Mobile Networks and Applications
https://doi.org/10.1007/s11036-020-01550-2

A DE-ANN Inspired Skin Cancer Detection Approach Using Fuzzy C-Means Clustering

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Abstract
As per recent developments in medical science, the skin cancer is considered as one of the common type disease in human body. Although the presence of melanoma is viewed as a form of cancer, it is challenging to predict it. If melanoma or other skin diseases are identified in the early stages, prognosis can then be successfully achieved to cure them. For this, medical imaging science plays an essential role in detecting such types of skin lesions quickly and accurately. The application of our approaches is to improve skin cancer detection accuracy in medical imaging and further, can be automated using electronic devices such as mobile phones etc. In the proposed paper, an improved strategy to detect three type of skin cancers in early stages are suggested. The considered input is a skin lesion image which by using the proposed method, the system would classify it into cancerous or non-cancerous type of skin. The image segmentation is implemented using fuzzy C-means clustering to separate homogeneous image regions. The preprocessing is done using different filters to enhance the image attributes while the other features are assessed by implementing rgb color-space, Local Binary Pattern (LBP) and GLCM methods altogether. Further, for classification, artificial neural network (ANN) is trained using differential evolution (DE) algorithm. Various features are accurately estimated to achieve better results using skin cancer image datasets namely HAM10000 and PH2. The novelty of the work suggests that DE-ANN is best compared among other traditional classifiers in terms of detection accuracy as discussed in result section of this paper. The simulated result shows that the proposed technique effectually detects skin cancer and produces an accuracy of 97.4%. The results are highly accurate compare to other traditional approaches in the same domain.

Keywords Melanoma · Skin Cancer detection · DE-ANN · Image segmentation · Fuzzy clustering

1 Introduction

In the last decade, the growth of skin cancer has been expedited. There exist multiple types of skin cancer such as Basal cell carcinoma, Squamous cell carcinoma, Melanoma, Actinic keratosis (solar keratosis) and Squamous cell carcinoma. Compared with actinic keratosis (solar keratosis) and squamous cell carcinoma Melanoma is deadly. This type of cancer accounts only for 7% of skin cancer but is responsible for 75% of deaths. As per dermatologists, if melanoma is detected in early stages then there is 90% possibility for diagnosing it [1]. If no treatment is provided ahead of time then it continues to spread in other parts of the body and becomes difficult to cure. In this case, the percentage of diagnosis came down to even less than 50%. The main causes to form skin cancer are the presence of melanocytes and exposure of skin to UV radiations [2]. Figure 1 shows melanoma image patch with certain features like blue whitish as red arrows, pigment networks as blue arrows and dots and globules as white circles.

The identification of skin cancer is challenging owing to various skin textures or injuries hence the use of dermoscopy to identify it. Dermoscopy uses polarized amplifying glass with incident light to detect surface properties of skin. Using this technique, cancer detection is higher compared with unaided based observations. Still, the detection accuracy purely depends on the experience of a dermatologist [3]. An old study done in 2003 shows that the dermatologist's accuracy for skin cancer detection varies from 75% to 84% [4]. To increase the detection accuracy, computer-based techniques

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Published online: 08 June 2020

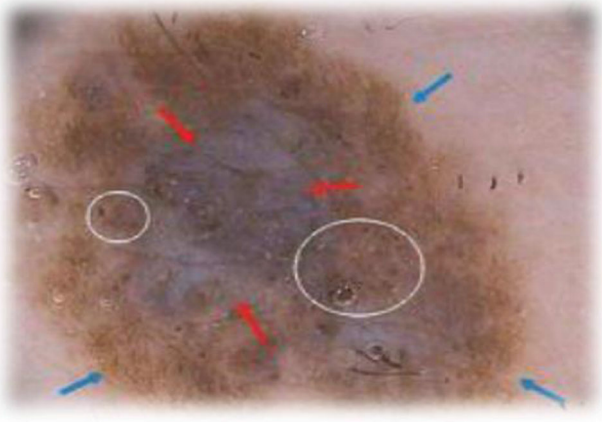


Fig. 1 A sample image of melanoma with specific features

or computer-aided diagnostics (CAD) are implemented. CAD advances future directions to analyze medical images using image processing practices. These techniques help to extract more relevant features from the images including color patterns, textures, asymmetry, shape etc. Further, the identification of lesion depends on these features using machine-based methods. In computer-based methods the key steps are the acquisition of skin lesion image, segmentation of skin regions, feature extraction and classification, etc. There exist various classification methods which are used to identify skin lesion. Some of popular methods are discussed in the next section of this paper. This work suggests a robust technique to identify image features and enhance optimization and classification accuracy. We implemented differential evolution (DE) with artificial neural network (ANN) to produce improved grouping on dermoscopic images. The fuzzy C-Means clustering is used to isolate the image regions. The basic idea of this is to assess the relationship between each data point and corresponding cluster centers on the basis of the distance between the cluster center and data point. Texture features are extracted using GLCM (Gray Level Co-occurrence Matrix) and LBP (Local Binary Pattern) while color features are extracted using rgb approach. Finally, DE-ANN is executed to detect image regions based on estimated features. The proposed approach successfully detects cancerous and non-cancerous cells with high accuracy.

