Support System Based Computer-Aided Detection for Skin Cancer: A Review

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Abstract

According to the American Society of Clinical Oncology, Computer-Aided Diagnosis (CAD) techniques have the tremendous possibility for the screening and early identification of melanoma. They are evaluated in terms of their current state-of-the-art, as well as current practices, challenges, and prospects in the areas of image screening, pre-processing of an image, segmentation of Region of Interest (ROI), feature extraction, feature selection, and classification of dermoscopic images. It is stated in this study that statistical information and outcomes from the most major implementations that have been reported to date are presented. We investigated the evaluation performance of many classifiers that had been developed specifically for the diagnosis of skin cancer. The fundamental aim of this paper is to develop a framework that will serve as a complete guideline for choosing relevant techniques for various elements of an automatic detection technique.

Keywords: Computer-Aided Detection, Dermoscopic images, Skin cancer, Machine learning, Deep learning.

1. Introduction

Breast cancer is the leading cause of death around the globe [1, 2]. Cancer researchers and doctors are both confronted with the challenges of cancer research and treatment [2], which can be overwhelming. 96,480 deaths are expected to be caused by skin cancer in 2019, according to the American Cancer Society's new cancer release report. Lung cancer is expected to cause 142,670 deaths, breast cancer is expected to cause 42260 deaths, prostate cancer is expected to cause 31,620 deaths, and brain cancer is expected to cause 17,760 deaths. In the clinical environment, the standard technique of diagnosing melanoma is by an ocular examination performed by a dermatologist. Although clinical diagnostics have improved in recent years, their accuracy remains somewhat disappointing. When compared to conventional clinical examinations, dermoscopy is a non-invasive diagnostic method that bridges the gap between clinical dermatology and dermatopathology by permitting the observation of morphological characteristics that are not visible to the naked eye during a clinical examination. According to the literature, dermoscopy is more accurate than the naked eye in terms of diagnosis, with an increase in diagnostic sensitivity of 10–30 percent [4, 5]. Although not previously known, it has been illustrated that dermoscopy can actually minimize diagnosis accuracy when conducted by untrained dermatologists due to the fact that it takes substantial expertise and experience to distinguish between skin lesions. Also revealed is that only professionals have attained 90% sensitivity and 59% specificity in skin lesion detection; however, these data drop dramatically to approximately 62–63 percent for general practitioners [6].

Doi : https://doi.org/10.54216/FPA.070103

When it comes to cancer, early detection is the most critical step in preserving the lives of many individuals. The majority of the time, visual examination and manual methods are used to make the diagnosis of different types of cancer. Performing a manual interpretation of medical photographs requests a substantial time commitment and is particularly prone to errors, which makes it an undesirable option. Computer-aided diagnosis (CAD) systems, which were first introduced in the early 1980s [4] to help doctors in enhancing the effectiveness of medical image interpretation, were developed to address this problem. The feature extraction process is the initial step in the implementation of machine learning. In the literature, different approaches for extracting features for various types of cancer have been discovered in greater depth than others, with some approaches being examined in greater depth than others. While these feature extraction-based strategies have some advantages [6, 7], they also have significant drawbacks. As a means of overcoming these drawbacks and boosting performance, representation learning has been advocated in the literature as a method of enhancing performance. Other methods, such as machine learning, are determined in their ability to produce high-level feature representations from raw photos, whereas deep learning can do so directly from raw images. As well as deep learning, GPUs are being used in conjunction with deep learning to do feature extraction and picture recognition in parallel with each other. Convolutional neural networks, for example, have exhibited promising performance in the diagnosis of cancer [8].

This work provides based on semantic analysis of malignant cases and further classification of distinguishing items that are often present in pigmented skin lesions. Specifically, the goal of this study is to discuss and analyze sophisticated dermoscopic algorithms that are used for lesion classification, as well as to address significant difficulties that have been identified as being detrimental to the effectiveness of the classification procedure. The authors also provide a succinct and in-depth evaluation of feature extraction and selection approaches that have been used to date for extracting different characteristics of melanoma, as well as a comparison of the methods used in the past. In the course of analyzing various research, a variety of criteria, for example, segmentation of ROI, feature extraction, feature selection, classification algorithms, and performance indicators utilized in presenting diagnosis results, are taken into consideration.

