International Journal of Engineering Sciences & Research Technology

(A Peer Reviewed Online Journal)
Impact Factor: 5.164

IJESRT

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

IMPROVED CONVOLUTIONAL NEURAL NETWORK BASED SEGMENTATION AND DETECTIONOF SKIN CANCER FROM DERMOSCOPY IMAGES USING MSER DESCRIPTOR

Ikhlas Ahmad Lone[*1] & Manmeen Kaur[2]
[*1]Punjab Technical University, India
[2]Assistant Professor at SVIET, Ramnagar Banur, India

DOI: 10.5281/zenodo.3692902

ABSTRACT

Segmentation of skin lesion from a dermoscopic images is a predominant footstep in computerized analysis approaches. Inaccurate skin lesion region segmentation could unfavorably impact the successive processing phases of anautomated skin cancer diagnosis system based on computer-aided because in these days, skin cancer is the most predominant forms of cancer diseases for descendant and light-skinned people.The most malignant type of skin cancer is “Basal Cell Carcinoma (BCC)”and in medical science, classification of BCC in earlier stage is a biggest issue for researchers. In the wake of patient, early detection of BCC is being a curable and useful of cancer diagnosis. On the way toachieve this significant goal, we designed a model for BCC classification that combines optimization segmentation approach with Convolutional Neural Network (CNN). Segmentation is a major concern of this research because skin lesion region extraction from dermoscopic image has a critical role in the early and accurate diagnosis of BCC cancer. However, automatic segmentation of skin lesions in dermoscopic images isa challenging task owing to difficulties including artifacts (hairs, gel bubbles, ruler markers), indistinct boundaries, low contrast and varying sizes and shapes of the lesion images. This paper proposes a novel and effective approach for skin lesion segmentation in dermoscopic images combining a deepconvolutional neural network with K-means and Cuckoo Search Algorithm (CSA). This research performs several steps for skin lesion segmentation using a dermoscopic image which is known as Region of Lesion (ROL) and used steps are: 1. Removalof hairs from images, 2. Exact lesion location detection, 3. K-means with CSA for segmentation of ROLas a foreground by subtracting the background data, 4. At last morphological operators are plied for post processing. The developed architectureis evaluating on publicly available and well-known ISBI Datasets. When the evaluation parameters of proposed segmentation and detection of skin cancer work is compared with a few other existing state-of-art methods, the proposed method achieves the best performance of 98.1% in terms of Area Under the Curve (AUC) in differentiating BCC from benign lesions using only the Maximally Stable Extremal Regions (MSER) Features.

KEYWORDS: Computer Assisted Dermoscopy, Skin Lesion, Pattern Recognition, K-means Algorithm, Cuckoo Search Algorithm (CSA), Maximally Stable Extremal Regions (MSER) Feature Descriptor, Convolutional Neural Network (CNN).

1. INTRODUCTION

Cancer is a preventive disease that extends throughout the human body’s bloodstream. The human body contains millions of cells; conventionally it grows divides and dies. When old cells grow or become abnormal, they die and replace with the new cells according to the need of cells in human body. The mechanism sometimes goes incorrect and uncontrolled number of cells grows, leading to cancer. When all cells combines and form extra mass tissue it forms into tumour. Not all tumours spread around whole body but they grow in uncontrollable manner such as ***benign tumour***. There is no possibility or methods to find out the exact reason for cancer, but here is the cause of cancer such as tobacco consumption, bad diet, absence of physical activity, obesity, UV exposure and alcohol consumption [1].

Skin cancer is starts from the division cells initially, later on it becomes cancer, and it’s a disease that begins in the skin cells [2]. The part of skin affected by cancer is known as the lesion [3]. There are different kinds of skin

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

cancer like Melanoma is the most serious skin cancer other skin cancers are known as the non-melanoma skin cancer which includes:

- Basal Cell Carcinoma (BCC)
- Squamous Cell Carcinoma (SCC)
- Markel Cell Carcinoma (MCC)
- Cutaneous T- Cell Lymphoma (CTCL)
- Kaposi Sarcoma

BCC, now a day it becomes the most usual kind of skin cancer. It initiate in part of skin that are directly affected by sun rays, like face, head, neck, hands and arms. Any type of cancer initially small, shiny but this is not fixed it can initiate from any kinds. They grow slowly and sometimes spread it to other regions of the body. This category of cancer mostly can be cured and treated, sometimes they may again appear after treatment, but this cancer rarely spreads to other parts of the body. If it is not within the certain time duration, there is a chances to extend inside the skin to the bone.

