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Intelligent Prognostics Model for Disease Prediction and Classification from Dermoscopy Images using a Convolutional Neural Network

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Abstract*: Skin cancer has been reported to be one of the most leading forms of cancer diseases, especially amongst Caucasian descendant and light-skinned people. Basal Cell Carcinoma (BCC) is the malignant types of skin cancer and their classification in earlier stage is biggest issue. While remediable with primary classification is useful, only extremely trained specialists are capable of accurately recognizing the disease from skin lesions dermoscopy images. As expertise is in limited contribute, an automated systems capable of classifying disease could save human lives, and also help to reduce unnecessary biopsies, and reduce extra costs. On the way to achieve this goal, we proposed a disease classification system that conglomerates current developments in deep learning with Convolutional Neural Network (CNN) structure, creating hybrid algorithm of segmentation with Particle Swarm Optimization (PSO) that are capable of segmenting accurate skin lesions region from dermoscopy images, along with analyzing the detected area and surrounding tissue for BCC. Using k-means segmentation technique, the foreground and background component is separated into two regions. To improve the segmentation results, PSO is used with the novel concept of hair removal from lesion region. The proposed system is evaluated using the largest publicly accessible standard skin lesions dataset of dermoscopic images, containing 600 training and 400 testing images. When the evaluation parameters of proposed work is associated with not many other state-of-art methods, the proposed technique attains the best performance of 98.5%in terms of area under the curve (AUC) in distinguishing BCC from benign lesions utilizing only the extracted vascular Speed Up Robust Features (SURF). These concerns have propelled the need to provide automated systems for medical diagnosis of skin cancer diseases within a strict time window towards reducing the unnecessary biopsy, increasing the speed of diagnosis and providing reproducibility of diagnostic results.

Index Terms*: Computer-assisted dermoscopy, Convolutional Neural Network (CNN), Intelligent prognostics model, Lesion hair removal, Particle Swarm Optimization (PSO), Pattern recognition, Skin lesion segmentation, Speed Up Robust Features (SURF) analysis on Medical image.

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I. INTRODUCTION

Malignant Basal Cell Carcinoma (BCC) is one of the most quickly increasing cancer diseases in the whole world, with the predictable novel cases of 76, 380 and predictable death of 10, 130in the United States in 2016. At the present time, despite the fact that some highly developed treatment practices, such as radiation therapy and immunotherapy, are progressively united with surgery in clinical practice, the three year survival rate for advanced stage melanoma is still as low as 20% while it is over90% for early-stage malignant BCC [1]. This inconsistency highlights the critical consequence of sensible diagnosis and treatment of malignant BCC for patient survival.

The skin is the largest organ of the body, with a total area of about 20 square feet and antonym of skin is given in figure 1. The skin protects us from microbes and the elements, helps regulate body temperature, and permits the sensations of touch, heat, and cold. The human skin consists of two principal layers:

1. The epidermis and
2. The dermis

The epidermis is a stratified squamous epithelium, a layered scale like tissue, which serves as protection against external aggressions (injuries, infections, ultraviolet radiation and water loss). The skin's color is created by special cells called melanocytes, which produce the pigment melanin. Melanocytes are located in the epidermis [2]. It consists of four types of cells:

❖ Keratinocytes: These represent the majority (95%) of cells in the epidermis and are the driving force for continuous renewal of the skin. Thanks to their abilities to divide and differentiate, they undertake a journey (which lasts around 30 days) from the basal layer to the stratum corneum, the horny layer [3]. During this journey, the daughter keratinocytes produced by division in the basal layer (here they are called basal cells) move to the next layers transforming their morphology and biochemistry (differentiation). As the result of this movement and transformation, the flattened cells without nuclei, filled with keratin, come to form the outermost layer of the epidermis and are called corneocytes [4]. Finally, in the end of the differentiation program, the corneocytes lose their cohesion and separate from the surface in the desquamation process.

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- ❖ Melanocytes: Dendritic cells found in the basal layer of the epidermis. They distribute packages of melanin pigment to surrounding keratinocytes to give skin and hair its colour [5], [6].
- ❖ Langerhans cells: Dendritic cells, like melanocytes, but their function is to detect foreign bodies (antigens) [7]-[9] that have penetrated the epidermis and deliver them to the local lymph nodes.
- ❖ Merkel cells: Probably derived from keratinocytes. They act as mechanosensory receptors in response to touch.

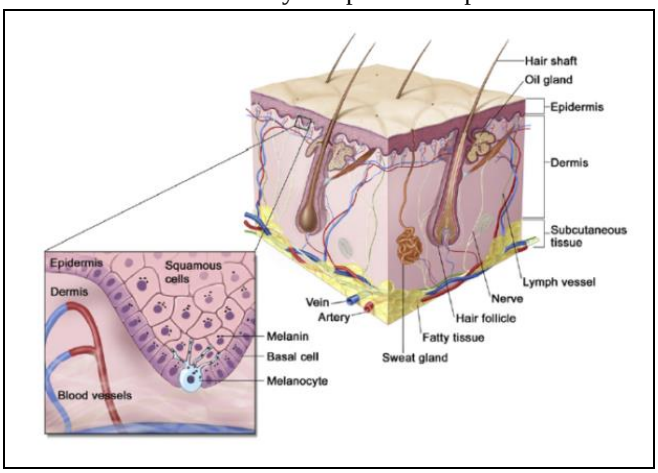

Figure 1: Anatomy of the skin

In the medical science, Dermoscopy tool is a most popular in vivo non-invasive imaging tool that utilizes the polarized light to aid dermatologists in investigative pigmented skin lesions based on a set of morphological features [5]. Even though dermoscopy has been revealed to lead to improved analytical accuracy comparing to the predictable criteria, suitable elucidation of dermoscopic skin lesion images [6] is usually more complex, time consuming, and prone to experience from inter and intra-observer variability's. Consequently, computerized psychotherapy methods have been developed to support dermatologists in improving their efficiency and objectivity of visual interpretation of dermoscopic images for prognostics model to predict diseases and their classification. Automatically segmenting melanoma skin lesion from the surrounding skin is an indispensable phase in computer based analysis of dermoscopic images. However, this assignment is not inconsequential because melanoma skin lesion usually has a large variety of appearance n outline, dimension and color along with dissimilar types of human skin and their texture. For the time being, some skin lesions have asymmetrical and blurry borders, and in several cases the contrast of lesion and the surrounding skin is pretty low [10], [11]. In additional case, artifacts and intrinsic features of human skin, such as blood vessels, hairs and space bubbles are able to make the automatic segmentation of particular lesion more challenging, as illustrated in figure 2.

