REVIEW ARTICLE

Deep Learning Espoused Imaging Modalities for Skin Cancer Diagnosis: A Review

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Abstract

Purpose: Skin Cancer (SC) is one of the most threatening diseases worldwide. Skin cancer diagnosis is still a challenging task. Recently, Deep Learning (DL) algorithms have demonstrated exceptional performance on many tasks compared to the traditional Machine Learning (ML) methods. Particularly, they have been applied to skin disease diagnosis tasks. The aim is to provide a comprehensive overview of the advancements, challenges, and potential applications in this critical domain of dermatology.

Materials and Methods: The review encompasses a wide range of scholarly articles, research papers, and relevant literature focusing on integrating deep learning techniques in skin cancer diagnosis. Materials include studies that employ various imaging modalities such as dermoscopy, histopathology, and other advanced imaging technologies.

The initial phase involves acquiring images of SC from various patients through primary sources and standardized databases. Subsequently, a thorough data cleaning process is implemented, encompassing noise reduction, resizing, and contrast enhancement. Further refinement occurs through the segmentation of the malignant sections, employing edge-based, region-based, and morphological-based techniques. Feature extraction is followed by deep learning approaches, it enhanced with Federated Learning (FL) that is applied to image classification. Finally, leveraging FL-aided deep learning techniques, the images are categorized as either malignant or non-cancerous.

Results: The metrics include Accuracy (AC%), Specificity (Spe%), Sensitivity (Sen%), and Dice Coefficient (DC%), providing a comprehensive evaluation of the classification performance. Generative Adversarial Network (G-AN) demonstrates the highest accuracy 98.5% among the considered techniques, making it the top-performing neural network architecture for skin cancer classification.

Conclusion: This review was undertaken by pulling data from 90 papers published between the years 2019 and 2023, it provides a thorough statistical analysis. A review of various neural network algorithms for skin cancer identification and classification, despite Generative Adversarial Network, has emerged as the most promising approach, underscoring their potential to revolutionize the accurate early diagnosis of skin cancer. Finally, this survey will be beneficial for SCD researchers.

Keywords: Artificial Neural Networks; Convolutional Neural Networks; Dermatology; Generative Adversarial Network; Malignant; Melanoma; Skin Cancer Detection.

DOI:

1. Introduction

Detecting skin cancer is very important due to its increasing prevalence and potentially life-threatening consequences. Skin cancer is the most prevalent type of cancer [1]. Early identification plays a critical role in reducing morbidity and mortality associated with skin cancer. Skin cancer, when identified in its initial stages, is highly treatable, and patients have a considerably higher chance of survival and reduced medical costs. Moreover, with the advancements in technology and artificial intelligence, innovative tools for skin cancer detection have emerged, promising faster and more accurate diagnoses. Therefore, the importance of this topic lies not only in its potential to save lives, but also in its ability to use cutting-edge technology to increase the effectiveness and accessibility of skin cancer detection [2].

As a consequence of the widespread use of deep learning over the past ten years, ML has grown quickly. Large training datasets have helped these data-driven methodologies advance quickly [3]. Convolutional Neural Networks (C-NNs) have continuously improved at challenging computer vision duties like segmentation, object detection, and classification as a result of quickly changing designs. Due to the creation of novel algorithms like transformers, Deep Learning Recommendation Machines (DLRM), and Recurrent Neural Network Transducer (RNN-T) [4–7], and other branches of ML, have also achieved great success in their various applications [8–10]. The healthcare sector has already been disrupted and changed by these advances in AI and ML through applications ranging from protein sequencing to clinical image analysis. There are more obstacles to implementing the solutions presented during training [11–13]. The investigated deep learning methods for Skin Cancer Detection (SCD) systems include A-NN, C-NN, KSNN, and G-AN, as presented in the proposed manuscript. The existing method [14] focused on Federated Machine Learning convolutional neural network with an asynchronous and weighted approach for skin lesion diagnosis, emphasizing collaborative learning across distributed devices. On the other hand, the existing method [15] intended into Privacy-Aware Collaborative Learning for the prediction of Skin Cancer and Support Vector Machines (SVMs), prioritizing the protection of sensitive information during collaborative model training. The proposed work presents a deep analysis of various deep learning approaches tailored for SCD systems, potentially offering insights into the effectiveness and limitations of these methods and their applicability in diverse scenarios. The majority of healthcare groups, however, hardly ever keep data in such massive quantities when it comes to homogeneous populations or rare diseases with few cases [16–20].

The four major problems that Federated Learning (FL), a distributed learning paradigm, was designed to address were data imbalance across nodes [21], statistical heterogeneity of data across nodes [22], the potential for learning loss, and limited contact in the distributed network [23]. Before sending changes to a server, models are trained locally in the FL environment by a "federation" of client sites, each of which has its own dataset. The only data sent over communication channels intended to protect private are the weights [24, 25]. The weights of the models are forwarded back to the clients for the following training session after they have been incorporated into the server using the client updates. Due to its powerful ability to protect information with client premises like clinics by maintaining their data privately, FL has grown in popularity over the past few years, particularly in the clinical sector [26–30].

