Non- invasive method of Melanoma Detection through Skin Surface and Extract Image Feature through Modified Cat Optimization Algorithm (Revised Version Clean)

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Abstract

Early detection of melanoma through optimization algorithm detects skin cancer in terms of pixel size, shape, and intensity. The optimization algorithm detects the skin cancer in an earlier stage and diagnoses it through the non-convex border in the affected image. Skin diseases are very dangerous once affected they spread through the entire surface and they should be stopped in the earlier stage by the proposed optimization algorithm. The proposed optimization algorithm is suitable for extracting large and complex dermoscopic images to extract image features and it also stops preventing from the entire surface. The lesion image analyses the melanoma disease with non-convex refinement and boundary localization in image features for extraction and Measurement. The non-convex refinement identifies the discriminative melanoma disease based on Region of Interest (ROI) and scaling. The proposed optimization algorithm delineates the affected area which concerns the non-convex border and edge with the accuracy of detection of the infected area is about 85% of skin lesion image through the proposed optimization algorithm.

Keywords: Dermoscopic images, contour refinement, Region of Interest (ROI), Thresholding.

(i) Introduction

According to the statistics of the Cancer Institute survey, the mortality rate of skin cancer increases every year by 25% throughout India [1]. The dermoscopic identification of melanoma disease always depends on the experience of professionals to diagnose the melanoma at an earlier stage. Melanoma diseases are the most dangerous form of cancer screened through skin lesion images [2]. The lesion image appears with irregular shape and boundary requires a very illuminated skin image for clear identification of lesions. The risk factor of skin cancer disease is reduced and detected in the earlier stage, so the mortality rate is reduced [3]. The skin lesion image extract with image feature according to the nature of skin image, color, texture, shape, and pixel intensity. The Region of Interest from the skin lesion image segment through the non-convex border in the skin lesion image and processed automatically to extract discriminative features and handle the imbalance effect of skin [4]. The discriminative image feature identified with clinical studies of skin lesions includes asymmetric and diameter greater than 6 mm which relies on testing skin cancer. The testing of a cancer cell is very difficult to differentiate

Comment [M1]: Include the citation.

melanoma or benign tissue which always examines the surface of the skin and penetrates the skin. However, the surface of skin lesion image segment image with poor contrast will lead to bad selection [5]. The OTSU method classifies with high accuracy of optimization algorithm and optimize through the non-convex border in skin lesion images. The optimization algorithm is based on some morphological characteristics concerned with a change in size, shape, color, and texture and focuses on images to extract image features [6]. The morphological operator examines the error concerning similarity and more accurate diagnosis used in the computational analysis for detection of melanoma. Furthermore, decomposition of an image concerning color filter (noise) to remove artifact enhancement of contrast, correction in terms of illumination variation improves the prediction of melanoma [7]. The classification of skin lesions is based on features combined with histogram analysis. The histogram analysis classifies based on shape, color, and pixel intensity. The segmentation algorithm analysis the lesion boundary, lesion feature, and visualization concerning real-time nature [8]. Automatic detection of melanoma analysis visualizes with 3 main stages, the stages segment the lesion image automatically accuracy is high in segmentation, the feature extraction extracts the physical features of lesion image and predicts the accuracy, then the feature selection finds the difference and represents the rule of the lesion and predict with high accuracy [9]. The novel method of predicting skin cancer lesion image through segmentation algorithm achieves the overall efficiency compared with threshold and OTSU method of lesion segmentation [10]. The proposed work highlights optimization of 3 images such as benign, melanoma, and nevus are the dataset identifies for earlier detection of skin cancer and which dataset is very harmful for patient. Moreover, the research also highlights the non-convex border optimization of skin lesion image to extract with high features for the detection of skin cancer. The texture features are also highly delineated for extracting skin cancer detection in the earlier stage. Section (ii) related work for extracting skin cancer detection in the earlier stage. Section (iii) proposed methodology for optimization of Skin dataset through non-convex border in benign, melanoma, and nevus images. Section (iv) discusses the result of optimization and how the non-convex border of optimization extract with pixel shape, size, and intensity. Section (vi) future scope of skin cancer detection in the earlier stage.

