Review

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A Review of Skin Cancer Detection: Traditional and Deep Learning-Based Techniques

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مراجعة لأكتشاف سرطان الجلد: التقنيات التقليدية– والقائمة على التعلم العميق

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ABSTRACT

One of the most serious types of cancer is skin cancer. The rising number of skin cancer cases, high mortality rate, and high cost of medical treatment necessitate early detection of its symptoms. Skin cancer is detected and differentiated from melanoma using lesion criteria such as symmetry, color, size, and shape.

Given the significance of these challenges, researchers have developed a variety of early-detection approaches for skin cancer.

This paper comprehensively reviews classical and deep-learning techniques for detecting early skin cancer. The performance of these techniques is evaluated based on various metrics, and the datasets used for training and testing are analyzed. Studies using techniques such as clinical examination, dermoscopy, and histopathology are identified, and the architecture of the deep neural networks used for skin cancer detection is analyzed. A comprehensive comparison of classical and deep-learning techniques for skin cancer detection is provided in this review paper.

Keywords: Skin cancer; Deep learning; Convolutional neural network.

الخلاصة

واحدة من أخطر أنواع السرطان هي سرطان الجلد. إن ارتفاع عدد حالات سرطان الجلد ومعدل الوفيات العالي وتكلفة العلاج الطبي العالية تستدعي الكشف المبكر عن أعراضه. يتم اكتشاف سرطان الجلد والتمييز بينه وبين الميلانوما باستخدام معايير الأورام مثل التماثل واللون والحجم والشكل.

ونظرًا لأهمية هذه التحديات، قام الباحثون بتطوير مجموعة متنوعة من النهج للكشف المبكر عن سرطان الجلد. تتم مراجعة هذه المقالة بشكل شامل للتقنيات التقليدية وتقنيات التعلم العميق للكشف المبكر عن سرطان الجلد. يتم تقييم أداء هذه التقنيات بناءً على مقاييس مختلفة، وتحليل المجموعات البيانية المستخدمة للتدريب والاختبار. وتم تحديد الدراسات التي تستخدم تقنيات مثل الفحص السريري و تنظير الجلد والأنسجة الطبية، وتم تحليل بنية الشبكات العصبية العميقة المستخدمة للكشف عن سرطان الجلد. تم تقديم مقارنة شاملة للتقنيات الكلاسيكية وتقنيات التعلم العميق للكشف عن سرطان الجلد في هذه المقالة الاستعراضية.

الكلمات المفتاحية : سرطان الجلد , التعلم العميق , الشبكة العصبية التلافيفية.

1. INTRODUCTION

Skin cancer detection is a crucial area of research in computer science that involves developing algorithms and models that can accurately detect skin cancer from images of skin lesions [1]. Traditional techniques for skin cancer detection involve manual inspection and analysis by dermatologists, which can be time-consuming and subjective.

With the advancements in deep learning techniques, there has been a significant shift towards developing deep learning-based models for skin cancer detection [2]. These models use convolutional neural networks (CNNs) to automatically learn features from the input images and make predictions about the presence of skin cancer.

In recent years, several studies have compared the performance of traditional and deep learning-based techniques for skin cancer detection [3]. These studies have shown that deep learning-based models outperform traditional techniques regarding accuracy and speed.

However, some challenges are still associated with using deep learning-based models for skin cancer detection [4]. One major challenge is the need for large amounts of high-quality labeled data for training the models. Another challenge is the need for interpretability and explainability of the models to gain the trust of dermatologists and patients.

Generally, skin cancer detection is an important area of research in computer science that has the potential to improve the early detection and treatment of skin cancer significantly. Developing accurate and reliable skin cancer detection models will require continued research and collaboration between computer scientists and dermatologists.

It is possible to see that the skin has two primary layers when dissecting: the epidermis, the outermost and most visible layer, and the dermis, which is the innermost and least visible layer. The epidermis has two major parts: squamous (flat) and basal cells (round). Mesodermal melanocytes, pigment cells that create melanin, make up the lowest fraction of the epidermis. Melanin is the pigment responsible for skin color. In direct sunlight, melanocytes produce more pigment, deepening the skin's melanin and color. This layer of the skin contains lymphatic veins, blood flow, hairs, and glands. The glands in the dermis are separated into two types: those that create sweat to assist the body in regulating temperature and those that produce sebum to help prevent the skin from getting out. These glands reach the outer layer of the skin through pores, which are very small openings on the skin's surface.

