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Melanoma detection using Particle Swarm Optimized Artificial Neural Network

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Abstract

Melanoma, the most dreadful cancer of the skin with a high mortality rate is initially diagnosed visually by a clinical screening, dermoscopic analysis, a biopsy, and histopathological examination. It becomes dangerous with delays in diagnosis and early treatment. Recent developments in image processing techniques help in detecting melanoma in an efficient way as it is a difficult job due to fine-grained variability in the lesion. This paper looks into a new classification procedure for analyzing lesion irregularities using Particle Swarm Optimized Artificial Neural Network. In this research paper, the color features from the lesion are extracted and classification is done using the PSO-ANN classifier. Receiver Operating Characteristics obtained from marking false positive and true positive rates have a vital role in analyzing the diagnostic potential of the computer-aided diagnosis system. Classification techniques applied to the ISIC database indicate 0.96853 as the area under the curve with a specificity of 90.0%, a sensitivity of 94.07%, and an accuracy of 93.04%.

1. Introduction

The most lethal skin cancer, Melanoma, occurs due to mutation and uncontrollable division of melanocytes, the pigment-producing cells. Once detected at the early stages it can be brought under control. A high density of sun tan, multiple moles, light-colored skin, etc are some factors that lead to Melanoma. The risk of skin cancer can be lowered by keeping away from intense sun exposure. According to The American Cancer Society, in 2022, one lakh new melanoma patients will be there in the United States, and around eight thousand Melanoma deaths are anticipated to happen in 2022 [1-2]. A non-invasive type of skin examination by a clinical specialist, dermoscopy, usually has a high prediction accuracy. But sometimes it fails in timely intervention of some specific dermoscopic features which can lead to dangerous conditions. Also, the insufficiency of expert professionals and high prognosis costs are some of the challenges. In this paper to enhance the prognosis accuracy, an innovative automated computer-aided diagnosis (CAD) system to increase melanoma survival rate is presented. The most common aid for Malignancy diagnosis is the ABCD (Asymmetry, Border, Colour, and Diameter) rule [3]. Ihab S. Zaqout, in his work, designed a CAD system for malignancy detection based on the ABCD procedure [4]. New

methods have been adopted for asymmetry detection as asymmetric patterns with unhealthy growth rates are the benchmark for malignancy [5-6]. An early sign of melanoma and the highest predictable diagnosis of malignant melanoma is the variation in color from red to black of the skin lesion [7]. R. J. Stanley et.al studies included a comparative color histogram to classify malignancy using colour clustering ratio attributes from lesion [8]. In the work by Sahani. M and et.al, explains histogram colour equalization method to reinstate the actual skin colour [9].

Lequan Yu et. al, proposed a successful training process incorporating very deep FCNNs to study complex lesion.[10]. The paper by Joanna Jaworek- presents a detailed explanation of the SVM classifier for the identification of malignancy [11]. Oludare Isaac Abiodun et. al did a study on applications of NN in fields that include communication, health care, etc [12]. The work by Iftiaz A. Alfi et.al explained deep learning and machine learning algorithms for Malignancy detection [13]. Thin et al. in their work utilized MATLAB for the analysis of melanoma [14]. Grzegorz Surowka explained in his work the use of ANN classifier for the analysis of skin cancer [15]. Sugiarti et al. implemented a Multilayer Perceptron neural network with texture feature extraction for the analysis of melanoma [16]. Identification of melanoma using SVM and kNN classifiers is explained in the work by Murugan et al. [17]. The work by Thaajwer and Ishanka, used an SVM classifier with GLCM method for lesion classification [18]. Alquran et.al in their study utilized ABCD attributes with SVM classifier [19].

The development of a CAD system that yields high accuracy is the need of the hour. Advanced research utilizing machine learning methods will reduce the rate of human error and increase the chance of early melanoma detection [20]. A CAD methodology to detect melanoma from ISIC database using MATLAB was included in this analysis.

The key contribution of the study is presented below:

Colour attributes have an important part in melanoma detection. In this study, we utilized opponent color and normalized red and green color feature extraction methods for melanoma classification. Here normalization guarantees identical data distribution in all pixels aiding quick convergence while training process is carried out. Opponent color features are utilized for superior colour perception.

