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Review Article

An overview of skin cancer classification based on deep learning

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ABSTRACT
Skin melanoma is one of the most dangerous diseases in the world. Correct classification of skin lesions in the first step can help create clinical judgment by providing an optimal judgment of the disease. As a result, the odds of treating the spread of cancer early may be increased. However, the automatic classification of skin cancer is tough because of the imbalance in most skin cancer images used in training. Several methods based on deep learning have been broadly used recently in skin cancer classification to resolve the problems in classification and attain acceptable outcomes. Nevertheless, reviews containing the aforementioned borderline difficulties in skin melanoma classification are still rare. Thus, this paper presents a summary of the newest deep learning procedures for classifying skin cancer. This paper starts with a discussion of skin cancer types, followed by the presentation of a public dataset available for skin cancer. Subsequently, some pretrained models of CNN used for classification are highlighted. Finally, some opportunities for skin cancer, such as data imbalance and limitation, generative adversarial network, various data sets, and data augmentation, are summarized.

Keywords:* *Skin cancer; Deep learning; Melanoma; CNN.

1. INTRODUCTION

Cancer poses a serious threat to human life and can be a cause of death. Various kinds of tumors may occur in the human body. One of these tumor types is skin cancer; this tumor grows quickly in the skin and can lead to death. Many factors, such as exposure to ultraviolet (UV) rays, inflammatory viruses, environmental changes, smoking, allergies, and alcohol consumption, can contribute to the development of skin cancer. Recent research has shown that UV radiation can damage the DNA of the skin and that approximately 86% of skin cancers are caused by UV radiation from the sun [1]. Moreover, abnormal swellings in the human body may cause skin cancer. Skin cancer has many types, with the main ones including squamous cell carcinoma (SCC), melanoma, basal cell carcinoma (BCC), and actinic keratosis [2]. According to the World Health Organization, one out of every three cases of cancer identified is skin cancer [3]. The number of people with skin cancer has been steadily increasing over the past decades in Canada, Australia, and the United States [4]. According to [5], skin cancer accounts for approximately 15,000 deaths each year. In the United States alone, an estimated 178,560 new cases were reported in 2018, which included 87,290 nonsurgical cases and 91,270 surgical cases. The number of deaths from melanoma in the United States was 9,320, including 3,330 women and 5,990 men [6, 7].

Only 4% of skin cancers are caused by malignant melanoma, yet it accounts for approximately 75% of all skin melanoma patients. Initial diagnosis and detection are crucial for the odds of survival for affected patients [3]. At present, patients with skin lesions are examined through visual examination by specialist dermatologists and with the help of polarized light. The result of the diagnosis depends on the patient's habits, history, work, duration of exposure to sunlight, and skin color. A sample of these lesions is taken and examined in the laboratory by a specialist. Then, the appropriate diagnosis is provided to the patient before it is too late. Nonetheless, early diagnosis can be difficult even though dermoscopy improves diagnostic accuracy compared with visual inspection alone [8]. Significant variation depending on professional training and experience can be observed, with even a few specialists reaching sensitivity levels higher than 80% [9].

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Computer-aided diagnosis with artificial intelligence (AI) is one of the most important technologies that can assist doctors during diagnosis; thus, it revolutionizes healthcare and medicine, particularly in medical imaging methods, such as magnetic resonance imaging, computed tomography, and ultrasound [10]. In many studies, AI methods used in diagnosis match or outperform clinician performance [11, 12]. Nowadays, deep learning algorithms provide various solutions for classifying human body abnormalities, such as lung cancer, foot ulcers, esophageal cancer, stomach cancer, brain tumors, and breast cancer, using different image methods [13]. Moreover, the convolutional neural network (CNN) is a deep learning technique used for skin cancer classification through supervised learning, thereby allowing the image label to be given in training [14].

This study aims to provide readers with the latest report on the development, performance, and limitations of AI algorithms based on skin cancer classification using different modalities on skin cancer datasets. It also aims to provide a comparative survey on the use of deep learning algorithms and dermatologist assessment in diagnosis. Moreover, it offers the readers in-depth information about different types of skin cancer imaging techniques, the datasets most widely used by researchers, and the availability of these datasets. Finally, some skin cancer possibilities, such as data imbalance and limitations, generative adversarial network (GAN), different datasets, and data augmentation, are summarized.

The rest of this paper is organized as follows: Section 2 introduces three types of skin images. Section 3 summarizes 13 types of common public datasets. Section 4 reviews several deep learning models for skin cancer classification and compares them with dermatologists' diagnoses in some studies. Sections 5 and 6 present some limitations and brief discussions.

2. SKIN CANCER DATASET AND IMAGES

High-resolution images are essential for accurately diagnosing skin cancer [15]. Moreover, deep learning procedures need a large number of labeled images to obtain high accuracy [16]. Consequently, high-quality images are important for clinical and surgical imaging diagnoses and planning for new procedures. In this section, three kinds of images that are usually used in skin cancer diagnosis and some general datasets are presented.

