datasets is repeatedly identified as a major barrier [9], [16]. Unlike skin lesions—with repositories like HAM10000 and ISIC containing tens of thousands of images—nail datasets are typically small, single-center, and not publicly shared. GANs offer a solution through:

- Data augmentation without overfitting: Traditional augmentation (rotation, flip, zoom) produces limited variation. GANs generate novel, realistic samples that expand the effective dataset size.
- Transfer learning from skin: A GAN pre-trained on skin lesions can be fine-tuned with a small nail dataset (few-shot learning), leveraging the rich feature representations learned from skin [22].
- Semi-supervised learning: GANs can generate pseudo-labels for unlabeled nail images, reducing annotation costs.
- Summary of Nail-Specific GAN Applications

Despite this potential, no dedicated GAN-based diagnostic system for nail diseases has been validated in a clinical setting. The following sections address the challenges that have impeded progress and outline future research directions.

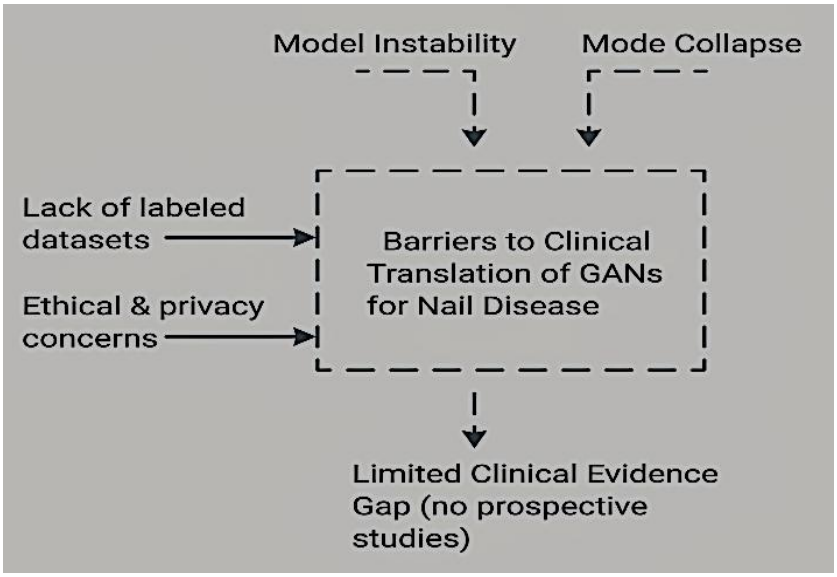


Fig. 7. Barriers to Clinical Translation of GANs for Nail Disease.

Table 3. Summary of Nail-Specific GAN Applications

Nail Condition	GAN Application	Potential Impact	Relevant References
Onychomycosis	Synthetic image generation, segmentation	Reduced need for fungal culture, faster diagnosis	[4], [8], [18], [43]
Nail psoriasis	Image translation, differential augmentation	Improved distinction from onychomycosis	[9], [16]
Fungal classification	Microscopy image synthesis, super-resolution	Species identification without expert microscopist	[8]
General enhancement	Color/illumination normalization, artifact removal	Standardized teledermatology images	[7], [34]

VI. Challenges and Limitations

The use of GANs in dermatology, and nail disease recognition, in particular, has a number of technical, data-related, and clinical issues. These limitations are important also to be understood to come up with tough systems which are reliable. This sections address research question 3 by identifying barriers and proposed solutions.

A. Training Instability

The adversarial minimax game is known to make the training of GAN unstable. A Nash equilibrium has to be achieved between the generator and the discriminator but in reality, oscillations or divergence are usual. Symptoms include:

A discriminator overpowering generator: The discriminator is too precise, and it does not leave the generator anything to learn.

In case of generator overpowering discriminator: The generator generates unrealistic samples that also mislead a weak discriminator.