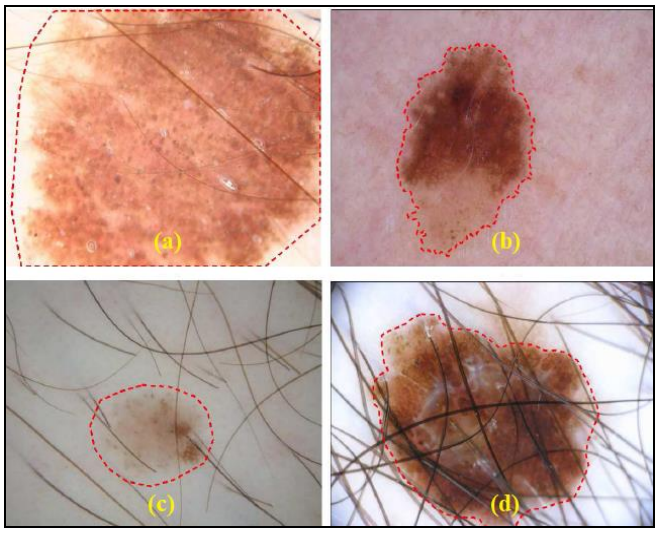

Figure 2: Dermoscopic images with automated lesion segmentation. (a) bulky size of lesion; (b) irregular and blurry borders; (c) low contrast of with respect to the surrounding skin; and (d) lesion with hair.

This paper presents an intelligent prognostics model for disease prediction and classification from dermoscopy images using a Convolutional Neural Network (CNN) and their comparison with existing trends [12]-[14]. Specifically, in section 2, we present the literate survey (background survey) of existing work for detection and segmentation of vascular structures of skin lesions. The architecture of proposed work is described in the section 3. The simulation result is cover in section 4 and we conclude with discussions on current challenges and future trends in section5.

II. BACKGROUND SURVEY

In this section, we present the survey of existing work based on the segmentation of vascular structures of skin lesions for disease classification using different techniques. Pegah Kharazmi et al. [1] proposed an automated detection and segmentation of vascular structures of skin lesions seen in dermoscopy with an application to basal cell carcinoma classification. They present a novel framework for detection and segmentation of cutaneous vasculature from dermoscopy images is presented and the further extracted vascular features are explored for skin cancer classification. K-means clustering is used by the authors with shape filters to classify the erythema cluster at different scales. Due the lack of optimization and classifier technique, the classification and segmentation result is not acceptable for medical science research point of view because there are lots of non melanoma regions are consider as melanoma. Lequan Yu, et al. [2] presented automated melanoma recognition in dermoscopy images via very deep residual networks. They proposed a novel method for melanoma recognition by leveraging very deep convolutional neural networks (CNNs). This technique can ensure that the proposed networks benefit from the performance gains achieved by increasing network depth.

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After that, they construct a fully convolutional residual network (FCRN) for accurate skin lesion segmentation, and further enhance its capability by incorporating a multi-scale contextual information integration scheme. This framework enables the classification network to extract more representative and specific features based on segmented results instead of the whole dermoscopy images, further alleviating the insufficiency of training data. The execution time and CNN and FCR Nare high and it is not acceptable in medical science, so improvement need in the segmentation phase. Yading Yuan et al. [3] proposed an automatic skin lesion segmentation using deep fully convolutional networks with jaccard distance. In this purposed work, they presented a completely automatic context for skin lesion segmentation on dermoscopic images based on deep convolutional neural network. Several effective training strategies were implemented to tackle the challenges that training a deep network may face when only restricted training data is presented. They designed a novel loss function that is based on the Jaccard distance to further improve the segmentation performance but the segmentation time is more and need to reduce the execution time in future work. The results of proposed work are evidently demonstrated that the proposed technique is strong to numerous image artifacts and imaging acquisition conditions even though using minimum pre and post-processing. The proposed medical image segmentation tasks is better as compare to the other but only time complexity is major drawback. N. C. F. Codella et al. [4] proposed novel deep learning ensembles for melanoma recognition in dermoscopy images. They have proposed a system for the segmentation and classification of melanoma from dermoscopic images of skin. The method was evaluated on the largest public benchmark for melanoma recognition available. The proposed work is only applicable for linear image during the classification process and need to improvement in the pre-processing steps for further usages of non linear images. Fengying Xie et al. [5] proposed a melanoma classification on dermoscopy images using a neural network ensemble model. They develop a novel method for classifying melanocytic tumors as benign or malignant by the analysis of digital dermoscopy images. The algorithm follows three steps: first, lesions are extracted using a self-generating neural network (SGNN); second, features descriptive of tumor color, texture and border are extracted; and third, lesion objects are classified using a classifier based on a neural network ensemble model. To deal with this difficult presentation, new border features are proposed, which are able to effectively characterize border irregularities on both complete lesions and incomplete lesions but border detection for all database image are not possible and the detection result is not appropriate. The results show that classification accuracy is greatly enhanced by the use of the new border features and the proposed classifier model but results may be better for the medical application. Euijoon Ahn and Ashnil Kumar [6] proposed saliency-based lesion segmentation via background detection in dermoscopic images. In this paper, authors have implemented a saliency-based segmentation framework for the identification and characterization of skin lesions in dermoscopic images. The proposed framework can be used as a saliency optimization algorithm for lesion segmentation in dermoscopic images but due to the lack of major pre-processing steps the segmentation results is not acceptable and need to improvement. Benazzi et al. [7] proposed a model angiogenesis in spontaneous tumors and implications for comparative tumour biology. They proposed a comparative study on tumour analysis using the different techniques. From the survey they founded that, the tumour classification accuracy may be high if the training and classification of system will be proper. The training of a classification system is totally depending on the feature sets so need to an optimization algorithm with classification system. B. Cheng et al. [8] proposed automatic telangiectasia analysis in dermoscopy images using adaptive critic design. They have chosen BCC detection rather than vessel detection as the endpoint. Although vessel detection is inherently easier, BCC detection has potential direct clinical applications. Small BCCs are detectable early by dermoscopy and potentially detectable by the automated methods described in this research. Experimental results yielded a diagnostic accuracy as high as 84.6% using the ADHDP approach, providing an 8.03% improvement over a standard multilayer perception method. Based on the survey we conclude some important point which helps to short out existing problem. Our contributions in this paper to solve above mention problems are presented in three-fold. Initially, we present a completely mechanized hybrid technique for the skin lesion segmentation by using K-means with Particle Swarm Optimization (PSO) technique. To the best of our cognizance, our proposed work is surrounded by the first few efforts to use the concept of hybridization of PSO to tackle this challenging problem. Furthermore, we projected a suitable hair removal function that logically handles the lesion-background imbalance of pixel-wise grouping for medical image segmentation. Our outcomes demonstrate that this hair removal function can further increase the segmentation performance by removing the hair over the lesion region then apply feature extraction. So the uniqueness of extracted feature is more for BCC and Non-BCC data. At end, we comprehensively assess the effectiveness efficiency as well as the generalization capability of the proposed exemplarywithISBI-2016 dataset using CNN as a classifier which shown in figure 3. Our model may be effortlessly generalized to additional challenging medical image segmentation problems and also improve the accuracy of prognostics model for disease prediction and classification from dermoscopy images.

