An Efficient Skin Cancer Recognition Using Hybrid GAN Model And Deep GRU-CNN Neural Network

Mohammed Saeb Nahi

Department of Cyber Security, AL-Kadhim-college (IKC), Baghdad, Iraq

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Abstract

Accurate detection of skin melanoma plays a vital role in clinical diagnosis and treatment planning. In this study, we propose an advanced deep learning approach—a hybrid GAN-CNN-GRU model—for skin cancer classification. Leveraging deep learning techniques allows healthcare providers to efficiently analyze large volumes of images, leading to faster and more accurate diagnoses. However, the requirement for large centralized datasets to train these models poses challenges, particularly due to privacy regulations surrounding medical data. To address this issue, we develop a model that uses a Generative Adversarial Network (GAN) to generate synthetic melanoma images. These images are then classified using a combined CNN-GRU architecture. The hybrid model achieves impressive results, reaching a classification accuracy of 96.07%.

Keyword: *Skin Cancer; Medical Image; GAN Network; Convolutional Neural Network*

1. Introduction

The human body is composed of various components, with the skin being the largest organ. Any condition affecting the skin is classified as a skin disease. Skin diseases rank among the most contagious illnesses globally. One major form, skin cancer—characterized by the abnormal growth of skin cells—affects millions worldwide [1-2]. Early-stage diagnosis greatly improves the chances of successful treatment. However, delayed detection can cause the cancer to spread to other organs, sometimes resulting in fatal outcomes. Therefore, despite the high costs, early detection of skin cancer is critical to improving treatment outcomes and lowering mortality rates [3-5].

Traditionally, dermoscopes were employed to diagnose skin cancer. Yet, this method posed challenges due to the device's high cost and the requirement for a dermatology specialist. Skin diseases can arise from several causes, such as allergic reactions, bacterial or fungal infections, viruses, or hereditary factors [6]. Typically, these conditions originate in the epidermis—the outermost skin layer—and are visible to the naked eye, often causing emotional distress and physical complications.

Various types of skin lesions exist, including Melanocytic Nevus (NV), Dermatofibroma (DF), Vascular Lesion (VASC), Actinic Keratosis (AK), Melanoma (MEL), Squamous Cell Carcinoma (SCC), Benign Keratosis (BKL), and Basal Cell Carcinoma (BCC). Each lesion type exhibits distinct symptoms and severity levels. Symptoms can be either persistent or temporary and may range from painless to painful experiences. Among these conditions, melanoma poses the greatest threat and risk. Importantly, approximately 95% of individuals with skin diseases can survive if diagnosed early. Automated computer-assisted diagnostic systems offer significant benefits in the accurate detection of skin disorders [7-9].

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There remains a notable gap between dermatologists and patients, as many people lack awareness of the different types, symptoms, and progression of skin diseases. Symptoms may take time to manifest visibly, making early and precise diagnosis crucial. Nonetheless, identifying the type and stage of skin diseases remains challenging and often expensive. The introduction of automated systems based on machine learning techniques has significantly improved the speed and accuracy of skin disease diagnosis.

Over the past three decades, considerable research has been dedicated to skin disease classification, establishing it as a major and highly active field of study. Despite these efforts, gaps persist in the literature, with many studies focusing on the diagnosis of single diseases rather than multiclass categorization [10-11]. Classifying multiple types of skin lesions remains difficult due to the overlapping features among different diseases.

Advancements in computational technologies, particularly in machine learning and computer vision, have enhanced disease classification capabilities. Imaging technologies, being cost-effective, user-friendly, and non-invasive, provide major advantages. The integration of computer vision and machine learning significantly improves the classification performance of skin lesions. Recent developments, such as Convolutional Neural Networks (CNNs), enable automatic image classification without manual feature extraction or segmentation.

In this work, we propose a method for skin cancer diagnosis using a hybrid deep neural network based on CNN and GRU architectures. The key contributions of our study are as follows:

- We employ a hybrid CNN-GRU deep neural network to classify skin melanoma images, enabling the simultaneous learning of sequential and spatial features, thereby enhancing diagnostic accuracy.
- Our CNN-GRU-GAN hybrid model demonstrates strong learning capabilities even with limited datasets and effectively reduces diagnostic errors.
- We introduce a Conditional Generative Adversarial Network (CGAN) to generate synthetic medical images, thereby augmenting the training dataset.

The structure of this paper is organized as follows: Section 2 reviews related works. Section 3 elaborates on the proposed methodology. Section 4 presents the dataset and experimental results. Finally, Section 5 offers conclusions, future research directions, and recommendations.

