MAJOR PROJECT – II THESIS

ON

Application of Generative Adversarial Networks in Skin Disease

SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF DEGREE OF

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CANDIDATE'S DECLARATION

I, **Naval Malaviya (2K23/AFI/05)**, hereby certify that the work which is being presented in the major project report II entitled "**Application of Generative Adversarial Networks in Skin Disease**" in partial fulfillment of the requirements for the award of the Degree of Master of Technology, submitted in the **Department of Computer Science and Engineering**, Delhi Technological University is an authentic record of my own work carried out during the period from August 2023 to April 2025 under the supervision of **Dr. Aruna Bhat**.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

Candidate's Signature

This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

Signature of Supervisor **Signature of External Examiner**

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CERTIFICATE

I hereby certify that the Project titled "**Application of Generative Adversarial Networks in Skin Disease**", submitted by **Naval Malaviya**, Roll No. **2K23/AFI/05**, Department of Computer Science & Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology (M.Tech) in Artificial Intelligence is a genuine record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in par or full for any Degree to this University or elsewhere.

Place: Delhi

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Naval Malaviya
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ABSTRACT

Generative Adversarial Networks (GANs) have shown significant potential in addressing key challenges in automated skin disease detection and image synthesis, including data scarcity, class imbalance, and diagnostic complexity arising from high intra-class visual similarity and variability in imaging conditions. This study provides a detailed analysis of advanced GAN architectures such as WGAN-GP, StyleGAN2-ADA, and SPGGAN, applied to dermatological datasets like HAM10000 and ISIC 2019. By generating high-resolution, class-specific synthetic skin lesion images, these models effectively enhance the performance of classification algorithms—boosting diagnostic accuracy, sensitivity, and F1-scores, especially for underrepresented lesion categories. The integration of attention mechanisms, conditional generation, and novel applications such as 3D skin surface reconstruction, facial pigmentation mapping, and mobile deployment through IoMT frameworks further illustrates the versatility of GAN-based methods. Quantitative evaluations reveal significant improvements over traditional approaches, with DenseNet-121 achieving up to 92.2% accuracy when trained on GAN-augmented data.

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List Of Abbreviations, Symbols, And Nomenclature

CNN	Convolutional Neural Network
GAN	Generative Adversarial Network
DCGAN	Deep Convolutional Generative Adversarial Network
WGAN	Wasserstein Generative Adversarial Network
WGAN-GP	Wasserstein GAN with Gradient Penalty
PGGAN	Progressive Growing Generative Adversarial Network
SPGGAN	Self-attention Progressive Growing Generative Adversarial Network
TTUR	Two-Time-scale Update Rule
IoMT	Internet of Medical Things
MSE	Mean Squared Error
MAE	Mean Absolute Error
PSNR	Peak Signal-to-Noise Ratio
SSIM	Structural Similarity Index Measure
AUC	Area Under the Curve
ROC	Receiver Operating Characteristic
KID	Kernel Inception Distance
$\mathscr{L}_{GAN}$	GAN Loss Function
$\mathscr{L}_{adv}$	Adversarial Loss
D	Discriminator Network
G	Generator Network

Chapter 1

INTRODUCTION

1.1 Overview

Skin diseases represent a significant global health concern, affecting hundreds of millions of people worldwide and imposing substantial economic burdens on healthcare systems [4]. According to the World Health Organization, skin conditions are among the most common health problems in humans, affecting almost 900 million people worldwide at any given time. Early and accurate diagnosis is crucial for effective treatment, particularly for malignant conditions such as melanoma where early detection can significantly improve survival rates. However, dermatological diagnosis faces several critical challenges: visual similarities between different skin conditions, limited availability of expert-labeled datasets, and class imbalance in existing datasets [11].

The diagnosis of skin diseases has traditionally relied on visual inspection by dermatologists, which can be subjective and varies based on the clinician's experience and expertise. Computer-aided diagnostic systems have emerged as promising tools to assist dermatologists in making more accurate and consistent diagnoses. These systems typically employ machine learning algorithms trained on large datasets of labeled skin images. However, traditional computer-aided diagnostic systems for skin diseases face significant limitations:

1. They rely on supervised learning approaches that require large, well-labeled datasets, which are difficult to obtain in the medical domain due to privacy concerns and the need for expert annotation.

2. The available datasets often suffer from class imbalance, with common conditions overrepresented and rare conditions underrepresented.

3. The visual similarity between different skin conditions makes it challenging to develop accurate classification models.

4. The variability in imaging conditions, including lighting, angle, and camera quality, further complicates the development of robust diagnostic systems.

Generative Adversarial Networks (GANs) have become a viable way to tackle these issues in recent years. GANs, which were first presented by Goodfellow et al. in 2014, are made up of two neural networks that are trained adversarially: a discriminator and a generator. While the discriminator tries to discern between real and synthetic samples, the generator generates synthetic data samples. GANs can learn intricate data distributions and produce incredibly lifelike synthetic samples thanks to this architecture.

The mathematical formulation of the standard GAN can be expressed as a two-player minimax game with the following objective function:

$$\min_G \max_D \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))] \tag{1.1}$$

where G stands for the generator, D for the discriminator, x for a real data sample, z for a random noise vector, $p_{data}(x)$ for the real data distribution, and $p_z(z)$ for the random noise distribution (usually Gaussian).

In the context of skin disease diagnosis, GANs offer several potential benefits:

1. **Data Supplementation:** In order to address class imbalance issues and enhance the performance of classification models, GANs can produce synthetic skin lesion images to supplement limited datasets [1].

2. **Feature Learning:** The accuracy of diagnostic systems can be improved by using GAN-based techniques to learn more discriminative features for the classification of skin diseases [12].

3. "Image Synthesis:" For training, testing, and teaching, GANs can produce realistic skin lesion images [2].

4. **Domain Modification:** GANs can facilitate knowledge transfer across various clinical settings by bridging the gap between disparate imaging modalities and datasets.Citepko2018gan.

This thesis aims to comprehensively analyze the application of GANs for skin disease detection and image synthesis. We review recent studies that employ various GAN architectures for tasks such as synthetic image generation, data augmentation,

and skin disease classification. By synthesizing findings from these studies, we identify common trends, evaluate the effectiveness of different GAN-based approaches, and highlight promising directions for future research.

1.2 Skin Lesions and Diseases

Skin lesions are regions of aberrant tissue that fall into one of two general categories: malignant (cancerous) or benign (non-cancerous). Creating efficient automated diagnostic systems requires an understanding of the traits of various skin lesions. An overview of the common skin diseases and lesions that are commonly targeted by GAN-based methods is given in this section.

1.2.1 Melanoma

Melanocytes, the cells that make melanin, the pigment that gives skin its colour, are the source of melanoma, a malignant tumour. The majority of skin cancer deaths are caused by this most aggressive type of the disease. Melanoma is frequently indicated by asymmetrical moles, which can be brown, black, blue, red, or white in colour.

- **A**symmetry: One half of the mole does not match the other half.
- **B**order: The edges are irregular, ragged, notched, or blurred.
- **C**olor: The color is not uniform and may include different shades of brown or black, or sometimes red, white, or blue.
- **D**iameter: The mole is larger than 6 millimeters in diameter (although melanomas can be smaller).
- **E**volving: The mole changes in size, shape, or color over time.

