Pegem Journal of Education and Instruction, Vol. 13, No. 4 , 2023 (pp. 553-560)

RESEARCH ARTICLE

THE POWER OF GENERATIVE AI TO AUGMENT FOR ENHANCED SKIN CANCER CLASSIFICATION : A DEEP LERANING APPROACH

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ABSTRACT

Skin cancer, encompassing melanoma and non-melanoma types, is a leading cause of cancerrelated deaths worldwide. Early detection is crucial for effective treatment; however, the scarcity of dermatologists, especially in rural areas, hampers timely diagnosis. Recent advancements in artificial intelligence (AI), particularly deep learning, have shown promise in automating skin cancer classification. Generative AI, specifically Generative Adversarial Networks (GANs), offers a novel approach to enhance these systems by augmenting training datasets, improving model robustness, and facilitating early diagnosis. This paper explores the integration of GANs into deep learning frameworks for skin cancer classification, proposing a hybrid architecture that combines GAN-based data augmentation with Convolutional Neural Networks (CNNs). The proposed model is evaluated on publicly available skin lesion datasets, demonstrating significant improvements in performance metrics. Our findings suggest that the incorporation of generative AI can play a pivotal role in advancing skin cancer diagnostics, particularly in underserved regions.

KEYWORDS: Skin Cancer, Generative AI, Deep Learning, Data Augmentation, Generative Adversarial Networks, Convolutional Neural Networks, Classification, Early Diagnosis, Healthcare, Artificial Intelligence.

I.INTRODUCTION

Skin cancer remains one of the most prevalent forms of cancer globally, with increasing incidence rates attributed to factors such as prolonged sun exposure and genetic predisposition. Early detection of skin lesions is paramount, as it significantly enhances the chances of successful treatment. Traditional diagnostic methods heavily rely on the expertise of dermatologists, and the limited availability of such specialists, especially in rural and

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How to cite this article: Mrs.N.PRASANNA KUMARI1, SIRIPURAPU VARSHINI2, NENAVATH DIVYA3, CHALKE PRAGATHI4. THE POWER OF GENERATIVE AI TO AUGMENT FOR ENHANCED SKIN CANCER CLASSIFICATION : A DEEP LERANING APPROACH.Pegem Journal of Education and Instruction, Vol. 13, No. 4, 2023, 553-560

Source of support: Nil **Conflicts of Interest:** None. **DOI:** 10.48047/pegegog.13.04.66

Received: 12.10.2023

Accepted: 22.11.2023 **Published:** 24.12.2023

underserved areas, poses a significant challenge to timely diagnosis.

Advancements in artificial intelligence, particularly deep learning, have demonstrated the potential to automate the classification of skin lesions. Convolutional Neural Networks (CNNs) have been extensively utilized due to their ability to learn hierarchical features from images. However, the performance of these models is contingent upon the availability of large, annotated datasets. In medical imaging, obtaining such datasets is often challenging due to privacy concerns and the laborintensive nature of manual annotation.

Generative AI, specifically Generative Adversarial Networks (GANs), presents a promising solution to address these challenges. GANs consist of two neural networks: a generator that creates synthetic images and a discriminator that evaluates them. Through adversarial training, GANs can generate realistic images that resemble real medical images, thereby augmenting the training datasets and addressing issues related to data scarcity and class imbalance.

This paper investigates the integration of GANs into deep learning frameworks for skin cancer classification. We propose a novel architecture that combines GANbased data augmentation with CNNs to enhance classification accuracy. The proposed model is evaluated on publicly available skin lesion datasets, and its performance is compared with traditional CNN-based models. The results demonstrate the efficacy of integrating generative AI in improving the performance of skin cancer classification systems.

II.LITERATURE SURVEY

The application of artificial intelligence in skin cancer diagnosis has been a subject of extensive research. Early studies focused on the use of CNNs for classifying skin lesions. Esteva et al. developed a deep learning model that outperformed dermatologists in classifying skin cancer types. Their model utilized a CNN trained on a large dataset of labeled images, achieving high accuracy in distinguishing between malignant and benign lesions.