Symptoms:

This kind of cancer appears on the exposure part of body, it occurs rarely on the trunk and legs. Means it cannot detect on the body part which are protected from the sun like genitals. It has following symptoms given below:

1. ***Pearly white, skin-colored or pink bump:***Small vessels of the blood are often noticeable. The area which is affected would be lighter but still somewhat opaque in individuals with lighter skin shades. This lesion often forms on the head, lips or throat, the lesion is formed on the affected area due to the influence of cancer which goes bigger as the time passes on. The lesion can break, swell, and scab.
2. ***Brown, black and blue lesion:***The part of body affected through cancer which is visible as dark spots, with a small transparent border.
3. ***Flat, scaly, reddish patch:***It appears frequently on the back and chest, and can develop rapidly later on these patches.
4. ***White, waxy, scar- like lesion:***Without any clearly visible border, known as morpheaform basal cell carcinoma, this appears rarely. This is easy to highlight,but it may have different forms of cancer such as invasive and cancer disfiguring.

Causes:

Basal cell happens in the reduced epidermis region, which implies the outermost layer of the skin, creating fresh skin cells.This process of producing new skin cell is dominated by a cells Deoxyribonucleic acid (DNA). The change in the DNA causes a basal cell to develop quickly when it usually dies. Basically the collection of defected cells sometimes becomes a tumour cancer- this type of lesion appears on the skin.Most of the component damage to DNA in basal cells arises from ultraviolet (UV) radiation implies through sunlight and commercial tanning lamps and tanning beds. The sun exposure cannot detect skin cancer that comes on skin not usually disclosed to sunlight.

Prevention:

1. ***To avoid the midday sun:***It should avoid go to outside when the rays are stronger. Most of the places around 10:00 am to 4:00pm, during this time period sun rays are stronger even in winter season.
2. ***Protect through sunscreen:*** To choose a sunscreen that protects against both UVA and UVB kinds of rays from the sun and has SPF of at least 15. Apply this sunscreen on visible part of body after the interval of two hours.
3. ***To wear protective cloth:*** Sunscreen do not provide entire preservation from UV rays, so to protect from this rays wear tight clothes that covers properly exposure part of body and a broad-brimmed hat which provides more protection than other hats.
4. ***Avoid tanning beds:***To release the UV radiation from these tanning beds, increase the chances of skin cancer.
5. ***Become familiar with skin that will notice changes occur:*** It should to examine the skin to notice the occurred changes in the part of body.

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

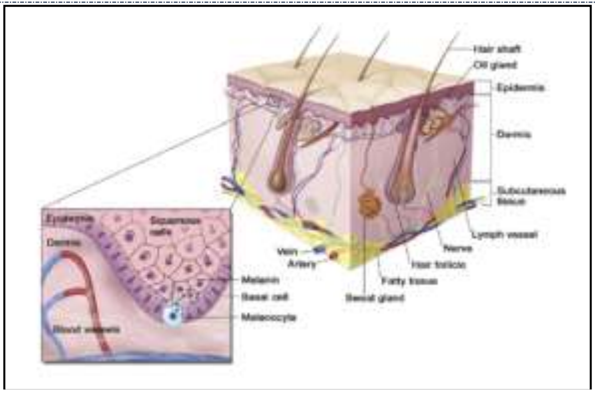

Figure 1: Analysis of the Skin

Automatically segmenting melanoma skin lesion from the surrounding skin is an indispensable phase in computer based analysis of dermoscopicimages. However, this assignment is not inconsequential because melanoma skin lesion usually has a large variety of appearance in outline, dimension and color along with dissimilar types of human skin and their texture. Meanwhile, some skin lesions have irregular and blurry borders, and in several cases the contrast of lesion and the surrounding skin is pretty low. In additional case, artifacts and intrinsic features of human skin, such as hairs, blood vessels and space bubbles can make the automatic segmentation of particular lesion more challenging, as illustrated in figure 1.

