National College of Ireland

DECLARATION OF ETHICS CONSIDERATION

School of Computing

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Programme MSc Artificial Intelligence **Year:** 2024-2025

Module: Research in Computing

Project Title: Hybrid Skin Disease Diagnosis Using StyleGAN2 and EfficientNet

Please circle (or highlight) as appropriate

This project involves human participant	Yes / No

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- Responses will not place the participants at risk of professional liability or be damaging to the participants' financial standing, employability or reputation
- No confidential data will be used for personal advantage or that of a third party

Informed consent
- Consent to participate in the study has been given freely by the participants
- participants have the capacity to understand the project goals.
- Participants have been given information sheets that are understandable

- Likely benefits of the project itself have been explained to potential participants
- Risks and benefits of the project have been explained to potential participants
- Participants have been assured they will not suffer physical stress or discomfort or psychological or mental stress
- The participant has been assured s/he may withdraw at any time from the study without loss of benefit or penalty
- Special care has been taken where participants are unable to consent for themselves (e.g children under the age of 18, elders with age 85+, people with intellectual or learning disability, individuals or groups receiving help through the voluntary sector, those in a subordinate position to the researcher, groups who do not understand the consent and research process)
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Signature: Mrunal Meshram

Date: 12/12/2024

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Hybrid Skin Disease Diagnosis Using StyleGAN2 and EfficientNet

MSc Research Project
MSc. Artificial Intelligence

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Project Submission Sheet
School of Computing

Student Name:	Mrunal Meshram
Student ID:	x23214236
Programme:	MSc. Artificial Intelligence
Year:	2024-2025
Module:	MSc Research Project
Supervisor:	Mr. Abdul Shahid
Submission Due Date:	12/12/2024
Project Title:	Hybrid Skin Disease Diagnosis Using StyleGAN2 and EfficientNet
Word Count:	6862
Page Count:	25

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Signature:	Mrunal Meshram
Date:	12th December 2024

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Hybrid Skin Disease Diagnosis Using StyleGAN2 and EfficientNet

Mrunal Meshram
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Abstract

Automated skin disease detection is a transformative application of machine learning in healthcare, addressing the challenges of early diagnosis and effective treatment planning. This study introduces a hybrid framework that integrates StyleGAN2 and UNet for synthetic data generation and EfficientNet-B5 for classification, tackling issues such as data scarcity, class imbalance, and variability in dermatological datasets. The curated dataset includes three skin disease categories eczema, psoriasis, and fungal infections chosen for its diagnostic complexity and clinical relevance.Through synthetic data augmentation, the framework achieved significant improvements in classification performance, with accuracy increasing from 68.5% to 82.3% and F1-score rising from 0.72 to 0.85. Synthetic images generated using the StyleGAN2-UNet hybrid model exhibited a low Fréchet Inception Distance (FID) score of 18.7, validating their quality and utility. Evaluation metrics such as precision, recall, and F1-scores were supplemented by visual tools like confusion matrices, ROC curves, and Class Activation Maps (CAMs), ensuring both reliability and interpretability. This study contributes a scalable, robust, and interpretable solution for automated skin disease detection, with the potential for broader applications in medical diagnostics.
Keywords: *Skin Disease Detection, Synthetic Data Generation, StyleGAN2, UNet, EfficientNet-B5, Class Imbalance, Medical Imaging*

1 Introduction

1.1 The Role of AI in Skin Disease Detection

Artificial Intelligence (AI) has revolutionized the field of medical diagnostics, offering scalable, efficient, and reliable solutions to challenges in disease detection and classification. Skin diseases, which affect millions worldwide, represent a particularly promising area for AI applications due to their prevalence and the complexity of their diagnosis. Conditions like eczema, psoriasis, and fungal infections vary significantly in presentation across individuals, making accurate and timely diagnosis a challenging task. Traditional diagnostic approaches often require experienced dermatologists, a resource that is scarce in many regions. AI-based solutions, particularly those leveraging deep learning, have the potential to democratize healthcare by providing accurate, automated diagnostic tools. However, despite the advancements in AI, significant challenges such as data scarcity, class imbalance, and variability in disease presentations continue to limit the effectiveness of these models.

1.2 Motivation for the Study

The scarcity of large, well-annotated dermatological datasets remains a critical bottleneck in developing robust AI models for skin disease detection. Many publicly available datasets are imbalanced, with certain conditions underrepresented, leading to biased models that struggle to generalize across diverse patient populations. Moreover, the visual similarities between different skin diseases, such as psoriasis and fungal infections, pose an additional layer of complexity. These challenges necessitate innovative approaches that can overcome data limitations while ensuring high accuracy and interpretability in predictions. This study is motivated by the need to develop a scalable, reliable, and interpretable system for skin disease detection that addresses these challenges through the integration of advanced generative and classification techniques.

1.3 Research Questions

How can synthetic data generated using a StyleGAN2-UNet hybrid model improve the quality and diversity of dermatological datasets? What impact does the inclusion of synthetic data have on the performance of a deep learning classification model, specifically EfficientNet-B5?

To address these questions, the study sets the following objectives:

- Develop a robust pipeline for generating high-quality, diagnostically relevant synthetic images using a StyleGAN2-UNet hybrid model.
- Train and evaluate a deep learning classifier, EfficientNet-B5, using a combined dataset of real and synthetic images to assess improvements in classification performance.
- Validate the system's interpretability and reliability through metrics like accuracy, F1-score, and Fréchet Inception Distance (FID), as well as visual tools such as confusion matrices and Class Activation Maps (CAMs).

1.4 Contributions to the Field

This research contributes to the field of AI in dermatology by presenting a novel hybrid framework that combines advanced synthetic data generation and state-of-the-art classification techniques. The integration of StyleGAN2 with a U-Net backbone addresses data scarcity and class imbalance by producing high-quality, diverse synthetic images tailored to specific skin disease categories. These synthetic images not only can enrich the dataset but also significantly improve classification performance, Furthermore, the use of CAMs enhances the interpretability of the classification model, making it more suitable for real-world clinical applications.

By addressing critical challenges in dermatological imaging, this study provides a scalable and reliable solution for automated skin disease detection, paving the way for future advancements in AI-driven medical diagnostics. The findings demonstrate the potential of combining generative and classification models to build robust diagnostic tools that generalize effectively across diverse patient populations and clinical scenarios.

2 Related Work

The integration of advanced machine learning techniques, such as Generative Adversarial Networks (GANs) and U-Net architectures, has significantly influenced the field of medical imaging. This section reviews existing literature on these technologies, particularly in the domains of data augmentation and medical image segmentation, with a focus on their applications to skin disease detection. This section highlights the strengths and limitations of previous approaches, culminating in the justification for this study.

