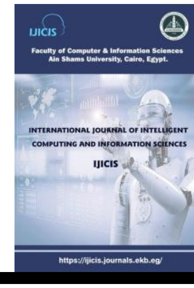
IJICIS, Vol.24, No.2, 1-17
DOI:10.21608/ijicis.2024.273450.1325

International Journal of Intelligent Computing and Information Sciences

https://ijicis.journals.ekb.eg/



AN IMPACT ON CONVOLUTIONAL NEURAL NETWORKS AMELIORATION FOR EARLY DETECTION OF SKIN CANCER

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Received 2024-02-28; Revised 2024-04-17; Accepted 2024-05-31

Abstract: *Skin cancer, one of the deadliest cancers globally, poses a significant threat to life. It is a type of tumor that originates in the skin and can spread to other areas of the body. Early detection significantly reduces mortality rates. Unfortunately, current diagnosis methods, primarily relying on visual inspection, lack accuracy. Deep learning techniques emerge as promising tools to aid dermatologists in achieving early and accurate skin cancer diagnosis. Specifically, convolutional neural networks (CNN) have emerged as the go-to method for tackling such challenges. The effectiveness of deep learning in medical image segmentation and detection surpasses the accuracy achieved by humans. By examining the latest research papers on the categorization of skin cancer through the utilization of convolutional neural networks, this comparative study delved into the subject matter. A comprehensive summary was given on the prevalent deep-learning models and datasets employed in the classification of skin cancer showing that convolutional neural networks may become a powerful tool for early detection of skin cancer and saving lives.*

Keywords: *Skin Lesion Detection, Deep learning, Convolutional neural networks, Segmentation, Classification.*

1. Introduction

Since the 1970s, skin cancer has been recognized as the most prevalent disease in the globe [1]. In the United States, 5.4 million new cases of skin cancer are reported each year [2]. Skin cancers are a type of tumor that originates in the skin and can spread to other areas of the body. The growth of abnormal cells with the capability to proliferate is responsible for their development [3]. Factors such as exposure to UV radiation, a compromised immune system, a family history of cancer, viruses, environmental changes, allergies,

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infections, an increase in body swelling and other influences may all contribute to the development of cancer in an individual [4].

There are many types of skin cancer, the most prevalent form of skin cancer is Basal Cell Carcinoma (BCC), which usually manifests as a shiny lump or a rosy area. Its growth is gradual, and it seldom metastasizes to other areas of the body. The second most prevalent form of skin cancer, known as Squamous Cell Carcinoma (SCC), tends to appear on areas of the skin that are frequently exposed to the sun. Its manifestation is typically characterized by the presence of a scaly, red patch or an elevated growth. Unlike Basal Cell Carcinoma, Squamous Cell Carcinoma has the potential to grow at a faster rate and carries a greater likelihood of metastasis. Melanoma, an aggressive variant of skin cancer, originates from melanocytes and is less prevalent compared to other types. It typically manifests as a new or evolving mole, characterized by asymmetry, irregular borders, multiple hues, and a larger size. Detecting melanoma at an early stage is crucial as it poses a higher likelihood of metastasis and can be potentially fatal. Merkel Cell Carcinoma (MCC) is an uncommon and highly aggressive form of skin cancer characterized by the appearance of a solid, painless lump on the head and neck region. This type of cancer develops from Merkel cells and carries an elevated likelihood of metastasis. Additional uncommon variations include dermatofibrosarcoma protuberans (DFSP), sebaceous gland carcinoma, and cutaneous lymphoma. DFSP is characterized by its gradual growth, sebaceous gland carcinoma originates from the sebaceous glands, and cutaneous lymphoma encompasses a collection of lymphocyte-derived cancers [5].

Basal cell carcinoma (BCC), Squamous cell carcinoma (SCC), and Melanoma are the three most prevalent forms of skin cancer. Out of these, Melanoma is the most severe and can regrow even after removal. The stage of the disease has a direct impact on the mortality rate of skin cancer. Skin cancer treatments are available, but the best chance of survival is only supported in people with the early stages [6]. The survival rate for skin cancer at an advanced stage is less than 14%. However, the likelihood of survival is roughly 97% [7] if skin cancer is discovered in its early stages. Early and accurate detection of cancer may improve the likelihood that it can be successfully treated. When cancer is discovered early, its 10-year survival rate is higher. Because skin lesions resemble one another and it is challenging to distinguish between benign and malignant lesions, early identification of skin cancer is a challenging undertaking. The lesion is often examined using a dermatoscope. It is an expensive tool that is exclusively available to dermatologists.

Today, computer-aided diagnosis employing deep learning and machine learning has emerged as a crucial tool for the early detection and diagnosis of lethal diseases [8]. In the realm of medical image analysis, deep learning models have made significant strides in achieving extraordinary outcomes. Specifically, convolutional neural networks (CNN) have emerged as the go-to method for tackling such challenges. Numerous deep learning models have been put forth to address the task of automated skin cancer detection [9]. These methods have shown great promise due to their capacity to extract intricate features from skin lesion images with exceptional precision. Unlike other approaches, deep learning algorithms possess the ability to acquire task-specific attributes and exhibit superior efficiency. The effectiveness of deep learning in medical image segmentation and detection surpasses the accuracy achieved by humans. Within the field of dermoscopy, various machine learning and deep learning algorithms have been employed to enhance the classification, segmentation, and analysis of melanoma. These algorithms are trained using extensive datasets of melanoma images, encompassing both malignant and benign cases, which have been meticulously annotated by experts.