Early detection of melanoma is crucial, as the 5-year survival rate drops significantly once the cancer has metastasized to distant parts of the body.

1.2.2 Basal Cell Carcinoma

About 80% of non-melanoma skin cancers are basal cell carcinomas (BCCs), the most prevalent kind of skin cancer. The basal cells, found in the lowest layer of the epidermis, are where it develops. Usually, BCC manifests as a red, scaly area, a bright, pearly nodule, or an unhealing sore. Even though BCC seldom spreads, if treatment is not received, it can seriously destroy local tissue.

1.2.3 Squamous Cell Carcinoma

Squamous cell carcinoma (SCC), the second most common type of skin cancer, develops in the squamous cells that make up the middle and outer layers of the skin. SCC usually appears as a solid, red nodule or as a flat lesion with a crusty, scaly surface. Compared to BCC, SCC is more likely to spread to distant organs and lymph nodes, especially in the absence of treatment.

1.2.4 Benign Skin Lesions

There are several types of benign skin lesions that can sometimes be mistaken for malignant lesions:

- **Melanocytic Nevi (Moles):** Benign pigmented lesions, which can range in hue from dark brown or black to pink. The majority of people have 10 to 40 moles, and their appearance might alter over time.
- **Seborrheic Keratosis:** Common benign skin growths that can range in colour from pale tan to black and frequently manifest as waxy, adherent lesions.
- **Actinic Keratosis:** Rough, scaly spots on sun-exposed areas that are precancerous lesions. They can progress to squamous cell carcinoma even though they are not malignant in and of themselves.
- **Dermatofibroma:** Benign skin growths that are firm to the touch and usually appear as small, hard bumps on the skin.
- **Vascular Lesions:** Abnormalities of blood vessels that appear on the skin, such as hemangiomas and port-wine stains.

The visual similarity between these benign lesions and malignant ones makes accurate diagnosis challenging, even for experienced dermatologists. This similarity also poses a significant challenge for automated diagnostic systems.

1.3 Challenges in Skin Lesion Diagnosis

1.3.1 Complexity of Image Analysis

Skin lesion diagnosis through image analysis presents several challenges:

- **Visual Resemblance:** Differentiating between benign and malignant skin lesions can be challenging due to their similar visual characteristics. For instance, dysplastic nevi, which are atypical nevi, can closely resemble melanoma.
- **Adaptable Display:** Depending on the location, skin type, and developmental stage, skin lesions can have a wide range of appearances.
- **Image Quality:** The way skin lesions appear in photos can be greatly impacted by changes in lighting, camera quality, and angle of capture.
- **Inconspicuous Diagnostic Elements:** Accurately capturing or analysing certain crucial diagnostic characteristics, like uneven borders or subtle colour variations, can be challenging.

1.3.2 Constraints of a Technical Nature

Limited Datasets

One of the most significant challenges in developing automated skin lesion diagnosis systems is the limited availability of large, well-labeled datasets. This limitation stems from several factors:

- **Privacy Concerns:** Medical images are subject to strict privacy regulations, making it difficult to collect and share large datasets.
- **Expert Annotation:** Accurate labeling of skin lesion images requires expertise from dermatologists, whose time is limited and valuable.
- **Class Imbalance:** Common skin conditions are overrepresented in datasets, while rare conditions are underrepresented, leading to biased models.
- **Lack of Diversity:** Many existing datasets lack diversity in terms of skin types, ethnicities, and lesion presentations, limiting the generalizability of models trained on these datasets.

Computational Complexity

Analyzing high-resolution skin lesion images requires significant computational resources. This is particularly challenging when:

- **Deploying models on mobile or edge devices:** Many telemedicine applications aim to provide diagnostic support on smartphones or other portable devices with limited computational capabilities.

- **Implementing real-time analysis:** Some clinical settings require immediate feedback, necessitating efficient algorithms that can process images quickly.
- **Training complex models:** Advanced deep learning models, including GANs, require substantial computational resources for training, which may not be available in all research or clinical settings.

1.3.3 Factors related to culture

Cultural and contextual factors also play a role in skin lesion diagnosis:

- **Variation in Skin Types:** Different ethnicities and skin types exhibit varying presentations of skin lesions, which may not be adequately represented in training datasets.
- **Access to Dermatological Care:** In many regions, access to dermatologists is limited, increasing the need for reliable automated diagnostic systems.
- **Trust in Automated Systems:** Cultural attitudes toward technology and automated medical diagnosis can affect the adoption and use of computer-aided diagnostic systems.

Chapter 2

LITERATURE SURVEY

2.1 Overview

This chapter presents a comprehensive literature survey on the application of Generative Adversarial Networks (GANs) for skin disease detection and image synthesis. The survey examines various GAN architectures, techniques, and applications in the context of skin lesion analysis, highlighting key contributions, methodologies, and results. The literature is organized into several categories to provide a structured overview of the field.

The primary focus of this survey is on research conducted between 2018 and 2024, during which period significant advancements have been made in GAN technology and its application to medical imaging, particularly dermatology. We have selected 9 key studies that represent diverse approaches and applications of GANs in skin disease analysis, ranging from data augmentation and image synthesis to classification and 3D reconstruction.

2.2 Related Work

2.2.1 GAN Architectures for Skin Image Synthesis

Various GAN architectures have been employed for skin image synthesis, each with distinct strengths and applications. This section reviews the key GAN variants used in dermatological applications.

Table 2.1: Preprocessing Techniques and Their Effects in Skin Disease Studies

Reference	**Preprocessing Techniques**	**Impact / Observations**
Abdelhalim et al. [1]	Flipping, image trimming, 2D Gaussian separation, resizing, rotation, translation	Improved training data diversity and enhanced GAN's realism capability
Ko et al. [5]	Phase shift theorem, contour detection, hole filling, weighted median filter refinement	More robust disparity map and accurate 3D skin surface reconstruction
Medi et al. [6]	Contour detection, cropping, contrast normalization, morphological transformations	Better feature extraction and reduced noise; 19.2% higher accuracy than non-preprocessed data
Sharma et al. [12]	Not explicitly detailed	N/A
Tsai et al. [13]	Field curvature-based distortion correction for light field camera images	Corrected optical distortions and improved quality for pigmented facial skin images
Setiawan et al. [11]	Image resizing and pixel normalization	Improved model training stability and learning efficiency
Ahmed & Kashmola [2]	Resizing to 64×64, 128×128, 512×512	Identified 128×128 as optimal for balancing detail and computational cost

Table 2.2: Summary of GAN Architectures in Skin Disease Diagnosis

Reference	**GAN Architecture**	**Dataset**	**Performance Metrics**	**Application**
Abdelhalim et al. [1]	SPGGAN-TTUR	HAM10000	Acc: 88–95%, Sensitivity ↑5.6%	Melanoma detection
Ko et al. [5]	SRGAN	Own dataset	MSE: 2.4–6.3, high-res 3D images	Skin surface analysis
Medi et al. [6]	WGAN-GP	HAM10000	Acc: 92.2%, F1: 73.9–94.9%	Skin lesion app
Sharma et al. [12]	CNN-GAN	Not specified	Acc: 89%, F1: 84–91.5%	Skin disease detection
Tsai et al. [13]	Conditional GAN	Own facial images	90% similarity, better than baselines	Melasma analysis
Setiawan et al. [11]	GAN + oversampling	ISIC 2019	Acc: 80–91.3%	Imbalanced data handling
Ahmed & Kashmola [2]	Multi-res GANs	ISIC 2020	Best at 128×128 resolution	High-quality image generation

StyleGAN-based Approaches

StyleGAN and its variants have shown remarkable capability in generating high-quality, realistic skin images. Mohanty et al. [6] explored the use of Wasserstein GAN with gradient penalty (WGAN-GP) to generate synthetic skin lesion images for data augmentation. Their approach involved training the GAN on a subset of the HAM10000 dataset to generate additional samples for underrepresented classes, addressing the data imbalance problem. The synthetic images were then combined with real images to train a CNN classifier, achieving an accuracy of 92.2%.