(ii) Literature Survey

The Fuzzy C-means clustering algorithm for accurate classification and detection is proposed using a multi-scale encoder-decoder network for skin lesion as shown superior performance than any other classification algorithm. The classification algorithm evaluated to perform unsegmented image to segment image for preprocessing on skin lesion image by a deep learning algorithm, the parameters are accurately tuned using Decoder-Encoder segmentation algorithm.[11]. Automatic detection of skin lesions using yolov4 highly correlated with the non-infected and infected region and to improve the accuracy the proposed method detects skin lesions using dark net and contour edge detection. This method is utilized for medical image segmentation with 3 phases: skin enhancement for accuracy detection, melanoma localization for prediction, and finally the segmentation using yolov4 for automatic segmentation of skin lesion image.[12]. The segmentation of lesion image analyzed by ABCD rule where the dermatologist finds difficult to analyze melanoma image, similarly, the physician learn the feature of melanoma by enhancing the skin lesion image with irregularity in the border, color variegation concerning diameter highlighted in ABCD rule.[13]. A low-power continues radar wave design with the frequency of 77GHz for medical imaging application used for skin detection; however, the radar detects dielectric properties of the tissue with high accuracy in terms of a micron, the proposed method integrated with MHMIC technology with 6 ports interferometer. However, the proposed method is a low cost without any calibration in input parameters for the treatment of skin cancer.[14]. The region of interest with the K-Means clustering algorithm identified and extracts ROI from melanoma cells by using data augmentation. The feature of extracting the region of interest outer performs the radar design in terms of skin lesion image.[15]. Earlier detection of a skin lesion with deep learning method segment and locate the boundary of the skin lesion is a huge cost and expensive the proposed method of skin lesion ensemble with high sensitivity in ensemble network meanwhile, the proposed method outer performs the Deep Learning method exhibiting the performs of SegNet and U-Net.[16]. Skin disease by medical imaging was analyzed progressively using the transfer learning method by fine-tuning the entire Dataset the trained model of melanoma detection cohorts with a different skin disease and improving the effectiveness. [17] The melanoma detection using neural network system trained with pre-samples of network for detection of skin lesion using perception model with histogram gradient coupled with ABCD rule which achieves low-level features of texture shape color and pixel intensity. The proposed method highlights the features and enhances skin lesion image towards accuracy.[18]. The optical parameter of human skin is detected through pigmented lesion by the probability of False Positive pixel where the error is inaccurate from the pigmented tissue and illuminated through several laser and tissue penetrated by varying the frequency. The proposed method differentiates the object of pigmentation from benign tissue.[19]. A fast and accurate method of skin lesion detection by designing probe near far-field with a frequency of 40 GHz as well as the metric the more suitable for skin surface detection from the body region. The proposed method was tested and simulated with CST Microwave studio; the accuracy of a skin lesion is well defined.[20]. The skin disease classification by using Convolution Neural Network accuracy of skin disease is well delineated when compared with the dermatologist. The proposed method compares with an unrecognized dataset where the accuracy of delineation with other methods is presented.[21]. Improving skin lesion image by classification technique will imbalance the performance and the result is less accurate, to overcome the problem of imbalance performance the proposed method customized with mini loss function by the technique of mini- batch logic. The proposed method balances through the real-time augmentation method and the accuracy of detection of the skin lesion are 90%.[22]. Furthermore, the imbalance of skin lesion image is not well extracted through segmentation algorithm, the segmentation algorithm where the pixel intensity is very poor to overcome the effect of imbalance and pixel intensity the author proposed the loss function termed as Jaccard. The proposed method outer performs the classification and segmentation and loss function is overcome.[23]. Hair Removal and segmentation in the dermoscopic image is the critical task for the physician to measure its accuracy, the author proposed a novel method of removal of hair from lesions using the Encoder- Decoder method. The proposed method is overcome with the effect of encoder and decoder with a loss function and accuracy of delineation of hair removal by deep learning method find the state-of-the-art.[24]. Automatic classification of lesion images with large background accuracy is not enhanced. The deep learning model predicts the extra background in the lesion image and recognizes the lightweight segmentation of the lesion area and visualizes the feature with respective size, shape, and pixel intensity.[25]. With the help of optimization algorithm the non- convex border of image is optimized to extract high features and identifies which types of skin cancer is very dangerous. The research also highly delineates skin cancer detection through the non-convex border in skin lesion images such as benign, melanoma, and Novus images. Furthermore, the earlier detection of skin cancer identified and diagnosed by the radiologist to reduce the mortality rate of skin cancer in India.

Comment [M4]: Highlight the research gaps.

(iii) Methodology

Figure 1. Represent the proposed block diagram for extracting skin cancer detection in the earlierstage and diagnosis. The proposed cat optimization extracts image features in the earlier stage and helps the radiologist to diagnose skin cancer.

(a) Skin Dataset

The datasets are available for extraction of skin lesion image is validated concerning ground truth verification to improve and diagnose the skin cancer in the earlier stage. Optimization algorithm detects the edge and boundary in skin surface and diagnoses it. The algorithm achieves better results when compared with previous existing algorithms validated with accuracy, sensitivity, specificity, and precision. The ground truth verification measures with true boundaries of skin lesion images concerning high specificity through an optimization algorithm. Meanwhile, the optimization algorithm predicts edges and boundaries concerning the skin lesion image with available datasets. The datasets are requested from Royal Mother Hospital K. K. Nagar, Chennai which contain training dataset of 2000 images and 1 ground response of CSV file taken from (Human Against Machine) HAM10000 with 2000 images. The benign keratosis Lesions, melanoma and nevus images are validated on the data which contains 2000 Images from HAM10000 dataset of skin lesion images. The test data are taken from ISBI 2021[72]

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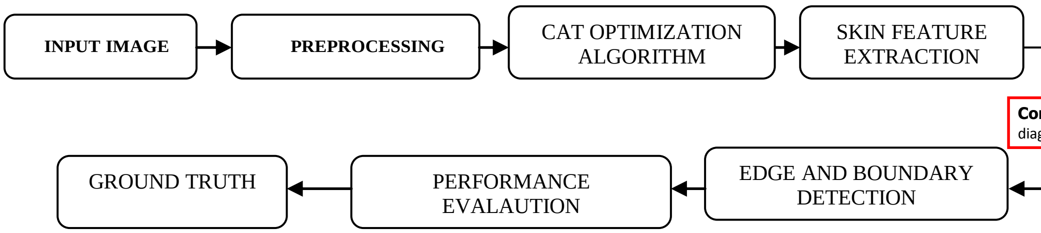
and PH1[44] with 8- bit RGB color images with resolution of 560×560 pixels containing a total of 250 Dermoscopic images of skin lesions and ground truth respectively for segmenting images.



Comment [M6]: Present the proposed work in diagram or workflow.

Figure 1. The block diagram of skin cancer detection in the earlier stage through modifiedcat swarm Optimization algorithm

(b) Preprocessing

The Preprocessing of skin lesion image differentiates the image into many clusters to classify the region of contour i.e., the non-convex border, and removes unnecessary artifacts in the skin image through a modified cat optimization algorithm. The algorithm enhances the cluster area and compares with pixel and enhances with feature representation of skin lesion image. The Preprocessing technique is compared with other existing optimization algorithms and optimizes solutions in space concerning skin lesion images.

