

Skin Cancer Detection with Optimized Neural Network via Hybrid Algorithm

Ganeshan R

ST. Joseph College of Engineering
Chennai, Tamil Nadu, India
ganeshanr14@gmail.com

Abstract: Skin lesion segmentation is a crucial but challenging task in computer-aided diagnosis of skin images. This work aims to propose a skin cancer detection model, which includes two major phases: Feature extraction and Classification. Initially, feature extraction takes place, where the Gray-Level Co-Occurrence Matrix (GLCM) features and Gray Level Run-Length Matrix (GLRM) features are extracted from the input image. These extracted features are subjected to the classification process, where Optimized Neural Network (NN) is exploited for classifying the skin lesion. In addition, to attain more enhanced output, the weights of NN is tuned finely using Cuckoo-Grey Wolf based Optimization (CGWO). Finally, the superiority of the adopted scheme is analyzed by determining both the positive as well as negative measures through the comparison over several conventional methods.

Keywords: Skin Cancer; GLCM; GLRM; Neural Network; CGWO Approach; Accuracy.

Nomenclature

Abbreviations	Descriptions
CGWO	Cuckoo-Grey Wolf based Optimization
CNN	Convolutional Neural Network
DL	Deep Learning
DT	Decision Tree
FN	False Negative
FP	False Positive
GLCM	Gray-Level Co-Occurrence Matrix
GLRM	Gray Level Run-Length Matrix
HoG	Histogram of Gradients
KNN	K-Nearest Neighbours
LR	Logistic Regression
LBP	Local Binary Pattern
NN	Neural Network
NB	Naive Bayes
PSO	Particle Swarm Optimization
RF	Random Forest
SVM	Support Vector Machine
SMP	Skin Magnifier with Polarized light
TP	True Positive
TN	True Negative
WOA	Whale Optimization Algorithm

1. Introduction

Recently, disease prediction systems have attained huge attention amongst the individuals, and it was observed as a notable topic, as a prediction of the diseases is crucial for human beings to survive a better life [1] [2] [3]. Therefore, it remains imperative for health care groups to proffer enhanced medicinal care for patients [4] [5]. The disease prediction approach takes account of diverse classification schemes such as KNN, DT, NB, NN, SVM, LR, and so on. By using these schemes, the diseases are categorized in an exact manner [7] [6] for effectual prediction of fatal diseases. Currently, skin cancer has turned out to be the most destructive form of cancer found amongst individuals [8].

The skin is the bigger organ and it protects the body from light, infection, and heat. In addition, it helps to normalize the temperature of the body and aids in storing fat and water. A considerable issue of skin in the body is its “infection risk to skin cancer” [9]. In general, the skin cell grows-up and split into new cells. However, at certain times older cells expire when they should not and newer cells are developed while the skin doesn't require them. Such extra cells form a group of tissues known as tumors [1].

For automatic extraction of skin lesions from skin images [2] [3] [6], a variety of segmentation schemes such as, “thresholding, edge detection, and region merging” were developed. These schemes rely on features attained from shape, texture, and color that cause difficulty while implementing. Moreover, this feature usually considers pixel-level information, which hinders the revelation of higher-level attributes. Nowadays, CNNs are exploited for carrying out computer vision tasks [7] [3]. Even though the CNN-oriented schemes perform superior to traditional techniques [16] [17], certain limits remain to be resolved [1].

The main contribution of this paper is to propose a skin cancer detection model, which includes two major phases: Feature extraction and Classification. The rest of the paper is organized as: Section 2 portrays the reviews on skin cancer. Section 3 depicts the architecture of the skin cancer detection framework. Further, Section 4 addresses the extraction of GLCM and GLRM features. CGWO based NN optimization for skin cancer detection is depicted in Section 5. The resultants are briefed in Section 6 and the conclusion is elucidated in Section 7.

2. Literature Review

In 2018, Tan et al. [1] suggested an intellectual skin cancer detection scheme that deployed the PSO model for optimizing the features. Accordingly, “Probability distribution and dynamic matrix representations” were exploited for expanding the searching process. In the end, the evaluation was done on varied modalities; in which the presented PSO has exposed an enhanced performance over conventional frameworks for identifying the discriminate features.

