Review on Automated Skin Cancer Detection Using Image Processing Methods

Raju S. Maher[1(✉)] and Shobha K. Bhawiskar[2]

[1] Department of Computer Science & IT, Dr. Babasaheb Ambedkar, Marathwada University, Aurangabad, Maharashtra, India
rajumahercs@gmail.com

[2] Government Institute of Forensic Science, Aurangabad, Maharashtra, India

Abstract. The skin is the most crucial component of the human body because it protects the muscles, bones, and entire body. One of the most common illnesses affecting people nowadays is skin cancer. These days, a great number of people are affected by skin cancer. Skin cancer develops as a result of genetic flaws or mutations brought on by unrepaired deoxyribonucleic acid in skin cells. A novel spectral approach is devised to acquire a number of measurements of those discovered in malignant skin areas using the sample photos that were taken by medical researchers. The two stages of the automated diagnosis system's operation are the detection of skin abnormalities and the assessment of melanoma's malignancy. This paper outlines the procedures and approaches for automated skin cancer diagnosis. This article offers early-stage researchers helpful details on methods, databases, and the essential procedures for a skin cancer diagnosis.

Keywords: Skin cancer · Melanoma · Image Processing

1 Introduction

The outer area of skin around 20 square feet, the skin is the largest organ in the human body. The main purpose of the skin is to help people experience touch, heat, and cold. Dermatologists examine suspicious skin lesions in order to find skin cancer. Additionally, they consider clinical details including the patient's age, the location of the lesion, if the lesion bleeds, and other factors. The majority of research focuses on malignant melanoma diagnosis. Additionally, it has been reported that the worldwide rate and age gap widen each [1]. Skin cancer is one of the conditions that arise when malignant cells on any layer of skin begin to grow and spread to other organs and tissues. The ability of early detection and treatment of skin cancer to lower morbidity is well acknowledged [2]. The incidence of skin cancer has sharply increased recently [3]. With an estimated 232,000 occurrences globally, melanoma is the most common kind of skin cancer that causes death, according to the World Health Organization [4]. There are three different forms of skin cancer: melanoma, squamous cell carcinoma, and basal cell carcinoma [5The most frequent skin cancer, basal cell carcinoma, is also the least lethal if caught early [6]. Squamous cell carcinoma, the second kind, is the most prevalent type of skin cancer and

S. Tamane et al. (Eds.): ICAMIDA 2022, ACSR 105, pp. 456–465, 2023.
https://doi.org/10.2991/978-94-6463-136-4_39

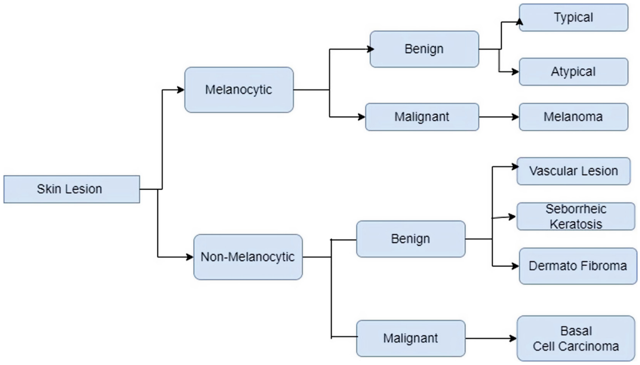

Fig. 1. Block diagnosis for skin cancer lesion detection

develops in the cells that make up the top skin layers [7]. Their primary goal has been to offer a thorough analysis [8]. Some image processing procedures have been created utilizing algorithms or systems for early detection and classification using methods and techniques that have been used to solve medical issues [9]. We will research and analyze them using different segmentation and feature extraction approaches in order to detect skin cancer at an early stage [10].

The most dangerous kind of skin cancer, melanoma, is shown in Fig. 1 above. If detected early, it is curable, but melanoma that has progressed is deadly [12].

The two primary layers of skin are the epidermis and dermis. The dermis, which is the term for the top layer, is composed of the cellular layers Squamous, Basal, and Melanocytes. These cells shield the skin from harm [14]. Neurons, blood arteries, and sweat glands are all found in the epidermis, sometimes referred to as the inner layer. The three main types of skin cancer are melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma. One of the deadliest forms of cancer is melanoma [3].

