Computer-Aided Diagnosis of Melanoma Skin Cancer: A Review

Puneet Kumar Goyal, Nirvikar and Mradul Kumar Jain

Abstract Skin cancer has a major impact on society in India and across the world. According to the figures given by the National Cancer Institute and SEER, estimated new cases of Melanoma in 2017 are 87,110. This figure is approximated 5.2% of all new cancer in 2017. As per the data obtained from the WORLD HEALTH RANKINGS, the death rate per 1,00000 is highest in New Zealand with 7.68% then Australia with 6.52%. It has been proved from the study that melanoma skin cancer is almost curable if it is diagnosed early and treated correctly; otherwise, it can spread to other parts of the body and become incurable. This paper presents the comparative study of various phases of computer-aided melanoma skin cancer detection system with the aim of providing the development achieved in the melanoma skin cancer detection by the research community from earlier period to the current time. This method starts from the image acquisition step followed by image preprocessing, segmentation, feature extraction, feature selection and classification steps. The input to this system is an image of affected skin area, and output labels this input image benign or malignant melanoma.

Keywords Melanoma · Preprocessing · Segmentation · Classification · Benign
Malignant · Oncology · Epiluminescence microscopy · Neural network
Fuzzy C-means

P. K. Goyal (✉) · M. K. Jain
Uttarakhand Technical University, Dehradun, Uttarakhand, India
e-mail: puneet17jan@gmail.com

M. K. Jain
e-mail: mradul_ja@rediffmail.com

Nirvikar
COER Roorkee, Roorkee, Uttarakhand, India
e-mail: nirvikarlohan@yahoo.com

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1 Introduction

Cancer is a major disease in which a group of abnormal cells in the body exhibits uncontrolled growth, while in a normal cell life cycle, the cells generate from other cells, grow and die when they are damaged. These abnormal cells are defined as cancer cells, malignant cell, or tumor cells. The severity of the cancer can be imagined from the fact that it can also spread to other parts of the body. For example, cancer cells in the skin can travel to the lung and grow up there. So this process of spreading cancer cells to other parts is called metastasis. There are many different types of cancer such as leukemia sarcoma, melanoma, and many more [1].

According to the American Cancer Society, an estimated 87,110 new cases of malignant melanoma will be identified in the USA in 2017 and expected 9,730 people will die due to melanoma skin cancer in 2017 [2]. In India, skin cancers comprise about 1–2% of all diagnosed cancers. Various types of skin cancers produce almost 2.4% of total cancer patients who are treated in the surgical oncology department. There are basically three types of skin cancer. Among these, squamous cell carcinoma (SCC) was the widespread histological type (55.8%) followed by melanoma (26.1%) and basal cell carcinoma (BCC, 18.1%).

Among all these skin cancers, melanoma is the deadly form of skin cancer [3]. Melanoma skin cancer arises when the pigment-producing cells (melanocytes) exhibit uncontrolled growth and become cancerous. Most pigment cells are found in the skin and generate pigments which provide color to the skin. It can also arise in the other parts of the body, such as the eyes, intestines (this is rare). It is very rare in people with dark skin [4, 5].

Skin cancer may appear as a new spot or mole which could be benign or malignant melanoma. Benign melanoma is harmless, while malignant melanoma is dangerous which needs immediate attention. If the melanoma skin cancer is not identified at starting phase, it could be the basis of death of the patient. As per the melanoma: statistics approved by the Cancer.Net Editorial Board, 07/2016, the 5-year survival is 92%, if it is diagnosed at initial stage (Fig. 1).

Basically, doctors use clinical analysis and biopsy process for the analysis of the skin cancer [2]. Clinical analysis is done using a dermatoscope by expert dermatologists [6]. Biopsy method is painful and time-consuming as it undergoes removal of the skin, and these skin samples are tested by many laboratories [7]. Also, the

Fig. 1 Melanoma [2]

accuracy of clinical analysis was 64%, while accuracy for biopsy method was 68% which is very low. Considering all these facts, a computer-aided detection (CAD) method is required which is capable of performing complex image processing and machine learning to diagnose the skin cancer efficiently and correctly.