(c) Skin Feature Extraction

The Feature enhancement of the skin image is to evaluate the performance of the input image and improve the performance metric in the output. The similarity index determines the quality of the skin lesion image and classifies its accuracy through PSNR which predicts the output for feature extraction through a non-convex border. The quality of the image is retained in the output for extraction of the image with high accuracy. The PSNR technique removes the unwanted noise in the skin lesion image and the accuracy of detection of the infected area is highly well defined through the Modified cat optimization algorithm

$$PSNR = -20 * \log_{10} SL/MSE$$

Where

PSNR – Peak Signal to Noise Ration

Log – Logarithmic function

Sk – Skin Lesions

MSE – Mean Square Error

log = Logarithm function of Infected area in skin lesion image

$$SSIN(I, I_x) = [I(I, I_s)^{\alpha} . c((I, I_s)^{\beta} . S((I, I_s)^{\gamma}]$$

$$I(I, I_s) = \quad 2\mu_I\mu_{I_s} + C_1$$

$$c(I, I_s) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}$$

$$s(I, I_s) = \frac{\sigma\mu_x + C_3}{\sigma_I\sigma_{I_s} + C3}$$

The feature extraction of skin lesion image removes the noise factor and also identifies with the clear spreading of infection from the day of infection predicts with feature extraction

(d) Region of Interest (ROI):

The Region of Interest of skin lesion image determines the edges and boundaries concerning pixel size, shape, and intensity of the infected region of skin. The Region of Interest extracts multiple features in the skin and detects symptoms of skin in the earlier stage. The accuracy of skin lesion image is well delineated the infected, non-infected, and spreading area concerning with exact shape in ROI. The region of interest accurately detects the spreading part of the virus through the modified cat optimization algorithm. The infected area measures the feature measurement of the skin lesion image through the non-convex border in the skin lesion image. The accuracy is well defined through the proposed modified cat swarm optimization algorithm. Moreover, the region of interest specifies and classifies the melanoma detection in the earlier stage and diagnoses it. Furthermore, if any penetration occurs in the skin lesion image which highly differentiates the infected region and spreading of virus from the surface of the skin image in the earlier stage

(e) Edge and boundary Detection of sin lesion image

The affected area infected from skin cancer is processed through a modified cat optimization algorithm which extracts image features for further enhancement. The edges are detected and optimized through a modified cat optimization algorithm to extract the image feature in the earlier stage. The cat optimization algorithm differentiates the image features and texture property analyzed accurately. The differentiation of noise enhances the signal properties of noise and reduces the smoothing effect, particularly in the affected area through modified cat optimization. The origin of any optimization algorithm assumes with the weight associated with the particular pixel diagnoses the result accurately. The modified cat optimization algorithm differentiates the affected and non affected areas in the skin image and diagnoses in the earlier stage because the ultimate aim of the research work is that the infected area should not spread the entire surface of the skin.[26].The differentiation of skin cancer images based on a modified cat optimization algorithm analyzes the image feature through the non – convex border as it is represented in equations 4 and 5.

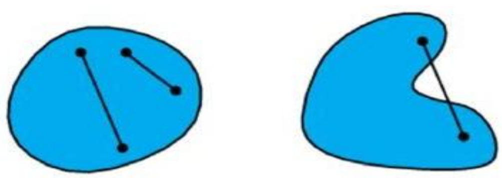
Gx (m,n) = (Z7+ 2Z8 + Z9) – (Z1 + 2Z2 + Z3) ....(4)

Gy (m,n) = (Z3 + 2Z6 + Z9) – (Z1 + 2Z4 + Z7) ....(5)

Where Gx (m,n) represents pixel location lies non-convex border of the boundary surface represent with edge detection in the surface of skin disease. Gy(m, n) represents the convex border for edge detection and Z represents the spread of skin diseases from the inner and outer boundary.

(f) Threshold segmentation algorithm- noise and noiseless image

In the (CSO) Cat optimization algorithm the population starts with seeking mode and tracing mode of threshold selection on each variable. The Modified cat optimization algorithm clusters the possible solutions to be optimized with pixel range from False Positive and False Negative. The fitness solution for each optimization fixes the best solution into the solution space and optimizes the best result. The cat moves towards the optimal area by updating its position and the velocity with less number of iteration which highly depends on the non-convex border in the solution space. The CSO optimizes the best threshold value on each solution which classifies the set of a pixel with a false negative and false positive. The threshold values are detected by optimization of the cluster through the non-convex border in the solution space at each level of iteration from the previously existing algorithm as shown in Figure 2.



.**Figure 2. Convex and Non –Convex border of optimization of Skin cancer images.**

(g) Skin Cancer Detection through Modified Cat optimization Algorithm

The modified cat optimization algorithm optimize not only the inner boundary of skin lesion image, but also optimize both inner and outer boundary of skin lesion image to detect skin cancer in earlier stages. The modified cat optimization algorithm optimize in seeking mode and tracing mode to optimize pixel intensity with respect to false positive and false negative pixel present in the skin lesion image to detect edges and boundary with MCSO(Modified Cat optimization algorithm). Furthermore, the input image when compared with output image after optimization algorithm is processed nearly 7% increase in skin surface which lead to type of skin cancer with benign, malignant and nevus which are listed from table (i – vi).