2. Types of Skin Cancer

Dermatological cancers are associated with extended exposure to ultraviolet (UV) radiation from the sun, which causes DNA damage in the skin's cells, allowing cancer to spread. The damage to DNA results in the occurrence of gene mutations, which cause skin cells to multiply uncontrollably, ultimately leading to the formation of tumors. Dermatological conditions such as skin cancer are caused by a mix of factors including ultraviolet radiation exposure and hereditary abnormalities [9]. Allergic reactions, malignant cells, and other factors can result in skin lesions that are difficult to treat or even disappear completely. Skin lesions caused by malignant cells, on the other hand, can be exceedingly serious and require immediate medical attention. If you have malignant skin lesions, some of the most severe symptoms you may experience can be fatal in the worst-case scenario. Melanoma is responsible for an 8 percent mortality rate among cancer-related lesions, which is regarded to be a disproportionately high rate [10].

3. Standard Skin Cancer Dataset

For evaluating the approaches presented in the literature, several publicly available datasets have been used, which may be found here. Digital camera photos were used to capture the dermoscopic images in PH2. The dermoscopic images in PH2 have a resolution of 768x560 pixels and were captured with a resolution of 768x560 pixels. There is a total of 200 dermoscopic images of melanocytic lesions presented, with 80 common nevi, 80 atypical nevi, and 40 melanomas among the lesions photographed. Each of the images is organized into three categories: That collection of images was compiled from the Hospital Pedro Hispano website (https://www.fc-up.pt/addi/ph2database.html), which is available on the internet. The International Skin Imaging Collaboration (ISIC) collection consists of 25,331 photographs, the largest of which is also the largest dataset in the collection. Within ISIC nests, there are various sub-datasets that include the ISIC 2016, ISIC 2017, ISIC 2018, ISIC 2019, and ISIC 2020 datasets, as well as other sub-datasets [13, 14].

Doi : https://doi.org/10.54216/FPA.070103

4. Challenges of Skin Cancer Detection

Skin lesions might be difficult to detect in some circumstances due to the large variety of image types and sources that are available. Because human skin color varies widely in appearance, skin detection is a difficult and time-consuming operation, especially in dark environments. Figure 1 gives an illustration of what I'm talking about. Because of the complicated visual features of skin lesions [10], there are various hurdles to overcome, such as the presence of diverse sizes and forms, the presence of noise and artifacts, uneven fuzzy borders, and low contrast.

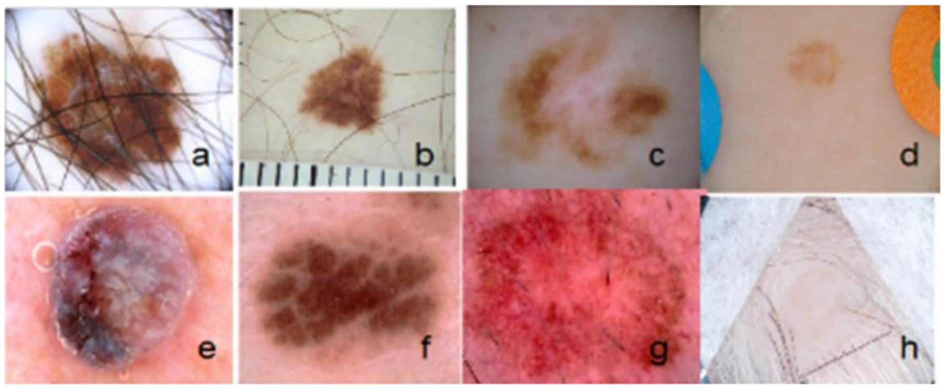

Figure 1. Skin cancer detection challenges: an artifact and hair, b ruler mark, c low contrast, d color illumination, e bubbles, f irregular boundaries, g blood vessels, h frame artifact: [10]

5. Skin Cancer Diagnosis

For diagnosis and evaluation purposes in medical imaging, computer-aided decision support systems (CAD) are becoming important, and they are becoming increasingly popular. General principles for developing a computer-aided diagnostic (CAD) system for skin cancer diagnosis include identifying a lesion and making an informed prediction about the possibility of that lesion progressing to cancer. Five primary steps form the CAD system, which is summarized in the following paragraphs.