Lack of convergence: Even with no increase in the quality of the samples, the values of the losses vary unpredictably. Training instability in dermatological imaging may cause synthetic images which have implausible lesions or artifacts that worsen the downstream classifier performance. Spectral normalization, gradient penalty, and progressive growing are some of the techniques that have been suggested but there is no universal solution [10], [15]. In case of nail images, where the fine structures (lunula, cuticle, hyponychium) are seen, the instability can be observed in the form of blurred or lack of anatomical structures.

B. Mode Collapse

Mode collapse is an extreme form of failure mode in which the generator is able to generate a poor range of output, with the same or very similar outputs being repeated many times. As an illustration, even a GAN trained on onychomycosis images may produce thick and yellow nails with subungual debris instead of the entire range of appearances (e.g., white superficial onychomycosis, proximal subungual onychomycosis). Mode collapse defeats the aim of data augmentation which is to enhance the diversity.

Mode collapse occurs more frequently when dealing with small datasets, as case is the case with nail research. Conditional GANs and unrolled GANs mitigate and not eliminate the issue [15], [31]. Measurements of evaluation such as FID are able to identify mode collapse by comparing the variety of the generated samples to actual information.

C. Lack of Labeled Datasets

The most important obstacle is the lack of big publicly accessible, professionally annotated datasets on nail illnesses. Whereas datasets of skin lesions are tens of thousands of histopathology-confirmed images, nail datasets are generally:

- Small: This category can have less than 1,000 pictures.
- Single-center: The data were captured using a single camera and under a single protocol, hence cannot be generalized.
- Incompletely annotated: Labels can be made on clinical diagnosis that is not confirmed by mycological or histopathological.
- Unpublicized: This is because of privacy issues or infrastructure deficiency.

Data poverty has been recognized as one of the significant impediments to AI in the dermatology field in systematic reviews numerous times [1], [17], [31]. Ravikumar et al. [31] presented in particular the relief of health data poverty in skin lesions by the use of ACGANs, however, it was observed that those attempts have not been applied yet to nail conditions. In the absence of quality real data, GANs will have no way to learn realistic distributions and synthetic data will contribute to or increase existing biases.

D. Ethical and Privacy Concerns

GANs produce fake images that can be similar to actual patients which poses a risk to privacy. Although the image that is generated may not be an exact copy, it may encode identifiable characteristics (e.g. unique nail pigmentation patterns or scars). GANs have been used to perform de-identification [30], although the opposite could happen, which is unintentional re-identification.

There are other ethical issues such as:

- Informed consent: the patients might have not agreed to the use of their images in generating synthetic data, particularly when data are retrieved in the clinical archives.
- Bias amplification: A GAN that is trained on a dataset of light skin will produce only light-toned nails, which may be wrongly diagnosed in darker populations [26], [41].
- As a GAN-augmented classifier makes a wrong diagnosis of a nail condition, the question is, who is at fault: the GAN, the classifier or the training data.

To resolve these issues, it is necessary to have clear data governance and bias audit and possibly specific

regulations governing the use of generative AI in healthcare [15]. [15].

E. Clinical Validation Issues

Most GAN-based dermatology studies stop at technical validation (e.g., FID scores, classifier accuracy on test sets). Clinical validation—demonstrating that synthetic data improve real-world diagnostic accuracy or patient outcomes—is rarely performed. Key issues include:

- Lack of dermatologist evaluation: Few studies ask clinicians to rate synthetic images for realism or diagnostic utility. A low FID does not guarantee that a generated lesion would be recognized as pathological by an expert.
- No prospective testing: Models are evaluated on retrospective datasets, not in live clinical workflows. Performance may degrade due to dataset shift (different camera, population, disease prevalence).
- Unclear clinical utility: Even if a GAN improves classifier AUC, it may not reduce unnecessary biopsies or improve treatment decisions. Clinical utility requires endpoint studies that are expensive and time-consuming [28].

For nail diseases, these validation gaps are even wider. No GAN-based nail diagnostic system has undergone even small-scale clinical piloting, according to the reviewed literature.