2 Literature Categorization

This section below provides the related references and review on work done in the field of computer-aided detection of melanoma skin cancer. There are various steps for computer-aided detection of skin cancer such as

(a) Image acquisition
(b) Image preprocessing
(c) Image segmentation
(d) Feature extraction
(e) Feature selection
(f) Classification

2.1 Image Acquisition

It is one of the most important steps of CAD system for melanoma skin cancer detection. There are numerous image acquisition methods under investigation which are confocal scanning, laser microscopy, ultrasound, magnetic resonance imaging (MRI), optical coherence tomography (OCT), biopsy, etc. The usual clinical practice of melanoma diagnosis is a visual inspection by the dermatologist. Accuracy of clinical diagnostic is bit unsatisfactory. On the basis of various studies, we can say that the naked eye clinical diagnosis of cutaneous melanoma has an accuracy rate of only 60%.

Dermoscopy readers may refer to [8, 9] for performance analysis of existing image acquisition techniques. From the study of these research papers, it could be concluded that dermoscopy is the best suitable noninvasive method for image acquisition. There are various types of dermoscopy such as dermoscopy using non-polarized light that visualizes the subsurfaces of the PSL by using the microscope and immersion fluid [10–12] which makes the skin layer more transparent. This technique is also known as dermatoscopy, cutaneous surface microscopy, magnified oil immersion bioscopy, and epiluminescence microscopy (ELM).

To further improve the accuracy of image acquisition, a modified dermoscopy was conducted with cross-polarized light which eliminates the need of immersion liquid and direct contact of instrument with skin [10, 13]. This method is sometimes referred as video microscopy or XLM (X-polarized epiluminescence [10, 14]. Another image acquisition related to dermoscopy is transillumination technique

(TLM) which provides the better clarity of the image by directing the light on the skin in a manner so that back-scattered light illuminates the skin lesion. The device used for this method is called nevoscope [2, 15, 16].

Therefore, dermoscopy is referred to all techniques that provide the visualization of PSL by using surface microscopy [comp. analysis of pigmented skin].

In simple ELM, the diagnosis accuracy could be extended up to a certain limit. To further improve the clarity of the acquired image, digital dermoscopy analysis and D-ELM have been developed [17, 18]. But this digital evaluation of PSL requires sophisticated image processing software to help physicians in diagnosis process.

2.2 Preprocessing

In CAD system, the major challenge is to differentiate or detect lesion from the healthy skin as transition between the lesion and the surrounding skin is smooth. In digital dermoscopy, an image is taken in digital format to obtain clear image but it could be possible that image might have various artifacts such as hair, air bubbles, ruler markings, specular reflections, interlaced video field misalignment. These artifacts further degrade the quality of the acquired image and increase the chances of inaccurate detection of the lesion because there is very much similarity between the lesion and surrounding skin [19].

Therefore, preprocessing is the first step to improve the quality of the acquired images by removing the noise (unwanted signals) or artifacts such as hairs, bubbles.

If image preprocessing is not performed properly, then it might cause the inaccurate classification of an image [19] as well as increases the computation time.

There are various image preprocessing techniques for each artifact type. To remove hairs in dermoscopic image, dull Razor is used [20, 21], Kiani and Sharfat [21], Hoshyar et al. [22] improved it further to remove light-colored hairs. We can also apply various filters such as adaptive median filter, median filter, Gaussian filter, mean filter, Wiener filter, and adaptive Wiener filter for removing various noises such as Gaussian noise, salt-and-pepper noise, Poisson noise, and speckle noise [23].

In addition to further improve the image quality, some image enhancement methods are also used. In these methods, most important is color correction or calibration.

This method involves in recovery of real colors of a photographed lesion which is taken from low-cost digital camera [21, 24, 25]. Other approaches are illumination correction, contrast enhancement, and edge enhancement. To improve the contrast various methods like histogram stretching, histogram equalization, FFT, homomorphic filtering [26] could be used.