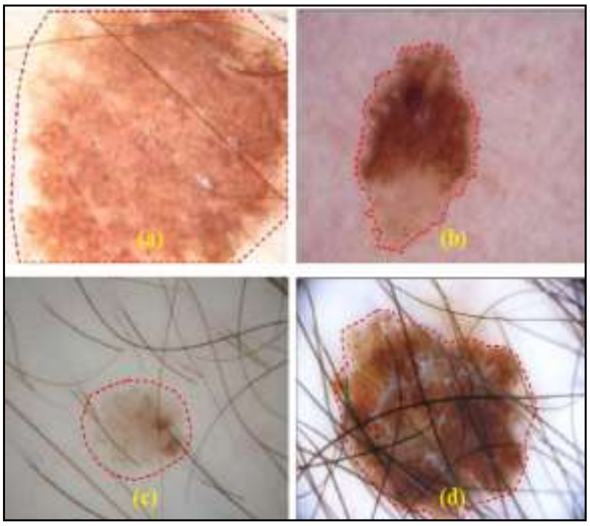

Figure 1: Dermoscopic images with automated lesion segmentation. (a) bulky size of lesion; (b) irregular and blurry borders; (c) low contrast of with respect to the surrounding skin; and (d) lesion with hair.

This paper presents an "Improved Convolutional Neural Network based Segmentation and Detection of Skin Cancer from Dermoscopy Images using MSER Descriptor"[12] and their comparison with existing trends. In this paper, we present the literate survey of existing similar work in section 2 and the architecture of proposed model is described in the section 3 with the evaluation parameters in section 4. At the last of paper, we conclude with discussions on current challenges and future trends in section5.

2. BACKGROUND SURVEY

In this segment, we present the review of existing work dependent on the division of vascular structures of skin sores for sickness order utilizing various techniques. ***PegahKharazmi et al. [1]*** proposed a robotized discovery and division of vascular structures of skin injuries seen in dermoscopy with an application to basal cell carcinoma arrangement. They present a novel structure for location and division of coetaneous vasculature from dermoscopy pictures is presented and the further extricated vascular features are explored for skin malignant