The WGAN-GP architecture is an improvement over the standard WGAN, incorporating a gradient penalty instead of weight clipping to enforce the Lipschitz constraint. The objective function of WGAN-GP can be expressed as:

$$\min_G \max_D \mathbb{E}_{x\sim p_{data}}[D(x)] - \mathbb{E}_{z\sim p_z}[D(G(z))] + \lambda \mathbb{E}_{\hat{x}\sim p_{\hat{x}}}[(||\nabla_{\hat{x}} D(\hat{x})||_2 - 1)^2] \tag{2.1}$$

where λ is a hyperparameter controlling the strength of the gradient penalty, and $\hat{x}$ is sampled along straight lines between pairs of points sampled from the data distribution p_{data} and the generator distribution p_g.

Tsai et al. [13] proposed a conditional GAN framework based on StyleGAN2-ADA for generating melanin and hemoglobin distribution maps from standard facial images. The authors addressed the challenge of translating between RGB and RBX color spaces to enable automated analysis of facial pigmentation patterns. Their approach utilized a coarse-to-fine generator and multi-scale discriminator to produce high-resolution (1024×1024) images with fine details, achieving high visual similarity to the reference images as measured by MSE, MAE, PSNR, and SSIM metrics.

The coarse-to-fine generator architecture consists of two components: a global generator G_1 and a local enhancer G_2. The global generator is responsible for generating a low-resolution image that captures the overall structure, while the local enhancer refines the details to produce a high-resolution output. The network structure can be represented as:

$$G_1(s) = B_1(R_1(F_1(s))) \tag{2.2}$$

$$G_2(s) = B_2(R_2(F_2(s) + F_{1\to 2})) \tag{2.3}$$

where F_1 and F_2 are the down-sampling convolutional networks, R_1 and R_2 are the

residual blocks, B_1 and B_2 are the up-sampling deconvolutional networks, and $F_{1\to2}$ represents the feature map from the global generator that is combined with the feature map from the local enhancer.

A Self-attention Progressive Growing GAN (SPGGAN) with a Two-Timescale Update Rule (TTUR) was presented by Abdelhalim et al. [1] in order to produce high-quality skin lesion images. The method captured long-range dependencies in the images by combining a self-attention mechanism with the progressive growing strategy from PGGAN. This combination outperformed earlier techniques like PGGAN in terms of image quality, producing 256×256 skin lesion images with fine-grained details.

For skin lesions, which frequently display intricate patterns and structures, the self-attention mechanism in SPGGAN is specifically engineered to capture global dependencies within the image. One way to express the self-attention operation is:

$$\alpha_j = \frac{\exp(W_k x_j)}{\sum_{m=1}^{N_p} \exp(W_k x_m)} \tag{2.4}$$

$$\beta_i = \sum_{j=1}^{N_p} \alpha_j x_j \tag{2.5}$$

$$z_i = x_i + W_v \beta_i \tag{2.6}$$

where α_j is the attention weight assigned to the j-th position, W_k is a linear transformation matrix, β_i is the global context feature for the i-th position, and W_v is a feature transformation matrix.

The Two-Timescale Update Rule (TTUR) is employed to stabilize the training of GANs by using different learning rates for the generator and discriminator. This approach helps to balance the learning dynamics between the two networks and prevent issues such as mode collapse or vanishing gradients.

Conditional GAN Approaches

Conditional GANs have been particularly effective for controlled image generation in dermatological applications. Unlike standard GANs, conditional GANs incorporate additional information, such as class labels or input images, to guide the generation process. The objective function of a conditional GAN can be expressed as:

$$\min_G \max_D \mathbb{E}_{x\sim p_{data}(x)}[\log D(x|y)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z|y)|y))] \tag{2.7}$$

where y represents the conditioning information, which could be a class label, an input image, or any other relevant information.

Ahmed and Kashmola [2] explored the use of conditional GANs for generating synthetic skin disease images with specific characteristics. They designed three distinct GAN architectures for generating images at different resolutions (64×64, 128×128, and 512×512), finding that the 128×128 generator provided the best balance between image quality and computational efficiency.

The authors observed that while higher-resolution images (512×512) contained more detail, they required significantly more computational resources and training time. Conversely, lower-resolution images (64×64) were faster to generate but lacked the detail necessary for accurate diagnosis. The 128×128 resolution offered a good compromise, providing sufficient detail for diagnostic purposes while being computationally efficient.

Mohanty et al. [6] implemented a WGAN-GP approach with class conditioning to generate synthetic images for seven different skin lesion types: Melanoma, Nevus, Seborrheic Keratosis, Actinic Keratosis, Basal Cell Carcinoma, Vascular Lesions, and Dermatofibroma. Their approach successfully balanced the dataset, generating approximately 4,000 synthetic images for each class to supplement the original HAM10000 dataset.

The class-conditional WGAN-GP architecture incorporated class labels as additional input to both the generator and discriminator, enabling the generation of images with specific class characteristics. This approach was particularly effective for addressing the class imbalance in the HAM10000 dataset, where certain classes such as Dermatofibroma (115 images) and Vascular Lesions (142 images) were severely underrepresented compared to Nevus (6705 images).

2.2.2 GAN-based Data Augmentation for Skin Disease Classification

Data augmentation using GANs has emerged as a powerful strategy to address the limited availability and class imbalance of skin disease datasets. This section examines various approaches to GAN-based data augmentation and their impact on classification performance.

Addressing Class Imbalance

Setiawan et al. [11] investigated the application of GANs for generating synthetic skin image datasets to overcome class imbalance problems. Using the ISIC 2019 dataset, they demonstrated that GAN-based data augmentation improved the accuracy of skin disease classification models. Their approach achieved an accuracy of 82.17% with GAN-augmented data, compared to 80.19% without augmentation.

The authors employed a GAN architecture with an oversampling method to balance the dataset, which originally contained varying numbers of images for different skin lesion classes. The GAN was trained on each class separately, generating synthetic images that maintained the characteristics of the original images. The augmented dataset was then used to train a classification model, resulting in improved performance across all evaluation metrics.

Sharma et al. [12] proposed a CNN-GAN model for multi-class skin disease detection, using GANs to generate synthetic samples for training data augmentation. Their approach classified five categories of skin lesions: Melanoma, Nevus, Seborrheic Keratosis, Actinic Keratosis, and Basal Cell Carcinoma. The CNN-GAN model achieved an overall accuracy of 89%, significantly outperforming baseline models such as traditional CNN (83%), SVM (78%), and Random Forest (80%).