In 2019, Dascalu and David [2] have examined the accurateness of image quality using the sonification process that employed SMP. Accordingly, the output audio was further analyzed using a varied DL model. Further, the analysis was performed in terms of sensitivity and specificity that were examined by an F2-score. As a result, the skin images processed via the DL model resulted in exact outcomes, thus showing the advantage of the SMP model in skin cancer analysis.

In 2017, Alfred and Fouad [3] have presented a system for automatic treatment of skin cancer that united diverse textural and color features. Novel color and textural features were exploited in a “bag-of-features approach” for precise and proficient recognition. It was stated that HoL and HoG were more suitable for the classification and analysis of dermoscopic images. In the end, the improvement of the model was examined using varied classifiers on the skin image dataset.

In 2020, Zhang et al. [4] have proposed a novel image processing technique for prior recognition of skin cancer. This method utilized an optimized CNN for this purpose. Here, enhanced WOA was used for optimization purposes. Here, for evaluating the presented method, it was distinguished over different schemes on 2 varied datasets. Simulation outcomes have exposed that the suggested scheme was enhanced than other existing techniques.

In 2019, Teck et al. [5] have developed an intellectual “decision support system” for detecting skin cancers. Particularly, clinically significant “asymmetry, border irregularity, color, and dermoscopic structure features” were unified with GLRM, LBP, and HoG feature for denoting lesions. Subsequently, 2 enhanced PSO frameworks were developed for optimizing the features. In addition, DCNN was exploited, whose parameters were tuned via the PSO model.

3. Architecture of Skin Cancer Detection Model

3.1 Proposed Architecture

In this paper, a new skin cancer detection model is proposed with two major phases' viz. Feature extraction and Classification, which is illustrated in Fig. 1. At first, the input skin image I_m is subjected to feature extraction, where GLCM and GLRM based features are extracted. The extracted features are subjected to the NN classifier for classification, which offers the precise detected output. For classification purposes, this paper exploits the NN framework. Further, in order to make the system more precise, the weights of NN are fine-tuned using the CGWO algorithm. Thus, the final result determines the presence of disease.

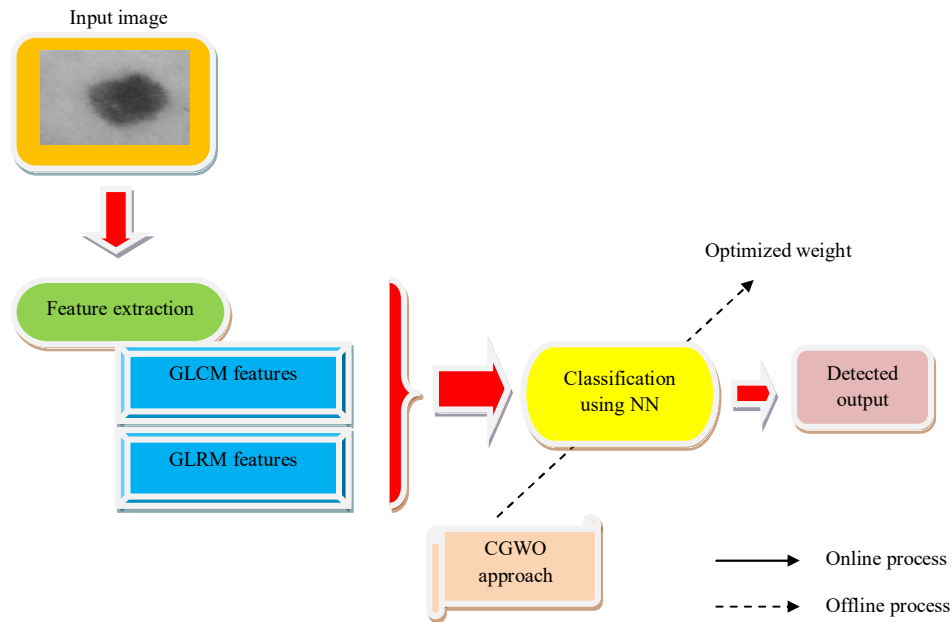


Fig. 1. Block diagram of Proposed skin cancer detection Framework

4. Extraction of GLCM and GLRM based Features

4.1 GLCM

GLCM is the factual approach that evaluates the spatial association among the pixels [10]. The brief explanation of GLCM features is given in Table 1. The features extracted from GLCM are denoted as Fe^{GLCM} .