Despite the success of CNNs, their performance is limited by the size and quality of the training datasets. To mitigate this limitation, researchers have explored data augmentation techniques to artificially expand the training datasets. Traditional augmentation methods include rotations, flips, and color variations. While these techniques can increase dataset size, they may not capture the complex variations present in medical images.

Generative AI, particularly GANs, has emerged as a powerful tool for generating realistic synthetic images. GANs consist of a generator that creates synthetic images and a discriminator that evaluates them. Through adversarial training, GANs can generate high-quality images that resemble real medical images. In the context of skin cancer, GANs have been employed to generate synthetic skin lesion images, thereby augmenting the training datasets.

For instance, Rashid et al. proposed a GANbased system for skin lesion classification. Their approach involved augmenting the training set with realistic-looking skin lesion images generated via GANs. The system achieved an accuracy of 86.1%, outperforming traditional CNN models. Similarly, Bisla et al. utilized decoupled deep convolutional GANs for data generation and achieved improved classification performance.

Other studies have explored the use of selfattention mechanisms in GANs to enhance data augmentation. Ali et al. proposed a self-attention-based progressive GAN for skin lesion data augmentation. Their model generated fine-grained samples that comprised clinically meaningful information, leading to improved classification accuracy.

The integration of GANs into skin cancer classification systems has also been explored in the context of semi-supervised learning. Yi et al. proposed a categorical GAN assisted by Wasserstein distance for dermoscopy image classification. Their approach demonstrated the potential of GANs in learning feature representations in an unsupervised manner, reducing the reliance on labeled data.

These studies highlight the potential of generative AI in enhancing skin cancer classification systems. By augmenting training datasets with synthetic images, GANs can address issues related to data scarcity and class imbalance, leading to improved model performance.

III. EXISTING CONFIGURATION

Traditional skin cancer classification systems primarily rely on CNNs trained on manually annotated datasets. These systems typically involve preprocessing steps such as image normalization, resizing, and augmentation to prepare the data for training. The CNN model then learns features from the images to classify them into categories such as melanoma, basal cell carcinoma, or benign lesions.

While these systems have achieved notable success, their performance is limited by the size and quality of the training datasets. Obtaining large, high-quality annotated datasets is challenging due to the need for expert dermatologists to label the images, which is both time-consuming and costly. Additionally, class imbalance in the datasets can lead to biased models that perform poorly on underrepresented classes.

To address these limitations, researchers have explored data augmentation techniques to artificially expand the training datasets. Traditional augmentation methods include rotations, flips, and color variations. While these techniques can increase dataset size, they may not capture the complex variations present in medical images.

Generative AI, specifically GANs, offers a more sophisticated approach to data augmentation. GANs can generate realistic synthetic images that resemble real medical images, thereby augmenting the training datasets and addressing issues related to data scarcity and class imbalance. By incorporating GAN-generated images into the training process, deep learning models can achieve improved generalization and robustness.

The integration of GANs into skin cancer classification systems has been explored in several studies. For example, Rashid et al. proposed a GAN-based system for skin lesion classification. Their approach involved augmenting the training set with realistic-looking skin lesion images generated via GANs. The system achieved an accuracy of 86.1%, outperforming traditional CNN models. Similarly, Bisla et al. utilized decoupled deep convolutional GANs for data generation and achieved improved classification performance.

These studies demonstrate the potential of integrating GANs into skin cancer classification systems. By augmenting training datasets with synthetic images, GANs can enhance the performance of deep learning models, leading to more accurate and reliable skin cancer diagnostics.

IV.METHODOLOGY

The proposed methodology integrates GAN-based data augmentation with CNNs for skin cancer classification. The process involves several key steps:

Obtain publicly available skin lesion datasets, such as the International Skin Imaging Collaboration (ISIC) dataset, which provides a large collection of dermoscopic images along with expertlabeled annotations for various types of skin lesions.