5.1 Pre-processing

A pigmented skin lesion is distinguished from normal skin by performing the most critical processing step in completing a full inspection of the skin lesion. When viewing dermatoscopic pictures, identifying the lesion is a challenging task due to the smoothness between lesion of skin and surrounding skin, making it impossible to distinguish between the two even for highly trained dermatologists [3, 4]. On the other hand, the presence of artifacts in dermoscopy images has been documented [7–8], including uneven illumination, dermoscopic gel, black frames, marker ink marks, rulers, and air bubbles. Additionally, intrinsic cutaneous features that can impact boundary recognition, including blood vessels, hairs, and skin lines and texture, have been observed. The presence of these artifacts and superfluous elements not only makes the boundary detection technique more difficult, but they also cause accuracy to be reduced while computing time is raised, thus causing a drop in overall performance. Because of this, it is required to do various pre-processing procedures in order to make the segmentation process more efficient by removing undesirable items or artifacts and altering the color space [6].

5.2 Segmentation

Many segmentation strategies have been presented in the literature [3, 7], and it has risen to prominence as one of the most important study fields in recent years. During the study of lesion images, segmentation is a vital first step, and it has emerged as one of the most substantial research fields in recent years. Image segmentation is a vital step in automating the diagnosis of skin lesions in individuals who have been diagnosed with a skin lesion. In the interpretation of skin lesion photographs, this is a key step that should not be skipped. This approach, which isolates

Doi : https://doi.org/10.54216/FPA.070103

the diseased area from the healthy zone [10], allows for the creation of a region of interest [10, 11, 12]. The separation of the lesion of skin from the surrounding skin is depicted in Figure 2.

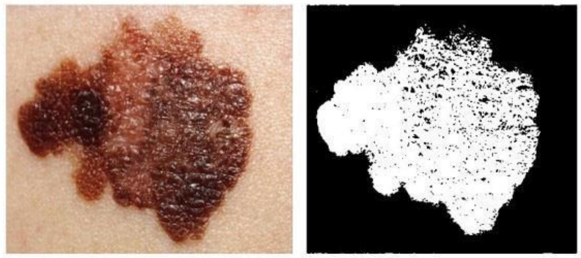

Figure 2. (a) original image (b) segmented image [11]

The development of automatic segmentation algorithms is essential for the creation of an automated diagnostic system for the diagnosis of skin lesions in the context of skin lesion detection. This paper addresses some procedures for segmenting skin lesions, including dermatoscopy. We have provided a quick summary of the various segmentation algorithms that are currently being utilized for dermoscopic image analysis, which are included in Table 1.

Table 1. Segmentation techniques for skin cancer

Technique	**Description**
Thresholding	The first threshold should be determined after that pixel are classified based different groups
Color-based segmentation	This type of segmentation includes principal component transform/spherical coordinate transform
Discontinuity-based segmentation	Edges of lesion identification based on zero crossings of Laplacian of Gaussian (LoG), active contours, and radial search techniques
Region-based segmentation	It is possible to combine sub-images that are adjacent and comparable in some way by first splitting the image into smaller components and then combining them. Statistics region merging, multiscale region growth, and morphological flooding are all examples of what is included.
Soft computing	The classification of pixels is accomplished by the use of soft computing techniques like neural networks, fuzzy logic, and evolutionary computation, among others.

5.3 Feature Extraction

Due to the fact that both malignant and benign melanoma appears at the same time in the early stages of the disease, it is difficult to distinguish between the two. There are various distinguishing characteristics between malignant melanoma and benign melanoma that can be detected, such as a blue tint, a white veil, uneven streaks, distinct colors, and numerous brown spots [11]. It is possible to reduce the size of the original data set with the help of feature extraction by measuring certain properties, or features, that identify one input pattern from another, and then combining these measurements. The feature extraction procedure is carried out by taking measurements on the pixels that make up a segmented object, which allows for the computation of numerous features to be computed at the same time. Multichannel filtering is the most successful and accurate feature extraction method, as demonstrated in the literature [10]. Statistical and model-based methods, as well as filtering-based methods, have been documented in the literature.

