Diagnosing skin cancer via C-means segmentation with enhanced fuzzy optimization

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Abstract
The early detection of cancer decreases the death rate as well, but mostly the disorder symptoms are unpredictable. Numerous skin cancer detection techniques are available in the dice, yet the effectiveness remains unachieved. This paper aims to introduce a skin cancer detection technique that characterizes the nature of cancer: normal, benign or malignant. The proposed technique includes three stages like Segmentation, Feature Extraction, and Classification. Here, the Fuzzy C-means Clustering (FCM) is used to segment the given input image. Then, the features are mined from the segmented image using Local Vector Pattern (LVP) and Local Binary Pattern (LBP). Subsequently, the Fuzzy classifier is used to do the classification process that gets the extracted features (LVP+LBP) as the input. The classifier outputs the nature of the image. As the primary contribution of this work, the limits of membership functions in the Fuzzy classifier are optimally selected by a new improved Rider Optimization Algorithm (ROA) termed as Distance Oriented ROA (DOROA). The performance of the proposed DOROA model is compared over other conventional models in terms of accuracy, sensitivity, specificity, precision, Negative Predictive Value (NPV), F1-score and Matthews correlation coefficient (MCC), False positive rate (FPR), False Negative Rate (FNR), and False Discovery Rate (FDR).

1 | INTRODUCTION

Recently, the WHO reports that skin cancer [1–3] is one of the fastest increasing diseases that threaten human life with a high death rate. This cancer is widely classified into two types: non-melanoma and melanoma. More than 2 to 3 million cases have been reported under non-melanoma cancer and greater than 132,000 melanoma cancer cases have also been reported annually. The United States itself reported a high mortality rate of 75%, which is due to the skin cancer melanoma while comparing with non-melanoma skin cancers [4–6]. It is well-known that malignant melanoma was the most dangerous type that affected more people in the United States in the year 2008. It drastically increased by 2010 and has reached an unexpected rate by 2020. Early diagnosis and treatment are crucial, as early detection helps the patients to survive the affected disease. Nowadays, skin cancer [7–9] screening is performed by visual inspection that is usually assisted by a dermatoscopy. However, the exact malignant melanoma diagnosis [10–12] needs advanced experience as well as training, which is hence restricted to specialized dermatologists. Even the experienced dermatologists could not obtain the best accuracy rate of diagnosis. Particularly, the accuracy rate on detecting this type is identified to be nearly 80%, which is specifically low for thin early-state melanoma. The computer-assisted system is normally a reliable and faster result for early diagnosis of skin cancer [13–16]. Implementation science can help in delays of skin cancer diagnosis and surgery thus improving the supply chain management for surgical equipment [17,18,19,35]. Moreover, so many modalities are there under development and some of them are confocal scanning laser microscopy, multispectral imaging, US imaging, optical coherence tomography, and so on.

More algorithms, particularly deep learning models, were used so far to fulfil the need for early skin cancer diagnosis. Some of the common and usual techniques are ANN, SVM etc. Further, the involvement of the optimization concept like PSO, GA [20] is also becoming familiar these days. However, the classification process is used in a straightforward manner in
the majority of the literature. To accomplish a significant performance, the amendment is essential. This paper attempts to enhance the fuzzy classifier, as the fuzzy classifier is known for its performance because of rule-based decisions in a straightforward manner. As an enhancement, this paper optimizes the bounds of the membership with respect to the characteristics of the extracted features. This paper also contributes by proposing an improved optimization algorithm called as DOROA, rather than sticking with the traditional optimization algorithms.

This paper proposes a novel skin cancer detection approach. The main contribution of the paper is as follows.

- Skin cancer detection involves segmentation, feature extraction, fuzzy classification.
- Initially, FCM is used to do the process of segmentation.
- LBP method is sensitive to image noise and lags in achieving the desired performance for texture classification with significant scale changes. LVP has a minimized index angles, it is sensitive to image rotations. To overcome this, hybrid LVP and LBP are used in feature extraction.
- The classification process is done using a fuzzy classifier that gets the mined LVP+LBP features as the input. The classifier output shows whether the given image is benign, malignant, or normal.

The organization of the paper is as follows: Section 2 reviews the literature work. Section 3 explains the proposed work in detecting skin cancer. Section 4 explains the proposed algorithm, DOROA. Section 5 explains the obtained outcomes and Section 6 ends the paper.

