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Skin Cancer Detection and Classification: A Review of Recent Advances

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Abstract—

Skin cancer is most common diseases find in humans worldwide and early detection can be assist to improve the doctors' diagnosis. Traditional diagnosis depends on visual examination by dermatologists using dermoscopy also time consuming and depends heavily on the experience of the clinician or doctor. In recent years, deep learning has become the leading approach for automatic detection and classification skin lesions from dermoscopic and clinical images. In this paper we present a focused review of the most recent deep learning methods, published recently, for skin cancer detection and classification. The review covers benchmark datasets, image preprocessing and classification and segmentation methods, and major deep learning architectures, which include convolutional neural networks (CNNs), hybrid CNN-Transformer models, vision transformers, generative adversarial networks (GANs), and multimodal fusion approaches. It also summarizes the main challenges that still limit the real-world use of these systems, such as complex lesion features, image noise, intra-class variation, inter-class similarity, and class imbalance. In this paper we discuss future research directions, such as explainable artificial intelligence, fairness across different skin tones, and uncertainty-aware models.

Keywords— Skin cancer; deep learning; dermoscopy; convolutional neural network; vision transformer; image classification; class imbalance

I. INTRODUCTION

Skin cancer has been develops when skin cells grow in an abnormal and uncontrolled way because of long-term exposure to ultraviolet (UV) radiation from the sun. It is divided into two groups: melanoma and non-melanoma skin cancer. Melanoma is common but far more dangerous, because it can spread quickly to other organs of body. Non-melanoma skin cancers, such as basal cell carcinoma (BCC) and squamous cell carcinoma (SCC), are more common but usually less aggressive than other. According to the American Cancer Society, an estimate 100,640 new cases of skin cancer and 8,290 deaths are expected in the United States in 2024 alone, show that how large the burden of this disease still is. Early detection is the most important factor is improving survival. If skin cancer is found early, it can often be removed with a simple surgery, and the survival rate is very high. Diagnosis is delayed, especially for melanoma, the cancer can spread to lymph nodes and other organs, and the chance of death rises sharply. For this reason, accurate and early screening tools are extremely valuable. Dermoscopy is a use to diagnose skin lesions in clinical practice. Dermatologists is use rules such as the ABCD rule, seven-point checklist, and Menzies' method to check a lesion is harmful or not. These rules, diagnostic accuracy among experts is reported to be only around 75 to 84 percent, and it can vary between different clinicians opinion. Due to that, skin lesions of the same disease show different features



from one patient to another, and lesions from different diseases can look the same. Skin images can also contain noise as hair, skin texture, air bubbles, and ruler marks that make visual diagnosis harder.

To reduce subjectivity, researchers built Computer assist automated systems using handcrafted features and classical machine learning, but such systems struggle to generalize to new patients. Currently, deep learning, especially convolutional neural networks (CNNs), has replaced handcrafted features with automatically extracted high-level features due that improve accuracy of the model. Now days, researchers are combined CNNs with attention mechanisms, vision transformers, and generative models to handle the open challenges in cancer detection such as complex lesion shapes, image noise, benign-malignant similarity, and severe class imbalance. This paper reviews the most recent deep learning research on skin cancer detection and classification, focus on studies recently published. The goal is to give a simple and well-organized summary that early-career researchers can use as a starting point. Section 2 explains how the studies discussed in this review have selected. Section 3 gives background on skin cancer imaging. Section 4 summarizes commonly used datasets. Section 5 covers preprocessing and segmentation and classification. Section 6 reviews the main deep learning approaches. Section 7 gives a comparison table of representative recent studies. Section 8 discusses the remaining challenges, Section 9 suggests future research directions, and Section 10 concludes the paper.

II. REVIEW METHODOLOGY

This review is built recent publish research articles on deep learning for cancer detection: a dermatology-focused review published in Biomedical Signal Processing and Control, and a broader 12-cancer-type survey published in Critical Reviews in Oncology/Hematology [62]. These surveys used a systematic, PRISMA-style article selection process, searching databases such as PubMed, Web of Science, IEEE Xplore, Scopus, and Elsevier ScienceDirect, and keeping only peer-reviewed journal articles that used deep learning for medical image-based cancer detection.

III. BACKGROUND: SKIN CANCER AND DIAGNOSTIC IMAGING

1. TYPES OF SKIN CANCER

Skin cancer is usually grouped into seven diagnostic classes when working with dermoscopic image datasets: actinic keratosis (AKIEC), basal cell carcinoma (BCC), benign keratosis-like lesion (BKL), dermatofibroma (DF), melanoma (MEL), melanocytic nevus (NV), and vascular lesion (VASC). Melanoma is the most dangerous class, while nevus and benign keratosis are usually harmless. A good detection system is able to separate the dangerous classes from the harmless ones, even they can look visually similar features.