The rest of the paper is discussed in five sections. Section 2 is about the related recent works which are followed by the proposed methodology in Section 3. Section 4 presents the outcome of the technique and Section 5 concludes the work.

2 Recent work

Skin diseases are the results of infection and bacteria. Different techniques have been so far implemented on the images to identify skin diseases at the early stages. A review has been done to discover skin diseases in plants and humans so that researchers can select efficient approaches as per their work requirements. Also, comparisons have been done on different techniques like color-based image retrieval approaches, expert system, and case-based reasoning methods on various attributes like accuracy, reliability, speed, scale and clarity of outputs [5]. These techniques use classification-based approaches to display the results for a skin lesion. Moreover, to produce better results the selection of a classifier is a difficult task for cancer detection. Arora et al. [6] provided a report for a better understanding of different methods, parameters and techniques to choose the classifier for the detection of cancer cells. An overview of various recent studies in this domain are discussed in this section.

Hameed et al. [7] proposed a new hybrid approach based on CNN and SVM for skin cancer detection. Results of their approach for different images were also compared with other approaches such as Genetic algorithms, ANN and SVM. Their result shows that the proposed work increased the detection accuracy by 3.21%. Esteva et al. [8] used Deep Neural Network for the classification of skin cancer in human beings. The experiment was performed on different images using three-way and nine-way classification methods. They trained the neural network (CNN) using 129,450 clinical images. Their technique was able to detect cancer in images. Zhao et al. [9] suggested real-time Raman Spectroscopy approach to detect skin cancer. They used 645 image cases and good accuracy was obtained by their approach. This approach is mainly inspired by Multi-variant statistical data analyses including principal component with general discriminant analysis (PC-GDA). They used partial least squares (PLS) for lesion classification. Georgakopoulos et al. [10] proposed a different approach for augmenting the input of convolutional neural network (CNN) using the response of image filters to improve the accuracy of the classifier. Researchers also used the concept of transfer learning to train the datasets. Their results achieved better classification accuracy. Dorj et al. [11] used Deep Convolutional Neural Network and ECOC SVM approaches to classify skin cancer. Classification is done using 3753 images using ECOC SVM and other existing approaches. Their comparison with other approaches is based on the accuracy, sensitivity and specificity parameters. The results are quite commendable for their approach. It is conferred that feature selection is the most difficult task to define skin lesions. Thus, Oliveira et al. [12] suggested an approach to deliver a set of features based on shape, color variation and texture analysis for identifying skin cancer. Various classifiers were adopted to evaluate the proposed feature extraction step, and several feature selection procedures were compared for the classification of skin lesions. The results were obtained using 1104 images and the percentage of accuracy, sensitivity and specificity was estimated.

To increase the accuracy and efficiency of skin cancer detection, deep learning algorithms can be used. Li and Shen [13] proposed deep learning approach with two convolutional residual networks to carry out the segmentation and the classification. Their experiment was carried out on ISIC 2017 dataset. Experimental results depict the promising accuracies for their proposed framework. In another work by Razmjooy et al. [14] the World Cup Optimization (WCO) algorithm was implemented to detect melanoma at an early stage. Results were analyzed using Multi-Layer Perceptron (MLP) method, also the WCO was used to reduce the error rate and to improve the efficiency of MLP approach. Recently, Tang et al. [15] proposed an enhanced Particle Swarm Optimization approach to detect skin cancer. The results of this algorithm were also compared with other optimization approaches. Their algorithm was found to be able to produce a superior result for feature selection and helped to achieve an optimum solution for skin cancer detection. Salem et al. [16] suggested a new genetic approach for skin cancer detection. Their Experimental results observed that the proposed genetic algorithm increases the cancer detection accuracy by 2 to 9% and specificity by 9%. To enhance the image segmentation process, the Object Scale Oriented Fully Convolutional Network approach is proposed by Huang et al. [17] in 2019. Training and testing are carried out on international skin imaging collaboration (ISIC) dataset and the results were compared with other state-of-the-art algorithms [18–23]. Their result demonstrates that the accuracy of the proposed algorithm is greater or very close to the accuracy of other algorithms. In the proposed work differential evolution based classification using artificial neural network is suggested. The DE-ANN is used by other researchers in this domain to detect cancer [24–27]. Yet, the proposed technique using DE-ANN established good detention accuracy and opens the paradigms to implement this type of classification algorithm in the future for problems related to cancer diseases. Table 1 shows a comparative study for various techniques discussed in this section.

3 Methodology

The proposed technique is implemented in various steps to achieve the best and the most accurate results of skin lesion detection. The challenges with skin lesion detection is that with dermoscopy image it is very difficult for the skin doctors to identify whether the particular skin is cancerous or not. For identifying results for skin cancer, they need to carry out certain medical tests which becomes expensive and time consuming with less accuracy for the patients. As a result, a highly accurate automated analysis is required which is centralized, coordinated and less expensive. Hence, a novel technique is suggested with high accuracy. Also, the feature extraction techniques sometimes lead to inaccurate results. Therefore, in the proposed technique features extraction and with DE-ANN it improves the accuracy of the technique. If the features are accurately estimated then the probability of getting highly accurate result increases and also reduces the computational cost.

