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An Effective Approach to Detect Melanoma Using Semantic Mathematical Model and Modified Golden Jackal Optimization Algorithm

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Abstract: Melanoma skin cancer is the most life-threatening and fatal disease in the family of skin cancer diseases. Detecting melanoma at its early stage can improvise survival which requires an effective classification technique to categorize dermoscopic images as melanoma and non-melanoma. Based on the quality of the extracted features, the classification accuracy of the classifier is determined. However, the classification accuracy of the existing approaches is poor due to the presence of improper image boundaries and low quality. To overcome the fore-mentioned issues, this research introduced an optimization-based feature selection approach using the modified golden jackal optimization (MGJO) algorithm. The pre-processed image is segmented using a semantic mathematical model known as saliency-based level set with improved boundary indicator function (SLSIBIF) and the feature extraction is performed using the GoogleNet architecture. After this, the proposed MGJO algorithm was used to select the relevant features which aid in precise classification performed using multiclass-support vector machine (MSVM). The obtained results show that the proposed MGJO-MSVM achieves enhanced classification accuracy of 98.89 % for the ISIC-2017 dataset whereas the accuracy of the existing feature adaptive transformer network (FAT-NET), multi-attention fusion convolutional neural network-based skin cancer diagnosis (MAFCNN-SCD), W-net inception residual network, region-based convolutional neural network with fuzzy k-means clustering (RCNN-FKM) and gated fusion attention network is 93.26%, 92.22%, 96.97%, 95.6% and 93.97% respectively.

Keywords: Melanoma, Modified golden jackal optimization, Multiclass-support vector machine, Semantic mathematical model, Skin cancer.

1. Introduction

In recent decades, cancer arouse as the deadliest disease which claims the lives of millions of people. The growth of abnormal cell tissues in various parts of the body is known as cancer which takes place in the individual in various types such as cancer in the skin, brain and so on [1]. Among various types of cancers, cancer in the skin element of the human body is often exposed to various environmental conditions. Skin cancer results in uncontrolled cell proliferation due to the damage of Deoxyribose-Nucleic acid (DNA) when it is exposed to ultra-violet (UV) radiation [2]. In general, skin cancer is classified into two classes such as melanoma and non-melanoma based on the type of cancer-affected cell [3, 4]. Recently, more clinicians are using computer aided diagnosis (CAD) as a tool to predict and classify skin cancer diseases. Dermatologists use two types of approaches such as manual screening and the usage of dermoscopic tools to detect melanoma. The dermoscopy is a type of microscopic method that helps to examine the skin surface and helps to distinguish the malignant and benign lesions [5, 6].

However, accurate screening and classification of image lesions remain a challenge for dermatologists due to improper image boundaries and varying sizes [7, 8]. The growth of machine learning and deep learning techniques acts as an effective solution to detect skin cancer from medical images. Moreover, the classification models which are built using machine and deep learning techniques are effective to classify cancer cells. However, the performance of the classifier relies on selecting the qualities and features which help to ease the categorization process [9]. Features play an important role in processing the image and they are considered based on texture, shape, and color. So, it is important to develop an effective feature selection technique that selects the appropriate features for finalized classification of melanoma [10]. Recent optimization approaches such as guided pelican optimization (GPO) algorithm [11], Stochastic Komodo optimization algorithm (SKOA) [12] are vastly utilized by more researchers to perform an effective classification of skin cancer. But, classification accuracy relies as a major crisis due to inappropriate feature selection and poor segmentation [13]. So, this research introduced a modified golden jackal optimization (MGJO) algorithm to select the useful features which ease the process of classification with better accuracy.

The major contributions of this research are listed as follows:

1. The Modified golden jackal optimization algorithm is introduced to select the appropriate features which ease the process of classification.

2. The segmentation is performed using a semantic mathematical model named SLSIBIF, the feature extraction is performed using GoogleNet architecture, and the MSVM is used as a classifier to categorize the skin cancer as melanoma and non-melanoma.

3. The performance of the proposed approach is evaluated using four benchmark datasets such as ISIC-2016, ISIC-2017, and PH2.

The rest of this research paper is organized in the following manner: Section 2 represents the related works of this research and the proposed methodology is described in section 3. Section 4 presents the results obtained while evaluating the proposed method and the overall conclusion of this research is described in section 5.

2. Related works

This section presents some of the recent approaches which are based on skin cancer classification using various approaches.

