Skin Lesion Classification Based on Deep Convolutional Neural Networks Architectures

Abstract

Skin cancer is among the primary cancer types that manifest due to various dermatological disorders, which may be further classified into several types based on morphological features, color, structure, and texture. The mortality rate of patients who have skin cancer is contingent on preliminary and rapid detection and diagnosis of malignant skin cancer cells. Limitations in current dermoscopic images, including shadow, artifact, and noise, affect image quality, which may hamper detection effort. Attempts to overcome these challenges have been made by analyzing the images using deep learning neural networks to perform skin cancer detection. In this paper, the authors review the state-of-the-art in authoritative deep learning concepts pertinent to skin cancer detection and classification.

Keywords: *skin lesion classification, skin cancer, melanoma detection, convolutional neural networks, Deep Learning.*

I. Introduction

Cancer is a concoction of several disease states whereby body cells perform out-of-control replication and division that may spread viciously and invade neighboring tissues. Cancer forms vary, in which skin cancer has the highest chance of occurrences with a significant malignancy risk [1]. As the most common cancer type, skin cancer is generally classified into melanoma and non-melanoma categories [2, 3]. Malignant lesion type involves a substantial cost to healthcare and contributes to cancer morbidity. Due to these factors, researchers have invested research efforts towards developing algorithms that possess high accuracy with flexibility in detecting early melanoma. Early detection is crucial as cancerous melanocyte cells could perform cell division uncontrollably, invade nearby tissues, and become highly metastasized, leading to high mortality rates [4]. Physicians often rely on Dermiscopy or Epiluminicence Microscopy (ELM) method to determine malignant or benign skin lesions.

Such a method utilizes a dermatoscopy, which amplifies medical pattern visualization through a lens with a light source to highlight colors, veils, pigmented networks, globs, ramifications, and various others. Dermatologists identify melanoma through assessing visible features such as Asymmetrical form, Border anomaly, Color discrepancy, Diameter, and Evolution (ABCDE rule) [5]. Despite this, caution is exercised due to limitations in dermoscopic images that need to be addressed. Since the emergence of image processing techniques, improvements have been pursued to improve Computer-Aided Detection (CAD) systems and approaches in Pigmented Skin Lesion (PSL) segmentation and classification, leading to easing patients' early diagnoses with less invasive or traumatizing medical procedures [6, 7]. State-of-the-art advances in machine learning, particularly deep neural networks, have made great strides in various areas. A required field in which deep neural networks may be exploited is processing medical images such as skin lesion images in the medical field. The skin lesion is referred to as anomalies in skin appearances such as visible signs of sore, abnormal lump, or colored skin color. Physicians may use machine learning techniques to recognize and classify skin lesions in images before making decisions that would affect patients' health [8, 9]. In general, there are four primary machine learning steps in the detection and diagnosis of melanoma cancer, comprising preprocessing of images, segmentation, feature extraction, and classification of images capturing the lesions (see Fig. 1) [10]. Litjens *et al*. 2017 [11] reviewed authoritative deep learning concepts relevant to analyzing medical images, which covered images' classification, detection of objects, segmentation, registration, and several others. In 2018 Okur *et al*. [12] carried out a survey focusing on melanoma and methods used to visualize and detect melanoma autonomously in dermoscopic images. In 2019, Kassani et *al*. conducted a comparative study of the latest deep learning approaches on

dermoscopic images in classifying skin lesions [4]. In another study in the same year, Munir *et al*. (2019) presented their chronological advancements in cancer diagnosis and the application of machine learning on medical images in [13]. In this paper, the authors aim to review the state-of-the-art deep learning architectures with dominant concepts and challenges of a cancer diagnosis on dermoscopic images.

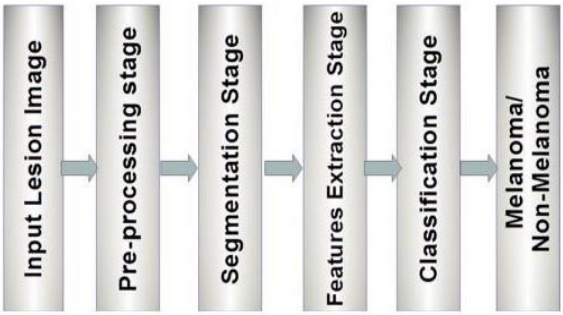

Fig. 1 Pipeline process of a melanoma cancer diagnosis from skin lesion image analysis [10]

The rest of the paper is organized as follows: Section 2 presents skin cancer types and summarizes dermoscopic image datasets. Section 3 illustrates a detailed description of the steps involved in the diagnosis of skin lesion images. Meanwhile, Section 4 lays authoritative Deep Convolutional Neural Networks (DCNN) techniques and performance evaluation measures. Finally, Section 5 offers a discussion and concludes this review.