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

growth grouping. K-implies bunching is utilized by the creators with shape channels to group the erythematic group at various scales. Due the absence of optimization and classifier technique, the arrangement and division result isn't acceptable for therapeutic science research point of view on the grounds that there are heaps of non melanoma districts are consider as melanoma. ***Lequan Yu, et al. [2]*** presented computerized melanoma acknowledgment in dermoscopy pictures through extremely deep leftover systems. They proposed a novel technique for melanoma acknowledgment by utilizing deep convolutional neural systems (CNNs). This technique can guarantee that the proposed systems profit by the performance additions accomplished by expanding system depth. From that point forward, they develop a completely convolutional remaining system (FCRN) for accurate skin sore division, and further improve its capability by incorporating multi-scale logical data coordination conspire. This system empowers the characterization system to extricate progressively representative and specific features dependent on divided outcomes rather than the entire dermoscopy pictures, further reducing the deficiency of preparing information. The execution time and CNN and FCRN are high and it isn't acceptable in restorative science, so improvement need in the division phase. ***Yading Yuan et al. [3]*** proposed a programmed skin injury division utilizing deep completely convolutional systems with Jaccard separation. In this work, they proposed a completely programmed structure dependent on deep convolutional neural system for skin sore division on dermoscopic pictures. A few powerful preparing strategies were implemented to handle the difficulties that preparation a deep system may confront when just restricted preparing information is accessible. They structured a novel misfortune capacity dependent on the Jaccard separation to further lift the division performance however the division time is more and need to lessen the execution time in future work. The aftereffects of proposed work are unmistakably demonstrated that the proposed technique is strong to different picture curios and imaging securing conditions while utilizing least pre and post-processing. The proposed therapeutic picture division undertakings is better as compare to the next however just time complexity is significant disadvantage. ***N. C. F. Codella et al. [4]*** proposed novel deep learning groups for melanoma acknowledgment in dermoscopy pictures. They have proposed a system for the division and grouping of melanoma from dermoscopic pictures of skin. The strategy was assessed on the biggest public benchmark for melanoma acknowledgment accessible. The proposed work is applicable for direct picture during the grouping process and need to improvement in the pre-processing steps for further utilizations of non straight pictures.***FengyingXie et al. [5]*** proposed a melanoma order on dermoscopy pictures utilizing a neural system outfit model. They develop a novel strategy for grouping melanocytic tumors as generous or threatening by the examination of computerized dermoscopy pictures. The calculation pursues three steps: first, injuries are removed utilizing a self-producing neural system (SGNN); second, features descriptive of tumor shading, surface and fringe are extricated; and third, sore articles are grouped utilizing a classifier dependent on a neural system outfit model. To manage this troublesome presentation, new outskirt features are proposed, which can viably describe fringe anomalies on both complete sores and incomplete sores however fringe recognition for all database picture are unrealistic and the location result isn't appropriate. The outcomes show that arrangement accuracy is enormously upgraded by the utilization of the new fringe features and the proposed classifier model however results might be better for the therapeutic application. ***EuijoonAhn and Ashnil Kumar [6]*** proposed saliency-based sore division by means of foundation location in dermoscopic pictures. In this paper, creators have implemented a saliency-based division structure for the distinguishing proof and portrayal of skin injuries in dermoscopic pictures. The proposed system can be utilized as a saliency optimization calculation for injury division in dermoscopic pictures yet because of the absence of major pre-processing steps; the division results are not acceptable and need to improve. ***C. Benazzi et al. [7]*** proposed model angiogenesis in spontaneous tumors and implications for comparative tumor science. They proposed a comparative report on tumor examination utilizing the various techniques. From the study, they established that, the tumor characterization accuracy might be high if the preparation and grouping of the system will be proper. The preparation of an arrangement system is absolutely depending on the feature sets so need to an optimization calculation with the grouping system. ***B. Cheng et al. [8]*** proposed programmed telangiectasia examination in dermoscopy pictures utilizing adaptive pundit structure. They have picked BCC identification as opposed to vessel discovery as the endpoint. In spite of the fact that vessel recognition is characteristically simpler, BCC location has potential direct clinical applications. Little BCCs are perceivable ahead of schedule by dermoscopy and potentially noticeable by the mechanized strategies depicted in this examination. Experimental outcomes yielded an analytic accuracy as high as 84.6% utilizing the ADHDP approach, providing an 8.03% improvement over a standard multilayer perception technique.

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

In view of the study we finish up some important point which helps to short out the current problem. Our commitments in this paper to tackle the above notice problems are presented in triple. Right off the bat, we present a completely robotized half and half strategy for skin sore division by utilizing K-means with CSA technique. To the best of our mindfulness, our proposed work is among the initial scarcely any attempts to utilize the concept of hybridization of CSA to handle this difficult problem. Also, we plan an appropriate hair removal work that normally handles the injury foundation awkwardness of pixel-wise characterization for medicinal picture division. Our outcomes show that this hair removal capacity can further improve the division performance by expelling the hair over the injury area at that point applies MSER feature extraction.

3. METHODOLOGY OF MODEL

The proposed an improved CNN based segmentation and detection of skin cancer from dermoscopy images using MSER descriptorconsists of three main steps which are written as:

- Various digital image pre-processing techniques are appliedon dermoscopic images to improve image quality by removing hair on the skin lesion. After that, K-means with CSA is applied as a suitable segmentation technique to separate out background and foreground of image which helps to extract exact Region of Lesion (ROL). CSA is applied on K-means output as an optimization algorithm to minimize the unwanted background region from ROL using the novel fitness function based on threshold.
- When ROL is extracted then MSER as feature descriptor is applied to extract unique feature from the segmented ROL to feed as input to the CNN model.
- As a final point, BCC classification is performed using CNN model to produce desired output for the proposed model.
- The block diagram of proposed model for segmentation and detection of skin cancer from dermoscopy images using MSER descriptor is shown in the figure 2 with above written steps which are used to develop this model.