In the first step of the proposed method, some preprocessing is carried out to make the input image smooth, enhanced and noise free. Therefore, a median filter is used to remove the noise. It enhances the image features and eradicates skin lines, oil effects on the skin. This filter is non-linear in nature and keeps sharp curvatures, edges and spatial frequency information intact in the image as compared to other filters [28]. The flowchart of the proposed method is shown in Fig. 2. In the next step, image segmentation is performed which divides an image into disjoint areas based on various parameters such as intensity, color and surface properties. To segment or to make homogeneous clusters, Fuzzy C-Means clustering approach is applied. This technique is better compared to other popular clustering schemes such as k-means because of its ability to produce better results for overlapped data sets. Irrespective of the k-means algorithm, in this, the data point is assigned membership to every cluster so that more appropriate cluster can be formed [29]. Fuzzy C-Means works by providing membership to the data point based on the distance between the cluster center c and data point. If more data is near to c then more is the data point membership for that cluster.

After every iteration of the algorithm, the estimated membership will be increased. In the proposed method, an

Table 1 Comparative study of various skin cancer detection approaches

Reference	Features/ Methodology used	Detection accuracy
[7]	CNN, error-correcting output codes (ECOC) support vector machine (SVM)	86.21%
[12]	Features analysis based on shape, color and texture	91.6% and 92.3%
[13]	deep learning with two convolutional residual networks	90.2%
[15]	Particle swarm optimization and pprobability distributions-based approach	95.23%
[16]	Features extraction from symmetry, border irregularity, color variation and diameter and genetic algorithm-based methodology	Accuracy Testing – 76.17%

Fig. 2 Steps involved to carry out the proposed work

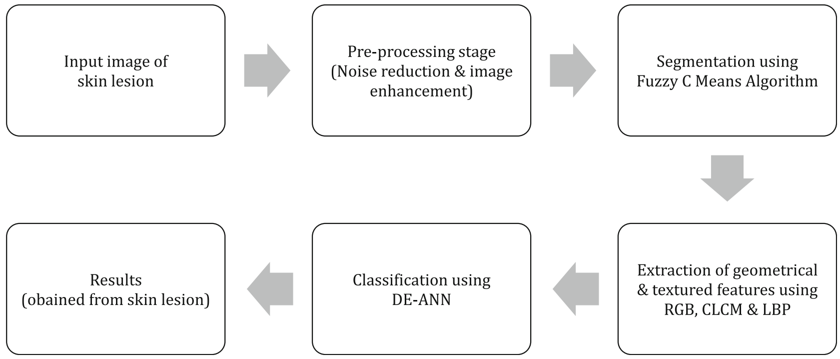
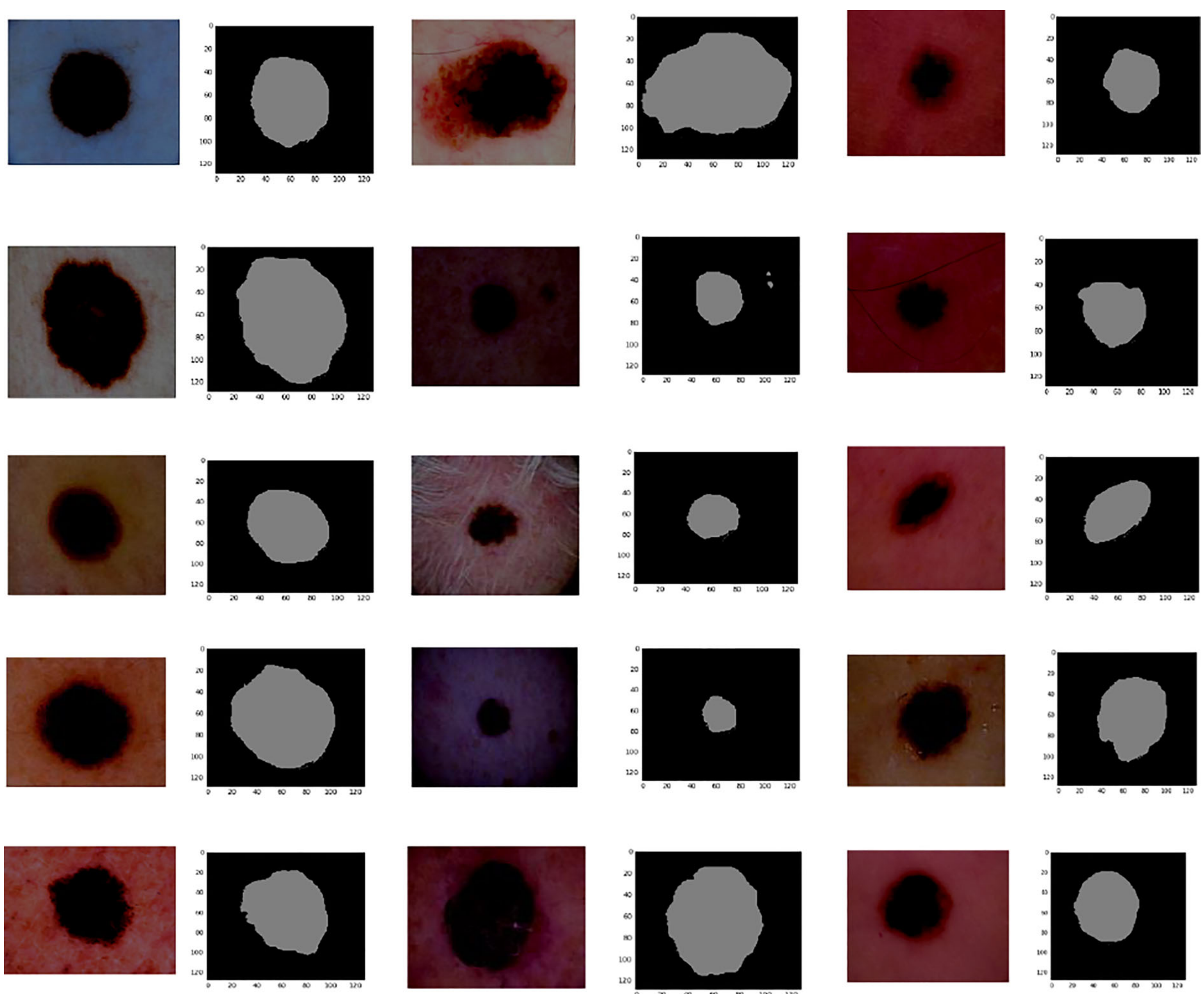