II. Background Theory

A. *Skin Cancer Types*

The occurrence of skin cancer is associated with UV ray exposure from the sun, contributing to skin cells' DNA impairment. Gene mutations would trigger when DNA is damaged, whereby skin cells multiply excessively, leading to tumors' formation. In addition to UV ray exposure, genetic defects are also a contributing factor for skin cancer [14]. Fig. 2 illustrates the effect of skin cancer on the skin [15, 16]. Lesions on the skin could be due to different causes such as allergies, cancerous cells, etc. However, among these, skin lesions due to cancerous cells are perilous. In the worst case, certain manifestations of cancerous skin lesions are fatal. Among cancer-related lesions, melanoma contributes to an 8% mortality rate, which is considered a significantly high rate.

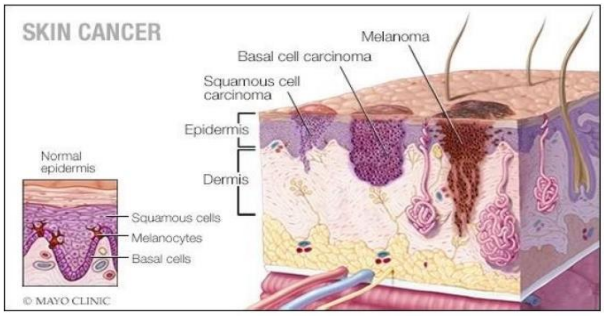

Fig. 2. Skin cancer affected skin image

Skin cancer is classified into two categories:

- Melanoma Skin Cancer (MSC)
- Non-Melanoma Skin Cancer (NMSC)

The following are eight categories of cancerous skin lesions shown in Fig. 3:

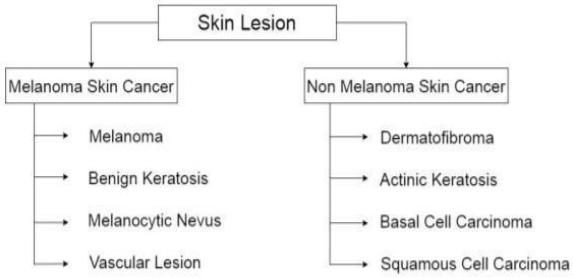

Fig. 3. Classification of skin lesions

ABCDE rule has been generally utilized to diagnose skin cancers, as following [17] clinically:

- **A: Asymmetry property.** Two halves of skin lesions are assessed for similarity in aspects of edges, shape, and color.
- **B: Border property.** Skin lesion edges are assessed in appearance to see if they are well-defined and smooth. Otherwise, the lesion is likely to be melanoma if the edges are jagged, fuzzy, and uneven.
- **C: Color property.** Melanoma visibly shows color contrast between different skin regions with shades varying from black, red, brown, and tan.
- **D: Diameter property.** Skin lesion diameter that exceeds 6mm generally tells a sign of melanoma.

AS DESCRIBED, the ABCDE rule is typically carried out by conducting a physical assessment of skin with the naked eye. Despite this, there have been cases whereby melanoma appears identical to benign lesions while following the ABDCE rule (see Fig.4), leading to erroneous judgment. On the other hand, different clinical assessments such as biopsy are prone to errors. Specialists' accuracy in predicting whether a skin lesion is malignant or otherwise falls in the range of 49% to 81%, where a third of melanomas have been inaccurately declared as benign lesions. These low accuracies have prompted the application of dermoscopy [17-19].