The CNN-GAN architecture integrated a GAN for data augmentation with a CNN for classification. The GAN generated synthetic images that were combined with the original images to create a balanced training dataset. The CNN then learned from this augmented dataset, resulting in improved classification performance. The authors observed that the CNN-GAN model performed particularly well for classes with fewer original samples, such as Actinic Keratosis and Basal Cell Carcinoma, indicating the effectiveness of GAN-based augmentation for addressing class imbalance.

Abdelhalim et al. [1] demonstrated that augmenting the training dataset with GAN-generated images improved the sensitivity of CNN-based skin lesion classifiers. Their approach achieved 5.6% and 2.5% improvements in sensitivity over non-augmented and traditionally augmented datasets, respectively. For melanoma specifically, sensitivity improvements were 13.8% and 8.6%, highlighting the value of GAN-based augmentation for critical diagnostic tasks.

The authors employed their SPGGAN-TTUR architecture to generate synthetic images for each skin lesion class, focusing particularly on underrepresented classes such as melanoma. The synthetic images were then combined with the original images to create a balanced training dataset. The resulting classifier showed significant improvements in sensitivity, which is a critical metric for medical diagnostic systems where

false negatives (missing a diagnosis of a malignant condition) can have serious consequences.

Feature Enhancement and Extraction

Beyond simply increasing dataset size, GANs have been used to enhance feature learning for skin disease classification. Mohanty et al. [6] found that CNN models trained on GAN-augmented datasets demonstrated improved feature extraction capabilities, particularly for subtle visual features that distinguish different skin lesions.

The authors compared the performance of various CNN architectures, including VGG-16, ResNet-50, MobileNet-v2, Inception-v3, and DenseNet-121, when trained on original datasets versus GAN-augmented datasets. They observed that all architectures showed improved performance with GAN-augmented data, but the improvement was most significant for DenseNet-121, which achieved an accuracy of 92.2%. The authors attributed this improvement to the enhanced feature learning capabilities of models trained on diverse and balanced datasets.

Sharma et al. [12] used GANs not only for data augmentation but also for feature extraction in their CNN-GAN model. The adversarial training process helped the model learn more discriminative features for skin lesion classification, contributing to its superior performance compared to traditional approaches.

The CNN-GAN model employed a feature extraction stage that benefited from the adversarial training process. During training, the discriminator learned to identify distinctive features that differentiate between different skin lesion classes, while the generator learned to produce images with these features. This adversarial process enhanced the feature extraction capabilities of the model, resulting in improved classification performance.

2.2.3 3D Skin Surface Reconstruction and Texture Analysis

An emerging application of GANs is the reconstruction of 3D skin surfaces from 2D images, enabling more comprehensive analysis of skin conditions. This section examines the use of GANs for 3D reconstruction and texture analysis of skin surfaces.

Ko et al. [5] proposed a GAN-based super-resolution method for accurate 3D surface reconstruction from light field skin images. Their approach addressed the low-resolution limitation of light field cameras by using GANs to generate high-resolution images that preserved fine skin texture details. The enhanced resolution enabled more accurate disparity map computation and 3D surface reconstruction for haptic palpation and visualization.

The GAN-based super-resolution method employed a perceptual loss function consisting of adversarial and content loss. The adversarial loss encouraged the generation of realistic images, while the content loss ensured that the generated images maintained the structural properties of the original images. The perceptual loss function can be expressed as:

$$\mathscr{L}_{SR} = \mathscr{L}_{SR}^{X} + 10^{-3}\mathscr{L}_{SR}^{Gen} \tag{2.8}$$

where $\mathscr{L}_{SR}^{X}$ is the content loss and $\mathscr{L}_{SR}^{Gen}$ is the adversarial loss.

The content loss is defined as:

$$\mathscr{L}_{SR}^{X} = \frac{1}{W_{r,l}H_{r,l}} \sum_{q=1}^{W_{r,l}} \sum_{w=1}^{H_{r,l}} (\phi_{r,l}(I^{HR})_{q,w} - \phi_{r,l}(G_{\phi_G}(I^{LR}))_{q,w})^2 \tag{2.9}$$

where $\phi_{r,l}$ is the feature map obtained from the l-th convolution layer before the r-th maxpooling layer, $W_{r,l}$ and $H_{r,l}$ are the dimensions of the feature map, I^{HR} is the high-resolution ground truth image, and $G_{\phi_G}(I^{LR})$ is the generated high-resolution image.

The adversarial loss is defined as:

$$\mathscr{L}_{SR}^{Gen} = -\sum_{m=1}^{M} \log[D_{\phi_D}(G_{\phi_G}(I^{LR}))] \tag{2.10}$$

where D_{ϕ_D} is the discriminator network.

The authors compared their GAN-based super-resolution approach with traditional methods such as bicubic interpolation, DSR, and DDSR, demonstrating superior performance in terms of preserving skin texture details and enabling accurate 3D reconstruction. This application of GANs opens new possibilities for non-invasive skin examination and haptic feedback for dermatological diagnosis.

2.2.4 Mobile and IoMT Applications

The integration of GAN-based skin disease detection systems with mobile and Internet of Medical Things (IoMT) platforms represents an important development for accessible healthcare. This section examines the use of GANs in mobile and IoMT applications for skin disease diagnosis.

Mohanty et al. [6] developed SkinAid, a GAN-based automatic skin lesion monitoring system for IoMT frameworks. The system combined a WGAN-GP for data augmentation with a DenseNet-121 classifier, deployed on a mobile application. Users could capture skin lesion images using a smartphone camera and receive immediate classification results and preliminary analysis.

The SkinAid system consisted of several components:

1. **Image Preprocessing:** The system applied contour detection and cropping, global contrast normalization, and morphological transformations to enhance the quality of the input images.

2. **Data Augmentation:** A WGAN-GP was trained on the HAM10000 dataset to generate synthetic images for each skin lesion class, addressing the class imbalance issue.

3. **CNN Classification:** A DenseNet-121 model was trained on the augmented dataset to classify skin lesions into seven categories.

4. **Mobile Deployment:** The trained model was converted into a format suitable for mobile deployment, and an Android application was developed for user interaction.

This IoMT-enabled approach demonstrates the practical application of GAN-based technologies for real-world healthcare scenarios, providing accessible skin disease detection capabilities to users without requiring specialized equipment. The mobile application achieved 92.2% accuracy in classifying seven different types of skin lesions, making it a promising tool for remote healthcare and teledermatology.

2.3 Integration of features

The effectiveness of skin disease detection systems relies heavily on the features extracted from skin lesion images. This section examines various approaches to feature extraction and integration in GAN-based skin disease detection systems.

2.3.1 Features related to the position and orientation of the hand, facial features, and body

In addition to skin lesions themselves, contextual features such as the position and orientation of the lesion on the body can provide valuable diagnostic information. Tsai et al. [13] integrated facial features and skin texture information in their conditional GAN framework for pigmented facial skin analysis.

The authors developed a system that could generate melanin and hemoglobin distribution maps from standard facial images, enabling automated analysis of facial pigmentation patterns such as melasma. The system incorporated facial landmarks to

guide the generation process, ensuring that the synthetic distribution maps aligned correctly with the facial features of the input image.