2 | LITERATURE REVIEW

2.1 | Related works

In 2004, Philipsen et al. [21] approached the NN classifier to classify the skin via Raman spectroscopy. This model was automatic and probabilistic. Further, this model has included certain phases like feature extraction and classification. Raman spectra was used for extracting features and NN was used for classification purposes. The rules in classification might be mined and assessed for reproducibility purposes, which makes the class assignment more accurate. Finally, they evaluated the performance of the proposed work over other conventional models by experimenting with different datasets. The results proved that the developed approach was really good regarding the classification rate.

In 2004, Aberg et al. [22] aimed to differentiate skin cancer from benign nevi with the use of multi-frequency impedance spectra. They measured 100 skin cancers and 511 benign nevi via electrical impedance spectra. They measured the impedance of reference skin to the lesions. Then they utilized the impedance relation among lesion and reference skin for distinguishing the cancers from nevi. The results proved that it was feasible to divide malignant melanoma from benign nevi having more specificity and sensitivity.

In 2009, Alcon et al. [23] described an automated system to inspect the pigmented melanoma diagnosis and skin lesions that have supported skin lesion images. Particularly, the proposed system had the component of decision support that combined the classification results along with context knowledge including age, gender, skin type, and infected body part. This allowed the assessment of the personal risk of melanoma, thereby adding confidence to the process of classification. It was founded that the proposed system has classified the given image with a high accuracy rate.

In 2011, De et al. [24] proposed the SKAN that was the system to detect the presence of cancer via adaptive models. This has combined the concepts of computer engineering with some of the areas including oncology and dermatology. The major aim was to discern skin cancer images, particularly melanoma that reviews only common spots by image recognition. This research work has used the ABCDE visual rule that was normally utilized by dermatologists to make the identification of melanoma. This was for defining which characteristics were analyzed through the software. This was then applied to different models and techniques that were included as the ellipse-fitting algorithm for extracting and measuring those characteristics. This later decided on the respective cases. Then, the attained outcomes were presented along with a distinctive focus on taking decisions for diagnosis purposes.

In 2015, Töpfer et al. [25] presented an elaborate technical characterization of a micromachined millimeter-wave to diagnose the presence of skin cancer. They have optimized the broadband probe, and have included an dielectric-rod waveguide. It was tapered and metalized to the tip for achieving a high resolution with the concentration of the electric field in the small sample area. They have also fabricated various probes having a number of tip sizes from high-resistivity silicon. The probes have shown high responsivity with permittivities that were in two ranges: healthy and cancerous skin tissue. The depth of sensing was defined via the simulations as well as measurements from 0.3 to 0.4 mm.

In 2017, Naser and Fouad [26] proposed an automatic skin cancer diagnosis model that has combined various colour and textural features. They also used some novel features in the bag-of-features model that would make the detection effective. Particularly, they claimed that the HG and the HL were appropriate for the image analysis and classification than the traditional HOG and the HOL, respectively. Both the HL and HG were separately bagged by a codebook. Zernike moments were there in the system for exploiting the colour data in the image. Finally, the system was implemented and experimented with, and the betterment of this was proved over the conventional models.

In 2017, Satheesha et al. [27] introduced a dermoscopy system, which has considered the assessed skin lesions depth for diagnosis purposes. This research work introduced a 3D skin lesion reconstruction model by the assessed depth that was attained from regular dermoscopic images. Based on the 3D reconstruction, they extracted the features. Additionally, they extracted features like regular colour, 3D features, texture, and 2D shape features. Moreover, the extraction of features was
critical in attaining accurate results. The developed system was designed for diagnosing blue nevus, basal cell carcinoma, normal mole lesions and so on. Finally, the investigational outcomes revealed the significance of the proposed work over conventional models.

In 2018, Teck et al. [28] undertook the automated detection of skin cancer that was based on dermoscopic images by a variant of PSO. This was for optimizing the features. The used algorithm included the subswarms, global and local food, enemy signal, and mutation basis exploitation. However, there are various matrix representations for mitigating PSO’s premature convergence. Particularly, two remote swarm leaders illustrate the same fitness. However, they used low position proximity for leading the subswarm-basis search and also for enabling the exploration of distinctive search regions. They developed new altered velocity updating models for enabling the particles. This was for following multi-swarm leaders and also for avoiding the global and local worst distinctive. They used the dynamic matrix representations and probability distribution for diversifying the search process. The proposed model was evaluated under different databases and has proven the betterment of the proposed work.

In 2017, [29] presented a modified fuzzy approach to diagnose the skin damage in dermoscopy images. In this method, the image brightness was arranged by coloured contrast modification and the area edge was achieved by the FLICM algorithm. The efficiency of this method was evaluated on the real dermoscopy images which were taken from damaged skins with different colours and sizes. The presented parameter evaluation and their results were compared with the level set partitioning. An increasing amount of partitioning sensitivity compared to the conventional methods demonstrated the efficiency of the proposed method and its application in cad systems.