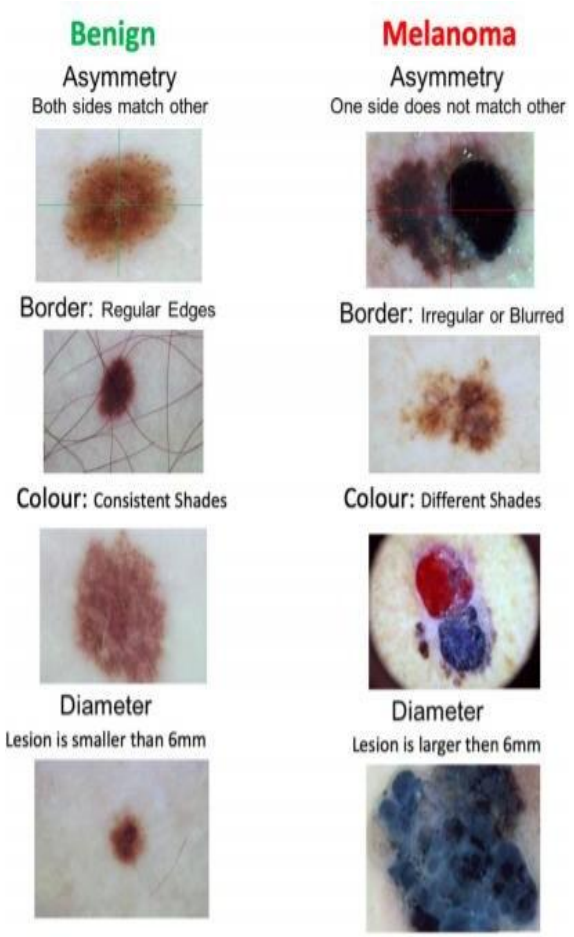

Fig.4. Lesion diagnosis by dermatologists. ABCD criteria for lesion diagnosis focuses on finding the certain properties of lesions[20].

B. *Dermoscopic Image Datasets*

Table I list`s both commercial and open-access, well-known datasets containing dermoscopic images that have been utilized in the studies of segmentation and classification. Dermot and Atlas of Dermoscopy are commercial datasets, while the remaining as listed in Table I are accessible for free to be used for scholarly purposes. In terms of dataset size, commercial datasets are small in comparison to the biggest open-access dataset size. The largest dataset from the International Skin Imaging Collaboration ISIC repository contains 25,331 images. Within ISIC nests, several sub-datasets comprising ISIC 2016, ISIC 2017, ISIC 201811, and ISIC 2019 datasets. The growth in dataset size in ISIC over the years has allowed researchers to conduct fully and semi-autonomous methods in performing segmentation and classification. These openly-accessible free datasets comprising dermoscopic images were obtained from varying clinical institutions. Respective ground truth of the obtained datasets had either been verified by expert consensus, pathologists, or supplementary techniques [21]. Despite the laudable diversity of image samples, most openly available datasets still lack highly diversified skin lesion samples covering vast populations and extremely rare cases (out-of-distribution category) [22-24].

TABLE I: WELL-KNOWN DATASETS FOR DERMOSCOPIC IMAGE CLASSIFICATION AND SEGMENTATION.

Dataset	Total Images	Number of Classes	Reference
Dermofit	1300	10	[25]
Atlas of Dermoscopy	1024	7	[26]
PH2	200	2	[27]
Derm7pt	1011	5	[28]
ISBI-2017	2750	3	[29]
ISIC	900	2	[30, 31]
	2000	7	[21]
	25331	9	[31]

C. *Skin Lesion Images Diagnoses Steps*

1. *Preprocessing*

Detection procedures require preprocessing of raw data as the data may contain noise [32-34]. In skin lesion images, captured images typically carry noises encompassing uneven illumination, skin surface light reflection, and hair. Such noises may affect the performance of segmentation undesirably and thus, need to be resolved [6, 35]**.** One of the techniques to resolve noises in preprocessing is the usage of filters. Filters such as adaptive wiener filter, Gaussian filter, adaptive median filter, mean filter, and median filter may be used to purge noises including salt and pepper noise, Poisson noise, Gaussian speckle noise. The presence of noise such as hair might lead to the inaccurate classification of skin lesions. Relevant preprocessing on images should be carried out to remove or adjust noises through strategies such as localization, normalization, hair removal, image smoothing, color correction, removal of the vignette, and adjustment of contrast. Greater accuracy would be obtained with an appropriate combination of preprocessing tasks [13, 36-38].

2. *Segmentation*

Detection of melanoma through automation is initiated with the segmentation of the lesion. This phase is deemed the least difficult to be understood but is also a critical phase. This is because skin lesions' segmentation has a knock-on effect on the segmentation of clinical features and generation of features for classification[39]. The phase involves separating the background from the lesion (i.e., skin) and other artifacts. The separation is often manifested in the form of a binary image (also known as a binary mask), whereby labels are assigned to a region of background skin removed and the lesion region that will be analyzed further. Upon separation of lesion region from the background, clinical features would undergo segmentation. The segmentation would reveal distinct global features, including border irregularity and asymmetry information. Fig.6 illustrates the segmentation of lesions with much success. Segmentation is considered successful if the background is removed entirely.