Considering the vital function of the skin in the body, Skin Cancer (SC) has become the most common cancer in the last ten years. It is categorized into melanoma and non-melanoma. Melanoma is an aggressive and lethal form of SC, it originates in melanocytes and forms malignant tumors that can affect various body parts. Timely detection is critical, as early-stage melanomas are treatable, whereas advanced cases can metastasize, leading to significant health challenges and potentially fatal outcomes [31-35]. Among the numerous melanoma SC subgroups, acral lentiginous, nodular melanoma, and lentigomaligna are a few of them [36]. The majority of cancer instances belong to non-melanoma categories, like Sebaceous Gland Carcinoma (S-GC), Squamous Cell Carcinoma (S-CC), and Basal Cell Carcinoma (B-CC). B-CC, S-GC, and S-CC are produced in the upper and middle layers of the epidermis. Nonmelanoma cancers are easier to treat than melanoma malignancies. Therefore, early identification is essential for SC treatment [37–39]. Doctors frequently use the swab mode to identify SC. This process removes a sample of a potentially malignant skin lesion so that a medical practitioner can examine it. This process is challenging, difficult, and slow [40–42] for computer-based technologies. SC symptoms can be swiftly, conveniently, and more reasonably identified. The

symptoms of SC can be investigated using a number of noninvasive techniques to ascertain if they are melanoma or non-melanoma [43–45]. The cancer research community needs an assessment of the most recent advances due to the expanding use of FL in healthcare. Here, an exhaustive list of FL Assisted DL approaches for SCD analysis has been provided in this review.

The continual paper is organized as: section 2 depicts an FL overview, section 3 describes deep learning methods for SCD, section 4 presents datasets, section 5 provides performance evaluation metrics, section 6 gives performance analysis of FL-assisted DL methods, section 7 depicts unsolved research concerns and section 8 provides conclusion.

1.1. FL Overview

Technology businesses must carefully handle user data in compliance with user privacy rules in many parts of the world [46]. A new decentralized method for creating ML models that protect data privacy is FL. In FL systems, a server orchestrates the learning while a number of clients (such as mobile devices, and businesses) participate during the training process. The master receives updates comprising the client's local models, which are aggregated to accomplish the learning aim and create a global model. The raw data of the client is retained locally and never shared [47].

The learning task is orchestrated by a master server in the typical centralized FL system represented by this architecture. For FL systems, other architectural designs have been put out to reduce communication costs or get around the centralized approaches the single point of failure issue. Peer-to-peer FL architecture is one illustration [48-52]. FL uses an iterative procedure with multiple rounds. (1) The server provides a true global model to a subset of clients first. These clients are either chosen at random or in accordance with predetermined client selection algorithms. (2) Each participant optimizes the global model using local data in the local model training stage. (3) A client transmits its local model to the server after it has finished training it locally. (4) The server then aggregates the updates it has received from clients in the model aggregation step using an aggregation method, such as FedAvg algorithm, which determines a weighted average depending on the volume of data from each client. The subsequent round chose the clients to receive the aggregated model. Repeat these actions until a stopping point is reached [53-55].

Due to the value of patient privacy, FL is now engaged in the medical sector. Prior research on FL in the medical field has produced results that are on par with centralized learning. These investigations solely examined Electrocardiogram (ECG) and Electronic Health Record (EHR) data. They also randomly sample the data to introduce heterogeneity [56]. The feature space is heterogeneous in reality though as well. In this work, concentrate on various and significant healthcare modalities (pictures, EHR, and ECG), and also take into account a realistic scenario, in which the clients are from various hospitals. Empirically proven FL frameworks for each given modality, such as EHR and medical pictures are used for a variety of tasks [57].

1.2. FL-Assisted Deep Learning Based Techniques for SCD

Deep learning is a subset of machine learning that utilizes multiple-layer neural networks (deep neural networks). These networks try to mimic the performance of the human brain to "learn" from big data. Each layer of the network processes information and passes it on to the next layer, allowing the network to automatically learn hierarchical depictions of the data. Federated learning is trained in the model without exchange among several decentralized devices and servers that store local data samples. Each device learns from its local data to train the model collaboratively, then shares only the updated model (not the raw data) along the central server. The updates are combined by the server to enhance the overall model, which is subsequently transmitted back to the devices for further improvement.

In SCD, the FL-assisted deep learning models [58], including CNN and GAN leverage the collaborative power of distributed learning. This technique permits learning from diverse datasets without directly accessing individual patient information. The synergy of FL with deep learning in skin cancer detection not only contributes to improved privacy preservation, but also facilitates the development of robust and generalized models capable of recognizing intricate patterns across various dermatological images. The

integration of FL to deep-learning techniques marks a significant stride towards the advancement of accurate and privacy-conscious skin cancer diagnostic tools. The goal of this review is to study FL based on DL-fostered SCD.

The simplified example of Deep learning is a collection of images depicting various skin lesions. These images represent training data for a deep-learning model. Deep learning involves training artificial neural networks, which are computer programs inspired by the structure and function of the human brain to recognize patterns in data. In skin cancer diagnosis, deep learning analyzes the images, learns to identify subtle visual cues that distinguish between benign and malignant. After training, the deep learning model can be utilized to diagnose skin cancer from new images. When presented with an image of a skin lesion, the model will analyze its features and compare them to the patterns it learned during training. Based on this comparison, the model will output a probability that the lesion is malignant. This probability can then be used by a dermatologist to make an informed diagnosis.

