MELANOMA SKIN CANCER DETECTION USING IMAGE PROCESSING: A REVIEW

Authors: Ishpinder Kaur, Laxmi Likhitha Musriff, Diwen Shi

Authors UW-IDs: 20911296, 20923293, 20743096

ABSTRACT

Skin cancer is a broad category of cancers that includes melanoma, the most aggressive and dangerous skin cancer. As with most diseases, it is better to diagnose melanoma in early stages as patient outcomes worsen with time. Computer vision today plays a key role in many fields and similarly it can be applied in medical image diagnosis. The use of deep learning approaches to implement an automatic lesion classification system aids doctors in detecting malignant melanoma and correctly distinguishing it from benign pigmented lesions and other cancers. In this paper we present a computer sided method of melanoma diagnosis using image processing with convolutional neural networks (CNN). The skin image is the input to the process and then we apply various image processing techniques in which use of convolutional neural networks is a part to extract the features of the image and thereby detect whether the image is of normal skin or melanoma cancer lesion.

Index Terms— *Melanoma, Lesion, Convolutional neural network, Deep learning.*

1. INTRODUCTION

Cancer is one of the most prevalent life-threatening diseases for humans. Cancer is caused by uncontrollable growth of body cells, this rapid growth spreading to other body parts and causing the formation of tumors that are made up of these cancerous cells. Skin cancer is one of the most common types of cancer. The three primary kinds of skin cancer are squamous cell carcinoma, basal cell carcinoma, and melanoma. Melanoma is far less prevalent than the other cancers, but it is far more likely to invade adjacent tissue and spread to other parts of the body. Melanoma is the most common type of skin cancer that leads to mortality. Melanoma and other skin cancers are being studied by researchers to learn more about how to treat them, and progress has been made in treating those who have melanoma that has spread throughout their body [1]. If detected and treated early on, melanoma is easier to treat and cure. If detected in later stages, melanoma can spread deeper into the skin and to other regions of the body. Its spread to other sections of the body, which is more difficult to treat, results in worse treatment outcomes [2]. One of the main causes of melanoma is excessive exposure of skin to ultraviolet radiation, but other causes such as genetic factors play a role.

This paper focusses on diagnosis of melanoma using image processing. Use of deep learning convolutional neural network shows potential for melanoma diagnosis [3]. We review the convolud8fferent machine learning algorithms including traditional classifies, ANN, deep learning CNN in melanoma diagnosis by employing 5 key steps, and classifying into different types of skin cancer

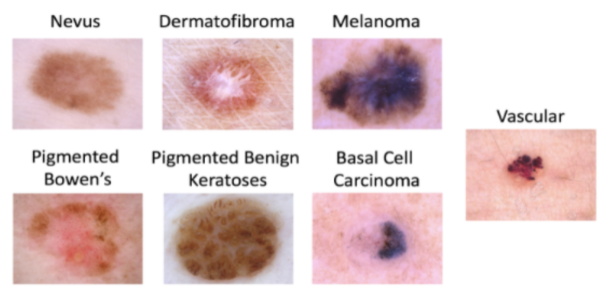

Figure 1.1. Different types of skin cancer

2. METHODS OF SKIN CANCER DETECTION

The process of skin cancer detection has 5 phases, namely, image acquisition, image pre-processing, image segmentation, feature extraction of image and classification [4]. The following figure represents the process of cancer detection with different techniques at each phase. The highlighted techniques were analyzed and found suitable and accurate for future work.

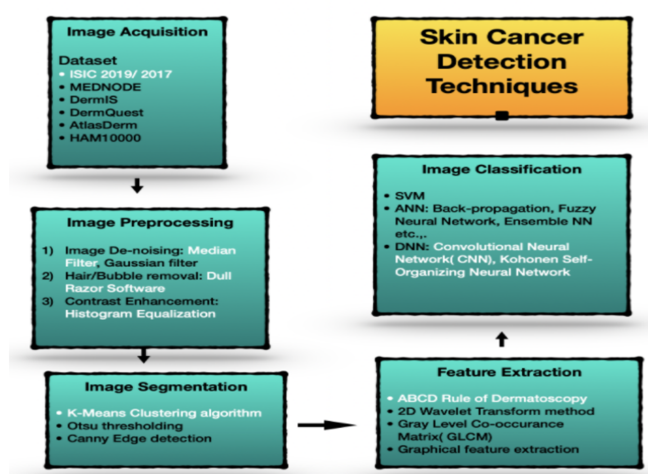

Figure 2.1. Different Skin Cancer Detection techniques

3.1 IMAGE ACQUISITION

The images required for cancer diagnosis process can be either obtained from google sites or raw camera, among which one depicts cancer and other does not. Many researchers used normal mobile images and then preprocessed it accordingly. These images were then compared and classified with dataset.