On the other hand, a less effective segmentation would sometimes retain pixels of background within the region where the lesion is segmented, particularly in the vicinity of borders. This could have an adverse effect as inaccurate local

and global border features would be produced, in addition to extraction of color features that are purposeless in the subsequent feature segmentation phase. Numerous techniques to achieve lesion segmentation, essentially a task of image segmentation, have been proposed by researchers[12, 40].

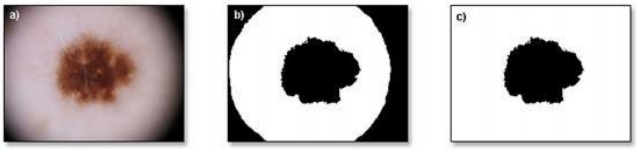

Fig. 5. Color space optimization system with clustering-based histogram thresholding for lesion segmentation: (left) block diagram of optimization procedure, and (right) color channels used in color space transform [12].

3. Features extraction

Extraction of features holds the key to an effective classification system[41, 42]. In this phase, crucial information in the skin lesion image is extracted, which then will be used to describe a lesion, leading to a successful classification of whether the lesion is a melanoma or otherwise [43]. In recent years, substantial advancement has been achieved in the computer vision field utilizing larger datasets. Researchers that use deep Learning have extracted a greater extent of features in various layers [44, 45].

4. Classification

Medical image analysis has shown a greater inclination towards applying machine learning methods, particularly deep learning-based algorithms attributed to favorable outcomes. For instance, a deep convolution algorithm can exhibit greater accuracy, become more objective-oriented, and generate reproducible results once training is conducted successfully. Therefore, this review offers a glance at state-of-the-art on skin cancer classification [46, 47].

III. Deep Learning-based Techniques

Deep learning-based classifiers' application is widespread as they can exceed human capability in performing classifying tasks for objects in general [48, 49]. For instance, Deep Neural Networks can compute complex tasks attributed to nonlinear neuron processing and greater prediction power, rendering them suitable to be applied in clinical images[50, 51]. Most recent advancements in deep learning models include VGG, AlexNet, ResNet, and Xception [38]. Various research works have also utilized these models in Computer-Aided Diagnose (CAD) as their performance is efficient.

A. Deep Convolutional Neural Networks (DCNNs)

DCNNs took inspiration from the biological visual cortex to perform analysis on visual imagery based on computer models. The models have shown great reliability, accuracy, and efficiency in classifying images. In various complex classification tasks involving natural and medical visual imageries for classifying diseases, the models had successfully attained close to baseline humans' results[11, 52]. The CNN, commonly referred to as ConvNet, is a distinct category of feedforward neural networks, where the outputs do not form feedback and hence will not be fed to itself. The CNN comprises a convolutional layers stack, accompanied by a pooling layer responsible for extracting input data's features. Subsequently, high-level feature maps are produced upon each convolution level. As the reduction of feature maps' parameters is critical for efficiency, pooling layers summarize their information. Fig. 6 represents an illustration of a conventional convolutional neural network [53]. A CNN with five layers has been proposed in [54] to classify skin lesions into three classes, including melanoma class that is a form of terminal skin cancer. With training and testing on dermoscopic images from the PH2 dataset, the proposed CNN classifier attained an accuracy rate of 95%.

Moreover, a greater accuracy rate of 97.78% was obtained in[55] when the number of layers in CNN was increased to 14 layers on dermoscopic images from the ISIC dataset. Despite this, greater resources and computation complexity would be expended when layers are increased. CNN has also been used to classify rashes and skin cancer detection[15]. [56] utilized Deep Learning Studio to exploit a Model-Driven Architecture to construct Deep Learning. The researchers introduced the studio suite features, which were used to facilitate the development of a Deep Learning Model. The researchers further elaborated dermal cell image preparation and demonstrated the DLS model in detecting cancer cells. The model obtained an AUC of 99.77% to detect cancer cells based on their medical images. In [57], a Deep Residual Network (DRN) was applied in the classification phase's training model. A fair accuracy was attained at the classification phase when Fully Convolutional Network (FCRN) was utilized. However, given that the application is meant for medical image classification, the rate of false positives must be reduced to be effective for medical applications. Towards achieving this, emphasis on the recall factor must exceed the emphasis on overall accuracy in conducting studies.