VII. Future Research Directions

Referring to the literature gaps outlined, multiple potential paths of moving GAN-based nail disease detection and, more generally, generative AI in dermatology, there are a number of opportunities. This sections address research questions 3 by identifying barriers and proposed solutions.

A. Integration with Real-Time Diagnostic Systems

The existing GANs are computationally expensive, hence they cannot be used in point of care scenarios [51]. Further research needs to be conducted in the future should address:

1)Gathering:

Lightweight GAN architectures Lightweight GANs Lightweight GANs are designed to execute on edge devices (smartphones, portable dermatoscopes) with low latency [52].

2)Augmentation in real-time at the moment of acquisition:

The enhancement of nail images during their capture with the help of GANs to give the clinician an immediate feedback (e.g., "image too dark, repositioning may be necessary, etc.).

3)Automated microscopy:

A GAN module can be used to augment low-quality frames or to create synthetic training images of rare morphologies of the fungi, based on the automated microscope of Gao et al. [8].

In primary care clinics, real-time systems might be implemented, which would not require the use of specialists as well as allow treating onychomycosis and nail psoriasis earlier [54].

B.Hybrid Models (GAN + CNN/Transformer)

The best dermatological classifiers currently have got both generative and discriminative elements [58]. The future nail disease systems should investigate:

1)End-to-end GAN-classifier training

Training a GAN and a CNN/ViT together, which was shown by Sharma and Mehta [37] and Varghese et al. [40].

2)Attention-guided GANs

Adding attention-based generators to target diagnostically significant parts of the nail (e.g. nail bed, hyponychium) like in the attention-based LeSegGAN [18].

3)Lessons learned

Convolutional generators could be substituted by transformer-based generators to learn long-range dependencies in nail images that can be more effective to generate both global nail shape and local texture [57].

It is possible to have higher accuracy of hybrid models compared to either one of the components as demonstrated in skin lesion research [14], [40]. It is only logical to transfer these architectures to nail data.

C. Development of Large Dermatological Datasets Including Nails

The most significant step that can be taken would be the development and publication of massive, annotated datasets of nail diseases. Future efforts should:

1)Multi-center collaboration:

The use of images of many dermatology centers will provide heterogeneity in the presentation of diseases, types of skin, and imaging equipment [60].

2)Standardized annotation protocols

Design a set of standard labels (e.g., onychomycosis subtype, psoriasis severity, fungal species) that are histopathologically or mycologically verifiable [54].

3)Synthetic data:

Since GANs are becoming better, the synthetic nail pictures of a proven quality may be added to the dataset, as done with skin lesion augmentation [31], [41].

4)Active mitigate bias:

Oversample rare events and dark skin tones to produce balanced datasets or can use diffusion models to produce missing distributions [26], [41].

Such dataset initiatives should be given priority by the funding agencies and professional dermatology societies because they are essential in all downstream AI research [53].

D. Explainable AI for Medical Trust

A black box GAN-based diagnostic system is unlikely to be believed by the clinicians [55]. Clinical adoption can thus only be explained. Promising approaches include:

1)Visual concept discovery

Visual-based models (such as SAM (Segment Anything Model)) are used to discover interpretable visual features (e.g., "subungual hyperkeratosis," "onycholysis edge") that are used to generate GAN output or influence classifier decisions [13].

2)Latent space visualization

Visualizing the latent space of StyleGAN to learn what dimensions control particular nail disease features [23].

3)Counterfactual generation:

Finding what-if images, that depict how a nail would look in the case of a feature being altered (e.g. taking out yellow discoloration) which enables clinicians to learn about model reasoning.
Quality control can also be explained GANs: in case a generated image does not contain the expected anatomical structures, it can be considered as low confidence.