Table 1: GLCM features

S.No.	Features	Mathematical Expression
1.	Energy	$E = \sum_u \sum_v g_{du,v}^2$ <p>where $g_{du,v}$ refers to $(u, v)^{th}$ entry in GLCM</p>
2.	Entropy	$Ent = - \sum_u \sum_v g_{du,v} \log_2 g_{du,v}$
3.	Contrast	$Con = \sum_u \sum_v (u - v)^2 g_{du,v}$
4.	Variance	$V = \sum_u \sum_v (u - \mu)^2 g_{du,v}$ <p>, where μ points out the mean of $g_{du,v}$</p>
5.	Homogeneity	$H = \sum_u \sum_v \frac{1}{1 + (u - v)^2} g_{du,v}$
6.	Correlation	$C = \frac{\sum_u \sum_v (uv) g_{du,v} - \mu_x \mu_y}{\sigma_x \sigma_y},$ <p>here $\sigma_x, \sigma_y, \mu_x, \mu_y$ specifies the std deviations and mean of g_{dx}, g_{dy}</p>
7.	Sum Average	$SA = \sum_{u=2}^{2N_g} \ddot{u}_{g_{dx+y}}(u),$ <p>where N_g point out the varied gray levels in the image.</p>

8.	Sum Entropy	$SE = \sum_{u=2}^{2N_g} g_{dx+y}(u) \log \{g_{dx+y}(u)\}$
9.	Sum Variance	$SV = \sum_{u=2}^{2N_g} (u - SA)^2 g_{dx+y}(u)$
10.	Difference Variance	DV = variance of g_{dx-y}
11.	Difference Entropy	$DE = \sum_{u=0}^{N_g-1} g_{dx-y}(u) \log \{g_{dx-y}(u)\}$
12.	MCC (2 nd higher Eigen value of $Q^{0.5}$)	$MCC = \sum_k \frac{g_d(u, k) g_d(v, k)}{g_{dx}(u) g_{dy}(k)}$
13.	Information Measures of Correlation 1	$of IMC1 = \frac{HXY - HXY1}{\max\{HX, HY\}}$
14.	Information Measures of Correlation 2	$of IMC2 = \sqrt{(1 - \exp[-2.0[HXY2 - HXY1]])}$, where $HXY = - \sum_u \sum_v g_{du,v} \log_2 g_{du,v}$ $HXY1 = - \sum_u \sum_v g_{du,v} \log_2 \{g_{dx}(u) g_{dy}(v)\}$ $HXY2 = - \sum_u \sum_v g_{dx}(u) g_{dy}(v) \log_2 \{g_{dx}(u) g_{dy}(v)\}$

4.2 GLRM

“GLRM is represented in the form of a matrix for geometrical features and it gives a measure of the intensity of the pixels along the given direction mentioned as Run-length” [11]. The brief elucidation on GLRM features is denoted in Table 2.

Table 2: GLRM features

S.No.	Features	Mathematical Expression
15.	Small Run Emphasis	$SRE = \frac{1}{m} \sum_{u,v} \frac{p(u,v)}{v^2}$ where p is the probability of (u,v) in various distances
16.	Long Run Emphasis	$LRE = \frac{1}{m} \sum_{u,v} v^2 p(u,v)$
17.	Grey Level Non Uniformity	$GLN = \frac{1}{m} \sum_u \left(\sum_v p(u,v)^2 \right)$
18.	Run Length Non Uniformity	$RLN = \frac{1}{m} \sum_u \left(\sum_v p(u,v)^2 \right)$
19.	Run percentage	$RP = \sum_{u,v} \frac{m}{p(u,v)v}$
20.	Low Grey Level Run Emphasis	$LGRE = \frac{1}{m} \sum_{u,v} \frac{p(u,v)}{u^2}$
21.	High Grey Level Run Emphasis	$HGRE = \frac{1}{m} \sum_{u,v} u^2 p(u,v)$

The features extracted from GLRM are signified by Fe^{GLRM} .

