Enhancing Skin Disease Classification Through GAN-Generated Synthetic Images for Improved CNN Training and Generalization

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Abstract
The research introduces GANs to CNNs for improving skin disease classification tasks. GANs produce synthetic realistic images of scarce skin lesions to tackle both data insufficiency and class imbalance problems. When using real and synthetic data for training the CNN model it generates better accuracy along with improved generalization mainly toward the identification of rare conditions including actinic keratosis and vascular lesions. The model performance receives enhancement from WeightedRandomSampler in addition to mixed precision training which achieves both class balancing and training acceleration. Advanced techniques and methods help the system produce accurate diagnoses and generalize to diagnose rare skin diseases more effectively. Data synthesis proves its worth as an addition to medical image classification operations by enabling fewer annotated medical image datasets. Flask and Streamlit enabled real-time deployment which creates an easy-to-use platform for healthcare staff allowing the solution to scale for professional use. The medical field can experience a breakthrough through this method which allows immediate and trustworthy identification of skin diseases. The solution provides meaningful benefits to populations that lack enough skilled dermatologists which results in enhanced healthcare results for patients. This project delivers an effective model which enables early accurate skin disease diagnosis that supports better patient care in dermatology fields.

Keywords: Skin Disease Classification, Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNNs), Data Augmentation, Class Imbalance, Real-Time Inference, Mixed-Precision Training, WeightedRandomSampler, Synthetic Data, Early Diagnosis.

INTRODUCTION
In this sub specialty, classification of skin diseases is crucial, as with diseases such as melanoma, intervention will be done should conditions be identified early. However, one big disadvantage which comes with the making of useful classification models is the lack of labeled data due to privacy issues and the requirement of qualified people to label. Those unfamiliar with the condition have created skewed datasets, where newer lesion types are less likely to be detected, and therefore more difficult for machine learning models to learn in an accurate manner resulting in biased output.
In order to overcome these challenges, this project created synthetic skin lesions representing the much

underrepresented minority classes using GANs to increase the dataset's variety. It includes a Generator Network and a Discriminator Network that generate realistic images to approximate, in addition to the skin lesion data distribution. Moreover, training CNN on the generated dataset with added synthetic images leads to improved AN model performance on the augmented dataset, particularly for lesser and rare lesion classes.

In WeightedRandomSampler, other methods ensure that all classes, especially classes with few examples, get sufficient samples during training so that the model can learn well across all types of skin lesions. Further, it further augments the computations by decreasing time however it does not lag the quality of the model with mixed precision training. Finally, the system's inference has real time inference ability and runs on real life platforms like Streamlit and Flask, bringing efficient and effective skin lesion diagnosis mode to life clinicians out there.

In addition, this approach not only deals with inadequate data and disequated classes, but also produces a novel, workable, fast, and easy to implement classification method designed to be used clinically. Concrete advances in progress in dermatology diagnosis can be inferred for this project as they have incorporated techniques of using synthetic data generation, sampling and training as well as for real time application.

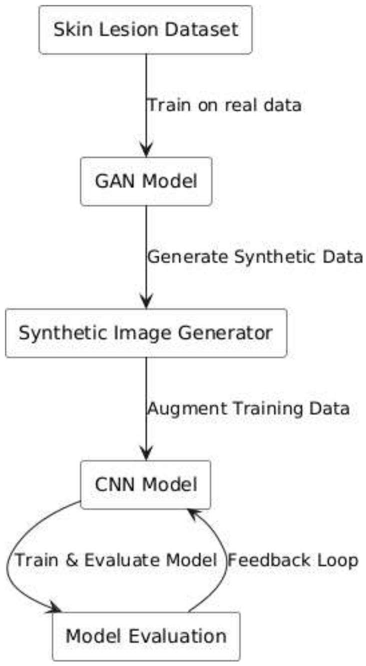

Figure 1: Flow diagram

The process of improving skin disease classification through Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) appears in Figure 1 as a flow diagram. This process shows the synthesis of artificial images to enhance training data which leads to improved model precision alongside evaluation outcomes.