2 Related Work

Skin cancer is currently a significant public health issue. The detection of skin lesions has been handled in several types of research in various methods. (Fig. 2) Researchers can contrast alternative methods using a variety of readily available datasets. Following are some researchers' studies on the pre-processing and segmentation phases: Their pre-processing methods include image enhancement techniques, removing noise (hairs, artifacts, and microscopic particles) from the input photographs, and specific lighting correction algorithms [4]. These methods range from segmentation approaches to automated skin lesion diagnosis systems.

Maximum Entropy Threshold-based skin detection, Gray Level Co-occurrence Matrix (GLCM)-based feature extraction, and Artificial Neural Network-based categorization (ANN). For classification, the Back-Propagation Neural Network (BPN) is employed [5]. This system used a rule-based, forward chaining method to identify skin diseases. Users of the suggested technology can provide pertinent medical

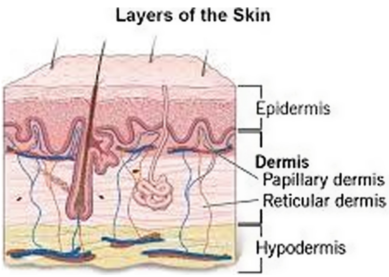

Fig. 2. Layers of skin

advice and online diagnoses for children's skin conditions. Several data mining classification approaches (AdaBoost, BayesNet, MLP, and NaiveBayes) were utilized to predict and diagnose skin conditions. Only three forms of skin issues (Eczema, impetigo, and melanoma) are helped by this [6]. As a clustering technique, the ABCD (Asymmetry Index Border Colour Index Diameter) approach may be utilized to extract features from segmentation [7].

A variety of image processing techniques are used to segment images. Region-expanding techniques, morphological processes, and adaptive thresholding and binarization were utilised [17]. Dermoscopic images were segmented using methodologies, and the outcomes were compared to the specified segmentation algorithm. They were accurate to 93.71 percent [18].

As mentioned before, utilising deep convolution networks yields more accurate results than doing so with conventional methods. a system for automatically detecting The image is first given a preprocessing step in which the effects of shading are reduced. The region of focus is then accurately segmented out using a segmentation algorithm that takes into account the texture and colour patterns of the image. Noise and other inherent problems are then eliminated from the images. The watershed method is used to isolate cancerous liver cells. The manual detection of these problems takes a lot of time. Utilizing automated methods to find cancer advances medical knowledge, helps to diagnose the disease early, and produces the best results quickly. The instruments used to detect skin cancer are briefly covered in the next section [19], along with our recommended methodology (Table 1).

3 Research Methods for Skin Cancer

3.1 Image Pre-processing

The three process phases of image enhancement, image restoration, and hair removal can all be used to achieve the pre-processing stages' goal. As shown in Fig. 3, there are three kinds of image enhancement. These consist of picture enlargement, color space conversion, and contrast improvement. The two categories of image restoration are noise restoration and blur restoration. Morphological methods, curvilinear structure detection, and other methods can be used to remove hair. We must convert the input photos to a common size and color, and remove any extraneous details like noise, bubbles, hair, and so on [20] because they come from a variety of sources.

Table. 1 Summary of literature work in skin cancer

Ref	Techniques	Year	Results
[8]	19-layer deep (CNNs)	2017	96.3%
[9]	Fully Convolution Net	2017	89.7%
[10]	Robust Saliency-based Skin Lesion Segmentation (RSSLS) Framework	2017	91.05%
[11]	combination of Otsu thresholding and K-means clustering	2017	89.7%
[12]	normalizing pixels into [0–1] range, resizing, cropping	2017	81.33%
[13]	2D Otsu with morphological operations on color channel derived from RGB and CIELAB color space	2016	93.71%
[14]	used a set of 84 directional filters	2016	96.3%
[15]	Comparison Statistical region merging (SRM) Iterative stochastic,Adaptive Thresholding Color Enhancement and Iterative Segmentation Multilevel Thresholding	2015	96.8%
[16]	11 x 11 median filter, Gabor filter	2015	94.0%
[17]	Filter adjusting the gamma values, morphological operation closing median filter	2016	93.71%
[18]	Image enhancement, noise removal and resizing	2015	96.8%