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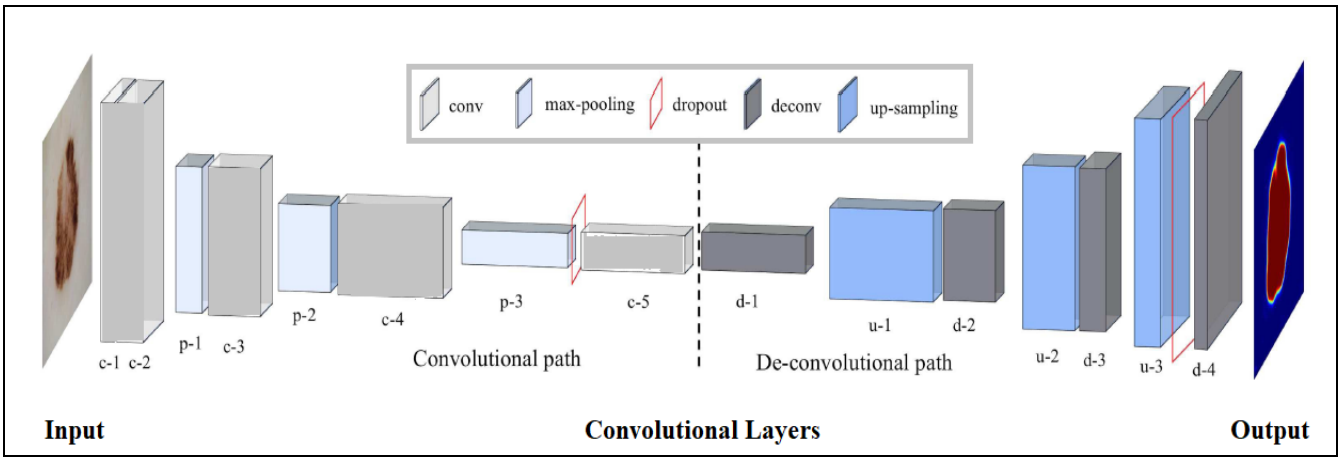

Figure 3: Architecture of the Convolutional Neural Network (CNN). In the architecture, (c) is convolution and (p) is pooling in the convolutional path and full image resolution is recovered via de-convolution (d) and up-sampling (u) in the de-convolutional path.

In the above figure 3, training structure of proposed CNN is shown in which a dermoscopy image is passed as an input. The network of proposed work contains15 layers with convolutional and de-convolutional trainable parameters. For output layer, we utilize tan-sigmoid function as well as the activation function which returns trained structure of CNN with the succeeding convolution as well as pooling layers. In this means, the CNN can take both fine details and global information into account for lesion segmentation.

III. Structure of Proposed Methodology

The proposed intelligent prognostics model for disease prediction and classification from dermoscopy images using a convolutional neural network consists of three main steps. Firstly, various image pre-processing techniques will be applied to improve image quality and suitable segmentation technique will be applied to separate out background from the image to extract exact Region of Interest (ROI). Here, to enhance the segmentation accuracy, PSO is as an optimization algorithm to minimize the unwanted background region from ROI using the fitness function. Then features will be extracted from the segmented ROI lesion region and reduced further (if required) to feed as input to the CNN model. To extract the feature from ROI, SURF feature descriptor is used which helps to returns best key points from lesion ROI. Finally, recognition will be performed using CNN model to produce desired output for the automatic intelligent prognostics model.

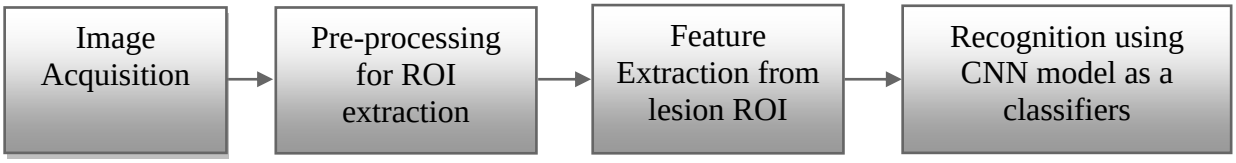

Figure 4: Block diagram of proposed model

The challenge of this research work is to predict and classify the disease using dermoscopy images and train the system using Convolutional Neural Network (CNN) on the basis of the features extracted from the ROI of lesion using SURF descriptor. The subsequent steps demonstrate the variety of phases that need to be accomplished.

