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Design an Optimization Based Ensemble CNN Technique to Classify the Various Stages of Skin Cancer

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ABSTRACT

The skin is one of the few places in the body where cancer can begin. The size of the main tumor and the extent of the cancer's dissemination are both described by the cancer's stage. The classification of the various stages is more important for the treatment of skin cancer because it is impossible to take treatment measures without knowing the stage. The current study has proposed a cat swarm optimization with an ensemble CNN model (CSO-ECNN) for the exact prediction of the skin cancer stages. This method updates the cat swarm fitness in the classification layer to improve the prediction level of skin cancer. The six-phased proposed technique is shown in Figure 1. The selection of a dataset for the experiment is the first step in the suggested method. The studies in this study make use of the HAM 10,000 dataset. Before model training, several steps in the preprocessing stage must be finished. The relevance of the features is then assessed using the features extraction approach. Segmentation is employed using the GrabCut algorithm. Following that, prediction and classification are carried out using an ensemble deep learning approach. The developed model used cat swarm fitness in the classification phase for accurate prediction and classification of skin cancer. KDNN and DNN are the two DL classifiers used to determine the stages of skin cancer. Additionally, the proposed technique gained outcomes are validated with other conventional models in term of accuracy, specificity, recall, and precision.

Keywords: *medical image processing, deep learning, ensemble learning, skin cancer prediction, cat swarm optimization.*

1. INTRODUCTION

Skin cancer is a form of cancer that develops in the skin tissue and can harm nearby tissues, resulting in disability, or death. Skin cancer is a condition brought on by modifications in the capabilities of healthy skin cells to turn malignant, where cells continue to divide uncontrollably into abnormal shapes as a result of DNA damage [1, 2]. According to histology, skin cancer exhibits uneven separation of cells at distinct levels of the nucleus, chromatin, and cytoplasm [3]. Early identification and precise diagnosis of skin cancer can aid in the recovery process, ensure correct medical care, and help prevent the worst side effects [4]. Therefore, an early detection system is essential that can help to raise public awareness for detecting various kinds of skin cancer [5]. The automatic classification of skin illnesses can assist individuals in recognizing skin conditions. It develops and prompts early consultation with medical professionals to receive the necessary medical care. Skin cancer is an unchecked expansion of abnormal cells that develop on our skin [6, 7]. It occurs due to typical DNA damage that stimulates mutations and enables for rapid proliferation of skin cells into malignant tumors. Basal Cell Carcinoma (BCC), Seborrheic Keratosis (SEK), Squamous Cell Carcinoma (SCC), Actinic Keratosis (ACK), Nevus (NEV), and malignant melanoma are a few common kinds of skin cancer. These tumors become more active in response to ultraviolet exposure [8, 9]. These cancerous cells are typically found on exposed skin to the sun like the scalp, hand, lips, neck, face, and areas around the eyes. Early cancer identification can help save a lot of lives [10].

With limited resources, early detection of skin cancer is important. In general, proper diagnosis and identifying viability are critical for skin cancer treatments [11]. Dermatologists also have trouble diagnosing skin cancer in its early stages. In the past few years, deep learning has been widely applied in both supervised and unsupervised learning situations [12]. The use of deep learning is an innovative technique that evolved from machine learning. Deep learning is more sensitive than conventional machine learning algorithms. Object recognition, natural language processing, and image classification are all areas of deep learning [13, 14]. One of those algorithms that have excelled in object detection and classification tasks is Convolution Neural Networks (CNN). CNNs have been utilized to categorize skin cancer lesions. CNNs eliminate the requirement for physical handcrafting features by mastering extremely discriminative features [15, 16]. Deep learning's success rate is influenced by the resources employed in the training process and the quantity of datasets used.

Early identification and treatment of skin cancer can help to reduce and manage its negative effects [17]. Because skin cancer and benign tumor lesions have similar shapes, physicians spend substantially more effort to diagnose the lesions. Several related research based on computerized image processing is developed for predicting and classifying skin malignancies [18, 19]. That is more reliable identify skin problems with quick computing time. But, still has the issues of less reliability, error, overfitting issue, less accuracy, and high execution time. Another difficulty in detecting skin cancer in images is that the ratio of skin cancer to normal skin patches is usually unbalanced [20]. Normal skin is typically greater in size than cancerous skin. The suggested method can classify different types of skin cancer and determine the stages such as benign and malignant. The primary goal of the developed model is to improve skin cancer prediction outcomes by precise segmentation and classification.

The key roles of this proposed model are summarized as,

- Initially, the HAM 10000 dataset was collected and trained in the system using the Python tool.
- Subsequently, a novel CSO-ECNN Model was developed to predict and classify skin cancer types and stages.
- Hence, preprocessing and feature extraction methods are employed to enhance the data quality and prediction performance.
- Then, the segmentation process is carried out using the GrabCut algorithm.
- Hereafter, the fitness of the CSO is updated in the fully connected layer of the developed model to predict the stages of skin cancer.
- Moreover, the developed approach is validated using recent prevailing approaches in terms of detection accuracy, specificity, recall, F-measure, and precision.

The manuscript is structured as follows: The literature review on the detection of skin cancer is covered in session 2. Describe the problem statement from session 3. Session 4 covered the suggested technique, and Session 5 covers the results and comparative analyses. The conclusion of the work is covered in more detail in Session 6.

2. RELATED WORKS

Some recent literature surveys based on skin cancer detection are detailed below,

Deep Convolution Neural Network (DCNN) was used by Zafer, et al. [21] to construct an automated skin cancer diagnosis system. In addition, neural networks, random forests, and naive Bayes methods are used to find skin cancer. The findings of this study indicated that DL techniques are superior to ML for detecting skin cancer. The performance has been assessed to that of other research projects. Finally, it performs better than all traditional systems.

To successfully perform the classification task while using fewer processing resources and maintaining accuracy, Saddam Hossain, et al. [22] designed a shallow CNN architecture. The total performance was determined using a variety of performance measuring criteria.

The accuracy of the suggested model is 98.81%. By beating the other TL algorithms in terms of accuracy, the suggested model showed its robustness.

Convolution Neural Network (CNN) was used by Masum Shah, et al. [23] to create a DL model for identifying and categorizing skin cancer. Initially, expand the total data size and then train the dataset to the created deep CNN model. The performance outperforms using two pre-train models, GoogleNet by 1.76% and MobileNet by 1.12%, on the test data, receiving an accuracy score of 95.98%.

To find the best designs for categorizing these images and obtaining incredibly acceptable results, Mijwil developed [24] a DL network and learned with three frameworks such as ResNet, InceptionV3, and VGG19 with many parameters. This network is highly accurate at recognizing the type of cancer as benign or malignant. With this architecture, a diagnosis accuracy of about 86.90% has been attained.

Using photos of skin lesions, Mohammad Fraiwan, et al. [25] investigate the usefulness of raw deep transfer learning to categorize the lesions into seven different groups. 13 deep transfer learning models were used to create a system using HAM1000 dataset without feature extraction or preprocessing. The highest overall accuracy was dropped to 82.9% even though some cancer types were successfully recognized with high accuracy.

An automatic computer-aided diagnosis approach for multi-class skin (MCS) cancer categorization model was developed by Tausif, et al. [26]. In MCS cancer classification, the suggested strategy performed better than both experienced dermatologists and current DL techniques. As a result of the developed architecture and capacity for greater accuracy use of MCS cancer classification models.

3. PROBLEM DEFINITION

Early diagnosis is essential in skin cancer treatment. The biopsy approach is typically used by doctors to find skin cancer. Through this treatment, a sample of a potentially malignant skin lesion is removed for testing [27]. This procedure is difficult, cumbersome, and slow. Skin cancer signs are quickly, comfortably, and more affordably diagnosed because of computer-based technology. But some challenges are there to detect and classify skin cancer such as imbalanced datasets, images with varying resolutions, large datasets, insufficient gradients, noisy data, and non-stationary problems [28]. The common issue to detect and classify skin cancer is image acquisition problem, classification problem, low-quality images, resolution problem, computer vision, and overfitting problem [29]. Many deep learning and machine learning models are developed to improve skin cancer detection but still suitable solution was not found. These challenges and issues are motivated to improve the skin cancer prediction system using an optimization-based transfer learning method.

4. PROPOSED METHODOLOGY

The current study has proposed a Cat Swarm Optimization with an Ensemble CNN model (CSO-ECNN) for the exact prediction of the skin cancer stages. This method updates the cat swarm fitness in the classification layer to improve the prediction level of skin cancer. The six-phased proposed technique is shown in Fig.1. In this study, HAM 10,000 dataset is used to predict skin cancer. Before model training, several steps in the preprocessing stage must be finished. The relevance of the features is then assessed using the features extraction approach. Following that, segmentation is employed using the GrabCut model, and classification is carried out using ensemble deep learning. Two DL classifiers are used in this research such as Keras Deep Neural Network (KDNN) and Deep Neural Network (DNN) to determine the stages of skin cancer.