Table 2: Samples of segmented images using three types of skin cancer

Melanoma Cancer Images		**Benign Keratosis-Like Images**	**Lesions (BKL)**	**Melanocytic Nevi (NV) Cancer Images**	
(Sample Image)	(Segmented Image)	(Sample Image)	(Segmented Image)	(Sample Image)	(Segmented Image)



enhanced fuzzy C-Means algorithm is implemented as inspired by Szilágyi et al. [30]. The implemented algorithm is shown below:

Step1: The number c of clusters varies from 2 to c_{max}. Consider a certain value c and then select initial class prototypes and use $\epsilon > 0$.

Step 2: Compute a new linearly weighted sum image ς in terms of ς_k using Eq. 1.

$$\varsigma_k = \frac{1}{1+\alpha}\left(x_k + \frac{\alpha}{N_R}\sum_{j\in N_k} x_j\right) \tag{1}$$

where, ς_k and x_k are the gray value of k^{th}pixel of ς (gray value is usually encoded as 8-bit resolution) and gray value of k^{th}-pixel respectively. The x_j is the neighbor of x_k, N_k holds the set of neighbor lies in a window nearby x_k. The value of $\sum_{j\in N_k}\frac{x_j}{N_R}$ is the mean-filtered pixel value where α controls the effect of neighbor terms with value approximately close to 1.

Step 3: Update the partition image matrix ς as f_{il} using Eq. 2.

$$f_{il} = \frac{\left(\varsigma_l - v_i\right)^{\frac{2}{s-1}}}{\sum_{j=1}^{c}\left(\varsigma_l - v_j\right)^{\frac{2}{s-1}}} \tag{2}$$

v_i is the prototype of i^{th}cluster and f_{il} is the fuzzy membership of gray value l w.r.t. cluster i. The value of l varies from 1 to the number of gray levels represented as d (maximum 256 levels for gray level) of image and parameter s is weighted component for each fuzzy membership which estimates the fuzziness of the final classification.

Step 4: Revise the prototype v_i using Eq. 3.

$$v_i = \frac{\sum_{i=1}^{d} x_l f_{il}^{s}\varsigma_l}{\sum_{i=1}^{d}\chi_l f_{il}^{s}} \tag{3}$$

Further, repeat step 3 and 4 until achieving the convergence criteria as $|v_{new} - v_{old}| < \epsilon$ and v holds vectors of cluster prototypes and represented as $v = [v_1, v_2 \ldots\ldots v_c]$. Implementing this step helps to achieve better and quick segmented quality of skin images. The results of the segmentation method are shown in Table 2 for three types of cancer cells.