The GLCM, as well as GLRM features denoted by, $Fe = Fe^{GLCM} + Fe^{GLRM}$ are provided as input to the NN classifier for classification purposes.

5. CGWO Based Neural Network Optimization for Skin Cancer Detection

5.1 Neural Network

Here, the extracted features Fe are subjected to NN for classification. NN [12] consider the features Fe as input, as shown in Eq. (1), in which nupoint out the total feature count.

$$Fe = \{Fe_1, Fe_2, \dots, Fe_{nu}\} \quad (1)$$

The model includes input, output, and hidden layers. The output of the hidden layer $e^{(H)}$ is portrayed in Eq. (2), where A denote the “activation function”, i and j signifies the neurons of hidden and input layers correspondingly, $w_{(Bi)}^{(H)}$ denotes bias weight to i^{th} hidden neuron, n_i signify input neuron count and $w_{(ji)}^{(H)}$ denotes the weight from j^{th} input neuron to i^{th} hidden neuron. The output \hat{G}_o is determined as in Eq. (3), where \hat{o} is the output neurons, n_h indicates the hidden neuron count, $w_{(Bo)}^{(G)}$ denotes output bias weight to the \hat{o}^{th} output layer, and the weight from i^{th} hidden layer to \hat{o}^{th} output layer is denoted by $w_{(io)}^{(G)}$. Consequently, the error amongst the predicted and actual values is computed as per Eq. (4) that should be reduced. In Eq. (4), n_G symbolizes the output neuron count, $G_{\hat{o}}$ and $\hat{G}_{\hat{o}}$ refers to the actual and predicted output respectively.

$$e^{(H)} = A \left(w_{(Bi)}^{(H)} + \sum_{j=1}^{n_i} w_{(ji)}^{(H)} Fe \right) \quad (2)$$

$$\hat{G}_{\hat{o}} = A \left(w_{(Bo)}^{(G)} + \sum_{i=1}^{n_h} w_{(io)}^{(G)} e^{(H)} \right) \quad (3)$$

$$Er^* = \arg \min_{\{w_{(Bi)}^{(H)}, w_{(ji)}^{(H)}, w_{(Bo)}^{(G)}, w_{(io)}^{(G)}\}} \sum_{i=1}^{n_G} |G_{\hat{o}} - \hat{G}_{\hat{o}}| \quad (4)$$

As mentioned above, the training of the NN model is carried out using the CGWO algorithm via optimizing the weights $W = w_{(Bi)}^{(H)}, w_{(ji)}^{(H)}, w_{(Bo)}^{(G)}$ and $w_{(io)}^{(G)}$.

5.2 Solution Encoding

The presented work focuses more on the precise prediction of skin cancer disease, for which optimization logic is insisted on this work. Here, the weights of NN signified by W are also defined optimally. In this context, the CGWO approach is used for optimization purposes. The input solution to this presented model is revealed in Fig. 2, where Nu indicate the entire counts of weights. Further, the objective function (Obj) defined in the work is stated in Eq. (5), where Er^* denotes the error.

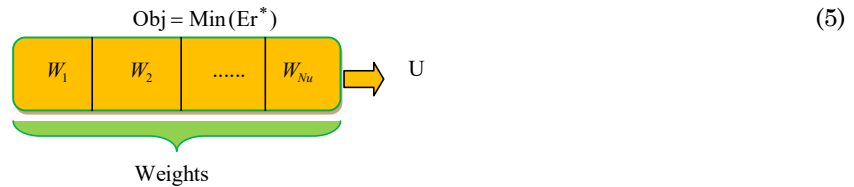


Fig. 2. Solution encoding

5.3 CGWO Algorithm

In the CGWO approach [13], the GWO update is integrated with the update of CSA. The steps of CGWO are described below.

The prime phase of CGWO is the initialization of the grey wolf's population. Subsequently, the fitness of every solution is computed using the fitness function shown in Eq. (22). GWO exploits the 3 fittest solutions, α as 1st best solution, β as 2nd best and δ as 3rd best solutions.

