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Original Article

An Intelligent Early Detection of Melanoma Using Fuzzy Neural Networks with Java Optimization (FNN-JO) Classifier

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Abstract *- Cancer, characterized by uncontrolled cell growth, poses a significant threat to health, with skin cancer being particularly hazardous due to its prevalence across the body's tissues. Typically originating in the outer layers of the skin, skin cancer presents initially as abnormal growths or lesions. To address this issue, various computer-aided techniques have been employed. In this study, we propose a novel approach combining a Fuzzy Neural Network with Jaya Optimization classification (FNN-JO) for skin cancer image analysis. Initially, a hybrid strategy integrating Particle Swarm Optimization (PSO) and Anisotropic Diffusion Filter (ADF), known as ADF-PSO, is utilized to enhance the quality of input medical images while preserving edge details. Subsequently, the Modified Marker Controlled Watershed Algorithm is employed for image segmentation, followed by morphological post-processing for refinement. To enhance prediction accuracy, specific features such as area, perimeter, GLCM, Major and Minor axes, concavity, eccentricity, and filled area are extracted. The FNN-JO classifier is then employed for skin cancer classification, leveraging JO to classify features effectively. Simulation results demonstrate that the proposed FNN-JO outperforms existing classification schemes, including the Adaptive Neuro Fuzzy Inference System (ANFIS) and conventional FNN approaches, in terms of accuracy and performance.*

Keywords *– FNN-JO, Particle Swarm Optimization (PSO), Anisotropic Diffusion Filter (ADF), Modified Marker Controlled Watershed Algorithm, Adaptive Neuro-Fuzzy Inference System (ANFIS).*

1. Introduction

The skin, as the body's largest organ, performs vital roles such as facilitating touch sensation, regulating temperature, and shielding against harmful agents such as bacteria and UV radiation. Comprised of three distinct layers. The epidermis (outermost), dermis (middle), and hypodermis (innermost). The skin functions as a protective barrier for internal organs. UV rays pose a significant risk to skin health, causing cellular damage, particularly to DNA, which can potentially lead to skin cancer. Melanoma, the most dangerous type of skin cancer, has the potential to spread rapidly if not detected and treated early, posing a considerable challenge for effective intervention. While skin cancer predominantly affects individuals with fair skin, it can manifest in various forms, with malignant melanoma being among the deadliest. Dermatologists typically assess skin lesions based on characteristics such as contour, colour, diameter, and symmetry to identify potential malignancies. The term "ABCD rules" encompasses all of these characteristics.Dermatologists frequently look for these characteristics and perform skin biopsies to draw firm conclusions. This method of melanoma diagnosis takes a long time and can cost money for some people. Due to the fact that the majority of skin lesions are removed for testing, skin biopsy frequently results in visible scars on the skin. Skin cancer can be detected early enough to prevent death. The disease is currently a serious health issue; Dermatologists constantly worry about making an accurate clinical diagnosis. Various image processing methods, alongside computational techniques and systems for detection and classification, have been extensively employed in addressing medical issues.

These approaches offer non-invasive and highly efficient solutions to medical challenges. The paper is organized as follows: Section 2 offers a review of pertinent literature. Section 3 delves into the preprocessing of skin cancer images, covering the hair removal algorithm, segmentation methodology, feature extraction from segmented images, and classification using four distinct classifiers. Section 4 presents the experimental results derived from these procedures. Lastly, Section 5 summarizes the conclusions drawn from the study.

2. Related Works

Betta et al.[1]illustrated a method for identifying unique pigmented networks. This approach is built upon a combination of structural and spectral techniques. The structural method aims to ascertain texture by analyzing local disruptions such as lines and/or points. This can be applied by contrasting the image without the median filter. An image Fourier analysis was applied to determine the texture's spatial period. The researchers presented a deep learning-based supervised method for treating skin lesions. Twenty-one medical images were used to validate the effectiveness of the method, and they had two crucial binary classifications: malignant and benign groups and these were analyzed. The researcher created an automated dermatological tool for melanoma detection. Three categories serve as the foundation for their algorithms: globular, reticular, and uniform blue pigmentation. The extraction of the skin lesions' shape and any interesting features is an essential part of their work. In order to make a correct diagnosis, they will create a system that links all algorithms because each algorithm cannot make a final decision. Xu et al. [2] proposed a melanoma automatic diagnosis method.