Data Acquisition: Upload the dermoscopy images of skin lesion database of different classes to train and test the system. In both section of model, training as well as testing skin lesion images is uploaded for processing. In training the number of images is more but in testing single test image is uploaded. The data uploading process is known as Skin Lesion Data Acquisition (SLDAQ) and the algorithm of SLDAQ is given as:

Algorithm: SLDAQ Algorithm

Input: Num→Number of Images
Output: Skin Lesion Images

Define image browsing option for the image acquisition
Pathname = Browse (Image format (jpeg, png, bmp, tif), Title of uploading)
For i→ Num
    Full-path = (Pathname with Filename)
    Images (i) = Read (Full-path)
End
Return: Images (i) as a skin lesion image
End

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Pre-processing: Pre-Processing is done to remove various type of noise that are inherited in the skin lesion images to enhance the quality of image in proposed system. In every recognition system, selection of popper image region is the major factor and need to remove extra part form the images. In pre-processing after that, image segmentation is used to find out the better region of interest (ROI) which helps to achieve better detection accuracy. For the selection of skin lesion ROI from images, PSO based K-means (Optimized K-means) is used which is based on the morphological operations like binarization, thinning, etc. Morphological operation is a collection of non-linear operations related to the shape or morphology of features in an image. Apply Morphological operations on the binary image to find out the exact region of lesion within the image using the some basic operations. There are a lots of morphological operations are available but used operations are given in the below figure.

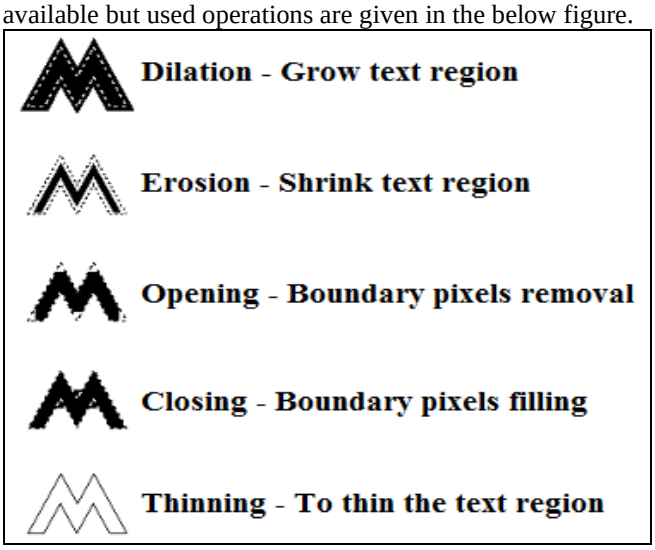

Figure 5: Morphological Operations

Above figure 5 represents the morphological operations which are used in the proposed intelligent prognostics model. In the proposed work, morphological operations help to find out the exact lesion region and separate the extra region from images. The used pre-processing steps are:

1. ***Image enhancement:*** Image enhancement is used to improve the specific pixel points of a dermoscopy image, rather than fix problems. In the proposed work, Atmospheric Light Intensity Adjustment based Hair Removal (ALIA-HR) image enhancement technique is used to improve the quality of image which helps to remove the hair from lesion so that the feature of skin lesion is appropriate. The ALIA-HR algorithm is given as:

Algorithm: **ALIA-HR Algorithm**

Input: Gimg→Gray Image
Output: Eimg→Enhanced Image

I=double (Gimg)
[Height, Width, Plane] = size of I
Patch Size = 15
Pad Size = 7
Pmat = Pad array (I, [Pad Size, Pad Size]) // It is blank mask according to the Pad Size
For j → 1 to Height
For I → 1to Width

$$Patch = Pmat(j:(j + PatchSize - 1), i:(i + patchSize - 1), All) \quad \ldots\ldots (1)$$

$$Zmat(j,i) = min(Patch(:)) \quad \ldots\ldots (2)$$

End
End
A= atm Light (double (I), Zmat, Plane) // Apply Atmospheric Light Adjustment

Oimg=1-Zmat
Eimg = zeros (size (I)) // Blank matrix with size of I
Forind→ 1to Plane

$$Eimg(All\ rows, All\ Columns, ind) = A(ind) + (I(:,:,ind) - A(ind))./max(Oimg, 0.1) \quad \ldots.. (3)$$

Where, 0.1 is lightning coefficient
End
Structure Elements = strel ('disk', 3)
Close img = im close (Eimg, Structure Elements)
Image Error = double (Closeimg) - double (Gimg)
Dilated Image = (Image Error>5)
Eimg = Dilated Image
Return: Eimg as an enhanced image
End

2. ***Binarization:*** The binarization process is carried out using the following equation with threshold value.

$$Bimg(i,j) = \begin{cases} 1 & if Eimg(i,j) \geq Threshold \\ 0 & else \end{cases} \ldots (4)$$

As shown in the equation (4), Bimg is binary image and Eimg is enhanced image with row (i) and columns (j). The binarization algorithm of proposed work is given as:

Algorithm:Binarization Algorithm

Input: Eimg→ Enhanced Image
Output: Bimg→Binary Image

Define Row (R) and Columns (C) of Eimg
Fori=1→R
For j=1→C
Using equation (4)
IfEimg (i, j) > Average (Eimg)
Bimg (i, j) = 1
Else if Eimg (i, j) < Average (Eimg)
Bimg (i, j) = 0
End
End
End
Return: Bimg as a binary image
End

Area Opening: The area opening is performed to remove the pixels from the boundary of lesion region in image so we can find out the well appropriate region. The opening is performed by using the given equation:

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$$OpenImage = \begin{cases} 0, & Pixels < Threshold \\ 1, & Pixels \geq Threshold \end{cases} \quad \ldots (5)$$

Where, $Pixels$: Binary image pixels
$Threshold$: Threshold pixels value which helps to remove the boundary pixels
On the basis for morphological operations, Optimized K-means is designed and the algorithm of Optimized K-means is given as:

Algorithm: Optimized K-means

Input: SL Image →Skin Lesion Image
Output: ROI→Skin LesionROI Image

[R, C, P]=size (SL Image)
SL Image =double (SL Image)
Number of Part= 2
SimgIndex = kmeans (SL Image, Number of Part)
SegLabelImg=reshape (SimgIndex, R, C)
DataPos=find (SegColLabelImg>0)
Data=SegColLabelImg (DataPos)
Initialize PSO parameter – Iterations (T)
– Swarm Size (S)
– Lower Bound (LB)
– Upper Bound (UB)
– Fitness function
Calculate T = Size (SL Image)
Fitness function:

$$f(fit) = \begin{cases} 1 & if pixel is less \\ 0 & otherwise \end{cases} \quad \ldots (6)$$

For → T

$$fs = \sum_{i=1}^{P} Data(i)$$

$$ft = \frac{\sum_{i=1}^{P} Data(i)}{Length of feature}$$

$f(fit)$ = fitness function which define by above given equation (6)

$$Threshold_{value} = PSO(P, T, LB, UB, N, f(fit))$$

End
While T ~= Maximum
$Threshold = Threshold_{value}$
MaskImg=Morphological (SimgIndex, Threshold)
Boundaries = bwboundaries (MaskImg)
Segmented Region = Boundaries
For i→1: P
Segmented Image = SL Image * Segmented Region
End
Return; Segmented Image as ROI of Skin Lesion Image
End

After the Optimized K-means applied on the enhanced dermoscopy skin lesion images, we obtained below given results which are useful in next process of proposed work.