Federated learning is a more privacy-preserving method for training deep learning, particularly for sensitive data, like medical records. Here, the training data remains distributed through multiple devices, such as smartphones or hospital computers. Instead of centralizing all the data, the model is trained on local devices, and only the updated model parameters are shared with a central server. In this way, the data never leaves the device, ensuring patient privacy and security. The consolidation of deep learning and federated learning has the possibility to revolutionize skin cancer diagnosis by providing accurate, decentralized, and privacy-preserving solutions [59]. Figure 1 displays the Taxonomy of deep learning based on SCD. This work investigated several deep-learning techniques for SCD systems, such as A-NN, C-NN, KSNN, and G-AN.

Figure 2 shows Different types of SCD, they are Actinic keratosis, Basal cell carcinoma, Dermatofibroma, Melanoma, Nevus, Pigmented benign keratosis, Seborrheic keratosis, Squamous cell carcinoma, and Vascular lesion. The deep learning techniques for SCD systems, such as A-NN, C-NN, KSNN, and G-AN are discussed below:

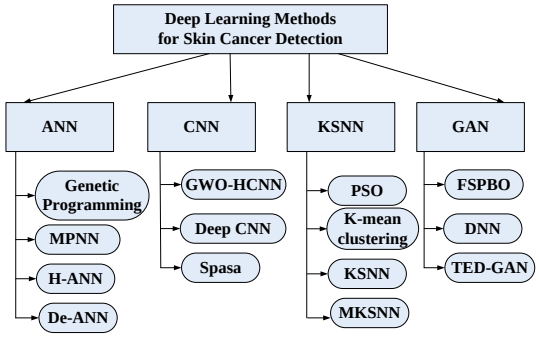

Figure 1. Taxonomy of deep-learning methods based on SCD

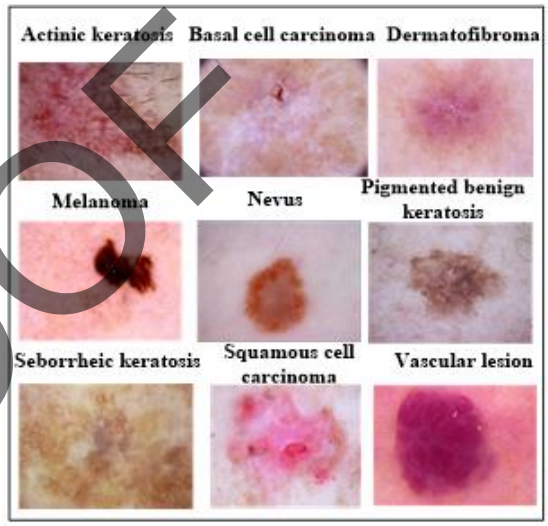

Figure 2. Different types of Skin Cancer

A. Artificial NN (A-NN)

Artificial NN was created with inspiration from the molecular structure of the brain and it has 3 layers. The intermediate layer, or second layer of neurons, receives data from the input layer, or first layer of neurons. The hidden layers are the intermediate layers. A typical A-NN may contain a number of hidden stages. The 3rd layer of output neurons derives signals from intermediate neurons. Back Propagation (BP) is employed to understand the intricate connections among the input and output layers as computations are carried out in every layer. It demonstrates NN characteristics. A-NN and NNs are terms that are frequently used equally in computer science [60–61].

SCD systems classify retrieved traits using A-NN. After the training set is effectively trained and

categorized, input pictures are classified as melanoma or non-melanoma. A-NN's hidden layer count is based on the volume of incoming images. The input dataset combines the A-NN algorithm' input/first layer and hidden layer. A labeled or an unlabeled collection is managed by supervised or unsupervised learning techniques, respectively. Data transmission in feed-forward Neural Networks is limited to one way. There is only one phase of data movement: input to output.

Hossen *et al.* [58] introduced the objective of this study as to aid in the early detection of SC through feature extraction based on texture using the first-order extraction method with six parameters, namely standard deviation, variance, contrast, mean, smoothness, and kurtosis. The classification method is using by Multilayer Perceptron Neural Network (MPNN). The two diagnostic identification processes are melanoma and non-melanoma.

Kumar *et al.* [59] developed three different forms of SC that are identified more accurately using a new technique. Using the suggested method as the input, the system categorizes a skin lesion image as malignant or non-cancerous. Fuzzy C-means clustering was employed for segmenting images and partitioning homogeneous image regions. Various filters are employed in preprocessing to enhance the image characteristics. RGB color space, LBP, and Gray Level Co-occurrence matrix techniques were combined to assess the factors and a differential evolution algorithm was used to train the A-NN for classification.

Tumpa and Kabir [60] introduced dermoscopic pictures that are enhanced after being preprocessed with the Maximum Gradient Intensity method to remove hairs. Segmentation under Otsu Thresholding was employed to distinguish skin lesions on the imageries. The segmented images generate various features, such as asymmetry index (A), border irregularity (B), color score (C), diameter (D), GLCM, and LBP, which are fed to NN to be trained. It was discovered that the suggested method was both more accurate and included a significant amount more feature information from the photographs.