The focus of this paper is to provide an overview of recent studies that have utilized various deep learning algorithms to achieve precise diagnoses of skin cancers. By examining these articles, we can establish a solid groundwork for the advancement of more effective and efficient deep learning algorithms specifically designed for the detection of skin cancer. In this paper, you will find a comprehensive exploration of numerous CNN models, along with a detailed analysis of their respective methodologies in order to determine the most optimal outcomes. To classify skin cancer, CNN models, including VGG16, ResNet50 were utilized. Each of these models operates in a distinct manner due to variations in the number of layers they possess. This study aims to compare and analyze the outcomes achieved by these models based on their respective work processes. The objective behind conducting this comprehensive analysis of literature was to identify and classify the most effective methodologies for detecting skin cancer through the utilization of convolutional neural networks (CNNs). By adhering to predetermined evaluation criteria, systematic literature reviews gather and assess existing research, enabling us to ascertain the existing knowledge within the specific field of study.

The rest of the paper is arranged as follows: Section 2 offers a concise introduction to the process of detecting skin cancer. In section 3, challenges of skin lesion detection are provided. Section 4 provides the methodology of convolutional neural networks, various architectures of CNNs are introduced. An analysis of several deep learning-based techniques for detecting skin cancer is provided in section 5, along with a comparative study. Section 6 overviews the most common datasets used in skin cancer detection. Finally, the conclusion and the future scope of this research are mentioned in section 7.

2. Skin Cancer Detection Process

Generally, there are five steps in computer-aided skin cancer diagnosis: image acquisition, pre-processing, segmentation, feature extraction, and classification [10]. The first step involves image acquisition which starts with capturing digital images of the skin lesion, either through specialized medical devices or smartphone cameras. The second step is the image preprocessing stage, which is the initial stage in detecting skin cancer, it improves image quality by removing extraneous areas and objects from the backdrop of skin photos. Dermoscopic images may contain unwanted particles like fur, gel, air bubbles, and other sounds, which might decrease the accuracy of subsequent processes like segmentation and classification jobs. The dermoscopy images are therefore pre-processed using various image processing techniques. The raw data or dermoscopic images undergo noise removal, contrast enhancement, filtering, etc. [11]. For example, unwanted background elements are eliminated from the skin image by cropping, followed by hair removal achieved through image filtering. Image segmentation is a critical step in image recognition and detection, as it simplifies the process of image classification. This involves dividing a visual input into segments, which are collections of pixels that represent objects or fragments within the image.

There are two main types of segmentation: instance segmentation and semantic segmentation [12]. Accurately segmenting skin images can be instrumental in pinpointing the precise location of cancer, akin to partitioning the image. By categorizing images into distinct groups, it becomes possible to assign a specific set of pixels to each group. This approach allows for the separation of pixels that make up a skin lesion from those that compose the background. Feature extraction refers to the procedure of isolating particular attributes from an image. These features serve as representations of the unique qualities present in the input image. This process is commonly referred to as dimensionality reduction, as it involves reducing the dimensionality of the input pixels in order to capture the relevant characteristics of the skin image. After the extraction of features, the subsequent step in the automated detection of skin cancer involves categorizing the lesions as either malignant or benign, distinguishing between cancerous and non-cancerous conditions see figure 1.

Figure. 1: Skin cancer detection Steps using CNNs

3. Challenges of Skin Lesion Detection

The challenges of accurately identifying skin cancer can be attributed to the diverse range of image types and sources. The wide variation in human skin color greatly complicates the detection process, making it a complex and challenging task. This is visually depicted in figure 2, which showcases the different appearances of skin. The complexity of visual characteristics in skin lesion images presents various obstacles that need to be addressed [13].

- Image acquisition can introduce unwanted elements like noise and artifacts, such as hair strands, bubbles, and blood vessels. These signals that are not originally part of the image can hinder both manual and automated skin lesion identification by distorting the image and potentially obscuring crucial details.

- Skin lesions come in a diverse range of sizes, shapes, and locations, posing a significant challenge for accurate identification. This vast variability makes image analysis for skin cancer diagnosis complex and often necessitates image pre-processing before reliable analysis can be achieved.

- Unpredictable, fuzzy borders are a common feature of some skin lesion images. This poses a significant obstacle for techniques aiming to refine contours and pinpoint lesion boundaries. Accurately identifying the margins during pre-processing can be critical for accurate predictions, particularly asymmetry, but fuzzy edges often make this a daunting task.

- The interplay of skin color, texture, and unpredictable light variations in dermoscopic images creates a spectrum of illumination levels, leading to a "multi-resolution" challenge that complicates consistent analysis.