2. Related Work

In the study conducted by [12], both dermoscopic and digital images were employed for melanoma classification, using a Support Vector Machine (SVM) algorithm. Dermoscopic images require expert dermatological analysis for accurate disease identification. In their approach, the authors applied Gaussian filtering for hair removal and lesion segmentation before utilizing SVM for classification. However, further research is needed to enhance classification using dermoscopic images.

The method proposed in [13] was assessed using the HAM10000 dataset, achieving high training and testing accuracies with the SVM technique. Nevertheless, challenges arose during image analysis, primarily due to factors such as skin surface reflections and image variability.

The framework introduced in [14] focuses on an automated skin lesion analysis system comprising image acquisition, lesion segmentation, hair detection and removal, feature extraction, and characterization. However, its limitation lies in the identification of only a single type of skin cancer, without distinguishing among various skin tumors.

In [15], the authors proposed a novel computer vision-based method for diagnosing multiple skin diseases. Their approach incorporated Convolutional Neural Networks (CNNs) comprising convolution, activation, pooling, fully connected layers, and a SoftMax classifier. A performance analysis of the model was conducted through the DermNet database where the study focused exclusively on keratosis along with acne and urticaria and eczema herpeticum with 30–60 samples for each condition. This research faced a major drawback because it contained a minimal sample set which spanned only a few classes.

The authors in [16] demonstrated a technique which uses computer vision methods to detect multiple skin conditions. The authors used ResNet and MobileNet and InceptionV3 as deep learning architectures to extract features while Logistic Regression handled the classification process. The combination of deep learning architectures provided promising efficiency but proved to be costly while managing only three types of skin disorders thus limiting wider practical use.

A new computer-aided diagnosis framework was developed in [17] which diagnosed malignant as well as benign melanoma cases. Gaussian filtering operated in preprocessing followed by applying Otsu's thresholding for Region of Interest extraction. The Support Vector Machine employed various textural and color attributes from which it learned through a quadratic kernel function.

The authors in [18] developed an improved classification method which included preprocessing followed by segmentation followed by feature extraction and finally classification stages. The author conducted experiments using simulation data from approximately 1800 images belonging to six distinct classes that produced acceptable classification results.

The authors in [19] developed a detection technique for skin disorders which used color phase extraction methods. The research team utilized K-Nearest Neighbor (KNN) algorithm after extracting characteristics through both LAB and HSV color spaces.

The study published in [20] introduced a new diagnostic technique which diagnosed three types of skin conditions namely Nevus, Atypical lesions and Melanoma. Adaptive filtering operations served to decrease noise levels at the preprocessing level of the system. The research adopted 2D discrete wavelet transform (2D-DWT) with texture and shape features for integrated feature extraction which led to CNN-based classification testing on a melanoma dataset.

A classification framework for skin lesion categorization into normal and abnormal and melanoma types was developed by the authors in [21]. The model's ability to handle multiple classification types is limited because the available dataset included three categories only independent of the deep learning methods employed.

The authors in [22] established a deep learning approach to classify melanoma in their work. The researchers employed Gaussian filtering for image denoising before extracting relevant skin image patterns by using statistical feature extraction techniques.

The research by [23] dedicated attention to the classification of skin disease images by focusing on four types of skin tumors. The authors used deep learning strategies that incorporated transfer learning with pretrained models namely DenseNet together with CNNs. Their analysis included Support Vector Machines (SVM) and Random Forests as machine learning classifiers which improved classification results.

3. Material And Method

The research investigates the dataset traits alongside GAN network operations for synthetic image creation and CNN and GRU neural network implementation. The proposed method outline appears in Fig. 1 and receives additional explanation in the next subsections.