Particle Swarm Optimization algorithm is utilized in optimizing the neural network attributes to attain an excellent architecture in order to rise the final accuracy of the suggested system. The experimental outcome of the suggested system conveys the significance of the optimization algorithm and color attributes in melanoma diagnosis. Our suggested optimized classifier exhibits better accuracy compared to state-of-the-art methods which is advantageous for melanoma classification. The rest of the study is organized as given below: Section 2 gives the details of the material and methods used. The results and discussions are presented in section 3 and section 4 explains the conclusion of the study.

2. Materials and Proposed Method

MATLAB R2018a programming along with the image processing tool box can be utilized as a computing platform for the development of a CAD system for melanoma diagnosis. Images for the analysis are taken from the ISIC database. The suggested approach basic flow diagram is shown in Figure 1. The different stages of the approach are pre-processing, extraction of lesion features, and detection. Color features extracted from the ROI of the lesion are given as input to the optimized ANN for classification.

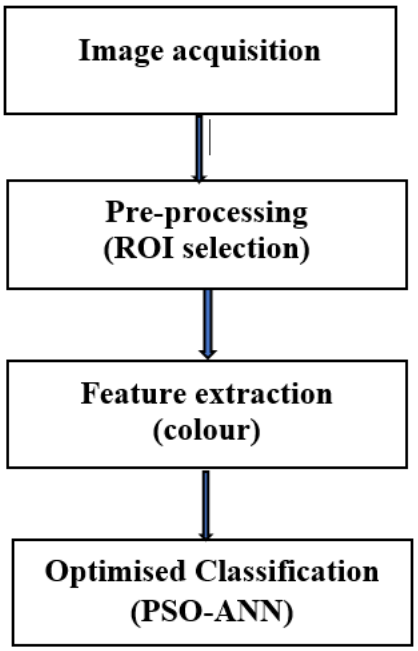

FIGURE 1. Proposed system flow diagram

2.1 Pre-processing

In this stage the Region of Interest of the skin is separated from the image.

2.2 Feature extraction

Out of the features like texture, shape, colour etc , the prime feature that differentiate malignant Melanoma is the colour. Colour variegation in the skin lesion can be inferred by exploring the Red, Green and Blue chromatic values. [21-22]. From the RGB colour space, these RGB values are calculated. By dividing each individual values of chromaticity, normalized red (r_N) and green (g_N) chromaticity values are calculated as mentioned in the Eqn (1) and (2).

$$r_N = \frac{R}{(R+G+B)} \quad (1)$$

$$g_N = \frac{G}{(R+G+B)} \quad (2)$$

From opponent colour space two components, luminance channel (Op1) and G-R channel (Op2) are used to increase the perception of colour as show in the Eqn (3) and (4).

$$\mathrm{Op1}\ (\mathrm{R},\mathrm{G},\mathrm{B}) = \frac{R-G}{2} \quad (3)$$

$$\mathrm{Op2}\ (\mathrm{R},\mathrm{G},\mathrm{B}) = \frac{2B-R-G}{2} \quad (4)$$

PSO ANN classifier is fed with these four colour features in equations 1 to 4.

2.3 PSO optimized ANN based classification

The goal of this study is to work out an optimized PSO-ANN for designing an innovative melanoma detection system with negligible misclassification rate. ANN imitates the neuron networks in human brain by which it starts learning things and making decisions. They can be trained to understand the interrelation of data fed to them.

From the extracted features, skin lesion details are identified and interpreted in classification stage. Database with features of images stored are fed to ANN which identifies the melanoma lesion. New images can be classified as cancerous or non-cancerous by the learned classifier, after training. The network weights are updated by backpropagation learning algorithm which curtail the standard Mean Square Error. ANN structure is shown in Figure 2.

ANN is depending on parameter like Momentum constant (Mc), number of hidden neurons and layers and Learning rate (Lr). Momentum constant quickens the convergence of Back propagation which may confine to local minima. Proper adjustments of learning rate (Lr) is important otherwise it can lead to infinite training time and oscillations. Complexities and time consumption can he handled with optimum hidden layers. So, in the suggested system, to rise the classifier efficiency, these parameters were tuned by PSO algorithm to develop an optimised architecture which is perfectly linked. The learning rate optimization can save the shift in learning direction due to the presence of unfamiliar specimens. The input/output neuron count is set according to the system implemented.