2.3 Segmentation

Image segmentation is the most important techniques after the preprocessing step. It is a process of continuously dividing an image into multiple parts until the region of interest (ROI) related to particular application has been detected. This step determines the eventual success or failure of the image analysis. There is a rare chance of failure of an efficient segmentation method. Here we have briefly provided an overview of various segmentation algorithms which are being used for dermoscopic image analysis as provided in

Method used	Advantages and disadvantages
Threshold-based segmentation It is the simplest image segmentation method. In this method, a single threshold value t is considered and the pixel located at coordinates(x, y) with grayscale value f is assigned to class 1 if $f \leq t$ or else the given pixel is allocated to class 2 The selection of the threshold depends on the value at which ROI becomes identified correctly. This method converts a grayscale image into binary image. Here are some algorithms of thresholding: (Otsu's method, local and global thresholding, maximum entropy, histogram based, etc.) [2, 19, 27–29]. Among all these segmentation algorithm, it has been concluded that Otsu algorithm gives optimum result	Advantages: • Computationally inexpensive • Fast and simple for implementation Disadvantages • Extremely susceptible to noise • The choice of correct threshold value is critical because incorrect choice may result in over- or under-segmentation
Region-based segmentation In this segmentation, the main concept is to classify or categorize a particular image into number of categories or regions. So we need to assign a class or category to which each pixel in the image belongs Region growing is a simple region-based segmentation method that merges or groups pixels by examining neighbor pixel of initial seed point and determine whether that pixel should be added to the group or not Region splitting and merging is another region-based segmentation method which divides an image into uniform regions. This algorithm starts by assuming that the entire image is a single region. Then calculate the homogeneity criteria if it is false, then divide the region into four smaller regions, and repeat this splitting until no further splitting is required [30]. Now, these small square regions are merged to form larger irregular regions. This process ends when no further merges are possible Some other famous algorithms for region-based segmentation are: (seeded region growing, watershed segmentation, etc.) [19, 27–29]	Advantages: • Gives better result in comparison with other segmentation methods • Proper selection of seed gives accurate result than any other methods Disadvantages: • Computationally expensive • Selection of noisy seed by user leads to flawed segmentation

Method used	Advantages and disadvantages
Fuzzy C-means method [19, 27–29]. It is one of the most popular unsupervised segmentation techniques. It is a method which categorizes one piece of data into two or more clusters. This method was developed by Dunn in 1973 and later enhanced by Bezdek in 1981. It is widely used in medical image segmentation like brain tumor detection, MRI.	Advantages: • FCM unsupervised and converge very well Disadvantages: • Sensitive to noise. Determination of fuzzy membership is not very easy
Edge detection approach [31, 32] It is a process of locating an edge in the selected image [33]. The edge representation of the image not only consists of significant information but also reduces the amount of data to be processed; therefore, this method is used by advance computer vision algorithms like medical image processing, biometric. The following steps are used for edge-based segmentation: Transform the original image into edge image which consists of all edges Now process the image to identify object boundaries Transform the result in simple segmented image [34] The edge detection method could be categorized into two classes such as Gradient and Laplacian The most frequently used edge detection techniques are Roberts edge detection, Sobel, Prewitt, Canny, Log edge detection, Marr–Hilderth edge detection [35]	Advantages: • This method is suitable for images which have good contrast among regions Disadvantages: • This method is not suitable for the images which have too many edges or ill-defined • It is less resistant to noise as compared to techniques
Neural network approaches [19, 27–29]. In neural network segmentation, an image is processed using ANN or a set of neural networks. In this method, small area of an image is given as input, and after performing the decision-making process, it marks the area of the input image into lesion or healthy tissues for medical image processing such as brain tumor, MRI.	Advantages: • There is no requirement to develop complex programs • This method uses the parallel processing capability of neural networks Disadvantages: • Training time is long; • Initialization may affect the result; • Overtraining should be avoided

2.4 Feature Extraction

In computer-aided detection of melanoma, features of skin image play an important role to determine whether it is benign or malignant melanoma. In the initial stage, both benign and malignant melanoma appear very much similar [2]. All these features are categorized as internal and external features. Internal features such as blue-white veil, cancerous area of skin, irregular streaks are extracted from dermoscopic image. External features are age of a person, family history related to cancer, itching on the skin, etc. [2]. Basically, which features should be extracted depend on the diagnosis method used for identifying melanoma. For example, asymmetry, border, color, and diameter are the features of the ABCD rule for melanoma skin cancer detection [21]. Therefore, for an effective computer-aided detection system, it is required to extract only those features which can be understood by a computer.