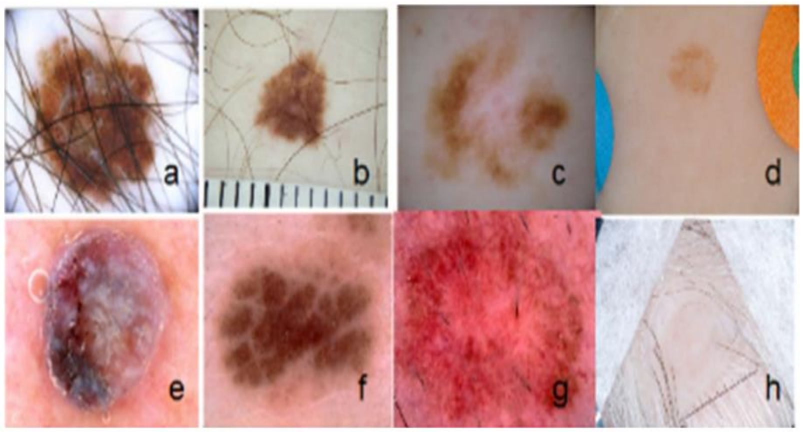

Figure. 2: Challenges of skin cancer detection: a) hair artefact, b) ruler mark artefact, c) low contrast, d) color illumination, e) bubbles, f) irregular boundaries, g) blood vessels

4. Convolutional Neural Networks Techniques for Skin Cancer Detection

When it comes to achieving optimal results, CNNs outperform traditional machine learning techniques. The key lies in the multiple layers of CNNs, which greatly enhance the architecture's capacity to learn. Unlike traditional algorithms or basic feedforward networks, CNNs do not break images down into a single column vector. Instead, they preserve the pixel stacking while adjusting the dimensions as needed. This approach enables superior feature extraction and overall improved performance, which is crucial when dealing with lesion or tumor classification where every detail matters. While traditional techniques may be limited to classification or minor feature extraction tasks, CNNs offer exceptional flexibility due to the incorporation of various filters and layers into the architecture. This allows for the creation of customized architecture tailored to the specific images or dataset at hand [14].

Convolutional Neural Networks are a type of artificial neural network that employs deep learning techniques to analyze visual image-based data. They utilize feedforward and backpropagation to learn the features of a training set and classify the classes of a test set. Compared to basic machine learning techniques, CNNs offer superior performance, although they require more computational resources. Convolutional neural networks (CNNs) are extensively utilized for image recognition and classification, as they possess the ability to learn directly from data. These networks have gained recognition as one of the top machine learning algorithms for analyzing grid-like structured data, particularly in the realm of images. Their remarkable performance in image processing and computer vision tasks is well-documented. The tasks involved in image analysis, including localization and segmentation, classification, and detection, are commonly performed using convolutional neural networks [14]. Typically, CNNs consist of three types of layers: convolutional, pooling, and fully connected layers, usually arranged in that sequence. The complexity of the network and its ability to identify patterns increases with the number of layers employed. These networks consist of numerous layers, often numbering in the tens or hundreds, each of which is trained to recognize different aspects of an image. During training, filters are applied to convolve the input image, and the resulting convolved pictures serve as the input for the subsequent layer. The filters initially detect basic features like brightness and edges, gradually progressing to more complex features that are specific to the object being identified. Hidden layers are present between the input and output layers of a CNN. The primary purpose of these layers is to manipulate the data in order to extract unique features from it. The convolution, activation (or ReLU), and pooling layers are the most commonly utilized in this process. The Conv layer serves as the fundamental component of a Convolutional Network, carrying out the majority of the computational workload. Through convolution, the input images are subjected to convolutional filters, which highlight different aspects of the images. By eliminating negative values and preserving positive ones, an activation function aids in expediting and enhancing the training process. This is achieved by only passing on the activated features to the subsequent layer. The process known as activation is often referred to as pooling, which effectively decreases the number of parameters that the network must learn by implementing nonlinear down-sampling on the output. This operation is repeated over numerous layers, allowing each layer to acquire the ability to identify different features. Finally, the output is provided by a classification layer in the CNN architecture's top layer. The basic architecture of a CNN is presented in figure 3 [15].