Tajjour *et al.* [61] developed a network structure called the "hybrid model" controls structured with unstructured data. The findings show that the average top-1 along top-2 accuracy for the seven courses is 86%, 95%, and 96%, respectively. Table 1 shows that Comparative SCD analysis using A-NN techniques

The first GP-based techniques for categorizing skin image data were introduced by Sun *et al.* [62]. These techniques have effectively produced useful features from a variety of pre-extracted features by utilizing the built-in feature creation and selection capabilities of Genetic Programming (GP) models. The effectiveness of these GP approaches is examined by 2 real-world skin picture datasets obtained via common cameras and specialized devices, and compared with six widely employed classification approaches and alternative GP techniques.

Table 1. Comparative SCD analysis using A-NN techniques

Algorithm	SC Diagnoses	Explanation	Result	Ref No
MPNN	Melanoma	To facilitate early recognition of SC	Accuracy 98%	[58]
A-NN based fuzzy C-means clustering	Cancerous or non-cancerous	An approach for spotting three types of SC in its early stages.	Accuracy 96%	[59]
Artificial NN (A-NN)	Melanoma	The suggested method was found to incorporate substantially more feature information from the photos and to be more accurate than existing methods.	Accuracy 97.7%.	[60]
(H-A-NN)	Cancerous or non-cancerous	Using color spectrum transformations of the source images, early SC diagnosis	Accuracy for the seven classes is 86%, 95%, and 96%	[61]
A-NN-GP	Cancerous or non-cancerous	SC image classification	Accuracy-98%	[62]

B. Convolution NN (C-NN)

Convolutional Neural Networks (C-NN) have gained widespread popularity as a powerful deep learning technique, particularly well-suited for processing two-dimensional data like images. This specialized type of multilayer neural network creatively trains hierarchical layers using digital filters to capture various features of the input image. Comprising convolution, pooling, and fully connected layers, the C-NN structure efficiently combines input images with adjustable output coefficients from different convolution layers. Following the convolution layer, the pooling layer is commonly applied to reduce network dimensions and parameters. Employing strategies such as maximum pooling, this layer selects the highest value within blocks (e.g., 2 by 2), effectively decreasing the feature size. Ultimately, fully connected layers convert 2-dimensional features as 1-dimensional vectors, demonstrating the comprehensive and intricate process through which C-NNs extract meaningful information from input images. The softmax activation function in the final layer transforms the network's output into a probability distribution over different classes, enabling confident and normalized predictions for accurate lesion categorization [63]. Figure 3 displays C-NN architecture.

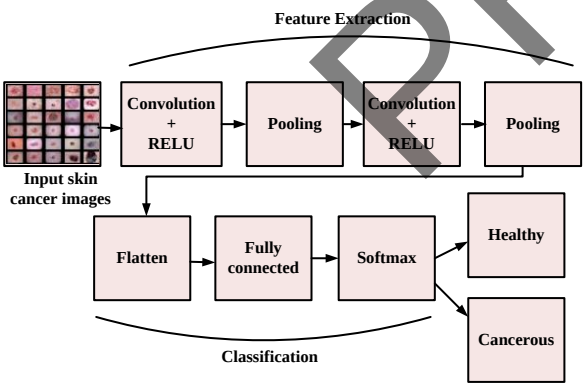

Figure 3. C-NN architecture

The right number of humans is trained via feed-forward after the settings have been adjusted. The regional features of the input image are extracted in this situation via local feature extraction. The major characteristics of the dermoscopy SC images can be recovered here by using learning to create a number of kernel matrices. The weights of network connections are optimized in the current study using the BP method. Convolution, adding weights, and computing the dot product are all done using a moving window as a vector. The activation function $f(x)$ is applied using rectified linear unit (ReLU) resulting in Equation 1,

$$f(x) = max(x, 0) \quad (1)$$

here x represents input given to ReLU. Then Max pooling is applied to scale back the production. The sliding grid's next layer is believed to have the highest value in the current research. Once the C-NN has been initialized, an optimization technique is needed to decrease errors in both the real and predicted output by adjusting the internal weights. BP method must be employed in this circumstance. The use of the Gradient Descent (GD) method is the foundation of BP. A method for reducing the cross-entropy loss is GD. The following cost function L was taken into consideration for the situations that were described in Equation 2:

$$L = \sum_{j=1}^{n}\sum_{i=1}^{m} -f_j^{(i)} \log d_j^{(i)} \quad (2)$$

Where n denotes the count of samples, m denotes the count of classes; $f_j = (0,\ldots,0,1,\ldots 1,0,\ldots,0)$denotes a vector with desired output, and $d_j$denotes the softmax function of m^{th}class using Equation 3:

$$d_j^{(i)} = \frac{c^{g_i}}{\sum_{i=1}^{n} c^{g_i}} \quad (3)$$

Consequently, by adding a coefficient α according to the weight penalty-based cost function L_p in Equation 4:

$$L_p = \sum_{j=1}^{n}\sum_{i=1}^{m} -f_j^{(i)} \log d_j^{(i)} + \frac{1}{2}\alpha \sum k \sum mA^2 k, m \quad (4)$$

Let m is the number of classes, k implies the count of layer l connections, and A_k is the weight of the link. Thus CNN predicts the input image as healthy and cancerous. Zhang *et al.* [64] introduced SCD as essential since some forms of the disease, such as melanoma and focal cell carcinoma, can be stopped by it. However, various things have a negative influence on the identification accurateness. The use of machine vision and image processing in medical applications is increasing. This research suggests a novel approach

based on image processing for the early identification of SC. The method uses a perfect C-NN for this. In this work, an improved whale optimization technique is used to optimize the C-NN. The suggested method is assessed by contrasting it with other methods on two separate datasets.