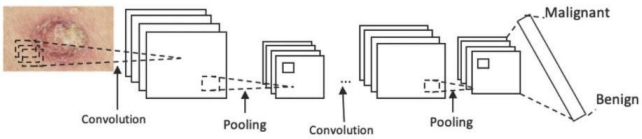

Fig. 6. The architecture of a typical convolution neural network

B. Deep Learning and Classical Machine Learning Techniques (Hybrid Approach)

Several studies have proposed approaches that would facilitate skin lesion categories by inspecting established features or exploiting well-known deep learning models' capability. Despite this progress, a combination of established features with deep learning models in an integrated framework has been sparsely reported in the literature. Constructing an effective strategy in extracting local and global features would greatly improve differentiating between normal skin and certain lesions. Motivated by these factors, researchers in [58] introduced an integrated model that extracts global-local

features through combining local binary pattern(LBP) features and deep Conv-features. Various studies have also attempted the combination of Local-DNN and Global-DNN in the hunt for superior outcomes. Researchers typically leverage segmentation models to purge background noise in the detection of apparent features from visual imagery. Researchers in [59] implemented a hybrid approach using three models for predicting lesions. The approach involves a CNN model and two conventional machine learning classification models trained using a collection of features that describe skin lesion's color, texture, and borders. The models were then hybridized with the objective of performance improvement through votes of the majority.

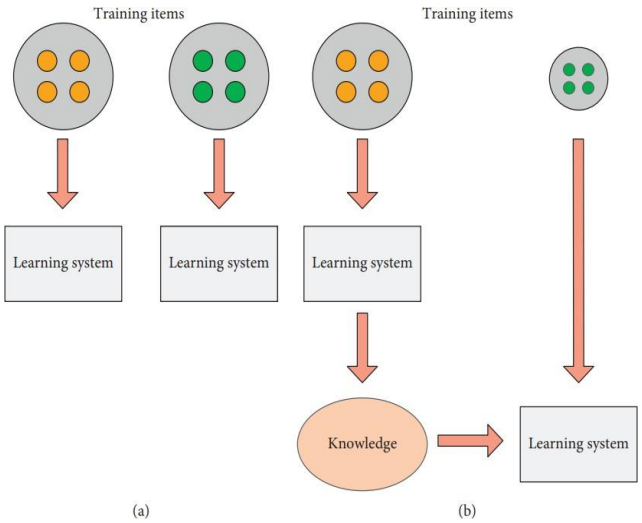

Fig. 7. (a) Traditional machine learning vs. (b) transfer learning

C. *Deep Learning with Transfer Learning and Image Augmentation*

Transfer learning involves applying a sub-machine learning technique that learns new tasks based on previous knowledge of learned tasks. Adaptation of domain and transfer learning generally refers to improving generalization capability in a subsequent setting based on a previous single set training [60]. Significant dataset size is required to train a new DCNN model, which poses an obstacle to the model as existing skin lesion datasets lack labeled images in large datasets. Theoretical understanding of transfer learning is essential in solving the obstacle. Fig. 7 illustrates key differences between conventional machine learning and transfer learning. Transfer learning can address small datasets, leading to augmenting model learning performance [61, 62]. Fine-tuning of trained models allows adaptation to problems to be achieved [63]. Besides, strategies to augment small datasets have been adopted broadly in classifying raw images and melanoma. Augmentation of small datasets solves the issue of data scarcity prone to overfitting in the classification of melanoma. The fundamental concept in the augmentation of images lies in the convention that data annotation does not alter labels' semantic meaning [64]. Fig. 9 illustrates augmented images created through the application of several data augmentation approaches.

Researchers in[65] proposed automation of discriminative features extraction via ROIs. The system is also capable of addressing an imbalance of classes through augmenting data. As the proposed system utilized transfer learning, improvement of low-level features learning of the AlexNet model was achieved with an efficient false positives reduction in the CAD system. Challenges in classifying multiple classes may be resolved into a two-class classification type via transformation using the Error-Correcting Output Codes (ECOC) method. Work in [66] applied a pre-trained AlexNet CNN model. A classifier based on ECOC SVM was implemented in classifying four classes of skin cancer (i.e., Melano, Squamous cell carcinoma, Basal cell carcinoma, and Actinic Keratoses). In[67], ImageNet's pre-trained data, including DENSENET121, RESNET50, and VGG11, were used in a transfer learning model.