In 2018, [30] used FCM-S, which was an effective algorithm suitable for image segmentation in dermoscopy images. Its effectiveness has contributed not only to the introduction of fuzziness for the belongingness of each pixel but also to the exploitation of spatial contextual information. However, FCM-S was time-consuming because the spatial neighbour’s term was computed for all iteration.

2.2 | Review

Table 1 shows the advantages and disadvantages of some traditional skin cancer detection models. Here, NN [21] can avoid overfitting, which also paves the way for the classification rate. However, the model is not effective in solving complex problems. The authors in [20] introduce a Bag-of-features model
that aims to inaccurate feature extraction that increases the accuracy rate. Yet, the model suffers from a poor performance rate concerning FP. Ellipse-fitting algorithm [24] processes the adaptiveness in decision making and ensures an effective diagnosis. Still, the model needs advancements to improve the classification rate. Multi-frequency electrical impedance [22] grants high specificity and sensitivity; however, the model uses the same frequency interval and depth settings. The broadband millimeter-wave probe [25] resolves the tumour inhomogeneities, yet the lateral resolution must be examined more precisely. A non-invasive computerized dermoscopy system [27] aids in the extraction of 3D shape features and it also enhances the performance rate. The enhancement of estimation models is still an issue. CFS[23] has the capability of recreating controlled lightening conditions. PSO [28] is an optimization algorithm, which is more robust, obtains a faster convergence rate and also has less computational complexity. Yet, the model cannot solve scattering problems.

3 | PROPOSED NEW SKIN CANCER DETECTION MODEL

The proposed skin cancer detection approach is illustrated in Figure 1. The model includes three stages like Segmentation, Feature Extraction, and Classification. Initially, the input skin cancer image is given, from which the type of tumour is defined by this model. The initial step is the segmentation process, where the C-means clustering [31] algorithm is used for the segmentation process. Once the segmentation is completed, the features are extracted from the segmented image by deploying the LVP technique [32] and LBP techniques. Finally, the extracted (LVP and LBP) features are subjected to the classification process by fuzzy classification. The classifier results in the respective tumour types. Further, the limits of the membership functions are optimally chosen using the new DOROA algorithm. Finally, the type of skin cancer image is detected in terms of whether it is normal, benign or malignant.

3.1 | Segmentation

Segmentation is the initial process of this work, and the FCM [31] clustering algorithm is utilized to do the process. FCM is generally a data clustering model [33], where a data set is grouped or clustered into n clusters having each data point in the dataset associated with each cluster. The data would have a great connection with that cluster and other data points that lie away from the cluster centre might have a low degree of belonging or connection to that corresponding cluster. The algorithmic steps of FCM are as follows:

Fixing C, where C is \(2 < C < n\), and subsequently chooses the parameter value \(m\). Then, initialize the partition matrix \(M^{(0)}\).

1. Calculate the \(C\) centre vector \((V^\prime_k)\) as per Equation (1).
   \[
   V_k = \frac{\sum (\mu_{ik})^m x_i}{\sum (\mu_{ik})^m} \tag{1}
   \]

2. Formulate the distance matrix \(D_{i[k]}\) as per Equation (2).
   \[
   D_{i[k]} = \left( \frac{\sum (\mu_{ij})^m (x_i - V_{k,l})^2}{\sum (\mu_{ij})^m} \right)^{1/2} \tag{2}
   \]

3. Do position matrix update for \(\theta\) step, \(M^{(0)}\) as in Equation (3).
   \[
   \mu_{ik}^{-1} = \left( \frac{1}{\sum (\mu_{ij})^m} \frac{D_{i[j]} / D_{i[k]}}{D_{i[j]} / D_{i[k]}} \right)^{2/m} \tag{3}
   \]
   where \(i = 1, 2, ..., n\) and \(j = 1, 2, ..., C\).
   The segmented image is then subjected to extract the features (LVP+LBP).

3.2 | Feature extraction

The segmented image is subjected to LVP [32] and LBP [34] for feature extraction. LVP is the improvement of LTrP that determines the connection of pixels with 8 neighbours at \(D\) distance that encodes them by using CST. The LVP performance seems to be the best in terms of illumination, pose, and lighting devi-
\[ C_{Yz}^{t} = \left[ \frac{i_{x+45}^{b}(\bar{p})}{i_{b}^{b}(\bar{p}) + i_{a}^{b}(\bar{p})} \right] \]  

(6)

\[ \mu_{\bar{x}}(\bar{p}) = \frac{x}{\mu_{\bar{x}}(\bar{p})} \]  

(7)

Similarly, LBPs attain both greyscales as well as rotation in variances with the consideration of signs of centre's grey value differences and local neighbourhood pixels, rather than considering accurate values and identifying the minimum value between possible operator values.