Huisi Wu [14] have introduced a feature adaptive transformer network based on the architecture of the encoder and decoder known as FAT-NET which was effective in the process of segmenting the skin lesion. The transformer encoder utilized a sequence-to-sequence prediction approach to segment the images of lesions. The suggested approach enhances the feature fusion for multi-level features using the memory-efficient decoder. However, the feature correlations were not captured which hinders the classification accuracy of the model. Marwa obayya [15] have introduced an optimal multi-attention fusion convolutional neural network-based skin cancer diagnosis (MAFCNN-SCD) approach to detect cancer in the skin using the images obtained from dermatologic data. Initially, pre-processing is accomplished and the feature extraction was performed using henry gas solubility optimization (HGSO) algorithm to optimize the hyper-parameters. Finally, the classification was performed using deep belief network (DBN). The deep instance segmentation performed using the suggested approach can effectively minimize the error rate. But, complexities that occurred at the time of computation of the suggested approach are reliably greater due to pixel wise segmentation.

Sahib Khouloud [16] have introduced a deep learning system to detect melanoma and the deep learning system was comprised of W-net and inception ResNet. The suggested approach is comprised of three stages such as pre-processing, segmentation, and classification. The architecture of W-net consists of ResNet and ConvNet encoders and decoders with a feature pyramid network. The presence of two architectures of encoder and decoder enhance the segmentation result and the inception ResNet helps to achieve an effective classification of skin lesions. However, the architecture of ResNet was not effective for minimal training data, if it was evaluated with minimal training data, the accuracy got diminished. Marriam Nawaz [17] have developed an automated approach to segment melanoma at its early stage using region based convolutional neural network (RCNN) with fuzzy K-means clustering (FKM). Initially, the noises and the illuminations from the images were removed and the segmentation of skin lesions for various boundaries and sizes was performed using FKM and finally, the classification was performed using RCNN.

Litao Yang [18] have introduced an effective approach to segmenting the skin lesion using a multi-attention convolutional neural network known as Rema-Net. The useful features were extracted using the down-sampling module and the pooling layer with the spatial attention mechanism. Moreover, the reverse attention operation on skip connections was used to enhance the segmentation performance. The process of training networks requires less hardware requirements and less cost for the process of segmenting images in the clinical domain. However, the complexities occurred while evaluating the pixel of the lesions with improper pattern. Priti Bansal [19] have introduced harris hawk optimization (HHO)

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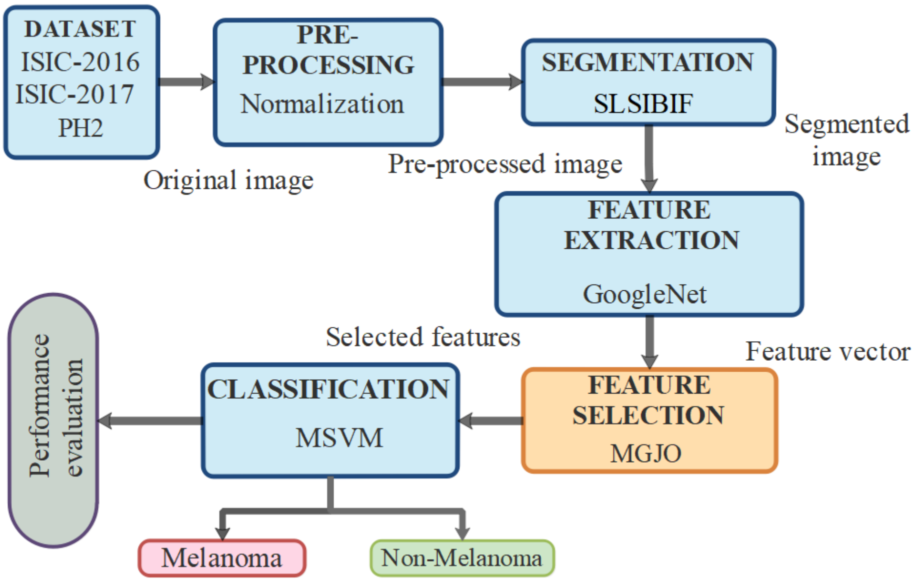

Figure. 1 The overall process involved in the classification of skin cancer

algorithm with two classes such as BHHO-S and BHHO-V with S-shaped and V-shaped transfer functions to select features from the skin cancer images. The feature extraction was performed using gray level Co-occurrence matrix (GLCM), local binary pattern (LBP), and oriented FAST and rotated BRIEF (ORB). Then, the feature selection was performed using BHHO-S and BHHO-V to eliminate the irrelevant and inappropriate features. Finally, the classification was performed using the radial basis function kernel support vector machine (RBF-SVM). However, the suggested approach offers diminished accuracy for small lesions due to their irregular patterns.