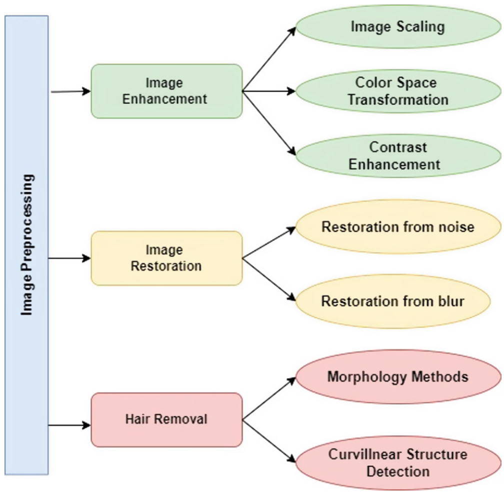

Fig. 3. Image pre-processing

3.2 Image Segmentation

Segmentation is used to isolate the ROI image from the surrounding area. We are interested in looking at ROI. The result of this stage differentiates the picture's cancerous from healthy areas. Segmentation techniques may be divided into four main categories [21].

- **Threshold basis** - Techniques that fall under this category include Otsu's technique, local and global thresholding, maximum entropy, histogram-based, and others.
- **Region-based** - This category includes strategies like segmenting watersheds and seeded region growth.
- **Pixel-based** - techniques include fuzzy logic, Markov random fields, artificial neural networks, reinforcement learning, and more.
- **Model-based -** strategies include level sets, parametric deformable models, and others.

3.3 Feature Extraction

There are several approaches utilized in the diagnosing procedure, including as

- **ABCD Rule**

Asymmetry, irregular border crossing, Clinical indicators of melanoma include colour variation (including intralesional colour variation and a colour that varies from the patient's other nevi), diameter more than 6mm, and evolving (a new or changing lesion). Later, the "ugly duckling sign" was developed as a replacement for the ABCDE rule to address its flaws [22].

- **Menzies Method**

If neither colour homogeneity nor pattern symmetry is present, together with at least one of the following:

Pseudopods with blue and white veils, flowing radially the depigmentation of scars, Broadened network, five to six colours, numerous blue/gray dots, and periphery black dots/globules are a few instances of multiple brown dots [23].

- **Seven-Point Checklist Method**

Unconventional pigment network, blue-and-white veil, and uncommon vascular pattern (2 points each). Minor criteria (1 point each) [24] include abnormal streaks, irregular pigmentation, irregular dots/globules, and regression structures.

- **Pattern Analysis**

Many knowledgeable dermoscopists employ pattern analysis to identify benign from malignant melanocytic lesions and diagnose melanocytic lesions. The simultaneous assessment of the diagnostic value of each dermoscopy characteristic made visible by the lesion is called pattern analysis [25].

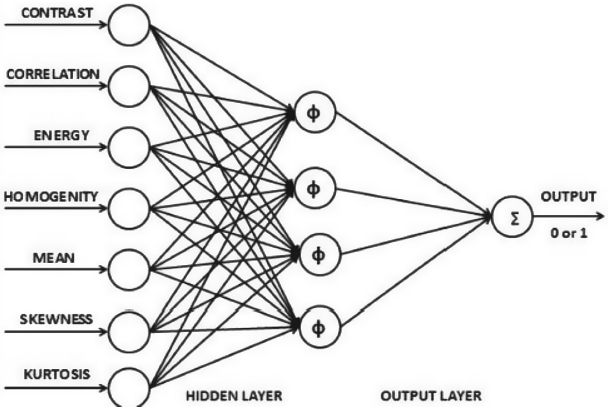

Fig. 4. Artificial Neural Network

3.4 Classification Methods for Skin Cancer

To distinguish between malignant and benign melanoma, a classifier is utilized. Artificial neural networks, fuzzy inference systems, and adaptive fuzzy inference neuro systems are a few examples of artificial intelligence approaches that can be employed. Not all researchers utilize this type of classifier. For instance, an uneven stripe and a blue-white veil are indicators of malignancy. Based on the angle and direction of the streaks, they identify aberrant streaks and confirm them using algorithms. Given that it just considers one feature or criteria, this type of diagnosis strategy is less precise than machine learning techniques [26]. We'll talk about the following machine learning algorithms:

- **Artificial Neural Network**

Neural networks can solve incredibly complex issues because neurons are capable of nonlinear processing. Artificial neural networks may be effectively used with medical images because of their prediction capability. Skin cancer diagnosis depends heavily on patient information, but the human brain struggles to make sense of it. This is where ANN comes into play.

Malignant melanoma can be difficult to distinguish from benign melanoma in the early stages, making skin cancer screening tricky. Artificial neural networks can address this issue since neurons learn from examples. Using a variety of validated dermoscopic pictures, neurons are first trained. The backpropagation method is used to train neurons. With reverse propagation, the flow will be in a forward direction. The fault propagates backward if the network output differs from the intended output, which generates an error signal. Weights are adjusted to reduce error. Up till the error is zero, this process is repeated. The discrepancy between the network output and the expected output is what is referred to as an error [27].