2. FROM MANUAL DIAGNOSIS TO DEEP LEARNING

Traditional diagnosis relies on dermoscopy and it is combination of expert judgment, using the ABCD rule, Menzies' method, or the seven-point checklist. Early computer-aided diagnosis (CAD) systems use to automate this process using low level or handcrafted image features such as colour histograms, texture descriptors, and edge information, apply to machine learning classifiers such as k-nearest neighbours (KNN) or support vector machines (SVM). These systems are an improvement over manual diagnosis, but they are few still limited because handcrafted or low level features cannot capture every important visual pattern or characteristics in a lesion. Modern deep learning systems follow a common pipeline: initially, collect dermoscopic or clinical images from various sources. In second stage preprocess the images to remove unwanted noise and normalize it. After noise removal segmented the lesion region and find lesion and extracted most important features using a neural network. After segmentation, the lesion has classify into benign or malignant categories (or one of the seven diagnostic classes), and lastly, evaluate the model performance using metrics such as accuracy, precision, recall, F1-score, and the area under the ROC curve. The following sections we describe each of these stages.

IV. BENCHMARK DATASETS

Freely Public available datasets play a central role in skin cancer research because they allow different research groups to train and fairly compare their models. Table 1 summarizes the datasets most



commonly used in the recent studies reviewed in this paper.

Table I: Commonly used skin lesion datasets in recent studies

Dataset	Approx. Size	Main Characteristic
ISIC Archive (2016–2020)	1,200 – 44,000+ images	Largest and most widely used dermoscopic collection; updated yearly; ISIC-2020 alone has 32,507 images with a strong benign/malignant imbalance (31,926 vs 581).
HAM10000	10,015 training images	Seven diagnostic classes (AKIEC, BCC, BKL, DF, MEL, NV, VASC); commonly used but still class-imbalanced.
PH2	200 images	Small but well-balanced dataset with pixel-level lesion masks; mainly used for validation.
Derm7pt	1,011 images	Includes clinical metadata and seven-point checklist labels, useful for multimodal studies.
SkinCon	3,230 images	Labelled with 48 clinical concepts, supporting concept-level and explainable models.
DermNet / MED-NODE	170 – 23,000+ images	General dermatology image collections used for broader skin-disease classification, not only cancer.

V. IMAGE PREPROCESSING AND SEGMENTATION

Dermoscopic images are affected various factors such as hair, air bubbles, ruler marks, uneven light, and low contrast between the lesion and the surrounding skin. Preprocessing is an important first step before feed images into a deep learning model. Preprocessing steps used in recent studies include hair and artifact removal such as Dull Razor algorithm or morphological filtering, noise reduction using Gaussian, median, bilateral, or Wiener-type filters, and contrast enhancement using techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE). Several recent papers also use combined filtering pipelines; Midasala et al. [23] applied a bilateral filter before extract texture features for skin cancer classification, and Rokade and Mishra [21] used adaptive bilateral filtering together with a modified segmentation method to reduce the effect of hair and lighting artifacts. After reduce the noise from images, the lesion area is usually separated from healthy skin through segmentation. The U-Net architecture remains the most common segmentation backbone because its encoder--decoder structure can capture both fine detail and overall shape. Deepa et al. [1] introduced an hybrid method that combine Transformer and Attention network to improve the precision of lesion boundary detection. Ahmad et al. [2] proposed Deeplabv3+ algorithm for segmentation with a vision transformer for classification. Nowadays, Watershed transforms algorithm, cluster-based unsupervised methods, and supervised k-means or fuzzy c-means are also used in smaller, limited studies.

VI. DEEP LEARNING APPROACHES FOR SKIN CANCER DETECTION

In this section, we review the deep learning methods used recently. These methods such as CNN-based models, hybrid and attention-based models, vision transformer models, GAN-based data augmentation methods, and approaches use to handle imbalanced datasets. A final subsection discusses multimodal fusion and uncertainty-aware learning methods.