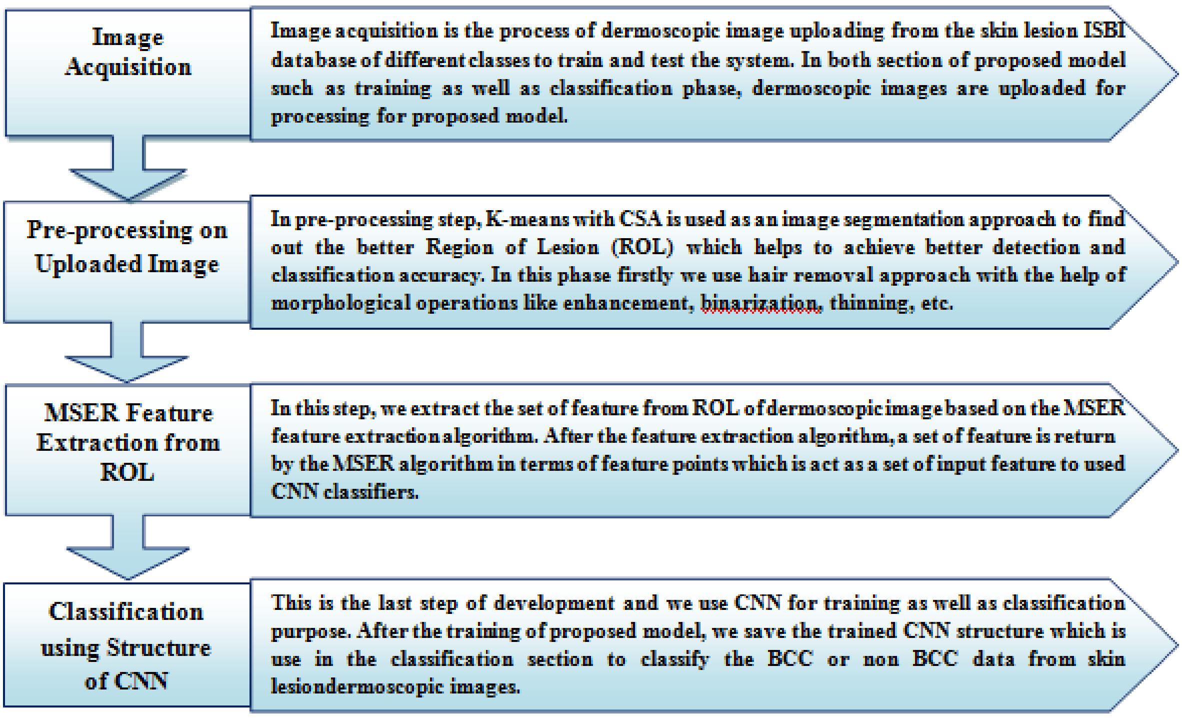

Figure 2: Block diagram of proposed model

The challenge of this research work is to segment and classify the BCC using dermoscopy images using CNN on the basis of the MSER features of skin ROL. Major section of this research is lesion segmentation on the basis of K-means with CSA and morphological operations which is known as Enhanced K-means and the algorithm of Enhanced K-means is written as:

Algorithm: Enhanced K-means

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

Input Attributes: SL Image → SkinLesion Image **Output Attributes:** ROL → Skin LesionROLImage
[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 CSA parameter** – Iterations (T) – Cuckoo Size (S) – Lower Bound (LB) – Upper Bound (UB) – Fitness function
Calculate T = Size (SL Image) Fitness function: $f(fit) = \begin{cases} 1 & if pixel is less \\ 0 & otherwise \end{cases} \dots (1)$ **For → T** $fs = \sum_{i=1}^{P} Data(i) = Current\ Egg$ $ft = \frac{\sum_{i=1}^{P} Data(i)}{Length of feature} = Threshold\ Egg$ $f(fit)$ = fitness function which define by above given equation (1) $Threshold_{value} = CSA(P, T, LB, UB, N, f(fit))$ **End** **While T ~= Maximum** $\boldsymbol{Threshold} = Threshold_{value}$ MaskImg=Morphological (SimgIndex, Threshold) Boundaries = bwboundaries (MaskImg) Segmented Region = Boundaries **For i→1: P** Segmented Image = SL Image X Segmented Region **End** **Return;** Segmented Image as ROL of Skin Lesion Image **End**

After the Enhanced K-means applied on the skin ROL, we obtained below given results which are useful in next process of proposed work.