(iv) Result and Discussion

Figure 3 shows the skin lesion image for the patient to predict earlier diagnostics. The input image with melanoma detection of 62.24 mm of the size is extracted from the skin lesion image. The image is processed in a segmentation algorithm to extract the feature of the skin lesion image. The input image is converted into the raw image to find the pixel intensity of the low-resolution image. The image is processed through the morphological filter to indicate the pixel as well as the neighboring pixel to predict the accuracy of the lesion image. The accuracy predicted accurately matches the dataset so that earlier detection of skin effect is analyzed periodically. The lesion image is marked with a ruler so that how the infection spreads in a small part of the skin. The skin is penetrated in the body as a clear indication through our proposed algorithm. The segmentation algorithm enhances the skin lesion image and compares it with the actual image with ground truth the result is validated and the accuracy of detection is exactly 85.60%. Cat optimization algorithm optimizes the skin lesion image through 2 modes seeking mode and tracing mode which outer performs the fuzzy c means clustering algorithm, Genetic algorithm, and Particle swarm optimization algorithm based on the complexity. So the proposed method convergence these 3 optimization algorithms into a modified cat optimization algorithm for better accuracy and less computational time to improve the efficiency in the fewer number of iteration. The input image is compared with the output nearly 7% increases in skin surface and in future the spread can increase till 9% as shown in Table 1. The 9% increase is benign.

Comment [M7]: Mention the system configuration and computational complexity of this method.

(a) Performance Evaluation

Comment [M9]: This section should be in results.

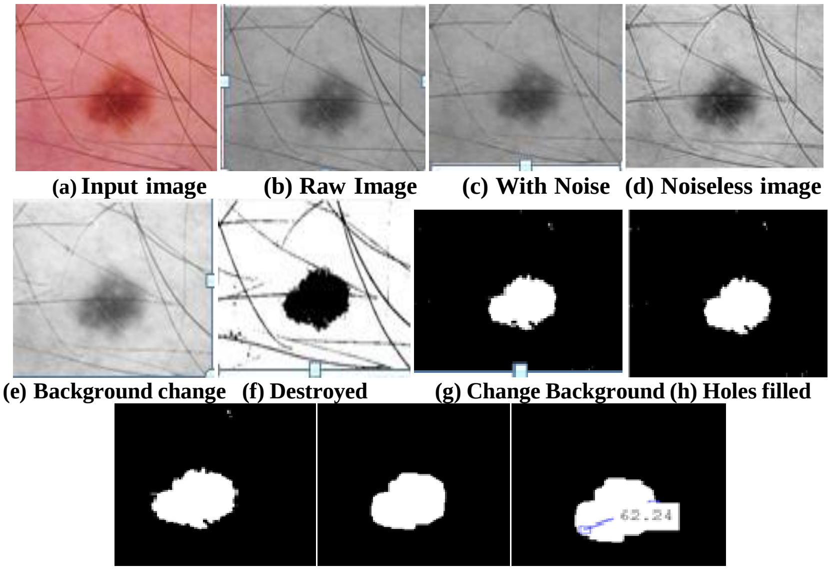
The performance of the modified cat optimization algorithm concerning the parameter such as similarity index, similarity coefficient, sensitivity, specificity, accuracy, and correlation coefficient linked with skin lesion image for extracting the non-convex border in the affected image. All the parameters are determined with the accuracy of the total number of pixels available over the cat optimization algorithm. The cat optimization algorithm classifies false pixels and converts them into true pixels so, the image is enhanced with feature extraction concerning high accuracy of infected region. The result is verified validated to predict the feature extraction of skin lesion images.

$$Sensitivity = \frac{\text{TP}}{TP + FN}$$

$$Specificity = \frac{\text{TN}}{FP + TN}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$JSI = \frac{TP}{TP + FP + FN}$$



(a) Input image (b) Raw Image (c) With Noise (d) Noiseless image

(e) Background change (f) Destroyed (g) Change Background (h) Holes filled

(i) Remove blob (j) Remove small blobs (k) Threshold Detection

Figure 3: Dataset of skin lesion image to extract skin cancer from Benign

Table:1 Statistical Parameter of the dataset of skin lesion image Benign

Method	Novus			Melanoma			SK (Seborrhoeic Keratosis)			Overall		
	SEN	SPE	ACCESS	SEN	SPE	ACCESS	SEN	SPE	ACC	SEN	SPE	ACC
MCSO-2	78.34	82.76	85.40	80.50	81.26	85.98	70.11	74.50	87.46	77.66	92.40	90.80
MCSO-4	80.67	92.20	90.59	81.56	88.80	85.86	70.58	78.96	89.20	80.10	95.28	92.65
MCSO-6	82.45	94.70	92.68	82.70	90.41	87.25	73.89	80.52	92.54	82.41	96.76	94.45
MCSO-8	85.54	96.61	93.45	85.98	93.74	90.46	77.74	84.93	94.74	83.65	97.32	96.35
MCSO-10	88.76	97.80	95.28	88.95	96.43	93.59	80.85	87.96	96.85	85.96	98.45	97.65
MCSO-12	90.58	98.48	97.46	91.85	98.74	95.58	85.85	92.72	98.96	89.42	98.78	98.45
MCSO-14	92.85	98.89	98.78	95.15	99.20	97.86	89.58	96.74	99.24	95.85	99.27	99.54