Additionally, CNN's output layer uses the softmax activation function and the convolutional layer updates the ReLU activation function. Finally, Cat Swarm Optimization (CSO) is updated in the classification phase for accurate prediction of skin cancer stages such as benign and malignant.

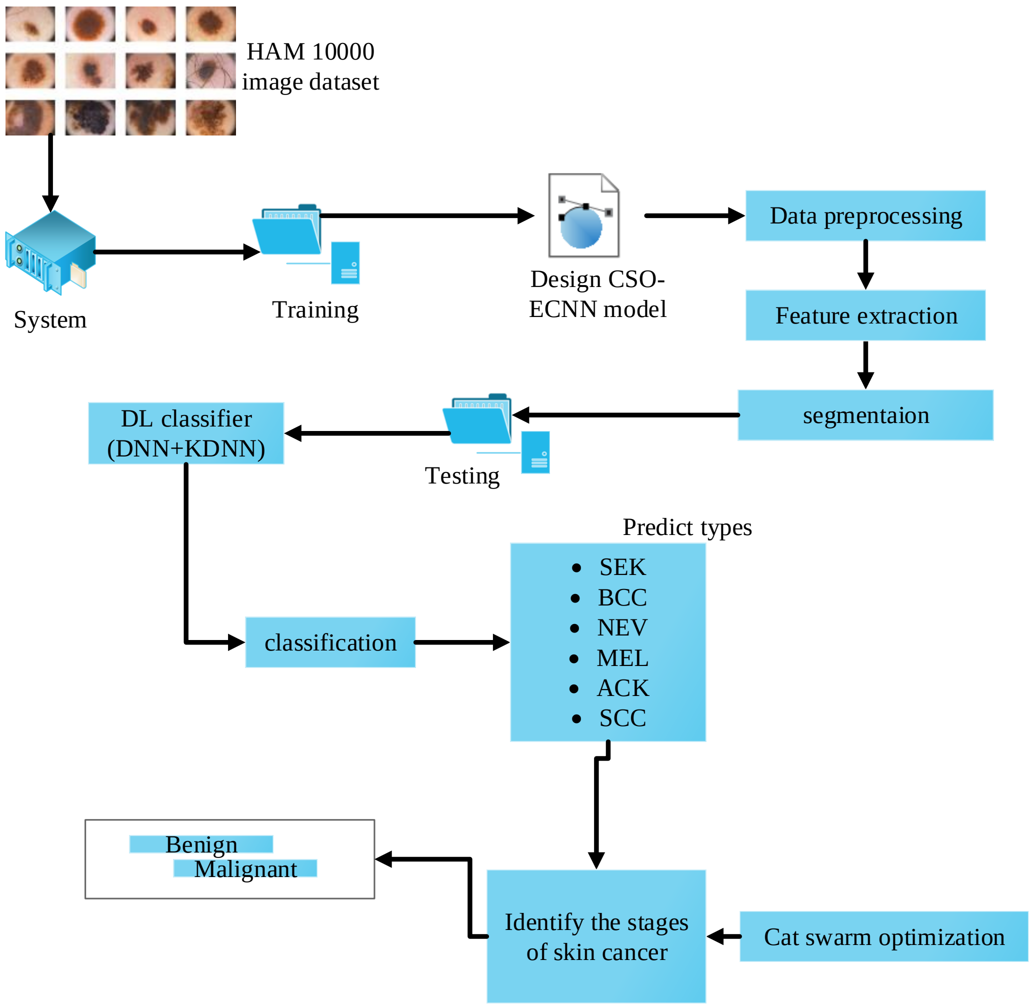


Fig. 1 Proposed Methodology

4.1 Dataset description

In recent years, the automatic diagnosis of skin cancer detection systems is vulnerable due to the absence of diversity, and the small size of dermoscopic images. To overcome these problems, create Human Against Machine (HAM) with a 10000 images dataset. The HAM10000 dataset [30] is an extensive set of dermoscopic images from several sources of typical pigmented skin lesions. Capture dermoscopic images from various populations, captured and stored using various modalities. The collected HAM 10000 dataset contains 10015 dermoscopic images of seven different types of skin cancer and is detailed in table.1. It can be used as a training set for artificial and deep learning algorithms. The dataset contains lesions with many pictures, which can be tracked using the HAM10000_metadata file and lesion_id sector. The data is seriously skewed.

Table.1 Different Types of Skin Cancer

Disease name	Short forms
dermatofibroma	df
melanoma	mel
melanocytic nevi	nv
basal cell carcinoma	bcc
vascular lesions	vasc
benign keratosis-like lesions	bkl
Actinic keratoses and intraepithelial carcinoma	akiec

In the training phase, 7000 samples (80%) of the dataset are used and in the validation phase, 700 samples (20%) of the dataset are used. Thus the collected dataset contains noise and less data quality. So, preprocessing is essential to improve the quality of the dataset.

4.2 Data preprocessing

Pre-processing is an important stage in skin cancer detection, it removes noise and improves the overall appearance of the original image. It was necessary to use it to limit the search for irregularities in the background effect on the result. The primary goal of this stage is to improve the quality of the HAM dataset image by deleting unrelated and surplus areas of the image in preparation for subsequent processing.

- **Hair removal**

Hair will influence the efficacy of feature extraction and segmentation. so, create an adaptive principal curvature method [31] to detect hairs and an inpainting approach to remove hair from the dataset. Thick hairs are a typical barrier that might confuse the segmentation procedure during an automated analysis of tiny skin lesions. The grayscale image of the collected dataset is $g(V)$, $V=(v_1,v_2)\in S^2$ is represented as regular surface. The substance's local shape and properties at a specific pixel are expressed in eqn. (1).

$$(q,r), q\in\{1,....,m\}, r\in\{1,....n\} \tag{1}$$

Let, m and n are denoted as the number of pixels by the vertical and horizontal image which are identified using a hessian function that is expressed in eqn. (2).

$$H(v,\tau)=\begin{pmatrix} \dfrac{\partial^2 w}{\partial v_1^2}(v) & \dfrac{\partial^2 w}{\partial v_1 \partial v_2}(v) \\ \dfrac{\partial^2 w}{\partial v_1 \partial v_2}(v) & \dfrac{\partial^2 w}{\partial v_2^2}(v) \end{pmatrix} \tag{2}$$

The standard deviation function is represented as τ that plays a important role to scale the parameter. Principal curvatures are the greatest (ϕ_{ij}^{+}) and smallest (ϕ_{ij}^{-}) eigenvalues of the Hessian. ϕ_{ij}^{+} identifies dark lines on light backgrounds, and ϕ_{ij}^{-} detects light lines on dark backgrounds. It is anticipated that the adaptive primary curvature will enhance the hair contrast more than the gradient magnitude. A solid structure will be produced by the adaptive primary curvatures. Additionally, obtained data was used to create an image of the inpainting regions needed to remove hair from skin lesions.

- **Noise removal**

The anisotropic Diffusion Function [32] is used to remove any noise and keep some elements of the original skin images like edges. The anisotropic diffusion is expressed in eqn. (3.

$$\frac{\partial F(a,b,t)}{\partial t}=div\left(\left\|\left(G\left(\nabla F(a,b,t)\right)\right)\right\|\right)\left\|\nabla F(a,b,t)\right\| \tag{3}$$

Let, t is denoted as the time parameter, $F(a,b,0)$ is represented as the original image, $\partial F(a,b,t)$ is considered as the gradient of the original image at t. Additionally, $G(\ )$ is denoted as reducing conduction function.

- **Contrast enhancement**

Contrast enhancement is used to enhance vision for skin cancer detection by sharpening the image border and increasing accuracy by accentuating the brightness discrepancy between foreground and background. Enhancing contrast is critical for improving image quality. Moreover, the histogram equalization method is used for contrast enhancement.

Histogram equalization [33]: Grayscale photos are created by converting original photographs to grayscale. The histogram is a graph that displays the number of pixel values within the grayscale range. Finally, the histogram is equalized to enhance the image. Histogram equalization is employed to create a homogeneous histogram. Transformation is the following for any s in the range [0, 1]: The converted grey level's density function of probability is as follows in Eqn. (4).

$$Q_k(k)=\left[Q_s(s)\frac{ds}{dk}\right]_{s=T^{-1}(k)} \tag{4}$$

Let, s is denoted as the level produced for every pixel value, k is considered the original image. The transformation function is detailed in Eqn. (5) and (6).