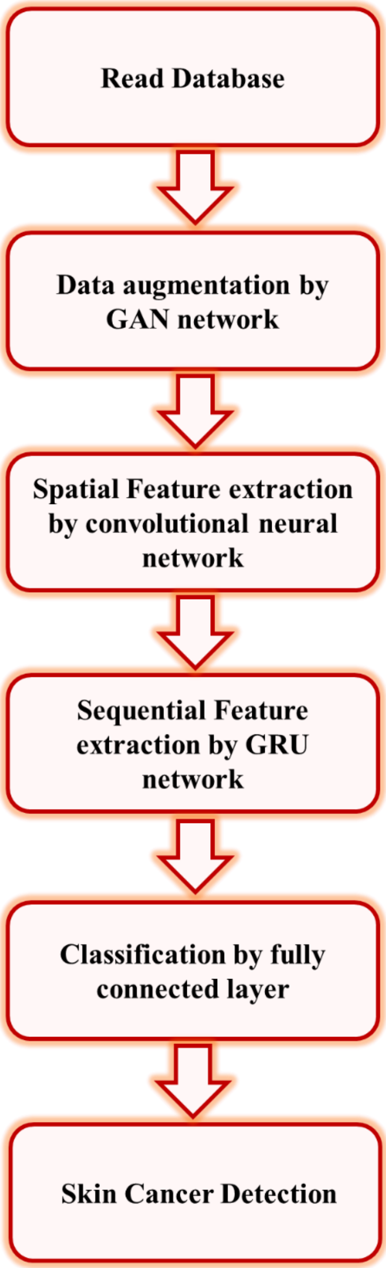

Figure 1- The flowchart of presented model

3-1-Dataset Description

The researchers use the HAM10000 database to perform skin cancer diagnosis tasks. The HAM10000 dataset features 10,015 skin lesion images which were obtained from patients in Australia and Austria. The images have a centered format and 600 × 450 pixel resolution. The dataset includes seven distinct classes, each corresponding to a different type of skin disease. Details of these classes are provided in Table 1.

Table 1: The Features of Ham10000 Dataset

Category Number	**Skin image category**
0	akiec (actinic keratoses and intraepithelial carcinoma/Bowen disease)
1	bcc (Basal Cell Carcinoma)
2	bkl (Benign lesions of the keratosis)
3	df (dermatofibroma)
4	mel (melanoma)
5	nv (melanocytic nevi)
6	vasc (vascular lesions)

A few sample images from the HAM10000 dataset are shown below.

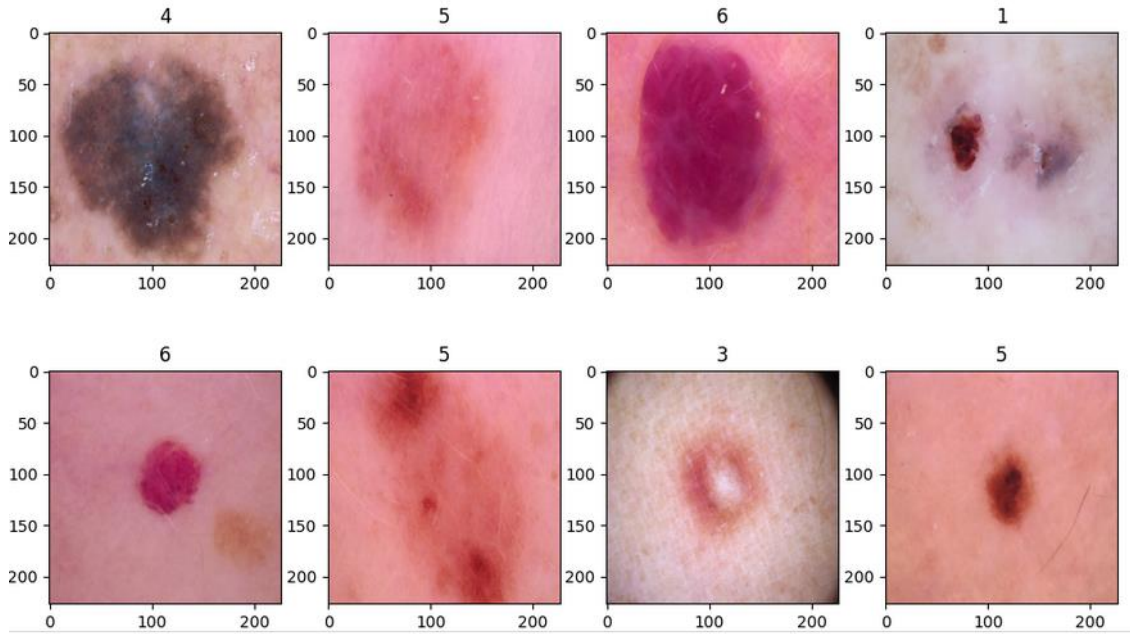

Figure 2- Some Instance of Ham-10000 Images

3-2- Generating Synthetic Images with GAN Network

Generative Adversarial Networks (GANs) enable the creation of synthetic data instances that closely resemble real data. This is accomplished through the interaction of two distinct neural networks: the generator and the discriminator, which are trained in competition with each other. In the following subsections, these models and their corresponding diagrams are introduced.

3-2-1- Generative Model

The generative model produces samples within the problem domain using a random input vector of fixed length. This vector, drawn from a Gaussian distribution, guides the generation process. After training, the model captures a compact representation of the data distribution, where points in the high-dimensional vector space correspond to points in the problem space. This vector space is commonly referred to as the "latent space" or "hidden space." Although these hidden variables are not directly observable, they play a critical role in modeling the underlying structure of the problem domain. The architecture of the GAN is illustrated in Figure 3.