2.1 Clinical Image

These kinds of images can be obtained by directly taking a picture of the skin using a camera [17]. The clinical images provide little information about the skin for the diagnosis because of the imaging settings (such as angle and lighting) [18].

Fig. 1: Various kinds of clinical skin images: (a) benign keratosis, (b) melanoma, (c) BCC, and (d) SCC [19].

2.2 Dermoscopic Images

A dermoscopic image can be obtained using an optical observation tool; this type of device provides a lot of information about skin cancer [20]. Nevertheless, the accuracy of the diagnosis is influenced by the knowledge of the clinical doctors [21].

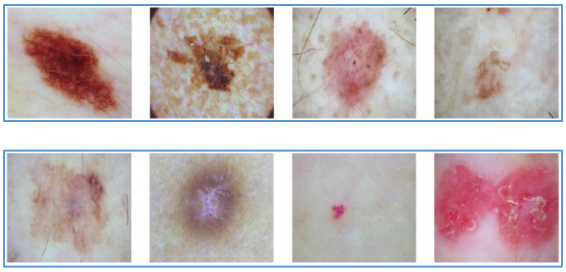

Fig. 2: Various kinds of dermoscopic skin images: (a) nevus, (b) melanoma, (c) BCC, (d) actinic keratosis, (e) benign keratosis, (f) dermatofibroma, (g) vascular lesion, and (h) SCC [22].

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2.3 Histopathological Images

This type of image is obtained with microscopes. Tissue slides are scanned and then converted into digital images. The internal and vertical structures of diseased tissue have been demonstrated in this way. Moreover, pictures of skin cancer come in different textures, sizes, shapes, and color distributions; thus, catching a mutual pattern for diagnosis becomes difficult [17].

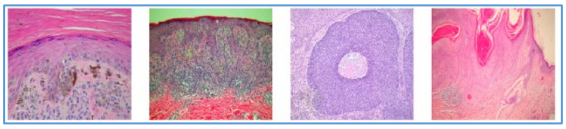

Fig. 3: Various kinds of histopathology skin images: (a) nevus, (b) melanoma, (c) BCC, and (d) SCC [19].

3. DATASETS

Many robust and trustworthy public skin cancer datasets available are used to assist researchers for various purposes, such as detection, segmentation, and classification. In this section, we present several commonly used datasets on skin diseases. These datasets are available for free or low-cost download. The free and paid datasets are presented as follows.

3.1 HAM10000 Dataset

The HAM10000 dataset is used to resolve the difficulties in dataset limitation. Composed by the International Skin Imaging Collaboration (ISIC), this dataset contains 10,015 dermoscopic images divided into seven types of skin cancer. It is freely available to researchers [22].

3.2 ISIC Dataset

ISIC created a dataset on skin diseases that is available publicly for the science of computer community worldwide to decrease skin melanoma mortality while promoting the development and the use of digital skin imaging [23]. The ISIC-2016 archive includes 1279 images, and the ISIC-2017 archive includes 2750 dermoscopy images. These images are annotated and examined by specialists to ensure the quality of the images. The ISIC dataset is freely available to researchers [24].

3.3 Interactive Atlas of Dermoscopy

This dataset consists of dermoscopic and clinical images, including 1000 clinical cases of seborrheic keratosis and 270 melanomas. The rest of the images are random. This dataset is available to researchers for a fee of $250 [25].

3.4 Dermofit Image Library

This library of images includes 10 categories from 1300 high-resolution dermoscopic images. It is available to researchers for a fee of $75 [26].

3.5 The Cancer Genome Atlas

The Cancer Genome Atlas images comprise one of the largest groups of slides of pathological skin lesions with 2871 cases. It is freely available to researchers [27].

3.6 SD-198 Dataset

This dataset is a clinical skin lesion taken with mobile phones and digital cameras. It includes 6584 pictures of 198 skin diseases. It is freely available to researchers [28].

3.7 SD-260 Dataset

This group of images is more stable than the last one because it panels the size of the distribution while maintaining 10–60 pictures per class. It involves 260 skin diseases with 20,600 images. It is freely available to researchers [29].

3.8 Derm7pt

Derm7pt contains 1011 dermoscopic images (759 nevus cases and 252 melanoma cases of skin cancer). It is freely available to researchers [30].

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3.9 DermNet NZ
This type of dataset contains the largest collection of histology, clinical, and dermoscopic skin cancer images for various diseases. Therefore, this dataset can be used for many purposes in academic research. It is available to researchers for a fee [31].

3.10 PH2 Dataset
This dataset contains dermoscopic images divided into 160 nevus cases and 40 melanoma cases. It is freely available to researchers [32].

3.11 Asan Dataset
The Asian dataset consists of 12 types of diseases from 17,125 clinical images of Asian people. It is freely available to researchers [33].

3.12 MED-NODE dataset
This dataset includes 170 clinical images (100 nevi cases and 70 melanoma cases). It is freely available to researchers [34].