1. CONVOLUTIONAL NEURAL NETWORK (CNN) BASED MODELS

CNNs are recently used in skin cancer classification systems because they can automatically extract important high-level features from pixel data. Different transfer learning approaches such as ResNet, DenseNet, and EfficientNet through better training strategies. Dillshad and Zafar [12] proposed lightweight CNNs with residual blocks, and hyperparameters are tuned using Bayesian optimization, achieving about 99.3% accuracy. Rashid et al. [13] improved a 3D ResNet50 model with transfer learning for skin cancer classification, and Zareen et al. [22] combined a ResNet-50 backbone with Long Short-Term Memory (LSTM) layers to model both spatial and sequential patterns in lesion images, achieve 99 % accuracy. Rokade and Mishra [21] integrate a CNN classifier inside a blockchain-based framework to keep patient data secure achieve best classification results.

2. HYBRID AND ATTENTION-BASED MODELS

A large group of recent studies combines two or more architectures to capture both fine local detail and broader global context, which is important because skin lesions vary greatly in size, shape, and texture.



Huo et al. [3] proposed HiFuse, a hierarchical multi-scale feature fusion network inspired by the Swin Transformer, which merges local convolutional features with long-range attention-based features. Jasil et al. [4] integrated DenseNet and ResNet into a single hybrid model trained for both lesion segmentation and classification at the same time (multi-task learning). Karthik et al. [6] designed a dual-track network that combines a Swin Transformer with a custom attention module, allowing the model to capture both fine-grained texture and long-range spatial relationships in dermoscopic images. Attention mechanisms, which allow a model to focus on the most important regions of an image, have become especially popular. Suleman et al. [25] built "Smart MobiNet," a lightweight MobileNet variant with added attention layers for mobile-friendly skin cancer screening. Tan et al. [30] proposed a dual-branch network with global-local attention (DGLA-ResNet50) that processes lesion images at different resolutions and uses both horizontal-vertical and local attention to better separate visually similar lesion types. Ozdemir et al. [9], [10] combined ConvNeXtV2 blocks, which are good at capturing fine local detail, with separable self-attention layers for global context, and reported around 93 to 94 percent accuracy on the large ISIC-2019 dataset in two related studies. Riaz et al. [26] fused deep CNN features with local texture to combine the strengths of learn and handcrafted middle level features.

3. VISION TRANSFORMER (VIT) BASED MODELS

A vision transformer is useful for capturing the overall shape and border pattern of a skin lesion. Ahmad et al. [2] combined Deeplabv3+ for segmentation with a vision transformer for classification, first localize the lesion and then classify using global context. Ntampakis et al. [20] develop a self-attention fusion framework built around vision transformers, combine with contrast enhancement and noise filtering, to improve robustness against noisy or occluded lesion images. Several studies explored transformer-based multimodal fusion. Vachmanus et al. [28] proposed DeepMetaForge, which uses a BEiT-style transformer as an image encoder together with a metadata fusion module that combines patient information such as age and lesion location with image features. Remya et al. [31] introduced a transfer learning framework using vision transformers with channel attention and region-of-interest extraction for multimodal skin lesion analysis, reporting close to 99 percent accuracy on HAM10000. Zhang et al. [35] proposed DermViT, a transformer-based model designed to imitate how a dermatologist observes a lesion at multiple scales before making a decision. More recently, Zoravar et al. [56] explored domain adaptation for vision transformers using a conformal ensemble method, aiming to make transformer-based classifiers more reliable when tested on data from a different clinic or scanner than the one used for training.

4. GENERATIVE ADVERSARIAL NETWORKS AND DATA AUGMENTATION

Because malignant skin lesion images are much rarer than benign ones, several recent studies use Generative Adversarial Networks (GANs) or diffusion models to create realistic synthetic images for training. Sorour and El-Bakry [5] combined a cascaded YOLO-v5 detector with a Conditional GAN (CGAN) to generate additional training images for melanoma and vitiligo detection. Chyad et al. [8] proposed a framework using adversarial machine learning and GANs together with a hybrid CNN-RNN classifier and achieve good accuracy 99 %. Rezk et al. [40] develop two techniques, Style Transfer and Deep Blending, to combine lesion features with dark-skin backgrounds to create a diverse dataset. Saeed et al. [18] combine a GAN with an Enhanced Super-Resolution GAN to increase image resolution and generate an additional dataset and train on a VGG19-SVM hybrid classifier. Akrout et al. [47] used diffusion probabilistic models to create tens of thousands of synthetic images per disease category, filtering out unrealistic samples using an ensemble of classifiers.