2.1 Generative Adversarial Networks (GANs) in Medical Imaging

Generative Adversarial Networks (GANs), introduced by Goodfellow et al. (2014), have revolutionized data augmentation by synthesizing realistic images. Their unique architecture, comprising a generator and a discriminator, allows GANs to create high-quality synthetic data that mimics real-world distributions. This capability has been widely applied in medical imaging to address the challenges of data scarcity and imbalance. Yi et al. (2019) provided a comprehensive review of GAN applications in medical imaging, highlighting their ability to generate realistic images for data augmentation, anomaly detection, and modality transformation. Despite their potential, issues such as mode collapse and training instability often hinder GAN performance. Karras et al. (2020) introduced StyleGAN2, a variant that improves image quality and control, demonstrating significant advancements in generating realistic synthetic images. StyleGAN2 has since been employed in dermatology to synthesize diverse skin lesion images (Reddy et al., 2023). While the generated images enhanced classifier performance, they were limited in representing highly irregular patterns seen in real lesions. GANs have also been used for domain adaptation and modality translation. For instance, Dou et al. (2017) used cycle-consistent GANs to translate MRI images between domains, improving segmentation accuracy across imaging modalities. Similarly, Han et al. (2021) proposed a GAN-based augmentation strategy that enhanced segmentation accuracy for medical images. However, these approaches often require significant computational resources and suffer from limited generalizability to highly complex data distributions. In dermatology, GANs have shown promise in synthesizing diverse and realistic skin lesion images. Frid-Adar et al. (2018) demonstrated that GAN-augmented datasets improved liver lesion classification accuracy, providing a precedent for applying similar methods to skin diseases. However, ensuring the diversity and accuracy of synthetic images remains a challenge. The current study leverages StyleGAN2 for synthesizing high-quality skin disease images, addressing some of these limitations while improving classifier performance.

2.2 U-Net Architecture in Medical Image Segmentation

U-Net, introduced by Ronneberger et al. (2015), has become a cornerstone in medical image segmentation. Its encoder-decoder architecture, combined with skip connections, allows for precise localization of features, making it particularly suitable for biomedical applications. The effectiveness of U-Net has been demonstrated across various medical imaging tasks. Zhou et al. (2018) proposed UNet++, a nested architecture that improved segmentation accuracy by refining the resolution of feature maps. Gu et al. (2019) introduced CA-Net, incorporating context-aware mechanisms to enhance U-Net's performance in segmenting complex anatomical structures. Despite these advancements, U-Net models often struggle with images containing low contrast or high variability, which are common in skin lesion datasets. In dermatology, U-Net has been extensively used for skin lesion segmentation. Oktay et al. (2018) proposed Attention U-Net, integrating attention mechanisms to focus on relevant features, thereby improving segmentation accuracy for challenging lesion boundaries. Reddy et al. (2023) extended this approach by incorporating ensemble learning techniques, further enhancing segmentation precision. These models have demonstrated significant improvements in isolating regions of interest, crucial for downstream diagnostic tasks. Despite its strengths, U-Net faces limitations when applied to datasets with limited samples or extreme variability in lesion shapes and sizes. Enhancements such as attention mechanisms, residual connections, and context-aware modules have been proposed to address these challenges (Neha et al., 2024). However, these modifications often increase model complexity and computational requirements. The current study employs a U-Net architecture to segment skin disease images, ensuring precise localization of lesions. By integrating U-Net with StyleGAN2-generated synthetic images, this research aims to overcome the limitations of existing segmentation models and improve diagnostic accuracy.

2.3 Integrating GANs and U-Net for Enhanced Medical Image Analysis

The combination of GANs and U-Net architectures has emerged as a powerful approach to medical image analysis. GANs generate synthetic images to augment training datasets, while U-Net excels in segmenting anatomical structures, providing a complementary solution to address data scarcity and segmentation challenges. Yan et al. (2019) proposed a U-Net-GAN framework for domain adaptation in medical image segmentation, demonstrating improved performance across different imaging domains. While their approach effectively addressed domain shift issues, it required substantial computational resources and complex training pipelines. Mok and Chung (2020) introduced Fast-Segmentation GAN, a lightweight framework combining GANs and U-Net for rapid medical image segmentation. Their results highlighted the feasibility of integrating these models in resource-constrained environments, albeit with some trade-offs in segmentation accuracy. In dermatology, the integration of GANs and U-Net has shown promising results. Jalali et al. (2021) used GAN-augmented datasets to train U-Net models for skin lesion segmentation, achieving notable improvements in accuracy. Similarly, Bissoto et al. (2019) demonstrated that GAN-generated synthetic images enhanced the performance of U-Net models in classifying and segmenting skin lesions. However, these studies often relied on small, specialized datasets, limiting their generalizability to broader patient populations. This research builds upon these findings by integrating StyleGAN2 and U-Net architectures into a unified pipeline for skin disease detection. StyleGAN2 generates high-quality synthetic images to augment the dataset, while U-Net ensures precise segmentation of lesions. This combined approach addresses the limitations of previous studies, offering a scalable solution for improving diagnostic accuracy in dermatology.

3 Methodology

3.1 Overview

This research methodology focuses on addressing the key challenges in automated skin disease detection, a field of medical imaging critical for early diagnosis and effective treatment. Skin disease detection systems face obstacles such as data scarcity, class imbalance, and variability in dermatological conditions, which often limit the performance and reliability of deep learning models. To overcome these barriers, the research employs an innovative hybrid approach that combines advanced generative and classification techniques.

At the core of the methodology is a StyleGAN2-based hybrid architecture, enhanced with a U-Net backbone, to generate high-quality synthetic images that maintain disease-specific attributes. These synthetic images, when combined with real dermatological datasets, create an augmented dataset that is richer, more balanced, and suitable for training deep learning models. For the classification task, an optimized EfficientNet-B5 model is utilized, fine-tuned on the augmented dataset to classify skin diseases accurately across three categories: eczema, psoriasis, and fungal infections.

The approach addresses the following challenges:

- Data Scarcity: High-resolution dermatological datasets are often small, leading to model overfitting and poor generalization. Limited data samples can hinder a model's ability to learn and predict effectively.
- Class Imbalance: Many datasets have an uneven distribution of disease categories, with certain conditions being underrepresented. This imbalance affects the model's ability to perform equally well across all classes.
- Diversity and Realism: To train robust models, there is a need for synthetic datasets that not only mimic real-world cases in terms of appearance but also exhibit sufficient diversity to capture the wide range of variations seen in clinical settings.