Shihan Qiu [20] have developed a gated fusion attention network (GFANet) for segmentation of skin lesion. Initially, the context feature gated encoder was used to fuse multiple level and prediction result was generated as initial guide map. After this, the features were combined with the help of channel reverse attention (CRA) which extracts the shape of features and boundary information. The suggested approach utilized gated convolution fusion (GCF) to fuse the low level features and helps in effective segmentation. However, the suggested approach has poor ability to capture long term dependencies which effects overall segmentation efficiency.

Purba Daru Kusuma and Astri Novianty [21] have introduced a multiple interaction optimizer (MIO) to solve the problems related to order allocation. MIO is comprised with two phases, first phase was based on interaction of each agent with random agents in population and the second phase was based on local search performed by every individual agent who minimize the search space and aids in better allocation. However, the suggested approach was limited for the application of allocation.

3. Classification of melanoma skin cancer using MGJO algorithm

This research proposed a modified golden jackal optimization (MGJO) algorithm to select the appropriate features which are useful in the process of classifying skin cancer. Initially, the image is pre-processed using data normalization techniques and the GoogleNet architecture is used in the process of feature extraction. After feature extraction, the proposed MGJO is used in the process of selecting the features and finally, classification is performed using MSVM classifier. Fig. 1 depicted below presents the process involved in the classification of skin cancer as melanoma and non-melanoma.

3.1 Data acquisition

The data acquisition is the primary stage where the raw data is obtained from international skin imaging collaboration datasets (ISIC-2016 [22], ISIC-2017 [23]) and PH2 [24]. The description of the fore mentioned datasets is presented as follows:

ISIC-2016 dataset: This dataset is comprised of a total of 1279 images where 900 images are used in the process of training and 379 images are used for testing. In the ISIC-2016 dataset, the ground truth value is used for both the training and testing sets, indicating every individual lesion as malignant and benign.

ISIC-2017 dataset: This dataset is comprised of a total of 2600 images of which 2000 images are used for training and 600 images are used for testing. The ground truth values and the metadata of the patients are used in both training and testing sets. Moreover, this dataset consists of four class groups such as melanoma, nevus or keratosis, and melanoma.

PH2 dataset: This image database is comprised of a total of 200 dermoscopic images with 80 common nevi, 80 atypical nevi, and 40 melanomas. The images present in the RGB color image are comprised of a resolution of 768×560 pixels. The dermoscopic images are obtained either from skin type II or skin type III based on the Fitzpatrick scale for the classification of skin type. So, the color of the skin varies from white to creamy white.

3.2 Pre-processing

After the stage of data acquisition, the raw data should be pre-processed to remove unwanted information from the images. Normalization is a general pre-processing technique that is used to transform data set values into a common scale. In this research, the min-max normalization technique is used to scale the data into a specified range of 0 and 1. The min-max normalization approach scales the feature based on the minimum and the maximum values. Moreover, this method converts the value of x to a feature X and it is evaluated using the Eq. (1) as follows:

$$I' = (I - min)\frac{newmax - newmin}{max - min} + newmin \quad (1)$$

Where I is represented as the input image, minimal and maximal intensities are represented as min and max respectively. The pre-processed image with new intensity value is represented as $newmin$ and $newmax$ respectively.

3.3 Segmentation

The pre-processed image obtained from the min-max normalization technique is fed into the stage of segmentation which is performed using the semantic mathematical model named saliency-based level set with improved boundary indicator function (SLSIBIF). The low intensity relies as a major reason to affect the segmentation process by improper identification of boundaries. So, the combination of the level set function (LSF) in the semantic mathematical model along with saliency is used in the process of segmenting the images. The energy function of LSF is evaluated using Eq. (2).

$$E(\varphi) = \varepsilon_{img}(\varphi, g_\rho) + \varepsilon_{reg}(\varphi, g_\rho) \quad (2)$$

Where the energy at the external stage is represented as ε_{img} and the regulation term that describes the internal energy is represented as g_ρ which is represented in Eq. (3) as follows:

$$g_\rho = \frac{1}{1 + \frac{1}{2}(1 - |\nabla I_\sigma|^2/\rho^2)(|\nabla I_\sigma|^2/\rho^2)} \quad (3)$$

Where the boundary of the threshold function is represented as ρ and it is evaluated using the Eq. (4) as follows:

$$\rho(I) = \frac{1 + \sqrt{S(I_\sigma)}}{3} \quad (4)$$

Where the standard image deviation is represented as S and the smoothened image using the Gaussian filter is represented as I_σ. The gradient operator provides the LSF gradient which is represented in Eq. (5) as follows:

$$\delta_\varepsilon(\varphi) = \begin{cases} \frac{1}{2\varepsilon}\left(1 + cos\left(\frac{\pi\varphi}{\varepsilon}\right)\right) & |\varphi| \le \varepsilon \\ 0 & |\varphi| > \varepsilon \end{cases} \quad (5)$$

Where the Dirac function is represented as δ_ε which is obtained from the Heaviside function. The value of parameter ε needs to be large to enhance the contour's capturing range and it is selected as 1.5.