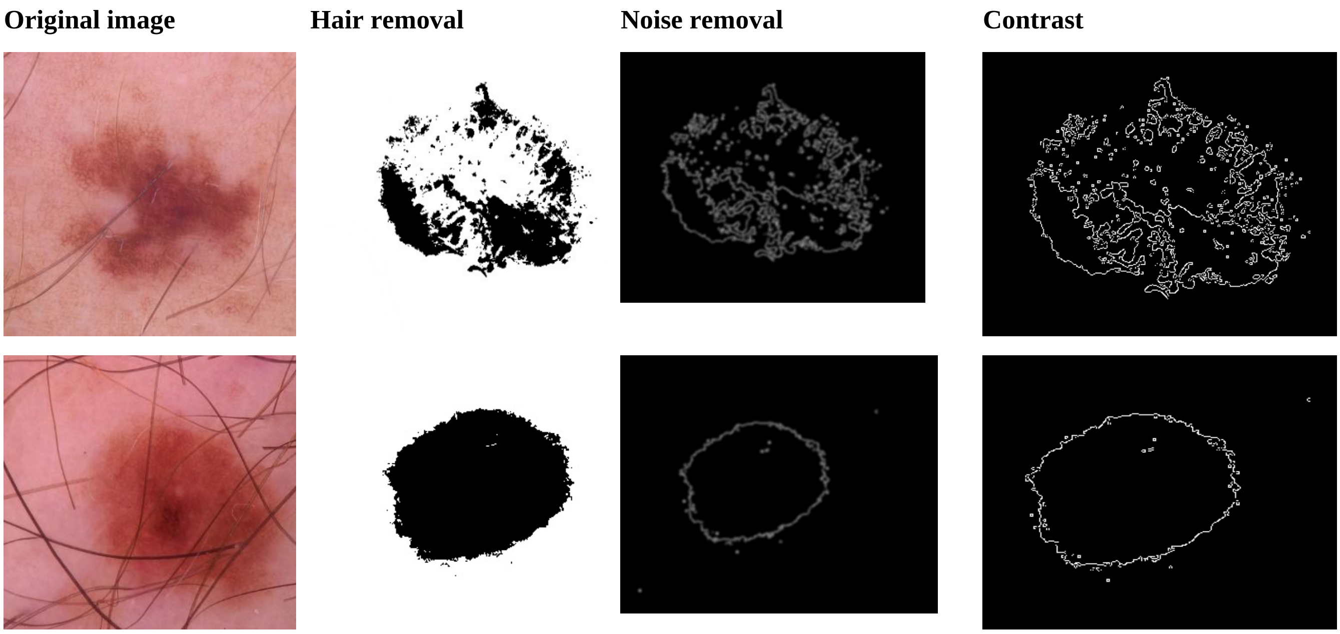
$$k = T(s)\int_{o}^{T} Q_s(p)dp \tag{5}$$

$$Q_k(k) = \begin{pmatrix} 1 & 0 \le k \le 1 \\ 0 & otherwise \end{pmatrix} \tag{6}$$

More contrast will come from the increase in dynamic range caused by histogram equalization. This can provide us with an optimal range of pixel values for further processing.

- **Resize and reshape**

Skin cancer photographs might come from a variety of sources and sizes, the initial action is to resize the images to have a stable width but an adjustable height. The HAM10000 dataset is large and imbalanced, and it contains images of skin lesions. Resizing is essential to changing the image's dimensions and size. Although individual photographs may have different resolutions or aspect ratios, scaling is occasionally necessary to uniformly scale the images. The images are different sizes so resizing is necessary to ensure the collected HAM10000 with same dimensions. Reshaping comprises changing the shape of a picture by flattening or reordering the pixel values. The HAM10000 data is reshaped using deep learning. Employing each image's pixel values as features to train a framework for deep learning models, which require the input of a particular size, involves flattening every picture into a vector of pixel values. There is an imbalance in the HAM10000 collection, with some photo types being overrepresented in contrast to others. In this case, scaling and reshaping may be employed to balance the dataset. The preprocessed dataset is shown in fig.2.



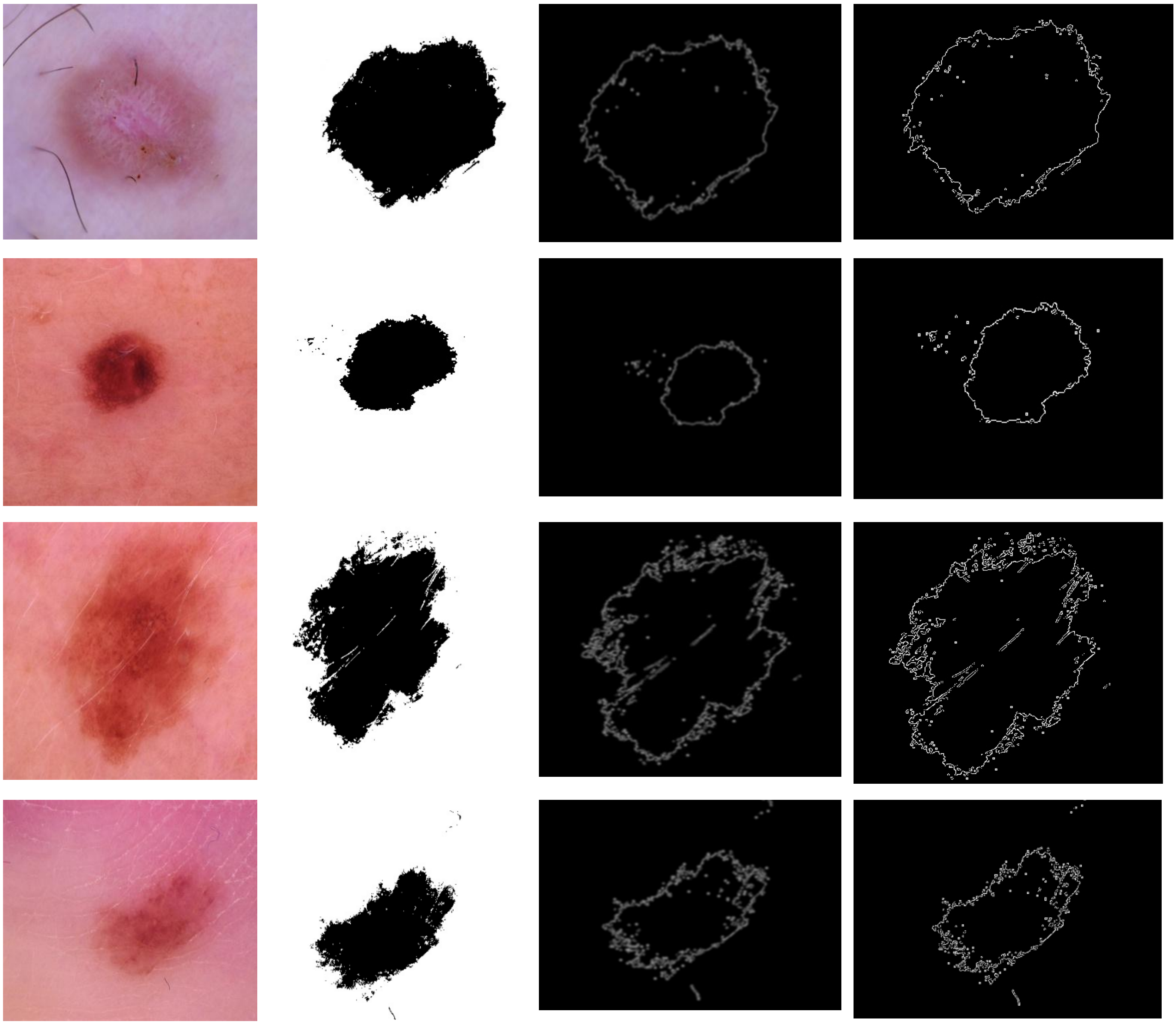


Fig.2 Preprocessed results

4.3 Feature extraction using the ABCD rule

Feature extraction is an essential step to improve the segmentation and classification results by extracting the important features from the dataset. In this paper, the ABCD rule [34] is employed for accurate feature extraction. A stands for asymmetry, B stands for a border, C stands for color, and D stands for diameter. The use of the ABCD rule is that separate the malignant and benign tumors of skin cancer by extracting relevant features. All feature values are expressed linearly to produce the TDS score. The TDS score is calculated using eqn. (7).

$$TDS = Aa + Bb + Cc + Dd \qquad (7)$$

Let, a, b, c, d and A, B, C, D are the effect factors and score of the asymmetry, border, color, and diameter.

- **Asymmetry**

The score of asymmetry is calculated based on the distribution of structure, contour, and colors of the dermoscopic images. It has the requirement to evaluate each axis and side of contour, structure, and color. The asymmetry contains no axis means, the asymmetry score is 0. The asymmetry contains single-axis means, the asymmetry score is 1. The asymmetry contains double-axis means, the asymmetry score is 2. Finally, the effect factors asymmetry score is 1.3.

- **Border**

The border score is determined based on the gradual, sharp, pigment pattern abrupt cut-off and indistinct cut-off of the skin lesion. The lesions are separated into eight sections to evaluate the border score. The border score is determined by the number of gradual or sharp cut-offs. The lowest and maximum border scores are 0 and 8, respectively. Finally, the effect factors border score is 0.1.

- **Color**

The color score is evaluated based on red, white, light brown, blue-grey, dark brown, and black. Moreover, the identification of affected areas with colors is detailed in table.1.