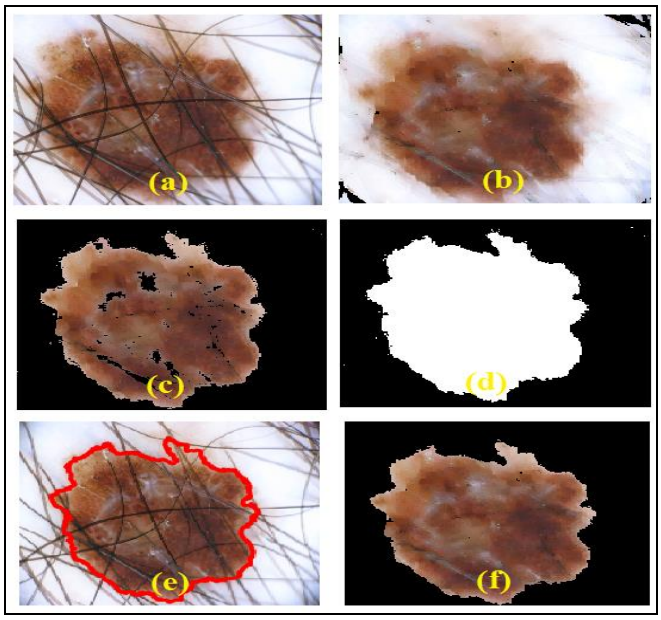

Figure 6: ROI Extraction Process using Optimized K-means

Above figure 6 represent the ROI extraction process with pre-processing steps. In figure 6, (a) is the original dermoscopy image, (b) is the enhanced dermoscopy image in which hair from lesion is removed, (c) presents the segmented image using K-means algorithm, (d) is the mask of lesion ROI, (e) is the region of lesion in dermoscopy image and (f) is the segmented ROI using the Optimized K-means algorithm. Form the figure, the achievement of proposed hybrid segmentation technique is represented and it helps in the proposed intelligent prognostics model for disease prediction and classification.

***Feature Extraction*:** Extract feature from the ROI of lesion image based on the SURF feature extraction algorithm. After the feature extraction algorithm, a set of feature is return by the SURF algorithm in terms of feature points. The HOG algorithm is given as:

Algorithm: SURF Algorithm

Input: ROI → ROI image
Output: Fpoints → Feature points

Load ROI data of lesion image
Calculate size of dataset [Row, Col.]
For i→1 to all Row
For j→1 to all Col
Scale image=scaling (ROI (i, j), scale size)
L_Keypoints=Localization (scale image (i, j))
O_Keypoints=Orientation (L_ Keypoint (i, j), Angle)
SURF_Keypoints=Filtering (O_Keypoint (i.j), Square Filter)
End
End
Return: Feature_descriptor as Fpoints
End

After the feature extraction algorithm applied on the lesion ROI, we obtained below given results which are useful in training as well as classification process of proposed work.

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To extract feature from lesion ROI, SURF Descriptor is used and applied on the lesion ROI. After the algorithm is applied on the ROI of lesion, the marked image with SURF point is given in the figure 7. The extracted feature is passes to the CNN as an input training data and store which is used in the classification process to classify the diseases from the images of skin lesion which is taken from ISBI-2016 dataset.

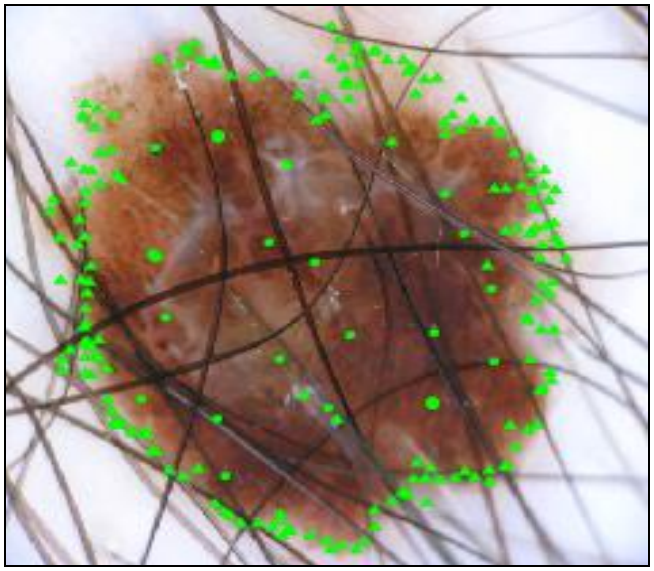

Figure 7: SURF Feature of ROI

Training: Initialize CNN for classification purpose using two phases, namely, training and testing. After the training of system, we save the trained structure which is use in the classification section to classify the diseases from skin lesion images. In the testing phase, the test dermoscopy skin lesion image is uploaded and repeats the all steps. In the classification section, test skin lesion image SURF feature is matched with trained CNN structure and return disease type and the used CNN algorithm is given as:

Algorithm: CNN Algorithm

Input: Fpoints → Feature points as training data (T), Target (G) and Neurons (N)
Output: Type of Disease

Initialize CNN with parameters
– Epochs (E)
– Neurons (N)
– Performance parameters: Cross Entropy, Gradient, Mutation and Validation
– Training Techniques: Scaled Conjugate Gradient (Trainscg)
– Data Division: Random
For each set of T
If Training Data ε BCC
$Group\,(1) = Trainingdata\ BCC$
Else if Training Data ε Non-BCC
$Group\,(2) = Trainingdataof\ Non - BCC$
Else
$Group\,(3) = Extra$
End
Initialized the CNN using Training data and Group
Net = patternnet (N)
Set the training parameters according to the requirements and train the system
Net = Train ($Net, Training data\ , Group$)
Classification Results = simulate (Net, Test Data Feature)
If Classification Results = True
Show classified results in terms of the disease and predicted level of disease
Calculate the performance parameters
End
Return: Classified Results
End

ISBI-2016 Dataset: Figure 8 represents the samples of used dataset in proposed intelligent prognostics model for disease prediction and classification from dermoscopy images using a convolutional neural network work based on the hybrid segmentation technique. In the database all images are dermoscopy image with jpg format and in the dataset image any type of compression is not applied. All images are non-compressed and electronic noise free. In the dataset, mainly two types of categories of skin lesion are presents, first is BCC and another is Non-BCC. Types of BCC images are also called as malignant type.