3.4 Feature extraction

After the stage of segmentation, feature extraction is performed to extract the relevant features. In this research, the architecture of GoogleNet is used to extract the appropriate features to categorize skin cancer. The GoogleNet is a type of CNN structure which is developed by Google researchers. The GoogleNet is based on the inception architecture which is comprised of multiscale convolutional transformation with concepts based on split, merge, and transforms. The architectural diagram of GoogleNet is represented in Fig. 2 as follows:

The inception block present in the GoogleNet architecture varies from other deep learning techniques which have a constant size of the convolutional layer. The convolution of $1 \times 1, 3 \times 3$ and 5×5 is accomplished with max pooling of 3×3 in a parallel way and combined to create the final output value. The GoogleNet is controlled by incorporating the bottleneck layer with 1×1 convolutional filters. Moreover, the usage of GoogleNet for feature extraction avoids unnecessary feature maps using sparse connections.

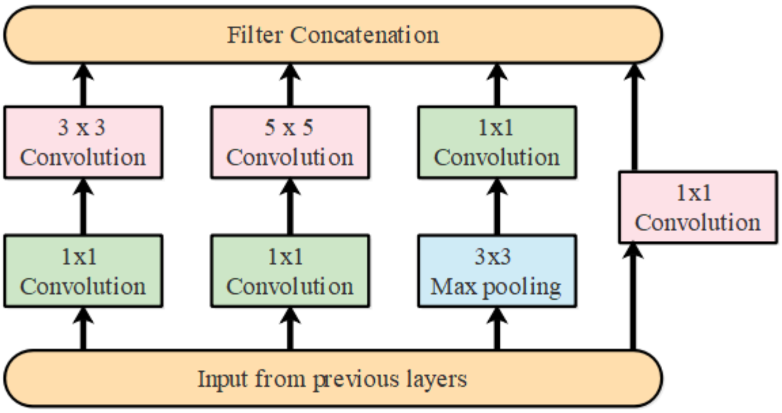

Figure. 2 Architecture of GoogleNet

3.5 Feature selection using modified golden jackal optimization (MGJO) algorithm

After the stage of feature extraction, feature selection is performed to select the relevant features which is useful in the process of classifying the skin cancer as melanoma and non-melanoma. This research introduced MGJO algorithm which is an improvisation of the GJO algorithm by introducing certain scaling factors. The GJO algorithm is inspired by the hunting behavior of golden jackals. The steps involved in GJO are penetrating the prey, encircling, and attacking.

3.5.1. Designing the search space

The GJO is based on the population where the initial position is located in a search area which is represented in Eq. (6) as follows:

$$X_0 = X_{min} + R_n(X_{max} - X_{min}) \tag{6}$$

Where the maximal and the minimal boundaries are represented as X_{max} and X_{min} whereas the randomized value which ranges from 0 to 1 is represented as R_n.

The step presented in Eq. (7) creates the starting $Prey$ matrix which is represented in Eq. (7) as follows:

$$Prey = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,v} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,v} \\ \vdots & \vdots & \vdots & \vdots \\ X_{n,1} & X_{n,2} & \cdots & X_{n,v} \end{bmatrix} \tag{7}$$

Where the jth element of the ith prey is denoted as X_{ij}, a total number of preys, and the variable is represented as n and v respectively. At the time of the optimization process, an objective function is used to find the fitness value of the prey and it is evaluated using the Eq. (8) as follows:

$$FPrey = \begin{bmatrix} f(X_{1,1}; X_{1,2}; \dots; X_{1,v}) \\ f(X_{2,1}; X_{2,2}; \dots; X_{2,v}) \\ \vdots \\ f(X_{n,1}; X_{n,2}; \dots; X_{n,v}) \end{bmatrix} \tag{8}$$

Where the objective function is represented as f.