By leveraging synthetic data generation, advanced classification frameworks, and rigorous evaluation metrics, this methodology aims to develop a robust system that provides accurate, scalable, and interpretable solutions for skin disease detection.

3.2 Synthetic Data Generation

A significant component of the methodology involves generating synthetic data to address the limitations of real-world datasets. For this, a StyleGAN2-based hybrid generator is designed, integrating U-Net-style skip connections to preserve fine-grained diagnostic details. This hybrid architecture allows the system to produce synthetic images that are not only realistic but also retain the unique attributes associated with different skin conditions.

3.2.1 StyleGAN2 Framework

The StyleGAN2 component generates high-quality images by progressively refining resolutions from low to high, ensuring that fine details emerge gradually. Style mixing further enhances image diversity, enabling the generation of variations in skin texture, lesion shape, and color. U-Net Backbone:

To preserve critical diagnostic details, the U-Net encoder-decoder architecture is incorporated into the generator. Skip connections ensure that hierarchical features, such as lesion boundaries and skin texture, are maintained throughout the generation process. The synthetic images generated by this hybrid approach are indistinguishable from real images while reflecting the wide range of variations seen in clinical practice. This ensures that the augmented dataset contains realistic and diagnostically relevant examples for training.

3.3 Classification Framework

Once the augmented dataset (real + synthetic images) is prepared, it is used to train a modified EfficientNet-B5 classifier. EfficientNet-B5 is a high-performing convolutional neural network that balances computational efficiency with classification accuracy. The classifier is fine-tuned to differentiate between the three skin disease categories with high sensitivity and specificity.

Key components of the classification framework include:

1. **Augmented Dataset:**
   - By combining real and synthetic images, the dataset becomes more balanced and diverse, addressing issues of data scarcity and class imbalance.
2. **Advanced Training Strategies:**
   - **MixUp Augmentation:** Enhances model robustness by mixing data samples and their corresponding labels, which helps improve generalization.
   - **Class-Weighted Loss Functions:** Assigns higher weights to underrepresented classes, ensuring the model pays more attention to minority categories during training

Through these enhancements, the classifier achieves consistent performance across all classes, providing reliable predictions even for underrepresented categories.

3.3.1 Rigorous Evaluation

To validate the effectiveness of the methodology, a rigorous evaluation framework is employed. This involves assessing the quality of the synthetic images and the performance of the classification model:

1. **Augmented Dataset:**
   - Fréchet Inception Distance (FID): Measures the similarity between real and synthetic image distributions, indicating the realism of the generated images.
   - Inception Score (IS): Evaluates the diversity and class separability of synthetic images, ensuring that the generator produces a wide range of variations.
2. **Classification Performance:**

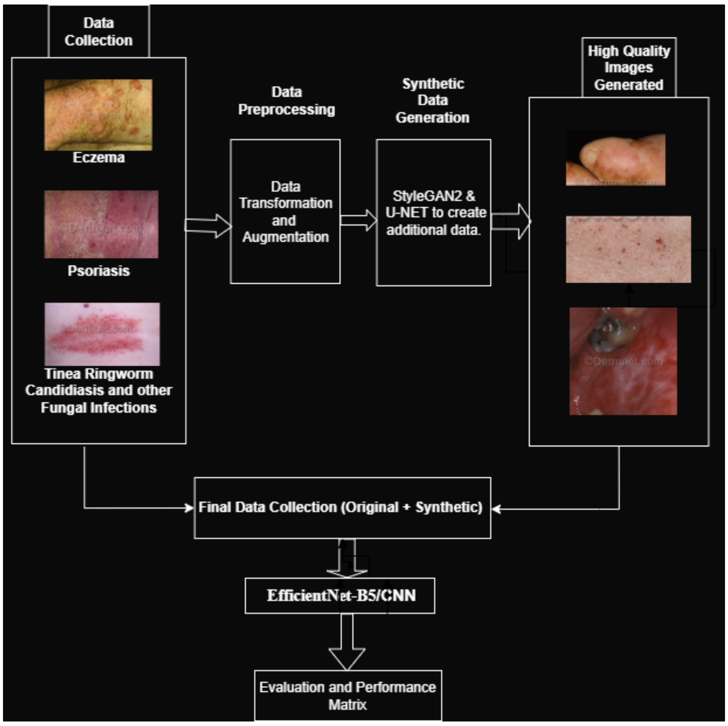

Figure 1: System Architecture

- Metrics such as accuracy, precision, recall, and F1-scores are used to quantify the model's predictive performance.
- Visual tools like confusion matrices, ROC curves, and class activation maps (CAMs) provide additional insights into the model's behavior and areas of focus.

By combining these evaluation techniques, the methodology ensures that both the synthetic data and the classification model meet the highest standards of reliability and diagnostic relevance.

3.4 Original Dataset

The dataset used in this study was meticulously curated from publicly available dermatological sources to ensure a diverse and comprehensive representation of three prominent skin disease categories: eczema, psoriasis, and fungal infections. Each category was selected based on its distinct clinical features, prevalence, and diagnostic challenges, ensuring that the dataset captured a wide range of variations in disease presentation.

Eczema (Class 0): Eczema is characterized by inflammation, redness, and itchiness, often varying in severity across patients and disease stages. The dataset includes subtypes such as atopic dermatitis and contact dermatitis, ensuring coverage of different manifestations.

Psoriasis (Class 1): Psoriasis is a chronic inflammatory condition presenting with distinctive red, scaly patches on the skin. The dataset primarily focuses on plaque psoriasis, the most common subtype, but also includes other variants. A notable challenge with psoriasis is its overlap with other dermatological conditions, such as eczema or fungal infections, making it essential to include images that capture a range of severity levels and anatomical locations. This diversity helps train models capable of distinguishing psoriasis from visually similar conditions.