E. Deployment in Mobile Healthcare Applications
Dermatology Smartphone based dermatology is becoming more popular, nail imaging is challenging (curved surface, small field of view, variable focus). Future studies need to come up with:
1)Mobile GAN enhancement
This is a small GAN that can be used on a smartphone to improve focus, light, and perspective effects on nail images prior to sending them to a remote dermatologist.
2)Privacy-preserving generation
GANs can be used to create synthetic nail images by using mobile captures that can be sent to a researcher without revealing the identity of the patient [30].
3)Low-bandwidth tele dermatology
The transmission of small latent codes of nail images (produced by an encoder-GAN) instead of entire images, minimizing bandwidth usage of rural or remote clinics [59].
The application of mobile deployment goes along with the general trends of smart healthcare systems [32] and may democratize nail disease diagnosis in the low-resource environment.

VIII. Discussion
This critical review has discussed the use of Generative Adversarial Networks (GANs) in dermatology with particular attention to nail disease detection, which is a field that has been under-investigated despite the clinical significance of nail conditions. The fact that the 43 synthesized studies include not only the pioneering work on neural networks to detect fungi [4] but also recent developments in diffusion models to reduce bias [26] demonstrates both the potential revolution that GANs can introduce and the fact that much still needs to be done before fungi can find its way to clinical practice [61].

A. Synthesis of Key Findings
This evidence consistently supports that GANs overcome three basic problems in image analysis of dermatology, namely, data scarcity, class imbalance, and domain shift.
1)Data augmentation efficacy
In various works, GAN-based augmentation increased the performance of classifiers on skin lesions with accuracy increment of between 5 and 12 percent on minority classes [11], [14], [22]. The conditional GAN type of architecture was especially successful, enabling the use of class-specific generation, which is critical in rare disease settings, with as few synthetic samples potentially being impactful to have an effect on model stability [31], [39]. In the case of nail diseases, where data sets are a million times less than that of skin lesions, the possible effect of GAN augmentation is even larger, but again this is yet to be empirically tested [50].
2)Architectural trade-offs
As demonstrated in the comparative analysis , trade-offs between the variants of GAN were evident. StyleGAN generates the best quality images but requires large training datasets and massive computational resources [23], which is less accessible to nail research when data are scarce. DCGAN has a reduced entry barrier and consistent training but reduced photorealism [22]. Conditional GANs provide a practical trade-off, allowing controlled augmentation at a moderate computational cost [11], [14]. In the case of nail applications, a conditional GAN based on the transfer learning of skin lesion models can be the most realistic starting point.
3)Bias mitigation potential
One of the most interesting recent literature results is the application of generative models to combat diagnostic bias. Munia and Imran [26], [27] have shown that diffusion models can produce realistic dermoscopic images of underrepresented skin tones, which lessen racial bias in downstream classifiers. The same was demonstrated by Wang et al. [41], who revealed that diffusion-based augmentation enhances model fairness. Although the studies involved the use of diffusion models, not GANs, the same principle applies directly: generative models can be useful in health equity. There is no similar literature on nail diseases where the bias with regard to skin color, nail shape difference, and cultural factors (e.g., nail polish, artificial nails) is not studied.

B. Addressing the Nail Disease Gap
The most notable result of this review is that based on GAN research, there is almost no study on nail conditions. Among the 43 sources, few cover the issue of nails altogether, and none of them introduce a full-fledged diagnostic system based on GAN. Artificial intelligence in nails is only present in the following literature:
Early neural network histopathological fungal detection [4].

- Deep learning of automated microscopy [8].
- Geometric nail segmentation [7].
- The narrative reviews that require additional studies.

Such a gap does not exist because of the absence of clinical need. Onychomycosis has an incidence of 1015 percent in the world, nail psoriasis has a high morbidity rate and subungual melanoma has a poor prognosis in case of late diagnosis. Instead, the disparity is indicative of systematic obstacles: there is no big, publicly available nail data; it is difficult to image curved, reflective nail plates, and nail diseases do not receive the same research priority as skin cancer [44].
GANs will be able to overcome these obstacles. As it can be seen in the analysis of skin lesions, GANs can be used to create synthetic data by using small collections of seeds [21], [35], enhance images to remove light and reflection artifacts [34], and cross-image modalities [10], [15]. The pipeline of nail GANs methodology already exists; the only thing that is required is specific application and domain-wise adaptation.