3.13 Hallym Dataset
The Hallym dataset contains 125 clinical images of BCC categories. It is freely available to researchers [35].

Table 1 summarizes the skin cancer datasets mentioned above with a download link for each dataset.

Table I: Different skin cancer datasets

Dataset	*Type*	*No. of images*	*No. of class*	*No. of images per class*	*Download link*
HAM10000	*Dermoscopic*	*10015*	*7*	*akiec – 327* *bcc - 514* *bkl – 1099* *df - 115* *mel – 1113* *nv - 6705* *vasc – 142*	https://challenge.isic-archive.com/data
ISIC-2016	*Dermoscopic*	*1279*	*2*	*mel – 248* *nv - 1031*	https://challenge.isic-archive.com/data
ISIC-2017	*Dermoscopic*	*2750*	*3*	*mel -521* *nv – 1843* *sk - 386*	https://challenge.isic-archive.com/data
Interactive Atlas of Dermoscopy	*Dermoscopic and clinical*	*1000*	*3*	*mel - 270* *sk - 49* *unk - 681*	http://www.dermoscopy.org/atlas/default.asp
Dermofit Image Library	*Dermoscopic*	*1300*	*10*	*akiec - 45* *bcc – 239* *df – 65* *hae – 97* *ic - 78* *mel - 76* *nv – 331* *pg - 24* *sk - 257* *scc - 88*	https://licensing.edinburgh-innovations.ed.ac.uk/i/software/dermofit-image-library.html
The Cancer Genome Atlas	*Pathology*	*2871*	*6*	*ade - 207 adn – 57 bcc - 44 mel and nv - 2319 scc - 197 oth - 47*	https://portal.gdc.cancer.gov/

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SD-198	*Clinical*	*6584*	*198*	*198 Classes of Skin Diseases*	http://xiaopingwu.cn/assets/projects/sd-198/
SD-260	*Clinical*	*20660*	*260*	*260 Classes of Skin Diseases*	http://xiaopingwu.cn/assets/projects/sd-198/
Derm7pt	*Dermoscopic*	*1011*	*2*	*mel-252* *nv-759*	http://derm.cs.sfu.ca/Welcome.html
DermNet NZ	*Clinical, dermoscopic, and pathological*	*20,000*	*-*	*-*	https://dermnetnz.org
PH2 Dataset	*Dermoscopic*	*200*	*2*	*mel - 40* *nv - 160*	https://www.fc.up.pt/addi/ph2%20database.html
ASAN	*Clinical*	*17125*	*12*	*akiec - 651* *bcc – 1082* *df – 1247* *hae - 2715* *ic – 918* *len – 1193* *mel - 599* *nv - 2706* *pg - 375* *scc – 1231* *sk - 1423* *wart - 2985*	https://figshare.com/articles/Asan_and_Hallym_Dataset_Thumbnails_/5406136
MED-NODE	*Clinical*	*170*	*2*	*mel - 70* *nv - 100*	http://www.cs.rug.nl/%7Eimaging/databases/melano ma_naevi/
HALLYM	*Clinical*	*125*	*1*	*bcc - 125*	https://figshare.com/articles/Asan_and_Hallym_Dataset_Thumbnails_/5406136

4. CNN FOR MEDICAL IMAGE CLASSIFICATION

CNNs are considered the latest technology in the field of AI and have been used in many applications [36]. One of these applications is medical image classification [37]. In this section, skin melanoma classification is overviewed based on many deep learning and machine learning algorithms using three types of skin cancer images: dermoscopic images (the focus of most studies), clinical images, and histopathology images. In this systematic survey, we focused on the accuracy, specificity, and sensitivity of the performance measures for comparison between the studies included in this research and to demonstrate their superiority. These studies are summarized in Tables 2 to 4**.**

4.1 Automated skin cancer classification of clinical dermoscopic images

1. Achim Hekler et al. used a technique for combining deep learning and human skills for skin cancer classification. They sought the help of 112 dermatologists from 13 German hospitals. The authors used 11444 dermoscopic images divided into five categories from the ISIC archive. They used ResNet 50 for classification and achieved an accuracy of 81.59%. In comparison, the accuracy of physicians is 42.94%. The true class label of CNN and dermatologist's information was learned through another machine learning algorithm, XGBoost; an accuracy of 82.95% was obtained [17].
2. Ashutosh Lembhe et al. proposed a classification model with enhancement to classify skin cancer as benign and malignant. They used 1497 benign and 1800 malignant images in JPEG format from ISIC archives. The authors initially applied the image super-resolution (ISR) approach using GAN to generate high-resolution images. They used three pretrained models, namely ResNet, VGG16, and Inception V3, for classification. The proposed methodology enhances the initial accuracy by 13.85%, 15.59%, and 7.78% for ResNet, VGG16, and InceptionV3, respectively [38].