5. HANDLING CLASS IMBALANCE

Class imbalance is malignant cases are far fewer than benign ones, is one of the most challenge in skin cancer datasets, and recent studies focus on this issue. Besides GAN-based augmentation, researchers also modify the loss function used during training so that the model pays more attention to rare classes. Nie et al. [43] built a hybrid CNN-Transformer model trained with focal loss, a loss function that reduces the influence of easy, well-classified examples and focuses more on hard or rare cases, reporting a 15 percent accuracy improvement over a baseline model. Gayatri and Aarthy [44] combined a ResNet-50 backbone with focal loss and augmentation to reduce overfitting on the highly imbalanced ISIC-2019 dataset. Other studies rely on resampling and ensemble strategies. Mahmud et al. [46] compared VGG16 and ResNet50 using



random resampling to balance the training data. Selvaraj et al. [49] built an ensemble of six CNNs together with cost-sensitive learning and hair-removal preprocessing to improve performance on imbalanced data. Askale et al. [45] combined three different CNNs (SKDCNET, FVGG16, and InceptionV3) using a majority voting scheme so that the final decision does not rely on a single, possibly biased, model. More recent approaches use advanced learning strategies: Ju et al. [50] combined dilated convolutions with a reinforcement-learning technique called Off-policy Proximal Policy Optimization (PPO) to directly optimize the model for handling imbalance during training, and Akinrinade and Du [51] applied few-shot learning together with GAN-based synthesis so that the model could learn to recognize rare disease classes from only a handful of real examples.

6. MULTIMODAL FUSION AND UNCERTAINTY-AWARE LEARNING

The recent direction in skin cancer research papers is combine image data with other information sources and accumulation a measure of confident the model is in its own prediction. Sasithradevi et al. [53] proposed EffiCAT, a model that merges features from two EfficientNet backbones using several attention modules, and showed that it keeps strong accuracy even when tested on a completely different dataset than the one it was trained on, a property known as cross-dataset generalization. Cai et al. [54] built a hybrid CNN-Transformer-U-Net model for skin cancer segmentation that fuses high-frequency and low-frequency image information using wavelet-based transforms. Uncertainty-aware learning tries to solve a different but related problem: even highly accurate deep learning models can give a wrong answer with high confidence, which is dangerous in a medical setting. Shamsi et al. [57] proposed an uncertainty-aware deep learning technique using Monte Carlo Dropout, a method that runs the same input through the network multiple times with slightly different internal settings to estimate how uncertain the prediction is. Asgharnezhad et al. [55] extended with a four-step framework that estimates uncertainty and calibrates the model's confidence scores. Zoravar et al. [56] combine uncertainty estimation with domain adaptation for vision transformers, propose classifiers that remain trustworthy when used in a new hospital or with a new imaging device. Together, these directions suggest that future skin cancer detection systems may not only classify lesions but also assists doctors and clinician how much confident they are, which is an important step towards safe clinical application use.

VII.COMPARATIVE SUMMARY OF RECENT STUDIES

Table 2 shows that the lists presently published articles include main method used, the dataset, and the accuracy.

Table I: Commonly used skin lesion datasets in recent studies

Study [Ref.]	Main Method	Dataset	Reported Result
Deepa et al. [1]	Adaptive boundary-aware transformer with gated attention for segmentation	PH2, ISIC-2016/2018	96.3% accuracy
Huo et al. [3]	HiFuse: hierarchical multi-scale CNN-Transformer fusion	ISIC-2018	85.9% accuracy
Sorour & El-Bakry [5]	Cascaded YOLO-v5 with CGAN augmentation	Custom	97% accuracy
Ahmad et al. [2]	Deeplabv3+ segmentation with vision transformer classifier	ISIC 2016–2018, PH2	97.7% accuracy
Karthik et al. [6]	Swin Transformer with dense attention network	HAM10000	94.2% accuracy
Verma et al. [19]	Ensemble of DenseNet201, Xception, and MobileNet features	HAM10000, ISIC	98.7% accuracy
Zareen et al. [22]	Hybrid CNN-RNN (ResNet-50 + LSTM)	ISIC-based	99.1% accuracy
Tan et al. [30]	Dual-branch global-local attention ResNet-50	ISIC-2018/2019	90.7% accuracy
Remya et al. [31]	ViT with channel attention, multimodal fusion	HAM10000	99% accuracy
Rokade & Mishr	Blockchain-secured CNN (TCIO-LeNet)	HAM10000, ISIC-2019	92.5% accuracy