C. Comparison with Broader Medical Imaging Literature
Some of the difficulties that were found in this review, training instability, mode collapse, and the lack of data are not specific to dermatology. The medical imaging field

has come up with a number of solutions that may be replicated to nail GANs:

- Progressive growing GANs: Searching: Gradually enhance the resolution in images in training, enhancing the stability of high-resolution nail images.
- Spectral normalization: This is an additional constraint imposed on the weights of the discriminators, which reduces mode collapse.
- Self-attention GANs: Long-range dependencies are learned, which is useful in the synthesis of coherent nail plate structures.

Architectures that are directly transferable are provided by studies on color normalization [34] and lesion segmentation [18], [43] studies. An example of how generative models can be applied to segmentation tasks, which is required to isolate nail plates in a dermatological image, is the segmentation-aware generative reinforcement network suggested by Zeng et al. [42] to ultrasound images, but not to dermatological images.

D. Reliability and Interpretability Concerns

Although there has been the advancement in technology, a number of obstacles to clinical implementation do exist.

1) Reliability:

The images produced using GAN cannot always be diagnosed. An image of a synthetic onychomycosis may not have the delicate details (e.g., dermatophytoma, spiral hyphae) that may be important in the identification of a species. The existing measures of evaluation (FID, Inception Score) are not much correlated with clinical utility. The GAN framework proposed by Saranya et al. [36] included the dermatologist recommendation, which is a part that should be extended. Clinician-in-the-loop validation should be included in future nail GANs, the images of the synthetic nails are rated by expert dermatologists as to the realism and retention of diagnostic features.

2)Interpretability:

Clinicians will not be able to trust a system that creates or categorizes nail images without clarification. The recent research on interpretable concept discovery with the use of SAM [13] is an avenue. The models can also give human-interpretable explanations of their results by revealing visual concepts (e.g. onycholysis margin, subungual hyperkeratosis) that direct GAN generation. In the same way, the factorization of latent space provided by StyleGAN [23] allows visualizing manipulations with features, which can be used by clinicians to understand how manipulation of a latent dimension would change the nail.

3)Clinical validation:

The literature reviewed is technical in overwhelming numbers. Not many studies incorporate the dermatologist examination [22], [36] and none of them incorporates prospective clinical trials. To develop nail GANs to bench-to-bedside, they must be validated, and it must include:

4)Technical validation:

FID, diversity measures, improvement of classifiers.

5)Clinician validation:

Ratings of the synthetic image realism and diagnostic utility by Dermatologists.

6)Clinical validation:

Prospective trials of GAN-augmented diagnosis against gold standard (mycology, histopathology).

7)Outcome validation:

Testimonies of GAN-based systems enhancing patient-relevant outcomes (time to treatment, cure rates, unnecessary reduction of biopsy).

E. Ethical and Regulatory Considerations

Medical diagnostic GANs present ethical concerns that are increased in dermatology since the specialty is visual based.

1)Privacy

GANs have the ability to memorize and reproduce samples of training, which may include information that may be identified to a patient. A report by Park et al. [30] has reviewed GANs in facial deidentification in dermatology, and the authors have shown that GANs are capable of creating anonymized images with diagnostic features. The same should be done to nail images, which can be unique (e.g. tattoos, scars, jewelry).

2)Bias and fairness

A GAN that has been trained on an unrepresentative dataset will produce biased synthetic images, which will lead to increased health disparities. The DermDiff by Munia and Imran [26] is particularly aimed at diminishing racial prejudice. In the case of nails, the data sets should have a variety of skin tones (Fitzpatrick scale I- VI), nail shape, and cultural alterations (polish, artificial nails). It can be followed by the creation of balanced datasets using conditional GANs [31].