Table.1. Affected area with colors

Color	**Affected area**
Light and Dark brown	• Reflect melanin that is primarily found in the outer layer of skin • Superficial dermis
Black	• Melanin in the upper granular layer, • Stratum corneum, • All epidermal layers
Blue Grey	• Melanin in the dermal papillary layer
White	• Regressive areas
Red	• Degree of neovascularization or inflammation

One point will be added to the color score if any of the above colors are present. The maximum and minimum color scores are 6 and 1, respectively. Finally, the effect factor of the color score is 0.5.

- **Diameter**

Based on its measurement, the diameter score is assessed. A skin lesion's diameter is calculated as the largest distance between its two pixels. A malignant skin lesion is indicated if the area's diameter is greater than 6 mm. The diameter score is multiplied by 1 for every millimeter of diameter. Finally, the effect factor of the diameter score is 0.5.Based on the extraction of the different features of asymmetry, border, color, and diameter, the partial scores are assessed.

The effect factors have fixed values $a = 1.3, b = 0.1, c = 0.5, d = 0.5$. The design improves the feature extraction process using the ABCD rule and predicts the levels of skin cancer such as malignant, suspicious, and benign.

4.4 Segmentation using the GrabCut technique

Image segmentation is the method of dividing an image into non-overlapping sections or regions. It is based on various characteristics such as brightness, texture, contrast, color, and gray level. It divides similar lesions from the surrounding healthy skin. It is the most important phase in accurately evaluating photos because it affects the accuracy. Due to the enormous variations in the shape, size, and color of the lesions, precise segmentation in microscopic pictures is difficult. The GrabCut technique [35] is used to segment the images and enhance the accuracy of the image segmentation. The GrabCut technique predicts the color distribution between the background and target object via Gaussian Mixture (GM) technique that efficiently constructs a rectangle and removes the foreground from background photos. GM learns and develops new pixel distributions based on the data. In other words, the unknown pixels are categorized as either probable foreground or probably background based on their color statistical relationship with the other hard-identified pixels. To further analyze the pixels, a GM can be utilized to separate them into similar segments. GrabCut was achieved automatically by merging two algorithms utilizing a single threshold value. As a result, the probable lesion region was first obtained as a mask before being used for GrabCut segmentation. If the extracted mask is larger than the threshold, the collected mask is sufficient, and a rectangle is constructed to conduct the GrabCut. In the HSV color space, almost all of the skin lesions show green. As a result, the image's green color was taken and used to create a thresholding mask (M).

$$M = \begin{Bmatrix} 1, & foreground \\ 0, & background \end{Bmatrix}$$

Additionally, extraction of the skin lesion using a green channel failed in masking because of small variation in intensity among lesion and skin. So, the threshold-based segmentation technique is used for skin lesion segmentation. The threshold value is computed using intensity value and mask dimension. If the mask value is exceeded the threshold value means generating a rectangle, that rectangle is helpful for skin lesion segmentation. Furthermore, the rectangle dimension is obtained using eqn. (8) and (9).

$$h_r = h_i - (0.3 \times h_i) \tag{8}$$

$$w_r = w_i - (0.3 \times w_i) \tag{9}$$

Let, h_r is denoted as rectangle height, h_i is represented as image height, w_r is considered as rectangle width, and w_i is denoted as image width. The outside of the rectangle is denoted as the background. Finally, skin lesions are segmented accurately with GrabCut segmentation.

Classification and prediction using deep ensemble classifier

A variety of deep learning issues have been addressed by researchers using ensemble learning. An ensemble learning method is utilized to identify diseases and properly categorize data due to each dataset comprises a wide variety of issues. Every time a new data point is received, each classifier in the ensemble guesses a class label. The class label chosen in that situation is the one that the majority of classifications predicted, or the class labels it received the most votes. Utilize a variety of DL classifiers and different voting methods to boost performance. The developed ensemble model (KDNN+DNN) used Deep Neural Network (DNN) [36] for assessing skin cancer detection and classification. The designed DNN model contains an input layer, a dense layer, and a fully connected layer. Moreover, the ReLU activation function is employed in the input layer which has the unit value of 16. Three dense layers are used that have the unit values of 12, 8, and 4. Finally, employ the sigmoid activation function in a fully connected layer with a specific value. The input layer contains 176 parameters, the first hidden layer contains 204 parameters, the second hidden layer contains 104 parameters, and the final hidden layer contains 36 parameters.

To determine the loss and improve fine-tuning, the Keras Deep Neural Network (KDNN) model [37] was developed. The designed KDNN model is built with a single input layer, numerous hidden layers, and a single fully connected layer. Keras Deep Neural Network (KDNN) is employed in the DL-based classifier for overcoming overfitting problems. It prevents the overfitting issue and enhances the robustness of medical image processing. The input layer contains 132 parameters, the hidden layer contains 130 parameters, the second hidden layer contains 88 parameters, and the final hidden layer contains 54 parameters. The fine-tuned DNN and KDNN model is successfully tested and trained on the HAM 10000 dataset. In the training process, input vector $q^{(i)}, r^{(i)}$ are updated to the designed model using eqn. (10)

$$E_i = \{(q^{(i)}, r^{(i)} / i \in [1, n])\} \tag{10}$$

Let, $q^{(i)}$ is denoted as the input position vector, $r^{(i)}$ and i are considered as the desired output. The network performance of the negative log probability error function is obtained using eqn. (11).

$$E_f = \phi \rightarrow -\frac{1}{m}\sum_{i=1}^{m} \log\left(ClsNet_{\phi}\left(q^{(i)}\right) \cdot r^{(i)}\right) \tag{11}$$

Let, $\cdot$ is represented as the output space dot product, $ClsNet$ is denoted as the mapping of the input layer, and ϕ is denoted as all the parameters in the network. A hidden layer can be broken down more precisely into several feature maps, whose neurons have similar weights and simply differ in terms of receptive field. This indicates that neurons within the same feature map can recognize the same feature across various picture receptive fields. A total of hidden operations can simplify the limits based on local connectivity and weight sharing. The feature map's (f) of layer l neuron output is expressed in eqn. (12).

$$J_b^a = \theta\left(\sum_x B_{x,f}^l * J_x^{l-1} + n_x^l\right) \tag{12}$$

Let, $*$ is considered a convolution operation, and $B_{x,f}^l$ is represented as the feature map weight matrix of layer l. Moreover,

J_x^{l-1} is considered as a feature map x of layer $l-1$, and n_x^l is denoted as scalar bias. The last layer is the fully connected layer J^l, in this phase update cat swarm optimization (CSO) [38] for enhancing the performance of skin cancer prediction and classification. When cats are awake, resting takes up the majority of their time. They shift positions carefully and gently while they are sleeping, or they may not move at all. Cats exhibit two different behavioral patterns: seeking and tracing. The movements are slow and close to the starting point in seeking mode. A cat travels in the tracing mode at its speed in every dimension. To solve the optimization challenge, CSO is employed and enhances the categorization and prediction outcomes via searching and tracing cat behavior. It indicates the M-dimensional location vector and velocity. The fitness function should be generated based on the location of each cat.

The final prediction is obtained using eqn. (13).

$$J^l = ClsNet^l\left(J^{l-1}\right) = \theta\left(B^l J^{l-1} + n^l\right) * C_s \tag{13}$$

Let, C_s is represented as cat swarm fitness, J^{l-1} is considered as input of layer l, and θ is represented as activation function.

Activation function

In this model two activation functions are used, ReLU and softmax activation function. A rectifier neuron is referred to as a Rectified Linear Unit (ReLU). It is less susceptible to the vanishing gradient issue than the more conventional sigmoid or tanh processes, which has hampered the training of deep networks for many years. The ReLU function is expressed in eqn. (14).

$$\theta = x \rightarrow \max(0, x) \tag{14}$$

The softmax activation function is updated in the top layer of the network. The output of the neuron (o) is expressed in eqn. (15).