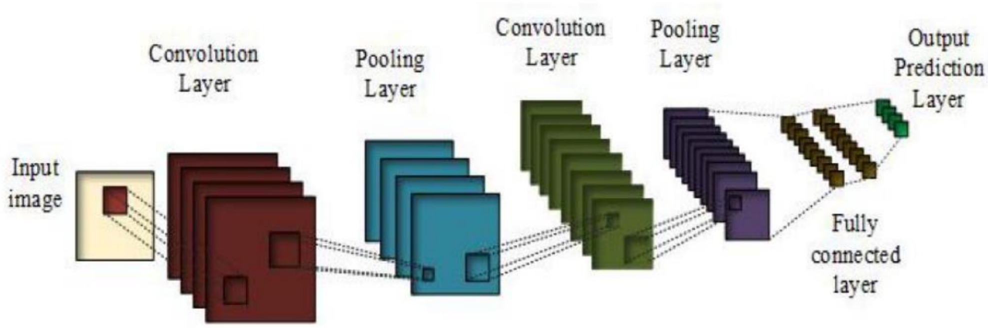

Figure. 3: Basic CNN Architecture

Several CNN models, including AlexNet, VGG16, ResNet50, DenseNet, and InceptionV3, have been developed to deal with skin cancer detection. However, when it comes to gathering a substantial volume of data for medical purposes to train a CNN, it poses a significant challenge. To address this challenge, all of these studies employed transfer learning, a widely recognized technique in which a model that has been trained for a specific source task is partially utilized for a new target task. As a result, the models were initialized with the weights from the ImageNet dataset and subsequently fine-tuned using their own dataset [9]. In the realm of image classification, there are several CNN architectures that are widely utilized. Let's take a moment to provide concise summaries of these commonly employed models. It is worth noting that researchers have leveraged these architectures to develop skin cancer detection systems that rely on deep learning techniques.

4.1 AlexNet

The groundbreaking convolutional neural network (CNN) architecture known as AlexNet was introduced by Krizhevsky et al. [13]. This innovative network, depicted in figure 4, consists of five convolutional layers and three fully connected layers. With a staggering 60 million parameters, AlexNet had the capacity to extract intricate features from images, resulting in unparalleled performance compared to previous models. Its remarkable achievement came to light in 2012 when it triumphed over its competitors by a significant margin in the prestigious ImageNet Large Scale Visual Recognition Challenge (ILSVRC). This victory marked a monumental milestone in the realms of deep learning and computer vision. The success of AlexNet ignited a revolution, serving as a catalyst for the development of more sophisticated architectures such as VGG16, ResNet, and Inception, all of which build upon the foundational principles established by AlexNet.

Figure. 4: Layout diagram of AlexNet Architecture

4.2 VGG16

VGGNet which is also referred to as VGG16 supports 16 layers is a widely utilized CNN model that has gained immense popularity due to its simplicity and ease of use. The key factor that contributes to the widespread adoption of the VGG model is its utilization of small-sized convolutional kernels, which makes it a highly favored deep learning model. The architecture of VGGNet incorporates a 3 × 3 convolution kernel with max-pooling and ReLU layers, along with three fully connected layers, for feature extraction and classification. By employing smaller kernels, the VGG model achieves a reduction in the number of parameters, resulting in more efficient training and testing.

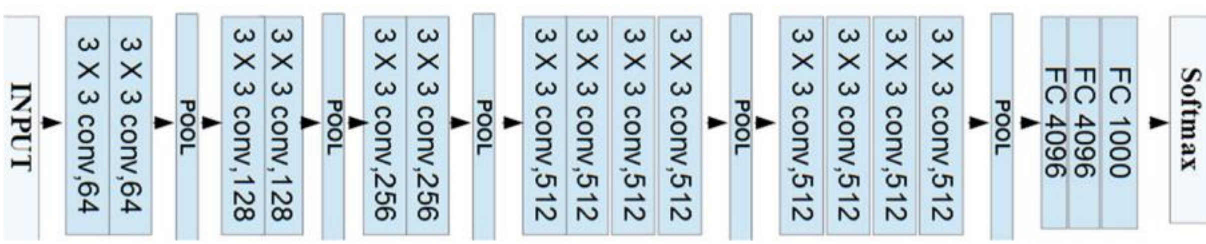

Figure. 5: Layout diagram of VGG 19 Architecture

The VGG16 model's 16 layers are split up into 5 different types: completely linked, max-pooling, convolution, ReLU, and Softmax. following the input layer. The VGG model processes pre-processed images sized at 224 × 224 with three RGB channels at the input layer. VGG-16 is notable for its focus on convolution layers with a 3 × 3 filter with Stride 1 and constant usage of the same padding and maxpooling layer with 2 × 2 filters with Stride 2, rather than an enormous amount of hyperparameters [16]. Depending on the number of convolution layers, VGG has several variations; the most popular VGG architectures are VGG-16 and VGG-19. Figure 5 displays the VGG-19 architecture [13].

4.3 ResNet

To address the issue of vanishing gradients, ResNet, a deep convolutional network, employs identity convolutional blocks. As the gradient is backpropagated through the network, it can diminish significantly. However, the use of shortcut connections in the identity block provides an alternative path for the gradient to flow, effectively solving the problem of vanishing gradients. Our implementation of ResNet consisted of 50 convolutions, organized into five stages as in figure 6. Each stage comprised a convolutional block and an identity block. Within each block, three convolutions were performed using 1 × 1, 3 × 3, and 1 × 1 filters. The 1 × 1 kernel was responsible for reducing and then restoring dimensions. The inclusion of parameter-free identity shortcuts is particularly crucial for bottleneck architectures. If the identity shortcut is replaced with a projection, the time complexity and model size would double, as the shortcut connects the two high-dimensional ends [17, 18].