Let \( G^{C} \) be the centre pixel's grey value, \( G^{E}(\hat{t} = 0, 1, \ldots, E - 1) \) is the grey value of \( E \) uniformly spaced nearby pixels on radius circle, \( RA(\hat{R}A > 0) \) from the circularly nearby set. The spatially structured LBP operator of image texture is defined by Equation (8).

\[ LBP_{E, M} = \sum_{E=0}^{E-1} t \left( G^{E} - G^{C} \right) 2^{E} \]  

(8)

where, in principle, \( (E, RA) \) can select any of the combinations of \( E \) and \( RA \).

Finally, the extracted LVP and LBP features are subjected to the classification process, where the nature of the input image is obtained (normal, benign or malignant).

\[ \mu_{\bar{x}}(\bar{p}) = \begin{cases} 0, & x \leq \text{low} \\
\frac{x - \text{low}}{\text{medium} - \text{low}}, & \text{low} < x \leq \text{medium} \\
\frac{x - \text{medium}}{\text{high} - \text{medium}}, & \text{medium} < x \leq \text{high} \\
0, & x \geq \text{high} \]  

(11)

\[ \delta_{1} = \max (\bar{h}_{1}) - \min (\bar{h}_{1}) \]  

(12)

\[ \delta'_{1} = \frac{\delta_{1}}{N_{l}} \]  

(13)

\[ L_{\text{low}} = \min (\bar{h}_{1}) + \delta'_{1} \]  

(14)

\[ L_{\text{max}} = \text{arg max} = \frac{N_{l}}{N_{l}} \]  

(16)

where \( N_{l} \) is the number of correctly classified samples.

\[ \arg \max = \frac{N_{l}}{N_{l}} \]  

where, \( N_{l} \) is the number of training samples and \( N_{l} \) is the number of correctly classified samples.

\[ \mu_{\bar{x}}(\bar{p}) = \begin{cases} 0, & x \leq \text{low} \\
\frac{x - \text{low}}{\text{medium} - \text{low}}, & \text{low} < x \leq \text{medium} \\
\frac{x - \text{medium}}{\text{high} - \text{medium}}, & \text{medium} < x \leq \text{high} \\
0, & x \geq \text{high} \]  

The respective membership function limits are optimally chosen in this work to increase the detection rate (skin cancer) of the proposed work, and the solution encoding is illustrated in Figure 3. The objective function of this proposed work is given in Equation (16).

\[ \mu_{\bar{x}}(\bar{p}) = \begin{cases} 0, & x \leq \text{low} \\
\frac{x - \text{low}}{\text{medium} - \text{low}}, & \text{low} \leq x \leq \text{medium} \\
\frac{x - \text{medium}}{\text{high} - \text{medium}}, & \text{medium} < x \leq \text{high} \\
0, & x \geq \text{high} \]  

\[ 

4 \quad \text{NEW IMPROVED OPTIMIZATION ALGORITHM FOR MEMBERSHIP FUNCTION OPTIMIZATION}

As mentioned before, this paper aims to incorporate the optimization concept in fuzzy classification. More importantly,
the membership functions of the fuzzy classifier are optimally selected using a new improved ROA algorithm termed DOROA. Generally, ROA [36] is a well-known renowned optimization model, which is modelled based on four-rider groups who ride towards their target location.

The four groups are as follows: bypass rider, follower, overtaker and attacker [36].

### 4.1 Proposed algorithm: DOROA

The steps of the DOROA algorithm are as follows: (i) Group and Rider parameters initialization (ii) success rate identification (iii) leading rider identification (iv) Position update of rider (v) Success rate identification of (vi) Rider parameter updating (vii) Riding off time.

Step 1: Initialization: The initialization process is done by all the mentioned groups and that are specified as $X_i$, and their positions are arbitrarily initialized according to Equation (17).

$$
X_i = \{X_{(i,j)}\}; \quad 1 \leq i \leq RI; \quad 1 \leq j \leq DM
$$

where $RI$ indicates the count of rider that is equal to $I$, the rider ($i^{th}$) position at $t$ time is defined as $X_{(i,j)}$, $DM$ represents the coordinate count.

The count of the rider is also assessed based on rider count in each group and is defined in Equation (18).

$$
RI = BP + FL + OT + AK
$$

where $BP$ specifies the bypass rider, the follower is indicated as $FL$, the overtakers is also specified as $OT$ and the number of attackers is indicated as $AK$.