Skin cancer is among the most frequent cancers. It is the main cause of death worldwide [5]. Changes in the environmental conditions we live in today have caused cancer [6]. For example, ultraviolet (UV) rays are a primary risk factor for skin cancer. In 1975, Fitzpatrick proposed a scale e from I to VI. According to the skin type and its interaction with ultraviolet (UV) rays, the first type is very light skin and is more likely to develop some skin cancer. The sixth type is dark brown, strongly pigmented skin, and less effective. Therefore, this type of cancer is more common in countries with light skin. In recent decades, skin cancer incidence has climbed dramatically in the

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US, Europe, and Australia. Skin cancer affects one million Americans yearly, up over half of all cancers.

Furthermore, a quarter of all new malignancies are skin cancers, abnormal growth of skin cells. These cells grow without normal control to invade other body parts and multiply to form a mass called a lesion [7]. This type of disease, like many other types of cancer, can be fatal if not treated early. It begins as a precancerous lesion. It is not malignant but becomes malignant over time [8]. Therefore, early cancer detection is the highest priority to save many patients. So, researchers and doctors should fight cancer.

Skin cancers can be divided into two main types: melanoma skin cancer (MSC) and non-melanoma skin cancer (NMSC). NMSC is the most common type of skin cancer and occurs in 2-3 million people at least once a year. It is classified into three main types: Basal Cell Carcinoma (BCC) (which accounts for approximately 75% of all non-melanoma), Squamous Cell Carcinoma (SCC) (which accounts for approximately 24% of all non-melanoma), and Sebaceous Carcinoma (SC) (which accounts for approximately 1% of all non-melanoma), among others. Melanoma is less common but more serious and aggressive than other skin cancer; it is divided into benign and malignant melanoma. A benign melanoma is a simple mole that appears on the skin and is usually an evenly colored brown, black, or tan. It can be either round, oval, raised, or flat. In general, benign melanoma is less than 6 millimeters. Malignant melanoma is the deadliest type of skin cancer characterized by bleeding sores. A cancerous growth in a pigmented skin lesion creates it. Malignant melanoma is classified into three types: Superficial Spreading Melanoma (which accounts for approximately 75% of all melanomas), Nodular Melanoma (which accounts for approximately 15% of all melanomas), Lentigo Melanoma (which accounts for approximately 10% of all melanomas), and Acral Melanoma (constitutes about 5 percent of all melanomas). Melanoma is treatable if identified early enough, and the difference between benign skin cancer and malignant melanoma is important in determining treatment options. When they are first discovered, they seem to be the same. Table 1 lists the most common causes of melanoma and the risk factors for developing the disease. Numerous methods have been developed to distinguish between them, including the ABCD rule, the seven-point checklist approach, the Menzies process, and pattern recognition.

Therefore, researchers from the beginning of the seventies of the twentieth century used to research and models in different ways to be able to detect and diagnose early skin cancer and determine its type through image processing, either by traditional methods or by modern methods using artificial intelligence and deep learning, taking into account the typical classification methods used by doctors.

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Table 1. The risk factors for skin cancer and its causes [9].

Cause	Risk Factors
1. Sunlight	(a) UV radiations leading to cancer (b) Sunburn Blisters: sunburns in adults are more prone to cancer (c) Tanning
2. Tanning Booths	leads to cancer before the age of 30 and Sun lamps
3. Inherited	Two or more careers of melanoma from family inherit this disease to the descendants
4. Easily burnable skin	Gray/Blue eyes, Fair/Pale skin, Blond/Red hairs
5. Medications Side-Effects	Side effects of anti-depressants antibiotics and Hormones

2. MATERIALS AND METHODS

A comprehensive comparison of traditional and deep learning-based techniques for skin cancer detection was provided in this paper, with a rigorous and objective assessment of the available literature.