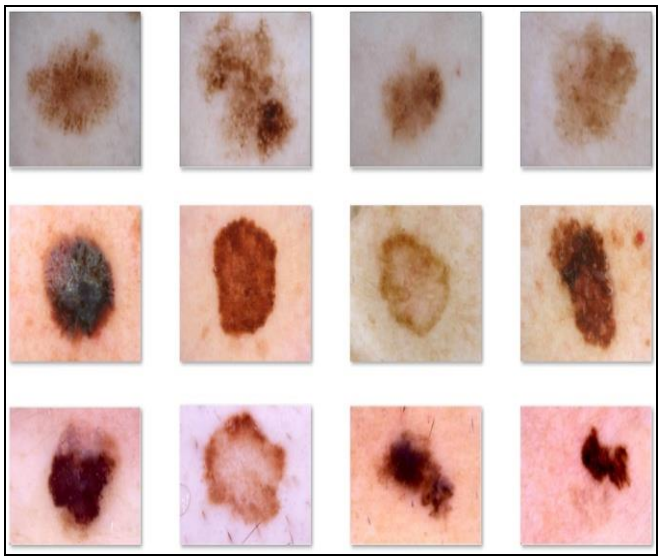

Figure 8: ISBI-2016 Dataset in Proposed Work

The flow chart of the proposed work is shown in figure 9 with training and testing process with ISBI-2016 Dataset.

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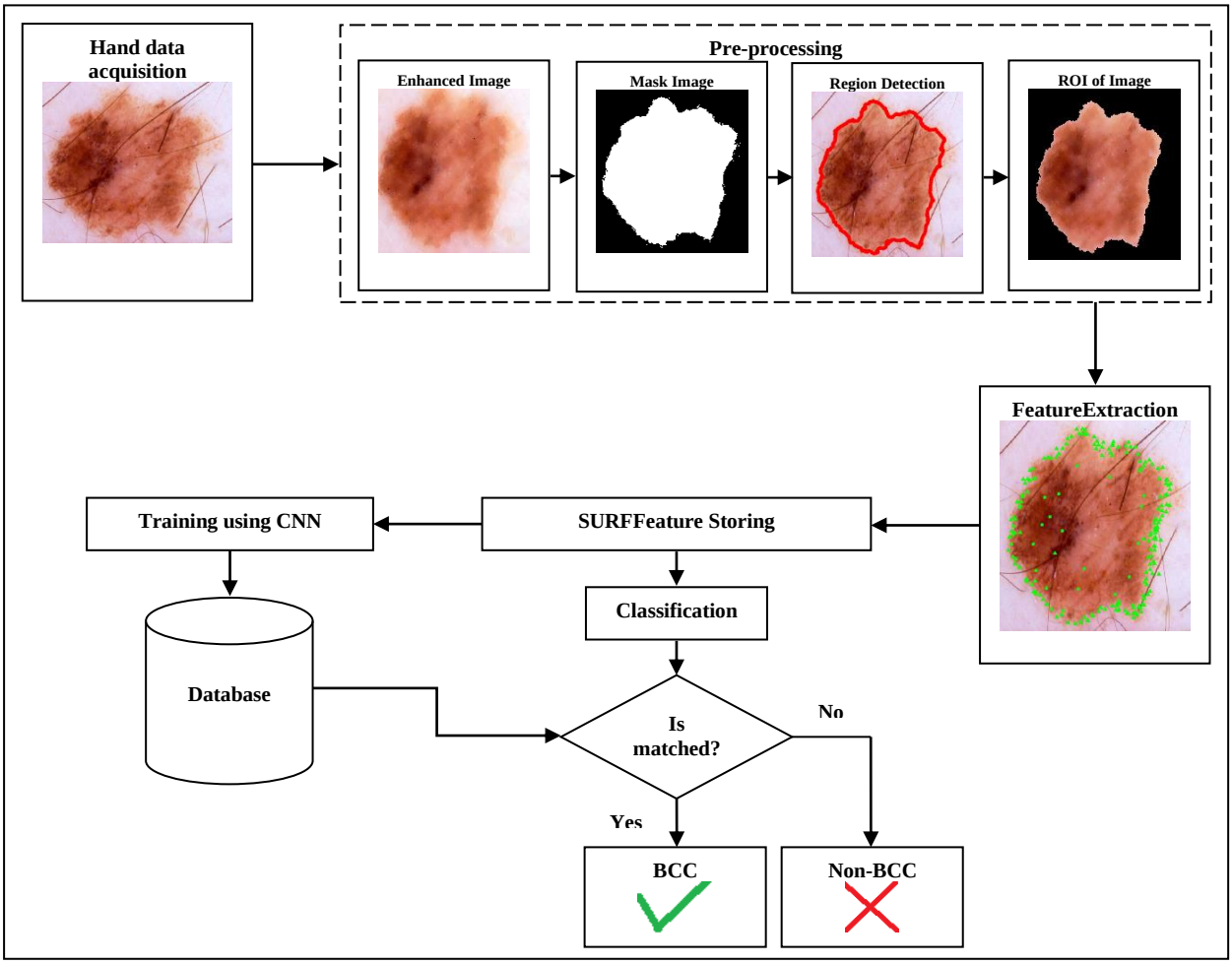

IV. RESULTS AND DISCUSSION

In this section, the simulation results of proposed intelligent prognostics model for disease prediction and classification is discussed and the efficiency of proposed work is compared with existing work [1]. The training and testing of the proposed mechanism is evaluated by ISBI-2016dermoscopy image dataset. By adapting the established proposed algorithms, below outcomes are computed with quality based parameters, such as, True Positive Rate, False Positive Rate, Precision and Accuracy. A comparison is drawn with the existing work [1] to shown the effectiveness of the proposed work with respect to the BCC and Non-BCC.