3.1.1. DATASET

The training, testing and validation data is required to train ant classifier for accurately diagnosing and classifying the appropriate cancer or non-cancer forms of image. There are many datasets available generated by medical departments, which includes DermIS, AtlasDerm, HAM10000, etc.,[17].

Mahbod et al. [17] evaluated their resulted image on ISIC 2017 dataset, an extended version of ISIC2016 data formed by merging various datasets, which was released in "International Symposium on Biomedical Imaging" (ISBI) challenge 2016, by the International Skin Imaging Collaboration.

Nasr-Esfahani et al. [18] used 170 color images of MEDNODE dataset, among which 70 represent melanoma and the remaining 100 represent naevus images, and converted it into total 6120 augmented images. MEDNODE is a digital image archive and was generated by the Department of Dermatology of the University Medical Center Groningen (UMCG).

3.2 IMAGE PREPROCESSING

Clean data is an essential component for successfully extracting features and detecting the presence of cancer cells. Therefore, data should be free from any kind of distortions, noise, air bubbles or hairs. Ansari UB et al. [5] suggested three steps for preprocessing data, conversion of RGB to grayscale image, image de-noising, and image enhancement. Conversion to grayscale is for time efficiency and to reduce complexity. Sanjay J et al. [6], described various techniques to preprocess the dermatoscopic images, using image resolution, equalizing illumination, and color range normalization. Further, Gaussian and median filters can be used for image de-noising such as in Jana et al. [18]. Jana E et al.[18] used non-linear median, replacing the analyzed pixel with the mean of its neighboring pixels and even preserved image edges. Mane S et al. [19] proposed using a Gaussian filter to blur the image and reduce its contrast for image de-noising. For removal of hairs, Hasan M et al. [20] implemented Dull Razor Software which located hairs using its intensity and thickness and replaced it using adaptive median filter. Finally, Hoshyar AN et al. [21], in their studies achieved contrast enhancement by gray scale conversion, replacement of pixels by incrementing 1 unit of contrast followed by adaptive histogram and histogram equalization for enhancement.

3.3. IMAGE SEGMENTATION

Image segmentation is dividing an image's pixels into various categories in accordance with individual pixel properties in the image such that pixels in each category have similar characteristics while distinctive characteristics exist between categories. Agarwal et al. [7] used an iterative and unsupervised K-means clustering algorithm to distinguish regions of interest from the background by randomly selecting centroids and forming k-clusters having similar characteristics. However, Anitha J et al. [8] segmented image using otsu thresholding, where the focused region is separated by comparing pixels against a threshold value and changing them to 0 or maximum. Further, for edge detection, Oliveira RB et al [9] implemented Canny edge detection approach where the edge gradient is obtained using a Sobel kernel and all non-maximum pixels are removed, which is then followed by applying hysteresis thresholding for obtaining the edges of the interested region.

3.4. FEATURE EXTRTACTION

The next step is extracting useful information or characteristics that can be fed as input to categorize the specific data. For instance, melanoma skin lesions have color variation and are irregular in shape whereas benign lesions are circular and have uniform color. Different approaches have been implemented to retrieve this data.

Thanh DNH et al [10] used the "ABCD" rule of Dermatoscopy with four parameters to calculate TDS (Total Dermatoscopy Score): A-Asymmetry, B-Border, C-Color, D-Diameter.

Formula for TDS:
$TDS = wA + xB + yC + zD$

Where w, x, y, z represents weight factors for Asymmetry, Border, Color and Diameter, respectively.

Abdul Jaleel J et al [11] extracted Mean, Mean Absolute Deviation, Standard deviation, L1 Norm, and L2 Norm with a 2D Wavelet Transform method. It involved 2 step decomposition using 2D wavelet packet and biorthogonal wavelets where the resultant image provided required details of dimensions of focused region in the image.

Abdul Jaleel J et al [11] took another approach and retrieved Entropy, Contrast, Cluster Prominence, Homogeneity, Correlation, Dissimilarity, Energy of image using Gray Level Co-occurrence Matrix (GLCM). In this, GCLM of gray scale image was created that was the frequency of an intensity pixel in particular intensity range, which further lead to reduction of intensity values from 256 to 8.