Consequently, this has led to improved accuracy at a 90% rate in training with a modest rate of losses. Meanwhile, transfer learning and DNN were applied in [68]along with data augmentation and fine-tuning. AlexeNet was utilized with transfer learning through substituting the final layer with a softmax in the classification of three lesion classes (i.e., atypical nevus, common nevus, and melanoma). PH2 dataset was utilized for training and testing with an accuracy rate achieved of 98.61%. Researchers tested CNN variants in [69], including DenseNet, EfficientNet, MobileNet, and Inception V3. The findings indicated that CNN Xception obtained a superior accuracy rate at 89%. A DCNN architecture for binary classification supporting multiple classes was proposed in[70] that offers greater outcome reliability in significant probabilities. An identical CNN architecture (GoofgLeNet Inception-v3) trained classification of multiple and binary classes concurrently. As reported in [71], Inception-v3 achieved superior performance in comparison to ResNet-101 architecture. DenseNet121, ResNet50, and VGG11 models are used in [59] by employing ImageNet's pre-trained data. The models augmented dataset size, which led to an improved model efficiency. In training, an accuracy rate of 90% was obtained with a modest loss rate. In [72], PH2 and HAM10000 datasets were employed in pre-trained innovative models (i.e., VGG16 and Mobilenet), subjected to two conditions (i.e., without augmentation and with augmentation). A tailor-made deep learning architecture was then constructed and evaluated against the two innovative models' performance. A conjecture that a thoughtful model design from the ground up would perform just as fine. From the results, Mobilenet and the tailor-made model fared well inaccuracy rate performance. Despite this, the result indicated an insignificant effect of data augmentation in comparison to non-augmented data in classification.

Fig. 8. Sample of melanoma augmented images [57].

Predominantly, past classification solutions inclined towards employing complex and sophisticated models to improve accuracy rate in detection. Research evidence on intraclass dissimilarity and inter-class similarity in lesion features is rather sparse in the literature. Employing a sophisticated model with a large computation overhead might render challenges to applicability in the real world. Motivated by using a less sophisticated model, researchers in [73]. Put forth a discriminant dermoscopy image lesion recognition model. The model extracts discriminant features by employing a pre-trained lightweight network, which builds a network of dermoscopy image lesion classification branches and a network of lesion feature discriminant branches. The model executes a shared training for the individual branch network, consequently enabling lesion type to be classified while lesion feature similarity is also established concurrently. As a result, this allows a greater extraction capability for discriminative lesion features. Ensemble-based approaches [74-76] are commonplace among researchers to enhance individual approaches' accuracy rate performance.

D. *Deep Learning and Generative Adversarial Network (GAN)*

Goodfellow *et al.* [77] pioneered Generative Adversarial Networks (GAN) into the deep learning field. As the name implies, GAN is a generative model that carries out training through an adversarial deep neural network setting. In operation, the GAN performs a generative model learning for data distribution by employing an adversarial strategy. Since its inception, the GAN has been recognized as the most dominant generative model explored in artificial intelligence research[78]. Despite that, such deep architecture demands actual samples to be used for training to learn meaningful representations. As mentioned previously, large datasets for medical imaging are currently unavailable to facilitate supervised Learning. This is largely due to the arduous process that consumes time and prohibitive cost involved in the labeling and acquiring datasets that often require sophisticated tools and expert human judgment. Consequently, the absence of readily accessible largescale datasets has prevented researchers from fully leveraging deep learning possibilities in medical imaging applications [79]. The work in[80] utilized GANs to generate imagery with close resemblances to dermoscopic images. The generated images are subsequently included in augmented trained data towards enhancing deep CNN's performance in classifying skin lesions. Discriminator and generator as outlined in algorithm one may be attained by using formal expressions [69], expressed in Equation (1) and (2), respectively, as follows:

$$\nabla\theta_d = \frac{1}{m}\sum_{n=1}^{m}[\log D(x^i) + \log(D(G(z^i)))] \quad (1)$$

