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Detection and Classification of Skin Cancer using Back Propagated Artificial Neural Networks

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Abstract

Skin cancer is leading type of cancer which causes millions of deaths of human beings. Early identification and appropriate medications for new harmful skin malignancy cases are fundamental to guarantee a low death rate as the survival rate. Most of the related works are focusing on machine learning based algorithms, but they failed to provide the maximum accuracy and specificity. In the preprocessing stage, sharpening filter and smoothening filters are used to remove the noise along with enhancement operations. Then Ostu segmentation used for efficient detection the region of skin cancer. Finally, to archive the maximum efficiency of the system in this research, back propagated based artificial neural network (BP-ANN) developed for classification of skin cancer with the spatially gray level dependency matrix (SGLD) features. Thus, the research work can be effectively used for classification of Benign and Melanoma skin cancers. The simulation analysis shows that the proposed method shows better qualitative and quantitative analysis compared to the state of art approaches.

Keywords: dermoscopic images, skin cancer, texture features, color features, artificial neural networks.

1. Introduction

In recent days, skin cancer becomes most effected disease of all the types of cancers, and it is divided as benign and malignant. In these two types of melanomas is recognized as most deadliest one while comparing with the non-melanoma skin cancers [1-2]. It is known fact that melanoma effects more people year by year wise and early treatment are really important for the survival of the patients. Inspection of malignant melanoma needs well experienced dermatologists. These people use computer-assisted system early detection of melanoma [2]. More algorithms in deep learning models were used for diagnosis of skin cancer diagnosis. The accuracy rate of these models is the challenging task are still facing more challenges For achieving the high accuracy rate , models are to be overcome all the drawbacks of conventional models. This paper proposes a novel skin cancer detection approach. Many research papers have utilized image preprocessing for the identification of the melanoma at the initial times, which leads to effective treatment. In this way, it is necessary to broaden the span of such essential diagnostic care by arranging efficient frameworks for skin disease classification. Many research papers have utilized image preprocessing for the identification of the melanoma at the initial times, which leads to effective treatment. Proficient dermatologists have set up the ABCDEs [3-4] (Asymmetrical shape, Border irregularities, Color, Diameter, and Evolution) as the standardized descriptions to help with visualizing standard features of severe melanoma cases. One of the main challenges of classifying harmful skin injuries is due to sheer proportions of varieties over the different skin tones from people of different ethnic backgrounds. Recently, new accomplishments in the improvement of convolutional neural networks (CNN) [5] have permitted computers to beat dermatologists in skin cancer classification tasks. The following phase is to improve the accuracy of melanoma location further. Our strategy for early

diagnosis of skin lesion incorporates deep learning which helps us to enhance the accuracy of automated framework compared methods. In this work, we proposed our custom network for lesion classification.

The remainder of the paper is structured as: Literature survey conducted for the paper is covered in Section II. The Section III covers the proposed melanoma detection method while Section IV describes the environment in which experiments were conducted. In Section V, the results obtained from experimentation and observations are discussed. Finally, Section VI has the remarks that conclude the outcomes and draws inferences from the presented research work.

2. Literature Survey

There have been several systems developed for detecting melanoma as early as possible using the dermoscopic images. The dermatologist's asses the skin lesions using the "ABCD Rule". Based on this rule, many methods have been devised to classify dermoscopic images. Researchers have used extracted features and attempted to train diverse machine learning classifiers such as k-NN, SVM [6]. In [7] authors used very deep and machine learning residual networks to classify the images. In order to cope with degradation and over fitting, first machine learning is applied. Then, Radial basis function network (RBFN) is constructed so that skin lesion segmentation can be accurate. Then, this RBFN and deep residual networks that are used to classify the images are taken together to make a two-stage framework. In paper [8], images have been obtained by Epi luminescence Microscopy, which enhances the chances of early recognition of melanoma as malignant or benign. Binary mask is done, and shape and radiometric features are extracted to detect how malignant a lesion is. After that, the CNN classifier is deployed for classifying images as malignant or benign.