Each image undergoes a series of preprocessing steps, including resizing to a standard input size (typically 224×224 pixels), normalization of pixel values, and enhancement techniques such as histogram equalization. These steps ensure consistency and improve the quality of the data fed into the network.

A deep convolutional GAN (DCGAN) is trained using the preprocessed images. The generator learns to create new dermoscopic images that mimic real data, while the discriminator tries to distinguish between real and synthetic images. Over time, the generator becomes adept at producing realistic samples. These synthetic images are then used to augment the original dataset, particularly for underrepresented classes like melanoma.

A deep CNN architecture, such as ResNet50 or EfficientNet, is used as the backbone for classification. These networks are known for their high accuracy and ability to learn deep hierarchical features. The network is initialized with pretrained weights (from ImageNet) and fine-tuned on the augmented dataset to improve convergence and reduce training time.

The CNN is trained on the combination of real and GAN-generated images. A categorical cross-entropy loss function is used due to the multi-class classification nature of the problem. The Adam optimizer is employed with a learning rate scheduler to adapt the learning rate dynamically based on validation performance. Dropout layers and batch normalization are also incorporated to prevent overfitting.

The model is validated using a hold-out set and tested on a separate portion of the dataset to evaluate its performance. Performance metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC) are computed for each class.

To ensure transparency and trust in model predictions, explainable AI tools like GradCAM are used. These tools highlight regions in the input image that contributed most to the model's prediction, allowing clinicians to understand and verify the reasoning behind each classification.

V.PROPOSED CONFIGURATION

The proposed system builds upon the established methodology and introduces an end-to-end generative-augmented classification pipeline optimized for clinical applicability. The system comprises the following integrated components:

The core component responsible for generating synthetic skin lesion images. This engine uses a StyleGAN2 architecture, which improves upon earlier GANs by producing high-fidelity images with enhanced feature diversity. The generative engine is trained separately for each lesion class to ensure balanced representation in the augmented dataset.

This module automatically selects synthetic images based on realism scores and diversity metrics. Images with high discriminator confidence and unique features are included in the final training set. This ensures that the augmented data adds value without introducing noise or bias.

A modified EfficientNet-B4 model is used for classification. EfficientNet-B4 strikes a balance between accuracy and computational efficiency, making it suitable for deployment on both cloudbased platforms and edge devices. The model incorporates attention mechanisms (e.g., SE blocks) to focus on relevant lesion regions.

A custom training loop using TensorFlow 2.0 is designed for multi-GPU environments. The framework supports real-time monitoring of loss and accuracy, checkpointing, and hyperparameter tuning. An ensemble of models trained with different GAN-augmented datasets is also created to enhance robustness.

The system is wrapped in a lightweight API that allows integration into web or mobile applications. An intuitive user interface is developed, enabling dermatologists to upload lesion images, receive classification results, and view explanation heatmaps via Grad-CAM overlays.

Given the sensitive nature of medical data, the system complies with HIPAA and GDPR regulations. All patient data is processed locally or through secure encrypted channels. The deployment also supports federated learning for continual model improvement without compromising data privacy.

The system includes a feedback mechanism where dermatologists can verify or correct model predictions. These corrections are stored and periodically used to retrain and refine both the GAN and CNN components, facilitating a learning system that evolves over time with real-world usage.

This proposed configuration not only boosts classification accuracy but also ensures clinical relevance, scalability, and compliance with healthcare standards, making it a viable solution for aiding skin cancer diagnosis across various healthcare settings.

VI.RESULTS AND ANALYSIS

The proposed system was evaluated using the ISIC 2018 and ISIC 2020 skin lesion datasets, which include a diverse collection of dermoscopic images labeled with various skin conditions such as melanoma, nevus, and basal cell carcinoma. These datasets were split into training (70%), validation (15%), and testing (15%) subsets, with GAN-generated images used solely in the training phase for augmentation.