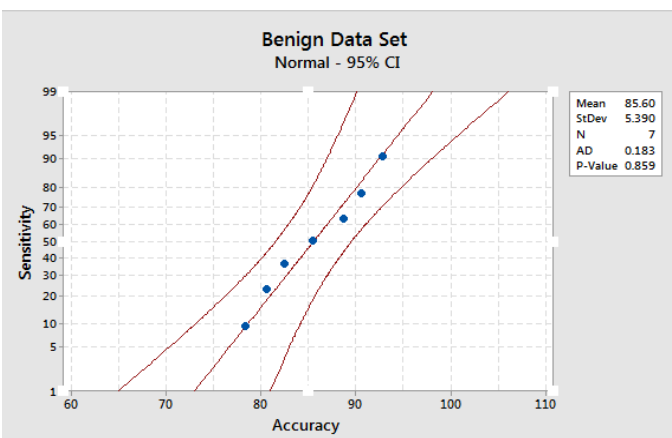
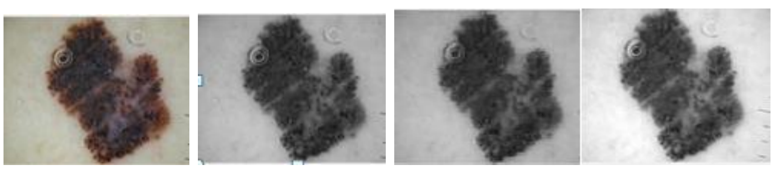
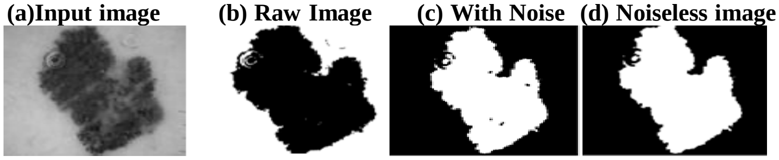


Figure 4: The Relationship between accuracy, sensitivity, and specificity of skin lesion image of Benign disease

Figure 5 depicts the patient's skin lesion to anticipate earlier diagnoses. The input image is a skin lesion image with a melanoma detection of 147.14 mm in size. To extract the function of the skin lesion image, the image is processed using a segmentation algorithm. To find the pixel intensity of a low-resolution image, the input image is converted to the raw image. To find the pixel intensity of a low-resolution image, the input image is converted to the raw image. To predict the accuracy of the lesion image, the given image is processed via a morphological filter to indicate high accuracy of both pixels as well as neighboring pixels. The estimated accuracy closely matches the dataset, allowing for earlier identification of skin effects to be evaluated regularly. The picture of the lesion has been labeled with a ruler to show how the infection hasspread to a small area of the skin. As a simple example, our proposed algorithm penetrates the skin. The skin lesion image is enhanced by the segmentation algorithm, which compares it to the real image with ground truth. The result is analyzed, and the detection of accuracy is exactly 86.11%.



(a)Input image (b) Raw Image (c) With Noise (d) Noiseless image



(e) Background change (f) Destroyed (g) Change Background (h) Holes filled

(i) Remove blob (j) Remove small blobs (k) Threshold Detection

Figure 5: Dataset of skin lesion image to extract skin cancer from melanoma

Table: 2 Statistical Parameter of the dataset of skin lesion image Melanoma

Method	**Novus**			**Melanoma**			**SK (Seborrhoeic Keratosis)**			**Overall**		
	SEN	**SPE**	**ACC**	**SEN**	**SPE**	**ACC**	**SEN**	**SPE**	**ACC**	**SEN**	**SPE**	**ACC**
MCSO-2	80.70	78.45	75.30	76.80	85.95	90.20	89.55	75.68	77.54	85.20	70.25	85.11
MCSO-4	82.52	80.59	77.59	78.58	87.96	91.97	92.56	77.85	79.65	86.48	72.96	86.85
MCSO-6	83.55	82.85	79.46	80.63	89.48	92.39	94.43	80.35	82.58	88.36	75.52	89.45
MCSO-8	85.93	84.59	82.65	83.59	93.55	95.44	95.65	83.24	86.14	90.65	78.66	91.78
MCSO-10	87.45	86.46	85.65	84.65	95.14	96.75	97.53	85.51	90.86	93.47	83.78	94.96
MCSO-12	89.15	90.65	87.95	88.42	97.23	98.12	98.52	87.65	94.85	96.45	85.15	96.92
MCSO-14	93.48	92.58	94.86	93.49	98.64	99.99	99.48	95.45	96.48	98.35	88.66	98.56

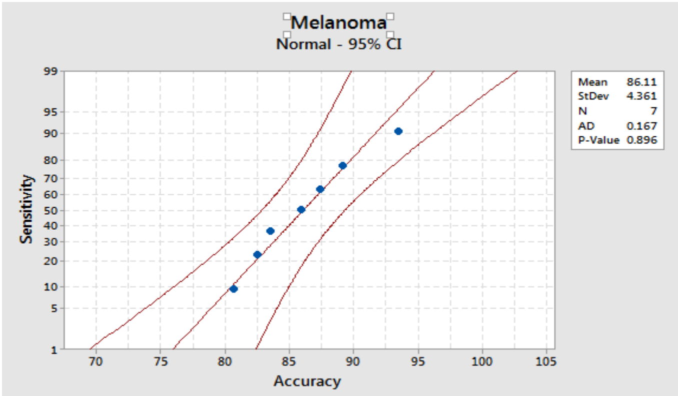
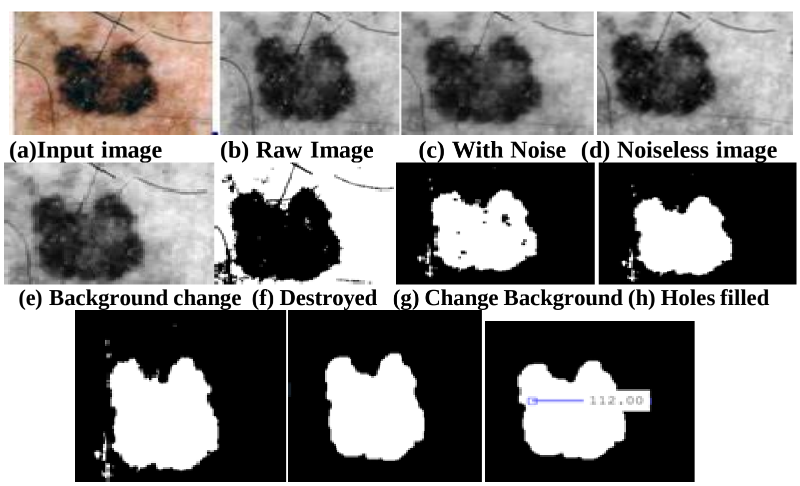