In paper [9], automatic border detection is performed and then shapes are extracted from these borders. Texture features are then computed using GLCM and Euclidean distance transform. Images are then classified using the SVM classifier. In Paper [10-11] uses fractional coefficients of cosine transformed skin image, which results in better space complexity and optimum performance in melanoma skin cancer identification. Ensemble of "SVM- AD Tree-Random Forest" gave the superior performance amongst all the classifiers used. Researchers are now focusing more on deep learning concepts as there have been significant advancements in deep learning. They are using the Neural Network Ensemble model, Very Deep Residual Networks, Artificial Neural Network. But they might have certain drawbacks like more processing power is required or more data is required which might get difficult to find as such datasets are not readily available. In paper [12-13], an overview of the most important implementations of melanoma detection is given and then comparison of the performance of numerous classifiers on the classification of dermoscopic images as benign or malignant is presented. All the existing approaches of Melanoma detection can be grouped in three streams as Melanoma detection with Machine Learning models using spatial domain features, melanoma detection with machine learning models using transform domain features and Melanoma detection using deep neural network models. The transform domain feature-based machine learning models of melanoma detection are time complexity wise heavier. The deep neural network models are more complex and do need heavy hardware as well as huge dataset for getting trained in melanoma detection. The spatial domain feature-based machine learning models are simple, faster and applicable to any size of skin dermoscopic images.

3. Proposed Method

The proposed research work majorly focusing on detection of following skin cancers such as Malignant – Melanoma, Malignant - Basal

Cell Carcinoma, Malignant - Basal Cell Carcinoma, Benign - Melanocytic Nevi, Benign - Melanocytic Nevi, Benign - Seborrheic Keratoses and Benign – Acrochordon. The detailed operation of the skin cancer detection and classification approach is presented in figure1.

3.1 database training and testing

Database is trained from the collected images of "International Skin Imaging Collaboration (ISIC)" Archive. ISIC is one of the biggest available collections of quality controlled dermoscopic images. The dataset consisted of 1000 benign and 1000 malignant images of melanoma. All the images are trained using the BP-ANN network model with SGLD features. And random unknown test sample is applied to the system for detection and classification respectively.

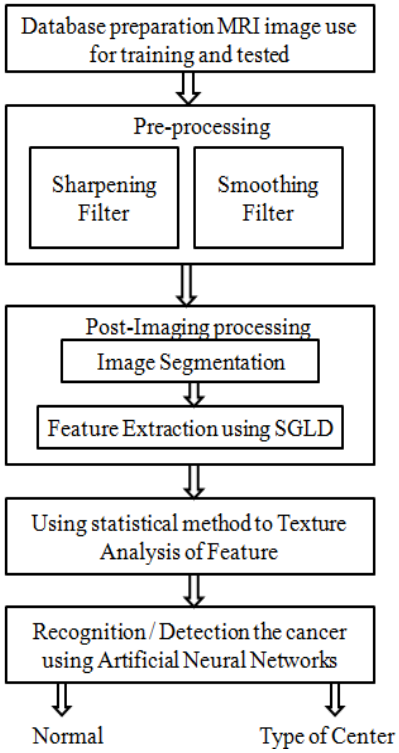


Fig 1: skin cancer detection and classification

3.2 Preprocessing:

The query image is acquired from image acquisition step, which includes background information and noise. Pre-processing is required and necessary to remove the above-mentioned unwanted portions. The pre-processing stage is mainly used for eliminating the irrelevant information such as unwanted background part, which includes noises, labels, tape and artifacts and the pectoral muscle from the skin image. The different types of noise occurred in the mammogram images are salt and pepper, Gaussian, and speckle and Poisson noise. When noise is occurred in an image, the pixels in the image show different intensity values instead of true pixel values. So by choosing the perfect method in the first stage of preprocessing, this noise removal operation will perform effectively. Reduction of the noise to a great extent and avoiding the introduction visual artifacts by the analysis of pixels at various scales, sharpening and smoothing filter denoising efforts to eradicate the noise presented in the pixel, as it conserves the image uniqueness, despite of its pixel satisfied. These filters can effectively detect and remove noise and thin hairs from the image; then we perform top-hat transform for removing the thick hairs. Contrast limited adaptive histogram equalization CLAHE is also performed on the skin lesion to get the enhanced image in the spatial domain. Histogram equalization works on the whole image and enhances the contrast of the image, whereas adaptive histogram equalization divides the whole image and works on the small regions called tiles. Each tile is typically 8*8 pixels, and within each tile histogram is equalized, thus enhancing the edges of the lesion. Contrast limiting is applied to limit the contrast below the specific limit to limit the noise.