The CNN was optimized by Satin Bowerbird Optimization (SBO), and the presented method was based on an optimized image segmentation technique. On the processed image, feature extraction was used after segmentation. Shalu et al. [6] developed a system for detecting melanoma skin cancer using a MED-NODE dataset of digital images. To address artifacts present in the raw images, preprocessing is performed initially. Subsequently, the Dynamic Shape division technique is employed to extract the region of interest. Suleiman Mustafa et al. [3] introduced an automated approach for identifying melanoma skin cancer from images of affected areas. Initially, the Grab Cut algorithm is applied to segment the input image into lesions resembling melanoma.

Following segmentation, image processing techniques are employed to extract features such as shape, color, and geometry. Cigdem Demirn et al. [9] have proposed the KNN and RF methods for identifying skin cancer. Another effective strategy in the field of cancer detection is acquisitive synthesis. In the real world, these methods fail to identify skin cancer, take longer to complete, and are less accurate. M.Chaithanya Krishna et al.[5] utilizing the ABCD (Asymmetry Index Border Color Index Diameter) method, features can be extracted using segmentation as a variety of clustering techniques. In [4], S. Jain et al. recommended actions include enhancing brightness, automatically applying Thresholding to isolate the lesion from the surrounding skin, extracting the area and perimeter of the lesion, and using this data to compute circularity and irregularity indices.

3. System Design

The background research indicates a growing trend in utilizing Machine Learning for processing medical images, particularly in diagnosing skin lesions. This study introduces an optimized technique for skin lesion segmentation employing Jaya Optimization, aimed at achieving higher performance in cancer type classification. The schematic representation of the proposed technique is illustrated in Figure 1. The primary contributions of this study are outlined as follows:

(i) Implementing an Anisotropic Diffusion Filter with Particle Swarm Optimization to achieve precise results.
(ii) Segmenting the region of interest using the Modified Marker Controlled Watershed Algorithm.
(iii) Utilizing feature extraction to identify beneficial features.
(iv) Employing a Novel Optimized FNN with Jaya Optimization algorithm for classifying melanoma cases.

3.1. Dataset Collection

More than 400 sample images were collected from the Kaggle Website and Dermnet dataset [10][11] for detecting Melanoma Cancer at an early period. There are 2 classes in the dataset: 1. Benign and 2. Malignant. By utilizing our Novel method of FNN-JO Classification, 250 samples of images were used for training and 150 samples of images were used for testing the Model.

3.2. Pre-processing

Pre-processing is geared towards enhancing image data by refining essential features for subsequent processing or rectifying unintentional distortions. The pre-processing steps in this proposed methodology involve:

1. Hair removal using the Dull Razor Technique to eliminate unwanted hair.
2. Converting the color image to grayscale using Image Enhancement Technique.
3. Employing the Anisotropic Diffusion Filter to enhance image quality by eliminating unnecessary noise.
4. Optimizing the random weights in the Anisotropic Diffusion Filter through Particle Swarm Optimization (PSO) to enhance filtration efficiency.
5. Figure 2 represents the Preprocessing Process.

Image preprocessing serves as the firstphase in image processing. It plays a crucial role in noise reduction and enhancing the quality of the original image, thereby serving as a fundamental step in the detection processes. It had to be used to limit the background influence on the result of the search for anomalies [12]. The main goal of this stage is to improve the quality of the melanoma image by eliminating irrelevant and unnecessary elements from the background to prepare it for further processing. The foremost step in the image processing technique for identifying skin cancer is the Dull Razor Technique, which is utilized to remove thick hairs from the skin area. After removing the thick hair, the next technique in preprocessing is an Anisotropic Diffusion Filter. Perona-Malik diffusion, also referred to as Perona-Malik denoising, is a method crafted to reduce image noise while retaining vital elements such as edges, lines, or crucial details essential for the interpretation of medical images.[13][14].