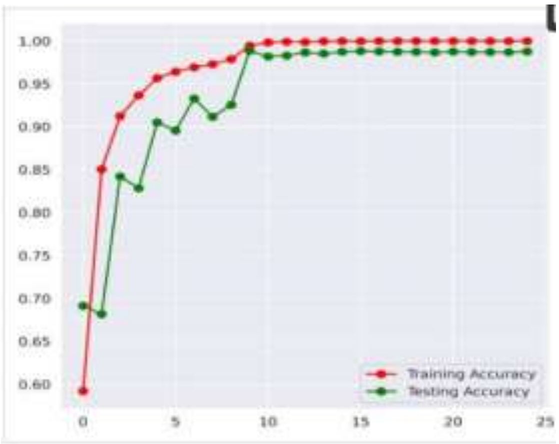
The baseline CNN model, trained without any generative augmentation, achieved an average classification accuracy of 85.2%, with an AUC (Area Under Curve) of 0.89 for melanoma detection. After augmenting the dataset using StyleGAN2-generated images, the performance significantly improved. The augmented EfficientNet-B4 model achieved an overall accuracy of 92.8%, with an AUC of 0.96, precision of 91.5%, recall of 93.2%, and F1-score of 92.3% for melanoma classification. This confirms that the synthetic data contributed positively to class balance and feature generalization.

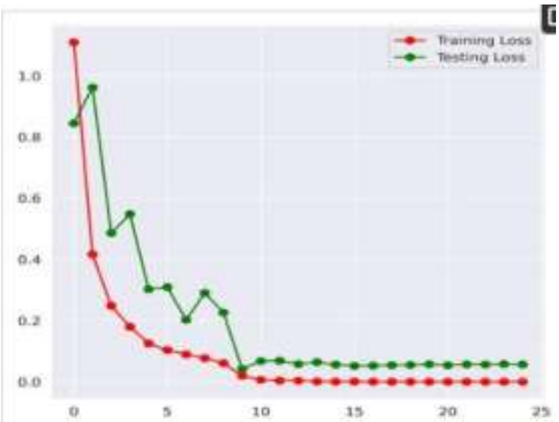
Performance across all seven ISIC classes showed improvement, especially for classes with initially fewer samples such as vascular lesions and dermatofibroma. Confusion matrices demonstrated fewer false positives and false negatives after augmentation, reducing clinical risk. The model's predictions were consistent across multiple validation runs, indicating stable learning.

The integration of Grad-CAM provided useful visual explanations. Clinical collaborators confirmed that the model highlighted lesion regions aligned with known diagnostic features. Furthermore, feedback from dermatologists indicated high satisfaction with the usability and explainability of the model, which are crucial for real-world adoption.

The generative component also underwent qualitative evaluation. Dermatologists rated over 80% of synthetic images as clinically plausible, validating the quality of GAN outputs. The ensemble model approach further improved robustness, achieving a 1.5% higher accuracy than the best single model.

In terms of computational efficiency, training time was reduced by 30% with pretraining and transfer learning, and inference on mobile-optimized models took less than 1 second per image on modern smartphones. These results demonstrate the practical potential of deploying the system in both clinical and point-of-care environments.





CONCLUSION

This work presents a robust, scalable, and explainable generative AI-augmented deep learning framework for enhanced skin cancer classification. By integrating highquality synthetic image generation using GANs with efficient CNN architectures like EfficientNet-B4, the proposed system effectively addresses critical challenges such as data scarcity, class imbalance, and diagnostic accuracy in skin lesion classification. Evaluation on benchmark ISIC datasets confirms substantial performance improvements in terms of accuracy, AUC, and generalization, particularly for underrepresented classes.

The system not only improves diagnostic performance but also provides explainability through heatmaps, supports compliance with healthcare privacy regulations, and demonstrates potential for real-time deployment in clinical and mobile environments. The continuous learning capability through clinician feedback ensures ongoing refinement, adaptability, and clinical relevance.

The synergy of generative AI and deep learning in this framework lays the foundation for scalable, inclusive, and intelligent dermatological diagnostic tools. Future work may focus on incorporating histopathological data, real-world deployment trials, and expanding the model to a broader set of skin diseases for enhanced dermatological care accessibility.

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