3.3 Image Segmentation: After the preprocessing stage, segmentation of lesion was done to get the transparent portion of the affected area of skin. On transformation, Ostus method is applied to the image to segment the skin lesion area based on thresholding. In the Ostus algorithm, Segmentation is the initial process of this work, at the cluster centers,

cost junction must be minimized which varies with respect to memberships of inputs.

3.3 Feature extraction: Several features can be extracted from the skin lesion to classify the given lesions. We extracted some of the prominent features which help us in distinguishing the skin lesions, those are statistical and texture features. SGLD is a statistical technique of scrutinizing textures considering spatial connection of image pixels. The texture of mage gets characterized by SGLD functions through computations of how often pairs of pixels with explicit values and in a particular spatial connection are present in image. SGLD matrix can be created and then statistical texture features are extracted from the SGLD matrix. SGLD shows how different combinations of pixel brightness values which are also known as grey levels are present in image. It defines the probability of a particular grey level being present in the surrounding area of other grey level. In this paper, the SGLD is extracted first from the image for all three color spaces i.e. RGB, CIE L*u*v, and YCbCr. Then the SGLD matrix is calculated in four directions which are 135°, 90°, 45°, and 0° degrees as shown in figure 2. In the following formulas, let a, b be number of rows and columns of matrix respectively, $S_{a,b}$be the probability value recorded for the cell (a, b), and number of gray levels in image be 'N'. Then several textural features can be extracted from these matrices, extracted textural features are as shown in following equations:

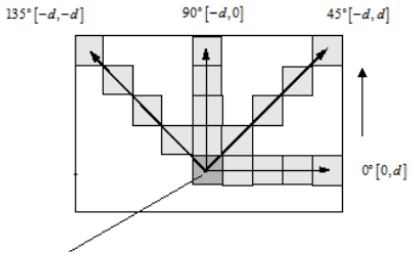


Fig 2: Orientations and distance to compute GLCM

1. Mean (μ) = $\frac{1}{N^2}\sum_{i,j=1}^{N} I(i,j)$
2. Variance = $\sum_{i,j=1}^{N}(i-\mu)^2\, I(i,j)$
3. Standard Deviation (σ) = $\sqrt{\frac{\sum_{i,j=1}^{N}[I(i,j)-\mu]^2}{N^2}}$
4. Skewness = $\frac{1}{\sigma^4}\sum_{i,j=1}^{N}(i-j)^3\ I(i,j)$
5. Kurtosis= $\frac{1}{\sigma^4}\sum_{i,j=1}^{N}(i-j)^4\ I(i,j)$
6. Contrast = $\sum_{a,b=0}^{N-1} S_{a,b}\,(a-b)^2$
7. Correlation = $\sum_{a,b=0}^{N-1} S_{a,b}\left[\frac{(a-\mu_a)(b-\mu_b)}{\sqrt{(\sigma_a^2)(\sigma_b^2)}}\right]$

here μ_a and μ_b are mean and σ_a *and* σ_b *are standard deviation.*

8. Dissimilarity = $\sum_{a,b=0}^{N-1} S_{a,b}|a-b|$
9. Homogeneity = $\sum_{a,b=0}^{N-1}\frac{S_{a,b}}{1+(a-b)^2}$
10. Angular Second Moment (ASM) = $\sum_{a,b=0}^{N-1} s_{a,b}^2$ and Energy = $\sqrt{ASM}$

3.4 texture analysis of features

Feature of lesion: According to previous work on skin lesion feature extraction, computing the variance and mean of various color channels would assist in classifying the melanoma from non-melanoma images. Hence on segmenting the skin lesion image, the binary image is converted into a red, green and blue (RGB) scale, Hue, Saturation Value (HSV) and grayscale. Thus computing the mean, variance, histograms and non-zero bins of skin lesions in different color spaces.

Border feature of lesion: Border feature of the lesion is essential as melanoma has a highly irregular border as compared to the normal skin lesions. Border feature can be computed by using the solidity, convex area, entropy and convexity features.

- Solidity- It is defined as the area of the image divided by the area of its convex hull, and it is used to quantify the size and the cavities in an object boundary.
- Entropy: It is defined as the randomness of the texture of the skin lesion.