Shivangi J et al [12], using graphical feature extraction methodology, relied on the graphical structure and location dimensions of image to extract meaningful information such as perimeter, area, diameter circulatory and irregular indexes.

3.5. IMAGE CLASSIFICATION

This is the final step used to classify the data in two or more categories. It involves learning, training, and testing of data by identifying a specific pattern and differentiation line to distinguish between the provided target values. There are numerous techniques, such as ranging from artificial neural networks to deep neural networks, implemented by researchers that have turned out to be accurate and efficient enough to detect the presence of skin cancer.

Alquran H et al [13] in their studies about skin cancer detection, classified the data using a supervised non-linear machine leaning algorithm called Support Vector Machine. Here binary classification was achieved based on n-hyperplanes (n defines number of classes) and using kernel function (for providing the required formatted input). They collected, preprocessed, and segmented the data, and extracted the features using GLCM and ABCD rule. Also, they selected the most expressive features using Principal Component Analysis (PCA) and resulted in classification accuracy of 92.1% with SVM.

Murugan A et al [14] implemented and compared the results of three classification algorithms, namely, SVM, KNN and Random Forest. Along with different classification methods, this study also showed the best combination with feature extraction techniques such as ABCD rule, GLCM and shape feature. They observed that SVM combined with ABCD rule provided the best and most accurate result.

Xie et al. [24] suggested a classification strategy combining backpropagation and fuzzy neural network technique using Ensemble NN. They optimally selected features using PCA components after its pre-processing, segmentation and extraction and resulted into accuracy of 91.1% which is comparatively better than other classifiers such as SVM or KNN.

Masood et al. [23] used an ANN-based skin cancer diagnostic technique, known as backpropagation feed-forward ANN, where they extracted features using ABCD rule of lesions and kept the threshold value of 6 mm for melanoma detection. Melanoma moles will usually be greater than 6 mm in diameter, so the threshold value of diameter for melanoma detection can be set to 6 mm. The proposed system successfully classified the images into the categories of common mole, uncommon mole, or melanoma mole, with accuracy of 97.1%.

The resulting deep learning techniques are considered among the best for solving complex and large datasets. One method is the Kohonen self-organizing map which consists of only two layers. Said et al. [25] suggested a system deployed with a median filter, extracted statistical features and KNN, categorized data as cancerous or noncancerous with accuracy of 98.3%.

Pomponiu V et al [15] suggested another deep learning approach with a Convolutional Neural Network for classifying the image data. They used image dataset from DermIS and DermQuest image library, containing 217 benign and 182 malignant images, augmented to total of 10,000 images. CNN architecture involved five convolutional layers, pooling layers and three fully connected layers. Batch Normalization and then Activation function is applied. It all gave two-class classification of accuracy 93.64%.

4. PERFORMANCE ANALYSIS

The performance of every method among previously mentioned series of steps is evaluated based on three metrics.

Sensitivity: It determines the correctly computed positive ratio; the results indicate negative as non-disease; the outcome results indicate positive as disease. Formula for Sensitivity is as following:

����������������������� = ����/(����+����) ∗100%

Specificity: It determines the correctly computed negative ratio; the results indicate negative as non-disease. Formula for Specificity is as following:

����������������������� = ����/(����+����) ∗100%

Accuracy: Accuracy determine the correctness of actual and predicted output. Formula for Accuracy is as following

���������������� = (����+����)/(����+����+����+����) ∗100%

Where,
TN is True Negative that represents correctly identified negative case.
TP is True Positives that represents correctly identified positive case.
FN is False Negatives that represents incorrectly identified positive case.
FP is False Positive that represents incorrectly identified negative case.

The following table describes performance analysis of various methods deployed for lesion detection.

References	Categories	Classifier and Training Algorithm	Dataset	Feature Extraction	Performance
[10]		SVM		GLCM and ABCD rule with PCA	Accuracy (92.1)
[21]	Malignant/ Benign	ANN Ensemble NN with BPN and fuzzy neural network	Caucasian race and xanthous-race datasets	Self-generating neural network	Accuracy (94.17) Sensitivity (95), specificity (93.75)
[19]	Common mole/ Non-common mole/ Melanoma	Feed-forward BPNN	200 dermoscopic images	ABCD Rule of Dermatoscopy	Accuracy (97.51)
[22]	Cancerous/ Non-cancerous	Modified Kohonen self organizing neural network	500 lesion images	Statistical feature extraction with Otsu method of thresholding segmentation	Accuracy (98.3)
[12]		CNN	DermIS and DermQuest image library		Accuracy 93.64%.
[10]		SVM		GLCM and ABCD rule with PCA	Accuracy 92.1%.