Doi : https://doi.org/10.54216/FPA.070103

5.4 Feature Selection

It is crucial to first define the features that will be employed in order to appropriately differentiate between malignant melanoma, benign nevi, and dysplastic nevi before proceeding with the procedure. The selection of an appropriate lowered number of valuable features while also eliminating superfluous, irrelevant, or noisy features is critical in order for the system to operate as efficiently as feasible. It is crucial, however, to guarantee that no critical information is lost during the process [5] and that the process runs smoothly. Using feature selection can provide a number of potential benefits from a classification perspective, including reduced feature extraction time and storage requirements for better generalization behavior, (ii) increased prediction accuracy for better generalization behavior, (iii) reduced training and testing times, and (iv) improved data understanding and visualization [10, 11].

5.5 Classification

The classification phase of the diagnostic system is in charge of drawing conclusions from the information gathered in the preceding phases in order to be able to construct a diagnosis for the input image in question in the future. Photos of skin lesions can be classified in order to improve the efficiency with which they are used in the detection of melanoma cancer [2, 3]. When it comes to classifying dermoscopic images, there are two approaches: the first considers only a dichotomous distinction between the two classes, while the second considers a combination of the two classes. The first approach is simpler (melanoma and benign). Attempts are made in the second one to categorize skin cancer into a number of different types. Different types of skin cancer exist, including Basal Cell Carcinoma, Actinic Keratosis, Squamous Cell Carcinoma, Seborrheic Keratosis, Solar Lentigo, Dermatofibroma, Nevi, Melanoma, and Vascular Lesions. Basal Cell Carcinoma is a type of skin cancer that develops from a keratosis on the skin's surface. Melanomas are malignant tumors that are the deadliest of all the cancers that may be found in the body [9, 11].

5.5.1 Classification Based Traditional Techniques

While these older classifiers are not as advanced as the more modern classifiers, they are still primarily based on the classic technique, which entails collecting features from images, either using pixel-based or region-based approaches, and then submitting them to the classifier to be classified. Recently, certain traditional techniques have been constructed on artificial intelligence [7], which is a development from the past. While working on this project, we will not be going too far into the technical specifics of anyone's categorization method. However, we believe that it is beneficial to quickly examine the approaches that are most typically used for dermoscopic image analysis in order to urge the reader to evaluate the effectiveness of the methods discussed in this section.

K-Nearest Neighbor Technique is a pattern recognition algorithm that is nonparametric in nature. It is based on the principle of least squares. We notice that the K vectors in the training set are those that are the most similar to the query vector for a lesion in the test set, and this is the case for both lesion types (query vector). It is then decided which class the unclassified sample belongs to base on how many of its K nearest neighbors belong to that class, with the remaining samples remaining unclassified [11]. *Decision Trees approach* is an example of a supervised machine learning technique that falls under this category, according to Wikipedia. The construction industry is well-known for its simplicity, efficiency in decision-making, and plain depiction, which is easily comprehendible by people, among other characteristics of the industry [11]. When two data sets are compared, the *Logistic Regression technique* creates a separating hyperplane between them, which is then used to define the distance from the hyperplane as a likelihood of belonging to a certain class [11]. *The Artificial Neural Network (ANN)* is one of the most significant and fundamental components of soft computing, yet it is also one of the most difficult to implement. In the ANN, there are numerous little processing units (the artificial neurons), all of which are tightly connected with one another. ANNs are constructed in such a way that information flows in a similar manner to that of the human brain [12].

Machine learning paradigms such as *Support Vector Machines (SVMs)* are based on the statistical learning theory of probability and are hence called support vector machines. Several studies have found that the algorithm's performance is on par with or better than that of other machine learning algorithms, which has been reported in the medical literature. SVMs outperform more traditional classifiers such as decision trees and neural networks in terms of accuracy and efficiency, and they outperform them by a large margin. A convex cost function is optimized during the support vector training process, and this paper is largely concerned with that optimization [14, 15].