CS-based position update

The position of the searching agent is updated based on the best searching agent as specified in Eq. (6), which is known as the encircling behavior of grey wolves. In Eq. (6), \vec{U} refers to the position vector, \vec{U}_p refers to the prey position, \vec{L} refers to the coefficient vector, and t refers to the present iteration.

$$\vec{Y} = \left| \vec{L} \cdot \vec{U}_p - \vec{U}^t \right| \quad (6)$$

The position of agents at subsequent iteration is specified by Eq. (7), in which \vec{J} is a coefficient vector and \vec{Y} refers to the distance among the agent and prey.

$$\vec{U}^{t+1} = \vec{U}_p - \vec{J} \cdot \vec{Y} \quad (7)$$

The coefficient vectors are portrayed using the arbitrary vectors and a parameter as shown in Eq. (8) and Eq. (9), in which \vec{b} point out a constraint that is reduced from 2 to 0 over every iteration and \vec{g}_1, \vec{g}_2 points out two arbitrary vectors that lie among 0 and 1.

$$\vec{J} = 2\vec{b} \cdot \vec{g}_1 - \vec{b} \quad (8)$$

$$\vec{L} = 2 \cdot \vec{g}_2 \quad (9)$$

As per the positions of best-searching agents, the positions of other agents are also updated as shown in Eq. (10), in which \vec{U}_α , \vec{U}_β and \vec{U}_δ refers to the 1st, 2nd, and 3rd best search agents in that order.

$$\left. \begin{aligned} \vec{Y}_\alpha &= \left| \vec{L}_1 \cdot \vec{U}_\alpha - \vec{U} \right| \\ \vec{Y}_\beta &= \left| \vec{L}_2 \cdot \vec{U}_\beta - \vec{U} \right| \\ \vec{Y}_\delta &= \left| \vec{L}_3 \cdot \vec{U}_\delta - \vec{U} \right| \end{aligned} \right\} \quad (10)$$

Accordingly, the positions of \vec{U}_1 , \vec{U}_2 and \vec{U}_3 at subsequent iterations are formulated depending on the 3 best positions of the searching agents as shown in Eq. (11).

$$\left. \begin{aligned} \vec{U}_1 &= \vec{U}_\alpha - \vec{J}_1 \cdot \vec{Y}_\alpha \\ \vec{U}_2 &= \vec{U}_\beta - \vec{J}_2 \cdot \vec{Y}_\beta \\ \vec{U}_3 &= \vec{U}_\delta - \vec{J}_3 \cdot \vec{Y}_\delta \end{aligned} \right\} \quad (11)$$

In Eq. (11), \vec{Y}_α , \vec{Y}_β and \vec{Y}_δ refers to the distance among the positions of 1st, 2nd, and 3rd best agents and prey respectively. Consequently, the positions of wolves are updated as shown in Eq. (12).

$$\vec{U}_{t+1} = \frac{\vec{U}_1 + \vec{U}_2 + \vec{U}_3}{3} \quad (12)$$

For formulating the position update in the CGWO approach, Eq. (12) is modified by establishing a 4th term in the numerator as shown in Eq. (13).

$$\vec{U}_{t+1} = \frac{\vec{U}_1 + \vec{U}_2 + \vec{U}_3 + \vec{U}_4}{4} \quad (13)$$

In Eq. (13), \vec{U}_4 refers to the position update vector of the CSA scheme. In CSA, every egg in the nest indicates a solution, which is substituted over-improved solutions. Based on this behavior, \vec{U}_4 is updated as shown in Eq. (14), in which, \vec{U}^t refers to the agent position at present iteration, γ refers to the step size, and \oplus refers to the entry wise multiplication.

$$\vec{U}_4 = \vec{U}^t + \gamma \oplus \text{Levy}(\lambda) \quad (14)$$

$\text{Levy}(\lambda)$ denotes the formulation of Levy flight, which offers the random walk as shown in Eq. (15) and λ lies among 1 and 3.

$$\text{Levy} \sim v = t^{-\lambda} \quad (15)$$

Finding optimal solution

After the agent's positions are updated, the fitness of every solution in the novel population is computed and the best solution is determined.

Termination

The steps are continued till the maximal count is attained. Thus, the optimal solutions in lower and upper bounds are optimally chosen using the CGWO model.