- Convex Area: It is defined as the area of the skin lesion

3.5 classifications of cancer

Neural networks have been effectively applied across a range of problem domains like finance, medicine, engineering, geology, physics and biology. From a statistical viewpoint, neural networks are interesting because of their potential use in prediction and classification problems. BP-ANN is a method developed using emulation of birth neural scheme. The neurons are connected in the predefined architecture for effectively performing the classification operation. Depending on the SGLD features, the weights of the neurons are created. Then, the relationships between weights are identified using its characteristic features. The quantity of weights decides the levels of layers for the proposed network. Figure 3 represents the architecture of artificial neural networks. BP-ANN basically consists of two stages for classification such as training and testing. The process of training will be performed based on the layer based architecture. The input layer is used to perform the mapping operation on the input dataset; the features of this dataset are categorized into weight distributions.

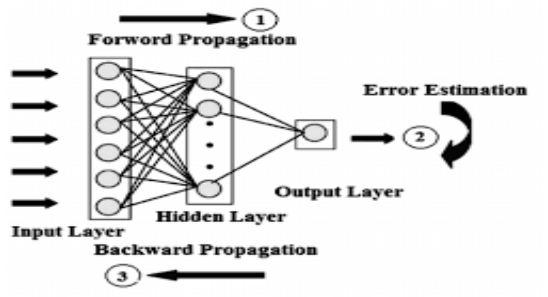


Figure 3. Layered architecture of BP-ANN model

The BP-ANN architecture has eight layers with weights. It contains the sequence of three alternating Convolutional2D layer and MaxPooling2D layer and three fully connected layers. The first convolutional2D layer of the net takes in 224 * 224*3 pixels skin lesion images and applies 96 11×11 filters at stride 4 pixels, followed by a ReLU activation layer and cross channel normalization layer. The second layer (MaxPooling) contains 3*3 filters applied at stride 2 pixels and zero paddings. Next convolutional2Dlayer applies 5 256*256 pixel filters at stride 4 pixels, followed by max pooling2D layer which contains 3×3 pixels filters applied at stride 2 pixels and zero paddings. The third convolutional2D layer of the net takes applies 384 3×3 filters at stride 1 pixel and one padding. The last dense layer of the BP-ANN contains three fully connected layers with ReLU activation and 50% dropout to give 60 million parameters.

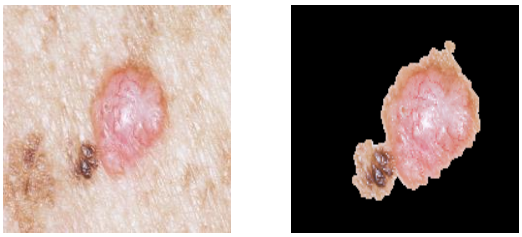
Then the classification operation was implemented in the two levels of hidden layer. The two levels of hidden layer hold individually normality and abnormalities of the skin cancer characteristic information. Based on the segmentation criteria, it is categorized as normal and abnormal classification stage. These two levels are mapped as labels in output layer. Again the hidden layer also contains the abnormal cancer types separately; it is also holds the benign and malignant cancer weights in the second stage of hidden layer. Similarly, these benign and malignant weights are also mapped as label into output layer. When the test image is applied, its SDM features are applied for testing purpose in the classification stage. Based on the maximum feature matching criteria utilizing Euclidean distance manner it will function. If the feature match occurred with hidden layer 1labels, then it is classified as normal skin image. If the feature match occurred with hidden layer 2 labels with maximum weight distribution, then it is classified as benign effected cancer image. If the feature match occurred with hidden layer 2 labels with minimum weight distribution, then it is classified as malignant affected cancer image.

4. Experimentation Environment

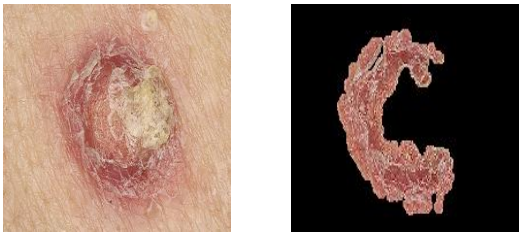
4.1 dataset

The experiments are done using the Matlab Programming language, and classification is

done using the Matlab R2018a tool. ISIC is one of the biggest available collections of quality controlled dermoscopic images. For the implementation of the proposed method, spatial domain, and frequency domain of 3000 dermoscopic skin lesion images (1000-benign and 1000-melanoma,1000 no cancer) have been obtained and augmented to 5943 images (2480-benign,983-melanoma,2480-dysplastic) respectively by applying rotations at different angles. Out of 2480-benign, 983-no cancer, 2480- melanoma images, eighty percent images of each label have been used to train the BP-ANN architecture with fifty Epochs, whereas rest twenty percent is used for testing. The features extracted by SGLD feature network is used to train Bp-ANN classifier to classify the images into its respective classes. The efficiency of the model can be computed using various performance metrics.



