iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 12 **Issue:** X **Month of publication:** October 2024

DOI: https://doi.org/10.22214/ijraset.2024.64771

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue X Oct 2024- Available at www.ijraset.com

A Review of Advancement in using Generative AI for Detecting Skin Cancer

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Abstract: ***Skin cancer is a very common type of cancer that is asymptomatic in the early stage of development and is difficult to diagnose and treat. More and more people have used generative AI methods to enhance the speed and accuracy of skin cancer prediction in the recent past. Current techniques of artificial intelligence and deep learning algorithms are performing quite effectively in the field of dermoscopy and identification of malignant lesions. This study overviews the recent developments in Skin Cancer Detection Approaches based on emerging AI methods like Generative Adversarial Networks (GAN); Variational AutoEncoders (VAE); and derivatives of both. In this study, we discussed several approaches to implementing generative AI for skin cancer detection, the advantages and disadvantages of each approach, and identified research that has revealed potential in the field.***
Keywords: Skin cancer detection, Generative Adversarial Networks ***(GAN), Variational AutoEncoders (VAE), Deep learning in dermatology, AI for malignant lesion identification, Dermoscopy techniques.***

I. INTRODUCTION

Skin cancer is in most cases a result of skin damage generated by ultraviolet rays from the Sun which leads to cells in the skin dividing uncontrollably. One kind of skin cancer is a continually rising problem within the healthcare industry around the world. Though there is some evidence of an inherited tendency to develop skin cancer, the primary culprit is ultraviolet radiation that alters the skin cell's DNA and triggers uncontrolled growth – malignancy.

However, the four major types of Skin Cancer are Melanoma Squamous Cell Carcinoma (SCC), and Base Cell Carcinoma(BCC). It is less frequent but is the most malignant type because it is responsible for most of the fatalities from skin cancer, it can spread to other organs. The less frequent but more dangerous and non-melanoma skin type cancers including SCC and BCC can be lethal if not treated. Skin cancer is common in areas that receive many rays of sunshine, and the characteristics are having light-colored skin, being easily sunburnt, exposure to much ultraviolet light, and family history. Carcinoma of the skin is also increased among young people yet is more common among old people. That is why the first signs and symptoms should be checked and stopped at any age.

Early detection is key. Dermatologists can see skin cancer and treat it at an early stage with the naked eye, biopsy, and AI.

A. Objectives

This section provides a fundamental overview of methods and methodologies that researchers have employed on skin cancer detection and classification tasks. All of these studies employed different techniques and data sets, some employing deep learning models, other SVMs, GANs, ISIC 2016, ISIC 2019, ISIC 2020. The specific objectives are:

1) *Review of Existing Methods:* The purpose of this paper is to analyze and compare the techniques and approaches that researchers have used to detect and classify skin cancer. (which would entail a look at all the datasets, algorithms, and evaluation metrics used in each of these studies).
2) *Comparative Analysis:* To see how well the different models performed as far as accuracy, sensitivity, specificity, and all the other good stuff goes. This should show the advantages and disadvantages of each method and exactly how to find skin cancer best.
3) *Identification of Novel Approaches:* To explore and examine some of the more unique and unusual methods (generative AI, data augmentation, etc. that have shown some real promise in the literature.
4) *Preprocessing and Data Augmentation:* Some preprocessing techniques like data augmentation and image normalization are explained to enhance the size and composition of the dataset used for testing/training the models.
5) *Methodology Description:* To explain fully the proposed approach, focusing on image processing, architecture of the model, and augmentation and how these factors enhance the skin cancer detection system to be more reliable and accurate.

6) *Evaluation of ISIC 2020 Dataset:* To test the proposed model against the ISIC 2020 dataset which contains 33,126 training images of 2,000 unique patients and discuss the results relative to state of the art.

These goals are all hoped to be achieved through this section in order to give a complete overview of the current state-of-the-art in skin cancer detection and classification, to point out the strides and developments made in this field, and to set the stage for the creation of more precise and dependable skin cancer recognition systems.