3.5.2. Stage of exploration

Jackals can detect and trail prey, the hunting process is performed by male jackal which is tailed by female ones. These activities of male and female jackal are represented in Eq. (9) and Eq. (10) respectively.

$$X_1(t) = X_M(t) - E.|X_M(t) - rl.Prey(t)| \tag{9}$$

$$X_2(t) = X_{FM}(t) - E.|X_{FM}(t) - rl.Prey(t)| \tag{10}$$

Where the present state of the prey at time t is represented as $Prey(t)$, the position of male and the female jackal at time t is represented as $X_M(t)$ and $X_{FM}(t)$ respectively. The updated location of male and female jackal is represented as $X_1(t)$ and $X_2(t)$ respectively. The energy of the escaping prey is referred as E which is evaluated using the Eq. (11) as follows:

$$E = E_1 \times E_0 \tag{11}$$

The energy of the prey at the initial level and the declined level is represented as E_0 and E_1 respectively. The value of E_0 varies from the range of -1 to 1 and it is evaluated using the Eq. (12) as follows:

$$E_0 = 2 \times r - 1 \tag{12}$$

Where the randomized value which lies in the range of 0 to 1 is represented as r and the value of E_1 is evaluated using the Eq. (13) as follows:

$$E_1 = C_1 \times (1 - ({}^{t}/_{T})) \tag{13}$$

Where the value of C_1 is equal to 1.5 and E_1 is minimized from 1.5 to 0.

The value of $|X_M(t) - rl.Prey(t)|$ Eq. (10) is used to evaluate the distance between the prey and the golden jackal. Moreover, rl is known as the arbitrary value which is evaluated based on the Levy Flight distribution function and it is represented in Eq. (14) as follows:

$$rl = 0.05 \times LF(x) \tag{14}$$

Where the value of LF is evaluated using the Eq. (15) as follows:

$$LF(x) = 0.01 \times (\mu \times \sigma)/\left(\left|r^{(1/\beta)}\right|\right);$$

Where

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\frac{\pi\beta}{2})}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times \left(2^{\frac{\beta-1}{2}}\right)}\right)^{1/\beta} \tag{15}$$

Where the arbitrary parameters which lie in the range of 0 to 1 are denoted as u, v and β is the constant whose value is 1.5. The location of the jackals is re-organized based on Eq. (16) as follows:

$$X(t+1) = \frac{X_1(t) + X_2(t)}{2} \tag{16}$$

3.5.3. Stage of exploitation

When the prey got threatened by the group of jackals, the energy of the prey gets diminished. After this, the jackal gets jumped on the prey to eat it and this action of the jackal is represented in Eq. (17) and Eq. (18) as follows:

$$X_1(t) = X_M(t) - E.|rl.X_M(t) - Prey(t)| \tag{17}$$

$$X_2(t) = X_{FM}(t) - E.|rl.X_{FM}(t) - Prey(t)| \tag{18}$$

Where rl present in the Eq. (17) and Eq. (18) offers randomized action in the stage of exploitation.

In the process of GJO, the value of E is used to move from the stage of exploration to exploitation and the evasion behavior of the jackal minimizes the energy of the prey. When the value of $E > 1$, the jackal searches to explore their prey, and when $E < 1$, jackal kills its prey in the stage of exploitation.

3.5.4. Modified golden jackal optimization (MGJO) algorithm

The existing GJO algorithm faced problems in detecting the better location of Jackal at its initial stage. So, enhancing the step size in the initial stage can help the jackal to select an optimal location. The movement of the jackals at the prior stage is controlled by sine cosine-based scaling factors. The presence of a scaling factor helps to modify the location of the jackal and helps to enhance the searchability during computation. The sine and cosine function helps to reposition the nearby solutions and helps to improve the performance in the stage of exploration and exploitation than the existing GJO algorithm. The scaled position of the jackal in the proposed MGJO algorithm is represented in Eq. (19) as follows:

$$X(t+1)_{modified} = scaling\ factor\left(\frac{X_1(t) + X_2(t)}{2}\right) \tag{19}$$

Where the value of the scaling factor is determined using the Eq. (20) as follows:

$$scaling\ factor = \begin{cases} \sin(W_{T1} - W_{T2} \times ({}^{t}/_{Tmax}) if\ RD < 0.5 \\ \cos\,(W_{T1} - W_{T2} \times ({}^{t}/_{Tmax}) if\ RD \geq 0.5 \end{cases} \tag{20}$$

Where the random value which lies among the range of [0,1] is denoted as RD. W_{T1} and W_{T2} are represented as the weighted factors. Thus, the MGJO helps in the process of extracting the appropriate features by performing an effective search using the scaling factors to find the optimal solution which eases the process of classification.