3. Md Shahin Ali et al. established a DCNN model for classifying skin cancer dermoscopy images from the HAM10000 dataset into 6136 benign and 979 malignant lesions. Before classification, the authors applied

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preprocessing steps, consisting of using a filter to remove artifacts and noise, feature extraction, data reduction, normalization, and transforming data into numerical data. Then, they used data augmentation to improve accuracy classification. The best accuracy achieved is 93.16% [19].

4. Duggani Keerthana et al. applied a hybrid model using pretrained models with machine learning classifiers for skin cancer dermoscopy classification. The authors used 490 images for benign lesions and 243 images for melanoma lesions from the available public ISBI 2016 dataset. They used 10 pretrained models with different optimizers, epochs, batch sizes, and learning rates. They also applied the features to three types of classifiers, namely, SVM, K-NN, and DT. The highest performance of accuracy is 88.02, which was obtained by concatenating DenseNet-201 and Mobile-Net with SVM [20].

5. KararAli et al. proposed a pipeline for the preprocessing image before the classification began with hair removal, augmentation, and image resizing. After processing, the authors trained Efficient Nets B0-B7 on the HAM10000 dataset to classify seven types of skin cancer. They employed fine-tuning and transfer learning in a pretrained model. The EfficientNet B4 gained a score of 87% [39].

6. Pratik Dubal et al. applied a methodology to skin cancer images for detection. They classified approximately 463 images as benign and malignant. These images were taken by a camera and divided into six classes. The images were converted into grayscale. A homomorphic filter was applied to improve the conflict in the background. Afterward, the images were subsequently passed through a median filter, followed by a bottom hat filter, to remove any noise. Dilation and erosion were used to remove any presence of hair. Then, the authors applied the segmentation method to the cleaned image. Afterward, the images were feature-extracted by applying the ABCD rule, and the neural network was applied for the classification that achieved an accuracy of 76.9% [40].

7. Sufiyan Bashir et al. used a custom CNN to classify seven types of skin cancer from the HAM10000 database. The authors used the enhanced super-resolution GAN for image enhancement and data augmentation before classification. The dataset is split into two groups for the training: testing as protocol_I, ((train+val):test) as protocol _II, and (train:val:test) as protocol_III. The experimental model obtains accuracies of 98.77%, 98.36%, and 98.89%, for protocol-I, protocol-II, and protocol-III, respectively [23].

8. Fekry Olayah et al. applied a hybrid system using the advantages of fused CNN on dermoscopy images from the ISIC-2019 dataset to classify skin cancer into seven types. The authors used geometric active contour to segment the area of cancer and isolate the area from the healthy skin. The system receives the segmented images using CNN-ANN and CNN models (GoogLeNet, AlexNet, and VGG16). CNN-RF receives the features and classifies cancer types. These hybrid models achieve an accuracy of 96.10%, an AUC of 94.41%, specificity of 99.44%, precision of 88.69%, and sensitivity of 88.90% [24].

9. Mahmoud Elgamal proposed a hybrid model consisting of three steps: feature extraction using discrete wavelet transformation, dimensionality reduction using principle component analysis, and classification using two classifiers. The first one uses feed-forward backpropagation ANN, and the second one uses a k-nearest neighbor. The total dataset consists of 40 images of malignant melanoma (20 abnormal and 20 normal). The accuracies of classification are 95% and 97.5% [25].

10. Codella et al. [41] designed a deep learning model using the ISIC-2016 dataset. Then, the results of this model were matched with eight dermatologists to classify 100 cases of skin cancer as malignant or benign. The result showed that the deep learning model performs better than the dermatologists by obtaining 76% accuracy and 62% specificity versus 70.5% and 59% obtained by dermatologists.

Table 2: Dermoscopic image classification survey based on DL.

Study	*Dataset*	*Binary classification / multiclassification*	*Methodology*	*Performance*
[17]	*11444 dermoscopic images from the ISIC archive*	*Multiclassification (5)*	*ResNet 50 / XGBoost / comparison with 112 dermatologists*	*Accuracy: 81.59%/82.95%/42.94%*
[38]	*1497 benign*	*Binary classification*	*ISR-GAN with ResNet,*	*Improved accuracy by*

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	and 1800 malignant cases from the ISIC archive		*VGG16, and Inception V3*	*13.85%/15.59%/7.78%*
[19]	*HAM10000*	*Binary classification*	*DCNN with preprocessing image and data augmentation*	*Accuracy: 93.16%*
[20]	*ISBI 2016*	*Binary classification*	*Used 10 pretrained models with three ML classifiers*	*Highest accuracy: 88.02%.*
[39]	*HAM10000*	*Multiclassification (7)*	*Efficient Nets B0-B7*	*The EfficientNet B4, scored 87%*
[40]	*-*	*Binary classification*	*ABCD rule with NN*	*Accuracy: 76.9%*
[23]	*HAM10000*	*Multiclassification (7)*	*CNN*	*Accuracies: 98.77%, 98.36%, 98.89%*
[24]	*ISIC-2019*	*Multiclassification (7)*	*GoogLeNet, AlexNet, and VGG16*	*Accuracy of 96.10%, AUC of 94.41%, specificity of 99.44%, precision of 88.69%, and sensitivity of 88.90%*
[25]	*40 images*	*Binary classification*	*Feed-forward backpropagation ANN / k-nearest neighbor*	*Accuracy: 95% and 97.5%*
[41]	*ISIC-2016*	*Binary classification*	*Deep learning model compared with eight dermatologists*	*76% accuracy and 62% specificity versus 70.5% and 59%*