The initial steering angle at $t = 0$ is as defined in Equation (19).

$$
S_{ij} = \begin{cases} 
\theta_j & \text{if } j = 1 \\
S_{ij-1} + \phi & \text{if } j \neq 1 \& S_{ij-1} + \phi \leq 360 \\
S_{ij-1} + \phi - 360 & \text{otherwise}
\end{cases}
$$

where $S_{ij}$ is the $i^{th}$ rider vehicles’ steering angle, $\theta_j$ is the $j^{th}$ rider vehicles’ position angle and $\phi$ is the coordinate angle. The maximum angle of 360° is given in Equation (20).

$$
\theta_j = i \times \frac{360°}{RI}
$$

Further, the coordinate angle helps in defining the steering angle, which is given in Equation (21). The vehicle’s gear in a distinctive group is determined in Equation (22).

$$
\phi = \frac{360°}{DM}
$$

$$
GE = \{GE_i\}; \quad 1 \leq i \leq RI
$$

where $GE_i$ is the gear of $i^{th}$ rider vehicle.

Subsequently, the next parameters called accelerator and brake are initialized as per Equation (23),

$$
ae = \{ae_i\}; \quad 1 \leq i \leq RI; \quad B = \{B_i\}; \quad 1 \leq i \leq RI
$$

where $ae_i$ and $B_i$ are the $i^{th}$ rider vehicle’s accelerator and brake.

The maximum driving speed is given in Equation (24). Depending on the assessed maximum speed, the speed limit of gear is assessed as in Equation (25).

$$
Z^j_{\text{max}} = \frac{X^j_{\text{MAX}} - X^j_{\text{MIN}}}{T_{\text{OFF}}}
$$

$$
Z^j_{\text{GE}} = \frac{Z^j_{\text{max}}}{|GE|}
$$

where $X^j_{\text{MAX}}$ indicates the maximum value and $X^j_{\text{MIN}}$ is the minimum value. $T_{\text{OFF}}$ is the total allowed time to reach the destination. $Z^j_{\text{max}}$ is the maximum speed of rider $i$ and $|GE|$ is the number of gears.

Step 2: Success rate and leading rider identification: The success rate is assessed based on distance, it is formulated and is measured between the rider position and that to the target as given in Equation (26).

$$
r_i = \frac{1}{||X_i - TX||}
$$

where $i^{th}$ rider position is specified as $X_i$ and the targets’ position is specified as $TX_i$. The rider who rides at the minimal distance from the target position is assigned to be the greatest success rate and the corresponding rider is considered as the leading rider.

Step 3: Position updating of rider: Similar to ROA, the proposed DOROA undergoes the position update for bypass riders, overtakers, followers and attackers. However, the proposed DOROA incorporates a distance based updating process for both the overtakers and attackers. The updating models are given below.

- The position updating of the bypass rider is done arbitrarily, which is determined in Equation (27).

$$
X_{i+1}^{BP} (i,j) = \delta \left[ X_i (\eta,j) + \beta (j) + X_{i+1} (\xi,j) + [1 - \beta (j)] \right]
$$

where $\delta$ refers to the arbitrary number, $\eta$ indicates the random number, $\xi$ is the count and $\beta$ indicates the random value.

- The update equation of the follower is given in Equation (28).

$$
X_{i+1}^{FL} (i,k) = X^{TX} (TX, k) + \left[ \cos \left( T_{\text{TTI}} \right) \cdot X^{TX} (TX, k) \cdot d_{ij} \right]
$$
RESULTS AND DISCUSSIONS

Simulation setup

...
TABLE 2 Parameter setting

| Algorithm | Parameters | Value |
|-----------|------------|-------|
| DOROA     | $B_i$      | 1     |
|           | $i$        | 0.1   |
|           | $B_j$      | 1     |
|           | $\delta$  | 0.1   |
|           | $\eta$    | 1     |
|           | $\zeta$   | 1     |
|           | $t_{iT}^j$ | [0,1] |
|           | $D_N^j(i)$ | [0,1] |
|           | $\beta$   | 0.1   |
| FCM       | Number of clusters | 2    |
|           | Number of iterations | 15   |

PH2- A dermoscopic image database. This database contains 200 dermoscopic images and the size of the image is 572 $\times$ 755.

The performance of the proposed model was compared over other conventional models such as GA [37], ABC [38], PSO [39] [40], FF [41] [42], GWO [43] [44], WOA [45], ISESW [46], ROA [36] algorithms in terms of Type I and Type II measures. Further, the proposed approach was compared over other conventional traditional features extraction models like LVP [32], LBP [34], CLBP [47] and LTrP [48] and the outcomes were attained.