2.1 Dataset

ImageNet is a collection of over 15 million high-resolution photos online that have been identified and organized into around 22,000 categories. The images were gathered from the internet and tagged by human laborers using Amazon's Mechanical Turk crowd-sourcing tool, which was made possible by the generosity of Amazon. Because of the widespread use of dermatoscopy [10][11], most skin cancer research focuses on dermoscopy images of skin cancer. For example, the HAM10000 data set [12] is a vast collection of multi-sources dermoscopy images of typical skin images assembled from many sources. Each of the seven forms of skin cancer represented in the data set has 10015 multiple dermoscopy images: basal cell carcinoma, malignant melanoma, non-melanoma melanoma, malignant melanoma, and melanoma. When evaluating the model's performance, it is necessary to use distinct images for the training and test or validation sets. Example images of skin cancer kinds obtained from the HAM10000 database are shown in

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Figure 1.

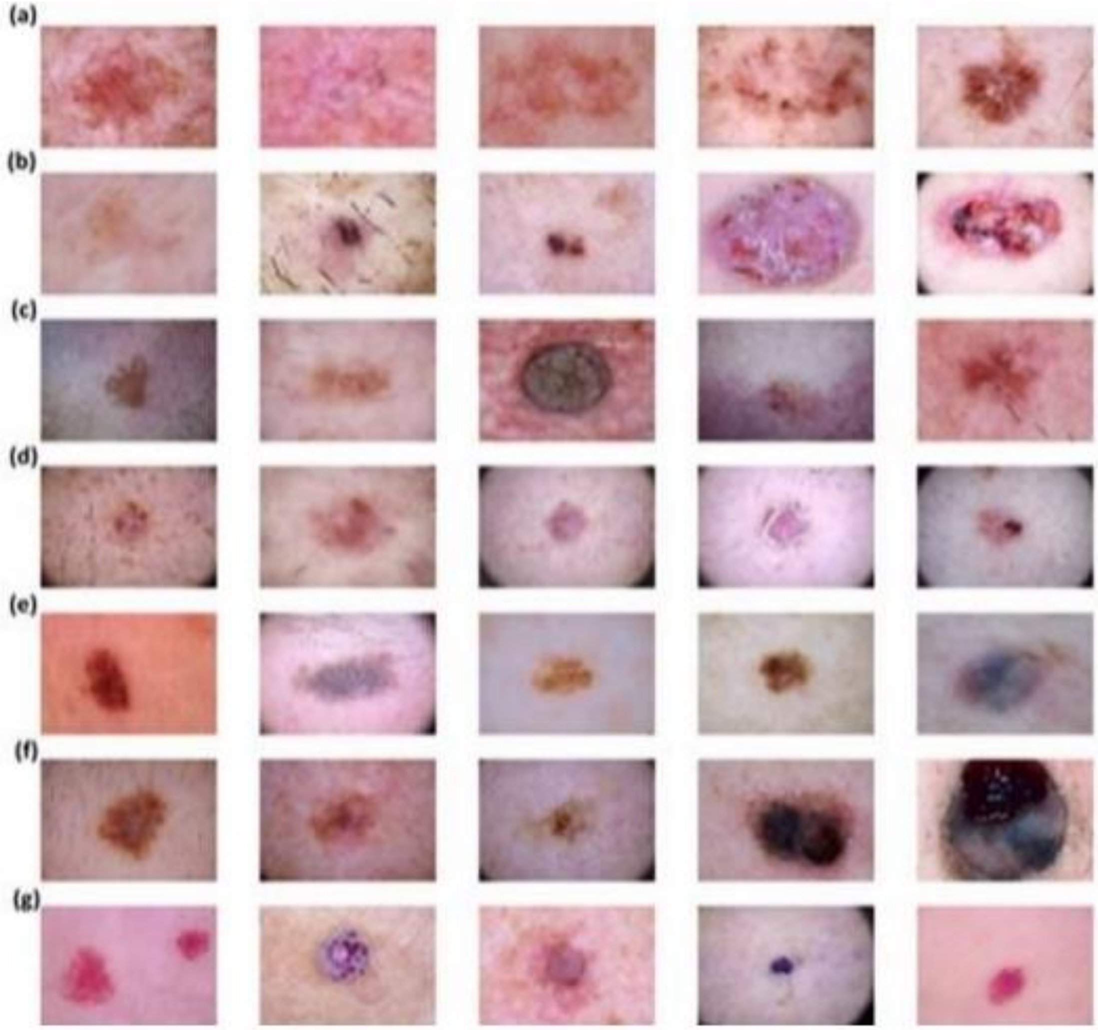

Figure. 1: A selection of skin cancer images from the HAM10000 dataset.