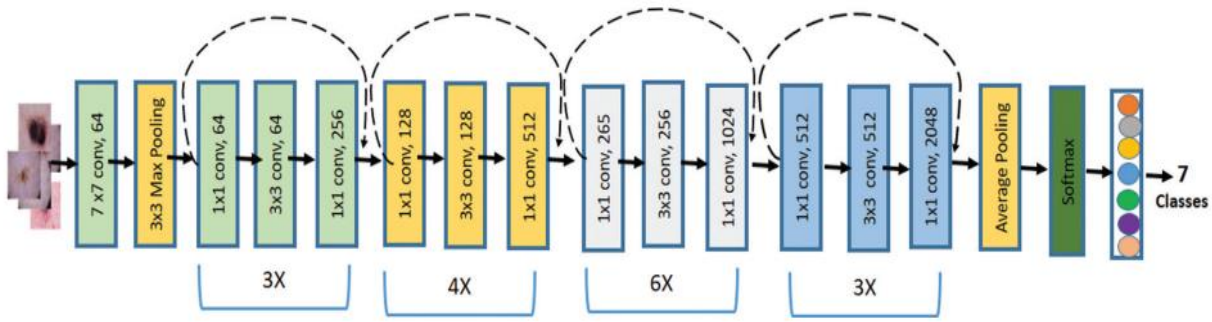

Figure. 6: Block diagram of the ResNet50 network

4.4 DenseNet

DenseNet, also known as Densely Connected Convolutional Network, is a remarkable architectural innovation within the realm of deep learning. It shares similarities with ResNet and was specifically designed to address the challenge of the vanishing gradient. By incorporating cross-layer connectivity, DenseNet establishes direct connections between each preceding layer and the subsequent layer in a forward-propagation manner. This approach effectively resolves the issue encountered by ResNet, wherein information preservation is achieved through additive identity transformations, leading to increased complexity. DenseNet employs dense blocks, enabling the utilization of feature-maps from all previous layers as inputs for all subsequent layers as shown in figure 7 [13, 19].

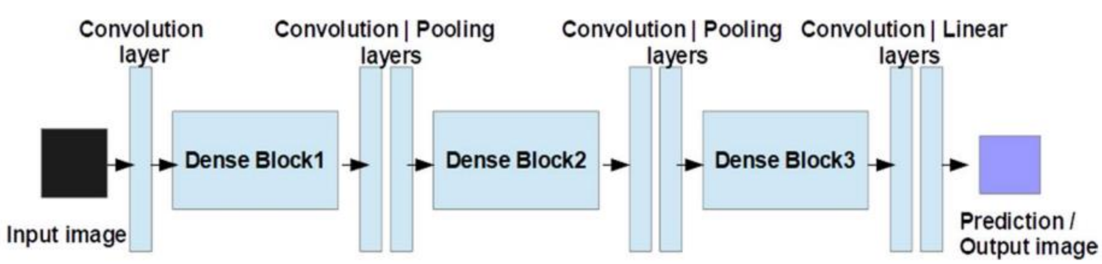

Figure. 7: Layout diagram of DenseNet Architecture

4.5 InceptionV3

To achieve the necessary depth, the deep neural Inception network employs replicated Inception modules [20]. Inception incorporates three convolutional layers and a max-pooling layer, each with filters of varying sizes. By combining all filter maps, the module learns from multiple parallel filters of different scales and sizes. Within a single network module, Inception serves as a "multi-level feature extractor" by performing convolutions with 1x1, 3x3, and 5x5 factors. Inception has different versions, with InceptionV3 being an enhanced variant utilized in biomedical applications. With a total of 48 layers, InceptionV3 boasts 24 million transfer learning parameters.

4.6 Xception

Xception [21] is an adaptation of the Inception architecture that incorporates the idea of depthwise separable convolution. In order to manage complexity, Xception employs larger blocks compared to the original inception block and replaces the multiple spatial dimensions with a single dimension (3x3) followed by a 1x1 convolution. By separating spatial and feature map operations, Xception achieves improved computational efficiency compared to Inception. Xception surpasses Inception V3, ResNet-50, ResNet-101, ResNet 152, and VGGNet in terms of performance on ImageNet. The architecture of Xception streamlines computation by applying separate convolutions to each feature map along the spatial axes. Enhancing performance through the use of pointwise convolutions (1x1 convolutions), Xception employs cross-channel correlation. The transformation in Xception maintains the same number of parameters, yet achieves superior performance. Xception's approach streamlines the learning process by minimizing the number of connections.

4.7 EfficientNet

EfficientNet, a convolutional neural network architecture and scaling technique, employs a compound coefficient to uniformly scale depth, width, and resolution. In contrast to conventional scaling methods that modify only one factor at a time, EfficientNet utilizes a compound scaling approach. This enhances the scaling process, resulting in superior performance and efficiency compared to alternative methods. EfficientNet models excel in image classification tasks, delivering exceptional accuracy and making them well-suited for demanding applications [22].