(a)



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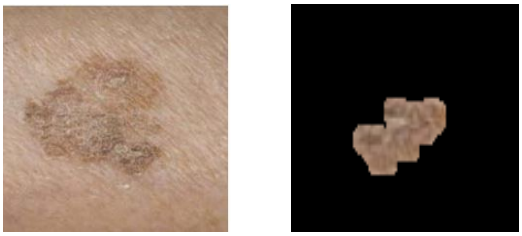
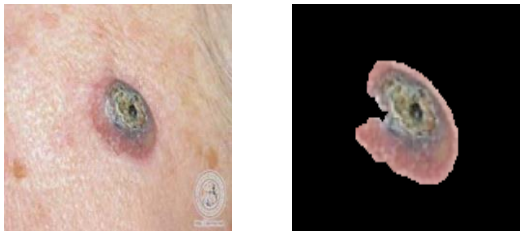
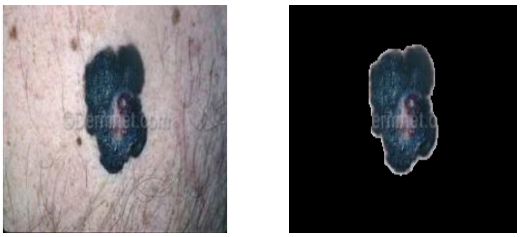


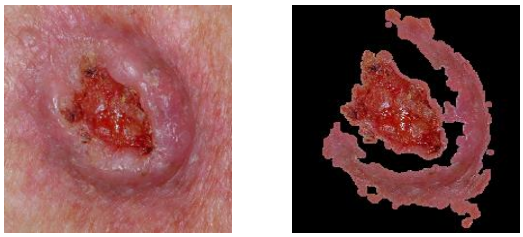
(c)



(d)



(e)



(f)

Fig 4: Input dermoscopic image (left). detected region of skin cancers (right). (a)Malignant – Melanoma, (b) Malignant - Basal Cell Carcinoma (c) Malignant - Basal Cell Carcinoma (d) Benign - Melanocytic Nevi (e) Benign - Melanocytic Nevi (f)Benign - Seborrheic Keratoses

From figure 4, it is observed that the proposed method can be effectively detect the regions of skin cancers, it indicates the segmentation done very effectively compared to the other approaches.

4.2 Performance metrics:

The performance metrics used to evaluate the proposed methods are Accuracy (AC), Sensitivity (SC), Specificity (SP). Let TP, TN, FP, and FN be the count of true positive, true negative, false positive, and false negative respectively. Then the equations are shown in following equations:

Accuracy: It is defined as the number of data points predicted correctly to the total sum of all data points.

$$AC = \frac{TP + TN}{TP + FP + TN + FN}$$

Sensitivity: It tells the proportion of people having skin lesion and tested positive.

$$SC = \frac{TP}{TP + FN}$$

Specificity: It tells the proportion of people not having any skin lesion and tested negative.

$$SP = \frac{TN}{FP + TN}$$

Precision: It tells the proportion of people diagnosed as having cancer, actually had cancer.

$$PR = \frac{TP}{TP + FP}$$

Table 1: Performance comparison.

method	Specificity	Sensitivity	accuracy	Precision
SVM [6]	82	92	87	83
RBFN [7]	90	93	91	89.5
SMP [13]	41.8	57.3	89.5	83.4
CNN [8]	93.6	94.3	97.49	95.6
DCNN [12]	98.61	98.93	98.33	97.73
Proposed	**99.12**	**99.04**	**99.13**	**98.60**