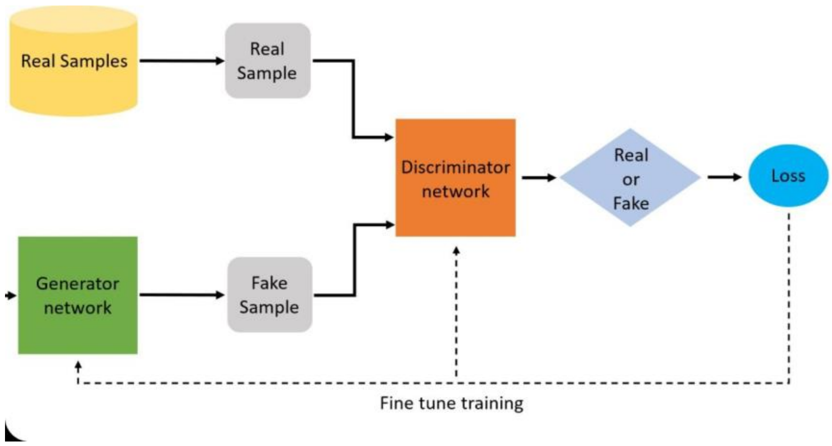

Figure 3: the architecture of a GAN Network

Latent variables and latent space are often regarded as predictors or compressed representations of the data distribution. Essentially, a latent space provides a condensed or abstracted version of the original observed data, such as the input data distribution. In the context of GANs, the generative model operates on points within this latent space, allowing new points sampled from the latent space to serve as inputs for generating unique output samples. After the training process is completed, the generative model is preserved and used to produce new instances.

3-2-2- Discriminator Model

The discriminator model is designed to assign a binary class label (true or false) to an input sample from the domain, with real-world examples drawn from the training dataset. The generative model is tasked with creating these samples. The discriminator is a widely-used classification model. However, the generative model can also be repurposed for other tasks, having learned to effectively extract features from samples in the problem domain. In transfer learning scenarios involving similar input data, either part or the entirety of the feature extraction layers can be utilized. Figure 4-a) depicts the generative model, while Figure 4-b) shows the discriminator model.

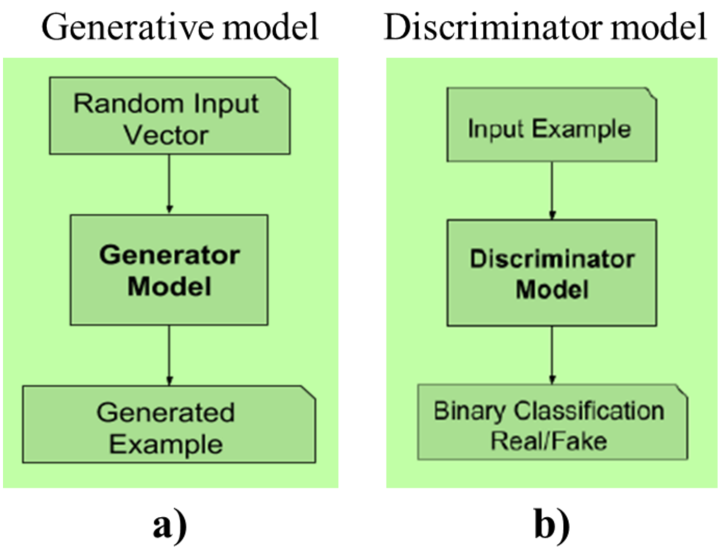

Figure 4: Generative and discriminator part in GAN model

In this study, a GAN network is utilized, consisting of two components: the generator and the discriminator. The two subsystems execute designs which stem from CNN network principles. With this GAN framework synthetic skin images are produced.

3-3- Feature Extraction Using CNN and GRUNeural Network

The detection and classification of skin cancer utilizing synthetic images becomes more effective through the extraction of optimal features. The outstanding capability of CNNs makes them ideal for image data analysis thus serving as the feature extraction stage. An implementation of GRU deep network follows the extraction stage to perform classification by exploiting its ability to process sequential patterns with long memory retention. The goal of this combined strategy is to obtain precise skin cancer evaluations from extracted meaningful features.

3-3-1- Convolutional Neural Network

CNN stands as a widely used architecture which operates within the field of computer vision. The main architectural difference between the Convolutional Neural Network (CNN) and Artificial Neural Network (ANN) exists in their data processing requirements. The purpose of CNNs is image processing while ANNs focus on numerical data.