5. Recent Applications of CNN Architectures

An overview of the most relevant methods for Deep Learning-based skin cancer detection is given in this section. Serte et al. [23] introduced a novel approach for detecting malignant melanoma and seborrheic keratosis using a deep convolutional neural network based on Gabor wavelets. Their method involves two models: a Gabor wavelet-based CNN and an image-based CNN. Initially, Gabor filters are applied to skin images, generating Gabor wavelets which capture directional information. These wavelets are then combined with the input from the skin images in the image-based CNN model. To enhance the accuracy of the system, data augmentation is performed on the ISIC 2017 datasets, including rotating the images at various angles. Among the different models proposed, the I-GR0235 model, which incorporates Resnet-18 for the image-based CNN and Alexnet for the Gabor CNN, achieved the highest performance. It demonstrated an accuracy of 83% for melanoma classification.

The classification system for skin cancer, developed by Mahbod et al. [24], involves the utilization of three pre-trained models: AlexNet, VGG16, and ResNet-18. Extracted features from the fully connected (FC) layers and the last convolution layers of these networks are inputted into separate SVM classifiers for the purpose of training. Finally, the outputs of all the SVM classifiers are combined to yield the final classification results. The training of the classifier is conducted using the ISIC-2016 and ISIC-2017 datasets. As a result, the proposed system achieves a melanoma classification with an impressive area under the curve for ROC of 83.83%.

The evaluation conducted by Demir et al. [25] involved the utilization of deep learning architectures, namely ResNet-101 and Inception-v3, to develop a classification system for skin cancer. ResNet-101 is comprised of an impressive 104 convolution layers, while Inception-v3 consists of 42 deep neural networks. The accuracy achieved by the ResNet-101 model was determined to be 84.09%, whereas the Inception-v3 model exhibited a slightly higher accuracy of 87.42%. It is worth noting that both models were trained on a data set sourced from the ISIC archive.

Gulati et al. [26] utilized pretrained networks, specifically AlexNet and VGG16, in two distinct manners: as a transfer learning approach and as a feature extractor. The dataset employed in their research was PH2, which was obtained from the Dermatology Service of Hospital Pedro Hispano in Portugal. This dataset consisted of a total of 200 images, with 160 falling under the benign category and 40 falling under the malignant category. Since the aforementioned networks required inputs of varying sizes, appropriate preprocessing steps were taken. Both AlexNet and VGG16 were individually employed for transfer learning and feature extraction. Among these techniques, VGG16 yielded the most favorable outcomes as a transfer learning model, achieving an impressive accuracy rate of 97.5% and a specificity of 96.87%.

Zhang [27] put a model for automated melanoma detection that utilizes EfficientNet-B6 to analyze skin lesion images. This model can capture more intricate details and features. To evaluate its performance, the researchers conducted experiments on the ISIC 2020 Challenge Dataset, a publicly available dataset generated by the International Skin Imaging Collaboration. The images in this dataset are sourced from various reputable medical institutions. The results of these evaluations showcased the model's exceptional classification performance, surpassing that of previously widely used melanoma classifiers on the same dataset.

According to Vipin et al. [28] their algorithm made use of a 13,000 picture ISIC dataset, which was whittled down to 7,353 photos by eliminating useless ones. The symmetric U-Net, which has three primary components—the bottleneck, the expanding/up sampling path, and the contracting/down sampling path—was used in the segmentation step. Maximum pooling layers and convolutional layers are used in each of these parts. The classification stage model was trained using a deep residual network. The network correctly identified melanoma lesions in 88.7% of cases, demonstrating its ability to distinguish between cancerous and benign examples.

Combining long short-term memory and MobileNet models, Srinivasu et al. [29] developed a deep learning-based model for assessing skin disease identification analysis. In order to assess the progression of the illness, the suggested hybrid model's performance was also examined. Its outcomes were contrasted with those of other cutting-edge models, including CNNs and fine-tuned neural networks. The accuracy of the suggested hybrid model was 85%.

A deep learning-based model for efficiently screening skin disease lesions was described by Khan et al. [30]. A mask recurrent neural network (MASK-RNN) was utilised for the trials, and Resnet50 was combined with a pyramid network to extract and classify the SoftMax classifier. Fraiwan et al. [31] classify skin lesion photos into seven categories (melanoma, benign keratosis-like lesions, and five different non-melanoma malignancies) using transfer learning of 13 deep convolutional neural network models.

Hoang et al. [32] suggest a technique for classifying skin lesions that makes use of wide-ShuffleNet and a fresh segmentation strategy. They begin by determining the skin image's first-order cumulative moment (EW-FCM) and entropy-based weighting. The lesion is distinguished from the background using these parameters. They next identify the type of skin lesion by feeding the segmentation result into a brand-new deep learning structure called wide-ShuffleNet.

A deep CNN architecture called VGG-16, initially trained, and then fine-tuned with three additional layers and five convolutional blocks, was introduced by Kalouche [33]. The VGG-16 models exhibited an accuracy of 78% when classifying images of skin lesions as melanoma skin cancer. In order to detect the boundaries of skin lesions in images, a deep CNN-based system was developed. This system was trained using 1200 normal skin images and 400 images of skin lesions. By employing this approach, the proposed system achieved an accuracy of 86.67% in classifying input images into two main categories: normal skin images and lesion images.