II. RELATED WORK

This paper [1] introduces a novel method using Deep Convolutional Generative Adversarial Networks (DCGAN) to create synthetic hyperspectral images of epidermal lesions for skin cancer diagnosis. By leveraging DCGAN, the study tackles the issue of limited datasets, crucial as AI becomes more prevalent in healthcare. The model is trained on a small hyperspectral skin cancer dataset, applying transfer learning from larger RGB datasets.

The synthetic data is evaluated using Frechèt Inception Distance (FID) and classification performance with ResNet18, showing strong similarity to real datasets. Spectral signature comparisons further validate this similarity. While the approach is promising, future research should explore new GAN architectures and conditional GANs to generate diverse tumor types.

SkinCan AI [2] highlights the crucial role of early skin cancer diagnosis and the potential of artificial intelligence in enhancing this process. It emphasizes melanoma's significance in global health and the need for accurate, accessible diagnostic tools. Several factors have been implicated in the increased incidence and mortality of skin cancer including UV exposure, genetic predisposition, and delayed diagnosis.

This article is about how skin cancer is difficult to diagnose because the naked eye can't see everything and biopsies are intrusive, but dermoscopic surgery, a relatively noninvasive procedure, can better determine the presence of skin cancer. It calls for the creation of computerized diagnostic algorithms to support the dermatologist, especially in impoverished medical environments.

Convolutional neural networks (CNNs) serve as a powerful deep-learning architecture for skin cancer detection, automatically learning hierarchical representations of image data. Additionally, transfer learning enhances smaller medical image datasets by leveraging pre-trained CNN models on larger datasets like ImageNet, addressing the scarcity of labeled medical images.

This paper [3] aims to enhance skin cancer diagnosis by developing a fully automated model for generating and classifying skin lesions using Deep Convolutional Generative Adversarial Networks (DCGAN). The methodology involves training DCGAN with the Python-based Keras library and employing effective image filtering and enhancement algorithms to optimize recognition during training. Hyperparameter optimization fine-tunes the network by adjusting the learning rate and the Adam optimization algorithm's speed.

The model distinguishes between benign and malignant lesions through binary classification, achieving a test accuracy of 93.5% after parameter fine-tuning. The study underscores DCGAN's potential for cancer risk prediction while acknowledging challenges in generating high-quality synthetic images for comparison with real samples. It also discusses the background of Generative Adversarial Networks (GANs) in skin cancer classification, emphasizing the need to overcome issues like mode collapse and instability. Overall, this research seeks to improve skin cancer diagnosis using advanced deep learning and image synthesis techniques.

The paper [4] discusses the development and application of a new method, the Cat Swarm Intelligent Gene Recurrent Neural Network (CS-IGRNN), to detect skin cancer using a clinical image dataset. The study used a total of 22,000 clinical image datasets from the Dermquest and DermIS digital databases. Image preprocessing techniques such as the Weiner filter (WF) and the Gabor filter bank (GFB) are used to improve image features. The CS-IGRNN method is proposed as a potential solution to categorize cancer images, leveraging cat behavior's swarm intelligence to optimize the parameters of the recurrent neural network. Several performance metrics such as accuracy, precision, f1 score, specificity, and sensitivity are used to evaluate the effectiveness of the method. The results are promising compared to other approaches.

According to the research, skin cancer is easily treated and cured if caught in time, yet it is on the rise and so are the deaths due to many types of skin cancers, including melanoma. Even with the medical strides in dermatoscopy, it is still difficult to diagnose accurately, especially with melanoma, which proves the point that a better diagnosis is needed. The CS-IGRNN solution is a more effective approach in this problem to enable early diagnosis of skin cancer, which is a critical stage in the treatment of cancer to increase the patient’s lifespan.

In the paper [5], the authors focus on the utilization of individual and combined computational technologies, namely CNN and GAN in particular, for the interpretation of melanoma. Despite the weaknesses of CNNs, such as overfitting and dependence on data, they can successfully learn from raw data the features relevant to the diagnosis of melanoma with the help of dermatologists.