5.2 Segmentation output

In the proposed work, the segmentation process is carried out using the FCM model. The segmented output in terms of performance measures of FCM, FCM-S, and FLICM are summarized in Table 3. Further, the sample images for normal, benign and malignant melanoma with the ground truth image and the
TABLE 3 Segmentation output in terms of performance measures

| Measures     | Segmented output(FCM)[31] | FCM-S [30] | FLICM [29] |
|--------------|---------------------------|------------|------------|
| Accuracy     | 0.87668                   | 0.81142    | 0.81067    |
| Sensitivity  | 0.43453                   | 0.14166    | 0.13749    |
| Specificity  | 0.99958                   | 0.9976     | 0.9978     |
| precision    | 0.99657                   | 0.9425     | 0.94566    |
| FPR          | 0.00041607                | 0.002402   | 0.00219    |
| FNR          | 0.56547                   | 0.85834    | 0.86251    |
| NPV          | 0.99958                   | 0.9976     | 0.9978     |
| FDR          | 0.0034327                 | 0.057497   | 0.054336   |
| F1-score     | 0.60519                   | 0.2463     | 0.24008    |
| MCC          | 0.61126                   | 0.32306    | 0.31896    |

FIGURE 7 Image results (a) Image 1 (normal), (b) Image 2 (benign), (c) Image 3 (benign) (d) Image 4 (malignant melanoma)

Segmented image are given in Figure 7. Segmentation of LBP and LVP is given in Figure 8. Figure 9 shows the visualization result of segmentation of (a) ground truth, (b) FCM-s and (c) FLICM (d) FCM of normal, benign and malignant. The computation period of FCM is 5.3275, FCM-S is 5.9782 and FLICM is 6.8685 s, respectively.

FIGURE 8 Segmentation of (a) original image, (b) LBP (normal) and (c) LVP (benign)

FIGURE 9 The visualization result of segmentation: (a) ground truth, (b) FCM-S and (c) FLICM (d) FCM of normal, benign and malignant

5.3 Performance analysis under features

This section explains the feature-based performance analysis of proposed and conventional models. Different measures have been used for the analysis purpose. The results are shown in Figures 10–12 by varying the learning percentage to 40%, 50%, 60%, 70%, and 80%, respectively. Figure 10a shows the performance of the proposed work in terms of accuracy rate. More importantly, the proposed model for 40% of learning percentage is 1.05%, 4.63%, 5.45%, and 4.70% better from LVP-DOROA-FC, LTrP-DOROA-FC, CLBP-DOROA-FC, and LBP-DOROA-FC, respectively. For learning percentage 50%, the proposed model attains high accuracy, and it is 1.93%, 5.60%, 4.28% and 3.16% better from LVP-DOROA-FC, LTrP-DOROA-FC, CLBP-DOROA-FC, and LBP-DOROA-FC, respectively.
For 70% of learning, the developed approach is 1.21%, 12.26%, 22.94% and 18.31% superior to LVP-DOROA-FC, LTrP-DOROA-FC, CLBP-DOROA-FC, and LBP-DOROA-FC, respectively with high accuracy rate. The specificity analysis of the proposed work is given in Figure 10c. From the graph, it is observed that the specificity of proposed work under 40% of learning is 2.47%, 3.79%, 2.57%, and 4.75% better than LVP-DOROA-FC, LTrP-DOROA-FC, CLBP-DOROA-FC, and LBP-DOROA-FC, respectively. For 50% of learning, the developed model is 4.53%, 4.13%, 4.03% and 5.27% superior to LVP-DOROA-FC, LTrP-DOROA-FC, CLBP-DOROA-FC, and LBP-DOROA-FC, respectively. For 60% of learning, the proposed model is 3.66%, 4.42%, 3.43% and 5.76% better than LVP-DOROA-FC, LTrP-DOROA-FC, CLBP-DOROA-FC, and LBP-DOROA-FC, respectively with high specificity. Similarly, Figure 11 represents the performance evaluation of F1-score, MCC and NPV.