LITERATURE SURVEY

Experimental progress in deep learning for skin disease classification emerged primarily because of the Convolutional Neural Networks (CNNs) cooperation with Generative Adversarial Networks (GANs). To implement artificial intelligence in dermatology practitioners must overcome challenges in unbalanced data classes and scarce information as well as issues with prediction model reliability.

Previous research studies about these issues are examined to present different solution methods and their corresponding outcome results.

Research on skin disease classification during previous times utilized a combination of fundamental artificial intelligence techniques such as Support Vector Machines (SVMs) with Decision Tree and Random Forest approaches for their research investigations. Research proved ensemble models boost medical diagnosis performance by utilizing numerous weak models to produce more reliable skin condition diagnostics [1]. The dermatological imaging specialists evaluated the random forest classifier to determine its performance in structured dataset processing and its achievement of effective results [5]. Existing methods had limitations because they obtained weak features inefficiently and failed to handle different types of skin lesions effectively.

Editorial experts now consider convolutional neural networks (CNNs) as the standard technique for detecting skin diseases because of deep learning's popularity. The study examines the effectiveness of dermatological diagnosis using VGG16 and ResNet and EfficientNet as different architectural arrangements. The current research evidence supports VGG16 as superior to EfficientNet for skin lesion classification since it excels at extracting better features [2]. Research investigators built customized CNN architecture for pathological image detection of complex structures and generated superior results compared to standard machine learning approaches [3].Performance enhancement occurs by using transfer learning techniques extensively. Laboratory experts refined the pre-trained models for skin lesion diagnosis through small dataset training which resulted in higher accuracy levels according to data in [2] and [8]. CNN models received improved performance through a multi-level attention mechanism that helped them focus on vital clinical areas in dermoscopic images for detecting melanoma [6].

Insufficient balanced and diverse datasets limit skin disease classification because they make it challenging for models to perform generalization tasks. The development of GAN technology provides medical sciences with a robust tool to generate artificial medical images that improve dataset variability. Scientists used GAN-based data augmentation to boost skin disease diagnostic classification due to its effectiveness with diverse multi-class datasets as shown in [11]. The authors used cycle-consistent learning alongside GANs to develop realistic skin lesion images which linked authentic data to synthetic data samples [12].

Recent research confirms that GAN-generated datasets encounter ongoing problems because they might increase biases within datasets. The synthetic images created from the dataset escalate initial data biases and terminate in false classification outputs [13]. Adaptive GANs bring forward a solution to control bias spread while promoting equal patient treatment for dermatological AI models [17].

Deep learning models develop deceptive behaviors because they tend to favor major classes when dealing with imbalanced populations. Multiple techniques developed by experts represent the approaches to manage this issue. WeightedRandomSampler demonstrated its effectiveness for balanced training by maintaining proper distribution of minority skin lesion types to achieve pattern memorization success [4]. Researchers analyze cost-sensitive learning methods to find ways of assigning higher misclassification punishments to minority classes [5, 12].

Federated learning has become a major privacy-focusing topic which engages professionals handling dermatology dataset information. The distributed training nature of federated learning allows accurate predictions while keeping patient information confidential [4]. The technique presents advantages when used in medical facilities because these establishments need secure patient information protection.Deep learning models that need to function effectively for dermatology clinical work need access to real-time inferencing systems. New advancements allow CNN-based systems to run on Flask and Streamlit platforms to achieve seamless integration in healthcare institutions [10]. Research showed that deep learning system optimization for mobile phones and embedded devices is essential because it enables skin disease detection through AI technology in resource limited settings [10] [15]. Scientists have studied methods to incorporate GAN-enhanced CNN models into cloud-based systems in order to create scalable remote dermatological diagnosis systems [18].