3.6 Classification

After the stage of feature selection, classification is performed to classify the skin cancer as melanoma and non-melanoma. In this research, the classification is performed using the multi-class support vector machine (MSVM) [21] which is based on linear and Radial Basis Function (RBF) which can classify the skin cancer as melanoma and non-melanoma. The binary classification is performed

Table 1. Performance analysis for various classifiers for ISIC-2016 dataset

	Classifiers	Accuracy (%)	Sensitivity (%)	Specificity (%)	PVV (%)	Error rate (%)
Actual Features	KNN	94.34	93.50	92.20	94.35	5.66
	RF	93.60	90.53	92.81	91.13	6.40
	DT	94.21	92.76	93.90	94.05	5.79
	MSVM	96.02	96.44	95.60	97.37	3.98
Optimized Features	KNN	95.80	95.81	96.70	96.32	4.20
	RF	94.14	93.92	94.50	93.04	5.86
	DT	96.35	97.97	95.98	94.53	3.65
	MSVM	98.82	99.17	99.39	98.66	1.18

Table 2. Performance analysis for various classifiers for ISIC-2017 dataset

	Classifiers	Accuracy (%)	Sensitivity (%)	Specificity (%)	PVV (%)	Error rate (%)
Actual Features	KNN	96.12	96.39	97.07	96.09	3.88
	RF	96.46	93.22	95.20	94.25	3.54
	DT	95.04	96.20	94.01	93.05	4.96
	MSVM	98.74	97.68	99.40	98.36	1.26
Optimized Features	KNN	96.81	96.89	98.02	96.93	3.19
	RF	96.56	93.22	95.20	94.25	3.44
	DT	96.51	97.15	94.47	94.43	3.49
	MSVM	98.89	99.91	99.44	98.57	1.11

Table 3. Performance analysis for various classifiers for PH2 dataset

	Classifiers	Accuracy (%)	Sensitivity (%)	Specificity (%)	PVV (%)	Error rate (%)
Actual Features	KNN	93.49	91.10	90.66	92.19	6.51
	RF	93.48	94.69	92.49	91.86	6.52
	DT	94.57	92.74	91.57	90.08	5.43
	MSVM	95.70	94.74	93.18	95.37	4.30
Optimized Features	KNN	97.54	95.98	96.69	97.41	2.46
	RF	96.95	94.51	96.55	95.65	3.05
	DT	96.77	96.86	95.15	94.86	3.23
	MSVM	99.37	99.12	99.20	98.37	0.63

using SVM and the one-against-one approach is used to transform SVM to MSVM which is used in categorizing the multiple type of skin cancer.

4. Results and analysis

This section describes the results obtained while evaluating the proposed approach with the existing methodologies. The result section is categorized into two sub-sections such as performance analysis and comparative analysis. In performance analysis, the performance of the classifier with actual and optimized features is evaluated and in comparative analysis, the proposed optimization technique is evaluated with existing techniques discussed in the related works. The performance of the proposed approach is evaluated for segmentation and classification performance. The segmentation performance is evaluated by considering the performance metrics such as Jacard, Dice, Accuracy, and sensitivity. Similarly, the classification performance is evaluated by considering the performance metrics such as accuracy, sensitivity, specificity, PPV and Error rate. The mathematical expressions listed in Eq. (21) to Eq. (27) are used to compute the fore mentioned performance metrics. The proposed approach is implemented in MATLAB r2020a software and simulated in a system that is configured with 16GB of random access memory, i7 processor and windows 10 operating system.

$$Accuracy = \frac{TP+TN}{TN+TP+FN+FP} \times 100 \tag{21}$$

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \tag{22}$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \tag{23}$$

$$PPV = \frac{TP}{TP+FP} \times 100 \tag{24}$$

$$Jacard = \frac{TP}{TP+FP+FN} \tag{25}$$

$$Error\ rate = 100 - Accuracy \tag{26}$$

$$Dice\ coefficient = \frac{TP\times 2}{TP\times 2+FP+FN} \tag{27}$$

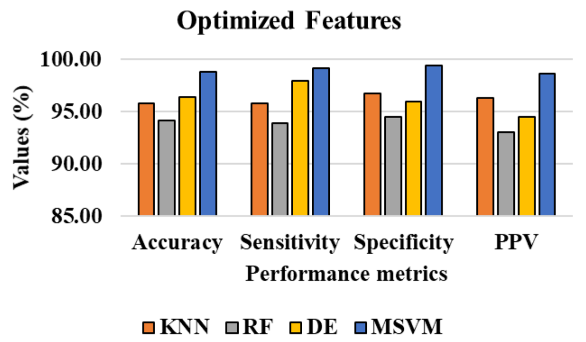

Figure. 4 Graphical representation for the performance of the classifier based on optimized features for the ISIC-2016 dataset