4.2 Automated skin cancer classification of clinical images

1. Fujisawa et al. [18] established a method for classifying skin lesions as benign and malignant. Moreover, they classified the lesions into MM in addition to 13 other skin diseases. Then, the results of the classifier were compared with the findings of nine dermatology trainees and 13 dermatologists. The result showed that the classification accuracy of the CNN is superior to that of the dermatologists and trainees in both groups. The accuracy of binary classification is 92.4% for CNN vs. 85.3% and 74.4% for dermatologists and trainees, respectively. In multiclass classification, the accuracy is 74.5% for CNN vs. 59.7% and 41.7% for dermatologists and trainees, respectively.

2. Brinker et al. [42] used the ResNet50 model to classify 100 clinical images into 20 melanoma or 80 nevi categories. The performance results were compared with 145 dermatologists. The deep learning model achieves a sensitivity of 89.4% and specificity of 69.2%, whereas the dermatologists obtain an overall specificity of 64.4% and a sensitivity of 89.4% by using the same dataset.

3. Han et al. [35] utilized a pretrained CNN model (ResNet-152) to categorize 12 skin diseases using the MED-NODE dataset, Asan training images, and the Atlas Location dataset. For testing, the authors used the Dermofit and Asan test set. The procedure’s performance is comparable with that of 16 dermatologists. The accuracy of the algorithm reaches 57.3% and 55.7%.

4. Jinnai et al. [43] presented an algorithm similar to that in [18]. The authors established a method for categorizing skin lesions as benign and malignant and classifying the lesions as MM in addition to five skin diseases. The use of CNN is superior to the results obtained by 10 dermatology trainees and 10 dermatologists. The accuracy of binary classification is 91.5% for CNN vs. 86.6% and 85.3% for dermatologists and trainees, respectively. However, the accuracy of multiclass classification is 86.2% for CNN vs. 79.5% and 75.1% for dermatologists and trainees, respectively.

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5. Yang et al. [28] used a pretrained model of CNN (ResNet) on the SD-198 dataset with the help of the ABCD rule, and 53.35% accuracy was achieved. Then, they compared the result with the accuracy of dermatologists, which was 57.62%. Only doctors with significant dermatology experience achieved an average accuracy of 83.29%.

Table 3: Clinical image classification survey based on DL.

Study	*Dataset*	*Binary classification / multiclassification*	*Methodology*	*Performance*
[18]	*-*	*Binary classification / multiclassification (13)*	*CNN / comparison with nine dermatology trainees / 13 dermatologists*	*Accuracy: 1. binary classification: 92.4% vs. 85.3%/74.4%. 2. multiclassification: 74.5% vs. 59.7%/41.7%*
[42]	*100 clinical images*	*Binary classification*	*ResNet50 / comparison with 145 dermatologists*	*sensitivity and specificity of 89.4% and 69.2%, respectively vs. 89.4% and 64.4%*
[35]	*MED-NODE, Asan training images, and Atlas dataset; for testing, Dermofit and Asan test set*	*Multiclassification (2)*	*ResNet-152 / comparison with 16 dermatologists*	*Accuracy: 57.3% vs. 55.7%*
[43]	*-*	*Binary classification / multiclassification (5)*	*CNN / comparison with 10 dermatology trainees / 10 dermatologists*	*Accuracy: 1. binary classification: 91.5% vs. 86.6%/85.3%, 2. multiclassification: 86.2% vs. 79.5%/75.1%*
[28]	*SD-198*	*198 diseases of the skin*	*ResNet and ABCD rule comparison with dermatologists*	*Accuracy: 53.35%/57.62%*

4.3 Automated skin cancer classification of histopathology images

1. Heckler et al. [44] used ResNet50 pretrained architecture to classify skin lesion cancers into two types: nevi and melanoma. The dataset used for training includes 595 histopathology images (295 nevi and 300 melanoma). Then, the results were compared with results gained by 11 dermatologists. The result showed that the accuracy of the CNN model is higher than the result of dermatologists. The sensitivity, specificity, and accuracy for the CNN model are 76.0%, 60.0%, and 68.0% vs. 51.8%, 66.5%, and 59.2% for dermatologists, respectively.
2. Jiang et al. [45] established a deep learning model to detect BCC using digital histopathology images captured by a smartphone. The authors achieved 98.7% for AUC, 97% for sensitivity, and 94% for specificity.
3. Xie et al. [46] used two pretrained models, namely, ResNet50 and VGG19, to classify the images of 1321 patients as melanoma and nevi. The authors used 2241 histopathology images collected for 10 years from 2008 to 2018. Finally, they achieved a high accuracy in terms of sensitivity (92%), specificity (94%), F1 (89%), and AUC (98%).
4. Cruz-Roa et al. [47] established a deep learning model to detect BCC from the normal tissue of the skin using 1417 histopathology images. This model achieves 91.4% accuracy.