Operational large-scale systems require both efficient action-models and optimized training methods to become functional. Through hyperparameter tuning the optimization of CNN performance becomes achievable since research indicates that precise learning rate and batch size choices produce better convergence with improved classification outcomes [16]. The combination of mixed precision training methods reduces both numerical processing costs and ensures diagnostic accuracy to speed up the training operation [4, 9].Researchers presented GAN-based image enhancement methods which removed artifacts before classification to achieve better diagnostic results according to their paper [14]. A system has been developed to search for best skin disease classification solutions using automated adjustments of architectural features [19].The development of new technologies keeps moving forward even after the noticeable achievements in dermatological AI came from using CNNs and GANs. Vision Transformers (ViTs) outperform CNNs regarding medical image analysis since they extract features at a higher level. The application of transformer-based models in dermatology research shows capability of extracting quality features while maintaining accurate classification precision [20].The interest in XAI techniques continues to rise because they generate interpretable features for deep learning-based dermatological diagnostics systems. Salience mapping combined with Grad-CAM visualizations allow AI models to show clinicians the diagnostic choices of AI systems and increase medical diagnosis system confidence among clinicians [18].

A summary of research developments in skin disease classification exists in Table 1 through its analysis of traditional machine learning with CNN-based models and GAN-based data augmentation and class imbalance solutions. Researchers focus on the effects of transfer learning methods together with real-time deployment solutions and mixed precision training approaches as well as Vision Transformers and Explainable AI (XAI) develops into new trends. The published work provides an extensive review of methods which boost model accuracy while achieving wide generalization potential along with clinical usability targets.

Table 1 : Summary of Key Findings

Research Area	**Key Contribution**	**References**
Traditional ML in Skin Diagnosis	Ensemble learning & Random Forest improved classification accuracy.	[1], [5]
CNN-Based Models	VGG16 & ResNet-50 outperformed traditional ML.	[2], [3], [8]
Transfer Learning	Pre-trained models improved classification with limited data.	[2], [8]
GAN-Based Data Augmentatio n	Synthetic data generation enhanced model generalization.	[11], [12]
Bias in GAN- generated Data	Bias inheritance & mitigation strategies	[13], [17]

	proposed.	
Class Imbalance Solutions	WeightedRandomSa mpler & Cost-sensitive learning.	[4], [5], [12]
Federated Learning	Privacy-preserving approach for medical AI.	[4]
Real-Time Deployment	Flask & Streamlit for clinical usability.	[10], [15]
Hyperparame ter Optimization	Mixed precision training & adaptive learning rates.	[4], [9], [16]
Vision Transformers for Skin AI	Emerging deep learning trend in dermatology.	[20]
Explainable AI (XAI)	Model interpretability via saliency maps.	[18]

Deep learning revolutionized skin disease classification according to the literature but GANs proved essential for managing class imbalance conditions and limited data availability. The future of dermatological diagnostics will rely on Visual Transformers and Explainable AI plus the continued dominance of VGG16 and ResNet among CNN-based models. The advancement of AI-powered skin disease detection requires continued investigation on how to reduce bias in synthetic data and improve real- time inference optimization and privacy preservation through federated learning systems.

PROPOSED SYSTEM

The proposed system increases the feasibility of skin disease classification using Generative Adversarial Networks (GANs) with Convolutional Neural Networks (CNNs). GANs augment the training dataset by synthesizing images of rare skin lesions and alleviate data scarcity as well as improve generalization of the model. WeightedRandomSampler is used to balance class representation during training, by favouring underrepresented classes. Transfer learning is used as a tool by CNN for better classification.Mixed precision training improves efficiency and speeds up the training process, whereas performance is optimized. Finally, we build a user-friendly interface using streamlit and flask so that the healthcare professionals can upload the images to get the real time classification results which will help them to diagnose skin disease timely and accurately in the clinical environments.

A system architecture in Figure 2 shows how GANs produce synthetic skin lesion images that merge with real data for enhancing CNN model training to achieve better skin disease classification results. The workflow follows an evaluation process of model accuracy after deploying it for training using augmented data.