6. Results and Discussion

6.1 Experimental Setup

The developed skin cancer prediction model was implemented in Matlab and the resultants were observed. Accordingly, the betterment of the CGWO model was compared over other traditional models like RF [14] and SVM [15]. Here, the analysis was done regarding various metrics namely, “accuracy, sensitivity, specificity, precision, F-score, TP, FN, FP, and TN” respectively.

6.2 Performance Analysis

The performance of NN over the conventional classification models with respect to TP, FN, FP, and TN is revealed in Table 3. Here, the performance analysis was carried out on the basis of the confusion matrix that shows the betterment of the optimized NN scheme. On noticing the outcomes, the optimized NN model has accomplished better TN and TP when compared to the existing models. In addition, on observing Table 4, the optimized NN method has achieved an accuracy of 0.99, whereas, the compared RF and SVM models have achieved a comparatively minimal accuracy of 0.7 and 0.8 respectively. Thus, when comparing the existing schemes, the optimized NN model has accomplished much higher accuracy. Similarly, the specificity of the adopted scheme is 25.32% and 22.22% superior to traditional schemes like RF and SVM. Thus, the superior performance of optimized NN is proved over conventional classifiers.

Table 1: Performances Measure based on Confusion Matrix

Measures	RF	SVM	NN
TP	12	14	16
FN	5	4	2
FP	5	4	2
TN	18	20	23

Table 2: Performance analysis of the presented approach over traditional classification schemes

Measures	RF	SVM	NN
Accuracy	0.7	0.8	0.99
Sensitivity	0.62	0.79	0.92
Specificity	0.79	0.81	0.99
Precision	0.7	0.8	0.9
F1-score	0.65	0.8	1

6.3 Analysis of Risk Factors

Fig. 3 revealed the analysis of risk factors using the presented approach over traditional classification schemes for 3 types of skin diseases namely, “common nevus, Atypical Nevus, and Melanoma”. On examining the outcomes, the optimized NN model has revealed minimal risk values, whereas, the existing algorithms have revealed comparatively higher risk values with respect to accuracy. Thereby, the enhancement of the CGWO + NN framework was proved over the existing models.

6. Conclusion

This paper had developed a skin cancer detection model, where the GLCM and GLRM features were extracted at the initial stage. In addition, optimization assisted classification was introduced, where training was carried out in NN by a new CGWO algorithm via tuning of optimal weights. Finally, a precise analysis was made for validating the enhancement of the CGWO + NN model over traditional schemes in terms of varied measures. Particularly, when comparing the existing schemes, the optimized NN model has accomplished much higher accuracy. Similarly, the specificity of the adopted scheme was 25.32% and 22.22% superior to traditional schemes like RF and SVM. Thus, the superiority of the developed model has been verified successfully.

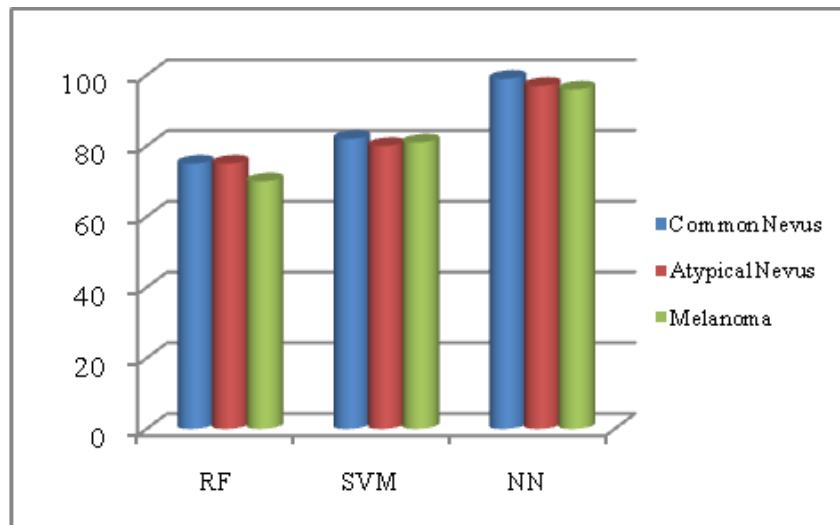


Fig. 3. Performance analysis of risk factors using the presented approach over traditional classification schemes for 3 skin diseases