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Table 4: Clinical image classification survey based on DL.

Study	*Dataset*	*Binary classification / multiclassification*	*Methodology*	*Performance*
[44]	*595 histopathology images*	*Binary classification*	*ResNet50 / comparison with 11 dermatologists*	*Sensitivity, specificity, and accuracy: 76.0%, 60.0%, and 68.0% vs. 51.8%, 66.5%, and 59.2%*
[45]	*Histopathology images captured by a smartphone*	*Binary classification*	*Deep learning model*	*AUC, sensitivity, and specificity: 98.7%, 97%, and 94%*
[46]	*2241 histopathological images*	*Binary classification*	*ResNet50 and VGG19*	*Sensitivity, specificity, F1, and AUC: 92%, 94%, 89%, and 98%.*
[47]	*1417 histopathology images*	*Binary classification*	*Deep learning model*	*Accuracy: 91.4%*

5. DISCUSSION AND OPPORTUNITIES

Considerable research has compared dermatologists with AI diagnostics. The result of most research, such as [17], [18], [41], [42], [35], [43], and [44], shows that AI outperforms doctors. However, in reality, this statement is inaccurate because of the many limitations of these services (such as skin tags and skin hair) and the small changes in the image input (such as rotation or gradient). Moreover, the diagnosis result is not as close to reality as the diagnosis of doctors. These algorithms only learn from the pixel values that make up the images and do not affect real-world inferences to build a relationship between skin lesions [43]. Therefore, they require human experts to avoid misdiagnoses. Thus, one of the main uses of AI with cancer classification may involve being an assistant system, which requires a complementary system rather than a comparative system. However, AI can achieve good results in the future through the following opportunities:

1. Data Imbalance

Balanced data are very important for the performance of learning algorithms to complete classification operations. However, they contain large sets of data related to medical institutions or websites. However, these data may not be confidential or may contain personal information, thereby affecting the individual classification. Therefore, classified and balanced data must be provided to ensure the success of classification accuracy [12].

2. GAN

GAN is one of the most important algorithms in neural networks. It attracts all researchers and those interested in deep AI, particularly in the field of medical imaging. The idea of GAN is to generate a high-resolution fake image to overcome the limitations in the dataset [44]. This approach can be done for skin cancer; in particular, an image of a skin lesion can be generated by this method [45]. GAN is used to generate rare categories of skin tumors, such as Kaposi's sarcoma, sebaceous carcinoma, and MCC, or produce data for a skin cancer image under representation.

3. Various Datasets

Most of the skin cancer datasets that deep learning uses for many purposes feature people with light skin. Therefore, datasets should include the distribution of skin lesions from dark-skinned and light-skinned humans to decrease socio-ethnicity bias in DL models. This bias can also exist in people's age; in particular, the grade of skin aging or sun damage may influence data collection and decision-making [13]. Moreover, deep learning algorithms validated for diagnosing skin cancer in people with light skin are likely to misdiagnose people of different races or ethnicities [46].

4. Data Augmentation

Data augmentation is used to reduce limitations in a dataset, such as heterogeneity in data sources and imbalanced data between categories of skin cancers. Many augmented methods exist, such as rotate, translate, crop, color, horizontal and vertical flip, jitter, random crop, and color space. Studies [47, 48] have demonstrated that an increase

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in data improves skin cancer diagnosis. One of the most prominent studies was conducted by Sadoon A. et al. [49, 50]. They used data augmentation methods to generate augmented copies of brain tumors and COVID-19 images.

6. CONCLUSION

The diagnostic performance of skin cancer classification has been constantly improving with the growth of diagnostic technology and science. According to the above clinical diagnosis scenarios, the final decision always depends on the dermatologists' experience and the quality of imaging methods and devices. In the case of skin diseases, a wrong and very subjective diagnosis often exists. With the advent of AI, different intelligence models have been intended for diagnosis.

In recent times, the success of machine learning with deep learning in medical imaging processing and analysis has led to the development of different skin cancer classification methods that have achieved better results than dermatological results.

In this study, the current state of the art in skin cancer staging based on deep learning was comprehensively investigated. First, three types of skin cancer images used for diagnosis were presented, and a common dataset used in diagnoses was introduced. Then, the typical CNN models for skin cancer classification were enumerated.

We also presented some limitations in the skin melanoma classification tasks, such as data limitation and imbalance, GAN, various datasets, and data augmentation.