$$Out_o = \frac{e^{w_o}}{\sum_{k=1}^{n} e^{w_o}} \tag{15}$$

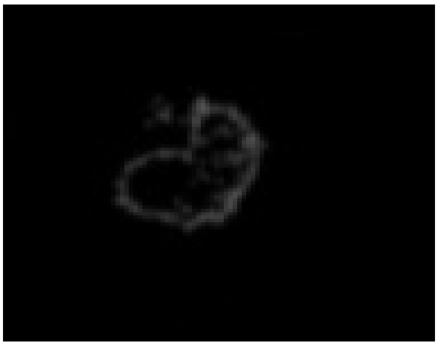
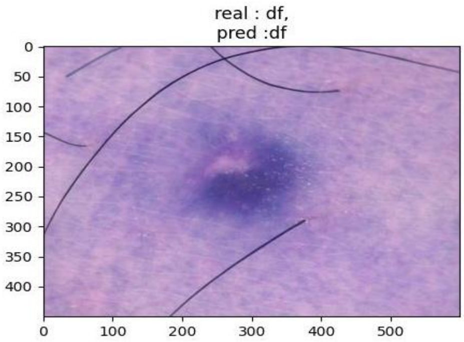
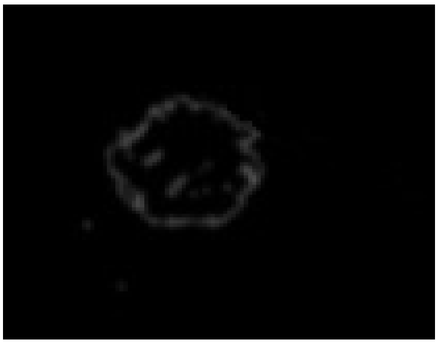
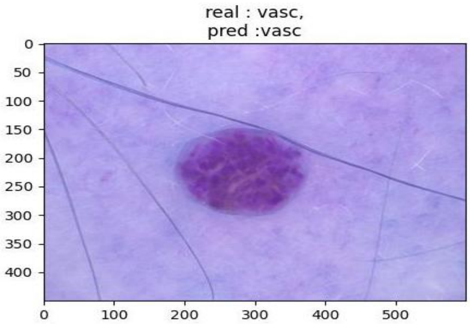
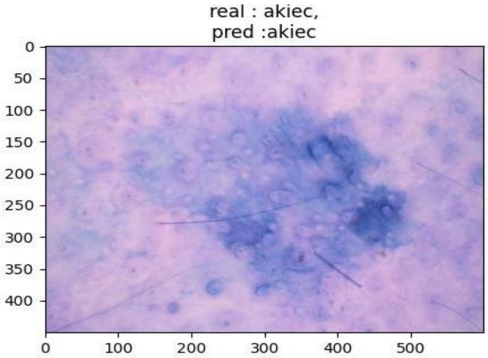
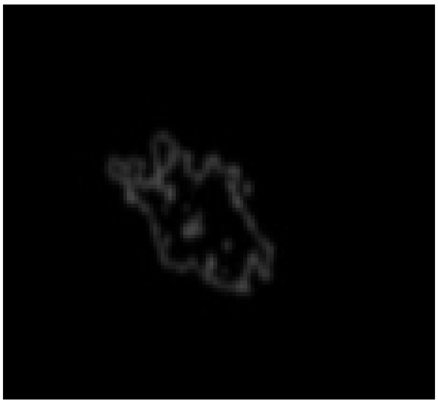
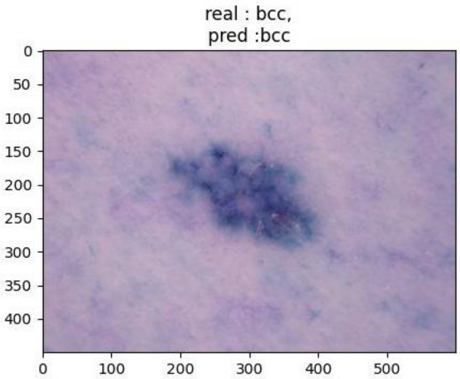
Let, w_o is considered as weighted input. The weighted inputs are mapped into the [0; 1] range using the softmax function, and the outputs are probabilities. In actuality, choose the output with the greatest probability of labeling a voxel. The designed model classifies the skin cancer types using the softmax activation function.

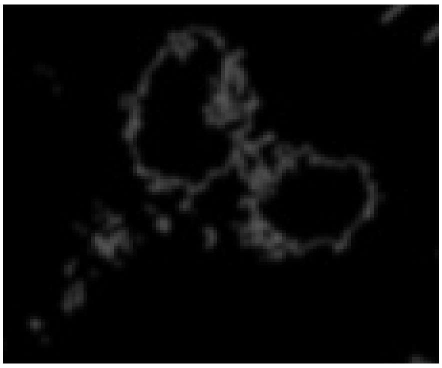
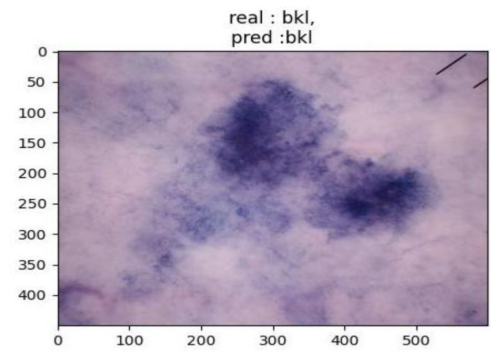
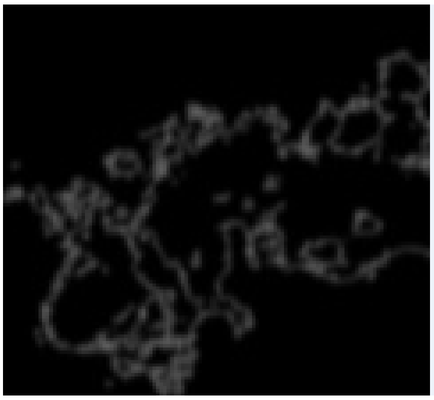
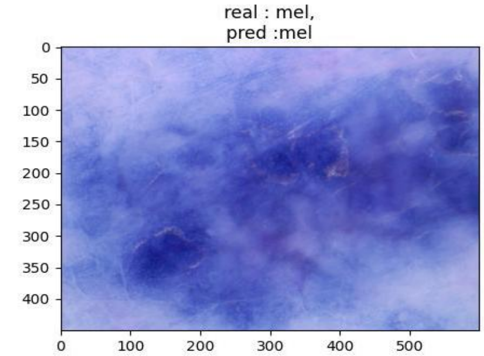
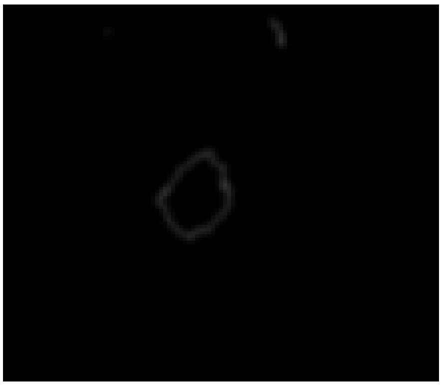
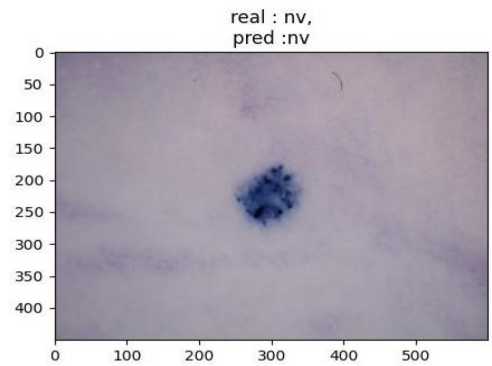
These methods produce better generalization outcomes than the traditional single-learning models. The suggested DL ensemble classifier uses a weighted majority technique to develop the outcomes after combining the predictions of various classifiers. The best outcomes from each categorization model are presented after it has been improved. The prediction of final votes is identified using eqn. (16).

$$\tilde{\tilde{M}} = \arg\max\left(Out_1\left(M_i^1\right), Out_2\left(M_i^2\right), Out_3\left(M_i^3\right) \ldots\ldots Out_i\left(M_i^n\right)\right) \tag{16}$$

Let, $M_i^1, M_i^2 \ldots M_i^n$ are the segmented mask images, and $Out_1, Out_1, \ldots Out_1$ are the majority prediction. Finally, the designed model predicts the stages of skin cancer based on the TDS score. If the TDS score is ≥ 5.45 means skin cancer is detected as malignant, and the TDS score is < 4.75 means skin cancer is detected as benign. The segmented and classified result of the developed model is shown in table.2.

Table.2 Predicted results

Segmented image	Classified image	Stage prediction
		Malignant
		Benign
		Malignant
		Malignant

		Malignant
		Malignant
		Benign

The developed model has the ability to classify skin cancer and predict the stages of skin cancer accurately. Moreover, CSO optimization is employed to enhance the prediction and classification results of skin cancer and attain better outcomes with less execution time.

5. RESULTS AND DISCUSSION

Python is used to process the created CSO-ECNN replica, and the predicted model's success rate is evaluated using the mechanisms in terms of accuracy, recall, F-measure, precision, and specificity. HAM 10000 dataset is used in this method to predict and classify skin cancer. The suggested CSO-ECNN technique identifies skin cancer and predicts the stages of skin cancer. As a result, the generated model performed well in segmentation and prediction. The developed model gained better accuracy in prediction and classification using CSO optimization. To prove the efficiency of the designed model, attained results are validated with other conventional models. The ROC and confusion matrix of the developed model is shown in Fig. 3.