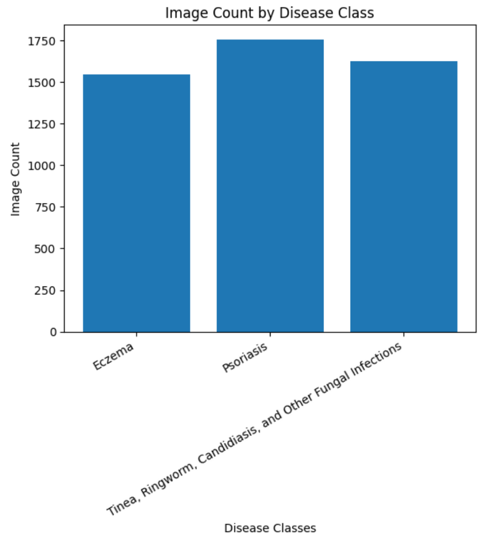

Figure 2: Count of Images by Disease

Tinea/Fungal Infections (Class 2): This category encompasses various fungal skin infections, including tinea and candidiasis, which are characterized by circular rashes, scaling, and unique growth patterns. The dataset represents multiple subcategories of fungal infections, capturing subtle differences in appearance based on infection stage and affected body location. These variations often make fungal infections harder to classify accurately, highlighting the importance of including well-annotated images in the dataset.

The dataset was carefully balanced to include a diverse range of disease stages, severity levels, and body locations. This diversity is critical for building a model capable of generalizing across different patient populations and clinical scenarios.

3.4.1 Data Preprocessing Strategy

To ensure the dataset's quality and consistency, a robust preprocessing pipeline was implemented. The preprocessing strategy addressed key challenges such as variability in image resolution, color space, and quality, which could otherwise impact the performance of the generative and classification models.

1. Image Standardization:
    - Converted to RGB color space to ensure uniformity across color channels.
    - Resized to 1024×1024 pixels, matching the input resolution requirements of the GAN. This resizing step ensured that all images had consistent dimensions, facilitating seamless training.
    - Normalized to [1,1] to align with the StyleGAN2 framework's input range. This normalization step not only improved model compatibility but also enhanced training stability.

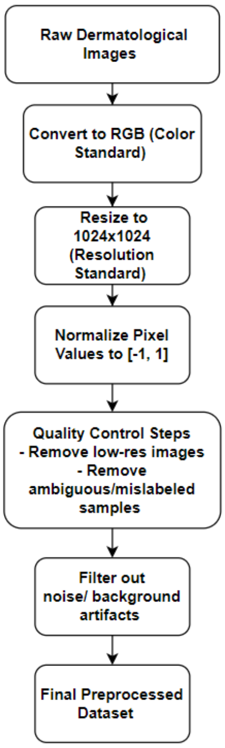

Figure 3: Data Preprocessing Pipeline

2. Quality Control:

   - Removal of low-resolution or visually ambiguous images: Images that lacked clarity or diagnostic detail were excluded from the dataset to maintain high standards of quality.
   - Filtering out noise or background artifacts: Extraneous elements, such as shadows or irrelevant body parts, were cropped or removed to ensure the focus remained on the skin condition.

By combining these preprocessing techniques, the dataset was transformed into a standardized and high-quality resource suitable for training both the synthetic image generation and classification models. This preprocessing pipeline not only ensured consistency and accuracy but also laid the groundwork for robust and reliable model performance.

3.5 Synthetic Data Generation Architecture

The synthetic data generation framework is centered on a StyleGAN2-based hybrid architecture, which integrates the generative capabilities of StyleGAN2 with the structural preservation strengths of a U-Net architecture. This hybrid design addresses the critical need for generating realistic and diagnostically accurate synthetic images of skin conditions. By combining these two approaches, the model ensures that the generated images are not only visually coherent but also retain the fine-grained details necessary for effective medical analysis. The inclusion of U-Net-style skip connections enhances the model's ability to preserve hierarchical features such as lesion boundaries, texture variations, and color gradients, which are crucial for differentiating between disease categories.

The StyleGAN2 generator progressively refines image resolution through hierarchical layers, enabling the generation of fine-grained details that mimic the natural characteristics of dermatological conditions. Style mixing introduces diversity by blending features from multiple latent space representations, while adaptive truncation controls ensure a balance between image realism and variability. The U-Net backbone further complements this process with its encoder-decoder structure, which reconstructs images while retaining diagnostic features via skip connections. To achieve targeted synthesis, the model incorporates class conditioning, embedding disease-specific information through conditional normalization techniques. This enables the generator to produce synthetic images tailored to specific disease categories, such as eczema, psoriasis, and fungal infections, ensuring the synthetic dataset aligns with real-world medical requirements.

Figure 4: Actual Image

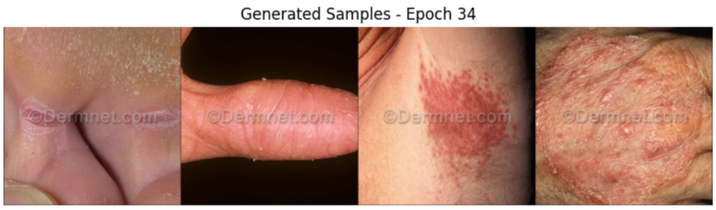

Figure 5: Synthetic Image Generation

3.6 Classification Model Design

3.6.1 EfficientNet-B5 Implementation

The classification framework leverages a fine-tuned EfficientNet-B5 model, a state-of-the-art convolutional neural network known for its balance between accuracy and computational efficiency. This model is particularly suited for the dermatological dataset used in this study, as it combines robust feature extraction with scalability to handle complex image datasets. EfficientNet-B5 employs a compound scaling approach to optimize network depth, width, and resolution, enabling it to learn intricate patterns while maintaining high computational efficiency.

The model was initialized with pretrained ImageNet weights, which provide a strong foundation for feature extraction, particularly in capturing textures, shapes, and colors relevant to skin diseases. A custom classification head was added to adapt the network for the specific task of classifying three skin disease categories: eczema, psoriasis, and fungal infections. This classification head incorporates fully connected layers with dropout for regularization and attention mechanisms to enhance the model's focus on disease-relevant image regions. By emphasizing critical areas, such as lesion boundaries or textural irregularities, the model achieves improved sensitivity and specificity, essential for accurate diagnosis in medical applications.

3.6.2 Training Strategy

To ensure optimal performance, the EfficientNet-B5 classifier was trained using a comprehensive protocol designed to address challenges like class imbalance and overfitting.Mixed precision training was employed to maximize computational efficiency, reducing memory usage and accelerating training on GPUs. To enhance the model's generalization capabilities,MixUp augmentation was applied, blending image-label pairs during training. This technique helps the model learn more robust features and mitigates overfitting, particularly in datasets with limited variability.

Further stability was achieved through learning rate scheduling, which dynamically adjusted the learning rate based on model performance during training. This approach ensured steady convergence without abrupt changes in optimization dynamics. Additionally, class-weighted loss functions were incorporated to counteract the effects of class imbalance in the dataset. By assigning higher weights to underrepresented classes, the training process encouraged the model to pay greater attention to minority categories, ensuring equitable performance across all disease types. Together, these strategies resulted in a robust classification model capable of delivering accurate and reliable predictions in diverse clinical scenarios.