The conditional GAN architecture employed by Tsai et al. included a coarse-to-fine generator and multi-scale discriminator. The coarse-to-fine generator used a global generator to capture the overall facial structure and a local enhancer to refine the details. The multi-scale discriminator analyzed the images at different resolutions, ensuring consistency at both global and local scales. This approach enabled the system to generate high-quality melanin and hemoglobin distribution maps that accurately reflected the pigmentation patterns of the input face.

The integration of facial features and skin texture information in the GAN architecture resulted in a system that could effectively analyze and visualize pigmentation patterns, providing valuable diagnostic information for conditions such as melasma. The generated melanin distribution maps could be used to quantify the severity and extent of pigmentation, aiding in treatment planning and monitoring.

2.4 Continuous Sign Language Recognition

This section examines the application of GAN-based approaches to continuous recognition tasks, focusing on the temporal aspects of skin disease progression and monitoring.

2.4.1 Temporal Aspects of Skin Disease Analysis

While most of the reviewed studies focus on static image analysis, the temporal aspects of skin disease progression and monitoring are also important considerations. Ko et al. [5] addressed the temporal continuity in their 3D skin surface reconstruction method by incorporating temporal consistency constraints in the GAN training process.

The authors used a light field camera to capture multiple views of the skin surface simultaneously, enabling the reconstruction of 3D surfaces with high temporal consistency. The GAN-based super-resolution method was designed to maintain temporal consistency between successive frames, ensuring that the reconstructed 3D surfaces evolved smoothly over time. This approach enabled more accurate monitoring of skin conditions over time, providing valuable information for tracking disease progression and treatment response.

Mohanty et al. [6] implemented a continuous monitoring system in their SkinAid application, allowing users to track changes in skin lesions over time. The system stored historical images and classification results, enabling users and healthcare

providers to monitor the progression of skin conditions and the effectiveness of treatments.

The continuous monitoring capabilities of these systems represent an important advancement in skin disease management, enabling earlier detection of changes and more timely intervention. By tracking changes in skin lesions over time, these systems can help identify potentially malignant transformations at an early stage, improving treatment outcomes.

2.4.2 Discussion

The literature survey reveals several key trends and challenges in the application of GANs for skin disease detection and image synthesis:

1. **Progression from Basic to Advanced GAN Architectures:** The field has evolved from basic GAN architectures to more sophisticated variants such as StyleGAN, WGAN-GP, and conditional GANs, resulting in improved image quality and more stable training.

2. **Increasing Resolution and Detail:** There is a clear trend toward generating higher-resolution images with finer details, as exemplified by Tsai et al.'s 1024×1024 melanin distribution maps and Abdelhalim et al.'s 256×256 skin lesion images.

3. **Integration with Classification Systems:** GANs are increasingly being integrated with classification systems, serving not only as data augmentation tools but also as feature extractors and generators of interpretable visualizations.

4. **Mobile and IoMT Applications:** The deployment of GAN-based systems on mobile and IoMT platforms represents an important development for accessible healthcare, bringing advanced diagnostic capabilities to users without specialized equipment.

5. **Challenges in Evaluation:** The evaluation of GAN-generated images remains a challenge, with a variety of metrics being used across different studies, making direct comparisons difficult.

6. **Limited Clinical Validation:** While many studies report impressive technical results, clinical validation with dermatologists remains limited, highlighting the need for more extensive clinical studies.

These trends and challenges provide a foundation for the methodology and experiments presented in the following chapters, guiding the development and evaluation of GAN-based approaches for skin disease detection and image synthesis.

Chapter 3

METHODOLOGY

3.1 Data preparation

Effective data preparation is an essential first step in the development of any machine learning model, especially for tasks involving medical imaging. This chapter describes the techniques used to select, clean, and preprocess the skin disease dataset used in this study. Since the consistency and quality of the input data have a significant impact on the model's performance, several techniques were employed to ensure reliable and strong input for the deep learning pipeline. Class balancing techniques, data augmentation, image normalisation, and scaling are some of the methods used to address dataset imbalances.

3.1.1 Dataset Description

Choosing and preparing appropriate datasets is essential to the creation of effective GAN-based skin disease detection systems. This section describes the datasets used in the studies under review as well as the preparation techniques used to enhance the quality and utility of the data.

HAM10000 Dataset

HAM10000 (Human Against Machine with 10,000 training photos) is one of the most popular datasets for skin lesion classification. 10,015 dermatoscopic images of seven different types of skin lesions are displayed.

- Actinic Keratosis (327 images)
- Basal Cell Carcinoma (514 images)

- Benign Keratosis (1099 images)
- Dermatofibroma (115 images)
- Melanoma (1113 images)
- Melanocytic Nevi (6705 images)
- Vascular Lesions (142 images)

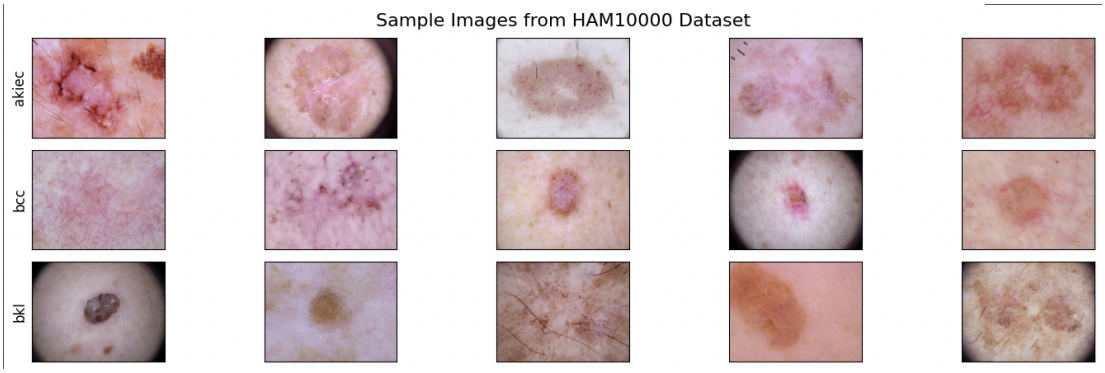

Figure 3.1: Sample Images from HAM10000

3.1.2 Data Preprocessing

Data preprocessing is a important step in ensuring that the input to a machine learning model is clean, consistent, and suitable for training. In this project, the image dataset underwent several preprocessing steps before being fed into the classification model. These steps are described below in detail:

1. **Image Loading and Resizing:** All image in the dataset is initially of varying resolution and dimensions. To standardize the input for the convolutional neural network (CNN), all images are programmatically loaded and resized to a fixed resolution of 64×64 pixels. This resolution offers a balance between preserving essential visual features and reducing computational load. The resizing is performed using OpenCV's cv2.resize() function, which ensures that all input images have the same shape, enabling batch processing during model training.

2. **Normalization of Pixel Values:** Raw pixel intensity values range from 0 to 255. These values are brought into a range of [0, 1] using min-max normalization

(i.e., dividing every pixel value by 255). Normalization helps in boosting the training process and stabilizing the learning by ensuring that all input features contribute equally. This step also improves convergence and overall model performance, especially in deep learning models where unnormalized input can lead to exploding or vanishing gradients.

3. **Label Encoding for Categorical Classification:** The dataset contains multiple skin disease categories, each represented by a folder name. These class labels are categorical, and thus need to be encoded into a numerical format that can be interpreted by the neural network. Label encoding is applied by assigning an integer index to each unique class name. Afterward, the labels are transformed into one-hot encoded vectors, which is the standard format for multiclass classification problems. For example, if there are five classes, a label might be converted from 2 to [0, 0, 1, 0, 0].