Table 3.1. Performance Evaluation of different classification algorithms

4. DISCUSSION

These techniques proposed by several researchers provided a great range of techniques for diagnosing skin cancer, which varies from step to step. The combination of different algorithms provided different results. Therefore, the hardest part is to find the best combination. ISIC2019 dataset will be deployed for future work as it is the latest and largest dataset, in which training data contains 25,331 images and test dataset contains 8,239 images. The images are classified into 8 distinct categories, namely melanoma, melanocytic-nevus, BCC, AK, benign keratosis, dermatofibroma, vascular lesion, and SCC. It also contains metadata that includes input features such as age, sex, and area [22].

As per the observation, two images will be obtained by raw camera which will be pre-processed through series of processes such as gray scale conversion, median filter for image de-noising, Dull Razor software for hair removal from image and contrast enhancement using histogram equalization. Following the studies of Agarwal *et al* [7], K-Means Clustering will be used for image segmentation as it scales to large datasets and adapts easily to new samples. Moreover, from the results of Murugan A et al [14], the best feature extraction method was the “ABCD” rule which provided better accuracy than other methods, even if applied with different classifiers. The most effective classification technique in the previous observations, turns out to be deep learning, among which CNN is implemented by many researchers with their pretrained models and achieved better performance of above 90% accuracy in maximum cases. Moreover, from the performance analysis table, Kohonen self-organizing networks gave the best performance with accuracy of 98%. Therefore, in proposed model, CNN and Kohonen SOM will be implemented and compared. The performance will be evaluated on three metrics: sensitivity, specificity and accuracy.

5. APPLICATION

Melanoma is one of the most common cancers diagnosed in the United States, with 100000 cases diagnosed on an annual basis [13]. Using image processing to detect melanoma can broaden early detection efforts and result in improved health care outcomes. In particular, the ability to distinguish with high accuracy melanoma from non-melanoma skin cancers, would be beneficial to melanoma treatments. Melanoma skin cancers only make up approximately 1% of all skin cancers but are much more lethal than basal and squamous skin cancers which have a significantly lower mortality rate [17].

The primary applications of melanoma detection based on image processing come from the ability to successfully pre-screen skin cancer patients and determine with high accuracy the nature of the patient’s affliction and develop the appropriate treatment methodology, particularly when the availability of skin cancer specialists is low. Additionally, such techniques can aid skin cancer specialists in improving the accuracy of patient diagnoses. In many impoverished regions of the world, a lack of skin cancer specialists would make image-processing based melanoma detection a vital aid in improving health care outcomes for skin cancer sufferers

6. FUTURE WORK

Melanoma detection using image processing is a field that can be further explored to provide more robust and less error-prone detection. Using deep learning techniques, models are trained to detect and evaluate the nature of skin lesions. Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Kohonen Self-Organizing Neural Networks (KNN), and Generative Adversial Networks (GAN) have been applied to melanoma detection, with varying success [22]. With improved and more abundant training data as well as more processing power better neural networks with higher accuracy can be developed. Further developments in pre-processing steps can improve the detection rate of deep learning techniques. As an example, enhanced techniques for image segmentation can lead to better isolation of the skin lesion in processed images. Image segmentation is the most critical stage in pre-processing, as it isolates the melanoma from the rest of the skin.

Further areas of study include making image-based detection techniques applicable to a broader set of cases. As melanoma primarily affects patients of lighter skin, little data exists for developing neural networks tailored to assessing skin lesions in darker skinned individuals. Additionally, the ability of the developed neural networks in evaluating lesions of abnormal size, particularly those that are in early stages and thus would usually be small, is limited. The inadequacies of existing datasets are further highlighted by the lack of training data for uncommon skin cancers, and for the elderly, as most standard datasets consist of images of youth. Furthermore, due to different genetic influences on melanoma likelihoods, combining image processing techniques with models using these genetic factors can lead to higher accuracy in detection.

7. CONCLUSION

Using deep learning, it is possible to classify images of skin lesions to predict cases of melanoma. Various models have been applied to solve this task and have had varying degrees of success. The key metrics to evaluate the efficacy of a model are sensitivity, specifity, and accuracy. Based on these metrics, the most promising results came from CNN, which will be used with resnet50 and inceptionV3, and SVM classifier.