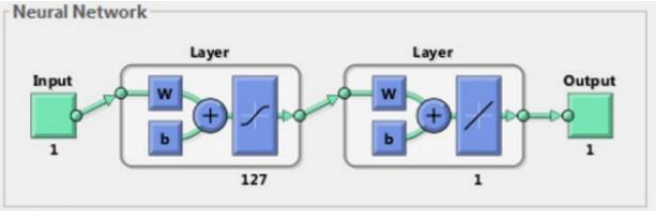

FIGURE 2. ANN structure

The behaviour of many of the optimization methods widely used are interestingly inspired by nature. PSO, put forward by James Kennedy & Russell Eberhart [23] uses population search and techniques to solve optimization drawbacks by mimicking similar patterns similar to the behaviour of species like fish schooling etc. In this algorithm, the optimization problem solutions are found by reconditioning the particles' velocity and position in solution space. The particles advance through the solution space according to the present optimal particle's fitness value and velocity, calculated using a fitness function on which further optimization has to be done. By running maximal iterations, the algorithm helps in precise classification of lesion as cancerous or non-cancerous.

PSO is initialised by a group of random variables to find optimal solutions. After each iteration, the movement of the particles in design space is updated using two best parameters: pbest , the finest position given by the i^{th} particle and

global best, is that tracked by every particles in the design space. By repeating the process, eventually an optimal solution is obtained.

$\mathbf{X_i} = \mathbf{X_{i1}}, \mathbf{X_{i2}}, \mathbf{X_{i3}}, \ldots . \mathbf{X_{in}}$ is the positions and $V_I = \mathbf{V_{I1}}, \mathbf{V_{I2}}, \mathbf{V_{I3}}, \ldots . \mathbf{V_{in}}$ is the velocities of particles in **n** dimensional design space and the equations for the updation of **i**th particles for **d**th dimension is given by

$$\mathbf{X_{id}(t+1)} = \mathbf{X_{id}(t)} + \mathbf{V_{id}(t+1)} \quad (5)$$

$$\mathbf{V_{id}(t+1)} = \mathbf{V_{id}(t)} + \mathbf{A_1} \times \mathbf{N_1} \times \left(\mathbf{p_{bestd}(t)} - \mathbf{X_{id}(t)}\right) + \mathbf{A_2} \times \mathbf{N_2} \times \left(\mathbf{g_{bestd}(t)} - \mathbf{X_{id}}\right) \quad (6)$$

Acceleration constants are $\mathbf{A_1}$ and $\mathbf{A_2}$,

Random numbers are $\boldsymbol{N_1}$ and $\boldsymbol{N_2}$

$\mathbf{p_{bestd}(t)}$ local best solution of individual particle till t^{th} iteration

$\mathbf{g_{bestd}(t)}$ best solution of particles in the entire design space till t^{th} iteration

$\mathbf{V_{id}(t)}$ Individual particle Velocity at t^{th} iteration in dimension d,

$\mathbf{X_{id}(t)}$ Individual particle Position at t^{th} iteration in dimension d,

PSOANN algorithm **pseudo code is given below**

Initialize population
  repeat
    for $i = 1\ to\ S$

    Using Eq. (7) find the fitness value
// update pbest
      If $\boldsymbol{f(X_i)} < \boldsymbol{f\left(P_{best}(t-1)\right)}$then
        $P_{bestt} = X_i$

      end if
// update gbest
      If $(\boldsymbol{P_{besti}}) < \boldsymbol{f(g_{best})}$ then
        $\boldsymbol{g_{best}} = \boldsymbol{P_{besti}}$

      end if
    end for
//Update position and velocity of particle in S domain
  for i=1 to S
    for d=1 to D
      Position is updated by eq. (5)
      Velocity is updated by eq. (6)
    end for
  end for
$i=i_t+1$
until $i_t < t_{max}$

The best output is attained from the PSO-ANN technique by optimizing momentum factor, hidden layer neurons and learning rate. The neurons in input and output are fixed for certain problem. Optimal learning rate accelerate the learning even in the presence of different training patterns and convergence of error propagation is accelerated by the momentum factor optimization.