TABLE 1: Test results of proposed method

	TP Rate	FP Rate	Precision	AUC
BCC	0.935	0.0383	0.983	0.973
Non-BCC	0.948	0.0459	0.937	0.985

TABLE 2: Test results of existing method [1]

	TP Rate	FP Rate	Precision	AUC
BCC	0.859	0.061	0.914	0.965
Non-BCC	0.939	0.141	0.898	0.965

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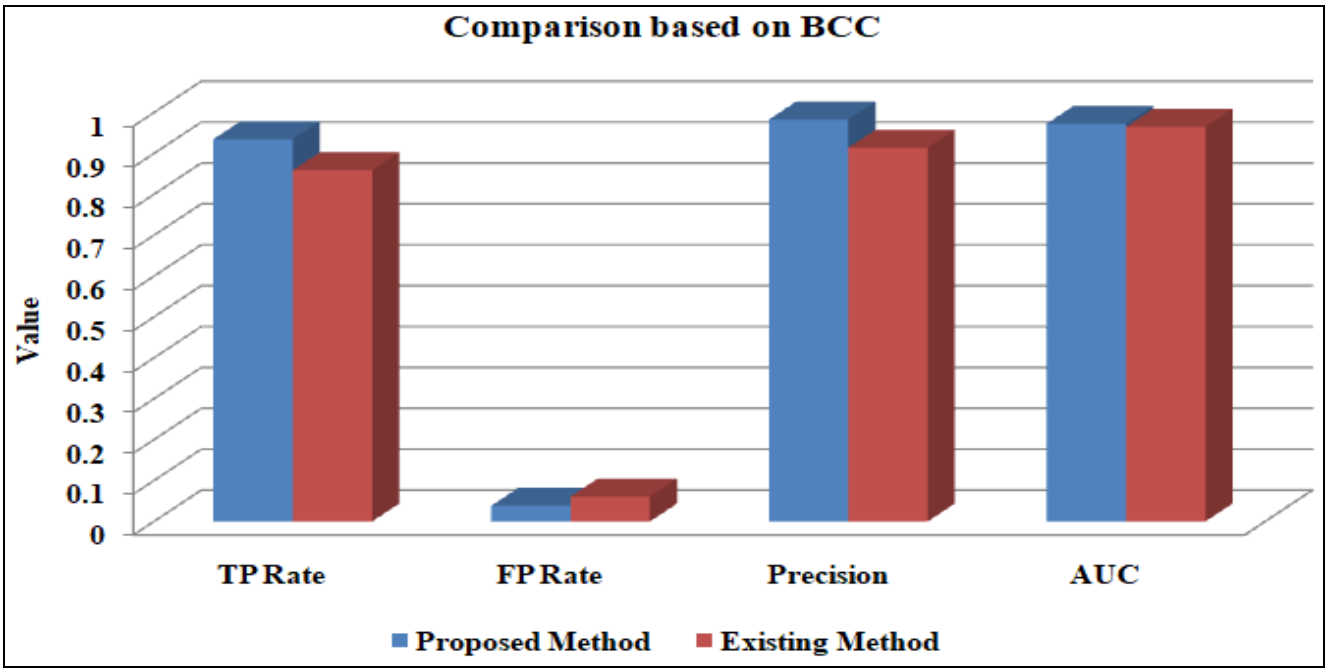

Figure 10: Comparison of evaluation parameters based on BCC

The comparison of evaluation parameters for proposed and existing work is depicted in figure 10. TP Rate is the probability of accurately enrollment of features which are included in the matching process and FP Rate is the rate of erroneously accepted feature during classification. Precision is the rate of TP and summation of TP and FP which represents the accuracy participating feature of classified category of disease. For the proposed work on the basis of BCC data, TP Rate is 0.935, FP Rate is0.0383 whereas; precision is 0.983 and accuracy (AUC) 0.973.