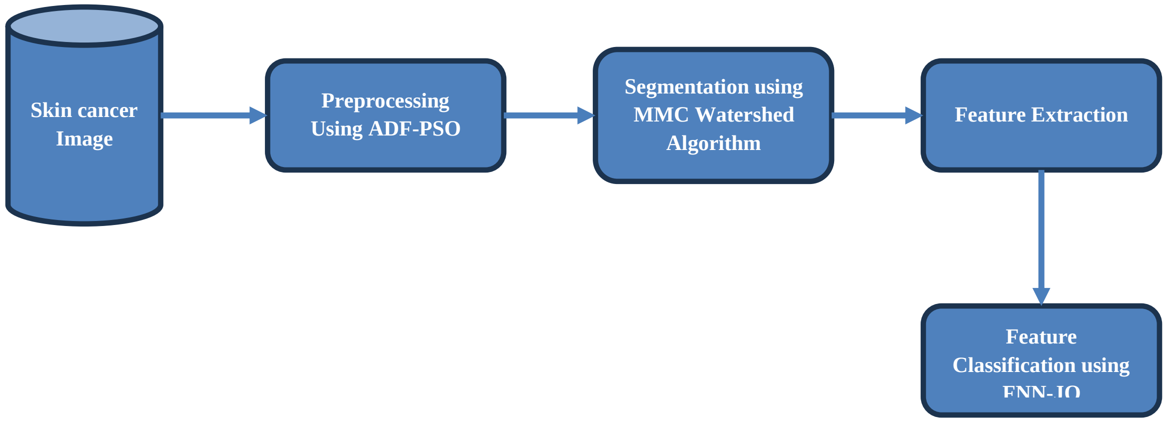


Fig. 1 System architecture of melanoma skin disease

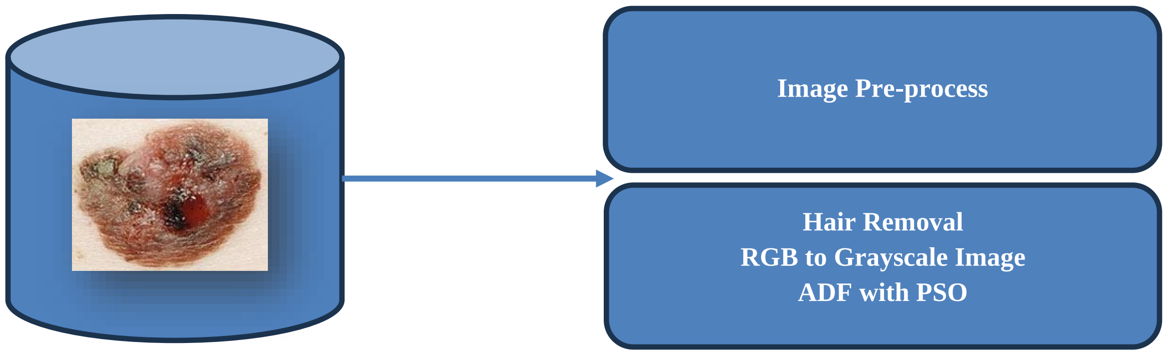


Fig. 2 Image Pre-processing

Anisotropic diffusion is defined as

$$\frac{\partial I}{\partial t} = div(c(m,n,l)\nabla I) = \nabla c.\nabla I + c(m,n,l)\Delta I \quad (1)$$

Where, In the equation, Δ represents the Laplacian operator, ∇ denotes the gradient, div(…) represents the divergence operator, and c(m,n,l)Δ signifies the diffusion coefficient. As l increases the resulting image, denoted as I(.,l), becomes progressively more blurred. The diffusion coefficient c(m,n,l) governs the diffusion rate and is typically chosen based on the image gradient to ensure the preservation of edges within the image.

$$c(\|\nabla I\|) = e^{-\left(\|\nabla I\|/K\right)^2} \quad (2)$$

3.2.1. ADF with PSO

Particle Swarm Optimization (PSO) is an intelligent population-based technique inspired by the collective behavior of birds searching for food. [15]. Through a series of iterations, a population of potential solutions is developed in PSO. In this proposed work, the gradient threshold has been optimized using the PSO for Anisotropic Diffusion Filter (ADF). Hence, anisotropic diffusion is not only used to denoise the images but also to sharpen the edges clearly by PSO.