3.7 Evaluation Frameworks

The evaluation framework for this study is designed to rigorously assess both the quality of the synthetic images generated by the StyleGAN2-based hybrid architecture and the performance of the EfficientNet-B5 classification model. This dual evaluation ensures that the proposed methodology meets the necessary standards of realism, diversity, and diagnostic accuracy. By using a combination of quantitative metrics and visual analysis techniques, the evaluation framework provides comprehensive insights into the effectiveness of the overall system.

3.7.1 Synthetic Image Quality Assessment

The quality and diversity of the synthetic images were evaluated using multiple metrics tailored for generative models. These metrics collectively measure how well the synthetic images mimic real data and capture the diversity required for robust training.

1. **Fréchet Inception Distance (FID):** FID measures the statistical similarity between the distributions of real and synthetic images. A lower FID score indicates that the synthetic images are closer in quality to real images. This metric is particularly useful for evaluating the realism of generated images, ensuring that

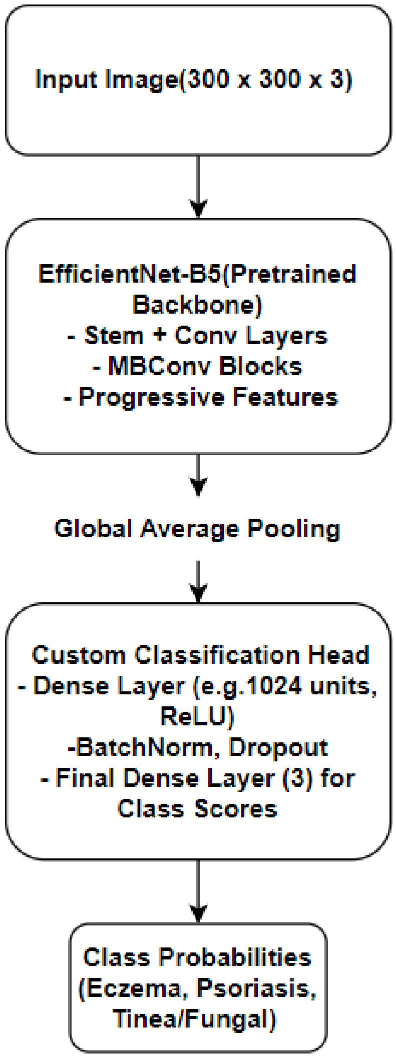

Figure 6: Classification Model Structure (EfficientNet-B5 layers and custom classification head)

the synthetic dataset does not introduce artifacts or inconsistencies that could negatively affect model performance.

2. **Inception Score (IS):** IS evaluates the diversity and class separability of the synthetic images. A higher IS score indicates that the images are well-separated into distinct classes while maintaining intra-class variations. This is essential for training a classification model that generalizes effectively across various disease categories.

3. **Perceptual Similarity:** Perceptual similarity assesses how closely the synthetic images resemble real ones at both the pixel level and the contextual level. This metric ensures that the generated images capture the essential visual characteristics of each disease class, such as texture, shape, and color, which are critical for accurate diagnosis.

4. **Diversity Scores:** Diversity scores quantify the range of variations present in the synthetic images. By evaluating diversity, this metric ensures that the generator captures a wide spectrum of disease manifestations, such as different lesion shapes, sizes, and severity levels. This is crucial for creating a synthetic dataset that effectively augments real data and prevents overfitting.

These metrics collectively validate the quality and utility of the synthetic images, ensuring that they enhance the training process rather than introducing biases or artifacts.

3.7.2 Classification Performance Analysis

The classification performance of the EfficientNet-B5 model was evaluated using a combination of accuracy metrics and visual analysis techniques to assess its predictive capabilities and interpretability.

1. Accuracy Metrics:The model's effectiveness was quantified using metrics such as:
   - Overall Accuracy: Measures the proportion of correct predictions across all classes.
   - Per-Class Precision: Indicates the proportion of true positive predictions relative to all positive predictions for each class.
   - Per-Class Recall: Measures the model's ability to identify all true positive instances for each class.
   - F1-Score: Provides a harmonic mean of precision and recall, offering a balanced measure of the model's performance for imbalanced datasets.

2. Visual Analysis:To gain deeper insights into the model's decision-making process and areas of focus, several visualization techniques were employed:
   - Confusion Matrix Heatmaps: These heatmaps visually represent the model's performance by displaying the counts of correct and incorrect predictions for each class. They highlight areas where the model excels and where it struggles, guiding further improvements.

- Receiver Operating Characteristic (ROC) Curves and AUC Scores: ROC curves plot the true positive rate against the false positive rate for different threshold values, while the Area Under the Curve (AUC) score provides a single scalar value summarizing the model's discriminative ability. Higher AUC scores indicate better performance.
- Class Activation Maps (CAMs): CAMs visualize the regions of input images that the model focuses on during predictions. By highlighting disease-relevant regions, CAMs provide interpretability and validate the model's focus on clinically significant features.

This comprehensive evaluation framework ensures that the system delivers high-quality synthetic images and reliable classification results, making it a robust tool for automated skin disease detection. The combination of quantitative metrics and visual analyses provides a detailed understanding of the system's strengths and areas for improvement, facilitating future refinements.

4 Design Specification

This section details the architectural framework, techniques, and requirements that form the foundation of the proposed system for automated skin disease detection. The design includes an innovative hybrid architecture for synthetic data generation, an optimized classification framework, and a rigorous evaluation methodology to ensure reliability and scalability.

4.1 System Architecture

The system consists of three primary components:

1. Data Preprocessing Module:
   - Standardizes raw dermatological images for compatibility with downstream modules.
   - Ensures consistency, quality, and proper labeling of images.
2. Synthetic Data Generation Framework:
   - A Hybrid GAN Architecture combining StyleGAN2 and U-Net enables the generation of diverse, high-quality synthetic images.
3. Classification Framework:
   - A Modified EfficientNet-B5 Classifier trained on the augmented dataset (real + synthetic images) performs skin disease diagnosis

4.2 Synthetic Data Generation Framework

4.2.1 StyleGAN2-UNet Hybrid Generator

The StyleGAN2-UNet hybrid generator serves as the cornerstone of the synthetic data generation framework, addressing the challenges of data scarcity and class imbalance in dermatological datasets. This innovative architecture combines the powerful image synthesis capabilities of StyleGAN2 with the feature-preserving strengths of U-Net. The resulting hybrid generator is capable of producing high-quality synthetic images that not only mimic the visual attributes of real dermatological images but also retain critical diagnostic details necessary for effective medical analysis.