References

- [1] Teck Yan Tan, Li Zhang, Siew Chin Neoh, Chee Peng Lim, "Intelligent skin cancer detection using enhanced particle swarm optimization", Knowledge-Based Systems, vol. 158, pp.118-135, 15 October 2018.
- [2] A. Dascalu, E. O. David, "Skin cancer detection by deep learning and sound analysis algorithms: A prospective clinical study of an elementary dermoscope", EBio Medicine, vol.43, pp.107-113, May 2019.
- [3] Naser Alfed, Fouad Khelifi, "Bagged textural and color features for melanoma skin cancer detection in dermoscopic and standard images", Expert Systems with Applications, vol. 9030, pp. 101-110, December 2017.
- [4] Ni Zhang, Yi-Xin Cai, Yong-Yong Wang, Yi-Tao Tian, Benjamin Badami, "Skin cancer diagnosis based on optimized convolutional neural network", Artificial Intelligence in Medicine, vol. 102, January 2020, Article 101756
- [5] Teck Yan Tan, Li Zhang, Chee Peng Lim, "Intelligent skin cancer diagnosis using improved particle swarm optimization and deep learning models", Applied Soft Computing, vol. 84, November 2019, Article 105725
- [6] Fengying Xie, Jiawen Yang, Jie Liu, Zhiguo Jiang, Yukun Wang, "Skin lesion segmentation using high-resolution convolutional neural network", Computer Methods and Programs in Biomedicine, vol.186, April 2020, Article 105241.
- [7] Amirreza Mahbod, Gerald Schaefer, Isabella Ellinger, Rupert Ecker, Chunliang Wang, "Fusing fine-tuned deep features for skin lesion classification", Computerized Medical Imaging and Graphics, vol. 71, pp.19-29, January 2019.
- [8] Balazs Harangi, "Skin lesion classification with ensembles of deep convolutional neural networks", Journal of Biomedical Informatics, vol. 86, pp. 25-32, October 2018.
- [9] Omar Abuzagheh, Buket d. Barkana and Miad Faezipour, "Noninvasive Real-Time Automated Skin Lesion Analysis System for Melanoma Early Detection and Prevention", IEEE journal of engineering in Health and medicine, April 2015;
- [10] Dhanashree Gadkari, "Image Quality Analysis using GLCM", 2004
- [11] Manavalan Radhakrishnan and Thangavel Kuttiannan, "Comparative Analysis of Feature Extraction Methods for the Classification of Prostate Cancer from TRUS Medical Images", IJCSI International Journal of Computer Science Issues, vol. 9, no.1, January 2012.
- [12] Yogeswaran Mohan, Sia Seng Chee, Donica Kan Pei Xin and Lee Poh Foong, "Artificial Neural Network for Classification of Depressive and Normal in EEG", 2016 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES), 2016.
- [13] Chitrakant Banchhor, N. Srinivasu, "Integrating Cuckoo search-Grey wolf optimization and Correlative Naive Bayes classifier with Map Reduce model for big data classification", Data & Knowledge Engineering, vol. 127, May 2020, Article 101788.
- [14] Md. Zahangir Alam, M. Saifur Rahman, M. Sohel Rahman, "A Random Forest based predictor for medical data classification using feature ranking", Informatics in Medicine Unlocked, vol. 15, 2019, Article 100180.
- [15] Prabhpreet Kaur, Gurminder Singh, Parminder Kaur, "Intellectual detection and validation of automated mammogram breast cancer images by multi-class SVM using deep learning classification", Informatics in Medicine Unlocked, vol. 16, 2019, Article 100151.
- [16] Amolkumar Narayan Jadhav, Gomathi N, "DIGWO: Hybridization of Dragonfly Algorithm with Improved Grey Wolf Optimization Algorithm for Data Clustering" Multimedia Research, Volume 2, Issue 3, July 2019.
- [17] Malige Gangappa, Kiran Mai C, Sammulal P, "Enhanced Crow Search Optimization Algorithm and Hybrid NN-CNN Classifiers for Classification of Land Cover Images", Volume 2, Issue 3, July 2019.