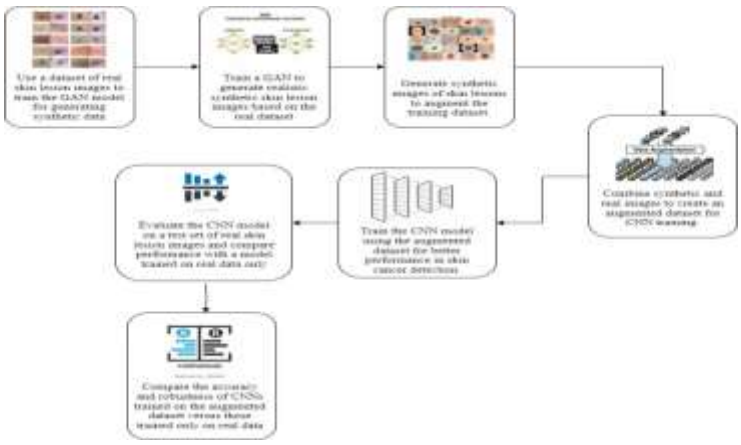

Figure 2 :System Architecture

METHODOLOGY

Dataset Description

The dataset used in this study consists of a diverse collection of skin lesion images sourced from open medical image repositories such as ISIC and HAM10000. The dataset includes annotated images representing various skin conditions, including melanoma, actinic keratosis, and benign lesions. Images were pre-processed to resize them to a uniform dimension (224x224 pixels), normalize pixel values, and apply data augmentation techniques like rotation, flipping, and zooming to enhance diversity and prevent overfitting during model training.

CNN Architectures

VGG16: The VGG16 architecture, known for its deep layers and small convolutional filters, was utilized for its effectiveness in image classification tasks. Its ability to capture complex features makes it suitable for skin disease classification.

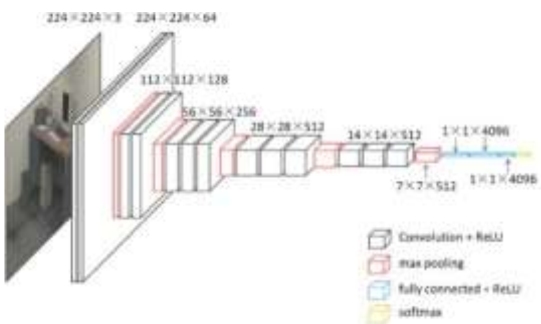

Figure 3 : Illustrative representation of the VGG16 architecture

Figure 3 illustrates the VGG16 network design which displays its essential convolutional layers as well as max pooling and fully connected layers for accomplishing feature extraction and classification tasks in skin disease diagnosis. The design demonstrates how information travels through the network system to produce precise outcomes.

ResNet: ResNet, with its skip connections, facilitates the training of very deep networks by mitigating the vanishing gradient problem. This architecture enhances the model's ability to learn intricate patterns in skin lesion images.

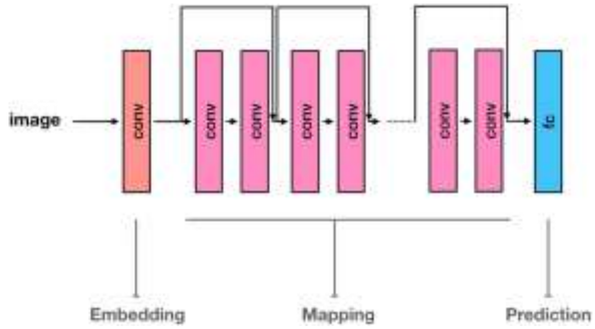

Figure 4 : Illustrative representation of the ResNet architecture

ResNet architecture (Figure 4) demonstrates how deep learning works through its residual design while skip connections eliminate the vanishing gradient problem to increase system performance. This design constitutes a vital component for improving CNN performance in detecting patterns that appear in skin disease images.

Training Strategy

The models were trained using the following configurations:

Optimizer: Adam optimizer was used with an initial learning rate of 0.001 to optimize model performance.