There are some conventional clinical diagnosis methods such as ABCD rule, Menzies method, and seven-point checklist. Among all these conventional methods, ABCD rule of dermoscopy works as the most effective method for many computerized melanoma detection systems due to its implementation simplicity [36]. After pigmented skin lesion was determined, the features extracted from affected skin lesion and its surrounded normal skin area are divided into color based, border based, symmetry and texture based [37]. Rahil et al. [36] proposed an effective feature extraction method which combines texture and border features extracted from pigmented skin lesion. Abdul et al. [19] used a graylevel co-occurrence matrix (GLCM) in which contrast, correlation, homogeneity, and energy features are used with three additional features related to geometry of the image. Therefore, feature extraction creates new features from functions of the original features.

2.5 Feature Selection

In machine learning, feature selection is the process of selecting a subset of relevant features (variables, predictors) for use in model construction. Basically, this step is done after feature extraction and before classification step. It is a technique which reduces dimensions widely used for efficient data mining and knowledge discovery. But it is required to ensure that important information should be preserved during dimensionality reduction.

For developing the method of feature selection, different researchers have taken different approaches [11]. A very useful review on feature descriptors was given by Maglogiannis and Doukas [4] in 2009. Others methods are leave-one-out (LOO), sequential floating forward selection (SFFS), and sequential floating backward selection (SFBS), considered for this purpose. Ganster et al. [38] used SBFS and SFFS with subset size between 10 and 15 features. But the performance of this method degrades for more than 20 features.

According to the study, melanoma recognition methods perform well for small subsets followed by a slight increase up to medium-sized subsets [12], while performance of melanoma identification decreases for larger subsets. This thing was confirmed by Ruiz et al. [14] using SBFS and SFFS evaluation and discovered that minimum error rate was achieved using subset of six features and a significant increase in classification error rate is observed for subset of more than 20 features.

Yashar et al. [39] defined a particle swarm optimization–support vector machines (PSO–SVM) feature selection method that reduced the number of features effectively and chosen the best subset for their purpose. PSO computationally is less expensive than other methods.

2.6 Classification

Lesion classification is the final step in computerized analysis of melanoma skin cancer detection. This step is used to decide whether the skin lesion is malignant or benign. To perform the classification task, the existing systems use different classification methods to the features that were extracted in prior stage. There exist some different classifiers such as logistic regression, discriminant analysis, artificial neural network, K-nearest neighborhood, support vector machine, decision trees, and support vector machine (SVM) [15]. The classification performance is evaluated w.r.t. classification accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), likelihood ratio, etc.

Year	Classification method [Source]	Sensitivity (%)	Specificity (%)	Accuracy (%)
2011	kNN classifier [40] Ramlakhan et al. [40] used the OpenCV kNN classifier to categorize skin lesion as benign or malignant. In this classifier, learning process is based on training instances. The class to which test sample belongs is based on the majority of its k-most similar instances of training set	60.7	80.5	66.7
2012	Multilayer perceptron [41] Mariam A. Sheha et al. used the MLP which is a three-layer feedforward neural network. It uses two techniques for classification which are automatic MLP and traditional MLP. In first one, given data are categorized into three subsets which are training, validation, and testing to perform classification, while in second one, complete data are used for training	70.5	87.5	76
		92.3	91.6	92
2015	SVM classifier with RelisfF filter-based method [42] Luis Rosado et al. [42] used the SVM classifier with ReliefF filter by using the features of asymmetry criterion, border, and color criterion	86	73	76.7
2015	The classification is performed by the SVM in two stages. In the first, classifier is constructed in training stage, and then classifier performance is done by using tests which are independent of training set [43]	95	83.33	90.63

3 Conclusion

Early detection of melanoma skin cancer plays an important role to decrease its death rate drastically. This paper has discussed all the phases of computer-aided melanoma skin cancer detection method in detail. From the review presented in this paper, it has been concluded that there are many algorithms for melanoma skin cancer detection starting from the painful laboratory testing to the computer-aided detection system, and among these algorithms, SVM classification gives more accuracy and sensitivity than kNN classifier and multilayer perceptron. Therefore in future to eliminate the drawbacks of these algorithms such as pain or problem that a patient feels during laboratory testing and to increase the accuracy of melanoma detection, the computer-aided diagnosis (CAD) by using some advanced algorithms like deep learning, machine learning are used.