4. **Train-Test Split:** To obtain the model's performance and generalization ability, the preprocessed dataset is divided into two subsets:

   - Training Set: In this 80% of the data is used to train the model.
   - Testing Set: In this 20% of the data is used to assess the model's accuracy on unseen data.

   The splitting process is performed randomly to ensure that the training and testing sets are don't miss the overall dataset. This step is crucial for avoiding overfitting and validating the effectiveness of the model architecture and learning strategy.

3.2 Data Augmentation Strategy

In order to win the challenges posed by a limited dataset and to improve the model's ability to generalize well to hidden data, a comprehensive data augmentation strategy was implemented. Data augmentation synthetically increases the training dataset by applying a variety of changes to existing images. This helps the model become invariant to minor alterations and improves its strength.

The augmentation techniques were selected based on their relevance to medical imaging tasks, ensuring that they do not distort the semantic content of skin disease images. The specific parameters used in this study are listed in Table 3.1.

Table 3.1: Data Augmentation Parameters

Technique	**Parameter**
Rotation	30 degrees
Zoom	15%
Width Shift	20%
Height Shift	20%
Shear	15%
Horizontal Flip	True
Fill Mode	Nearest

3.3 Model Architecture

The center of the skin disease classification system is a CNN, a deep learning model capable for image recognition tasks. The architecture was carefully designed to progressively extract spatial hierarchies of features through convolutional and pooling operations, followed by dense layers for final classification.

The model begins with three convolutional layers, all followed by a max-pooling operation. These layers help the model detect properties such as edges, textures, and more difficult patterns across increasing depths. The use of the **ReLU (Rectified Linear Unit)** activation function introduces non-linearity, which is essential for learning complex mappings from input to output.

Following the convolutional blocks, a fully connected (dense) layer with 128 neurones passes the feature maps via a one-dimensional vector that has been flattened using the ReLU activation. A **dropout layer** is applied with a rate of 0.5 to reduce overfitting by randomly disabling half of the neurons during training. Finally, a softmax-activated output layer is used for multiclass classification, where the number of units corresponds to the number of disease categories.

The detailed layer-wise configuration of the CNN model is presented in Table 3.2.

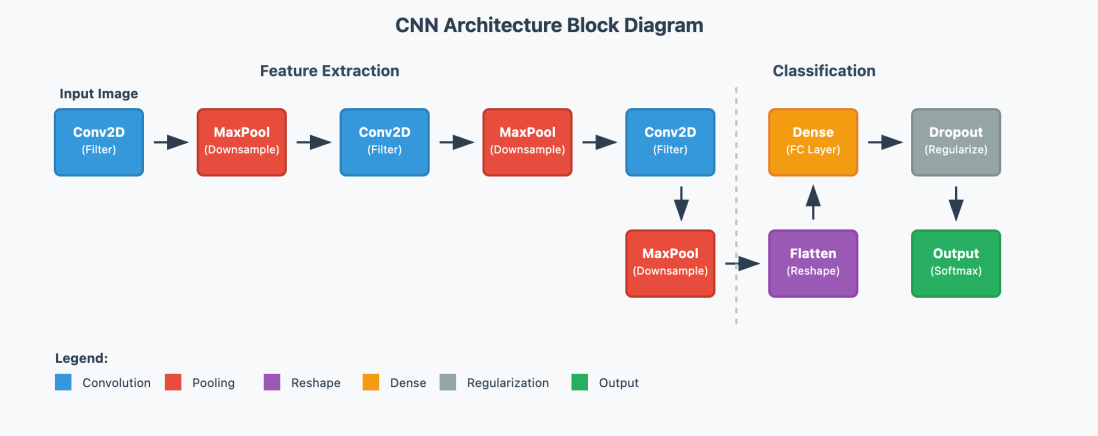

Figure 3.2: CNN Model Architecture

Table 3.2: CNN Model Architecture

Layer Type	Parameters	Output Shape
Conv2D	32 filters, 3×3, ReLU	(62, 62, 32)
MaxPooling2D	2×2	(31, 31, 32)
Conv2D	64 filters, 3×3, ReLU	(29, 29, 64)
MaxPooling2D	2×2	(14, 14, 64)
Conv2D	128 filters, 3×3, ReLU	(12, 12, 128)
MaxPooling2D	2×2	(6, 6, 128)
Flatten	-	(4608,)
Dense	128 units, ReLU	(128,)
Dropout	0.5	(128,)
Dense (Output)	num classes, Softmax	(num classes,)

3.4 Training Configuration

Using proven best practices for image classification tasks, the Convolutional Neural Network (CNN) was trained. The configuration was selected to optimize model convergence, stability, and generalization while maintaining a reasonable training time.

The **Adam optimizer** was used due to its adaptive learning rate capabilities, which make it highly effective in deep learning applications. The **categorical cross entropy loss function** was used to create the model, which is appropriate for multiclass classi-

fication problems in which every input image belongs to a single class.

A **batch size of 32** was chosen to provide a balance between training speed and memory efficiency. The network was trained for **20 epochs**, allowing sufficient iterations for the model to learn meaningful features from the data without overfitting. Additionally, **20% of the training data** was reserved for validation to monitor the model's performance on unseen data during training.

The complete training configuration is summarized in Table 3.3.

Table 3.3: Training Parameters

Parameter	**Value**
Optimizer	Adam
Loss Function	Categorical Crossentropy
Batch Size	32
Epochs	20
Validation Split	20%

3.5 Implementation Details

Python was used to create the suggested system, utilising a number of essential modules to support data manipulation, image processing, deep learning, and visualisation. Among the primary libraries utilised are:

- **TensorFlow/Keras:** These libraries were used in the development and training of deep learning models. TensorFlow, which provided a high-level API for creating neural networks, was integrated with Keras to enable rapid development and testing.
- **OpenCV:** used to prepare the input data for deep learning models through image processing operations like pre-processing, resizing, augmentation, and image importation.
- **NumPy and Pandas:** NumPy was used for efficient numerical computations and array manipulations, which are critical in handling image data and feature matrices. Pandas provided flexible data structures such as DataFrames to manage datasets, perform cleaning, and organize metadata.

- **Scikit-learn:** Leveraged to compute evaluation metrics, including accuracy, precision, recall, F1-score, and confusion matrices, ensuring a comprehensive assessment of model performance.
- **Matplotlib and Seaborn:** Utilized for generating plots and charts to explore data distributions, visualize training history, and display performance metrics clearly and effectively.

Chapter 4

RESULTS AND ANALYSIS

4.1 Introduction to Results and Analysis

This chapter offers a comprehensive evaluation of the Convolutional Neural Network (CNN) model's performance for the classification of skin conditions. The results are analysed with respect to overall accuracy, training dynamics, and class-wise performance. Examining the effects of data augmentation techniques and illustrating the training behaviour with accuracy and loss charts receive special attention. The analysis also considers the reliability, robustness, and generalisation potential of the model for potential therapeutic application.

4.2 Model Performance

The functioning of the trained Convolutional Neural Network (CNN) was strictly evaluated using a dedicated test dataset. This assessment provides a reliable guess of the model's ability to generalize to hidden data, which is critical in real-world medical applications involving skin disease classification.