2.2 Classification Techniques

Since 1997, much work has been done in this field, with two types: traditional classification and deep learning classification. We will review some of the methods in these two categories as follows:

2.2.1. Traditional Classification

In 1997, Karene Cheung found a way to find malignant melanoma at an early stage. She used asymmetric, border irregularity, and color analysis methods to look at the images of the lesions. The results of these methods were used to classify the lesions as either "potential malignant melanoma" or "non-melanoma."

In 2011, BareqaSalah et al. [13] proposed a system detecting several kinds of skin cancer. When a neural network and a fuzzy system were used to recognize skin cancer, the accuracy rate was 90.67% for the neural network and 91.26 % for the fuzzy system, greater than the diagnosis using a neural network.

To aid dermatologists in early detection, Shetty and Tukar [14] presented a melanoma decision model in 2011. Assist in calculating the ABCD Total Dermatoscopy Score (TDS) for detecting malignant melanomas using Matlab. A high ABCD rate indicates a malignant melanoma.

In 2012, Sheha et al. [15] presented an automated algorithm for diagnosing melanoma skin cancer applied to a group of dermoscopy images. This algorithm depends on the grey-level co-occurrence matrix (GLCM) method to extract features and uses a multilayer perceptron classifier (MLP) to recognize melanocytic nevi and malignant melanoma. MLP was suggested with two different approaches in the training and testing process: Automatic MLP and Traditional MLP. The Automatic MLP gives better accuracy of 92% for the training and testing, respectively. Automatic MLP is faster than traditional MLP.

In 2013, Bhuiyan et al. [16] presented feature extraction techniques for segmented images. The feature extraction is based on the ABCD rule of dermatoscopy. All the features that have been calculated are based on Otsu's segmentation method.

In 2013, Amelard [17] presented the design and evaluation of features for objectively and intuitively detecting melanoma and applied the High-Level Intuitive Features (HLIF) framework to design 10 HLIFs for skin cancer detection, following the ABCD rule. As presented, the feature sets were analyzed using a linear SVM classifier and statistical tests of the feature space independent of a classifier. The experiments show that HLIFs helped low-level features more accurately classify images. HLIFs were better at separating image data than the low-level features.

Furthermore, Aswin et al. [8] suggested an early skin cancer detection system for digital image processing. The ANN-based classifier demonstrated effectiveness in decision-making and pattern detection. The proposed approach is 84% accurate.

Cheerla et al. [18] established a revolutionary system in 2014. This system segments the images without manual involvement and gathers a comprehensive collection of features using new and better methodologies. The features were dynamically fed into multiple 5-stage classification algorithms with a sensitivity of over 97 percent and a specificity of over 93 percent.

In 2014, Choudhari et al. [19] proposed a computer diagnosis system for detecting skin cancer. The system was applied to a group of dermoscopy images, using the GLCM method for feature extraction and an artificial neural network to diagnose. It classified a given dataset into cancerous or non-cancerous images. The accuracy of the proposed algorithm was 96%.

According to Abbas and Baidaa [20], a digital image processing detection method can detect melanoma in its early stages. The technique includes two phases: determining if a pigment skin lesion is malignant or benign and identifying malignant melanoma skin cancer kinds. Either the first or second rounds have stages. The results are reasonable.

2.2.2 Deep Learning Classification

Han et al. [21] reported a classification model for diagnosing 12 distinct types of skin cancers in 2015, utilizing 19,398 images to train a ResNet network. Using the Asan dataset, the AUCs for squamous cell cancer, intraepithelial carcinoma, melanoma, and basal cell carcinoma were 0.83, 0.82, and 0.96.

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In 2016, Pomponiu et al. [22] used a regular camera to gather 399 images to identify benign nevi from melanoma. Preprocessing and data augmentation were carried out first. Pre-trained CNN and AlexNet were used to extract high-level features from the samples obtained. The K-nearest neighbor method was employed to classify the lesions. With a specificity of 95.18 percent and a sensitivity rate of 92.1 percent, they obtained an accuracy of 93.62 percent.

A total of 129,450 images were used for CNN pretraining by Esteva et al. [23]. There were two basic types: benign nevi's categorization, distinguishing benign dermatitis keratosis from keratinocyte carcinomas. They used transfer learning to categorize. In both cases, AUC was 0.96.