Mohakud and Dash [65] developed the Grey Wolf Optimization methodology that optimizes the hyper parameters of C-NN by choosing the appropriate encoding technique. The efficacy is compared with Particle Swarm Optimization (PSO) and hyper-parameter optimized C-NN based on evolutionary algorithms on the ISICSLMC data set. This model can produce testing accuracy of up to 98%, according to simulation results.

Junayed *et al.* [66] introduced Deep C-NN that are used in the SCD and DL classification methods. (C-NN). first obtained a dataset of four SC picture data before employing them in augmentation procedures to maximize the size of the whole dataset. Then, develop a deep C-NN model to train the dataset. With a 95% accuracy rating, the model outperforms the two pre-train models, Mobile Net and Google Net, on the test data.

Gouda *et al.* [67] developed SC that was swiftly and precisely identified using deep learning. The C-NN deep learning technique was used to identify malignant and benign tumors. Enhanced Super-Resolution G-AN (ESRG-AN) was initially used to improve and alter these images. The pictures were resized, normalized, and enhanced when the pre-processing stage. The C-NN technique can classify photos of skin lesions by combining the results of several repetitions.

Balaha and Hassan [68] SCD, classification, and segmentation are presented as threshold-based automatic solutions utilizing a Sparrow Search Algorithm (SSA). Five U-Net approaches with varied segment settings the data. In order to optimize the hyperparameters using the meta-heuristic SSA optimizer, eight pre-trained C-NN models are also used. For the dataset, two different kinds of datasets were created and gathered from five public sources. Table 2 displays Comparative SCD analysis using C-NN techniques.

Table 2. Comparative SCD analysis using C-NN techniques

Algorithm	SC Diagnoses	Explanation	Result	Ref No
C-NN	Cancerous or non-cancerous	An innovative strategy for the early diagnosis of SC has been proposed in this research and is based on image processing	Accuracy 97%	[64]
GWO-H-CNN	Cancerous or non-cancerous	For SC detection	Accuracy 96%	[65]
Deep C-NN	Melanoma or Non-Melanoma	SCD and classification	Accuracy 95.98%.	[66]
C-NN	Malignant and benign.	Resizing, normalizing, and enhancing the images were all part of the preprocessing step. Images of skin lesions may be categorized using the C-NN method by combining the results of numerous repetitions.	accuracy 96%	[67]
Sparrow Search Algorithm (Spasa) Based C-NN	Cancerous or non-cancerous	Automatic solution for SCD, classification, and segmentation	Accuracy 98%	[68]

C. Kohonen Self-Organizing Neural Network (KSNN)

KSNN is a type of deep NN. Due to the fact that C-NNs are trained using unsupervised learning, KSNNs require relatively little developer involvement during the learning period. KSNN has two levels. The competing layer and input layer are located at the bottom and top of the 2-D surface. Using the first layer dimension, each connection between these two layers is created. Data can be clustered using KSNN without knowing the relationships between the individuals in the input data collection [69].

In essence, dimensionality reduction and KSNN have the same function. It can convert data from high dimensions into low dimensions similar to 2-dimensional matrix. It offers distinct kinds of depictions for the provided data set. In terms of learning methodology, KSNN varies from other NN types and uses competitive learning in lieu of error-correcting learning. KSNN keeps the inbound data space's topological structure when going from high to low dimensionality. How far apart in space data components are from one another is referred to as preservation. As the dimensionality reduces, the topological structure of the raw data space modifies. How far apart in space data components are from one another is referred to as preservation [70].

This technique maps the data points farther apart from one another by considering their relative distance. In the input data space, this causes the data elements to be further apart. A KSNN is thus the most effective instrument for high-dimensional data. A KSNN also provides the crucial component of generality. Unidentified incoming data can be recognized and organized by the network. A KSNN's capacity is one of its main advantages to map intricate relationships among the data components, like nonlinear ones. These advantages lead to the widespread usage of KSNNs in SCD [71].

Tan *et al.* [72] developed an intelligent decision-making algorithm to identify SC. Since the creation of an efficient lesion representation was essential for the effectiveness of lesion classification, the capacity to distinguish between various feature types was employed. Then, for feature optimization, they suggest two improved PSO (Particle Swarm Optimization) models. The first model uses several remote leaders, comprehensive sub-dimension feature search, programmable acceleration coefficients, and initialization strategies to overwhelm stagnation.

Khan *et al.* [73] have presented that melanoma and nevus can be distinguished using contemporary image processing techniques. The skin lesion in the collected images was noise-free using the Gaussian filter before being segmented out using enhanced K-mean clustering. By removing the texture and color information, developed a unique hybrid super feature vector. Melanoma and SC nevus were distinguished using support vector machines.

Zghal and Derbel [74] the preprocessing step consists of filtering as well as contrast-enhancing approaches. Finding the lesion was the goal of the segmentation step. Asymmetry, border irregularity, hue, and diameter were four parameters that must be calculated in the third step of feature extraction. With respect to a weighted average of the four extracted parameters, the classification stage decides whether the lesion was benign or malignant.