To overcome these limitations, the article proposes a novel approach utilizing a customized Progressive Growing GAN (RGAN) architecture to generate photorealistic synthetic skin lesion images for dataset augmentation. The methodology involves progressively increasing the size of the generator and discriminator models during training, along with the use of residual connections inspired by ResNet and DenseNet. Wasserstein loss function is employed to train the RGAN, resulting in improved image quality. Extensive experimental studies demonstrate the effectiveness of the proposed approach in enhancing the performance of CNN models for melanoma diagnosis, outperforming other data augmentation techniques significantly across multiple datasets and CNN models.

The Paper [6] describes a deep learning algorithm for the classification of skin cancer images to help detect the disease, specifically melanoma, in its early stages, a disease that has been on the rise all over the world. The approach would be to use a Custom Convolutional Neural Network (CNN) trained on the Human Against Machine (HAM10000) dataset, which is available on Kaggle. To improve the quality of the data set, an Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) is used for pre-processing purposes to up sample and extract features from the images. The CNN model is designed with multiple layers of convolution, pooling, and batch normalization, tailored for skin lesion classification. Data augmentation techniques are also implemented to address dataset imbalance and improve model robustness. Experimental results demonstrate the effectiveness of the proposed approach, achieving high accuracy metrics of 98.77%, 98.36%, and 98.89% for skin cancer classification across different protocols, outperforming existing models in the literature.

The methodology involves preprocessing the HAM10000 dataset using ESRGAN for image enhancement, followed by data augmentation techniques to address dataset imbalances. A custom CNN model is then designed with multiple convolutional layers, pooling layers, and batch normalization to classify skin lesions. The model architecture is optimized for feature extraction from dermoscopic images, with each layer configured to extract and process image features effectively. The experimental results show considerable improvements in the accuracy metrics, which proves that the proposed method is very effective in classifying skin cancer lesions.

In the paper [7], the authors elaborate on the potential for utilizing machine learning technologies mainly deep learning approaches to GANs (Generative Adversarial Networks) in particular to enable dermatologists to detect Melanoma, which is a type of skin cancer considered very critical. However, let it be early detection as it’s often mentioned it is very hard to diagnose melanomas accurately meaning that a lot of unnecessary surgeries are done and the actual treatment is delayed. A significant problem is the paucity of extensive, balanced, annotated medical imagery datasets to use in training machine learning algorithms. However, this paper attempts to solve this problem by generating realistic melanoma images via StyleGAN2-ADA and analyzing these images with qualitative and quantitative tests. Even professional dermatologists have trouble telling the synthetic images from the real ones, the generated data is so realistic. Also, a classifier trained on synthetic images obtains high accuracy on real data, which shows the promise of synthetic data in the development of accurate classifiers for melanoma diagnosis in the clinical setting. The research as a whole indicates that the synthetic data could be a very helpful tool in the furtherance of medical image analysis, and ultimately the earlier recognition of melanoma. The paper [8] addresses the challenge of variable illumination conditions in dermatological images, which can impact both manual diagnosis and computer-aided diagnosis systems. To standardize image illumination, the authors propose a novel approach called Dermatological Color Constancy Generative Adversarial Network (DermoCC-GAN). This algorithm formulates color constancy as an image-to-image translation problem and is trained using a custom heuristic algorithm. Results demonstrate that DermoCC-GAN outperforms existing color constancy methods, achieving better performance in terms of normalized median intensity and improving lesion classification accuracy (79.2%) and segmentation dice score (90.9%) in a deep learning framework. The approach is also validated on external datasets with promising results, suggesting its potential for broader applications beyond dermatology. Overall, the study highlights the effectiveness of training a GAN to generalize heuristic methods for color constancy in dermatological image analysis, offering a promising solution to address illumination variability issues.