Let the given n-dimensional optimization problem's objective function as Max f (x), where

$$f: R^n \rightarrow R \quad (3)$$

Initialize the random positions and velocities as gradient thresholds,

$$a_i = (a_{i1}, a_{i2}, \dots a_{in}) \quad (4)$$

$$v_i = (v_{i1}, v_{i2}, \dots v_{in}) \quad (5)$$

Update the Velocity and Position based on the following equations:

$$v_i^{k+1} = v_i^k + con_1 rand_1 (p^k_{best,i} - a_i^k) + con_2 rand_2 (G_{best,i} - a_i^k) \quad (6)$$

$$a_i^{k+1} = a_i^k + v_i^{k+1} \quad (7)$$

Where, con_1 and con_2 are the two positive constants,$rand_1 and rand_2$ are the random numbers which lie between (0,1).

Update the best position and global best to attain the best solution for optimal gradient threshold.

$$p^k_{best,i} = (a_{i,1}p^k_{best,i1}, a_{i,2}p^k_{best,i2}, \dots x_{i,n} \quad (8)$$

$$G_{best,i} = x_{i,1}G_{best,i1}, x_{i,2}G_{best,i2}, \dots \quad (9)$$

Update the final velocity by using equation (10)

$$v_i^{k+1} = wv_i^k + con_1 rand_1\left(p_{best,i}^k - x_i^k\right) + con_2 rand_2\left(G_{best,i} - a_i^k\right) \quad (10)$$

3.3. Segmentation using Modified Marker Controlled Watershed Algorithm

Watershed Transformation, rooted in morphology, serves as a tool for image segmentation. Initially proposed by Digabel and Lantuejoul in the context of gray-scale mathematical morphology, the conventional Watershed Transform is computationally intensive and susceptible to noise.

To address these challenges, a modified Marker Controlled Watershed Algorithm is employed[16], [17]. This algorithm utilizes a series of morphological operations to perform marker-controlled segmentation, identifying homogeneous regions within the image. Markers represent interconnected parts of the image[18, 19].

The proposed algorithm is shown below:

The image is segmented using MCWS, which reduces over-segmentation.

a) Apply a watershed transform that is controlled by markers to the preprocessed image.
b) Calculate the preprocessed image's morphological gradient using the equation (11).

$$M(I) = (I \oplus S) - (I\Theta S) \quad (11)$$

Where, $M(I)$→ Morphological Gradient
S→ Structuring Element
I →Preprocessed Image

c) Calculate a morphological gradient at Multiscale using the equation (12)

$$MM(I) - {}^{1}/_{n} \sum_{i=1}^{m} (M(I)\Theta S) \quad (12)$$

d) By utilizing its dilated image as a reference image, reconstructing the multi-scale gradient image enables the computation of the final gradient image using the equation. (13)

$$F(I) = \Phi(MM(I) \oplus S)MM(I) \quad (13)$$

e) Utilize the top-hat transform and the bottom-hat transform to extract Markers.
f) The morphological watershed is applied to the average of the marker image and the final gradient image to create the segmented image.

3.4. Feature Selection

To characterize melanoma and provide input to the classifier. The goal of feature selection is to identify pertinent features within the skin lesion image. Among the extracted features used for skin lesion identification are geometrical features as well as additional attributes. These extracted features are subsequently employed for effective classification using the FNN with JO Classification.