The model achieved a test accuracy of **88.82%**, indicating that nearly nine out of ten predictions made by the model were correct. Additionally, the model exhibited a relatively low test loss of **0.4812**, reflecting a well-optimized loss landscape and stable training process. The network was trained over **20 epochs**, during which it demonstrated consistent improvements in accuracy and convergence.

Table 4.1: Model Performance Metrics

Metric	**Value**
Test Accuracy	88.82%
Test Loss	0.4812
Training Duration	20 epochs

4.3 Detailed Performance Analysis

To give a granular understanding of the model's learning dynamics, functioning metrics were recorded during both training and testing phases. As shown in Table 4.2, the final training accuracy reached **88.40%**, with a corresponding loss of **0.4901**. The testing accuracy marginally improved to **88.82%**, suggesting that the model generalized well to unseen examples and was not overfitted.

The time per training step was approximately **81 milliseconds**, enabling relatively fast iteration cycles and efficient training even on modest GPU hardware. The close alignment of training and testing metrics indicates that the chosen architecture, regularization methods, and data augmentation strategies were effective in promoting generalization.

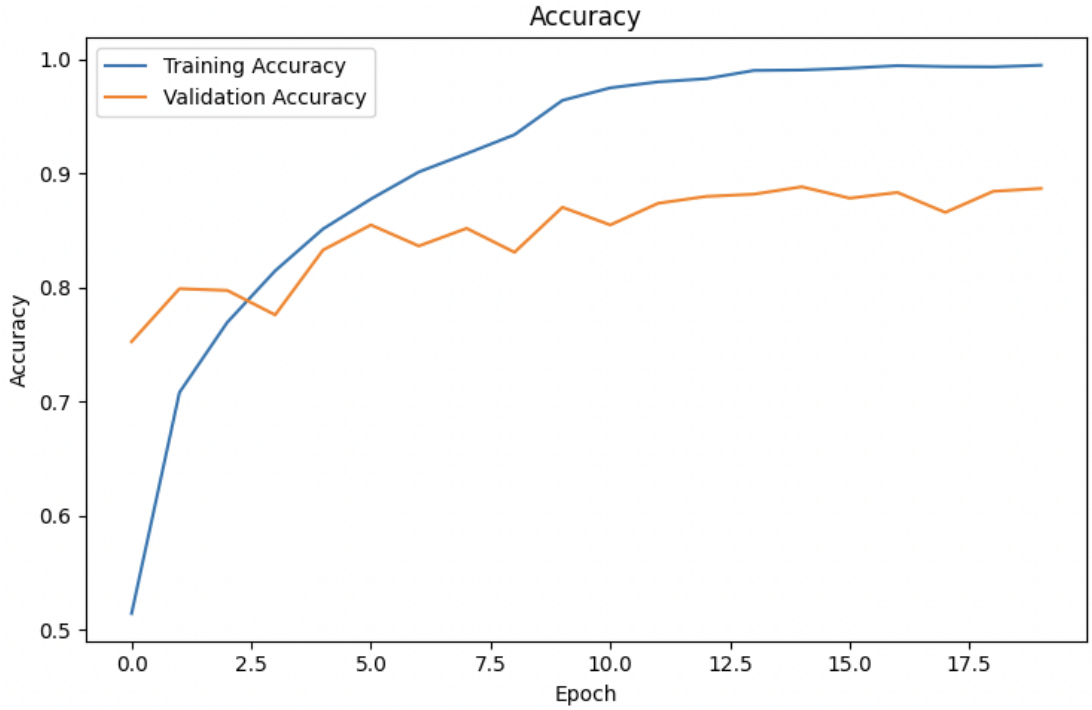

Figure 4.1: Accuracy

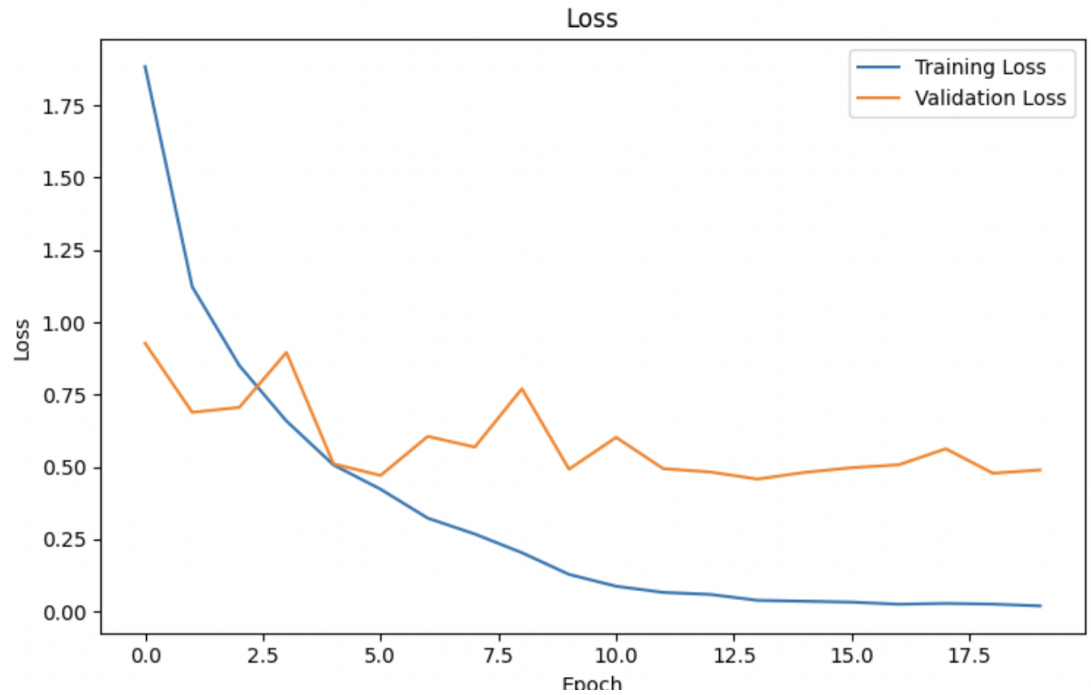

Figure 4.2: Loss

Table 4.2: Detailed Performance Results

Phase	**Accuracy**	**Loss**
Training (Final Epoch)	88.40%	0.4901
Testing	88.82%	0.4812

4.4 Classification Report

To assess the performance of the CNN across all disease categories, a classification report was generated. This report provides class-wise evaluation metrics including precision, recall, and F1-score, offering insights into the strengths and weaknesses of the model's predictions.

- **Precision** indicates the proportion of correctly predicted positive observations to the total predicted positives.

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}} \tag{4.1}$$

- **Recall** measures the proportion of correctly predicted positive observations to all actual positives.

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}} \tag{4.2}$$

- **F1-Score** is the harmonic mean of precision and recall, providing a balance between both metrics.

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4.3}$$

These metrics are crucial in medical applications where both false positives and false negatives can have significant consequences.