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

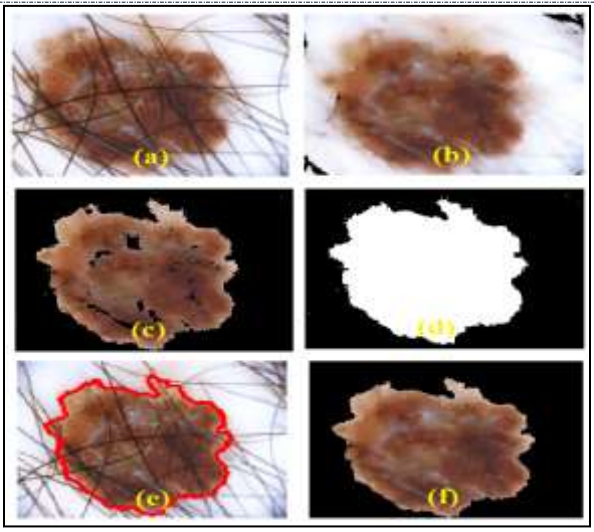

Figure 3: Skin ROL Extraction using Enhanced K-means

Above figure 3 represent the ROL extraction process with pre-processing steps. Original dermoscopy image is shown in the figure 3 (a)and figure 3 (b) is the enhanced dermoscopy image in which hair from lesion is removed, figure 3 (c) K-means based Segmentation. Figure 3 (d) masks of skin ROL and (e) is the localization of exact region of lesion in dermoscopy image. Figure (f) is the final segmented skin ROL using the Enhanced K-means algorithm. Form the figure, the achievement of proposed hybrid segmentation technique is represented and it helps in the proposed model to achieve better detection accuracy.To extract a set of feature from the skin ROL,MSER feature extraction algorithm. After the feature extraction algorithm is used which is shown is ht e figure 4. 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.

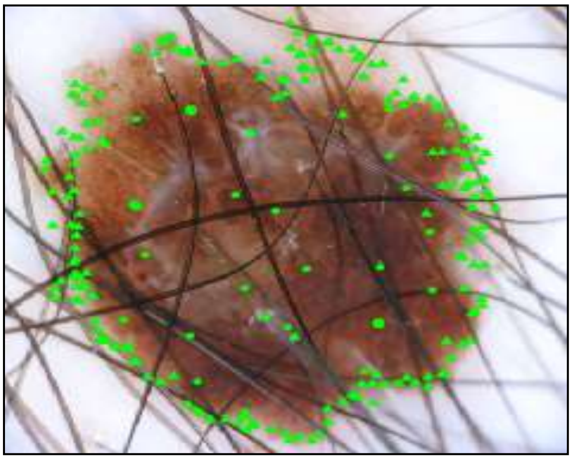

Figure 4: MSER Feature of Skin ROL

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 Attributes: Fpoints→ Feature points as training data (T), Target (G) and Neurons (N)
Output Attributes: 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 $(Net, Trainingdata\ , Group)$
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

The simulation of proposed model is done on the basis of ISBI Dataset 2016. 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.

4. RESULTS AND DISCUSSION

In this section, the simulation results of proposed improved CNN based segmentation and detection of skin cancer from dermoscopy images using MSER descriptor is discussed and the efficiency of proposed work is compared with existing work [1]. By adapting the set up proposed calculations, beneath results are computed with quality based parameters, for example, True Positive Rate, False Positive Rate, Precision and Accuracy. A comparison is drawn with the current work [1] to indicate the adequacy of the proposed work with respect to the BCC and Non-BCC dependent on the three sample information from every classification and for the graphical representation we figure their average worth like average TP Rate, average FP Rate, Average Precision and Average Accuracy of system.