In the next step, image features are extracted from a segmented image using LBP (Local Binary Pattern), rgb color space and GLCM (Gray Level Co-Occurrence Matrix) based methods. The general theory around cancerous skin is that the area of such parts of skin is highly influenced by color and texture. As a result, the color features are estimated using rgb and texture features such as contrast, correlation, homogeneity, mean and skewness are estimated using the GLCM method. These methods are explained as below:

A. LBP (Local Binary Pattern)

In this technique, the gray pixel is compared with its 8 neighbor pixels g_c is the gray value of middle pixel and g_G(G = 0 to G-1) are the gray values spaced in the neighborhood circle of radius R which form a circular pixels neighborhood set. In this work, the value of set (G, R) is taken as 8 and 1.0 respectively. The feature space is computed by subtracting gray value of center pixels with its neighbor pixels and finally, the LBP based feature is computed using Eq. 4.

$$LBP_{G,\mathrm{R}} = \sum_{G=0}^{G-1} s(g_G - g_c)2^G \tag{4}$$

and finally a feature vector is obtained [31]. In the proposed feature extraction scheme, the derivation of gray scale and rotation invariant texture operator is defined as Tin local neighborhood space defined in Eq. 5 as joint distribution of gray levels of $G > 1$ image pixels. G manages the quantization of angular space of pixels' domain.

$$T = t\left(g_c, g_0 \ldots\ldots\ldots g_{G-1}\right) \tag{5}$$

The implemented LBP feature set is invariant to monotonic transformations and therefore provides better texture particulars.

B. rgb Color Space Model.

This model is used to identify the color variations in the segmented areas. This method estimates the color spectrum of the segmented image patch with respect to various color channels. If the estimated color difference is more in image segmented patches, then it could be a positive sign for early detection of cancer. This difference is computed by means of statistical estimations of various color channels like standard deviation, mean etc. The red, green and blue bands are used to find the color space features using Eq. 6. The obtained values of normalized color invariants of r, g and b are insensitive to surface orientations, illumination directions and intensity of image patches [32]. The values, are, therefore, used to estimate color features.

$$\mathrm{r} = \frac{R}{R+G+B} g = \frac{G}{R+G+B} \qquad b = \frac{B}{R+G+B} \tag{6}$$

C. GLCM (Gray Level Co-occurrence Matrix)

To assess the characteristics of image texture in response to non-deterministic properties, the relationship between the grey levels of the image is required. This is achieved using second-order statistical technique with GLCM. The features of an image are computed using co-occurrence metrics based on angular and distance relationships between pixels. A matrix which includes rows and columns represent the gray

Table 3 Various Estimated GLCM Features to detect skin lesion texture information

GLCM Features	Implemented Equation
Mean	$\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}A(i,j)}{M\times N}$
Entropy	$\sqrt{\sum_{i=0}^{g-1}\sum_{j=0}^{g-1}A_d^2(i,j)}$
Contrast	$\sum_{i=1}^{g-1}\sum_{j=1}^{g-1}(i-j)^2A_d(i,j)$
Homogeneity	$\sum_{i=0}^{g-1}\sum_{j=0}^{g-1}\frac{1}{(i-j^2)}A_d(i,j)$
Dissimilarity	$\sum_{i=1}^{g-1}\sum_{j=1}^{g-1}\lvert i-j\rvert\times A_d(i,j)$

levels g in the image with $M \times N$ neighboring pixels and intensity $I(m, \mathrm{n})$. The elements of such matrix A_d are represented as Eq. 7

$$A_d = (i, \mathrm{j}|\Delta\mathrm{x}, \Delta\mathrm{y}) = \mathrm{BQ}(\mathrm{i}, \mathrm{j}|\Delta\mathrm{x}, \Delta\mathrm{y}) \tag{7}$$

In the equation, Δx and Δy denotes the distance between relative pixels and the value of $B$is obtained using $1/(M-\Delta x)(N-\Delta y)$ and i and j are the intensities between 0 and **Number of levels**-1.

The value of $Q((i, \mathrm{j}|\Delta\mathrm{x}, \Delta\mathrm{y})) = \sum_{n=1}^{N-\Delta y}\sum_{m=1}^{M-\Delta y}C$,

$[\ C = \{1 \quad if\ I(m, \mathrm{n}) = i \ \text{and}\ \mathrm{I}(\mathrm{m}+\Delta x,\ \mathrm{n}+\Delta\mathrm{y}\}$ otherwise $C = 0]$.

The matrix is generated using above mentioned mathematical notations and GLCM features are obtained as per Table 3 formulations.

After executing the previous two steps, a large set of features is obtained. Further, to assess more relevant features in the proposed approach the genetic optimization is implemented as a classification technique. The proposed DE-ANN classifier is used to predict the images of cancerous and non-cancerous cells. The designing process of artificial neural network is challenging and has various limitations. These limitations could be related to the selection of an efficient network, learning rate, learning procedure and training time etc. So, to achieve better accuracy and to address such limitations in the proposed work, ANN is trained using differential evolution (DE) [33]. The differential evolution weight-based optimization of neural network is achieved using the following procedure.

Step 1: Obtain the features from the skin image.