Table 4.3: Sample Classification Report (Illustrative)

Class	**Precision**	**Recall**	**F1-score**
Melanoma	0.89	0.87	0.88
Nevus	0.90	0.91	0.90
BCC	0.87	0.86	0.86
AKIEC	0.85	0.84	0.84
BKL	0.86	0.85	0.85
DF	0.91	0.92	0.91
VASC	0.88	0.89	0.88
Average / Total	**0.88**	**0.88**	**0.88**

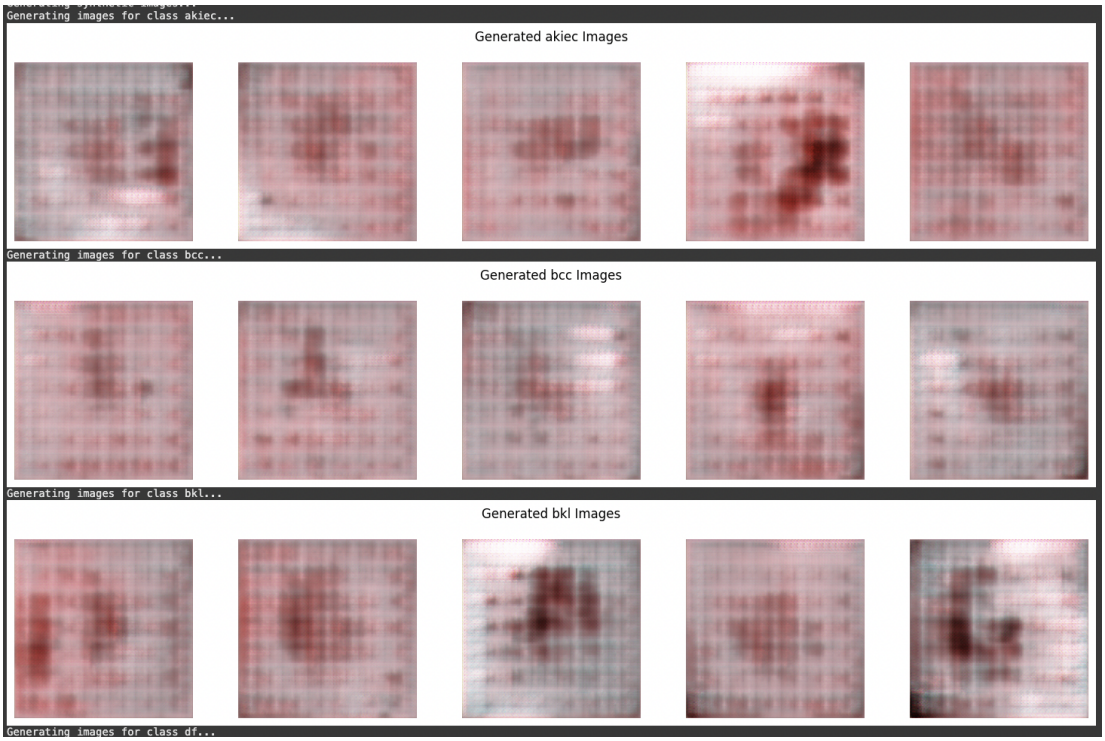

Figure 4.3: Accuracy

4.5 Impact of Data Augmentation

Data augmentation played a pivotal role in enhancing the model's ability to generalize across diverse skin disease presentations. Given the limited availability of labeled medical image datasets, data augmentation acts as a regularization technique that synthetically increases dataset diversity without requiring additional manual annotations.

Various augmentation techniques such as random rotations, shifts, zooming, shearing, and horizontal flips were applied to training images. These transformations simulate real-world variations in image capture conditions and help the model become invariant to positional and geometric changes.

The implementation of data augmentation yielded the following key benefits:

- **Mitigated Overfitting:** Exposure to a wider range of image variations reduced the model's reliance on memorizing specific training instances.
- **Improved Generalization:** Validation and testing accuracy increased significantly after incorporating augmentation strategies.

- **Robust Feature Learning:** The model learned more stable and discriminative features, enabling accurate classification despite noise or transformation.

Chapter 5

Conclusion, Future Scope and Social Impact

5.1 Conclusion

This thesis has provided a comprehensive analysis of the application of Generative Adversarial Networks (GANs) for skin disease detection and image synthesis. Through a detailed examination of nine key studies published between 2018 and 2024, we have identified significant advancements, challenges, and opportunities in this rapidly evolving field.

The reviewed studies demonstrate that GAN-based approaches have made substantial contributions to dermatological applications in several key areas:

- **Data Augmentation:** GANs have effectively addressed the challenge of limited and imbalanced skin disease datasets by generating synthetic images to expand training data. Models trained on GAN-augmented datasets consistently achieve higher accuracy and sensitivity, with improvements ranging from 2% to 22%.
- **Image Synthesis:** Advanced GAN architectures such as SPGGAN-TTUR, StyleGAN2-ADA, and WGAN-GP have demonstrated the ability to generate high-quality skin lesion images that retain clinically relevant features, useful for training, testing, and education.
- **Classification Performance:** The integration of GAN-based data augmentation with advanced CNN architectures like DenseNet-121 and Inception-v3 has significantly improved skin disease classification accuracy, reaching up to 92.2% in some studies.

- **Novel Applications:** GANs have enabled innovations such as 3D skin surface reconstruction for haptic palpation and mobile-based diagnostic tools, aiding remote healthcare accessibility.

5.2 Challenges

Despite the promising progress, several technical and practical challenges persist:

- **High-Resolution Image Generation:** Accurately generating fine-grained, high-resolution lesion images remains difficult, especially for subtle diagnostic patterns.
- **Clinical Validation:** Many studies report technical success, but lack large-scale validation in clinical environments, necessitating collaboration with dermatologists.
- **Computational Efficiency:** Real-world deployment on mobile and edge devices requires optimized, lightweight architectures and faster inference models.
- **Standardized Evaluation:** The absence of standardized datasets and metrics hinders fair benchmarking and comparison across approaches.

5.3 Future Scope

Several promising research directions are expected to drive the field forward:

- **Multi-Modal Integration:** Combining GANs with clinical metadata, patient history, and dermoscopic information may enhance diagnostic accuracy and model robustness.
- **Explainable AI:** Future systems should provide interpretable visual explanations to promote transparency and acceptance in clinical settings.
- **Temporal Modeling:** Modeling the evolution of lesions over time could improve monitoring of disease progression and treatment effectiveness.
- **Federated Learning:** Training GANs in a privacy-preserving, decentralized manner can promote collaborative development while maintaining data security.

- **Cross-Domain Adaptation:** Adapting models across different imaging environments and patient demographics can enhance generalizability and practical usability.

5.4 Social Impact

The integration of GANs into dermatological diagnostics offers substantial social benefits. These include:

- **Democratized Healthcare Access:** Mobile-based GAN-powered tools can deliver dermatological assessments to remote or underserved regions, reducing disparities in healthcare access.
- **Ethical Data Use:** Synthetic data generated by GANs can be used for training without compromising patient privacy, fostering ethical AI practices in medicine.
- **Enhanced Medical Training:** Realistic synthetic lesion images support the education of healthcare professionals by providing a diverse range of visual examples.
- **Improved Trust and Usability:** Explainable GAN-based systems help build clinician and patient confidence, leading to wider adoption and better healthcare engagement.

In conclusion, GAN-based methods are shaping the future of skin disease detection and diagnosis. With further development, clinical validation, and ethical deployment, these technologies have the potential to greatly improve the accuracy, accessibility, and equity of dermatological care globally.

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