Journal of Scientific & Industrial Research
Vol. 80, April 2021, pp. 328-335

Segmentation and Classification of Skin Lesions from Dermoscopic Images

Lakshmi Harika Palivela[1]*, Joshan Athanesious J[2], V Deepika[1] and M Vignesh[1]

[1]Department of Information Technology, MIT Campus, Anna University, Chennai, Tamilnadu
[2]Department of Artificial Intelligence and Data science, Saveetha Engineering College, Chennai

Received 02 June 2020; revised 06 February 2021; accepted 11 February 2021

Skin melanoma cancer, particularly among non-Hispanic white women and men, has been one of the highest risks of spreading disease among all cancers. It should be treated earlier for effective treatment. Due to high costs of screening each patient by dermatologists, it is important to establish an automated method to determine the risk of melanoma for a patient by using image scan of their skin lesions that can provide accurate diagnosis. The major challenge is segmenting the skin lesion from the digital scan image. For segmenting the lesion, a novel algorithm based on skin texture is proposed in which a set of representative texture distributions is analysed from a non-illuminated image. The ridge in the skin image is labeled as either normal segment or lesion, based on the presence of sample texture distributions by calculating the texture distinctiveness metrics. In comparison with other bench-mark models the suggested algorithm has greater precision in segmentation about 95% accuracy.

Keywords: Deep learning, Feature extraction, Image processing, Melanoma-cancer, Texture

Introduction

Skin, which aims to protect the internal sections of the body, is the strongest organ in the human body.[1] Skin functions in the human body are of greater significance for other areas of the body can be affected by a slight change in its functioning process. Hence, it is necessary to gain greater attention to skin disease. Skin melanoma is mainly caused by the production of anomalous cells that are capable of spreading or seizing other parts of the body.[2–4] The use of medical algorithms such as ABCD model and the 7-point checklist, it is not always easy to differentiate melanoma from other types of skin lesions. This decreases the sensitivity of dermatologists and increases the number of unnecessary histological exams, since this is the only way to correctly diagnose the lesions.[5] Furthermore, different dermatologists may disagree on their diagnosis of the skin lesions. This happens because the inspection of the different dermoscopic criteria is based on the visual acuity and the experience of the expert. Thus a CAD system possesses different assets that can be helpful for dermatologists.[6] To overcome the lack of clinical information in a CAD system, some research groups have tried to replace the abstract computer vision features by detectors of dermoscopic criteria. In particular, the specific objectives of the work stated in this context are to develop a fully automatic method to segment and classify the skin lesions.[7] A novel machine learning method is implemented to segment the actual lesion regions on the skin from the dermoscopic scanned images. Therefore, it is necessary to develop automatic method to ease diagnosis and treatment of skin diseases that will help dermatologists provide a more reliable diagnosis.[8] Today, the involvement of medical field highly reliant on computer-assisted diagnosis. For the inexperienced dermatologist the early detection of skin disease is more complex.[9] The diagnosis can be made by integrating optical image processing for skin cancer identification without any direct contact with the skin. The development of a CAD system with machine learning has become a major field of medical research for these purposes. In the distinction between low-level and high-level processing methods, the difficulty in algorithm implementation and its complication or the time required image processing computation plays a secondary role. Thus the dermatologists may use the development of an automatic diagnostic system for melanoma detection as a main opinion for fast and accurate results.