3.5. Feature Classification using FNN-JO

Skin cancer classification is conducted using the FNN classifier, with the incorporation of Jaya Optimization to enhance the training process. The classification process involves four layers: Level L1 serves as the input layer. Level L2 functions as the hidden layer, housing fuzzy truth values for each feature. Level L3 represents fuzzy rules derived from the fuzzification of features. Level L4 signifies the output variables, responsible for defuzzification and assigning output labels based on the features. In this process, fuzzy sets are transformed into (fuzzy) connection weights. Figure 3 shows the Architecture diagram of the Fuzzy Neural Network. We have chosen the sigmoid function as a membership function based on the input variables.

$$S(x) = \frac{1}{1+e^{-x}} \quad (14)$$

During the initial phase of learning, the weights between L2 and L3 undergo updating. In the subsequent phase, feature vectors, along with membership functions, are adjusted to identify the correct class label and determine the Mean Squared Error. Once learning is completed, the model is capable of classifying any unknown input sample.

Step 1: At Level L1, an input vector x = (x1, x2 ... xn) T with continuous values is received, while Level L3 generates an output vector o = (o1, o2... om) T. Calculations are then executed from Level L1 to Level L3 to derive the output vector o.

Step 2: The discrepancy in weight is determined, and subsequently, the mean squared error is Propagated backwards to compute changes in weights by comparing the output vector o with the desired output vector or target vector d.

$$\Delta w_{ij} = -\gamma \frac{\partial E}{\partial w_{ij}} \quad (15)$$

Where γ→ training coefficient and E →MSE at L3.

Step 3: Adjust the weights and membership functions. To optimize the weights, employ the Jaya Optimization (JO) algorithm.

3.5.1. Jaya Optimization Algorithm

A metaheuristic known as the Jaya algorithm[20] can deal with both constrained and unconstrained optimization issues. It is a population-based approach that repeatedly modifies individual solution populations. It is an optimization algorithm without gradients. It differs from the other optimization techniques by not having any hyperparameters.

__Algorithm: FNN-JO based Skin Cancer Identification__

__Input:__

A set of Training features, Test label y, Activation Function S(x).

__Output:__ Skin Cancer Identification

1. The hidden features are randomly generated.
2. At k=1;
3. Set the objective function as $x = (x_1, x_2 \ldots x_n)^T$
4. Update the weight of FNN
5. The population is scanned to pinpoint the optimal and suboptimal solutions, denoted by their respective γ values.
6. The best and worst solutions are adjusted using Equation (16).
7. If the modified solution $x'_{j,k,i}$ surpasses the original solution $x_{j,k,i}$, the former is adopted, otherwise, the current solution persists.
8. The termination condition is then assessed; if met, the optimal value is exhibited.
9. Otherwise, the process proceeds to step 7.
10. The Skin cancer features have been predicted and Classification Accuracy has been calculated.