5.4 Performance analysis of proposed model over conventional models

This section explains the performance of the proposed and conventional optimization algorithms under all the performance measures, which is illustrated in Figures 13–15. Here, the analysis is made by varying the learning percentage. The accuracy of the proposed over conventional models is given in Figure 13a. The graph proves that the proposed model for 40% of learning is 0.73%, 0.76%, 0.97%, 1.60%, 1.10%, 0.95%, 0.85% and 0.84% better from ROA-FC, ISESW-FC, WOA-FC, GWO-FC, FF-FC, PSO-FC, ABC-FC, and GA-FC, respectively. For learning percentage 50%, the developed model attains high accuracy rate, and it is 0.86%, 0.12%, 0.38%, 1.60%, 0.54%, 1.07%, 0.05%, and 1.44% better than ROA-FC, ISESW-FC,
WOA-FC, GWO-FC, FF-FC, PSO-FC, ABC-FC, and GA-FC, respectively. Similarly, Figure 14 represents the negative FPR, FNR, and FDR. The FDR of the proposed model is low when compared to other conventional models. Particularly, for 40% of learning, the proposed model is 6.67%, 13.71%, 19.66%, 4.76%, 0.71%, 9.03%, 3.30% and 6.25% better from ROA-FC, ISESW-FC, WOA-FC, GWO-FC, FF-FC, PSO-FC, ABC-FC, and GA-FC, respectively. For 50% of learning, the developed model is 11.72%, 24.33%, 4.02%, 12.42%, 10.70% and 11.02% better than ROA-FC, ISESW-FC, WOA-FC, GWO-FC, FF-FC and PSO-FC, respectively. Likewise, Figure 15 depicts the positive measures such as NPV, F1 score and MCC source better performance when compared to conventional models. Hence, the performance of the proposed model is proven over other conventional models under all the measures in the detection of skin cancer.

5.5 | Comparative analysis

Table 4 to VII summarizes the performance of the proposed over other models concerning features. Table 4 shows the performance of proposed models on the LBP feature. Various measures have been analyzed under this. For accuracy measure, the proposed model is 9.15%, 37.49%, 38.83%, 34.90%, 37.49%, 34.90%, and 42.99% better than ROA-FC, ISESW-FC, WOA-FC, GWO-FC, FF-FC, PSO-FC, ABC-FC, and GA-FC, respectively. For 50% of learning, the proposed model is 11.72%, 24.33%, 4.02%, 12.42%, 10.70% and 11.02% better than ROA-FC, ISESW-FC, WOA-FC, GWO-FC, FF-FC and PSO-FC, respectively. The performance of the proposed model is proven over other conventional models under all the measures in the detection of skin cancer.

5.6 | Comparative analysis on the combined features

Table 8 shows the results of combined features under proposed and other conventional models. Here, the sensitivity of the proposed model is very high when compared to other models, and it is 4% better than ROA-FC, ISESW-FC, and WOA-FC, 13.04%, 8.33%, 1.96% better than GWO-FC, FF-FC, and ABC-FC, respectively. Similarly, all the other measures defined in this work prove the superiority of the proposed work in detecting skin cancer.

5.7 | Convergence analysis

The convergence analysis of the traditional and proposed method is given in Figure 16. At the 40th iteration, the proposed DOROA has convergence in the range of 1.33 and for ROA the convergence value is 1.36. Moreover, the proposed method seems to achieve better performance with minimum convergence value for all iterations than conventional methods like ROA-FC, ISESW-FC, WOA-FC, GWO-FC, FF-FC, PSO-FC, ABC-FC, and GA-FC. Further, the
calculation time of DOROA and ROA is 169.48 and 177.25 s respectively.

It is well known that the fuzzy classifier is a conceptual classifier that functions based on expert knowledge, which is constructed as fuzzy rules. Though it is straightforward, it faces significant challenges such as tuning of membership functions. It is an open-ended problem, which is attended in this paper by optimizing the bounds of the membership functions. The experimental results have shown a significant difference in the performance after tuning the bounds of the membership function as well as the straightforward procedure. Moreover, it is highly required to select a sophisticated optimization algorithm. The
TABLE 7  Comparative analysis on LVP under proposed and conventional models

| Methods   | GA-FC [31] | ABC-FC[32] | PSO-FC[33] | FF-FC [34] | GWO-FC[35] | WOA-FC[36] | ISESW-FC [37] | ROA [28] | Proposed |
|-----------|------------|------------|------------|------------|------------|------------|---------------|-----------|----------|
| Accuracy  | 0.52778    | 0.46667    | 0.46667    | 0.48889    | 0.46667    | 0.45556    | 0.46667       | 0.87778   | 0.88889  |
| Sensitivity| 0.46667    | 0.7        | 0.7        | 0.65       | 0.7        | 0.68333    | 0.7           | 0.96667   | 0.85     |
| Specificity| 0.55833    | 0.35       | 0.35       | 0.40833    | 0.35       | 0.34167    | 0.35          | 0.83333   | 0.90833  |
| Precision | 0.34568    | 0.35       | 0.35       | 0.35455    | 0.35       | 0.34167    | 0.35          | 0.74359   | 0.82258  |
| FPR       | 0.44167    | 0.65       | 0.65       | 0.59167    | 0.65       | 0.65833    | 0.65          | 0.16667   | 0.09167  |
| FNR       | 0.53333    | 0.3        | 0.3        | 0.35       | 0.3        | 0.31667    | 0.3           | 0.03333   | 0.15     |
| NPV       | 0.68333    | 0.35       | 0.35       | 0.40833    | 0.35       | 0.34167    | 0.35          | 0.83333   | 0.90833  |
| FDR       | 0.65432    | 0.65       | 0.65       | 0.64545    | 0.65       | 0.65833    | 0.65          | 0.25641   | 0.17742  |
| F1-score  | 0.39716    | 0.46667    | 0.46667    | 0.45882    | 0.46667    | 0.45556    | 0.46667       | 0.84058   | 0.83607  |
| MCC       | 0.023689   | 0.05       | 0.05       | 0.056408   | 0.05       | 0.025      | 0.05          | 0.76104   | 0.7523   |