A digital image appears as a matrix consisting of pixels which measure their dimensions through width (w) and height (h) and depth (d). The depth of an image corresponds to the number of color channels it uses. For example, an RGB (Red-Green-Blue) image has a depth of three, representing its three color channels.

The structure of a CNN consists of various layers, including pooling, convolutional, and fully-connected layers. Convolutional layers extract specific features by applying filters to the image [24]. This is done through the convolution operation, represented by the star symbol (*), which is performed between the image, denoted as $I_{x,y}$, and a filter k of size $p \times p$ at each pixel location (x, y).

$$k * I_{x,y} = \sum_{i=1}^{p} \sum_{j=1}^{p} k_{i,j} . I_{x+i-1,y+j-1} + b_1 \qquad (1)$$

In this context, b_1 represents a bias. To optimize the image's file size, the pooling layer is applied, utilizing the function ω(.) to analyze the pixel and its neighboring area based on operations such as minimum, maximum, or average. The resulting reduced image retains the pixel that satisfies the ω(.) function. The pooling layer works to reduce the image size by employing the function ω(.) to examine pixels and their adjacent areas, selecting the pixel that meets the specified criteria.

$$\omega\left(I_{x,y}\right) = \max_{i,j\in\{-1,0,1\}} I_{x-i,y-j} \quad (2)$$

The image resizing operation requires the formula $\frac{w-k}{s+1} \times \frac{h-k}{s+1}$ which depends on the shift amount 's' that determines kernel or neighborhood size. The convolutional and resizing layers can be added repeatedly before the output reaches the final fully connected (FC) layer. CNNs share a similar structure with ANNs since they contain multiple hidden layers before their single output layer. A CNN model we built contains two sequential convolutional layers and subsequent pooling layers as illustrated in Figure 5. The output from the second pooling layer proceeds to the fully connected layer for classification processes. The developed CNN functions by processing images with 224x224 pixel resolution to generate two probabilities representing the class possibilities.

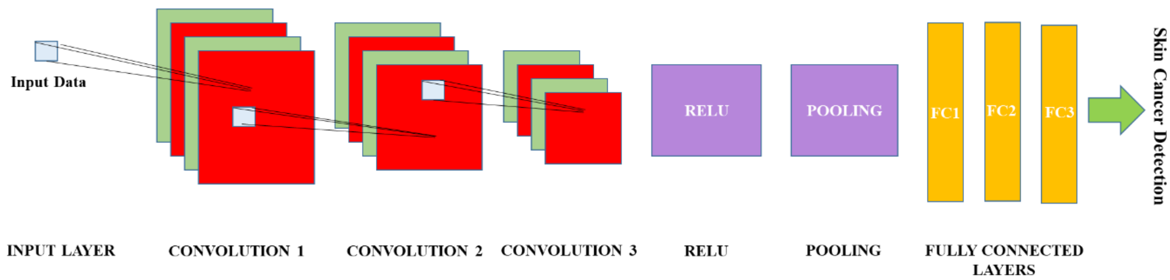

Fig. 5. Convolutional Neural Network Architecture

3-3-2- GRU Network

The specialized recurrent neural network type known as Gated Recurrent Unit (GRU) contains features to process sequential dependencies during prediction and classification tasks effectively. GRUs solve essential flaws in traditional RNNs because they handle the issue of information loss in sequential processing. GRUs address conventional RNN limitations by using mechanisms that enable error information flow across extensive sequences through their constant error carousel (CEC) structure. GRUs possess a design that enables the detection of time patterns across sequences that exhibit delays exceeding thousands of time steps.

The basic design of GRU cells allows error signals to stay stable within CECs which enables learning of complex dependencies across extended sequences. GRU units contain two regulatory gates which act as update and reset gates to control information transmission and retention at each processing step. The update gate functions to decide what amount of previous memory should move forward because it defends the stored information against superfluous incoming data. The reset gate enables the network to control how much previous memory gets forgotten so it can update its state according to incoming data significance. These gates work together as an information management system which enables important features to advance learning while blocking unnecessary data.

4. Experiment And Results

The proposed method for skin melanoma diagnosis performs as simulated in this section. The entire experimental work took place using MATLAB 2021 version. The simulation analysis used medical images which formed the basis for the dataset. Subsections within this section describe the evaluation parameters and detail the proposed network design while extensively analyzing the achieved numerical results.