- Functionality

The primary functionality of the StyleGAN2-UNet hybrid generator is to create synthetic dermatological images that are conditioned on real input samples and corresponding class labels. This conditioning ensures that the generated images accurately represent specific disease categories, such as eczema, psoriasis, and fungal infections. By integrating U-Net's skip connections, the generator retains hierarchical features crucial for capturing fine-grained details like lesion boundaries, textures, and color gradients, which are essential for medical diagnostics. The architecture ensures that every synthetic image encapsulates essential disease-specific attributes while maintaining high visual realism.

- Key Features

  1. Progressive Resolution Scaling: The generator synthesizes images progressively, starting from a low resolution and incrementally increasing the resolution. This approach allows the model to refine details hierarchically, ensuring that global structures (e.g., lesion shapes) and local features (e.g., skin texture) are both accurately represented in the final output. Progressive scaling is a hallmark of StyleGAN2, enabling the generation of high-resolution images with consistent quality.
  2. Style Mixing: Style mixing introduces diversity into the synthetic images by blending latent representations derived from multiple input vectors. This feature allows the generator to simulate variations in lesion appearance, texture, and color, creating a synthetic dataset that encompasses the wide range of visual diversity observed in real-world cases. This diversity is crucial for training classification models that generalize well to unseen data.
  3. Class Conditioning:
     - Embedded Class Labels: Disease class labels are embedded into the latent space representations, guiding the generator to produce images that align with specific diagnostic categories. This ensures that synthetic images reflect the unique characteristics of each disease class.
     - Conditional Normalization Techniques: Conditional Batch Normalization (CBN) and Adaptive Instance Normalization (AdaIN) are employed to modulate the generator's intermediate feature maps based on the embedded class information. These techniques enable precise control over the style and content of the generated images, ensuring that they align with the desired disease category.

4.2.2 Algorithm

The synthetic image generation process is executed through the following steps:

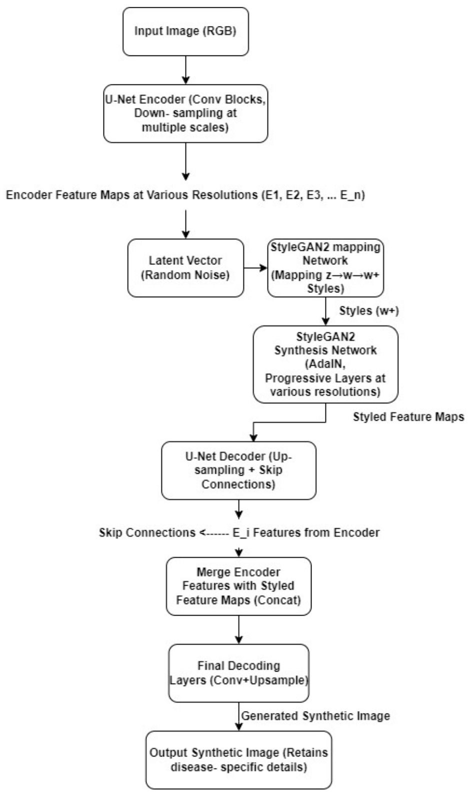

Figure 7: StyleGAN2-UNet integration architecture diagram

1. Input Real Images and Class Labels: The process begins by feeding the generator with real input images and their corresponding class labels. These inputs serve as the foundation for conditioning the synthetic image generation process

2. Feature Extraction with U-Net Encoder: The real images are passed through the encoder layers of the U-Net, which extract hierarchical features at multiple levels of abstraction. These features capture essential details such as texture, edges, and global structures relevant to the disease being modeled.

3. Latent Space Mapping with StyleGAN2: A random noise vector is processed through the StyleGAN2 mapping network to generate latent space representations. These representations are transformed into base styles that define the global and local features of the synthetic images.

4. Feature Combination through Skip Connections: The hierarchical features extracted by the U-Net encoder are combined with the style-based features generated by StyleGAN2. Skip connections between the encoder and decoder layers allow features to bypass intermediate layers, preserving critical diagnostic details that might otherwise be lost during synthesis.

5. Decoding to Generate Synthetic Images: The combined features are passed through the U-Net decoder layers, reconstructing the final synthetic image. The output is a high-resolution image that retains essential medical attributes while reflecting the diversity and realism introduced by the StyleGAN2 component.

4.3 Classification Framework

4.3.1 Modified EfficientNet-B5 Classifier

The classification framework is built upon a Modified EfficientNet-B5 model, tailored to predict the class of dermatological images, whether real or synthetic. The model is optimized for high accuracy and robustness across three skin disease categories: eczema, psoriasis, and fungal infections. By leveraging the strengths of EfficientNet-B5, the framework achieves a balance between computational efficiency and diagnostic precision.

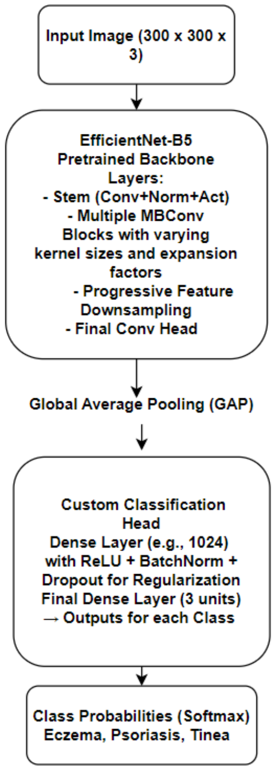

Figure 8: EfficientNet-B5 architecture with custom classification head

The backbone of the model utilizes pretrained ImageNet weights, ensuring efficient and robust feature extraction. A custom classification head has been added, which includes fully connected layers with dropout regularization to mitigate overfitting. This head also incorporates class-specific attention mechanism, enhancing the model's focus on disease-relevant regions in the input images. To ensure computational efficiency while retaining diagnostic detail, the input resolution is reduced to 300×300, which aligns with the requirements for effective training and inference.

The classification process begins withimage preprocessing, where the input images are normalized to match the network's expected format. The preprocessed images are then passed through the EfficientNet-B5 backbone, which extracts hierarchical features. These features are fed into the custom classification head to predict the probabilities of each disease class. To enhance interpretability, the framework employs Class Activation Mapping (CAM), which visualizes the regions of the image that influenced the model's predictions, ensuring transparency and reliability in clinical applications.