Rajesh [75] has presented an innovative Modified Kohenon Algorithm for Automatic Skin Cancer Identification. The Kohonen self – organizing map was a neural machine unsupervised learning method. It involves pre-processing, post-processing, segmentation curvelet domain Feature Extraction, and

Table 3. Comparative SCD analysis using KSNN techniques

Algorithm	SC Diagnoses	Explanation	Result	Ref No
KSNN based PSO	Cancerous or non-cancerous	SC diagnosis	Accuracy 97%	[72]
K-mean clustering	melanoma	SC is divided into melanoma and nevus using support vector machines	Accuracy 96%	[73]
KSNN	benign, suspected, or malignant	SCD and classification	Accuracy 95.98%.	[74]
MKSNN	Malignant and benign.	SCD	accuracy 96%	[75]

classifiers. Modified Kohonen Self-Organizing Neural Network (MKSNN) has been employed to separate the skin cancer types. Table 3 shows the Comparative SCD analysis using KSNN techniques.

D. Generative Adversarial Network (G-AN)

G-AN (Generative Adversarial Network for Skin Cancer Classification) architecture is an advanced deep learning mode designed specifically for skin cancer lesions categorization tasks as represented in Figure 4. It comprises a generator network and a discriminator network, which work in tandem to upgrade the accuracy of skin cancer categorization. The generator network generates synthetic skin lesion images to augment the training dataset, effectively increasing its diversity and size, which is particularly useful for enhancing the model's capacity to generalize to new and unseen cases [76]. The discriminator network is responsible for distinguishing between the real and synthetic images, driving the generator to produce more realistic lesions. By leveraging this adversarial training approach, G-AN can effectively learn intricate patterns and features in skin lesions, ultimately leading to improved classification performance and better detection of malignant and benign skin cancers. This architecture represents a significant advancement in the field of dermatology and holds great promise for more accurate and early diagnosis of skin cancer. Numerous G-AN versions, including the SR-G-AN (Super-Resolution G-AN), C-G-AN (Condition G-AN), V-G-AN (Vanilla G-AN), LP-G-AN (Laplacian Pyramid G-AN), and Deep Convolutional G-AN (DC-G-AN) have been used by researchers. Systems for SC diagnosis effectively employ G-ANs [77].

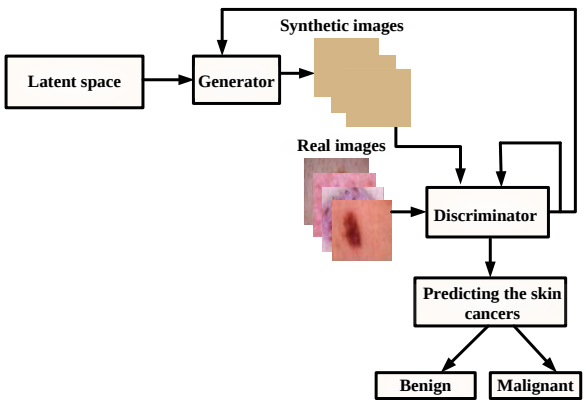

Figure 4. G-AN architecture

Teodoro *et al.*'s [78] method displays the development steps and benefits of the suggested categorization model at each stage. In the first stage, the hair surrounding the skin lesion is removed from the collection of photographs taken by the ISDIS (International Society for Digital Skin Imaging). Then, a G-AN model generates fake images to balance the training set's sample size for each class. The classification of skin lesions utilizing the attention mechanism based on a mask and efficient Attention Net training is the last step. Figure 4 shows that G-AN architecture.

Donné *et al.* [79] uses a G-AN along additional classifier that sampling the noise vector as of heavy-tailed student t-distribution as opposed to random noise Gaussian distribution results in more diverse images being produced. The suggested design was given the name TED-G-AN, where TED refers to the solution's encoder-decoder network and T refers to the t-distribution to make skin lesion images.

Qin *et al.* [80] to raise the precision of skin lesion categorization, the research has developed a detailed method for using G-AN-basis data augmentation. According to the fundamental concept of style-based G-ANs, the skin lesion style-basis G-ANs is introduced. To efficiently synthesize high-quality images of skin lesions, the suggested model alters the original generator's stylistic control and noise input components. The pre-trained deep NN is used to build the classifier for image classification using a transfer learning technique.

Kumar *et al.* [81] This research introduces an efficient SCD technique in the context of a wireless network using the suggested FSPBO-based DQN. The goal is to identify SC sooner and boost survival rates. The network region's simulated nodes are originally permitted to gather healthcare information to build the detection strategy using the suggested technique. After that, the suggested FSPBO approach is used to execute the routing while accounting for fitness factors like distance, energy, trust, and delay. Table 4 shows that Comparative SCD analysis using G-AN techniques.