Table 4 Proposed technique results for three types of cancer and non-cancer cells

Image No.	Type of Cancer	Mean	Entropy	Contrast	Homogeneity	Dissimilarity	Red Features	Green Features	Blue Features	Classifier Output	Label
1	Melanoma	207.18	0.467	0.0059	0.972	−1.267	0.3656	0.3412	0.3132	1	Cancerous
2	Melanoma	234.37	0.623	0.0063	0.997	−0.967	0.3841	0.3642	0.3063	1	Cancerous
3	Melanoma	199.92	0.634	0.0080	0.989	−1.767	0.3795	0.3492	0.3282	1	Cancerous
4	Melanoma	205.67	0.487	0.0078	0.996	−0.987	0.3721	0.3612	0.3140	1	Cancerous
5	Melanoma	97.6	0.901	0.5312	0.981	−5.361	0.3332	0.3254	0.3225	0	Non-Cancerous
6	Benign Keratosis-Like	156.25	0.845	0.1980	0.967	−0.972	0.3681	0.3546	0.3142	1	Cancerous
7	Benign Keratosis-Like	159.67	0.921	0.1899	0.932	−1.876	0.3588	0.3429	0.3182	1	Cancerous
8	Benign Keratosis-Like	173.64	0.892	0.0012	0.986	−1.732	0.3364	0.3212	0.3304	1	Cancerous
9	Benign Keratosis-Like	99.45	0.789	0.1234	0.996	−3.976	0.3154	0.3100	0.3145	0	Non-Cancerous
10	Benign Keratosis-Like	97.6	0.757	0.2412	0.994	−5.326	0.3112	0.3134	0.3198	0	Non-Cancerous
11	Melanocytic Nevi	251.37	0.499	0.812	0.987	−1.203	0.3812	0.3516	0.3112	1	Cancerous
12	Melanocytic Nevi	168.23	0.912	0.2506	0.899	−2.983	0.3365	0.3212	0.3334	0	Non-Cancerous
13	Melanocytic Nevi	152.16	0.863	0.0996	0.995	−0.932	0.3366	0.3429	0.3282	1	Cancerous
14	Melanocytic Nevi	198.56	0.592	0.0786	0.996	−1.896	0.3687	0.3458	0.3152	1	Cancerous
15	Melanocytic Nevi	221.66	0.632	0.0668	0.995	−0.963	0.3741	0.3612	0.3398	1	Cancerous

Step 2: Create input and target for cancerous and non-cancerous cells.

Step 3: Initializing and weight optimization for ANN is done using steps 4.1 to 4.3:

Step 4.1: Develop a population of individuals and store in *ps*. Each individual x_i is formed by n genes which represent number of weights in trained ANN. Every j^{th} gene of x_i can have values from min_j to max_j where $j \in [1 \ldots n]$. We assumed $min_j = -1$ and $max_j = 1$ to perform the experiment.

Step 4.2: In this step, the mutation is carried out using individual vector v_i for each x_i in populace as per Eq. 8.

$$v_i = x_{r_1} + F(x_{r_2} - x_{r_3}) \tag{8}$$

Here, $F \in (0, 3]$ and indices $r_1 \neq r_2 \neq r_3 \neq i$ but these values vary from $[1, ps]$. The indices r_1 is the best individual from the population with minimum training error and r_2 and r_3 are randomly chosen from the population.

Step 4.3: In this step, crossover operation is carried out. All the individuals are crossed over with mutated individuals v_i and a new individual u_i is obtained. This is achieved using the following process:

The selected individual say $x_i = (x_{i1}, x_{i2}, \ldots\ldots x_{ij}$ and individual $v_i = (v_{i1}, v_{i2}, \ldots\ldots v_{ij}; j \in [1, n]$ of x_i and generate a random $rand_j \in [0; 1)$ and follow the below shown rule.

$$\begin{aligned} &if\ \text{rand}_j < COR\ then \\ &set\ u_{ij} = v_{ij} \\ &else\ set\ u_{ij} = x_{ij} \\ &: COR \in [0; 1) \end{aligned}$$

Here, *COR* is obtained by using the product of a uniformly distributed random number and $\frac{best_i}{best_{i-1}}$.

Step 4.4: Here, the selection of the best individual is chosen for a new population. If the error of u_i is less than the error of x_i then replace x_i by u_i in the new population. If not meet the criteria then leave x_i, further, step 4.2 and so on is repeated to meet the desired stopping criteria.

Step 5: Output the result as a node classified or labelled as cancerous or non-cancerous.

Using this algorithm, the weights for the neural network are optimized and the type of skin lesion is identified. Therefore, outputs for input images are produced.

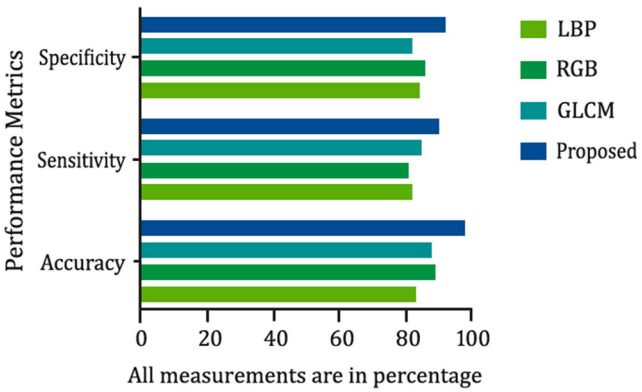


Fig. 3 Performance metrics of various feature extraction techniques

4 Results

The dataset used in this research work is MNIST: HAM10000 [34] PH2 [27]. These are freely available datasets which have a repository of 10,015 and 200 dermatoscopic images respectively for research purpose. The evaluation of the proposed techniques is done using these datasets. Using the HAM dataset, a collection of total 500 cancerous and non-cancerous images is taken for performing this experiment. Using these images, the proposed DE-ANN identified 326 images as cancerous while 174 images as non-cancerous. The experiment setup is done using MATLAB. Various parameters are used to setup the experiment with DE-ANN as shown below. Using the proposed experimental setup, the proposed method is able to produce an accuracy of 97%.