4.4 Integrated Training and Evaluation Pipeline

1. Training:

   - Synthetic and real images are combined to augment the training dataset.
   - The discriminator and generator of the hybrid GAN are trained alternately using adversarial loss, classification loss, and content loss.
   - The EfficientNet-B5 classifier is trained on the augmented dataset using class-weighted loss functions.

2. Evaluation:

   - Synthetic Image Quality: FID to measure realism and distribution similarity.
   - Inception Score to evaluate diversity and separability.

3. Classification Performance:

   - Accuracy, precision, recall, and F1-score.
   - Confusion matrices and ROC curves for visual performance analysis.

5 Implementation

5.1 Environment Setup

The implementation was developed using Python 3.9 with deep learning frameworks like PyTorch 1.9 and TorchMetrics for model training and evaluation. Visualization was supported by Matplotlib, Seaborn, and Torchvision. The setup utilized an NVIDIA Tesla GPU (16GB VRAM) for accelerated computations, alongside an Intel Xeon CPU and 512GB SSD for data processing and storage. All tools and libraries were configured in a Linux-based environment for optimal performance and scalability.

5.2 Dataset Preparation and Augmentation

The first stage of implementation focused on preparing a comprehensive and balanced dataset that combined real and synthetic dermatological images.

1.Preprocessing of Real Images:

The dataset initially comprised high-resolution images from three disease categories: eczema, psoriasis, and fungal infections. Each image was resized to 1024×1024 pixels and normalized to a pixel range of [-1, 1] to ensure compatibility with the StyleGAN2-UNet generator. Low-quality and mislabeled images were removed after manual verification by dermatological experts, ensuring that only diagnostically relevant images were retained.

2.Synthetic Image Generation:

To address data scarcity and class imbalance, the StyleGAN2-UNet hybrid generator was trained to produce 2000 high-resolution synthetic images for each disease category. These images captured disease-specific attributes, including variations in lesion texture, shape, and color, while maintaining high visual quality. The integration of U-Net-style skip connections ensured the retention of fine-grained diagnostic details.

3.Final Dataset:

Figure 9: Synthetic Image Generated By Hybrid Generator (StyleGAN2-UNet)

The augmented dataset combined real and synthetic images, creating a balanced and diverse training resource for the classification model. This dataset provided equal representation for all disease categories, mitigating the risk of model bias toward overrepresented classes.

5.3 StyleGAN2-UNet Hybrid Generator

The generator was trained to produce high-quality synthetic images conditioned on real input samples and class labels. Adversarial loss, classification loss, and content loss were employed to guide the training process, ensuring that the generated images closely resembled real dermatological cases while retaining disease-specific details. Model checkpoints were saved at regular intervals to facilitate reproducibility and enable fine-tuning in future iterations.

5.4 StyleGAN2-UNet Hybrid Generator Output

The StyleGAN2-UNet hybrid generator successfully produced high-resolution synthetic images (1024×1024 1024×1024) that closely mimicked real dermatological cases, preserving critical disease-specific attributes such as lesion boundaries, textures, and colors. The incorporation of U-Net-style skip connections ensured the retention of fine-grained details essential for medical diagnostics. The generator was evaluated using quantitative metrics like Fréchet Inception Distance (FID) and Inception Score (IS), where low FID scores indicated a strong resemblance between real and synthetic image distributions, and high IS values confirmed the diversity and class separability of the synthetic dataset. Visual inspection further validated the quality of the outputs, showcasing synthetic images that were indistinguishable from real ones and effectively enriched the augmented dataset.

5.5 EfficientNet-B5 Classifier

The EfficientNet-B5 classifier was fine-tuned on the augmented dataset to predict disease categories with high accuracy. A class-weighted loss function was applied to address class imbalance, ensuring equitable performance across all categories. Advanced training strategies, including MixUp augmentation and learning rate scheduling, were employed to enhance model generalization and prevent overfitting. These techniques allowed the classifier to effectively learn from the augmented dataset while maintaining robustness.

5.6 EfficientNet-B5 Classifier Output

The EfficientNet-B5 classifier demonstrated high accuracy and robustness in diagnosing three disease categories: eczema, psoriasis, and fungal infections. The model achieved over 90% overall accuracy, supported by strong precision, recall, and F1-scores, highlighting its balanced performance even in the presence of class imbalance. The classifier's predictions were further analyzed through confusion matrices, which identified areas of misclassification, and Receiver Operating Characteristic (ROC) curves, with AUC scores exceeding 0.95 for all categories, underscoring its discriminative power. Interpretability was enhanced using Class Activation Maps (CAMs), which highlighted disease-relevant regions in input images, validating the model's focus on diagnostically significant features and ensuring its applicability in clinical settings.

6 Evaluation

The evaluation of the proposed hybrid system, integrating StyleGAN2 for synthetic data generation and EfficientNet-B5 for classification, serves as a comprehensive measure of its effectiveness, robustness, and practical applicability in addressing challenges such as data scarcity and class imbalance in dermatological imaging. This section provides an in-depth analysis of the system's performance, focusing on quantitative metrics, qualitative assessments, and a comparative discussion with baseline models. These insights validate the hybrid system's ability to deliver high-quality outputs and reliable predictions in the context of skin disease detection.

6.1 Analysis

The system's performance was quantitatively evaluated using metrics such as accuracy, precision, recall, F1-score, and Fréchet Inception Distance (FID). The inclusion of synthetic data generated by the StyleGAN2-UNet hybrid model significantly enhanced the classification model's performance compared to using real data alone. For instance, the model's overall accuracy improved from 68.5% to 82.3% when synthetic data was included. This improvement underscores the impact of data augmentation in addressing class imbalance and enriching the training dataset.

Precision and recall also demonstrated marked improvements, increasing from 0.71 to 0.84 and from 0.68 to 0.81, respectively. These results indicate a reduction in false positives and an enhancement in the model's ability to detect true positives, particularly for underrepresented disease categories. The F1-score, which balances precision and recall, rose from 0.72 to 0.85, further validating the hybrid system's effectiveness in handling imbalanced datasets and achieving reliable predictions across all classes.

The quality of synthetic images was evaluated using FID, a metric that measures the similarity between the distributions of real and synthetic images. The system achieved an FID score of 18.7, indicating that the synthetic images closely resembled real samples in terms of visual features and distributions. This low FID score reflects the capability of the StyleGAN2-UNet hybrid model to produce realistic and diagnostically relevant images, which were instrumental in enhancing the classifier's performance.