4-1- Evaluation metrics

We evaluated the CNN framework performance through several evaluation metrics by using data augmentation techniques including precision, recall and specificity and F-measure. Precision reflects the model's ability to avoid misclassifying non-positive samples as positive. In contrast, recall measures the classifier's effectiveness in correctly identifying all relevant instances, corresponding to the True Positive rate. The F-measure is defined as the harmonic mean of precision and recall, offering a balanced evaluation of the model's performance. Specificity evaluates the classifier's ability to correctly identify healthy (non-diseased) individuals, representing the True Negative rate. In addition to overall accuracy, both weighted average and macro-average metrics are calculated to provide a comprehensive performance analysis. The corresponding evaluation equations are presented as follows:

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

$$F1score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \quad (5)$$

$$Accuracy = \frac{\sum TP}{Total\ Skin\ Cancer\ Sampels} \quad (6)$$

In these equations, TP (True Positive) refers to the number of instances where the model correctly predicts the positive class. FP (False Positive) indicates the number of instances where the model incorrectly predicts the positive class, when in fact the instance belongs to the negative class. FN (False Negative) corresponds to the number of instances where the model incorrectly predicts the negative class, despite the instance actually belonging to the positive class.

4-2- Evaluation of Simulation Results

This section examines the effectiveness of the proposed method. The confusion matrix, presented in Figure 4, is based on the test dataset. The classification system operates across seven categories, as detailed in Table 1. Based on the confusion matrix, all samples belonging to class 2 (bbc), class 4 (df), and class 7 (vasc) were correctly classified, achieving an accuracy rate of 100% for these categories. The remaining classes achieved accuracy rates of 98.4%, 99.1%, 91.8%, and 93.6%, respectively. Overall, the proposed method attained a classification accuracy of 96.07% in diagnosing various skin conditions.

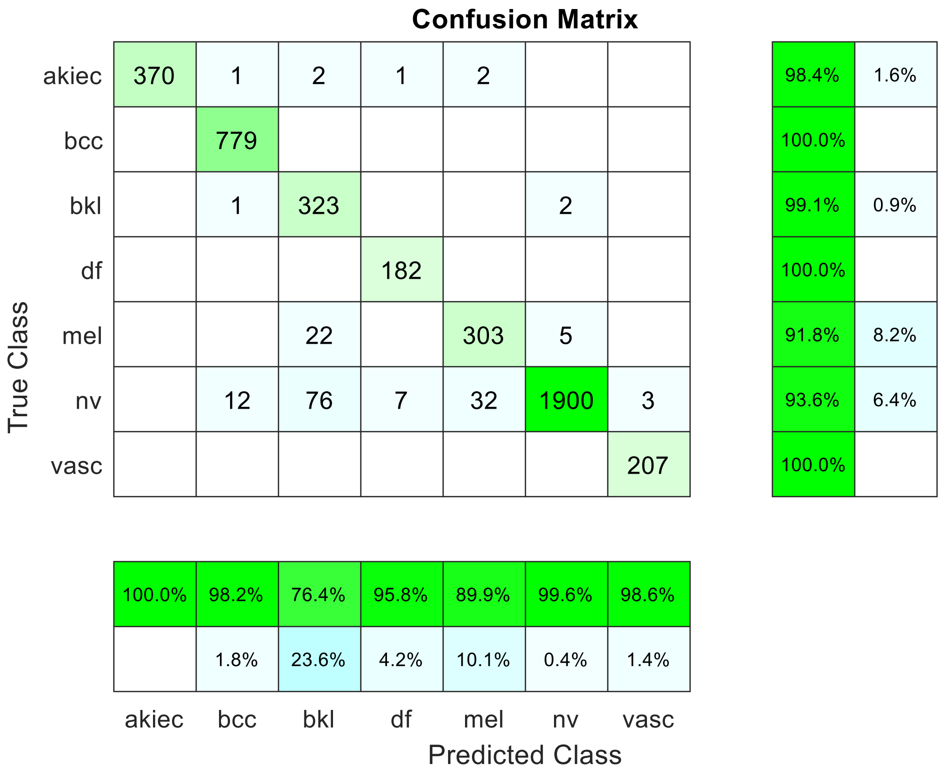

Figure 6: Confusion matrix for the presented GAN-CNN-GRU model

To more accurately evaluate the performance of the proposed method in skin cancer detection, the Receiver Operating Characteristic (ROC) curve has been plotted in Figure 7. The ROC curve illustrates the relationship between the False Positive Rate and the True Positive Rate at various decision thresholds. This curve demonstrates how well the model can distinguish between positive and negative samples. In this study, the area under the ROC curve (AUC) was obtained as 99.96%. This value, being very close to 100%, indicates the excellent capability of the proposed model in correctly detecting and classifying both skin cancer-affected and healthy samples. Generally, the closer the ROC curve is to the top-left corner of the plot, the better the model's performance; and a high AUC value reflects high accuracy and strong discriminative ability of the model. Moreover, the break point on the ROC curve indicates the best trade-off between Sensitivity (or Recall) and Specificity. At this point, the model achieves the highest correct classification rate with the minimum possible error. As observed in Figure 7, the break point for the proposed method is located at the top-left corner of the plot, which indicates that the proposed model not only has high accuracy but also excels in selecting an optimal decision threshold.