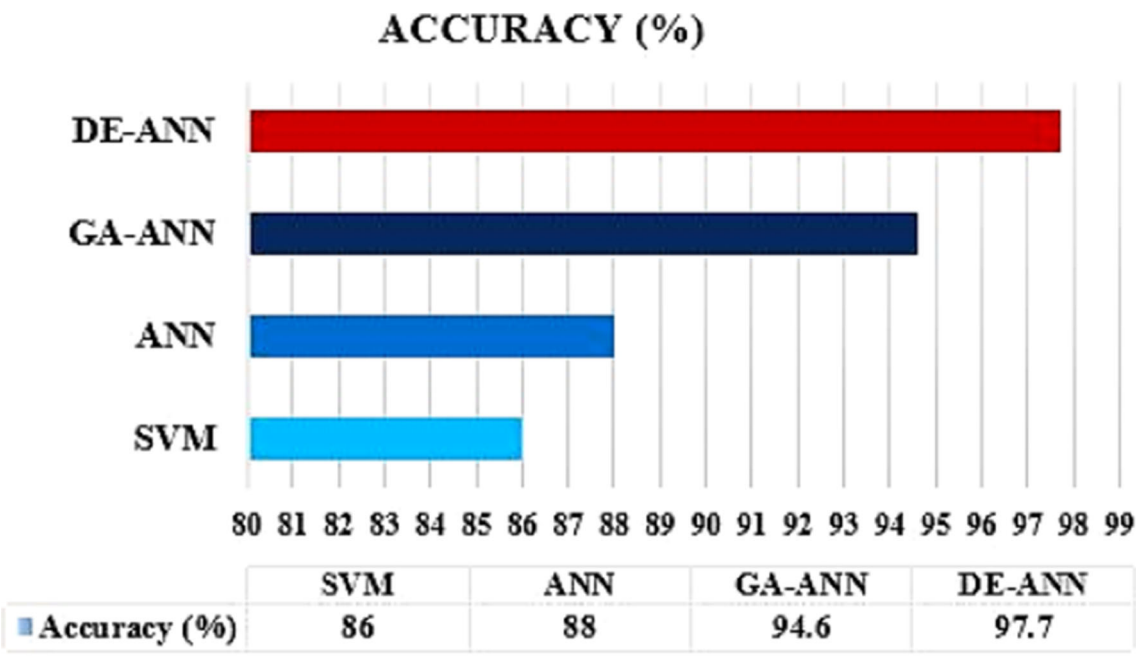
Name of the Parameter	Considered Value
No of Iteration	120
Population (NP) default	55
CR	0.8
Scale Factor (F)	0.15
Min Scaling Factor	0.6
Max scaling Factor	1.0
Threshold	0.7
Min and max. Inertia weight	.90 and .99

The demonstrated result verifies that the proposed method is effective for three types of skin cancer detection with high accuracy. Table 4 shows the extracted feature values and classifier outcomes. A sample result is shown in this table for randomly chosen 15 images (five- five images from three types of images). It is observed that the presented method accurately extracts the skin lesion and the assessed features are further used to train the DE-ANN classifier.

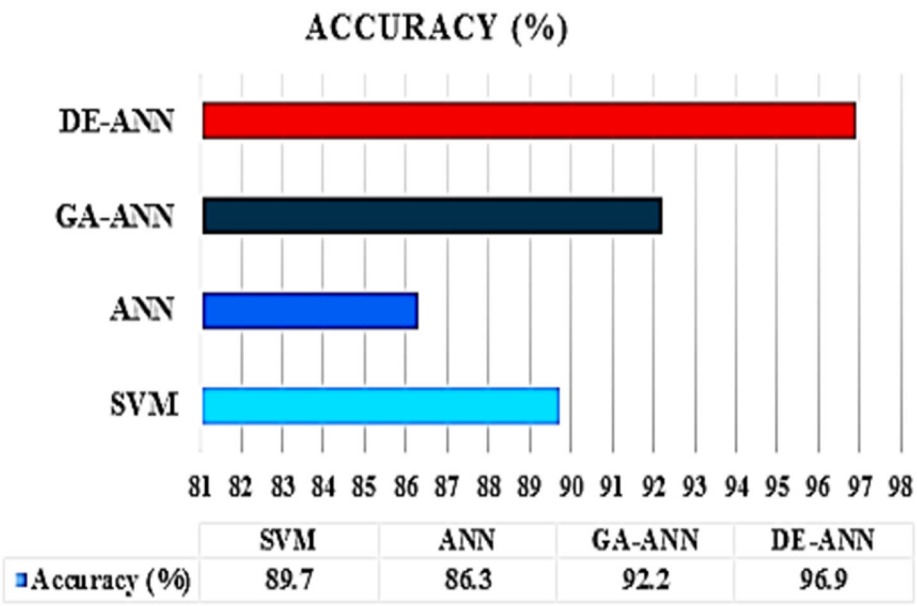
To analyze the feature extraction and classification results, three metrics are used namely: accuracy, sensitivity and specificity [35]. These matrices are computed using Eq. 9.