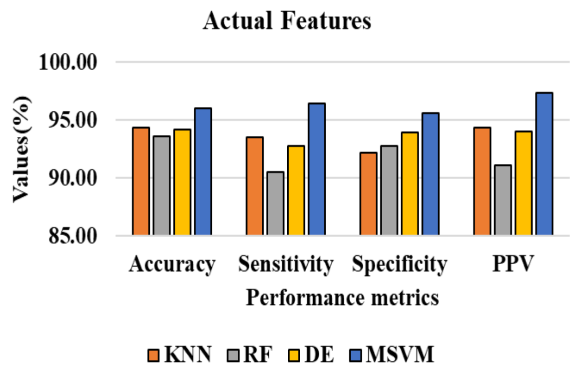

Figure. 3 Graphical representation for the performance of the classifier based on actual features for the ISIC-2016 dataset

Where, TP and TN represent true positive and true negative respectively. Similarly, the false positive and the false negative is represented as FP and FN respectively.

4.1 Performance analysis

In this sub-section, the performance of the classifier with actual and optimized features is computed and the performance of the segmentation approach for different datasets is evaluated. Table 1 presented below shows the performance of the MSVM classifier when it is evaluated with the existing classifiers such as K-nearest neighbor (KNN), random forest (RF), and decision tree (DT) for ISIC-2016 dataset.

Table 1, Table 2 and Table 3 present the overall results of the classifier for actual and optimized features when evaluated with ISIC-2016, ISIC-2017 and PH2 datasets respectively. Overall the MSVM classifier has achieved better results in overall metrics for all the datasets. For example, the MSVM classifier utilized in this research has obtained a classification accuracy of 98.82 % when evaluated with optimized features for the ISIC-2016 dataset. But, the existing classifiers such as KNN, DT and RF have achieved classification accuracy of 96.81%, 96.51% and 96.56% respectively. The better classification accuracy is due to the performance of the MSVM classifier or classifying multiple classes. Moreover, the presence of the MGJO algorithm also relies as a reason to select the optimal features which ease the process of classification. Fig. 3 is the graphical representation of the performance evaluation of various classifiers based on actual features for the ISIC-2016 dataset and the Fig 4 depicts the graphical representation of the performance evaluation of various classifiers based on optimized features for the ISIC-2016 dataset.

Secondly, the performance of the segmentation approach for different datasets is evaluated which is represented in Table 4. The results obtained from Table 4 shows that the proposed approach has obtained better segmentation accuracy of 98% for the ISIC-2016 and ISIC-2017 dataset.

Thirdly, the performance of the proposed MGJO algorithm is evaluated with some existing optimization techniques such as artificial bee colony (ABC), pelican optimization algorithm (POA) and gorilla troops optimization algorithm (GTOA). Moreover, the performance of the optimization techniques is evaluated for three datasets such as ISIC-2016, ISIC-2017, and PH2 which are presented in Table 5.

The overall results from Table 5 show that the proposed MGJO algorithm has achieved better performance in overall metrics when compared with the existing optimization techniques. For example, the accuracy of MGJO for PH2 dataset is 99.37% whereas the accuracy of existing ABC, POA, and GTOA is 93.88%, 94.16% and 92.16% respectively. The better result of MGJO is due to its efficiency in performing an effective search using the sine and cosine-based scaling factors.

4.2 Comparative analysis

In this sub-section, the performance of the proposed MGJO-MSVM is evaluated with various existing approaches such as FAT-NET [14], MAFCNN-SCD [15], W-net and Inception residual network [16], RCNN-FKM [17] and GFANet [20]. Table 6 presented below shows the accuracy, sensitivity and specificity of the proposed approach when it is evaluated with the existing methodologies.