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5.5.2 Classification Based Deep Learning Techniques

In recent years, deep learning-based classifiers have gained in popularity due to their ability to outperform humans in performing classification tasks for a broad range of objects in general. The nonlinear neuron processing of Deep Neural Networks, for example, allows them to execute complicated computations while also having a higher prediction power, making them well-suited for application in clinical images. Deep learning models such as the VGG, AlexNet, ResNet, and Xception are among the most recent advancements in the field of deep learning models. These models have been employed in a range of research investigations, including Computer-Aided Diagnosis, because of their great efficiency (CAD). `

6. Recent Works Based Traditional and Deep Techniques

Despite advances in medicine, skin cancer is a severe disease that continues to impact people all over the world. It is crucial to diagnose patients as soon as possible because the condition is fatal, and early diagnosis increases the likelihood that they will survive. Recent years have seen an increase in the use of deep learning models for skin cancer diagnosis, which can be attributed to their ability to deliver the concept of error-free decision-making for medical applications, which is intriguing to researchers. Deep convolutional neural network designs, which are still in the early stages of development, have been the focus of current research efforts. Deep convolutional neural network designs are still in the early phases of development. According to the information presented above, the goal is to mitigate the insufficiency of labeled data that is prone to overfitting while also improving the overall performance of skin lesion classification in computer-aided design (CAD) systems by incorporating transfer learning (pertained network), fine-tuning, the ensemble method, data generation, and augmentation. Among the most current studies on skin cancer detection and classification models that have been investigated are those listed in Table 2.

Table 2. Description of commonly used traditional techniques in skin lesion classification

Ref	Description	Pre-processing	Segmentation	Feature extraction/ selection	Classification
[12]	Classification based different classifiers using several texture features	-----	manual cropping	GLCM-texture-W 18 features	SVM-NB-ANN
[13]	Classifying skin cancer using shape and texture features	Lesion localization-Directional Gaussian filters	Chan-Vese	Shape-color-texture (132 GLCM and 144 DWT)	SVM-EDST-AdaBoost
[14]	Propose a model to classify skin cancer	Generating duplicate images, rotation	Cross correlation	Statistical- special-cross spectrum	SVM
[15]	Skin cancer classification based new form of ABCD features	Morphological operations (for hair removal)	Global thresholding, Otsu's thresholding	CLDM + modified-ABCD FS: ECFS	SVM
[16]	Design a deep model to extract deep features	Data augmentation-based GAN	-----	Deep feature-based inception	Transfer-ResNet50
[17]	Combine texture and deep features to classify skin cancer	Data augmentation, rotation	-----	Deep feature	Gabor and ResNet-18
[18]	fast and automated segmentation method	Resizing, morphological operations	probabilistic characteristics with the Parzen window (SPPW).	-----	-----

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[19]	Design a novel multiple convolution neural network model	-----	-----	FE: CNN (convolutional layer) FS: spatial pooling operator	neutrosophic multiple deep CNN
[20]	Different ensemble models based on different set of features and feature selection methods	Resizing 400 X 299	-----	FE: 18 shapes, 72 color, 420 textures (FD, DWT, co-occurrence matrix) FS: PCC, GRFS, relief F, PCA, CFS	OPF
[21]	Five pre-trained CNNs and four ensemble models	reconcile an image	CNN transfer learning	different layers of Xception model	ResNetXt101 and InceptionResNetV2
[22]	Deep Learning and L-type fuzzy number	DullRazor algorithm and	YOLO algorithm	ABCD rule	CNN
[23]	Fusion based handcrafted and pre-trained DL features	-----	-----	Handcrafted CNNs features	SVM
[24]	CNN based transfer learning technique in multiclass classification	Class balancing, Image size normalization, contrast enhancement, and hair removal	CNN	convolutional Fusion Unit	Convolutional Fusion Unit (CFU)
[25]	A novel method is proposed for feature selection of BUZO optimization.	Gaussian noise, sharp edges, and homomorphic filter	Otsu threshold	Buzzard optimization algorithm	SVM
[26]	Blends the efforts of both human ability and machine algorithm	Brightness and hair removal	-----	Inception-v3	GoogleNet
[27]	Segmentation and classification of skin melanoma	Anisotropic diffusion filtering, unsharp masking	K-means	Fast Fourier Transform-GLCM, and LBP	Random Forest
[28]	Skin disease detection based multi class	Image Resizing	-----	CNN	Multiclass SVM
[29]	Skin cancer detection based deep features	-----	Fully Convolutional Network (FCN)	Deep features	DenseNet