A novel approach to melanoma detection was introduced by Shorfuzzaman [34], utilizing a CNN-based stacked ensemble framework. By combining a pre-trained DenseNet12, Xception, and EfficientNetB0, the framework was able to accurately classify melanoma on a dataset consisting of 1497 malignant and 1800 benign mole images from the ISIC archive. The final prediction results were generated by aggregating the predictions of all sub-models. Remarkably, the proposed method achieved an impressive accuracy of 95.76%. However, it is important to note that the proposed method was specifically tested for the binary classification of melanoma versus non-melanoma cases. It would be intriguing to evaluate the performance of the proposed method on a multi-class classification problem. Additionally, further investigation is required to assess the generalizability of the proposed model on larger datasets.

Alenezi et al. [35] proposed a method that involves utilizing a pre-trained deep residual network trained on the ISIC 2017 and HAM1000 datasets. To ensure accurate classification, they employed wavelet transform and pooling operation to remove unwanted artifacts, such as hairs, from skin lesion images. In order to determine the most effective activation function, experiments were conducted using ReLU, PReLU, Sigmoid, and Hardlim. The results revealed that the ReLU activation function yielded the highest classification accuracy of 96.91% and an F1-score of 0.95 on the skin lesion datasets. However, it is important to note that this approach has limited generalizability and exhibits weak classification performance when applied to lesion images of varying sizes and colors [36].

Alenezi et al. [37] perform removal of hairs from skin lesion images through a technique that involved dilation, normalization, and pooling. They utilized relief feature selection to choose features extracted using ResNet-101, which were then used to train an SVM classifier for melanoma classification. Additionally, SVM was trained on features extracted from AlexNet, DarkNet19, GoogleNet, SqueezeNet, Xception, and MobileNetV2. The highest accuracy, reaching 96.15% and 97.15% on ISIC 2019 and ISIC 2020 datasets respectively, was achieved by SVM with features extracted using ResNet-101. It is important to note that Dataset 1 consisted of only 1168 images. However, it should be acknowledged that the use of deep architectures like ResNet-101 for feature extraction may lead to overfitting due to the small size of the training dataset. Furthermore, the proposed approach has limitations in terms of the time required for parameter selection of the SVM classifier [36].

The following table provides a detailed compilation of skin cancer detection systems that utilize CNN classifiers for accurate diagnosis.

Table. 1: A Comparison of Different Deep Learning Methods for Skin Cancer Detection

Ref.	Model	Datasets	Accuracy
Alenezi et al., (2023) [35]	deep residual network	ISIC 2017, HAM10000	96.971%
Alenezi et al., (2023) [37]	ResNet-101 with SVM	ISIC 2019, ISIC 2020	96.15%
Fraiwan et al., (2022) [31]	DenseNet201	HAM10000 dataset	82.9%
Hoang et al., (2022) [32]	Wide-ShuffleNet	HAM10000 dataset	86.3
Shorfuzzaman, (2022) [34]	DenseNet121, Xception, EfficientNet80	ISIC archive	95.76%
Zhang, (2021) [27]	EfficientNet-B6	ISIC 2020	-
Vipin et al., (2021) [28]	Classification done using CNN and recurrent neural network techniques	ISIC archive	88.7%
Srinivasu et al., (2021) [29]	MobileNet V2-LSTM	HAM10000 dataset	85%
Khan et al., (2021) [30]	Mask-RCNN	HAM10000 dataset	86.5
Serte et al., (2019) [23]	Gabor-wavelet + CNN based melanoma classification	ISIC-2017	83.0%
Mahbod et al., (2019) [24]	AlexNet, VGG16 and ResNet-18 are used with SVM classifier is given for each with fusion to produce final classification	ISIC- (2016, 2017)	83.83%.
Demir et al., (2019) [25]	Classification done using ResNet-101, Inception-v3 networks and compared their results	ISIC archive	ResNet=84.09%, Inception-v3= 87.42%
Gulati et al., (2019) [26]	AlexNet and VGG16	PH2	97.5%
Kalouche, (2016) [33]	VGG-16 and CNN	ISIC dataset	86.67%

6. Skin Cancer Images Datasets

This section offers a comprehensive overview of the commonly utilized datasets with different modalities in the field of skin cancer detection as shown in table 2 (where ak is Actinic Keratosis, bcc is Basal Cell Carcinoma, bk is Benign Keratosis, df is Dermatofibroma, hae is Haemangioma, ic is Intraepithelial Carcinoma, mel is melanoma, nv is Nevus, pg is Pyogenic Granuloma, sk is Seborrheic Keratosis, scc is Squamous Cell Carcinoma, vasc is Vascular Lesion).

1- HAM10000

Introducing the latest publicly accessible dataset for skin lesions, HAM10000, which successfully addresses the issue of limited diversity. This comprehensive collection comprises a total of 10,015 dermoscopic images, that includes seven classes, painstakingly compiled over a span of twenty years. In the pre-digital camera era, photographic prints of these lesions were meticulously archived and preserved at the Dermatology Department of the Medical University of Vienna, Austria. To facilitate digitalization, a Nikon-Coolscan-5000-ED scanner, manufactured by Nikon corporation Japan, was employed to convert these prints into 8-bit color JPEG images with a high-quality resolution of 300 DPI. Subsequently, each image underwent manual cropping and was saved at a resolution of 800 × 600 pixels and 72 DPI [37].