Study [Ref.]	Main Method	Dataset	Reported Result
a [21]			
Akrout et al. [47]	Diffusion-model based synthetic augmentation	Custom (synthetic + real)	~95% accuracy
Chyad et al. [8]	Adversarial ML with GAN and hybrid CNN-RNN	Custom (17M patches)	99% accuracy
Ozdemir et al. [9]	ConvNeXtV2 with separable self-attention	ISIC-2019	93.5% accuracy
Dillshad & Zafar [12]	Lightweight residual CNN, Bayesian-tuned	ISIC-2019	99.3% accuracy
Zhang et al. [35]	DermViT: multi-scale diagnosis-guided transformer	ISIC-2018/2019	86.1% accuracy
Saeed et al. [37]	EG-VAN dual-path (EfficientNetV2 + attention ResNet)	Custom	98.2% accuracy
Ju et al. [50]	Dilated convolutions with reinforcement learning (PPO)	ISIC-2020	91.8% F-measure
Hussain & Toscano [52]	Ensemble of DenseNet, MobileNet, NASNet, EfficientNet	ISIC-2020	99.6% accuracy

VIII KEY CHALLENGES

1. COMPLEX AND IRREGULAR LESION FEATURES

There are various unwanted noise can be skin lesions images such as blurred edges, irregular shapes, and uneven colour , this can be impact on feature extraction and model performance. Hybrid and transformer-based models described in Section 6.2 still rely on large amounts of training data and computational power

2 IMAGE NOISE AND ARTIFACTS

Hair, ruler marks, air bubbles, skin texture these can be create noise can impact of the performance of model, these artifacts appear more often in one class than another at time of train the model. Preprocessing can be solve these issue, but it usually depends on manually designed filters, that may not work equally well on images from different clinics.

3 INTRA-CLASS VARIATION AND INTER-CLASS SIMILARITY

Lesions from the same disease can seen very different from patient to patient, while benign and malignant lesions can sometimes look almost identical. This is one of the hardest problems in the field, and it is the main motivation behind attention-based and multi-scale models discussed in Section 6.2 and 6.3.

4 CLASS IMBALANCE

Malignant cases are much rarer than benign ones in almost every public dataset. So careful handle, a model can reach high overall accuracy simply by predicted the majority (benign) class most of the time, but still missing many dangerous cases. Section 6.5 described several ways researchers are addresses this problem, but it remains an open issue, especially for very rare cancer subtypes.

5 INTERPRETABILITY AND TRUST

Deep learning models, particularly large hybrid and transformer-based systems are often described as "black boxes" because it is hard to know exactly why they made a certain prediction. Some recent studies use visualization tools such as Gradient-weighted Class Activation Mapping (Grad-CAM) or SHapley Additive exPlanations (SHAP) to highlight particular area of an image influence the decision, but these explanations do not always match the true biological reasoning a doctor would use.

6 FAIRNESS AND GENERALIZATION

Most public datasets contain mainly light-skinned patients, that can cause models to perform worse for patients with darker skin tones. Models trained on images from one hospital can also perform poorly that tested on images from a different source, a problem known as domain shift. This is cross-dataset generalization and fairness-aware training, discussed in Sections 6.4 and 6.6, are become increasingly important.

7 COMPUTATIONAL COST

Recent publish hybrid and transformer-based models require graphics hardware and large amounts of memory that can make them difficult to deploy in smaller clinics or on mobile devices. Suleman et al. [25] introduce Lightweight designs Smart MobiNet try to solve this issue.



IX. FUTURE RESEARCH DIRECTIONS

Recently, researchers are made AI systems for skin lesion diagnosis more accurate and useful in real life for clinical application. The Proposed model must assist doctors clear reasons for its decisions that are easy to understand and to help for diagnosis. Researcher focus on fairness across skin tones, the models should work equally for all patients with different skin colors, more diverse datasets and techniques like style transfer or AI-generated images to fill data gaps. Researchers are also build lightweight, real-time models that are small and fast enough to run on mobile phones. Another direction is multimodal fusion; the model are not just diagnosis the skin images but also combines all high level features with patient medical history and even genetic data to compose more accurate diagnoses.. Finally, researcher require test their proposed models using the same datasets and score methods.

CONCLUSION

Most of researcher apply deep learning algorithm for skin cancer detection and classification over the past decade. This review summarize the most recent, preprocessing, and deep learning architectures, such as CNNs, hybrid attention-based models, vision transformers, GAN-based augmentation, and multimodal fusion approaches. Recent studies have remarkable accuracy on dataset such as ISIC and HAM10000 above 95% and new directions such as diffusion-based augmentation, reinforcement learning for imbalance and uncertainty-aware modeling are gives future direction. Complex and irregular lesion appearance, image noise, the similarity between benign and malignant lesions, and severe class imbalance these are challenges still open. In real-world clinical use requires models that are interpretable, fair across different skin tones.

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