Table 4. Comparative SCD analysis using G-AN techniques

Algorithm	SC Diagnoses	Explanation	Result	Ref No
Generative Adversarial Networks	Cancerous or non-cancerous	The methodology outlines the phases in the creation of the suggested categorization model as well as the benefits at each stage	Accuracy-96%	[78]
TED-G-AN	melanoma	The suggested architecture could be applied to numerous medical imaging applications.	Accuracy -96%	[79]
FSPBO- DQN	benign, suspected, or malignant	To detect the skin lesions	Accuracy -95.98%.	[80]
G-AN-DNN	Malignant and benign.	By changing the style control along the noise input components of the original generator, the proposed model effectively synthesizes high-quality skin lesion images.	accuracy -96%	[81]

2. Data Set

For SC diagnostics, a number of FL-based techniques are considered. A trustworthy collection is needed to assess the diagnostic performance of dermoscopic images and verify anticipated outputs. The variety and size of different SC databases have been constrained with the exception of nevi or melanoma lesions imageries. Due to the small sample sizes and dearth of diverse data, it is difficult for NNs to classify the skin lesions.

A. Project DERMOFIT Datasets

Project DERMOFIT Dataset [82] contains a total of 1300 photos, representing 46 actinic keratoses, 236 basal cell carcinomas, 330 melanocytic nevi, 87 squamous cell carcinomas, 256 seborrheickeratoses, 79 intraepithelial carcinomas, 23 pyrogenic granulomas, 95 haemangiomas, 64 dermatofibromas, and 75 melanomas.

B. PH2

Dermoscopic images on PH2 [83] have a 768x560 pixel resolution. Here, 200 dermoscopic images of melanocytic tumors are presented, including 40 melanomas, 80 common nevi, and 80 atypical nevi. Among these, each picture has medical annotations.

C. ISIC 2019

ISIC 2019 [84] includes pertinent metadata, including information on age, sex, and the general anatomic site, along with 25,330 JPEG images of training data. Additionally, it has a Ground Truth label that includes a summary of a typical lesion.

D. HAM10000

The HAM10000 dataset [85] contains 10,000 training images that were produced from dermatoscopic images of various groups. They were obtained and kept using a number of methods. Most academic settings use the dataset, which includes 10014 dermatoscopic images, for ML.

3. Performance Evaluation Metrics

Accuracy (Ac), Dice Coefficient (DC), Sensitivity, and AUC are the main metrics for assessing the performance of segmentation with categorization. These criteria are employed to assess the various models that are examined. The metrics are given below.

Dice Coefficient (DC): This scales how closely the estimated output and the actual result resemble each other. It is calculated by Equation 5,

$$DC = \frac{2tpo}{fpo + 2tpo + fne} \quad (5)$$

Sensitivity (SEN): It is the rate of anticipated (predicted) positive results that truly take place. The sensitivity is calculated by Equation 6:

$$sen = \frac{tpo}{tpo + fne} \quad (6)$$

Specificity (SPE): The rate of expected (negative) results amongst those who truly tested negative is shown here. The specificity is calculated by Equation 7,

$$spe = \frac{tne}{tne + fpo} \quad (7)$$

Accuracy (AC): It calculates the percentage of real outcomes (both real positives and real negatives) among all the instances studied. The accuracy is calculated by Equation 8,

$$Ac = \frac{tpo + tne}{tpo + tne + fpo + fne} \quad (8)$$

Area under the curve for ROC: This measures the performance across all feasible classification criteria. It ranges from 0 to 1. The percentage of true positive rate to false positive rate is defined as the area under the curve for the ROC.

Consider (tne) as true negative, (tpo) as true positive,(fne) as false negative, and (fpo) as false positive.

4. Performance Analysis of FL Assisted DL Methods

This section provides a summary of some cutting-edge algorithms that were recently employed in the ISIC 2019 competition to classify the skin lesion images. The skin lesion picture is gleaned from the ISBI 2019 dataset. Table 5 shows the efficacy of various categorization algorithms.

According to the ISIC 2019 classification results, the highest dice-coefficient reported is 97% from the C-NN method, and the highest sensitivity result is 89% from the C-NN. Furthermore, it is mentioned that the A-NN method produces the best specificity score of 92% and classification accuracy of 98%. Before these images are fed into the classification algorithms, they have experienced pre-processing and segmentation. This shows that segmented lesion image classification outperforms un-segmented lesion image classification in terms of performance.

Table 5. The efficacy of various categorization algorithms

Year	Techniques	AC%	Spe%	Sen%	DC%
2019 to 2023	A-NN	98%	93%	88%	90%
2019 to 2023	C-NN	97%	92%	89%	93%
2019 to 2023	KSNN	95%	90%	91%	92%
2019 to 2023	G-AN	98.5%	95%	92%	96%

Figure 5a-5d shows the (Receiver Operating Characteristic) ROC based on Project DERMOFIT, PH2, and the ISIC 2019 HAM10000 datasets, respectively. In the assessment, the Generative Adversarial Network (G-AN) emerges with a higher ROC (Receiver Operating Characteristic) compared to other neural network architectures, like A-NN, C-NN, and KSNN. This implies that G-AN exhibits a superior ability to balance sensitivity and specificity in skin cancer detection, resulting in more effective discrimination between true and false positive rates. The higher ROC value for G-AN underscores its potential as a robust and precise model for identifying skin cancer lesions, highlighting its promising performance in comparison to other architectures.

5. Unsolved Research Concerns

A. Extensive Training

NN-based SCD techniques require extensive training. The system must undergo an extensive training procedure that is both time-consuming and hardware-intensive. Only then will it be able to properly analyze and understand the features from dermoscopic images.