$$\nabla\theta_g = \frac{1}{m}\sum_{n=1}^{m} -\log(D(G(z^i))) \quad (2)$$

Where z is noise exhibiting uniform or normal distribution, G is the generator employed in image creation contingent on x = G(z). While m is the count of noise and samples realized as a result of data generation, D(x) is a function responsible for computing probability that x descended from data instead of generator distribution. Besides, ∇ it is stochastic gradient descent employed in training GANs adhering to θd and θg parameters. About algorithm one and compensating the training data scarcity, Sedigh et al.[81] put forth a CNN algorithm, a GAN variant towards generating mock images of skin cancer. Fig. 9 presents the GAN algorithm structure. Work in[82] proposed GAN to generate style-based mock skin lesion images with a close reference to the earliest proposed GAN algorithm. The proposed work alters style control structure and noise input in the generator. It modifies generator and discriminator intending to generate fine-quality mock images of skin lesions with efficiency in mind. Meanwhile, in classifying images, a classifier's construction on the pre-trained deep neural network expanded the transfer learning theory. Mock skin lesion images produced from the proposed work subsequently become additions to the existing training set, contributing to superior performance classification tasks.

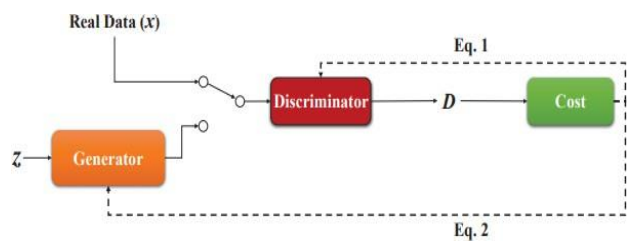

Fig. 9. The GAN algorithm structure[81].

E. *Performance Evacuation*

In predicting skin lesions employing DCNN architectures, several measures may evaluate performance, including accuracy, sensitivity, and specificity. Referring to Equation (3)-(6) [83-85], true positives (*TP)* are positive instances that are predicted correctly, false negatives *(FN)* are negative instances that are predicted incorrectly. Meanwhile, true negatives *(TN)* are negative instances that are predicted correctly. Finally, false positives *(FP)* are positive instances that are predicted incorrectly. Recall or sensitivity refers to correctly classified skin lesions [86]. Classification applications in the medical field require great sensitivity as it represents the measure of the system's worthiness. Sensitivity

is formally expressed as Equation (3): Sensitivity or True Positive Rate

$$TPR = \frac{TP}{(TP+FN)} = \quad (3)$$

Specificity refers to the measure of non-skin lesion labels that have been classified successfully, which is formally expressed as Equation (4): Specificity or True Negative Rate

$$TNR = \frac{TN}{(TN+FP)} \quad (4)$$

Precision or positive predictive value quantifies the percentage of correctly classified labels that are truthfully positive, which is formally expressed as Equation (5): Positive Predictive Value

$$PPV = \frac{TP}{(TP+FP)} \quad (5)$$

Accuracy (ACC) quantifies the count of correctly classified skin lesions divided by the total number of skin lesions, which is formally expressed as Equation (6):

$$Accuracy\% = \frac{TP+TN}{(TP+TN+FP+FN)} \quad (6)$$

IV. Discussion

Skin cancer continues to impact communities worldwide as a deadly disease. Early detection is important to increase the patients' survival chance as the disease is fatal. In recent years, research on deep learning models in detecting skin cancer has grown substantially, given that the models offer the concept of error-less decision-making for medical applications. Most recently, research effort has slowly progressed towards deep convolutional neural network architectures. From what has been reviewed above, it is clear that considering transfer learning (pertained network), fine-tuning, ensemble method, data generation, and augmentation aim to mitigate insufficiency of labeled data prone to overfitting and generally improving the performance of skin lesion classification in CAD systems. Table II summarizes the reviewed recent researches on models of skin cancer detection and classification.

Table II: Summary Of Recent Deep Learning Models For Skin Lesion Detection And Classification