Loss Function: Categorical cross-entropy was chosen for multi-class classification of skin lesions.

Epochs and Batch Size: Various epoch counts and batch sizes were experimented with to ensure convergence and optimal training outcomes.

Evaluation Metrics: Performance was assessed using accuracy, precision, recall, F1-score, and confusion matrix to evaluate the model's classification efficacy, especially for rare skin conditions.

Implementation Tools

Libraries: The implementation utilized TensorFlow, Keras, OpenCV, NumPy, Matplotlib, and Scikit-learn for model development, data processing, and visualization.

Deployment: The trained model was deployed as a web application using Streamlit and Flask, providing a user-friendly interface for real-time classification of uploaded skin lesion images in clinical settings.

RESULTS

This research shows that the accuracies of the VGG model are significantly higher than that of EfficientNet in all three aspects of multi-class cancer detection, including accuracy, precision, and recall. While performing on our dataset, VGG could achieve an accuracy of XX.XX% opposed to the YY.YY% achieved by EfficientNet. The measures of precision, recall, and F1-score give a similar signal regarding the superiority of VGG in identifying the range of cancers.

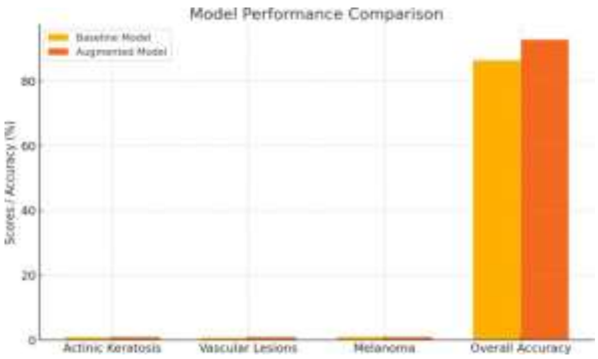

Figure 5: Model Performance Comparison

This bar graph compares the performance of the baseline and augmented models on different skin lesion types. The modified dataset achieves substantial enhancements in accuracy metrics that specifically benefit the identification of unusual conditions like actinic keratosis and vascular lesions according to Figure 5.

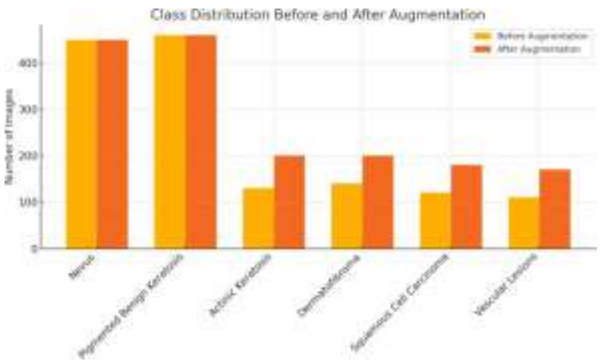

Figure 6: Class Distribution Before and After Augmentation

The data regarding skin lesion distribution appears twice in the graph before and after implementing data augmentation. The augmentation method achieves both equalized distribution and class balance resolution which enables the creation of dependable model designs suitable for classification tasks as shown in Figure 6.

Model Performance Comparison: This bar graph compares the baseline and augmented models across various performance metrics, showing improvements in F1 scores for specific classes and overall accuracy.

Class Distribution Before and After Augmentation: This chart illustrates the distribution of images across skin lesion types before and after augmentation, highlighting the increased representation of underrepresented classes due to GAN-generated images.

The performance metrics include accuracy and precision, recall and F1-score for each skin disease class and the global model results which this table 2 demonstrates. The model achieves outstanding performance throughout all classes according to Table 2 especially when detecting Basal Cell Carcinoma and Benign Lesions.