2- PH2

Within this dataset, there are a total of 200 dermoscopic images. These images are further categorized into three groups: 80 images of common nevi, 80 images of atypical nevi, and 40 images of melanoma skin cancers. In addition to the images themselves, this dataset also includes medical annotations. These annotations encompass a range of information, including the medical segmentation of pigmented skin lesions, histological and clinical diagnoses, as well as evaluations of different dermoscopic criteria [38].

3- ISIC Archive

The ISIC Archive, an invaluable resource in the field of skin cancer, offers a vast collection of over 13,000 top-notch dermoscopic images of various skin lesions. This publicly accessible archive encompasses a wide array of lesion types and characteristics, providing researchers and healthcare practitioners with detailed information about each image, including diagnosis and clinical context. Continuously expanding with new datasets and research studies, the ISIC Archive serves as a catalyst for advancements in research and education. Its open access nature empowers professionals to harness its extensive data for the development of enhanced diagnostic tools and the enhancement of patient care [39].

4- Atlas of Dermoscopy

The dataset known as AtlasDerm, or the Atlas of Dermoscopy dataset, comprises a variety of images. Specifically, it contains 5 images of ak, 42 images of bcc, 70 images of benign keratoses, 20 images of dermatofibromas, 275 images of melanocytic nevi, 582 images of melanoma, and 30 images of vascular skin lesions [35].

5- Dermofit

The Dermofit dataset consists of a total of 1300 images of skin lesions, which have been categorized into ten different classes. Specifically, there are 45 images of actinic keratosis (ak), 239 images of basal cell carcinoma (bcc), 331 images of melanocytic nevus/mole, 88 images of squamous cell carcinoma (scc), 257 images of seborrhoeic keratosis, 78 images of intraepithelial carcinoma (ic), 24 images of pyogenic granuloma (pg), 97 images of haemangioma, 65 images of dermatofibroma, and 76 images of malignant melanoma [35].

6- BCN20000

The Hospital Clinic in Barcelona provided a collection of 19,424 dermoscopic images of skin lesions captured from 2010 to 2016 for this dataset. These images, available in the BCN20000 database, can be categorized into various classes, including nevis, melanoma, basal cell carcinoma, seborrheic keratosis, actinic keratosis, squamous cell carcinoma, dermatofibroma, and vascular lesion [40, 41].

7- PAD-UFES-20

The PAD-UFES-20 dataset consists of 1373 patients, 1641 skin lesions, and 2298 images for six different diagnostics: three skin diseases and three skin cancers [42].

Table. 2: Brief details of commonly available skin lesion datasets

Dataset	No. of Images	No. of Classes	Classes and No. of Cases	Year
HAM10000	10015	7	ak – 327, bcc – 514 bk – 1099, df – 115 mel – 1113, nv – 6705 vasc – 142	2018
PH2	200	2	mel – 40, nv-160	2013
ISIC archive	25331	8	ak – 867, bcc – 3323, bk – 2624, df – 239, mel – 4522, nv – 12875, scc – 628, vasc − 253	2019
Atlas of Dermoscopy	1024	3	ak – 5, bcc – 42, bk – 70, df – 20, nv – 275, mel – 582, vasc – 30	2000
Dermofit	1300	10	ak – 45, bcc – 239, nv – 331, scc – 88, sk – 257, ic – 78, pg – 24, hae – 97, df – 65, mel - 76	2000
BCN20000	19424	8	(nv, mel, bcc, sk, ak, scc, df, vasc) - NA	2017
PAD-UFES-20	2298	6	bcc-845, scc-192, ak-730, sk-235, mel-52, nv-244	2019

7. Conclusion and Future of Deep Learning Techniques

Convolutional Neural Networks (CNNs), a type of deep learning technique, have been examined in this research as a means of early skin cancer diagnosis. These procedures have been proven to be useful and efficient in the diagnosis of skin cancer through a thorough examination of numerous research papers. According to the results, CNN can successfully identify skin cancer using a variety of data sets and hybrid models, suggesting that these technologies may be able to increase the precision of skin cancer detection. Despite their many benefits, there are still some challenges facing deep learning techniques in skin cancer screening.

- Need for high-quality data: Deep learning networks require large amounts of high-quality data for training, which can be difficult to obtain and organize.
- Skin image variation: Images of skin cells can vary greatly depending on skin color and type of lesion, which can be a challenge for deep learning networks.
- Interpretability and transparency: It can be difficult to understand how deep learning networks make their decisions, raising concerns about the transparency and reliability of their diagnostics.

Despite these challenges, the field of skin cancer screening using deep learning techniques is expected to continue to develop and improve. As more data continues to be collected and artificial neural networks improve, deep learning techniques may become a powerful tool for early detection of skin cancer and saving lives.

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