In 2018, Rehman et al. [24] used the CNN model and ANN to classify the lesion using the dataset supplied by ISIC in the 2016 event. Image segmentation was done first by intensity thresholding, and afterward, feature extraction was done with CNN. The ANN classifier used these features to accomplish the classification. They reached a 98.32 percent accuracy, surpassing the previous high of 97 percent.

Pham et al. [25] suggested a method to increase classification utilizing CNN and the data augmentation technique in 2018. They also attempted to address the issue of data scarcity and its impact on the classifier's efficiency. There were 600 images for testing and 6162 for training in the dataset. The AUC was attained at 89.2 percent, the ACC at 89.0 percent, and the AP at 73.9 percent. They looked at how picture augmentation affected three separate classifiers and discovered that they functioned differently and produced better results than the usual approaches previously utilized.

Rezvantalab et al. [26] defined eight skin malignancies with 10,135 photos of melanoma and nevi. The architectures employed were ResNet 152, Inception ResNet v2, and DenseNet 201. DenseNet 201 had an AUC of 98.16 percent for melanoma and BCC classification, while ResNet 152 had an AUC of 94.40 percent.

In 2020, Nadipineni [27] proposed a model that deals with deep learning in classifying skin lesions. He developed convolutional neural networks (CNN) through image analysis and applied certain characteristics, such as data augmentation techniques, to treat natural imbalances and image preprocessing techniques. The best accuracy achieved by this model could be 0.886.

Edgar et al. [28] proposed a system based on one-dimensional fractal fingerprints of texture-based characteristics mixed with in-depth learning features using Densenet-201 transmission of learning in 2020. The groups in the dataset of skin disease images are uneven since it is common. Make use of the clustering method. K-Nearest Neighbors and two main types of support vector machines are used as classifiers. Multicollinearity voting was used to determine diagnostic outputs. This research discovered an average accuracy of 97.35 percent, a mean precision of 91.61 percent, and a mean sensitivity of 66.45 percent.

Using training datasets to build a rapid, region-based CNN (FRCNN), Jinnai et al. [29] developed a technique for identifying skin cancer in 2020. With 86.2 percent accuracy, FRCNN outperformed board-certified dermatologists and dermatology residents. 91.5% accuracy, 83.3%

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sensitivity, and 94.55% particular for two different classes (benign or malignant). So FRCnn outclassed dermatologists in classification accuracy.

3. RESULTS AND DISCUSSION

In summary, the results of this review suggest that deep learning-based techniques have shown superior performance in skin cancer detection compared to traditional methods. Specifically, CNNs have achieved high accuracy, sensitivity, and specificity in detecting malignant and benign skin lesions. Nonetheless, using deep learning-based techniques comes with challenges, such as the requirement for large and diverse datasets and the potential for biases in certain datasets. Additionally, the lack of interpretability of deep learning models can raise ethical concerns. Therefore, combining traditional and deep learning-based techniques could be the most effective approach for skin cancer detection, as it could leverage the strengths of both approaches while addressing their limitations. It is important to note that further research is needed to address the challenges associated with deep learning-based techniques and ensure their ethical use in clinical practice. Additionally, developing standardized protocols and datasets could facilitate the comparison and reproducibility of results across different studies.

4. CONCLUSION

This research paper provides information about skin cancer, its danger, its various types, and its causes. Also, it explains that early diagnosis of this disease has an effective role in ruining the lives of many people with it, as well as the importance of building an electronic model to detect the disease easily using images of skin debridement for cancer. This research paper collects previous literature reviews completed to detect and diagnose the disease.

Since the seventies of the last century, researchers have been interested in presenting disease diagnosis by traditional methods. With the development of technology in the previous decade, deep learning has been used to detect and classify diseases early and with higher accuracy. From the literature that we presented in this research paper, it is clear that deep learning in classifying cancer is much better than traditional methods and more accurate in presenting the correct results. It is even more accurate than the diagnosis of doctors and experts in this disease. Given the high infection rates with this disease, there is an urgent need to develop more efficient models for detecting the disease early and with greater accuracy and benefit from the development of deep learning systems with the help of computers and cell phones to diagnose skin cancer.

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Conflict of interests.

There are non-conflicts of interest.

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