Ref.	Year	Author(s)	Objective	Model	Dataset	Accuracy
[15]	2020	Subha, S., et al.	Detecting and distinguishing between skin cancer from rashes images by employing CNN.	CNN	A/N	80.2%
[54]	2020	Alkarakatly, T., et al.	Diagnosing three skin lesion classes, including malignant skin cancer lesion, melanoma.	5-layer CNN	PH²	95%
[55]	2019	Mohamed, A., et al.	Autonomous dermoscopic detection pattern that employs deep convolutional neural networks.	14-layer CNN	(ISIC)	97.78%
[56]	2020	Kadampur, M.A. et al.	Construct deep learning models for dermal cell image classification and skin cancer detection without prior knowledge of employing Deep Learning Studio	DLS	HAM10000	AUC of 99.77%
[57]	2020	Vinay, B., et al.	Diagnosing melanoma and non-melanoma images in a two-stage network.	Deep Residual Network (DRN)	ISIC	88.7%.
[58]	2020	Xiao, F. et al.	Combining Global–Local model to enhance skin cancer representation's effectiveness, including tailor-made features and deep Conv-features.	LBP Resnet-50 and DenseNet-121	ISIC-2017	0.848 on MM and 0.913 on SK.
[59]	2020	Daghrir, J., et al.	Detecting melanoma skin cancer through a hybrid method that leverages the superiority of a particular method.	CNN, KNN, and SVM	ISIC	88.4%
[65]	2020	Ashraf, R., et al.	Transferring initial low-level feature layers of AlexNet model and evaluating ROI with augmentation for attaining ideal results.	AlexNet	DermIS	97.9%
					DermQuest	97.4%
[66]	2018	Dorj, U.-O., et al.	Diagnosing four skin cancer classes.	Alex Net	collected from the internet	94.2%
[67]	2019	Rahi, M.M.I., et al.	Employing architectures that rely on pre-trained data. Transfer learning models used include VGG11, RESNET50, and DENSENET121.	VGG, ResNet and DenseNet	HAM10000 ISIC	90%.

[68]	2018	Hosny et al.	Classifying three lesion classes (i.e., melanoma, common nevus, and atypical nevus) through transfer learning, fine-tuning, and data augmentation.	AlexNet	PH2	98.61%
[69]	2019	Gavrilov et al.	Classifying skin lesions into pathology and norm.	CNN Xception	ISIC archive	89%
[70]	2020	Harangi, B., et al.	Achieving significant improvement in a seven-class classification of skin lesions.	GoogLeNet Inception-v3	ISICC 2018	64.3%
[72]	2020	Salian, A.C., et al.	They are classifying skin lesions involving augmenting labeled images, extracting features, and predicting skin lesions.	MobileNet, VGG-16 and Custom model	PH2 and	97.25%
					HAM10000	80.61%
[71]	2019	Demir, A., et al.	Diagnosing between malignant and benign skin cancer from medical images.	ResNet-101	ISIC-Archive	84.09%
				Inception-v3		87.42%
[74]	2019	Li, X., et al.	Discovering new biomarkers for identifying lesions may not have been included in clinical criteria but are relevant to dermatologists.	An ensemble composed of VGG16 and ResNet50	ISIC 2018	85%
[73]	2020	Wei, L., K. Ding, et al.	Lightweight skin cancer recognition model that discriminates features guided by fine-grained classification code.	DC-MobileNetV1 DC-DenseNet121	ISBI 2016	96%
[75]	2019	Pacheco et al.	Diagnosing eight skin lesions by classification through constructing an ensemble of classifiers.	An ensemble composed of 13 CNN SENet architecture	ISIC 2019	91%
[76]	2018	Harangi, B., et al.	Organizing several CNNs into a principal architecture for enhanced efficiency in skin cancer classification.	An ensemble composed of the CNNs AlexNet and VGGNet	ISBI	84%
[80]	2019	Rashid, H., et al.	Enhancing DCNN performance on skin lesion classification via employing GAN to augment existing training set.	GANs	ISIC 2018	86%
[81]	2019	Sedigh, P., et al.	Generating mock medical images of skin cancer based on the primary dataset to detect skin cancer.	S-CNN	ISIC	With GAN 71%
						Without GAN, 53%
[82]	2020	Qin, Z., et al.	Obtaining accurate diagnostic decisions in skin lesion classification by applying data augmentation technique based on GAN.	ResNet50 GANs	ISIC 2018	95.2%

V. Conclusion

Skin cancer remains deadly cancer affecting populations worldwide. Since the disease is fatal, early detection is critical towards improving the survival chance of patients. Admittingly, a shortage of qualified experts and sophisticated medical equipment have affected the fight against skin cancer. This paper looked into the latest research efforts to advance skin cancer detection and classification through variants of DCNN architectures. Transfer learning, fine-tuning, ensemble approach, data generation, and augmentation are all effectively used for minimizing insufficiency of labeled data, which is prone to overfitting. It also contributes to improving the efficiency of skin lesion classification in CAD systems in general. Application areas such as medical imaging whereby largescale training datasets are technically unavailable, building a rich dataset covering skin lesion samples from vast populations that includes extremely rare cases (out-of-distribution detection) is crucial to tackling the problem of scarcity of labeled data, which will also facilitate the advancement of skin cancer detection field further.

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