TABLE 1: Test results of proposed method

Types	Test Sample	TP Rate	FP Rate	Precision	AUC
BCC	TS1	0.912	0.0379	0.993	0.985
	TS2	0.925	0.0495	0.945	0.982
	TS3	0.979	0.0243	0.983	0.974
Non-BCC	TS1	0.936	0.0459	0.941	0.983
	TS2	0.949	0.0343	0.959	0.982
	TS3	0.983	0.0234	0.983	0.979

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

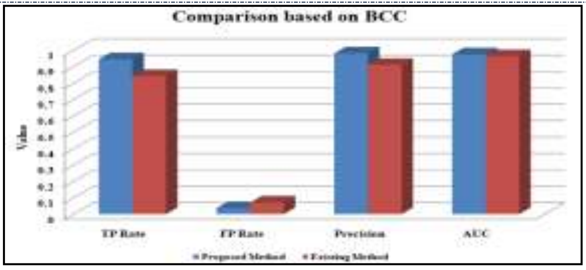

Figure 4: Comparison of evaluation parameters based on BCC

The comparison of assessment parameters for proposed and existing work is depicted in figure 4. TP Rate is the probability of accurately enlistment of highlights which are incorporated into the coordinating process and FP Rate is the rate of mistakenly accepted component during order. Precision is the rate of TP and summation of TP and FP which represents the accuracy participating component of ordered class of sickness. For the proposed work based on BCC information, average TP Rate is 0.946, FP Rate is 0.0367 while; precision is 0.981 and accuracy (AUC) 0.976.

TABLE 2: Test results of existing method [1]

Types	Test Sample	TP Rate	FP Rate	Precision	AUC
BCC	TS1	0.859	0.061	0.914	0.965
	TS2	0.837	0.073	0.922	0.973
	TS3	0.834	0.079	0.899	0.958
Non-BCC	TS1	0.939	0.141	0.898	0.965
	TS2	0.947	0.103	0.894	0.953
	TS3	0.934	0.098	0.819	0.975

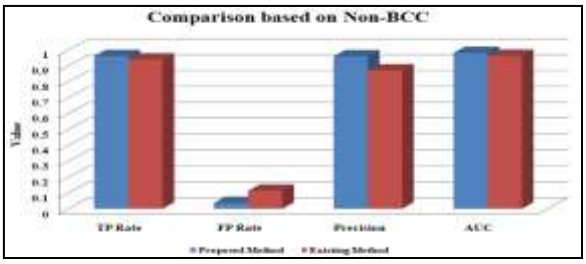

Figure 5: Comparison of evaluation parameters based on Non-BCC

The comparison of assessment parameters for proposed and existing work is depicted in figure 5 dependent on the Non-BCC information. For the proposed work based on Non-BCC information, the average TP Rate is 0.962, FP Rate is 0.037 though; precision is 0.961 and accuracy (AUC) 0.982. From the above perception, we finished up the accuracy of the proposed work is superior to existing work for BCC just as Non-BCC information. The comparison of proposed work with some other existing work, which is considered in the study of proposed work, is depicted in the underneath table.

Table 3: Comparison of accuracy of proposed work with existing works

Authors	Accuracy (%)
PegahKharazmi [2017]	96.5
Lequan Yu [2017]	93.1
Yading Yuan [2017]	96.3
N. C. F. Codella [2017]	71.5
FengyingXie [2017]	91.1
Proposed work	98.1

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

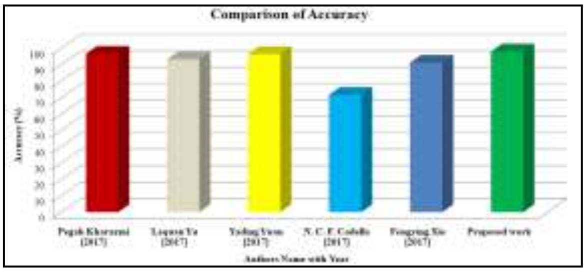

Figure 6: Comparison of accuracy of proposed work with existing works

Figure 6 represents the comparative examination of existing work dependent on arrangement accuracy. From the figure we see that the accuracy accomplishes by the proposed work is superior to different creators by utilizing the half breed division with the concept of CNN utilizing the MSER feature extraction technique.