8. REFERENCES

[1] National Cancer Institute, Skin Cancer https://www.cancer.gov/types/skin/research

[2] Computer aided Melanoma skin cancer detection using Image Processing, ICCC 2015, Shivangi Jain, Vandana Jagtap, Nitin Pise

[3] Melanoma recognition by a deep learning convolutional neural network-Performance in different melanoma subtypes and localisations. https://pubmed.ncbi.nlm.nih.gov/31972395/

[4] Shetty A., Shah K., Reddy M., Sanghvi R., Save S., Patel Y. (2022) Skin Cancer Detection Using Image Processing: A Review. In: Gunjan V.K., Zurada J.M. (eds) Proceedings of the 2nd International Conference on Recent Trends in Machine Learning, IoT, Smart Cities and Applications. Lecture Notes in Networks and Systems, vol 237. Springer, Singapore. https://doi.org/10.1007/978-981-16-6407-6_11

[5] Ansari UB, Sarode T (2017) Skin cancer detection using image processing. Int Res J Eng Technol 4(4):2875–2881Google Scholar.

[6] Sanjay J, Mehran K, Vaishali G (2015) Skin cancer detection using digital image processing. Int J Sci Eng Res 3(6):138–140Google Scholar.

[7] Agarwal A, Issac A, Dutta MK, Riha K, Uher V (2017) Automated skin lesion segmentation using k-means clustering from digital dermoscopic images. In: 2017 40th international conference on telecommunications and signal processing (TSP). IEEE, pp 743–748Google Scholar

[8] Anitha J et al (2018) Identification of melanoma in dermoscopy images using image processing algorithms. In: 2018 international conference on control, power, communication and computing technologies (ICCPCCT). IEEE, pp 553–557Google Scholar

[9] Oliveira RB, Filho EM, Ma Z, Papa JP, Pereira AS, Tavares JMRS (2016) Computational methods for the image segmentation of pigmented skin lesions: a review. Comput Methods Progr Biomed 131:127–141CrossRefGoogle Scholar

[10] Thanh DNH, Surya Prasath VB, Hien NN et al (2019) Melanoma skin cancer detection method based on adaptive principal curvature, colour normalisation and feature extraction with the ABCD rule. J Digit Imaging 1–12

[11] Abdul Jaleel J, Salim S, Aswin RB (2012) Artificial neural network based detection of skin cancer. Int J Adv Res Electr Electron Instrum Eng 1(3)Google Scholar

[12] Shivangi J, Nitin P et al (2015) Computer aided melanoma skin cancer detection using image processing. Procedia Comput Sci 48:735–740CrossRefGoogle Scholar

[13] Alquran H, Qasmieh IA, Alqudah AM, Alhammouri S, Alawneh E, Abughazaleh A, Hasayen F (2017) The melanoma skin cancer detection and classification using support vector machine. In: 2017 IEEE Jordan conference on applied electrical engineering and computing technologies (AEECT). IEEE, pp 1–5Google Scholar

[14] Murugan A, Nair SAH, Sanal Kumar KP (2019) Detection of skin cancer using SVM, random forest and KNN classifiers. J Med Syst 43(8):269CrossRefGoogle Scholar

[15] Pomponiu V, Nejati H, Cheung NM (2016) DEEPMOLE: deep neural networks for skin mole lesion classification. IEEE ICIP, pp 2623–2627Google Scholar

[16] Howlader N, Noone AM, Krapcho M, et al. (eds). SEER Cancer Statistics Review, 1975–2018. National Cancer Institute, posted to the SEER website, April 2021. Last accessed April 19, 2021.

[17] Mahbod A., Schaefer G., Wang C., Ecker R., Ellinge I. Skin Lesion Classification Using Hybrid Deep Neural Networks; Proceedings of the ICASSP 2019–2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP); Brighton, UK. 12–17 May 2019; pp. 1229–1233. [CrossRef] [Google Scholar] [Ref list]

[18] Jana E, Subban R, Saraswathi S (2017) Research on skin cancer cell detection using image processing. In: 2017 IEEE international conference on computational intelligence and computing research (ICCIC). IEEE, pp 1–8Google Scholar

[19] Mane S, Shinde S (2018) A method for melanoma skin cancer detection using dermoscopy images. In: 2018 fourth international conference on computing communication control and automation (ICCUBEA). IEEE, pp 1–6Google Scholar

[20] Hasan M, Mohsin M, Chowdhury MKH. Automatic detection and analysis of melanoma skin cancer using dermoscopy imagesGoogle Scholar