References

1. Lee H, Chen YPP (2015) Image based computer aided diagnosis system for cancer detection. Expert Syst Appl 42:5356–5365
2. Mehta P, Shah B (2016) Review on techniques and steps of computer aided skin cancer diagnosis. In: International conference on computational modeling and security, CMS 2016
3. Cancer scenario in India: as per the statistics. Posted on 2/11/2014 by Daily excelsior
4. Geller AC, Swetter SM, Brooks K, Demierre M, Yaroch AL (2007) Screening, early detection, and trends for melanoma: current status (2000–2006) and future directions. J Am Acad Dermatol 57:555–572
5. Maglogiannis I, Doukas CN (2009) Overview of advanced computer vision systems for skin lesions characterization. IEEE Trans Inf Technol Biomed 13(5):721–733
6. Garnavi R, Aldeen M, Bailey J (2012) Computer-aided diagnosis of melanoma using border and wavelet-based texture analysis. IEEE Tran Inf Technol Biomed 16(6):1239–1252
7. Vestergaard ME, Menzies SW (2008) Automated diagnostic instruments for cutaneous melanoma, pp 1085–5629. https://doi.org/10.1016/j.sder.2008.01.001
8. Rigel DS, Russak J, Friedman R (2010) The evolution of melanoma diagnosis: 25 years beyond the ABCDs. Wiley Online Library 60(5):301–316
9. Nakariyakul S, Casasent DP (2008) Improved forward floating selection algorithm for feature subset selection. In: International conference on wavelet analysis and pattern recognition, 30–31 Aug 2008, vol 2, pp 793–798
10. Madooei A, Drew MS (2013) A colour palette for automatic detection of blue-white veil. IEEE 2013
11. Celebi ME, Aslandogan YA (2004) Content-based image retrieval incorporating models of human perception. In: Proceedings of international conference on information technology: coding and computing (ITCC), vol 2, IEEE Computer Society Press, Los Alamitos, CA, p 2415
12. Zhou H, Chen M, Zou L, Gass R, Ferris L, Drogowski L, Rehg JM (2008) Spatially constrained segmentation of dermoscopy images. In: 5th IEEE international symposium on biomedical imaging, pp 800–803
13. Liu H, Yu L (2005) Toward integrating feature selection algorithms for classification and clustering. IEEE Trans Knowl Data Eng 17:491–502
14. Ruiz D, Berenguer V, Soriano A, SáNchez B (2011) A decision support system for the diagnosis of melanoma: a comparative approach. Expert Syst Appl 38(12):15217–15223