The results from the comparative table show that the proposed MGJO-MSVM achieved better results in overall metrics than the existing approaches for three datasets such as ISIC-2016, ISIC-2017 and PH-2. For example, the accuracy of the proposed

Table 4. Performance evaluation of segmentation approach for different datasets

Dataset	Jacard	Dice	Accuracy	Sensitivity
ISIC-2016	0.16	0.91	0.98	0.96
ISIC-2017	0.18	0.90	0.96	0.82
PH2	0.05	0.98	0.98	0.98

Table 5. Performance evaluation of optimization algorithm for ISIC-2016, ISIC-2017 and PH2 datasets

Optimization algorithms	Dataset	Accuracy	Sensitivity	Specificity	PPV	Error-rate
ABC	ISIC 2016	92.18	91.30	93.11	90.23	7.83
POA		94.04	93.92	94.50	93.04	5.96
GTOA		93.09	91.53	90.15	93.04	6.91
MGJO		98.82	99.17	99.39	98.66	1.18
ABC	ISIC 2017	89.87	86.81	88.17	86.32	10.13
POA		91.61	93.43	92.50	90.34	8.39
GOA		93.88	92.35	92.98	94.04	6.12
MGJO		98.89	99.91	99.44	98.57	1.11
ABC	PH2	93.88	92.82	94.15	92.44	6.12
POA		94.16	92.47	91.63	92.53	5.84
GTOA		92.19	93.35	90.70	89.64	7.81
MGJO		99.37	99.12	99.20	98.37	0.63

Table 6. Comparison of the proposed approach for different datasets

Methodologies	Datasets	Accuracy(%)	Sensitivity (%)	Specificity (%)
FAT-NET [14]	ISIC-2016	96.04	92.59	96.02
	ISIC-2017	93.26	83.92	97.25
	PH-2	97.03	94.41	97.41
MAFCNN-SCD [15]	ISIC-2017	92.22	77.07	88.67
W-net and Inception residual network [16]	ISIC-2016	98.1	98.1	98.1
	ISIC-2017	96.97	95.15	97.87
RCNN-FKM [17]	ISIC-2016	95.40	90	97.1
	ISIC-2017	95.6	-	98.2
	PH-2	96.1	-	97.2
GFANet [20]	ISIC-2016	96.04	92.95	97.25
	ISIC-2017	93.97	81.37	97.87
	PH-2	97.07	96.08	97.57
MGJO-MSVM	ISIC-2016	98.82	99.17	99.39
	ISIC-2017	98.89	99.91	99.44
	PH-2	99.37	99.12	99.20

approach for ISIC-2017 dataset is 98.89 % whereas the accuracy of the existing FAT-NET, MAFCNN-SCD, W-net and Inception residual network, RCNN-FKM and GFANet is 93.26%, 92.22%, 96.97%, 95.6% and 93.97% respectively. Moreover, for PH2 dataset, the proposed method achieved accuracy of 99.37% whereas the existing FAT-NET, RCNN-FKM and GFANet obtained accuracy value of 97.03%, 96.1% and 97.07% respectively. The better result is due to an effective feature selection performed by MGJO algorithm which utilizes the scaling factors to perform a robust search in selecting the relevant features and helps in the process of classification.

5. Conclusion

In this research, the handcrafted segmentation technique along with the proposed feature selection approach is used in the process of melanoma from the dermoscopic images obtained from different datasets. The feature selection is performed using the proposed MGJO algorithm which effectively selects the significant features and helps in the process of classifying skin cancer. The GJO is improved as MGJO by introducing the sine and cosine-based scaling factors which is effective for the selection of features and aids in better classification. The proposed approach outperforms well than the existing approaches in overall performance metrics, the classification accuracy of the proposed approach for ISIC-2017 dataset is 98.89% which is comparatively higher than the existing approaches. In the future, deep learning classifiers can be used to enhance the classification accuracy of detecting skin cancer.

Notation list

Parameter	Description
I	Input image
ε_{img}	Energy at the external stage
g_{ρ}	Regulation term
ρ	Boundary of threshold function
S	Standard image deviation
I_{σ}	The image smoothened using Gaussian filter
δ_{ε}	Dirac function
ε	The parameter used to enhance the contour range
X_{max} and X_{min}	The maximal and minimal boundaries of search space
R_n	Randomized value from 0 to 1
X_{ij}	jth element of ith prey
f	Objective function
n	Total number of preys
$Prey(t)$	Present state of the prey at time t
$X_M(t)$	Position of male jackal at time t
$X_{FM}(t)$	Position of female jackal at time t
$X_1(t)$	Updated position of male jackal
$X_2(t)$	Updated position of female jackal
E	Energy of the escaping prey
E_1	Energy of the prey at initial level
E_0	Energy of the prey at declined level
rl	Arbitrary value based on the Levy Flight distribution function
W_{T1} and W_{T2}	Weighted factors

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, have been done by 1st author. The supervision and project administration, have been done by 2nd author.

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