TABLE 8  Comparative analysis on combined features (LVP+LBP) under proposed and conventional

| Methods   | GA-FC [37] | ABC-FC[38] | PSO-FC[39] | FF-FC [41] | GWO-FC[44] | WOA-FC[45] | ISESW-FC [46] | ROA [36] | Proposed |
|-----------|------------|------------|------------|------------|------------|------------|---------------|-----------|----------|
| Accuracy  | 0.87222    | 0.89444    | 0.86111    | 0.86111    | 0.83889    | 0.88333    | 0.88333       | 0.88333   | 0.90556  |
| Sensitivity| 0.81667    | 0.85       | 0.81667    | 0.8        | 0.76667    | 0.83333    | 0.83333       | 0.83333   | 0.86667  |
| Specificity| 0.9        | 0.91667    | 0.88333    | 0.89167    | 0.875      | 0.90833    | 0.90833       | 0.90833   | 0.925    |
| Precision | 0.80328    | 0.83607    | 0.77778    | 0.78689    | 0.7541     | 0.81967    | 0.81967       | 0.81967   | 0.85246  |
| FPR       | 0.1        | 0.083333   | 0.11667    | 0.10833    | 0.125      | 0.091667   | 0.091667      | 0.091667  | 0.075    |
| FNR       | 0.18333    | 0.15       | 0.18333    | 0.2        | 0.23333    | 0.16667    | 0.16667       | 0.16667   | 0.13333  |
| NPV       | 0.9        | 0.91667    | 0.88333    | 0.89167    | 0.875      | 0.90833    | 0.90833       | 0.90833   | 0.925    |
| FDR       | 0.19672    | 0.16393    | 0.22222    | 0.21311    | 0.2459     | 0.18033    | 0.18033       | 0.18033   | 0.14754  |
| F1-score  | 0.80992    | 0.84298    | 0.79675    | 0.79339    | 0.76033    | 0.82645    | 0.82645       | 0.82645   | 0.8595   |
| MCC       | 0.71375    | 0.76354    | 0.69183    | 0.68885    | 0.63905    | 0.73865    | 0.73865       | 0.73865   | 0.78844  |

The requirement of the performance of the optimization algorithm is well-attended by the proposed optimization algorithm that has also been seen from the comparative results between the proposed and the conventional optimization algorithms. Succinctly, the performance of the proposed methodology mainly relies on the optimal bounds suggested by the proposed optimization algorithm.

6  | CONCLUSION

This paper has developed a new skin cancer detection model with three major stages: segmentation, feature extraction, and classification. In this, the FCM clustering model was used to do the segmentation process. Subsequently, the features were extracted from the segmented image via LVP and LBP. Finally, the fuzzy classifier was utilized to classify the image by getting the extracted features (LVP+LBP) as the input. This paper has optimized the limits of membership functions in the fuzzy classifier. This was attained by a new DOROA algorithm, which was also proposed in this paper. The performance of the proposed DOROA model was compared over other conventional models. It was observed that the accuracy of the proposed model with 40% learning was 0.73%, 0.76%, 0.97%, 1.60%, 1.10%, 0.95%, 0.85% and 0.84% better from ROA-FC, ISESW-FC, WOA-FC, GWO-FC, FF-FC, PSO-FC, ABC-FC, and GA-FC, respectively. For 50% learning data, the developed model attains high accuracy rate, and it was 0.86%, 0.12%, 0.38%, 1.60%, 0.54%, 1.07%, 0.05%, and 1.44% better than ROA-FC, ISESW-FC, WOA-FC, GWO-FC, FF-FC, PSO-FC, ABC-FC, and GA-FC, respectively.
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