$$\begin{aligned} \text{Accuracy} &= (TP + TN)/(TP + TN + FP + FN) \\ \text{Sensitivity} &= (TP)/(TP + FN) \\ \text{Specificity} &= (TN)/(TN + FP) \end{aligned} \tag{9}$$

Here, TP = True positive, FP-False positive, FN = False negative, TN = True negative. The performance of a classifier



(a) Using HAM 10000 Dataset



(b) Using PH2 Dataset

Fig. 4 (a and b) Various classifier accuracy obtained using proposed image dataset

is analyzed using true positive and false positives. The performance metrics for various feature extraction methods and proposed approach in terms of accuracy, sensitivity and specificity are shown in Fig. 3. All three parameters are measured in percentage.

The accuracy of the proposed approach for feature extraction is more compared with other techniques. The accuracy detection is about 98% for the proposed approach compared with 88% for GLCM, 89% for rgb and 83% for the LBP technique. Also, in the presented work, DE-ANN is proposed as a classifier to label the images into cancerous and non-cancerous forms of results. The novelty behind the use of DE-ANN is that this is considered as one of the best machine learning algorithms for its high predictive ability. Also, with

Table 5 Implementation comparison results between other recent works and the proposed approach

Technique Name	Accuracy (%)	Specificity (%)	Sensitivity (%)
Giotis et al. [39]	81	–	–
Almansour and Jaffar [40]	90.3	94	85.84
Esteva et al. [8]	72.1	–	96
Li and Shen [13]	90.2	69.3	90.2
Proposed	97.4	92	90

differential evolution it provides better and efficient tuning of ANN parameters. An analysis is presented regarding the classification accuracy of other traditional classifiers with proposed DE-ANN using the proposed image dataset. Fig. 4 shows a comparative study between conventional SVM [36], ANN [37], GA-ANN [38] and DE-ANN. The result indicates that DE-ANN accuracy is better compared with other approaches.

To validate the proposed approach, the implementation results in terms of accuracy, specificity and sensitivity parameters are compared with the previous research works and the proposed method. The results which are shown in Table 5 are obtained for Melanoma skin cancer. This study shows that the proposed method produces better outcomes for cancer detection. As concerned with the results of Table 5, the accuracy of the proposed method is higher but the specificity is low compared to work in [40]. Also, previous works show that Deep neural network (DNN) based approaches produces higher accuracy for skin cancer detection. Therefore, the proposed technique is compared with such techniques and result shows that our technique using proposed dataset have better accuracy. A comparison is shown in Fig. 5.

It is observed form the results that the proposed method is accurate for skin cancer detection. The proposed classifier is outstanding among other conventional classifying methods and produces high classification accuracy.

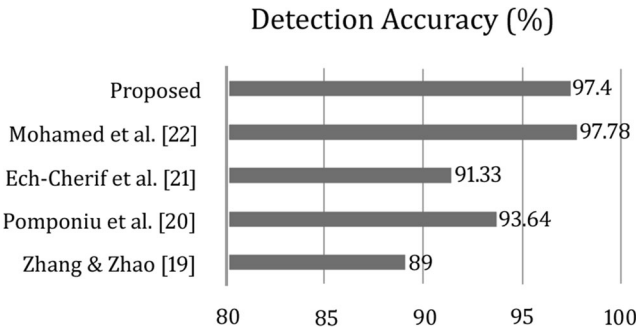


Fig. 5 Comparison of proposed method with DNN based approaches

5 Conclusion and future work

It is better if skin disease is detected as earliest before it turns into a life-threating ailment. Therefore, the presented work is an attempt to detect early symptoms of three types of skin cancer accurately using computer-based techniques. This research implements the classification of skin cancer using DE-ANN (Differential Evolution based Artificial Neural Network). All three types of skin cancer image features or elements are extracted using rgb color space, LBP and GLCM methods, which have a higher contribution in the classification of the skin disease. The result indicates that the proposed approach is progressive towards automatic segmentation using fuzzy C-Means clustering. Using the HAM10000 and PH2 dermatoscopic image dataset, the accuracy of the technique is around 97.4%. Specifically, the proposed framework is compared with other traditional classifiers and concludes that the proposed one is better. Our results are also better compared with other recent works. In the future, this research work can be extended for assessing the correlation between skin burns due to external factors such as sun burn, etc. Also, this work can be extended for other types of skin cancer diseases using deep learning-based approaches.

Acknowledgments This work was supported by the Deanship of Scientific Research (DSR), King Abdulaziz University, Jeddah, under grant No. (DF-813-611-1441). The authors, therefore, gratefully acknowledge DSR technical and financial support.

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