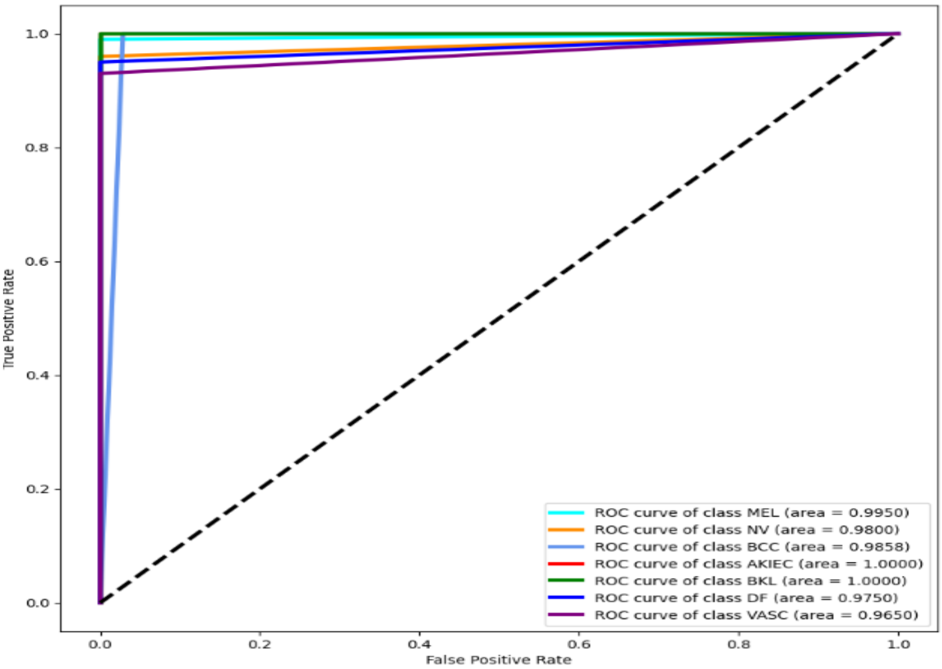


Fig.3 (a) ROC

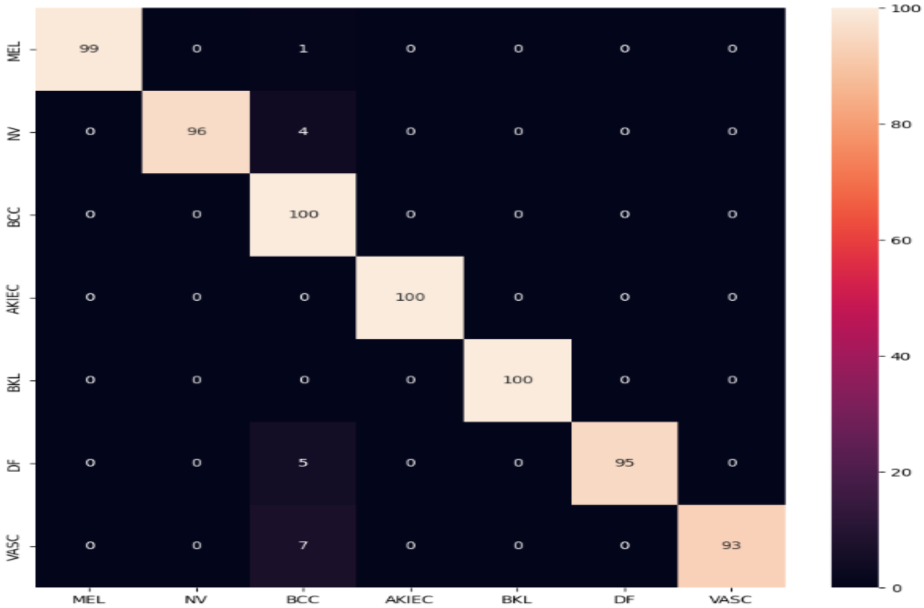


Fig.3 (b) Confusion matrix

5.1. Performance metrics

Python software is used to apply the designed CSO-ECNN method, and various metrics like accuracy, specificity, F1-measure, recall, and precision are evaluated. Furthermore, the presented approach is validated using recognized methods such as Efficient CNN (ECNN) model [22], Deep CNN Model (DCNN) [23], ConvNet model [24], and MCS Cancer classification using deep CNN (MCS-DCNN) [26].

5.1.1 Accuracy

A developed ensemble learning model's accuracy is measured as the proportion of correct classifications or the ratio of correct predictions to all other predictions. If the measured value matches the true value, it is deemed to be extremely accurate and error-free. Accuracy is calculated using Eqn. (17).

$$A_{c*} = \frac{t_{p*} + t_{n*}}{t_{p*} + t_{n*} + f_{p*} + f_{n*}} \tag{17}$$

Let t_{p*} is referred to as the genuine positive result of exact classification and accurate prediction, t_{n*} is shown as the actual inverse of a correct prediction and an inaccurate classification, f_{p*} is referred to as the false positive of a perfect classification and a wrong prediction, and f_{n*} is regarded as a false negative of an improper classification and inaccurate forecast.

The suggested CSO-ECNN model's accuracy is estimated and validated using well-established methods like ECNN, DCNN, ConvNet, and MCS-DCNN approaches.

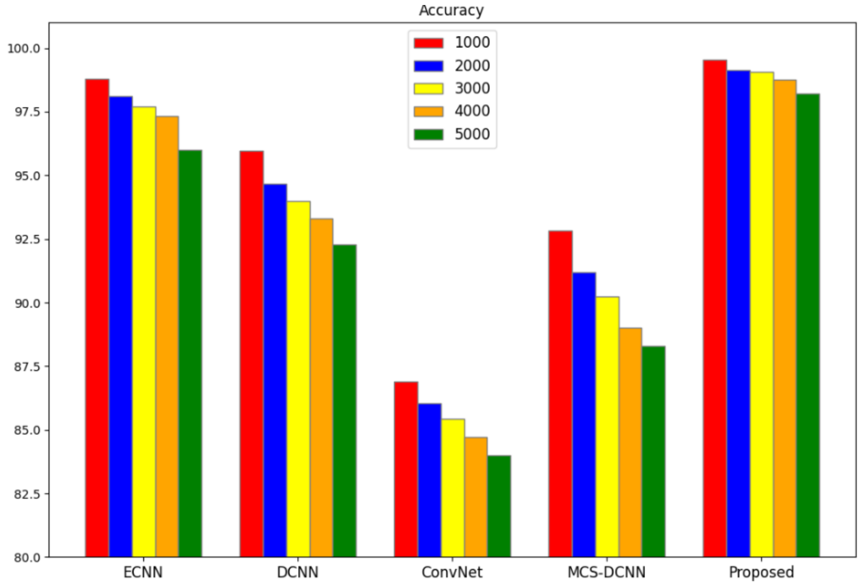


Fig. 4 Comparison of accuracy

The proposed method's usefulness is demonstrated by the fact that it attained an accuracy value of 99.56%, which is higher than other existing approaches. An overview of accuracy measurement findings is shown in Fig. 4.

5.1.2 Recall

The percentage of accurately identified positive instances is known as recall. The proportion of positive samples that were correctly identified as positive to all positive samples. The recall measurement shows the ability of the designed model to detect skin cancer stages. The recall is measured using Eqn. (18).

$$R_{e*} = \frac{t_{p*}}{t_{p*} + f_{n*}} \tag{18}$$

Using well-known techniques such as the ECNN, DCNN, ConvNet, and MCS-DCNN methods, the recall of the new CSO-ECNN technique is estimated and validated.

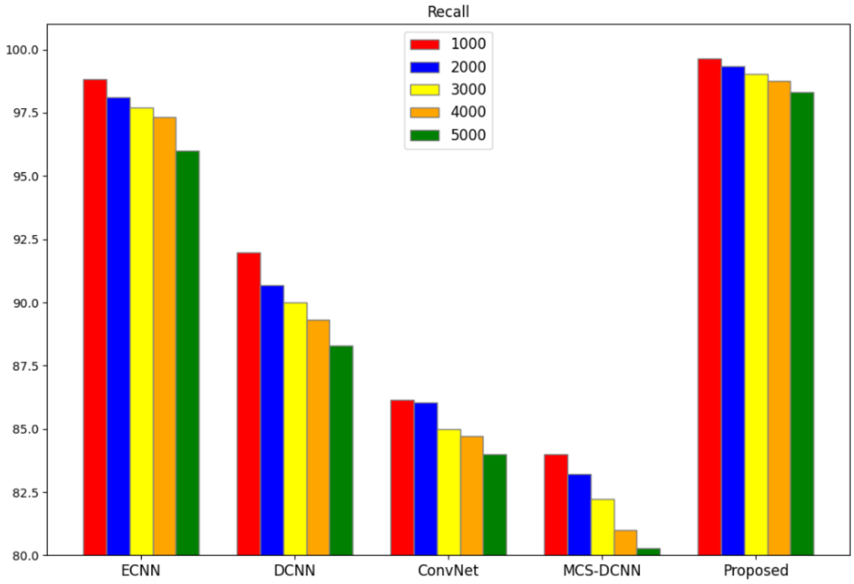


Fig.5 Comparison of Recall

The recall rate for existing methods is barely close to 98 percent. Additionally, the CSO-ECNN approach outperformed other methods with a 99.66% greater recall rate, highlighting the power of the created model. The recall contrast is visually shown in Fig. 5.

5.1.3 Specificity

The ratio to the real negatives correctly identified as a result of the test is known as specificity. The capability of a test to label someone who doesn't have a disease as negative is known as specificity. The specificity is measured using Eqn. (19),

$$S_{p*} = \frac{t_{n*}}{f_{p*} + t_{n*}} \tag{19}$$

Using widely used techniques like ECNN, DCNN, ConvNet, and MCS-DCNN approaches, the specificity of the new CSO-ECNN methodology is computed and validated.