B. Light-skinned people's images from common datasets

NN considers skin tone to identify SC in people with dark skin [70]. However, this is only possible if the NN is sufficiently trained on images of individuals

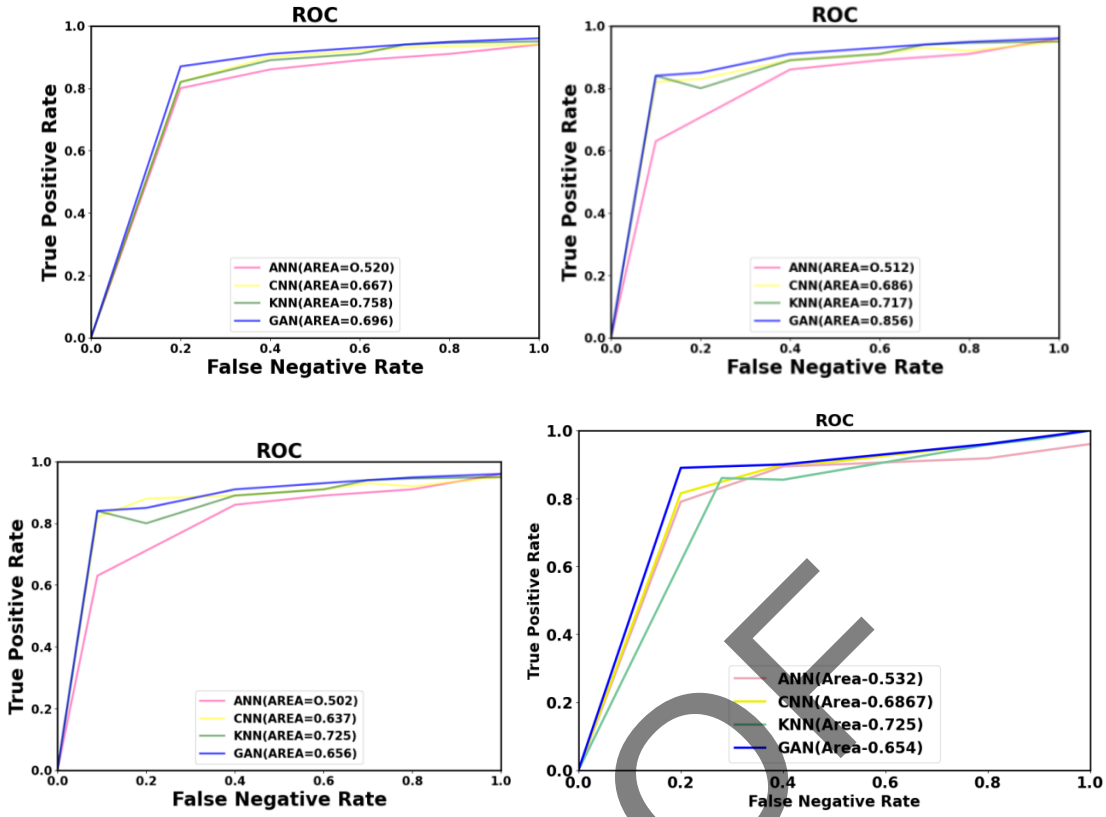

Figure 5. (a) False Positive rate of ROC based on Project DERMOFIT Dataset, (b) False Positive rate of ROC based on PH2 Dataset, (c) False Positive Rate of ROC based on the ISIC 2019 Dataset, and (d) False Positive Rate of ROC based on HAM10000 dataset

with dark skin. To increase the SCD systems' accuracy, th datasets with adequate lesion pictures of individuals with dark and light skin are required [86].

C. Insufficient Access to Strong Hardware

The precise features of the image that are needed for an improved SC diagnosis must be extracted by the neural network, which requires powerful hardware with maximal GPU powers. SCD training based on DL is significantly hampered through no strong processing [87].

D. Employing a Variety of Optimization Techniques

Preprocessing and lesion edge detection are two stages that are significant to the automated diagnosis of SC. A number of optimization methods, such as PSO, ACO, SSO [76], and ABC [88] are examined to improve the effectiveness of the automated SC diagnostic tools.

E. Examining genetic and environmental influences

Red hair, a propensity for moles, light eyes, fair skin, and a family history of SC are all identified as genetic risk factors for melanoma that rise when environmental hazards are added to them. Long-term UV exposure is one situation that significantly increases the chance of SC. To improve the performance, these elements are consolidated with contemporary deep learning techniques [89–91].

6. Conclusion

Several neural network algorithms are reviewed for the identification with categorization of skin cancer. This review focused on A-NN, C-NN, KSNN, and G-AN for the categorization of lesion imageries. Every approach has its merits and demerits. However, G-AN attains better outcomes than other neural networks when categorizing the image data that emerged as the top-performing neural network architecture. G-ANs have proven effective because of their special ability to create synthetic skin cancer lesion images and then use them for training. This approach not only

increased the training dataset size, but also enhanced the model's capacity to generalize previously unseen cases. By leveraging the adversarial training framework, G-ANs excelled in capturing intricate patterns and features within skin lesions, resulting in superior skin cancer classification performance. G-ANs stood out as the most promising approach, highlighting their potential to revolutionize the early diagnosis of skin cancer accurately.

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