References

[1] **Parkin, D., D. Mesher, and P. Sasieni, *13. Cancers attributable to solar (ultraviolet) radiation exposure in the UK in 2010.* British journal of cancer, 2011. 105(2): p. S66-S69.**

[2] **Dorj, U.-O., et al., *The skin cancer classification using deep convolutional neural network. Multimedia Tools and Applications, 2018. 77: p. 9909-9924.* 2018.**

[3] **Organization, W.H., *Radiation: Ultraviolet (UV) Radiation and Skin Cancer—How Common Is Skin Cancer.***

[4] ***Canadian cancer statistics 2014 - special topic: Skin cancers. Retrieved from https://www. cancer.ca/statistics. . Canadian Cancer Society's Advisory Committee on Cancer Statistics (2014). , 2014. (Accessed 30 December 2020).***

[5] ***WABASCSCACS. http://www.cancer.org/cancer/skincancerbasalandsquamouscell/detailedguide/skin-cancer-basal-and-squa mous-cell-what-is-basal-and-squamous-cell. Accessed Jan 31,2018.***

[6] ***CFAFACShttps://www.cancer.org/content/dam/cancer-org/research/cancer-facts-and-statistics/annual-cancer-facts-and-figures/2018/cancer-facts-and-figures-2018.pdf. Accessed May 3, 2018.***

[7] ***Akram T, Khan MA, Sharif M, Yasmin M (2018) Skin lesion segmentation and recognition using multichannel saliency estimation and M-SVM on selected serially fused features. J Ambient Intell Human Comput. https://doi.org/10.1007/s12652-018-1051-5.***

[8] ***Salerni, G., et al., Meta-analysis of digital dermoscopy follow-up of melanocytic skin lesions: a study on behalf of the International Dermoscopy Society. Journal of the European Academy of Dermatology and Venereology, 2013. 27(7): p. 805-814.***

[9] ***Vestergaard, M., et al., Dermoscopy compared with naked eye examination for the diagnosis of primary melanoma: a meta-analysis of studies performed in a clinical setting. British Journal of Dermatology, 2008. 159(3): p. 669-676.***

Iraqi Journal for Computers and Informatics
Information Technology and Communications University
Vol. 50, No. 2, 2024, pp. 173-185

DOI: https://doi.org/10.25195/ijci.v50i2.516
Print ISSN: 2313-190X, Online ISSN: 2520-4912

[10] *Würfl, T., et al. Deep learning computed tomography. in Medical Image Computing and Computer-Assisted Intervention-MICCAI 2016: 19th International Conference, Athens, Greece, October 17-21, 2016, Proceedings, Part III 19. 2016. Springer.*

[11] *Hekler, A., et al., Superior skin cancer classification by the combination of human and artificial intelligence. European Journal of Cancer, 2019. 120: p. 114-121.*

[12] *Lembhe, A., et al., Enhancement in Skin Cancer Detection using Image Super Resolution and Convolutional Neural Network. Procedia Computer Science, 2023. 218: p. 164-173.*

[13] *Ali, M.S., et al., An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models. Machine Learning with Applications, 2021. 5: p. 100036.*

[14] *Tschandl, P., et al., Expert-level diagnosis of nonpigmented skin cancer by combined convolutional neural networks. JAMA dermatology, 2019. 155(1): p. 58-65.*

[15] Sheng, M., et al., *The value of preoperative high-resolution MRI with microscopy coil for facial nonmelanoma skin cancers.* Skin Research and Technology, 2021. 27(1): p. 62-69.

[16] De, A. and C. Guo, *An adaptive vector quantization approach for image segmentation based on SOM network.* Neurocomputing, 2015. 149: p. 48-58.

[17] Goyal, M., et al., *Artificial intelligence-based image classification methods for diagnosis of skin cancer: Challenges and opportunities.* Computers in biology and medicine, 2020. 127: p. 104065.

[18] Fujisawa, Y., et al., *Deep-learning-based, computer-aided classifier developed with a small dataset of clinical images surpasses board-certified dermatologists in skin tumour diagnosis.* British Journal of Dermatology, 2019. 180(2): p. 373-381.

[19] Ching, T., et al., *Opportunities and obstacles for deep learning in biology and medicine.* Journal of the royal society interface, 2018. 15(141): p. 20170387.

[20] Zhang, L., G. Yang, and X. Ye, *Automatic skin lesion segmentation by coupling deep fully convolutional networks and shallow network with textons.* Journal of Medical Imaging, 2019. 6(2): p. 024001-024001.

[21] Lorentzen, H., et al., *Clinical and dermatoscopic diagnosis of malignant melanoma: assessed by expert and non-expert groups.* Acta dermato-venereologica, 1999. 79(4): p. 301-304.

[22] Tschandl, P., C. Rosendahl, and H. Kittler, *The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions.* Scientific data, 2018. 5(1): p. 1-9.

[23] Codella, N.C., et al. *Skin lesion analysis toward melanoma detection: A challenge at the 2017 international symposium on biomedical imaging (isbi), hosted by the international skin imaging collaboration (isic)*. in *2018 IEEE 15th international symposium on biomedical imaging (ISBI 2018)*. 2018. IEEE.