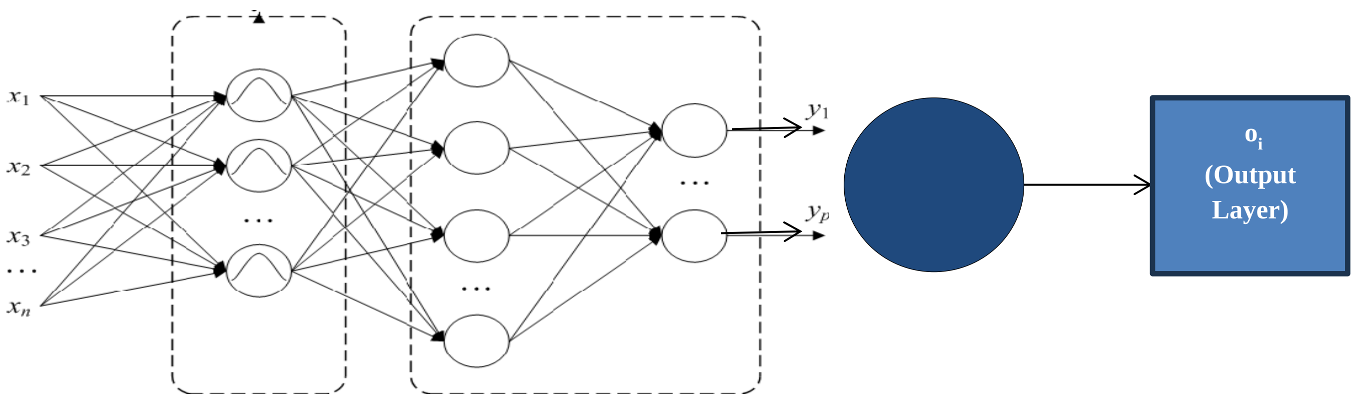


Fig. 3 Shows the architecture diagram of the fuzzy neural network

Assume that the target function to be minimized is f(x). Suppose there are n candidate solutions and m design variables at any given iteration i (with a population size denoted by k=1, 2... n). In all candidate solutions, let the best candidate receive the optimal value of f(x) while the worst candidate receives the least optimal value of f(x). The value of the jth variable for the kth candidate during the iteration is represented by Xj,k in equation (16).

$$x'_{j,k,i} = x_{j,k,i} + r_{1,j,i}\left(x_{j,best,i} - |x_{j,k,i}|\right) - r_{2,j,i}\left(x_{j,worst,i} - |x_{j,k,i}|\right) \tag{16}$$

Where,

$x_{j,best,i}$ → Value of variable j for the best candidate, $x_{j,worst,i}$ → value of variable j for the worst candidate. $x'_{j,k,i}$ → Updated value of $x_{j,k,i}$. $r_{1,j,i}$ and $r_{2,j,i}$ are two random numbers for the jth variable during the ith iteration in the range [0, 1]. $r_{1,j,i}\left(x_{j,best,i} - |x_{j,k,i}|\right)$ which provides better function value. $r_{2,j,i}\left(x_{j,worst,i} - |x_{j,k,i}|\right)$, which is used to avoid the worst solution. At the conclusion of the iteration, all acknowledged function values are preserved, and the values become input for the subsequent iteration. Based on the above equation (16), provide the optimized weight for the next layer in FNN in step 3.

Step 4: Update the optimized weights and Membership function.

Step 5: Obtain the Mean Squared error at Layer 3

$$\varepsilon = \frac{1}{2}\left(\sum_{i=1}^{n}(o_i - d_i)^2\right) \tag{17}$$

The algorithm will persist until the termination condition is met. Below is the proposed hybrid algorithm

3.6. Classification Assessment

In this paper, we employ suitable metrics to evaluate the efficacy of the FNN-JO-based skin cancer detection method. Metrics such as F-Measure (F-M), Recall (Rc), Sensitivity (Spy), Accuracy (Acc), and Precision (Pr) are utilized. Denoting the True Positive Rate as Tp, the False Positive Rate as Fp, the True Negative Rate as Tn, and the False Negative Rate as Fn, these metrics are calculated for all images.

$$Pr = Tp / (Tp + Fp) \tag{18}$$

$$Rc = Tp / (Tp + Fn) \tag{19}$$

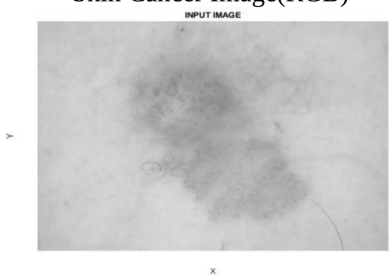
$$Spy = Tn / (Tn + Fp) \tag{20}$$

$$Acc = (Tp+Tn)/ (Tp+Fn+Tn+Fp) \tag{21}$$

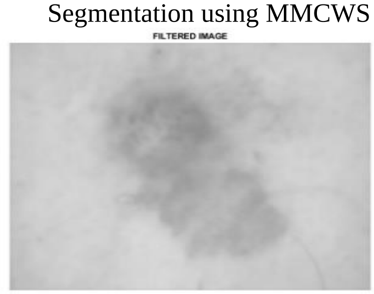
$$F\text{-}M = 2*\frac{Pr*Rc}{Pr+Rc} \tag{22}$$

Skin Cancer Image(RGB)