Internal dermatoscopic image properties including kurtosis, mean, skewness, energy, and contrast are provided as input in Fig. 3's diagram, and a log sigmoid activation function is employed to generate an output of zero or one. Malignant states are represented by one, whereas benign conditions are represented by zero (Fig. 4).

- **Fuzzy Rule Based System**

After filtering, fuzzy rules are applied to the image. As a result, a divided image is displayed. The resulting image is thresholded to produce the binary image. The pixel values of the red, green, and blue components are used as fuzzy input. A morphological technique called closing is used to remove noise from a binary image. The region of interest is finally located using area filtering. Next, categorization criteria are assessed for the retrieved ROI [28].

- **Adaptive Fuzzy Inference Neural Network**

By combining human expert knowledge, fuzzy inference capability, and neural network capacity for adaptation or learning, AFINN compromises the benefits of fuzzy inference rules and neural networks. As a consequence, our method performs better than fuzzy logic and neural networks. To reduce the number of inputs to the AFINN system, some researchers use the information gain strategy. AFINN has two layers: an input-output layer and a rule layer. Input and output make up the two components of the I/O layer. One fuzzy rule makes up each node in the rule layer. From the rule layer to the output component and from the rule layer to the input section, weights are completely connected. The input portion of their if-then rules holds the if sections, while the rule layer saves the then parts. The membership function's form is automatically changed during learning. AFINN modifies wij and weights are changed using the backpropagation method throughout the learning phase [29].

4 Skin Cancer Datasets [30]

- ISIC
- Dermofit Image Library
- PH2 Dataset
- MED-NODE
- Asan Dataset
- Hallym Dataset
- SD-198 Dataset
- Dermnet NZ
- Derm7pt

5 Conclusion

The purpose of this study is to examine skin cancer and its effective treatments. It has the potential to revolutionize patients' care, particularly in terms of improving the sensitivity and accuracy of screening for skin lesions detection, including the primary stage of skin cancer. Clinical and photographic data of all skin types are required, focusing on the problem of automatic skin lesion detection, particularly on melanoma detection, by applying semantic segmentation and classification from dermoscopic images using an image processing based approach.

References

1. Elgamal M. Automatic Skin Cancer Images Classification. IJACSA. 2013; 4 https://doi.org/10.14569/IJACSA.2013.040342.
2. Barr, A. E., & Barbe, M. F. (2004). Inflammation reduces physiological tissue tolerance in the development of work-related musculoskeletal disorders. Journal of Electromyography and Kinesiology, 14(1), 77-85.
3. Nguyen, J. T., Bakri, K., Nguyen, E. C., Johnson, C. H., & Moran, S. L. (2013). Surgical management of subungual melanoma: mayo clinic experience of 124 cases. Annals of plastic surgery, 71(4), 346-354.
4. Lopez-Ojeda, W., Pandey, A., Alhajj, M., & Oakley, A. M. (2020). Anatomy, skin (integument). StatPearls [Internet].
5. Filali, Y., Abdelouahed, S., & Aarab, A. (2019). An improved segmentation approach for skin lesion classification. Statistics, Optimization & Information Computing, 7(2), 456-467.
6. Gao, J., Jiang, Q., Zhou, B., & Chen, D. (2019). Convolutional neural networks for computer-aided detection or diagnosis in medical image analysis: an overview. Mathematical Biosciences and Engineering, 16(6), 6536-6561.
7. Yusof, M. M., Aziz, R. A., & Fei, C. S. (2013). The development of online children skin diseases diagnosis system. International Journal of Information and Education Technology, 3(2), 231.
8. Messadi, M., Cherifi, H., & Bessaid, A. (2021). Segmentation and ABCD rule extraction for skin tumors classification. arXiv preprint arXiv:2106.04372.
9. Y. a. C. M. a. L. Y.-C. Yuan, "Automatic skin lesion segmentation using deep fully convolutional networks with Jaccard distance," IEEE transactions on medical imaging, vol. 36, pp. 1876--1886, 2017.
10. N. C. a. N. Q.-B. a. P. S. a. G. D. a. H. B. a. H. A. a. S. J. R. Codella, "Deep learning ensembles for melanoma recognition in dermoscopy images," IBM Journal of Research and Development, vol. 61, pp. 5--1, 2017.
11. E. a. K. J. a. B. L. a. K. A. a. L. C. a. F. M. a. F. D. D.Ahn, "Saliency-based lesion segmentation via background detection in dermoscopic images," IEEE journal of biomedical and health informatics, vol. 21, pp. 1685--1693, 2017.
12. T. T. K. a. A. M. N. a. N. J. a. F.-R. R. Munia, "Automatic diagnosis of melanoma using linear and nonlinear features from digital image," in Engineering in Medicine and Biology Society (EMBC), 2017 39th Annual International Conference of the IEEE, 2017.
13. A. R. a. G.-i.-N. X. a. B. J. a. M. O. Lopez, "Skin lesion classification from dermoscopic images using deep learning techniques," in Biomedical Engineering (BioMed), 2017 13th IASTED International Conference on, 2017.
14. C. a. S. L. M. Sagar, "Color channel based segmentation of skin lesion from clinical images for the detection of melanoma," in Power Electronics, Intelligent Control and Energy Systems (ICPEICES), IEEE International Conference on, 2016.
15. O. a. B. B. D. a. F. M. Abuzaghleh, "Non invasive real-time automated skin lesion analysis system for melanoma early detection and prevention," IEEE journal of translational engineering in health and medicine, pp. 1–12, 2015.