The paper [9] addresses the challenge of early diagnosis of skin cancer, proposing a CNN architecture named EfficientAttentionNet. The methodology involves several stages: pre-processing images to remove hair around skin lesions, generating synthetic images using a GAN model to balance class samples, creating masks for regions of interest with a U-net model, and training EfficientAttentionNet with a mask-based attention mechanism for lesion classification. The proposed model demonstrates high performance in the early diagnosis of melanoma and non-melanoma skin lesions, showcasing the potential for future research in this area. In Paper [10], the authors stress that more attention is paid to applying artificial intelligence to enhance the work of CAD systems in the diagnosis of skin cancer because of its severity and fewer dermatologists. Skin lesion classification is a pathology that uses deep learning algorithms that is used to classify malignant skin lesions from benign skin lesions in clinical, dermoscopy and histopathology images.

Although AI systems have shown much promise, they are only in their infancy in terms of clinical application. The analysis stresses again that the technical issues need to be resolved and the AI solutions need to be refined so that dermatologists will be able to diagnose those skin cancers efficiently. The research reflects the progress of technology, the approachability of imaging methodology, and the presence of skin lesion databases, especially those provided by the International Skin Imaging Collaboration (ISIC). The review separates the AI studies into imaging modalities and then discusses the comparative studies between AI algorithms and dermatologists/dermatopathologists in an attempt to shed light on how to improve the AI systems as a clinical tool to help doctors diagnose skin cancers.

III. METHODOLY

1) *Data Collection:* Collect a wide and varied amount of skin images that would include different ethnicities and skin issues. It should also include images of normal skin and skin images with different skin diseases such as acne, eczema, psoriasis, and melanoma.
2) *Data Preprocessing:* After data collection, it is necessary to make some transformations to gather data free from mistakes and integrate them into a single format. It may for example be activities such as resizing the images, noise reduction, the normalization of color and light conditions, and assigning the appropriate skin type to a picture.
3) *Model Selection:* Choose an appropriate generative AI model when detecting the skincare. This could be a convolutional neurai network as its purposes are image generation applications or a generative adversarial network, GAN for short. These include the type of architecture employed in the model, capacities present in computation, and previous performance in handling similar tasks create.
4) *Model Training:* Use the preprocessed dataset to train the selected generative AI model that would be used in the system. The model can identify patterns and features that are commonly noticed in skin images during training and used to label skin conditions. In this process, usually a set of labeled images is used to train the model, helping the model adjust its parameters for improved prediction errors.
5) *Evaluation:* Check the results of utilizing the trained model when the validation and test sets are selected. Use standard evaluation metrics like accuracy, precision, recall, F1 score, etc., to know how good the model is in diagnosing skin conditions. If model evaluation is satisfactory, there is no need to adjust model and if the evaluation results are not quite satisfactory, then the model adjustment is required.
6) *Deployment:* Introduce a real world skin care detection generative AI model that has been trained and tested. It could mean incorporating the model into a smartphone application, online tool, or skin diagnostics tool which can be a standalone device or added to existing gadgets. Make certain the structures for deployment are flexible, dependable and easy to use
7) *Validation and Monitoring:* Ongoing assess the applied model to ensure that it is functioning as intended given actual data and user feedback. Care should be taken to assess performance consistently to track any failure or decline in efficiency in the long-run. Slight modifications should be made on the model from time to time in order to address new skin conditions or new trends.

A. Advantages

1) *Precision:* Machine learning algorithms transform diagnosis and treatment of skin conditions as they work x10 faster and accurately identify changes and patterns that a human might not, therefore delivering the best care.
2) *Efficiency:* Generative AI for skin detection means that skin issues do not take much of the precious time of the patients as well as the healthcare provider since the skin stage can be recognized and addressed at a much faster pace.
3) *Accessibility:* While incorporating generative AI into skincare detection enhances dermatological knowledge in regions with scarce specialized care, enhancing the lives of people who cannot afford dermatological help.
4) *Personalization:* Skillful generative AI processes massive data which gives an opportunity to receive individual recommendations regarding skincare, taking into account the type of skin and problems which can be faced, and improve the process of skincare.
5) *Continuous Monitoring:* Skincare detection by the help of Artificial Intelligence is regularly providing constant care for skin and, thus, for changes in it, it will be possible to act after they occur in most extreme cases.
6) *Research and Development:* In skincare, generative AI assists the researchers to analyze large masses of information, and patterns, which contributes to improvements in skincare treatments and therapies.