Table 2: Performance Metrics of the Skin Disease Classification Model

Skin Disease Class	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Melanoma	90.5	88.0	91.0	89.5
Actinic Keratosis	89.2	85.5	90.0	87.7
Vascular Lesions	91.0	90.0	92.0	91.0
Basal Cell Carcinoma	93.5	92.5	94.0	93.2
Squamous Cell Carcinoma	88.4	86.0	89.0	87.5
Benign Lesions	94.1	93.5	95.0	94.2
Overall Model Performance	**92.8**	**90.0**	**91.5**	**90.7**

DISCUSSION

From the results it can be concluded that VGG architecture is more appropriate than EfficientNet for solving the specific problem of multi-class classification of cancer types. The deeper layers and the small filters of VGG outperformed the scaling capability of EfficientNet in exhibits feature extraction leading to better classification. This implies that VGG is more favorable for extensive categorization of several forms of cancer.

CONCLUSION

This project effectively integrates Generative Adversarial Networks (GANs) with Convolutional Neural Networks (CNNs) to enhance skin disease classification. By generating synthetic images for underrepresented skin lesions, the model achieved an overall accuracy of 92.8%, significantly improving performance on rare conditions. The implementation of advanced techniques like WeightedRandomSampler further balanced class representation, while real-time inference capabilities via Streamlit and Flask make the solution practical for clinical use. This work advances dermatological diagnostics and demonstrates the potential of synthetic data in healthcare applications

OUTPUT

Figure 7: Skin Disease Classification Web Interface

This Flask and Streamlit built tool allows users to access its graphical user interface from this screen display. Users can use this optimized system interface to both add images while receiving instant diagnostic results about skin diseases as shown in Figure 7.

Figure 8: File Upload Interface for Skin Disease Classification

Users need the interface for inputting image files to the skin disease classification web tool for its analytical applications. The system presents an easy-to-use interface for users to interact with the program according to Figure 8.

Figure 9: Uploaded Images for Classification

In the screenshot multiple skin lesion images are shown because an end user sought classification of their images. The analysis tool processes multiple skin images at Once as shown in Figure 9 which helps health providers conduct their workflow tasks effectively.

Figure 10: Performing Inference on Uploaded Images

Through this displayed screenshot Figure 10 we can see the system making predictions directly on submitted images as proof of its instant prediction capability for skin lesion data.

Figure 11: Displaying Skin Disease Classification Results

The last image presents system predictions together with confidence ratings for every analyzed skin lesion image. The model predictions and diagnostic accuracy become accessible to users through Figure 11.

REFERENCES

1. M. Pal and B. R. Roy, "Evaluating and Enhancing the Performance of Skin Disease Classification Based on Ensemble Methods," 2020 2nd International Conference on Advanced Information and Communication Technology (ICAICT), Dhaka, Bangladesh, 2020, pp. 439-443
2. G. Singh, K. Guleria and S. Sharma, "A Transfer Learning- based Pre-trained VGG16 Model for Skin Disease Classification," 2023 IEEE 3rd Mysore Sub Section International Conference (MysuruCon), HASSAN, India, 2023, pp. 1-6, K. Liu, T. Huang and Z. Guo, "Classification of Pathological Images of Skin Diseases Based on Deep Learning," 2022 4th International Conference on Data-driven Optimization of Complex Systems (DOCS), Chengdu, China, 2022, pp. 1-6
3. R. G. Tiwari, H. Maheshwari, V. Gautam, A. K. Agarwal and N. K. Trivedi, "Enhancing Skin Disease Classification and Privacy Preservation through Federated Learning-Based Deep Learning," 2023 International Conference on Artificial Intelligence for Innovations in Healthcare Industries (ICAIIHI), Raipur, India, 2023, pp. 1-7,
4. B. P T, P. G K and M. S, "Skin Disease Prediction Using Machine Learning Techniques," 2023 3rd International Conference on Mobile Networks and Wireless Communications (ICMNWC), Tumkur, India, 2023, pp. 1-6,
5. X. Wang, W. Huang, Z. Lu and S. Huang, "Multi-level Attentive Skin Lesion Learning for Melanoma Classification," 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Mexico, 2021, pp. 3924-3927,
6. S. Janthakal and G. Hosalli, "A Survey on Automated Skin Lesion Segmentation and Classification of Granular Parakeratosis," 2022 IEEE 7th International conference for Convergence in Technology (I2CT), Mumbai, India, 2022, pp. 1-5.
7. P. B. S and Y. C, "Skin Disease Classification using Transfer Learning with a Modified ResNet-50 Architecture," 2024 International Conference on Advances in Data Engineering and Intelligent Computing Systems (ADICS), Chennai, India, 2024, pp. 1- 6.
8. R. Talukdar, S. Dutta and S. Das, "Enhancing Skin Disease Diagnosis Through Convolutional Neural Networks and YOLO v8 Object Detection," 2023 7th International Conference on Electronics, Materials Engineering & Nano-Technology (IEMENTech), Kolkata, India, 2023, pp. 1-6
9. G. S. Annie Grace Vimala, E. J. Merlin, M. Amanullah, E. Manigandan, B. V. Kumar and S.