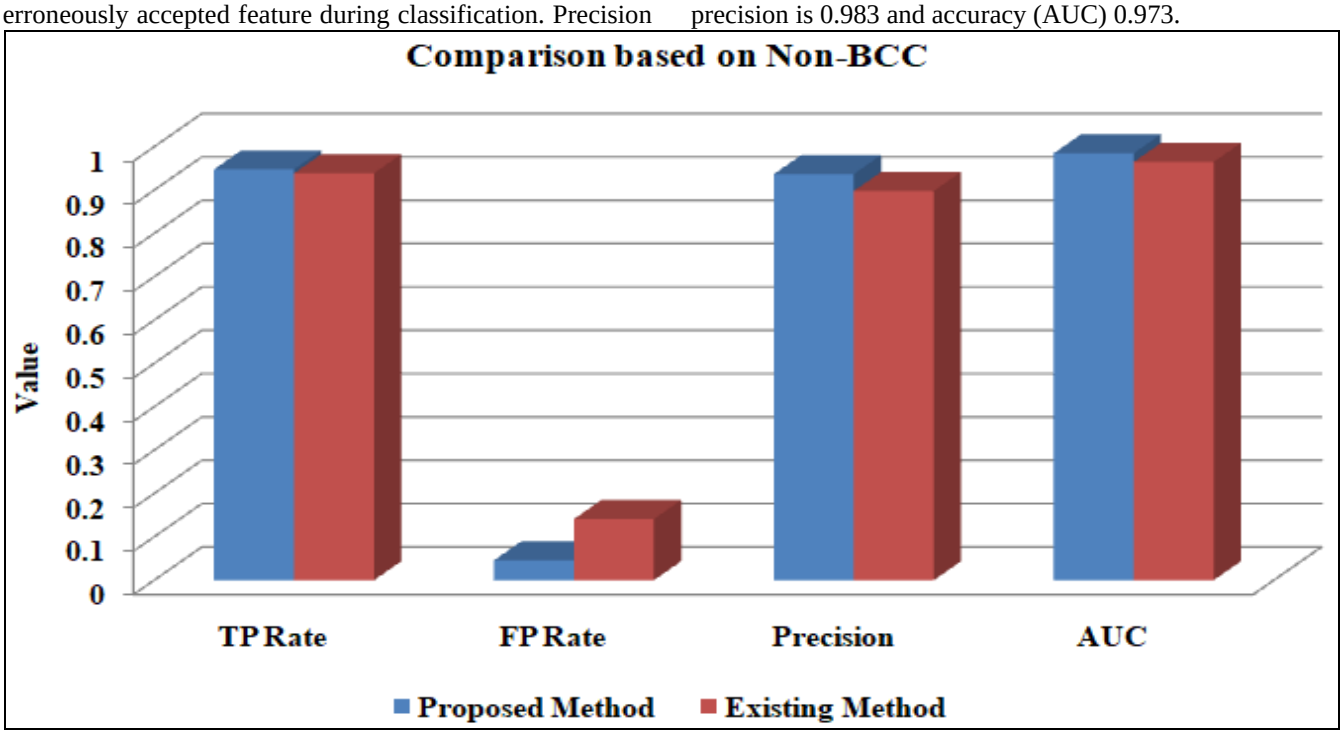

Figure 11: Comparison of evaluation parameters based on Non-BCC

The comparison of evaluation parameters for proposed and existing work is depicted in figure 11 based on the Non-BCC data. For the proposed work on the basis of Non-BCC data, TP Rate is 0.859, FP Rate is0.141 whereas; precision is 0.898 and accuracy (AUC) 0.965.

From the above observation, we concluded the accuracy of proposed work is better than existing work for BCC as well as Non-BCC data. The comparison of proposed work with some other existing work, which is considered in survey of proposed work, is described in below table.

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Table III: Comparison of accuracy of proposed work with existing works

Authors	Accuracy (%)
Pegah Kharazmi [2017]	**96.5**
Lequan Yu [2017]	**93.1**
Yading Yuan [2017]	**96.3**
N. C. F. Codella [2017]	**71.5**
Fengying Xie [2017]	**91.11**
Proposed work	**97.9**

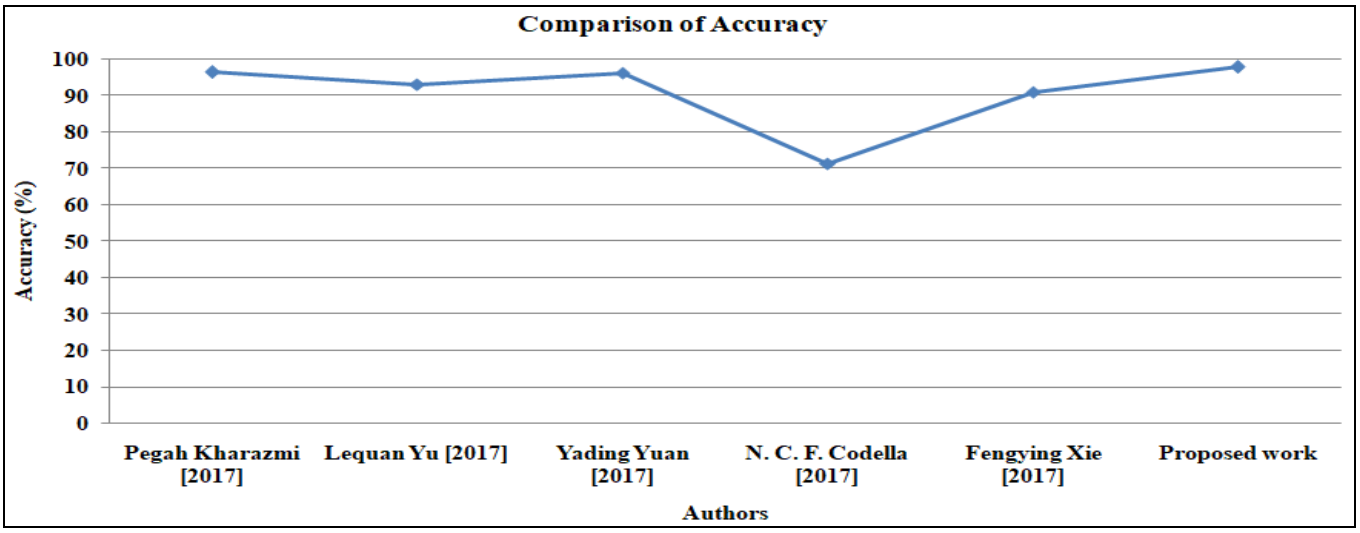

Figure 12: Comparison of accuracy of proposed work with existing works

Figure 12 represents the comparative analysis of existing work based on the classification accuracy. From the figure we observe that the accuracy achieve by proposed work is better than other author by using the hybrid segmentation with the concept of CNN using SURF feature extraction technique.

V. Conclusion and Future Work

In this paper, an intelligent prognostics model for disease prediction and classification from dermoscopy images using a convolutional neural network work based on the hybrid segmentation technique is proposed. It provides a detailed view of the different applications and potential challenges of segmentation and classification of disease from skin lesions which is a difficult task in medical science. For the detection and classification of skin diseases, segmentation of skin lesions is a major task and it is performed by hybridization of K-means with PSO. After that, in this paper we present a CNN with SURF descriptor for the segmentation and classification of BCC and Non-BCC data and ISBI-2016 dataset is used for validation of the proposed model. Utmost classification accuracy is reported when proposed work is simulated on dataset using the concept of CNN. With proposed method, the accuracy is 97.9% whereas with the existing work, the accuracy is less. In the future work, CNN is used as a classifier to train the system based on hybridization of SURF descriptor with soft computing based feature selection algorithm.

APPENDIX

It is optional. Appendixes, if needed, appear before the acknowledgment.

ACKNOWLEDGMENT

It is optional. The preferred spelling of the word “acknowledgment” in American English is without an “e” after the “g.” Use the singular heading even if you have many acknowledgments. Avoid expressions such as “One of us (S.B.A.) would like to thank ... .” Instead, write “F. A. Author thanks ” *Sponsor and financial support acknowledgments are placed in the unnumbered footnote on the first page*

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