Figure 6: The Relationship between accuracy, sensitivity, and specificity of skin lesion image of melanoma disease

To predict earlier diagnoses, Figure 6 represents the patient's skin lesion. A skin lesion image with a melanoma detection of 112 mm in size is used as the input image. The image is processed using a segmentation algorithm to extract the feature of the skin lesion image. The input image is transformed into a raw image to find the pixel intensity of a low-resolution image. The provided image is processed via a morphological filter to indicate high accuracy of both pixel and neighboring pixels to predict the accuracy of the lesion image. The predicted accuracy closely matches the dataset, allowing for earlier detection and periodic evaluation of skin effects. A ruler has been used to mark the image of the lesion to demonstrate how the infection has spread to a small region of the skin lesion image. In our proposed algorithm, the infection penetrates the skin. The segmentation algorithm improves the skin lesion image by comparing it to the actual image with ground truth. The data is processed, and the accuracy detection rate is exactly 85.37%.



(a)Input image (b) Raw Image (c) With Noise (d) Noiseless image
(e) Background change (f) Destroyed (g) Change Background (h) Holes filled
(i) Remove blob (j) Remove small blobs (k) Threshold Detection

Figure 7: Dataset of skin lesion image to extract skin cancer from melanoma

Table: 3 Statistical Parameter of dataset 1 of skin lesion image

Method	Novus			Melanoma			SK (Seborrhoeic Keratosis)			Overall		
	SEN	SPE	ACC	SEN	SPE	ACC	SEN	SPE	ACC	SEN	SPE	ACC
MCSO-2	75.56	75.85	83.85	74.12	80.77	76.58	89.45	90.12	87.15	82.63	80.15	75.12
MCSO-4	79.51	79.62	85.74	79.12	85.69	79.98	90.78	92.86	90.74	85.16	83.59	79.15
MCSO-6	83.85	85.96	87.15	83.74	86.98	83.96	93.95	94.75	93.35	89.85	87.96	82.14
MCSO-8	85.36	87.45	90.98	85.75	90.85	86.75	95.36	96.68	95.35	93.25	90.69	85.78
MCSO-10	87.98	90.45	93.15	87.12	93.45	89.54	97.45	97.62	96.74	95.78	93.96	89.15
MCSO-12	90.96	93.45	94.12	93.85	96.75	93.62	98.85	98.45	97.69	97.12	95.75	93.08
MCSO-14	94.35	96.15	97.96	97.94	99.72	96.37	99.81	99.30	98.64	99.50	97.68	96.82

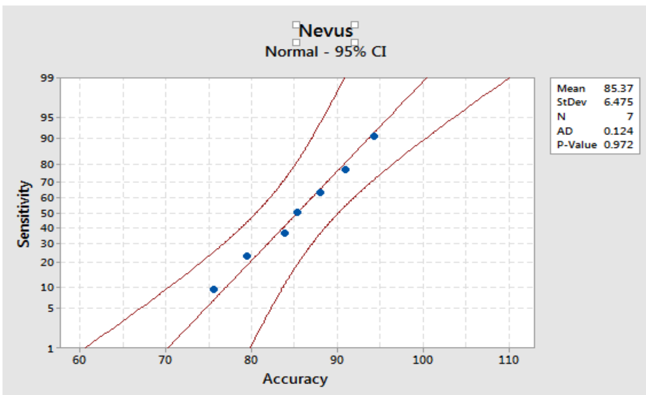
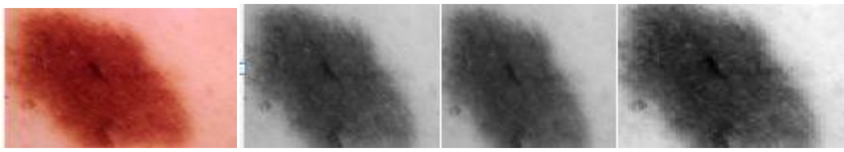
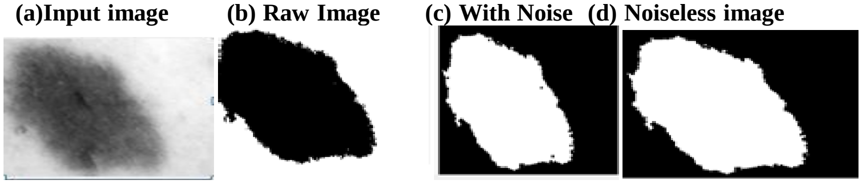


Figure 8: The Relationship between accuracy, sensitivity, and specificity of skin lesion image of Nevus disease

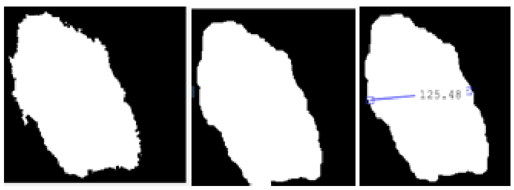
Figure 9 illustrates the patient's skin lesion to anticipate earlier diagnoses. The input image is a skin lesion image with a melanoma detection of 125.48 mm in height. To extract the function of the skin lesion image, the image is processed using a segmentation algorithm. To find the pixel intensity of a low-resolution image, the input image is converted to the raw image. To predict the accuracy of the lesion image, the given image is processed using a morphological filter to indicate high pixel and neighboring pixel accuracy. The estimated accuracy closely matches the dataset, allowing for earlier skin effect identification and evaluation. To show how the infection has spread to a small region of the skin lesion image, a ruler has been used to marke image of the lesion. The infection penetrates the skin, according to our proposed algorithm. By comparing it to the actual image with ground reality, the segmentation algorithm enhances the skin lesion image. The data has been analyzed, and the detection accuracy rate is exactly 79.03%.