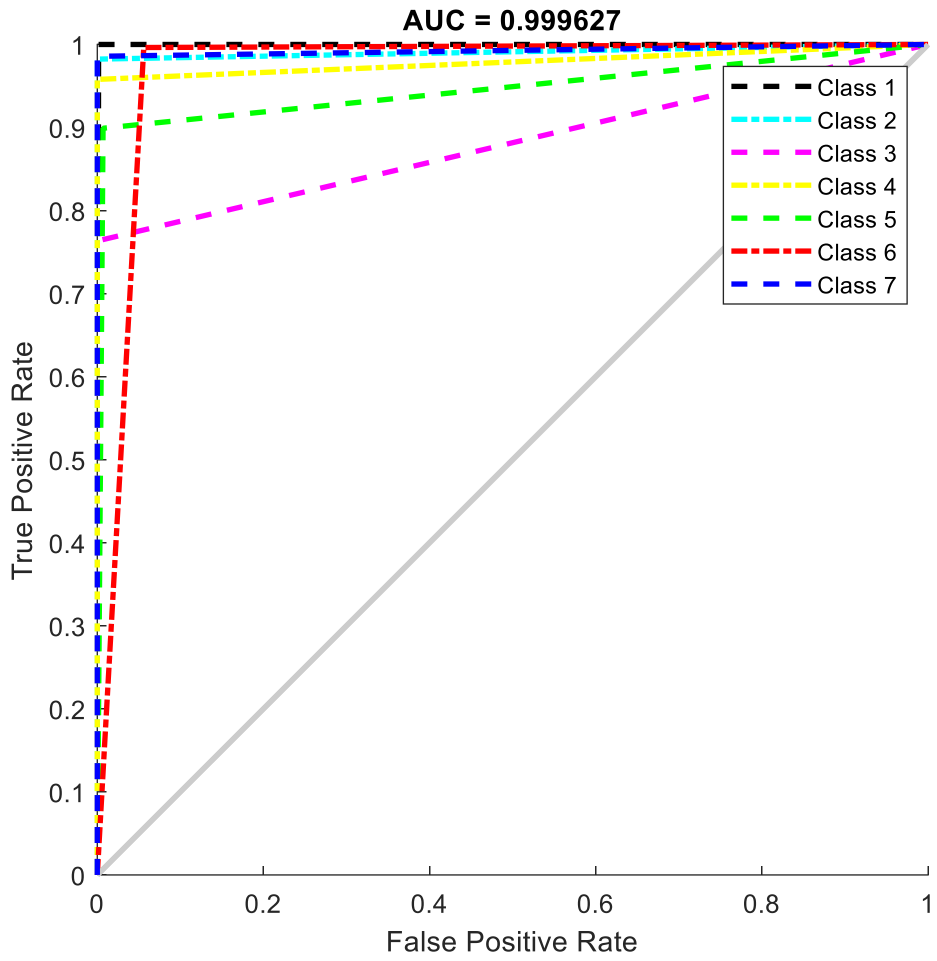

Figure 7: Receiver Operating Characteristic (ROC) curve

Figure 8 presents a comparative analysis of the proposed method with previous studies based on Precision, Recall, and F-Score metrics. As shown, the Random Forest method proposed by M. Ramachandro et al. [23] achieved a Precision of 91.00%, Recall of 89.00%, and an F-Score of 83.00%. Subsequently, the CNN network by the same authors demonstrated a higher Precision of 92.00%, Recall of 89.00%, and an F-Score of 91.00%. The DesNet network achieved a Precision of 93.00%, Recall of 84.00%, and an F-Score of 83.00%. The hybrid method combining Autoencoder, Densenet, and CNN, proposed by Gururaj et al. [25], exhibited lower performance, achieving a Precision of 75.00%, Recall of 69.57%, and an F-Score of 71.86%. The proposed model that combines GAN with CNN and GRU conquered previous techniques by attaining Precision 96.07% and Recall 96.63% and F-Score 96.19%. The proposed method demonstrates its ability to detect positive and negative samples accurately while maintaining favorable Precision to Recall ratios according to the experimental results. The combination between generative networks and deep sequence learning has significantly contributed to improving both accuracy and efficiency of skin cancer detection.