Abnormal represent the skin cancer, we can emphasize that 197 melanoma images, 496 benign and 496 dysplastic images have been used for testing the model. Out of 197 testing images for melanoma 179 images have been correctly identified as melanoma thus, TP=15.1% and rest 18 images have been wrongly identified as benign hence FN=1.5%, from the rest of the table we can say that TN=82.2% (39.1%+2.6%+1.9%+38.6%) and FP=1.2%, i. e 14 images have been wrongly identified as melanoma. Out of 496 images testing images for dysplastic 465 images have been correctly identified as dysplastic thus, TP=39.1% and rest 31 images have been wrongly identified as benign hence FN=2.6%, from the rest of the table we can say that TN=56.4% (1.2%+38.6%+1.5%+15.1%) and FP=1.9%, i.e., 19 images have been wrongly identified as dysplastic. Out of 496 images testing images for benign 459 images have been correctly identified as benign thus, TP=38.6% and 23 images have been wrongly identified as dysplastic and rest 14 images have been wrongly identified as melanoma and hence FN=3.1%, from the rest of the table we can say that TN=54.2% (39.1%+15.1%) and FP=4.1%, i. e 49 images have been wrongly identified as benign. Thus, the proposed model has 99.13% accuracy, 99.04% sensitivity and 99.12% specificity. Thus, from table 1, it is clearly observed that the proposed method shows much better efficiency compared to the literatures SVM [6], RBFN [6], SMP [13], CNN [8] and DCNN [12] approaches.

6. Conclusion

This article presented a computational methodology for detection & classification of skin cancer from MRI images using deep learning-based approach. Here, sharpening and smoothing filters are utilized for preprocessing, which eliminates any unwanted noise elements or artifacts innovated while image acquisition. Then otsu segmentation is employed for ROI extraction and detection of cancerous cells. Then SGLD matrix method was developed for extraction of statistical and texture features from segmented image respectively. Finally, BP-ANN was employed to classify the type of cancer as normal, benign or malignant using trained network model.

Thus on comparing with other works, we conclude that BP-ANN is better than other conventional approaches. In future, this work can be extended by implementing a greater number of network layers into the BP-ANN and can also be applied for other type of cancers.

References:

1. Kumar, P.M.Kumar. "Satellite image denoising using local spayed and optimized center pixel weights." *International Journal of Electrical and Computer Engineering* 4.5 (2014): 751.
2. Munir, Khushboo, et al. "Cancer diagnosis using deep learning: a bibliographic review." *Cancers* 11.9 (2019): 1235
3. Kumar, P.M. "A New Encryption and Decryption for 3D MRT Images." *Asian Journal of Electrical Sciences* 6.1 (2017): 1-6.
4. Akram, Tallha, et al. "A multilevel features selection framework for skin lesion classification." *Human-centric Computing and Information Sciences* 10 (2020): 1-26.
5. Marka, Arthur, et al. "Automated detection of nonmelanoma skin cancer using digital images: a systematic review." *BMC medical imaging* 19.1 (2019): 21.
6. Gaonkar, Rohan, et al. "Lesion analysis towards melanoma detection using soft computing techniques." *Clinical Epidemiology and Global Health* (2019).
7. Hekler, Achim, et al. "Superior skin cancer classification by the combination of human and artificial intelligence." *European Journal of Cancer* 120 (2019): 114-121.
8. Rajasekhar, K. S., and T. Ranga Babu. "Skin Lesion Classification Using Convolution Neural Networks." Indian Journal of Public Health Research & Development 10.12 (2019): 118-123.
9. Kalyanapu Srinivas, P.M.Kumar, Annam Jagadeeswara Rao. "A New Video Watermarking Using Redundant Discrete Wavelet in Singular Value Decomposition Domain." *Journal of Mechanics of Continua and Mathematical Sciences* 14.5 (2019): 476-486.
10. Roslin, S. Emalda. "Classification of melanoma from Dermoscopic data using machine learning techniques." Multimedia Tools and Applications (2018): 1-16.
11. Moqadam, Sepideh Mohammadi, et al. "Cancer detection based on electrical impedance spectroscopy: A clinical study." *Journal of Electrical Bioimpedance* 9.1 (2018): 17-23.
12. Hosny, Khalid M., Mohamed A. Kassem, and Mohamed M. Foaud. "Skin cancer classification using deep learning and transfer learning." *2018 9th Cairo International Biomedical Engineering Conference (CIBEC)*. IEEE, 2018.
13. Dascalu, A., and E. O. David. "Skin cancer detection by deep learning and sound analysis algorithms: A prospective clinical study of an elementary dermoscope." *EBioMedicine* 43 (2019): 107-113.