Every year, a huge number of diagnostic algorithms/models are published in peer-reviewed scientific journals, demonstrating their effectiveness. In recent years, there has been a significant surge in interest in the use of electronic databases containing dermoscopic images for the purpose of constructing categorization models that can "learn" from instances by recognizing patterns in the data. Due to the necessity of utilizing data and learning techniques in order to deliver an accurate diagnosis, the selection of appropriate learning algorithms, as well as the statistical validation of those algorithms, must be done in order to ensure accuracy. This problem is difficult to fix because of the relative scarcity of lesion data and, as a result, the poor quality of training data that has been provided, as well as the imbalance

Doi : https://doi.org/10.54216/FPA.070103

between the classes that exists. The classification of dermoscopic images is accomplished through the use of a variety of statistical and machine learning algorithms, as shown in Table 2. Different classification systems have their own set of advantages and weaknesses, which are listed below. The question of which categorization strategy is the most appropriate for a certain study is not an easy one to answer in a straightforward manner. Varying classification results may be obtained depending on the classifiers used, the sample size variances observed, the fraction of melanomas found in a sample, and the number of features used for discrimination, as shown in Table 3. When selecting a classification method, it is critical to take a number of factors into account, including the availability of various sources of dermoscopic images, the amount of time required for classification, the number of computational resources available, and the number of melanoma and benign images that can be used as training images.

The same collection of photographs was used in only a few studies, in which researchers tested various different classification algorithms, including PH2 [13, 14, 18, 22, 23], ISBI 2016 [13, 19], ISIC 2017 [17, 18, 22, 23], HAM10000 [21, 24, 29], ISIC 2018 [15, 16], and ISIC 2019. Following a thorough review of all of these comparative trials, it is obvious that SVM outperforms Bayesian and kNN classifiers, although CNN outperforms SVM and other statistical techniques on a consistent basis. In order to arrive at a final conclusion on which classifier should be employed as a final solution to the problem, the results of an experimental evaluation of alternative designs must be considered. It had been discovered during design experiments that while one of the designs would consistently outperform the others in terms of performance, the groupings of patterns misclassified by the various classifiers would not always overlap. These observations inspired a frenzy of study towards classifier combinations that has only recently evolved as a result of these observations. When making decisions, it is important to avoid falling back on a single decision-making technique in all scenarios. To make decisions, all of the designs, or a selection of them, are considered, and their different points of view are integrated to arrive at a consensus choice. [12, 13] [12, 13] [12, 13] [12, 13] [12, 13] [12, 13] On the basis of dermoscopic images, some classifier combination schemes have been devised, with experimental evidence suggesting that some of them outperform a single best classifier on a consistent basis. Although some combination schemes are superior to others, there is currently insufficient understanding of why they are superior to others and under what conditions they are superior.

We examined 18 recent studies that claimed to have fully autonomous diagnostic models and discovered that they lacked the necessary components. In both the reporting and the technique utilized, we noticed a number of flaws, which we investigated. Reviewed, A number of important shortcomings of the publications include that there is no calibration in picture acquisition, there is no established process for extracting and selecting variables in the model, and there is an increased risk of overfitting due to a lack of events per variable in the model. It has been reported that in certain research, the test and training photos were not stated, or that the quantity of melanoma and benign images used for training was uneven, which may have resulted in a biased categorization in some cases. On the other hand, there are certain studies that do not report on comparisons and cross-validation but instead only report on the performance of one particular technique. When writing papers, it is crucial to include specifics such as these because if they are not given, the reader will be unable to judge whether the allegations made in the papers are true or not. It is important to remember that if the expert user is the intended audience, research should be planned with the purpose of supporting doctors in identifying between benign lesions such as nevi, dysplastic nevi, and malignant skin tumors, among other things. When an automated system is intended at expert users, it is possible that the goal is to raise specificity while also increasing sensitivity to a level that is at least as good as the expert's ability to detect abnormalities.