[21] Hoshyar AN, Al-Jumaily A, Hoshyar AN (2014) The beneficial techniques in preprocessing step of skin cancer detection system comparing. Procedia Comput Sci 42:25–31CrossRefGoogle Scholar

[22] Dildar, M., Akram, S., Irfan, M., Khan, H. U., Ramzan, M., Mahmood, A. R., Alsaiari, S. A., Saeed, A., Alraddadi, M. O., & Mahnashi, M. H. (2021). Skin Cancer Detection: A Review Using

Deep Learning Techniques. *International journal of environmental research and public health*, *18*(10), 5479. https://doi.org/10.3390/ijerph18105479

[23] Masood A., Al-Jumaily A.A., Adnan T. Development of Automated Diagnostic System for Skin Cancer: Performance Analysis of Neural Network Learning Algorithms for Classification. In: Wermter S., Weber C., Duch W., Honkela T., Koprinkova-Hristova P., Magg S., Palm G., Villa A.E.P., editors. *Artificial Neural Networks and Machine Learning–ICANN 2014*. Volume 8681. Springer International Publishing; Cham, Switzerland: 2014. pp. 837–844. Lecture Notes in Computer Science. [CrossRef] [Google Scholar] [Ref list]

[24] Xie F., Fan H., Li Y., Jiang Z., Meng R., Bovik A. Melanoma Classification on Dermoscopy Images Using a Neural Network Ensemble Model. *IEEE Trans. Med. Imaging.* 2017;**36**:849–858. doi: 10.1109/TMI.2016.2633551. [PubMed] [CrossRef] [Google Scholar]

[25] Sajid P.M., Rajesh D.A. Performance Evaluation of Classifiers for Automatic Early Detection of Skin Cancer. *J. Adv. Res. Dyn. Control. Syst.* 2018;**10**:454–461. [Google Scholar] [Ref list]

2. RELATED WORK

Many researches have been done in context of medical imaging. Skin cancer has been one of the major topics since the evolution of technology. Apart from clinical perspective , there are different ways through which the skin cancer can be detected at earlier earlier just by its image. Various algorithms have been implemented using image processing , artificial neural networks and machine learning techniques which involves several steps including its preprocessing, segmentation, classification etc,.,

Sanjay J et al. [6], described various techniques to preprocess the dermatoscopic images, using image resolution, equalizing illumination, and color range normalization. Anitha J et al. [8] segmented image using otsu thresholding, where the focused region is separated by comparing pixels against a threshold value and changing them to 0 or maximum.

Alquran H et al [13] in their studies about skin cancer detection, classified the data using a supervised non-linear machine leaning algorithm called Support Vector Machine. They collected, preprocessed, and segmented the data, and extracted the features using GLCM and ABCD rule. Also, they selected the most expressive features using Principal Component Analysis (PCA) and resulted in classification accuracy of 92.1% with SVM.

Deep learning techniques are considered among the best for solving complex and large datasets. One method is the Kohonen self-organizing map which consists of only two layers. Said et al. [25] suggested a system deployed with a median filter, extracted statistical features and KNN, categorized data as cancerous or noncancerous with accuracy of 98.3%.

Pomponiu V et al [15] suggested another deep learning approach with a Convolutional Neural Network for classifying the image data. CNN architecture involved five convolutional layers, pooling layers and three fully connected layers. Batch Normalization and then Activation function is applied. It all gave two-class classification of accuracy 93.64%.

[6] Sanjay J, Mehran K, Vaishali G (2015) Skin cancer detection using digital image processing. Int J Sci Eng Res 3(6):138–140Google Scholar.

[8] Anitha J et al (2018) Identification of melanoma in dermoscopy images using image processing algorithms. In: 2018 international conference on control, power, communication and computing technologies (ICCPCCT). IEEE, pp 553–557Google Scholar

[13] Alquran H, Qasmieh IA, Alqudah AM, Alhammouri S, Alawneh E, Abughazaleh A, Hasayen F (2017) The melanoma skin cancer detection and classification using support vector machine. In: 2017 IEEE Jordan conference on applied electrical engineering and computing technologies (AEECT). IEEE, pp 1–5Google Scholar

[15] Pomponiu V, Nejati H, Cheung NM (2016) DEEPMOLE: deep neural networks for skin mole lesion classification. IEEE ICIP, pp 2623–2627Google Scholar

[25] Sajid P.M., Rajesh D.A. Performance Evaluation of Classifiers for Automatic Early Detection of Skin Cancer. *J. Adv. Res. Dyn. Control. Syst.* 2018;**10**:454–461. [Google Scholar] [Ref list]