In design space input layers neurons (Ni) and output layer neurons (No) is similar and fixed. Optimization process range is presented by Υ_{min}={$\mathbf{Lr}_{min}$,$\mathbf{Nh}_{min}$,$\mathbf{Mc}_{min}$} and Υ_{max}={ $\mathbf{Lr}_{max}$,$\mathbf{Nh}_{max}$, $\mathbf{Mc}_{max}$} where **Lr** shows learning rate, **Nh** shows hidden layer neurons and **Mc** shows momentum factor **.** f is the activation function. For optimal training, Mean Square Error (MSE) is the fitness function.

$$\boldsymbol{MSE_{PSO-ANN}} = \sum_{p\in T}\sum_{k=1}^{N_o}\left(\boldsymbol{t_k^p} - \boldsymbol{Y_k^{p,o}}\right)^2 \quad (7)$$

where t_k^p is the target output, actual output, $Y_k^{p,o}$ is in the outer most layer o and from k^{th} neuron in the training set with pattern p. PSOANN algorithm automatically finds the best solution from the framed fitness function. Input, hidden and output are the three layers.

3. Results and Discussion

After selecting the ROI, four colour features are taken from pixels from the ROI and further analysis is done. The PSO-ANN optimization was performed with hidden neurons ranging from 31 to 200 and momentum factor and learning rate also ranging from 0 to 1. Size of the population, N=50 and epochs =500 is performed for training a maximum of 100 generations. For the proposed PSO-ANN, Nh = 127, Lr = 0.01365 and Mc = 0.9532 is achieved.

Input for the optimised classifier are the extracted four colour features. For training 80% of the dataset and for testing 20% are used. During training time, unknown output is used by the classifier and in testing period, previously unknown lesions are classified. The classification results are shown in Figure 3.

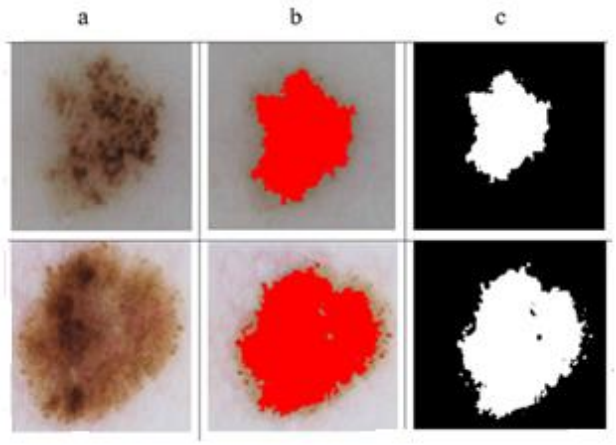

FIGURE 3. Detection results i) ISIC database image ii) ROI iii) Detected malignant image.

Classification process recognizes and separates melanoma lesion from non melanoma lesion. It helps to segregate skin lesion into discrete values like true/false. This section of the paper explains about different performance measures implemented like False Positive (*FP), False Negative (*FN), True Positive (*TP) and True negative (*TN) to analyse the potential of different identification techniques used for malignancy diagnosis. * TP shows that the skin lesion is truly melanoma and *FP is where the lesion predicted to have cancer is actually not. *TN shows absence of melanoma and *FN means the lesion predicted to be normal is actually cancerous. Receiver Operating Characteristics curve (ROC) [24] which is marked with TPR on y -axis and FPR on x-axis is for analysing the classifier performance is shown in Figure 4. Another important analytical measure for classification performance is sensitivity and selectivity shown in Eqn (8) and (9). Sensitivity assess true positives which means malignant lesion is correctly identified. Specificity shows true negatives, i.e malignancy is not present.

$$\text{Sensitivity} = \frac{*\text{TP}}{(*\text{FN}+*\text{TP})} \quad (8)$$

$$\text{Specificity} = \frac{*\text{TN}}{(*\text{FP}+*\text{TN})} \quad (9)$$

$$\text{F measure} = 2 * \frac{\text{Recall}*\text{Precision}}{\text{Recal}+\text{Precisionl}} \quad (10)$$

AUC measures the quality of the diagnostic system to distinguish between melanoma and non-melanoma lesions and it shows the probability that an abnormal lesion chosen at random is more indicative of malignancy than a similarly chosen normal lesion.