[24] Cassidy, B., et al., *Analysis of the ISIC image datasets: Usage, benchmarks and recommendations.* Medical image analysis, 2022. 75: p. 102305.

[25] Saba, T., et al., *Region extraction and classification of skin cancer: A heterogeneous framework of deep CNN features fusion and reduction.* Journal of medical systems, 2019. 43(9): p. 289.

[26] *A cognitive prosthesis to aid focal skin lesion diagnosis.* URL https://homepages.inf.ed.ac.uk/rbf/DERMOFIT/.

[27] *The cancer genome atlas program." [Online]. Available: https://www.cancer.gov/about-nci/organization/ccg/research/structuralgenomics/tcga.*

Iraqi Journal for Computers and Informatics
Information Technology and Communications University
Vol. 50, No. 2, 2024, pp. 173-185
DOI: https://doi.org/10.25195/ijci.v50i2.516
Print ISSN: 2313-190X, Online ISSN: 2520-4912

[28] Yang, J., et al. *Clinical skin lesion diagnosis using representations inspired by dermatologist criteria*. in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2018.

[29] Yang, J., et al., *Self-paced balance learning for clinical skin disease recognition.* IEEE transactions on neural networks and learning systems, 2019. 31(8): p. 2832-2846.

[30] Kawahara, J., et al., *Seven-point checklist and skin lesion classification using multitask multimodal neural nets.* IEEE journal of biomedical and health informatics, 2018. 23(2): p. 538-546.

[31] *Dermnet nz." [Online]. Available: https://www.dermnetnz.org/.*

[32] Mendonça, T., et al. *PH 2-A dermoscopic image database for research and benchmarking*. in *2013 35th annual international conference of the IEEE engineering in medicine and biology society (EMBC)*. 2013. IEEE.

[33] Han, S.S., et al., *Deep neural networks show an equivalent and often superior performance to dermatologists in onychomycosis diagnosis: Automatic construction of onychomycosis datasets by region-based convolutional deep neural network.* PloS one, 2018. 13(1): p. e0191493.

[34] Giotis, I., et al., *MED-NODE: A computer-assisted melanoma diagnosis system using non-dermoscopic images.* Expert systems with applications, 2015. 42(19): p. 6578-6585.

[35] Han, S.S., et al., *Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm.* Journal of Investigative Dermatology, 2018. 138(7): p. 1529-1538.

[36] Goodfellow, I., Y. Bengio, and A. Courville, *Deep learning*. 2016: MIT press.

[37] Hasan, A.M., et al., *Breast cancer MRI classification based on fractional entropy image enhancement and deep feature extraction.* Baghdad Science Journal, 2023. 20(1): p. 0221-0221.

[38] Lembhe, A., et al., *Enhancement in Skin Cancer Detection using Image Super Resolution and Convolutional Neural Network.* Procedia Computer Science, 2023. 218: p. 164-173.

[39] Ali, K., et al., *Multiclass skin cancer classification using EfficientNets–a first step towards preventing skin cancer.* Neuroscience Informatics, 2022. 2(4): p. 100034.

[40] Dubal, P., et al. *Skin cancer detection and classification*. in *2017 6th international conference on electrical engineering and informatics (ICEEI)*. 2017. IEEE.

[41] Codella, N.C., et al., *Deep learning ensembles for melanoma recognition in dermoscopy images.* IBM Journal of Research and Development, 2017. 61(4/5): p. 5: 1-5: 15.

[42] Brinker, T.J., et al., *A convolutional neural network trained with dermoscopic images performed on par with 145 dermatologists in a clinical melanoma image classification task.* European Journal of Cancer, 2019. 111: p. 148-154.

[43] Jinnai, S., et al., *The development of a skin cancer classification system for pigmented skin lesions using deep learning.* Biomolecules, 2020. 10(8): p. 1123.

[44] Hekler, A., et al., *Pathologist-level classification of histopathological melanoma images with deep neural networks.* European Journal of Cancer, 2019. 115: p. 79-83.

[45] Jiang, Y., et al., *Recognizing basal cell carcinoma on smartphone-captured digital histopathology images with a deep neural network.* British Journal of Dermatology, 2020. 182(3): p. 754-762.

[46] Xie, P., et al., *Interpretable classification from skin cancer histology slides using deep learning: A retrospective multicenter study.* arXiv preprint arXiv:1904.06156, 2019.

Iraqi Journal for Computers and Informatics
Information Technology and Communications University
Vol. 50, No. 2, 2024, pp. 173-185

DOI: https://doi.org/10.25195/ijci.v50i2.516
Print ISSN: 2313-190X, Online ISSN: 2520-4912

[47] Cruz-Roa, A.A., et al. *A deep learning architecture for image representation, visual interpretability and automated basal-cell carcinoma cancer detection*. in *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2013: 16th International Conference, Nagoya, Japan, September 22-26, 2013, Proceedings, Part II 16*. 2013. Springer.