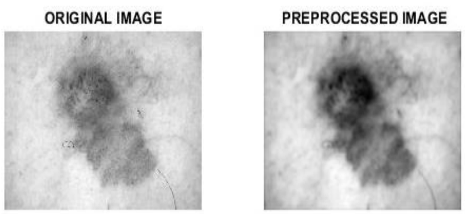
Segmentation using MMCWS



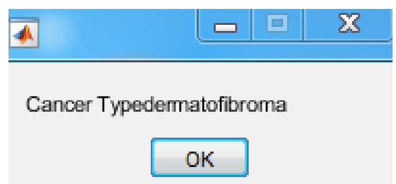
RGB-Gray Conversion



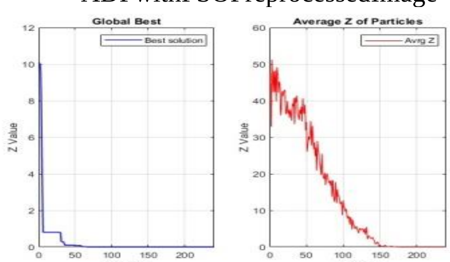
Filtered Image Using ADF



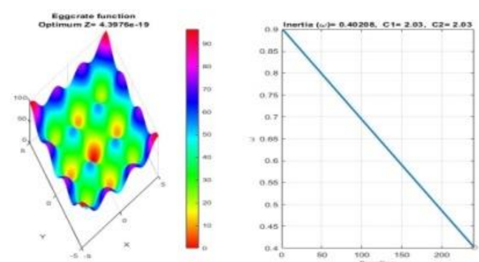
ADFwithPSOPreprocessedImage



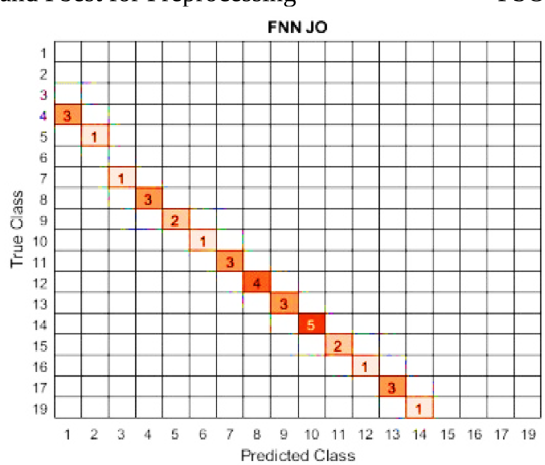
Classifiction result



Identification of GBest and Pbest for Preprocessing



PSO in Preprocessing



Confusion Chart for Classification Result

Fig. 4 Outcomes derived from the FNN-JO approach applied to skin cancer image inputs

Table 1. Numeric values reflecting the overall performance of Skin Cancer Identification

Metrics for Assessing Performance	Proposed FNN-JO	FNN	ANFIS
Accuracy (%)	89	76	61
Specificity (%)	80.13	61.92	40.53
Precision (%)	71.26	65.22	34.33
Recall (%)	72.69	53.48	42.51
F-measure (%)	74.12	66.48	30.17