5. CONCLUSION & FUTURE WORK

In this paper, an improved convolutional neural network based segmentation and detection of skin cancer from dermoscopy images using MSER descriptoris proposed. It provides a detailed view of the different applications and potential challenges of segmentation and classification of disease from skin lesions which a difficult task in medical science. For the detection and classification of skin diseases, segmentation of skin lesions is major task and it is performed by hybridization of K-means with CSA. After that, in this paper we present a CNN with MSER descriptor for the segmentation and classification of BCC and Non-BCC data and ISBI-2016 dataset is used for validation of 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 98.1% whereas with the existing work, the accuracy is less.

In future work, ANN is used as a classifier to train system based on hybridization of SURF descriptor with soft computing based feature selection algorithm.

REFERENCES

[1] Kharazmi, Pegah, et al. "Automated detection and segmentation of vascular structures of skin lesions seen in Dermoscopy, with an application to basal cell carcinoma classification." IEEE journal of biomedical and health informatics 21.6 (2017): 1675-1684.
[2] Yu, Lequan, et al. "Automated melanoma recognition in dermoscopy images via very deep residual networks." IEEE transactions on medical imaging 36.4 (2017): 994-1004.
[3] Yuan, Yading, Ming Chao, and Yeh-Chi Lo. "Automatic skin lesion segmentation using deep fully convolutional networks with jaccard distance." IEEE Trans. Med. Imaging 36.9 (2017): 1876-1886.
[4] Codella, Noel CF, et al. "Deep learning ensembles for melanoma recognition in dermoscopy images." IBM Journal of Research and Development 61.4 (2017): 5-1.
[5] Xie, Fengying, et al. "Melanoma classification on dermoscopy images using a neural network ensemble model." IEEE transactions on medical imaging 36.3 (2017): 849-858.
[6] Ahn, Euijoon, et al. "Saliency-based lesion segmentation via background detection in dermoscopic images." IEEE journal of biomedical and health informatics 21.6 (2017): 1685-1693.
[7] Benazzi, C., et al. "Angiogenesis in spontaneous tumors and implications for comparative tumor biology." The Scientific World Journal 2014 (2014).
[8] B. Cheng1, R. J. Stanley1, W. V. Stoecker2 and K. Hinton2, Automatic telangiectasia analysis in dermoscopy images using adaptive critic design
[9] J. W. Choi, B. R. Kim, H. S. Lee, and S. W. Youn, "Characteristics of subjective recognition and computer-aided image analysis of facial erythematous skin diseases: A cornerstone of automated diagnosis," Brit. J. Dermatol., vol. 171, pp. 252–258, Aug. 2014.
[10] S. C. Hames et al., "Automated detection of actinic keratoses in clinical photographs," PLoS One, vol. 10, p. e0112447, 2015.
[11] B. Cheng, R. J. Stanley, W. V. Stoecker, and K. Hinton, "Automatic telangiectasia analysis in dermoscopy images using adaptive critic design," Skin Res. Technol., vol. 18, pp. 389–396, Nov. 2012.

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

[12] B. Cheng et al., "Analysis of clinical and dermoscopic features for basal cell carcinoma neural network classification," Skin Res. Technol., vol. 19, pp. e217–e22, Feb. 2013.
[13] P. Kharazmi, H. Lui,W. V. Stoecker, and T. Lee, Automatic detection and segmentation of vascular structures in dermoscopy images using a novel vesselness measure based on pixel redness and tubularness, Proc. SPIE, vol. 9414, Computer-Aided Diagnosis, 94143M, Mar. 2015.
[14] I. Zalaudek, J. Kreusch, J. Giacomel, G. Ferrara, C. Catricala, and G. Argenziano, "How to diagnose nonpigmented skin tumors: A review of vascular structures seen with dermoscopy: Part II. Nonmelanocytic skin tumors," J. Amer. Acad. Dermatol., vol. 63, pp. 377–386, Sep. 2010.