(a)Input image (b) Raw Image (c) With Noise (d) Noiseless image



(e) Background change (f) Destroyed (g) Change Background (h) Holes filled



(i) Remove blob (j) Remove small blobs (k) Threshold Detection

Figure 9: Dataset of skin lesion image to extract skin cancer from melanoma

Table:4 Statistical Parameter of the dataset of skin lesion image

Method	**Novus**			**Melanoma**			**SK (Seborrhoeic Keratosis)**			**Overall**		
	SEN	**SPE**	**ACC**	**SEN**	**SPE**	**ACC**	**SEN**	**SPE**	**ACC**	**SEN**	**SPE**	**ACC**
MCSO-2	70.96	75.64	76.15	82.62	83.62	85.61	75.62	73.98	78.12	80.63	82.96	87.32
MCSO-4	73.67	77.92	78.36	85.45	85.24	86.75	77.21	75.43	80.91	83.64	84.73	90.27
MCSO-6	75.63	79.65	80.54	88.73	89.54	90.68	80.69	77.91	85.36	85.75	86.01	93.65
MCSO-8	78.56	83.70	84.90	93.60	92.75	93.54	84.02	81.64	88.09	89.20	88.24	95.69
MCSO-10	80.36	85.20	89.36	95.20	95.85	94.20	89.64	85.60	92.64	93.87	90.62	97.36
MCSO-12	84.32	89.36	92.50	97.36	97.12	96.35	93.84	89.36	94.60	96.32	94.67	98.65
MCSO-14	89.68	94.32	95.32	99.50	98.11	98.82	96.38	92.38	97.60	98.90	96.61	99.98

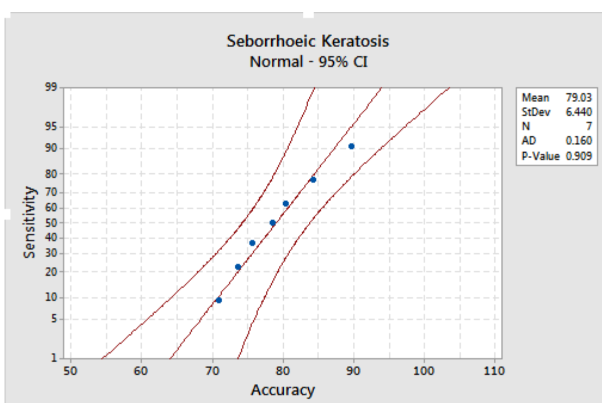
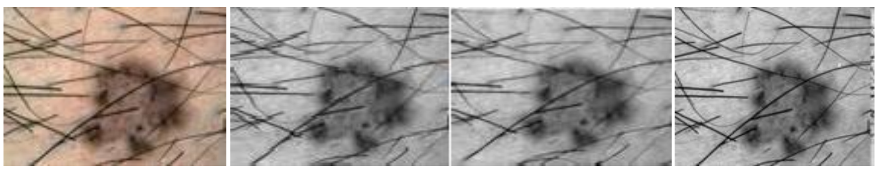
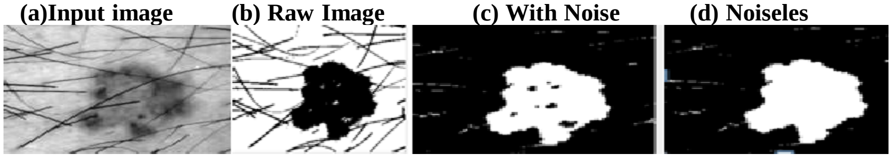


Figure 10: The Relationship between accuracy, sensitivity, and specificity of skin lesion image of Seborrhoeic Keratosis disease

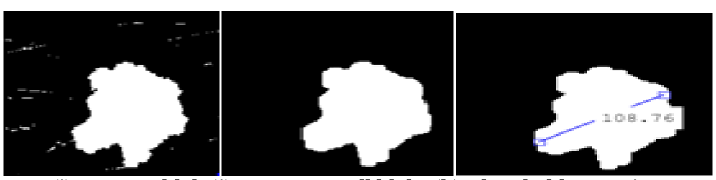
Figure 11 depicts the patient's skin lesion to help with early diagnosis. A skin lesion image with a Seborrhoeic Keratosis of 108.26 mm in height is used as the input image. The image is processed using a segmentation algorithm to extract the feature of the skin lesion image. The input image is transformed into a raw image to find the pixel intensity of a low-resolution image. The provided image is processed with a morphological filter to indicate high pixel and neighboring pixel accuracy to predict the accuracy of the lesion image. The calculated accuracy is very similar to the dataset, allowing for earlier detection and assessment of skin effects. A ruler was used to mark the image of the lesion to demonstrate how the infection has spread to a small area of the skin lesion image. According to our proposed algorithm, the infection penetrates the skin. The segmentation algorithm improves the skin lesion image by contrasting it to the actual image with ground truth. After analyzing the results, it was discovered that the detection accuracy rate is exactly 87.46%.