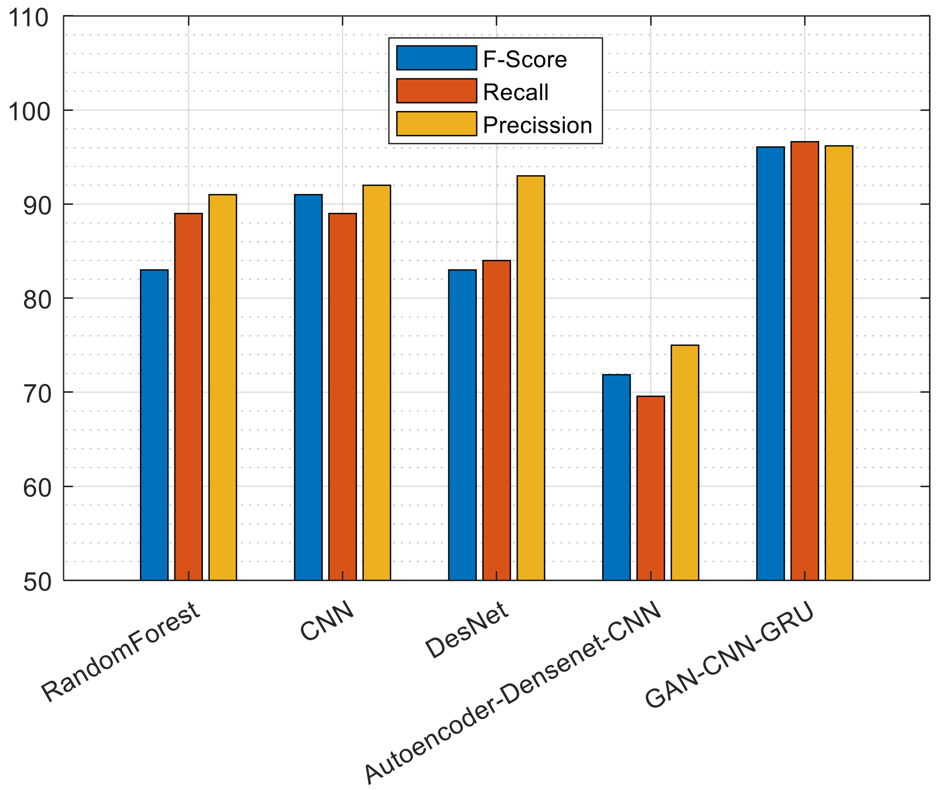

Figure 8: Comparison of the proposed method and other works based on Precision, Recall and F-score criteria

The proposed method for skin cancer detection from skin images receives performance evaluation which compares with previous studies' existing methods through Table 2. The study by M. Ramachandro et al. [23] using Random Forest demonstrated a detection accuracy of 92.00% according to observations. Research conducted by the same authors applied a CNN network which yielded 93.00% accuracy but the DesNet network achieved an even better accuracy result at 95.00%. The Autoencoder- Densenet-CNN hybrid method developed by Gururaj et al. [25] yielded an accuracy rate of 84.37% according to reported work. The proposed framework consisting of GAN and CNN and GRU networks delivered 96.07% accuracy. Research findings show that connecting generator and deep sequential learning networks creates effective features which improves detection accuracy for skin cancers.

Table 2: Comparison of the proposed method and other works based on Accuracy criteria

Author	Method	Accuracy
M. Ramachandro et al. [23]	Random-Forest-Model	92.00
M. Ramachandro et al. [23]	CNN-Network	93.00
M. Ramachandro et al. [23]	DesNet-Network	95.00
Gururaj, H. L. et al. [25]	Autoencoder- Densenet -CNN	84.37
Proposed	GAN-CNN-GRU	96.07

5. Conclusion

Researchers proposed a novel method to tackle the problem of insufficient medical data for skin cancer diagnosis. A Generative Adversarial Network (GAN) serves as the proposed method to augment medical data by creating synthetic images which enhance the training dataset. The approach joins CNNs and Gated Recurrent Unit (GRU) networks for better diagnosis accuracy. Deep learning techniques are combined through this approach to improve both accuracy and performance for detecting skin cancer. The research dataset includes 10,015 genuine dermatological images together with 4,085 synthetic images created by GAN which forms a total of 15,000 images. The CNN segment detects spatial components in skin lesion pictures and the GRU network tracks sequential patterns among the data. The dual architecture allows a thorough study which leads to better diagnostic results. The combination of CNN along with GRU models achieved 96.07% diagnostic accuracy which indicates the beneficial application potential of this proposed method within medical imaging research and practice.

6. Conflict of Interest

The authors declare that they have no conflict of interest.

7. Funding Declaration

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