3)Regulatory pathways

The diagnostic systems based on GAN are medical devices that are regulated in the country (FDA in the US, CE marking in Europe). The regulators demand the safety, effectiveness, and reduction of bias. The nail diagnostic system based on GAN is at the initial phase of its development as there is no such system that has passed through the regulatory pathway.

F. Comparison with Alternative Generative Models

Although the given review is devoted to the GANs, it should be noted that the diffusion models have also become a potent rival recently. Diffusion models are used in papers 26, 27, and 41 as opposed to GANs. Diffusion models have a number of benefits: it is easier to train, there is less mode collapse, and the samples are more diverse. They however are slower to compute inference time. Diffusion models should be given a serious consideration in situations where real-time diagnosis is not very pertinent compared to the quality of an image, as is the case of nail disease detection. Comparative analysis of GAN and diffusion model on nail datasets should be done directly in the future.

G. Limitations of This Review

There are various limitations of this review that must be mentioned:

1) Database coverage:

Although four large databases were searched some of the relevant studies might not have been identified especially those that are in the non-English journals or conference proceedings that are not covered by these databases.

2) Publication bias:
The literature that is reviewed is more than proportionate in reporting positive results. Articles that do not show any negative or null results (e.g., GANs which did not enhance classification) are less likely to be published.
3) Heterogeneity of metrics:
The lack of consistency in the reporting of performance measures, datasets, and evaluation procedures also made it difficult to do direct comparison. There is a need to have standardized reporting guidelines of GAN-based medical imaging studies [1], [28].
4) Nail-specific evidence scarcity:
Our findings are not as specific to nail disease detection because of the absence of nail GAN studies. To a great extent, the discussion is based on the extrapolation of the research on the skin lesions.
In spite of these shortcomings, the review offers a mapping of the field, which is comprehensive and an agenda of further nail-based research.

IX. Conclusion

The Generative Adversarial Networks have disrupted the way medical images are processed by enabling one to come up with real images, data augmentation and improvement in diagnosing. Being a systematic review, which is conducted according to the PRISMA principles, the paper has critically evaluated the current situation in the GAN-based dermatology research with a specific focus on the nail disease detection since this area remains underrepresented, yet it is clinically important.

A. Summary of Key Contributions

The review has demonstrated that:
1)GANs address critical data challenges in dermatology.
GANs reduce the class imbalance, minimize bias in data set, and enhance the resistance of the classifier to fake inputs by creating synthetic skin lesion images. The state-of-the-art results with conditional GANs and ACGANs on skin cancer detection have been reported to be over 95 percent accuracy in a number of studies [11], [14], [40].
2)Nail disease is one of the frontier opportunities.
Regardless of the high incidence of onychomycosis, nail psoriasis, and subungual melanoma, there is no specific GAN-based diagnosis system that is validated. Methodological principles of the study of skin lesions, i.e., segmentation GANs [18], [43], augmentation GANs [21], [22], and translation GANs [34] can be directly applied to nail imaging.
3)Significant challenges remain.
Training instability, mode collapse, lack of labeled datasets, ethical concerns, and absence of clinical validation impede translation. It will be necessary to not just deal with technical advancements but also multi-center data programs, clinician-in-the loop assessment, and regulatory involvement to overcome these challenges.

List of Abbreviations

Abbreviation	Full Form
ACGAN	Adaptive Conditional Generative Adversarial Network
AI	Artificial Intelligence
AUC	Area Under the Receiver Operating Characteristic Curve
cGAN	Conditional Generative Adversarial Network
CNN	Convolutional Neural Network
DCGAN	Deep Convolutional Generative Adversarial Network
FID	Fréchet Inception Distance
FN	False Negative
FP	False Positive
GAN	Generative Adversarial Network
GRU	Gated Recurrent Unit
IoU	Intersection over Union
IS	Inception Score
KOH	Potassium Hydroxide (microscopy)
ML	Machine Learning
PAS	Periodic Acid–Schiff (stain)
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SAM	Segment Anything Model
TN	True Negative
TP	True Positive

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Conflict of interest
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