Table 3. Results of commonly used traditional techniques in skin cancer classification

Ref	Dataset	No. of images	Classification	Results
[12]	ISIC	320 B - 110 M	B/M	Ac= 89 - Sn= 90 - Sp= 88
[13]	PH2 ISBI 2016	160 B - 40 M 1033 B - 246 M	B/M	PH2: Ac= 97 - Sn= 97 - Sp= 100 ISBI: Ac= 88 - Sn=95 - Sp= 82
[14]	IDS - DA ISIC 2017 PH2	2879 ME - 3013 N 796 BC - 512 SK	ME/N/BC/SK	IDS: Sn= 98.76, DA: Sn= 99.01, ISIC 2017: Sn= 98.87, PH2: Sn= 99.41
[15]	ISIC 2018	1200 300 ME - 300 N - 300 BC - 300 SK	ME/N/BC/BKL	Ac= 100 - Sn= 100 - Sp= 100
[16]	ISIC 2018	10,015 AKIEC 327 - BC 514 - SK 1099 - DF 115 - NV 6705 - ME 1113 - VASC142	AKIEC/BC/SK/DF /NV/ME/VASC	Ac=95.2 - Sn= 83.2 - Sp= 74.3 - Pre= 96.6 - BMA= 83.1
[17]	ISIC 2017	374 ME – 254 SK – 1372 N	ME/SK/MN	ME: AUC= 0.96 – Ac= 0.83 – Sn= 0.13 – Sp= 1.00 SK: AUC= 0.86 – Ac= 0.82 – Sn= 0.17 – Sp= 0.98
[18]	PH2 - ISIC 2017	---	---	Ac= 95.48 - Sp= 98.55 – Sn= 88.45 – Dice=91.12 – Ma= 87.86 – JI= 84.9
[19]	ISIC 2016	900 training – 379 testing	B (N)/M(BC)	Ac= 85.22 – Sn=77.1 – Sp= 86
[20]	ISIC	916 B - 188 M	B/M	Ac= 94.3 - Sn= 91.8 - Sp= 96.7
[21]	HAM10000	10,015 AKIEC 327 - BC 514 - SK 1099 - DF 115 - NV 6705 - ME 1113 – VASC 142	AKIEC/BC/SK/DF /NV/ME/VASC	Ac= 93.2
[22]	PH2 – ISBI 2017 – ISIC 2019	20250		Jac score= 79.84, 86.99, and 88.64
[23]	PH2 – ISIC 2017	1786 N – 414 M	ME/Non-ME	Ac= 98, Ac= 87.8
[24]	HAM10000	10,015 AKIEC 327 - BC 514 - SK 1099 - DF 115 - NV 6705 - ME 1113 - VASC 142	AKIEC/BC/SK/DF /NV/ME/VASC	Ac= 98.09, Sn= 93.35, Sp= 98.88,
[25]	---	200	ME/Non-ME	Ac= 94
[26]	---	1067 - 528	NV/SK/BC/ Psoriasis	Ac= 87.25, Ac= 86.63
[27]	ISDIS - ISIC	900	600 B/300M	Ac= 93
[28]	---	20 N, 20 ME, 20 Eczema, and 20 Psoriasis		Ac= 100
[29]	HAM10000	10,015 AKIEC 327 - BC 514 - SK 1099 - DF 115 - NV 6705 - ME 1113 - VASC 142	AKIEC/BC/SK/DF /NV/ME/VASC	Ac= 98, recall= 98.5, AUC= 99

7. Conclusion

Supporting the purpose of assessing its overall quality, evidence for the diagnostic accuracy of digital image-based ML classification of skin cancer was analyzed. The bulk of the research included in this review had substantial methodological problems, despite the fact that practically all of the studies included in this review demonstrated excellent diagnostic performance. Additionally, continuous refinement of current technologies and the development of new procedures will aid in our goal of a significant reduction in the melanoma death rate by 20 percent, which will be achieved in part through increased capacity to detect skin cancer.

Funding: “This research received no external funding”

Doi : https://doi.org/10.54216/FPA.070103

Conflicts of Interest: "The authors declare no conflict of interest."

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