The complete performance analysis of proposed system is measured using the parameter accuracy that gives correct predictions of the proposed CAD system. Accuracy is given in Eqn (11)

$$\text{Accuracy} = \frac{(*\text{TP} + *\text{TN})}{(*TP+*FP+*TN+*FN} \quad (11)$$

Another performance metric that evaluates the performance of a diagnostic system is Youden's index (J) whose value ranges from 0 to 1 and is expressed in Eqn (12) .

$$J = \text{sensitivity} + \text{specificity} - 1 \quad (12)$$

The automatic detection classifier may miss certain abnormalities and also miss predict, which is expressed as the misclassification rate in Eqn (13).

Misclassification Rate =1-Accuracy (13)

From Confusion matrix in Figure 5 the performance of the suggested system can be understood. System's Performance Measures for ISIC Dataset Using MATLAB parameters are shown in Table 1.

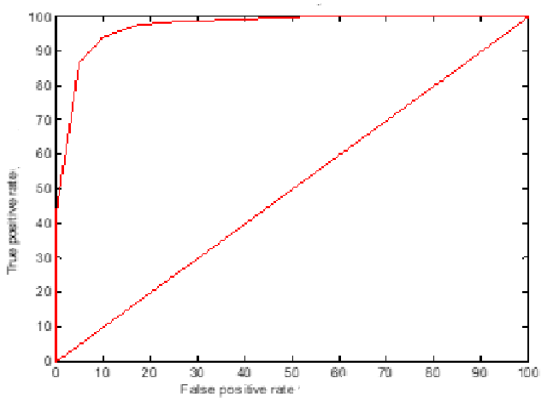

FIGURE 4. ROC curve for PSO-ANN classifier

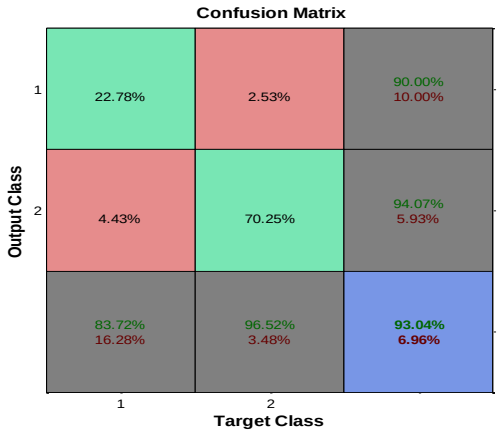

FIGURE 5. Confusion matrix for PSO-ANN classifier

TABLE 1. Shows System's Performance Measures for ISIC Dataset Using MATLAB

Parameters	PSO-ANN classifier
Sensitivity	94.07%
Specificity	90.00%
F-Measure	0.953
Accuracy	93.04%
Youden's index	0.8407
Misclassification	0.070
AUC	0.96853

The classification accuracy has increased after the introduction of optimised learning. The AUC under ROC curve is 0.96853 with a specificity of 90.00% and sensitivity of 94.07%. By the introduction of optimized learning, classification accuracy has reached to 93.04%. This makes the PSO-ANN suitable for the classification for the detection of Melanoma.

The comparison with previous state of art results is shown in Table 2.

TABLE 2. Comparison with previous work

Methodology	Accuracy
SVM (Babu et al.) [25]	76.0%
CNN (Gouda et al.) [26]	85.7%
SVM (Murugan et al.)	89.5%
KNN (Murugan et al.)	86.0%
CCNN (Sethulekshmi et al.)[27]	91.1%
Proposed system	93.04%

Conclusion

The research paper put forth a novel technique of PSO-ANN classifier used in computer aided analysis in Melanoma detection. Presence of melanoma is detected by the algorithm explained in the paper. Initially colour features are taken from skin lesion and an optimised PSO-ANN classifier is used in this classification process with increased accuracy. The AUC from the ROC is obtained as 0.96853 with a specificity of 90.02% and a sensitivity of 94.11%. Optimized ANN accelerates the convergence of the algorithm with an accuracy of 93.01%. These obtained results shows the potential of our suggested system in melanoma detection .It can be of use to dermatologists by utilizing it in dermoscopy systems. Implementing CAD system with more refined techniques can minimize the melanoma death rate.

Authors' Note

The authors declare that there is no conflict of interest regarding the publication of this article.

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