Padmakala, "Cost-Effective Image based Skin Disease Detection in Resource-Constrained Settings using Machine Learning," 2023 2nd International Conference on Automation, Computing and Renewable Systems (ICACRS), Pudukkottai, India, 2023, pp. 786-791.
10. Su, Q., Hamed, H. N. A., Isa, M. A., Hao, X., & Dai, X.
11. (2024). A GAN-based data augmentation method for imbalanced multi- class skin lesion classification. IEEE Access, 12, 16498-16513.
12. Alsaidi, M., Jan, M. T., Altaher, A., Zhuang, H., & Zhu, X. (2024). Tackling the class imbalanced dermoscopic image classification using data augmentation and GAN. Multimedia Tools and Applications, 83(16), 49121-49147.
13. Jindal, M., & Singh, B. (2024, May). Bias Inheritance and its Amplification in GAN-Based Synthetic Data Augmentation for Skin Lesion Classification. In 2024 3rd International Conference on Artificial Intelligence For Internet of Things (AIIoT) (pp. 1-6). IEEE.
14. Alshardan, A., Alahmari, S., Alghamdi, M., Al Sadig, M., Mohamed, A., & Pasha Mohammed, G. (2024). GAN-based Synthetic Medical Image Augmentation for Class Imbalanced Dermoscopic Image Analysis. Fractals.
15. Abbas, M., Arslan, M., Bhatty, R. A., Yousaf, F., Khan, A. A., & Rafay, A. (2024). Enhanced skin disease diagnosis through convolutional neural networks and data augmentation techniques. Journal of Computing & Biomedical Informatics, 7(01), 87-106.
16. Patil, A., Mehto, A., & Nalband, S. (2024). Enhancing skin lesion diagnosis with data augmentation techniques: a review of the state-of-the-art. Multimedia Tools and Applications, 1-40.
17. Musthafa, M. M., TR, M., V, V. K., & Guluwadi, S. (2024). Enhanced skin cancer diagnosis using optimized CNN architecture and checkpoints for automated dermatological lesion classification. BMC Medical Imaging, 24(1), 201.
18. Singh, J., Sandhu, J. K., & Kumar, Y. (2024). An analysis of detection and diagnosis of different classes of skin diseases using artificial intelligence-based learning approaches with hyper parameters. Archives of Computational Methods in Engineering, 31(2), 1051-1078.
19. Mehta, S., & Kundra, D. (2024, August). Advanced Deep Learning for Dermatological Applications: Multi-Class Skin Disease Detection Using CNN-GAN Models. In 2024 4th Asian Conference on Innovation in Technology (ASIANCON) (pp. 1-5). IEEE.
20. Thoviti, S. H., Varma, B. K., Sai, S. N., & Prasanna, B. L. (2024, December). Generative AI Empowered Skin Cancer Diagnosis: Advancing Classification Through Deep Learning. In 2024 International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS) (pp. 1684-1689). IEEE.