(a)Input image (b) Raw Image (c) With Noise (d) Noiseles



(e) Background change (f) Destroyed (g) Change Background (h) Holes filled



(i) Remove blob (j) Remove small blobs (k) Threshold Detection

Figure 11: Dataset 5 of skin lesion image to extract skin cancer

Table:5 Statistical Parameter of dataset 1 of skin lesion image

Method	Novus			Melanoma			SK (Seborrhoeic Keratosis)			Overall		
	SEN	SPE	ACC	SEN	SPE	ACC	SEN	SPE	ACC	SEN	SPE	ACC
MCSO-2	78.98	72.92	75.60	70.33	75.62	74.60	82.30	80.31	78.12	82.45	76.23	72.35
MCSO-4	80.32	75.32	77.32	74.36	77.50	77.60	85.32	83.15	80.60	85.61	79.75	75.78
MCSO-6	83.94	77.98	80.65	76.12	80.96	82.31	87.36	86.35	82.04	87.63	82.96	79.86
MCSO-8	87.96	80.98	82.64	77.95	83.55	85.82	92.25	90.18	85.36	91.68	85.41	84.58
MCSO-10	90.63	84.75	85.70	81.06	87.02	87.46	95.94	94.98	89.75	93.97	89.32	89.96
MCSO-12	93.54	85.12	89.20	85.54	90.32	93.21	96.21	97.59	93.57	95.31	92.82	92.85
MCSO-14	96.87	89.06	95.21	89.63	94.21	97.50	98.02	99.52	96.87	97.26	95.85	96.50

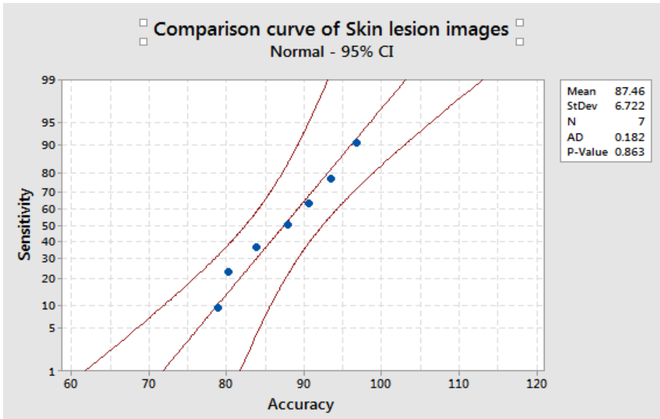


Figure 12: The Relationship between accuracy, sensitivity, and specificity of skin lesion image

The optimization algorithm clusters the lesion images through a non-convex border in the solution and optimizes the image with pixel ranges from true positive and true negative and finds the accuracy in skin lesions image. The cat optimization algorithm optimizes the skin lesion image through tracking mode and seeking the mode of operation of two modes and optimizing the best solution. But the complexity of the threshold region is not accurate from a table (1-5). The author proposed a modified cat optimization algorithm where the edges and boundary are detected through a non-convex border in the solution space. Table vi Performs the skin lesion image with and without optimization. It is observed from the table when optimized through Modified cat optimization algorithm accuracy of extraction of skin cancer in the earlier stage (70-80 %) but without optimization accuracy of extraction of skin cancer in the earlier stage is (45-50%). The image is optimized concerning modified cat optimization algorithm accuracy is well delineated with size, shape, and non-convex border in the lesion image.

Table vi Performs with and without optimization in the skin lesion image

Comment [M8]: What is the role of cat optimization in this paper. Perform the experiment for both with and without optimization.

Method	Melanoma (With optimization)			Melanoma (Without optimization		
	SEN	SPE	ACC	SEN	SPE	ACC
MCSO-2	78.98	72.92	75.60	32.18	30.62	31.28
MCSO-4	80.32	75.32	77.32	40.11	32.12	34.28
MCSO-6	83.94	77.98	80.65	41.28	32.33	40.22
MCSO-8	87.96	80.98	82.64	42.28	40.28	40.11
MCSO-10	90.63	84.75	85.70	45.00	41.23	41.28
MCSO-12	93.54	85.12	89.20	45.00	42.11	40.18
MCSO-14	96.87	89.06	95.21	42.18	40.18	41.28

The modified cat optimization algorithm is compared with fuzzy c- means clustering algorithm and Genetic Algorithm. The High accuracy is delineated with Modified cat optimization algorithm for detecting skin cancer in the earlier stage when compared with other algorithm in the solution space. The Table (vii) shows the comparison of skin cancer with other optimization algorithm.

Table (vii) Comparison of skin cancer with other optimization algorithm

S.No	Skin images	Fuzzy c – means Clustering			Genetic Algorithm			Modified cat Optimization Algorithm		
		FC1	FC2	FC3	GAC1	GAC2	GAC3	MCSO1	MCSO2	MCSO3
1	**Benign**	61%	71%	70%	53%	56%	69%	83%	85%	84.5%
2	**Malignant**	67%	72%	70%	71%	70%	68%	87%	8$%	85%
3	**Nevus**	67%	76%	71%	67%	78%	68%	85%	83%	85%

(vi) Conclusion

Skin Effect occurs normally at the age of 15 – 75 to be analyzed in the earlier stage as well as for diagnosis. The effect is very harmful and it affects the entire body. In our proposed segmentation algorithm the lesion image segment, pre-processed, remove artifact, detect edges, the pixel intensity is identified through segmentation process where the accuracy of detection when compared with the previously existing algorithm, the method is more suitable for melanoma detection. From the statistical parameter concerning ground truth verification, the accuracy of detection of skin effect is highly appreciable in our proposed method. In the proposed method segmentation using edge detection and compared with threshold algorithm detection of skin cancer-melanoma detection in an earlier stage is the crucible. The future scope of the proposed work of skin cancer is to find the earlier stage of skin cancer and diagnosis the skin surface detection to reduce and stop spreading through entire surface of the skin. The Proposed method cluster the skin lesion image through a non-convex border and spreading of the skin surface in the earlier stage is reduced by the proposed Modified cat optimization algorithm.

Comment [M10]: Mention the future work of this paper.

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