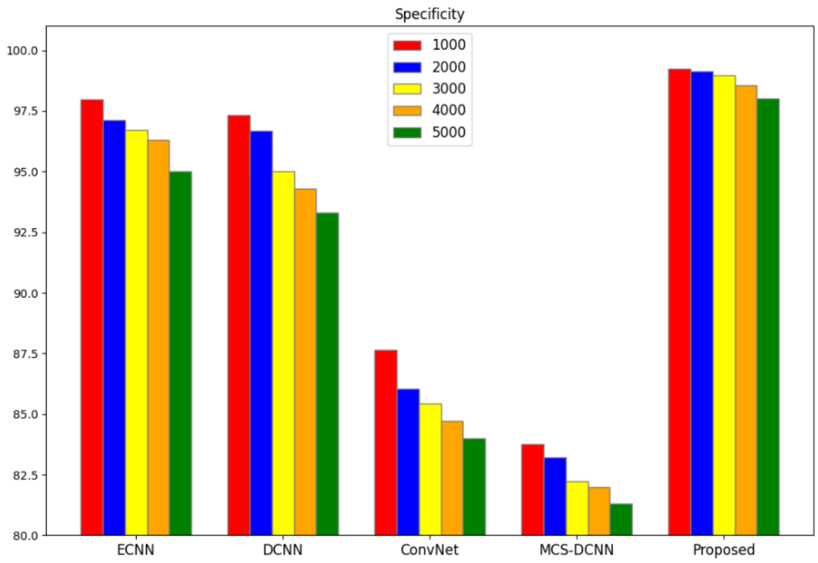


Fig.6 Comparison of Specificity

The specificity of the existing methods was only about 97 percent. The efficiency of the proposed model was shown by the developed approach's 99.24 percent higher specificity compared to other approaches. Fig. 6 shows a comparison of specificity.

5.1.4 Precision

The degree that the same results are produced by multiple measurements under the same circumstances is known as precision. The degree of precision refers to how well two measurements match. Furthermore, precision is calculated using Eqn. (20),

$$P_{r*} = \frac{t_{p*}}{t_{p*} + f_{p*}} \quad (20)$$

The recommended CSO-ECNN model's precision is calculated and validated using other prevailing methods like ECNN, DCNN, ConvNet, and MCS-DCNN.

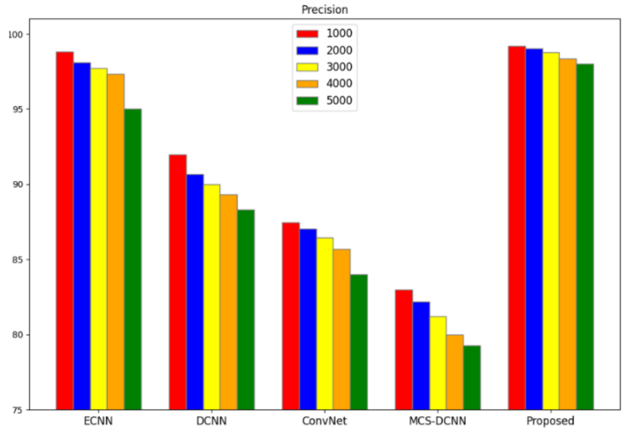


Fig.7 Comparison of Precision

Here, the existing techniques have only been able to achieve a precision that is about 98 percent lower. Additionally, the developed CSO-ECNN technique obtained a precision value that was 99.18% higher than that of other methods; Fig. 7 illustrates this comparison of precision.

5.1.5 F1-score

The F1-score integrates a classifier's precision and recall into an individual metric by calculating their harmonic mean. It is a metric used to assess the effectiveness of a deep learning model. Additionally, F1-score is calculated using an equation. (21),

$$F1_{s*} = 2\left(\frac{P_{r*} * R_{e*}}{P_{r*} + R_{e*}}\right) \quad (21)$$

Let, P_{r*} is represented as precision value and R_{e*} is denoted as recall value.

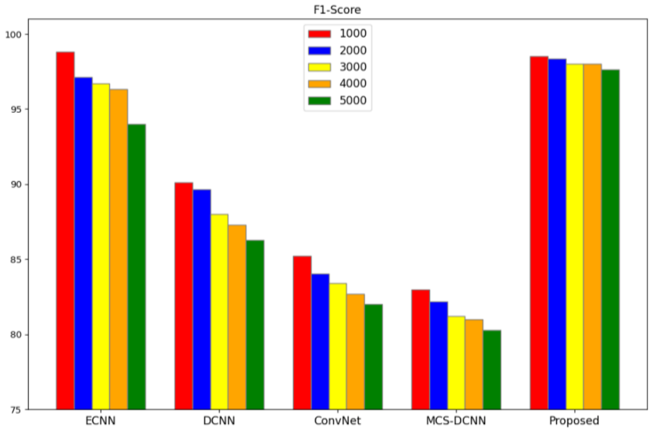


Fig.8 Comparison of F1-score

ECNN, DCNN, ConvNet, and MCS-DCNN methodologies are extensively utilized to calculate and validate the F1 score of the proposed CSO-ECNN model. The table.7 contains a list of the F1-score results. As demonstrated in Fig. 8, the proposed model passed previous approaches with a high F1-score value of 98.54% when compared to the existing methodologies.

5.2 Discussion

The recommended CSO-ECNN model has performed well, getting the top results in accuracy, specificity, recall, F-measure, and precision. As a result, the developed strategy resolved the initial training issues. The next stage is to extract features based on asymmetry, border, color, and diameter features. To effectively predict the skin cancer phase, segmentation, and classification are done using an ensemble deep learning approach. Because of this, the newly created CSO-ECNN technology performs better at predicting and classifying the various stages of skin cancer.

Table.3 Overall performance metrics

No.of. epochs	**Performance assessment with key metrics**				
	Accuracy	**precision**	**recall**	**specificity**	**F-measure**
10	98	98.03	98.31	98.06	97.98
20	98.32	98.34	98.57	98.54	98.05
30	98.87	98.77	98.88	98.93	98.18
40	99.12	99	99.26	99.04	98.38
50	99.56	99.18	99.66	99.24	98.54

Table.3 lists the outstanding metrics comparisons, and the suggested CSO-ECNN got the best results across all parameter validations. Furthermore, the developed framework enhanced prediction accuracy, recall, and precision. As a result, that suggested CSO-ECNN robustness is proven, and it can split the affected parts of the skin and identify its stages. The developed model accuracy and loss results are shown in Fig.9.

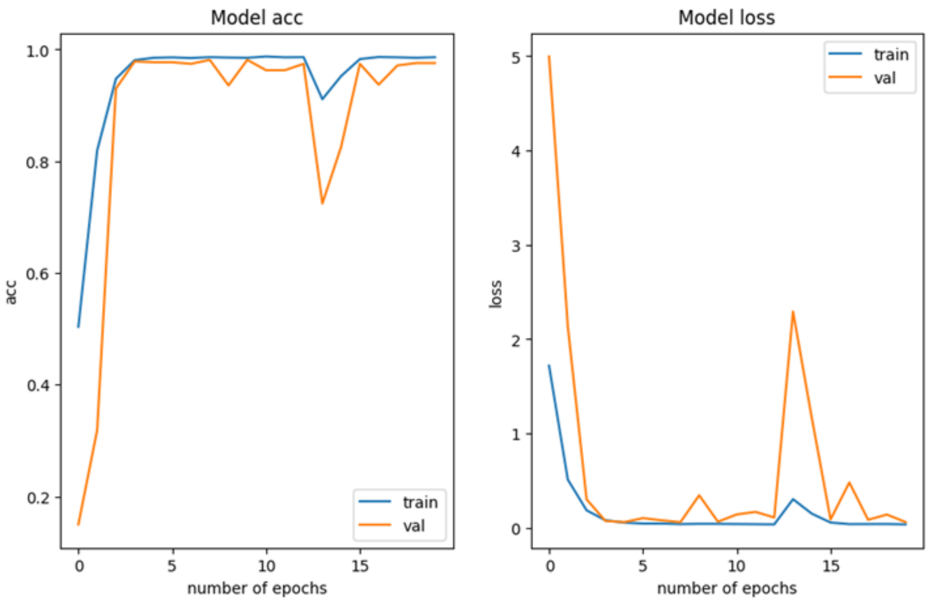


Fig.9 Accuracy Vs. Loss

The developed CSO-ECNN technique is utilized to accurately separate and categorize skin cancer. Using HAM 10,000 pictures, the proposed technique displayed excellent performance in segmenting and predicting skin cancer.