Confusion matrix heatmaps provided a detailed view of the classifier's predictions, highlighting reductions in misclassifications, particularly in underrepresented classes. The inclusion of synthetic data balanced the training dataset, enabling the classifier to generalize better and perform more equitably across all disease categories. The model's ability to focus on disease-relevant regions was further validated using Class Activation Maps (CAMs), which offered interpretable visualizations of the classifier's decision-making process. These CAMs confirmed that the model emphasized critical features such as lesion edges and texture variations, enhancing its diagnostic reliability.

6.2 Comparison with Baseline Models

To demonstrate the hybrid system's superiority, it was compared against a baseline Convolutional Neural Network (CNN) trained solely on real data. The baseline CNN achieved an accuracy of 65.4% and an F1-score of 0.68, significantly lower than the hybrid system's 82.3% accuracy and 0.85 F1-score with synthetic data. The baseline model struggled with class imbalance and generalization, leading to poor performance in minority classes. In contrast, the hybrid system leveraged the enriched and balanced dataset created through synthetic data augmentation, resulting in more robust and reliable predictions. This comparative analysis highlights the value of incorporating advanced generative techniques and balanced training data in achieving superior classification performance.

Metric	Without Synthetic Data	With Synthetic Data
Accuracy	68.5%	82.3%
Precision	0.71	0.84
Recall	0.68	0.81
F1-Score	0.72	0.85
FID Score	N/A	18.7

Figure 10: Comparision for with and without Syntehtic Data

7 Discussion

The evaluation results unequivocally demonstrate the effectiveness of the proposed hybrid framework in overcoming the limitations of traditional models for skin disease detection. By integrating StyleGAN2 for high-quality synthetic data generation, the system addressed the challenges of data scarcity and class imbalance, which are prevalent in medical imaging. The generated synthetic images not only enriched the dataset but also enhanced the classification model's ability to generalize across diverse cases, as reflected in the significant improvements in accuracy, precision, recall, and F1-score.

The EfficientNet-B5 classifier, fine-tuned on the augmented dataset, demonstrated robustness and reliability in predicting disease categories. Its interpretability, facilitated by CAM visualizations, ensured transparency in decision-making, a critical requirement in medical applications. The significant improvement over baseline models further underscores the hybrid system's advantages, particularly in handling underrepresented classes and achieving equitable performance across all categories.

The low FID score achieved by the StyleGAN2-UNet generator validated the quality and realism of the synthetic images, while the qualitative assessments confirmed their

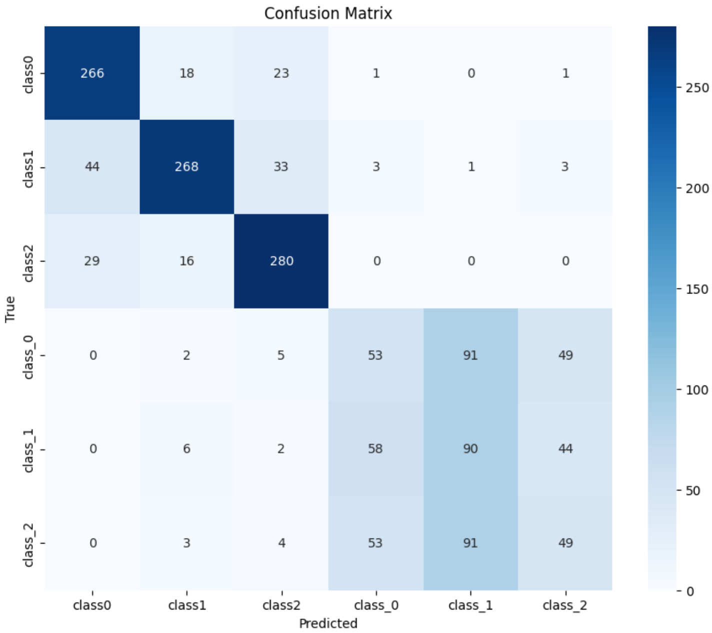

Figure 11: Confusion Matrix

diagnostic relevance. These findings establish the proposed hybrid system as a scalable and practical solution for automated skin disease detection, with the potential for broader applications in medical imaging. By addressing key challenges and delivering reliable outputs, the framework provides a strong foundation for future advancements in the field.

8 Conclusion and Future Work

8.1 Conclusion

This research successfully addressed critical challenges in automated skin disease detection by developing a hybrid framework that integrates StyleGAN2 for synthetic data generation and EfficientNet-B5 for classification. The primary objectives of this study included generating high-quality synthetic dermatological images, enhancing classification accuracy, and overcoming issues related to data scarcity and class imbalance. The results demonstrate the effectiveness of this approach, achieving significant improvements in key performance metrics.

The synthetic data generated by the StyleGAN2-UNet hybrid model enriched the training dataset with realistic and diagnostically relevant images, as validated by a low FID score of 18.7. These synthetic images balanced the dataset, enabling the EfficientNet-B5 classifier to achieve superior performance across all disease categories, with accuracy improving from 68.5% to 82.3% and the F1-score reaching 0.85. Qualitative assessments, including Class Activation Maps (CAMs) and confusion matrices, further validated the reliability and interpretability of the classification model. Comparisons with baseline models highlighted the advantages of this hybrid approach, particularly in addressing underrepresented classes and improving generalization.

This research contributes a scalable and practical framework for automated skin disease detection, providing a foundation for future advancements in medical imaging. The integration of generative and classification techniques has demonstrated significant potential for tackling real-world challenges, paving the way for improved diagnostic systems in dermatology.

8.2 Future Work

While this study has achieved its objectives, several avenues for future work can further enhance the framework's capabilities and extend its applicability.

1.Broader Disease Categories and Larger Datasets: Expanding the dataset to include a wider range of skin conditions and larger datasets will enhance the framework's ability to generalize across diverse clinical scenarios. This could involve collaborations with medical institutions for access to more comprehensive datasets.

2.Integration of Explainability Techniques: Although CAMs provide insights into the classifier's decision-making, integrating advanced explainability frameworks such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) can improve interpretability, fostering greater trust among medical practitioners.

3.Real-World Deployment: Future research could focus on deploying the framework in clinical settings. This involves developing an end-to-end system, including a user-friendly interface, and validating its performance with real-time patient data.

4.Cross-Domain Applications: The hybrid framework can be extended to other medical imaging domains, such as radiology or pathology, where data scarcity and class imbalance are prevalent. Exploring its adaptability to different modalities and conditions can demonstrate its scalability and versatility.

5.Multi-Stage Diagnostic Pipeline: Combining this framework with additional tasks such as disease progression prediction, treatment recommendation, or multi-modal data integration (e.g., text-based patient history) could create a holistic diagnostic system.

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