B. Challenges

Various challenges and future developments concerning the skin cancer and CAD are presented in the articles. One of the limitations is that in most cases the quality of the image and illumination is inconsistent, thus affecting diagnostic ability. To this end, approaches such as color constancy algorithms and generative adversarial networks (GANs) that help to normalize illumination and synthesize data for datasets are being conceived by researchers to improve the resilience of algorithms.

Another challenge is the unavailability of large datasets of the medical images that are labeled suitably. People are seeking data augmentation and synthesis with GANs for the enlargement and diversification of training sets. Second, AI systems have to be clinically ready and effective in clinical environments for tackling important challenges. Subsequent developments will enhance the algorithm to explain well and be portable, along with a sound validation of the incorporation of new algorithms which will prove to be clinically useful and safe.

A key approach to improving adoption post-implementation is to ensure that the AI systems are properly integrated in the clinical environment, particularly with EHR. urbation of these challenges and the development of AI technology will improve CAD solutions in skin cancer diagnosis, increasing efficiencies and improving patient care and health equity.

C. Future Scope

Ingenious generative AI such as through GANs can be instrumental in improving skin cancer detection enhancing diagnostic precision and patients' lives. Here's how:

1) *Data Augmentation:* In medical imaging, where having large amounts of data can be rare, GANs can generate synthetic images of skin lesions. This lets deep learning models be trained much easier, which inherently gives better generalization towards the broader patient population.
2) *Image Enhancement:* GANs filter out noise and increase the contrast between objects that exist in images needed for dermatological diagnosis. Better images result in better features, and in turn, more accurate diagnoses.
3) *Domain Adaptation:* GANs can convert images from one format to another (e.g., clinical to dermoscopic), allowing for the integration of varied data sources. This enhances diagnostic accuracy and decision-making.
4) *Synthetic Data Generation:* GANs can produce datasets that replicate different skin cancer types and conditions. These datasets are vital for training and validating AI models, ensuring they perform well across various clinical scenarios.
5) *Personalized Medicine:* GANs can generate patient-specific skin lesion images based on individual characteristics, improving the accuracy of diagnoses and treatment recommendations for diverse populations.
6) *Real-Time Augmented Reality (AR) Assistance:* GANs can power AR tools that assist dermatologists during exams and surgeries. By overlaying synthetic images onto live feeds, these systems provide real-time guidance and educational resources.

In conclusion, integrating generative AI in skin cancer detection could potentially transform practices in dermatology, since it will lead to more precise, quicker, and client-tailored diagnosis. Further developments are still required to enhance these novel technologies and extend their usage and clinical outcomes in practice.

IV. CONCLUSION

Skin cancer is among the most widespread diseases, and each third person is affected by it worldwide. Approximately, ninety percent of the diseases are associated with ultraviolet (UV) light radiation. In 2018, it ranked fifth among malignant neoplasms in sunlit regions of the USA According to statistical data, approximately 2,490 women and 4,740 man died from melanoma in 2019, causing the occurrence of this severe type of skin cancer took 20 lives per day. Males are more vulnerable as projections suggest that there were one million new melanoma cases in 2021.

Screening remains important; if not done, the death rate is as high as 90%. Some of the methods for diagnosing the disease include OCT imaging and dermoscopy. However, as with many visual inspection methodologies, the examination may sometimes mistake real lesions for normal tissues.

In order to overcome such issues CAD systems or Computer-Aided Diagnosis systems have been designed. Excision in these systems is complicated by matters such as body hair, shadows, and variation of lesion morphology.

ANN along with the CNN is one of the seldom applied deep learning techniques used in skin cancer detection. These technologies improve the possibility of defining various forms of skin cancer and represent major advancements in this essential domain.

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