6. CONCLUSION

This study develops a novel CSO-ECNN approach for detecting and classifying skin cancer. The HAM 10000 dataset is used in this research apart from that 7000 images are used for training and 700 images are used for testing. Pre-processing, feature extraction, segmentation, classification, and prediction are all part of the proposed CSO-ECNN model. Furthermore, cat swarm fitness is updated in the developed model for accurate prediction and classification. Furthermore, the proposed model achieved better accuracy, recall, specificity, and precision results. When compared to existing models, it achieved 99.56 percent accuracy, 99.18% precision, 99.66% recall, and 99.24% specificity to predict and classify skin cancer. Thus the designed model can predict and classify skin cancer accurately. In the future, hybrid optimization-based ensemble learning may improve the prediction results with less execution time.

Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interest.

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

Informed consent does not apply as this was a retrospective review with no identifying patient information.

Funding: Not applicable

Conflicts of interest Statement: Not applicable

Consent to participate: Not applicable

Consent for publication: Not applicable

Availability of data and material:

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Code availability: Not applicable

Competing Interests : Not applicable

REFERENCES

[1] Sethanan, Kanchana, et al. "Double AMIS-Ensemble Deep Learning for Skin Cancer Classification Expert Systems With Applications." *Expert Systems with Applications* (2023): 121047.

[2] Alshawi, Sarah Ali, and Ghazwan Fouad Kadhim AI Musawi. "Skin Cancer Image Detection and Classification by CNN based Ensemble Learning." *International Journal of Advanced Computer Science and Applications* 14.5 (2023).

[3] Kalpana, B., et al. "OESV-KRF: optimal ensemble support vector kernel random forest based early detection and classification of skin diseases." *Biomedical Signal Processing and Control* 85 (2023): 104779.

[4] Reddy, Dasari Anantha, et al. "Enhanced U-Net segmentation with ensemble convolutional neural network for automated skin disease classification." *Knowledge and Information Systems* (2023): 1-46.

[5] Shahsavari, Ali, Toktam Khatibi, and Sima Ranjbari. "Skin lesion detection using an ensemble of deep models: SLDED." *Multimedia Tools and Applications* 82.7 (2023): 10575-10594.

[6] SUTAJI, Deni, and Oktay YILDIZ. "WELDONNet: Weighted Ensemble DenseNet121, MobileNetV2, and NASNetMobile to improve skin lesion diseases classification." (2023).

[7] Ennaji, Asmae, et al. "Malignant melanoma detection using multi-scale image decomposition and a new ensemble-learning scheme." *Multimedia Tools and Applications* (2023): 1-16.

[8] Javid, Muhammad Hasnain, et al. "Design and Analysis of an Improved Deep Ensemble Learning Model for Melanoma Skin Cancer Classification." *2023 4th International Conference on Advancements in Computational Sciences (ICACS)*. IEEE, 2023.

[9] Duman, Erkan, and Zafer Tolan. "Ensemble the recent architectures of deep convolutional networks for skin diseases diagnosis." *International Journal of Imaging Systems and Technology* (2023).

[10] Jha, Sudan, et al. "Ensemble Learning-Based Hybrid Segmentation of Mammographic Images for Breast Cancer Risk Prediction Using Fuzzy C-Means and CNN Model." *Journal of Healthcare Engineering* 2023 (2023).

[11] Chowdhury, Yaser Al Rahman, et al. *An efficient deep learning approach to detect skin cancer using image*

data. Diss. Brac University, 2023.

[12] Swathi, B., et al. "Skin Cancer Detection using VGG16, InceptionV3 and ResUNet." *2023 4th International Conference on Electronics and Sustainable Communication Systems (ICESC)*. IEEE, 2023.

[13] George, Joseph, et al. "Skin Cancer Classification from Skin Lesion Images Using Modified Depthwise Convolution Neural Network." *2023 3rd International Conference on Advances in Computing, Communication, Embedded and Secure Systems (ACCESS)*. IEEE, 2023.

[14] Tsai, Wei-Xiang, Yu-Cheng Li, and Chang Hong Lin. "Skin lesion classification based on multi-model ensemble with generated levels-of-detail images." *Biomedical Signal Processing and Control* 85 (2023): 105068.

[15] Thepade, Sudeep D., and Varun R. Shriwardhankar. "Generalizing Melanoma Skin Cancer Detection with Feature Fusion of DenseNet121 and Thepade Sorted Block Truncation Coding." *International Journal of Computing and Digital Systems* 14.1 (2023): 1-xx.

[16] Thanka, M. Roshni, et al. "A hybrid approach for melanoma classification using ensemble machine learning techniques with deep transfer learning." *Computer Methods and Programs in Biomedicine Update* 3 (2023): 100103.

[17] Desale, R. P., and P. S. Patil. "An automated hybrid attention based deep convolutional capsule with weighted autoencoder approach for skin cancer classification." *The Imaging Science Journal* (2023): 1-15.

[18] Ali, Rizwan, et al. "A Novel Spasa Based Hyper-Parameter Optimized Fcedn for Adaptive Cnn Classification for Skin Cancer Detection." *Available at SSRN 4480342*.

[19] Tembhurne, Jitendra V., et al. "Skin cancer detection using ensemble of machine learning and deep learning techniques." *Multimedia Tools and Applications* (2023): 1-24.

[20] Chauhan, Rosey, and Sunil Gupta. "Melanoma Skin Cancer Detection by using Ensemble Model." *Journal of Namibian Studies: History Politics Culture* 34 (2023): 1930-1941.

[21] Civelek, Zafer, and Mohammed KFASHİ. "An Improved Deep CNN For an Early and Accurate Skin Cancer Detection and Diagnosis System." *International Journal of Engineering Research and Development* 14.2 (2022): 721-734.

[22] Fahad, Nur Mohammad, et al. "SkinNet-8: An Efficient CNN Architecture for Classifying Skin Cancer on an Imbalanced Dataset." *2023 International Conference on Electrical, Computer and Communication Engineering (ECCE)*. IEEE, 2023.

[23] Junayed, Masum Shah, et al. "A deep CNN model for skin cancer detection and classification." (2021).

[24] Mijwil, Maad M. "Skin cancer disease images classification using deep learning solutions." *Multimedia Tools and Applications* 80.17 (2021): 26255-26271.

[25] Fraiwan, Mohammad, and Esraa Faouri. "On the automatic detection and classification of skin cancer using deep transfer learning." *Sensors* 22.13 (2022): 4963.

[26] Chaturvedi, Saket S., Jitendra V. Tembhurne, and Tausif Diwan. "A multi-class skin Cancer classification using deep convolutional neural networks." *Multimedia Tools and Applications* 79.39-40 (2020): 28477-28498.

[27] Thepade, Sudeep D., and Aasim I. Sayyad. "Melanoma Skin Cancer Detection from Dermatoscopy Images Using Xception and Thepade SBTC Model." *International Journal of Computing and Digital Systems* 14.1 (2023): 1-xx.

[28] Venugopal, Vipin, et al. "A deep neural network using modified EfficientNet for skin cancer detection in dermoscopic images." *Decision Analytics Journal* (2023): 100278.

[29] Wu, Qing-E., Yao Yu, and Xinyang Zhang. "A Skin Cancer Classification Method Based on Discrete Wavelet Down-Sampling Feature Reconstruction." *Electronics* 12.9 (2023): 2103.

[30] //www.kaggle.com/datasets/kmader/skin-cancer-mnist-ham10000

[31] Shinde, Apurva, and Sangita Chaudhari. "Statistical Analysis of Hair Detection and Removal Techniques Using Dermoscopic Images." *International Conference on Computer Vision and Image Processing*. Cham: Springer Nature Switzerland, 2022.

[32] Sau, Kartik, Ananjan Maiti, and Anay Ghosh. "Preprocessing of skin cancer using anisotropic diffusion and sigmoid function." *Advanced Computational and Communication Paradigms: Proceedings of International Conference on ICACCP 2017, Volume 2*. Springer Singapore, 2018.

[33] Victor, Akila, and Muhammad Rukunuddin Ghalib. "Automatic Detection and Classification of Skin Cancer." *International Journal of Intelligent Engineering & Systems* 10.3 (2017).

[34] Thanh, Dang NH, et al. "Melanoma skin cancer detection method based on adaptive principal curvature, colour normalisation and feature extraction with the ABCD rule." *Journal of Digital Imaging* 33 (2020): 574-585.

[35] Jaisakthi, Seetharani Murugaiyan, Palaniappan Mirunalini, and Chandrabose Aravindan. "Automated skin lesion segmentation of dermoscopic images using GrabCut and k-means algorithms." *IET Computer Vision* 12.8 (2018): 1088-1095.

[36] Ali, Md Shahin, et al. "An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models." *Machine Learning with Applications* 5 (2021): 100036.

[37] Jayalakshmi, G. S., and V. Sathiesh Kumar. "Performance analysis of convolutional neural network (CNN) based cancerous skin lesion detection system." *2019 International Conference on Computational Intelligence in Data Science (ICCIDS)*. IEEE, 2019.

[38] Ahmed, Aram M., Tarik A. Rashid, and Soran Ab M. Saeed. "Cat swarm optimization algorithm: a survey and performance evaluation." *Computational intelligence and neuroscience* 2020 (2020).