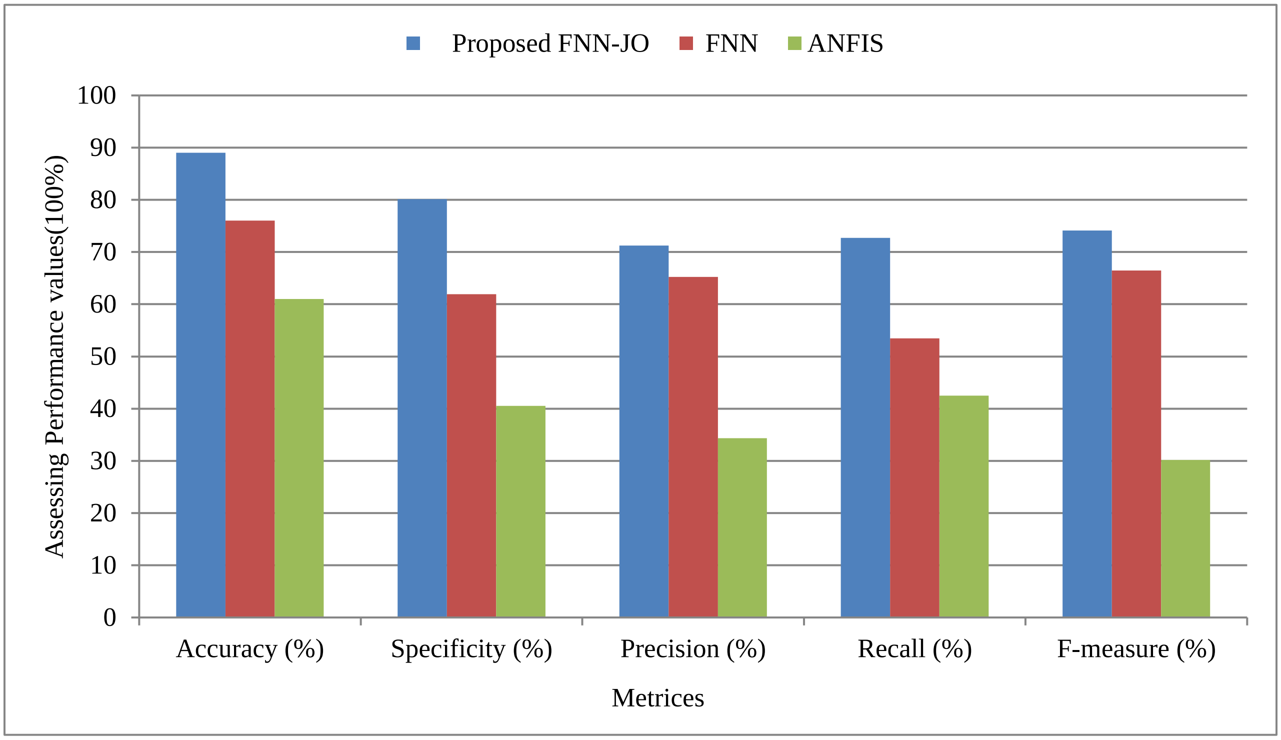


Fig. 5 Forecast the overall performance of skin cancer classification schemes

4. Outcomes and Disclosure

In this sector, we evaluate the FNN-JO classification scheme and compare it with existing classification methods such as ANFIS and FNN. Images from the Skin Database MRI were initially tested before training. The simulation outcomes were assessed using MATLAB. Approximately 400 sample images were considered for the estimation.This includes training on 250 images and testing on 150 images. Figure 4 depicts the proposed FNN-JO process in its entirety and its final product. Table 1 presents the mathematical assessment values for different skin disease location plans.

The outcomes demonstrate that the proposed FNN-JO outflanks both the current FNN and ANFIS techniques. The FNN-JO scheme's numerical evaluation scores can be improved by increasing the number of images with effective segmentation and feature extraction. The graphical representation of all skin cancer classification schemes is shown in Figure 5. Comparative analysis reveals that the proposed FNN-JO outperforms the FNN and ANFIS approaches with an Acc of 89%, a Spy of 80.13%, a Pr of 71.26%, an Rc of 72.69%, and an F-M of 74.12%. This improvement is credited to the proficient preprocessing and division strategies utilized in the proposed strategy.

5. Conclusion

The first step is to extract and choose the most suitable features using the ALO algorithm. This process is then carried out using a CNN-based classification method, which utilizes a ReLU activation function. The evaluation of the collected data was performed on the DermNet dataset, and the results achieved a remarkable accuracy rate.

To enhance prediction accuracy, we apply the Modified Marker Controlled Watershed Algorithm to segment optimized preprocessed images. This process effectively isolates the lesion area in skin cancer images. Subsequently, morphological post-processing techniques are applied, further refining the accuracy of our approach. After segmentation, pertinent features are extracted from the segmented region. These features are subsequently employed for cancer-type classification utilizing an FNN optimized with JO. Despite achieving an accuracy of only 89% in classification, future efforts will focus on increasing the sample size for evaluation.

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