15. Sumithra R, Suhil M, Guru DS (2015) Segmentation and classification of skin lesions for disease diagnosis. In: International conference on advanced computing technologies and applications (ICACTA-2015). Procedia Comput Sci 45:76–85
16. Celebi ME, Kingravi HA, Uddin B, Iyatomi H, Aslandogan YA, Stoecker WV, Moss RH (2007) A methodological approach to the classification of dermoscopy images. Comput Med Imaging Graph 31(6):362–373
17. Sasikala M, Kumaravel N (2005) Comparison of feature selection techniques for detection of malignant tumor in brain images. In: IEEE Indicon 2005 conference, Chennai, India, 11–1 3 Dec 2005
18. Nakariyakul S, Casasent DP (2008) Improved forward floating selection algorithm for feature subset selection. In: Proceedings of the 2008 international conference on wavelet analysis and pattern recognition, Hong Kong, 30–31 Aug 2008
19. Jaleel JA, Salim S, Aswin RB (2013) Computer aided detection of skin cancer. In: International conference on circuits, power and computing technologies (ICCPCT), IEEE 2013
20. Lee T, Ng V, Gallagher R, Coldman A, McLean D (1997) DullRazor: a software approach to hair removal from images. Comput Biol Med 27(6):533–543
21. Korotkov K, Garcia R (2012) Computerized analysis of pigmented skin lesions: a review. Artif Intell Med 56(2):69–90
22. Kiani K, Sharafat AR (2011) E-shaver: an improved DullRazor® for digitally removing dark and light-colored hairs in dermoscopic images. Comput Biol Med 41(3):139–145
23. Hoshyar AN, Al-Jumaily A, Hoshyar AN (2014) Comparing the performance of various filters on skin cancer images. In: International conference on robot PRIDE 2013–2014, Published by Elsevier
24. Quintana J, Garcia R, Neumann L (2011) A novel method for color correction in epiluminescence microscopy. Comput Med Imaging Graph 35(7–8):646–652
25. Wighton P, Lee TK, Lui H, McLean D, Atkins MS (2011) Chromatic aberration correction: an enhancement to the calibration of low-cost digital dermoscopes. Skin Res Technol 17(3):339–347
26. Maglogiannis I, Zafiropoulos E, Kyranoudis C (2006) Intelligent segmentation and classification of pigmented skin lesions in dermatological images. https://doi.org/10.1007/11752912_23. In: DBLP conference: advances in artificial intelligence, proceedings of 4th Helenic conference on AI, SETN 2006, Heraklion, Crete, Greece, 18–20 May 2006
27. Ebrahimi SM, Pourghassem H, Ashourian M (2010) Lesion detection in dermoscopy images using Sarsa reinforcement algorithm. In: 17th Iranian conference IEEE biomedical engineering (ICBME)
28. Ali AR, Couceiro MS, Hassenian AE (2014) Melanoma detection using fuzzy C-means clustering coupled with mathematical morphology. In: 14th international conference IEEE hybrid intelligent systems (HIS)
29. Sookpotharom S (2009) Border detection of skin lesion images based on fuzzy C-means thresholding. In: 3rd international conference IEEE genetic and evolutionary computing. WGEC'09
30. Splitting and Merging, [Online]. Available at http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL_COPIES/MARBLE/medium/segment/split.htm
31. Delgado D, Butakoff C, Ersboll BK, Stoecker WV (2008) Independent histogram pursuit for segmentation of skin lesions. IEEE Trans Biomed Eng 55:157–161
32. Zhou H, Chen M, Zou L, Gass R, Ferris L, Drogowski L, Rehg JM (2008) Spatially constrained segmentation of dermoscopy images. In: 5th IEEE international symposium on biomedical imaging, pp 800–803
33. Chapter 3. Review of image segmentation methods. Available at http://shodhganga.inflibnet.ac.in/bitstream/10603/9107/8/08_chapter3.pdf
34. Chapter 10. http://www.cs.uu.nl/docs/vakken/ibv/reader/chapter10.pdf
35. Muthukrishnan R, Radha M (2011) Edge detection techniques for image segmentation. Int J Compu Sci Inf Technol 3(6)
36. Garnavi R, Aldeen M, Bailey J (2012) Computer-aided diagnosis of melanoma using border and wavelet-based texture analysis. IEEE Trans Inf Technol Biomed 16(6):1239–1252

37. Ikuma Y, Iyatomi H (2013) Production of the grounds for melanoma classification using adaptive fuzzy inference neural network. In: IEEE international conference systems, man, and cybernetics (SMC)
38. Ganster H, Pinz P, Rohrer R, Wildling E, Binder M, Kittler H (2001) Automated melanoma recognition. IEEE Trans Med Imaging 20(3)
39. Maali Y, Al-Jumaily A (2012) Hierarchical parallel PSO-SVM Based subject-independent sleep apnea classification. ICONIP 2012, Part IV, LNCS 7666, pp 500–507
40. Ramlakhan K, Shang Y (2011) A mobile automated skin lesion classification system. In: Proceedings of the 23rd IEEE international conference on tools with artificial intelligence (ICTAI'11), pp 138–141
41. Mabrouk MS, Sheha MA, Sharawy A (2012) Automatic detection of melanoma skin cancer using texture analysis. Int J Comput Appl 42(20):22–26
42. Rosado L, João M, Vasconcelos M, Ferreira M (2015) Pigmented skin lesion computerized analysis via mobile devices. SCCG 2015, Smolenice, Slovakia, ACM, 22–24 April 2015. http://dx.doi.org/10.1145/2788539.2788553
43. Correa DN, Paniagua LR, Noguera JL, Pinto-Roa DP, Toledo LA (2015) Computerized diagnosis of melanocytic lesions based on the ABCD method. In: Computing conference (CLEI), 2015 Latin American, 19–23 Oct 2015, pp 1–12