16. A. a. J. R. Santy, “Segmentation methods for computer aided melanoma detection,” in Communication Technologies (GCCT), 2015 Global Conference, IEEE, 2015.
17. R. a. M. K. Kasmi, “Classification of malignant melanoma and benign skin lesions: implementationof automatic ABCD rule,” IET Image Processing, pp. 448--455, 2016
18. Tan, L., Roegiest, A., Clarke, C. L., & Lin, J. (2016, July). Simple dynamic emission strategies for microblog filtering. In Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval (pp. 1009–1012).
19. Sagar, C., & Saini, L. M. (2016, July). Color channel based segmentation of skin lesion from clinical images for the detection of melanoma. In 2016 IEEE 1st international conference on power electronics, intelligent control and energy systems (ICPEICES) (pp. 1–5). IEEE.
20. Atli, I., & Gedik, O. S. (2021). Sine-Net: A fully convolutional deep learning architecture for retinal blood vessel segmentation. Engineering Science and Technology, an International Journal, 24(2), 271-283.
21. Hoshyar, A. N., Al-Jumaily, A., & Hoshyar, A. N. (2014). The beneficial techniques in preprocessing step of skin cancer detection system comparing. Procedia Computer Science, 42, 25-31.
22. Nickoloff, E. L., Donnelly, E., Eve, L., Atherton, J. V., & Asch, T. (1990). Mammographic resolution: influence of focal spot intensity distribution and geometry. Medical physics, 17(3), 436-447.
23. Ilyas, M., Costello, C. M., Zhang, N., & Sharma, A. (2017). The role of the ugly duckling sign in patient education. Journal of the American Academy of Dermatology, 77(6), 1088-1095.
24. Menzies, S. W., Moloney, F. J., Byth, K., Avramidis, M., Argenziano, G., Zalaudek, I., ... & Kreusch, J. (2013). Dermoscopic evaluation of nodular melanoma. JAMA dermatology, 149(6), 699-709.
25. Bianconi, E., Piovesan, A., Facchin, F., Beraudi, A., Casadei, R., Frabetti, F., ... & Canaider, S. (2013). An estimation of the number of cells in the human body. Annals of human biology, 40(6), 463-471.
26. Herschorn, A. (2012). Dermoscopy for melanoma detection in family practice. Canadian Family Physician, 58(7), 740-745.
27. Alfi, I. A., Rahman, M. M., Shorfuzzaman, M., & Nazir, A. (2022). A Non-Invasive Interpretable Diagnosis of Melanoma Skin Cancer Using Deep Learning and Ensemble Stacking of Machine Learning Models. Diagnostics, 12(3), 726.
28. Shahid, N., Rappon, T., & Berta, W. (2019). Applications of artificial neural networks in health care organizational decision-making: A scoping review. PloS one, 14(2), 0212356.
29. Kulkarni, N. (2012). Color thresholding method for image segmentation of natural images. International Journal of Image, Graphics and Signal Processing, 4(1), 28.
30. Iyatomi, H., & Hagiwara, M. (2004). Adaptive fuzzy inference neural network. Pattern Recognition, 37(10), 2049-2057.