Related Work

In this section, segmentation and classification based on Skin Lesions are discussed. The segmentation uses a

*Author for Correspondence
E-mail: lakshmiharika@mitindia.edu

smoothing filter to threshold the disruptive areas from the output feature vector.[10] This leads in high value of correlation and overlapping score. This framework lacks its performance because of the presence of any unwanted hairs in the lesion region. An algorithm to classify dermoscopic images into benign and malignant was presented by Nezhadian *et al.*[11] In this approach it has three stages with the Bottomhatt filter to enhance image followed by the thresholding and classifying the disease. The final dermoscopic score is calculated to locate the presence or deficiency of cancer in dermoscopic image-scans. The performance of the developed method is assessed using classification accuracy. This framework may detect the non-melanoma pictures as melanoma due to lack of feature vectors.[12] An enhanced border line features for identifying the skin melanocytic lesions.[13]

The initial images were segmented using active contour models and by using morphological operations to extract the texture, color components. This work is to feed features to sequential classification without tuning and then transfer learning is applied.[11,14] In this work the lesion classification is by ensemble ResNet-50 and Inception network model and by averaging the performance probabilities of two networks and choosing the class with the highest probability.[15] The model that rapidly segments the tumour from the neighbouring skin and VGG-16 with tuning is designed to resolve the two distinct tasks of skin tumours classification.[16] The issues of automatic analysis of skin melanoma lesions by examining the raw images and for classification of melanocytic cancer by analysing digital dermoscopic images for color, texture and border of tumour features is extracted.[17,18] A framework for melanoma classification using CNN for feature extraction, region pooling method was implemented. This approach incorporates knowledge about segmentation into the task of classification.[19] In contrast with clinical diagnosis, the integration of image analysis and soft computing practices, provides more detailed results for the identification of lesions on skin. In many stages like pre-processing, segmentation, extraction of features and then detection are used to carry the reliable results.

Skin Lesion Diagnosis System (SLD)

Early diagnosis of skin cancer is necessary for effective treatment. One of the techniques used by dermatologists to diagnose melanoma is an imaging modality called dermoscopy. Even with dermoscopy the accuracy of melanoma diagnosis by expert dermatologists remains at 75–80%. Therefore, it is necessary to develop automatic method to ease diagnosis and treatment of skin diseases that will help dermatologists provide more reliable diagnosis.

SLD System Architecture

Skin lesions can be a benign or malignant, the datasets obtained as dermoscopic images are classified as training & testing sets in Fig. 1. The augmented datasets first pre-processed using adaptive histogram. Then for better classification result, the lesion region is segmented using automatic or semi-automatic method. Finally the segmented lesion region is processed and trained for classification.

The work flow model of SLD system shown in Fig. 2

Image Pre-Processing

The formations of lesions significantly depend on the type of skin which is very complicated in separation due to variations in contrast, bubbles & hair on skin and to get better precision in the segmentation, preprocessing should be done by scaling the image to avoid high resolution on scans. The input images are scaled to decrease the computational complexity. The scaling images is performed by resize each dermoscopic image by an average dimension of height and width of the image after this illumination correction has to performed to obtain the contrast limited images of skin lesions.

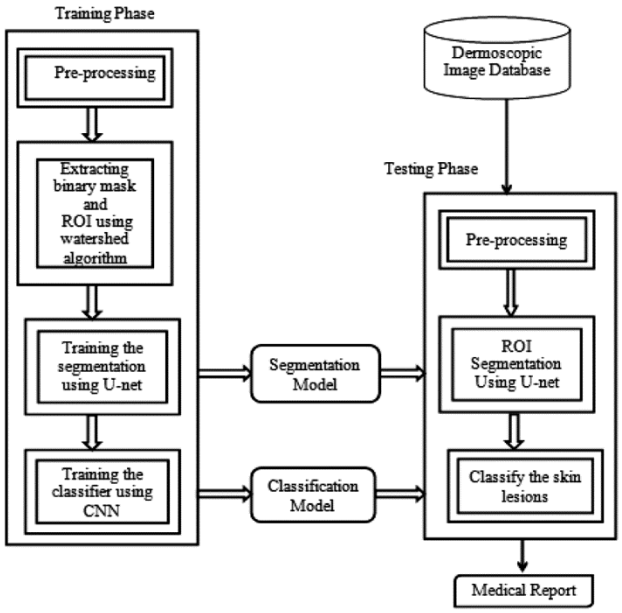


Fig. 1 — Skin Lesion Diagnosis System

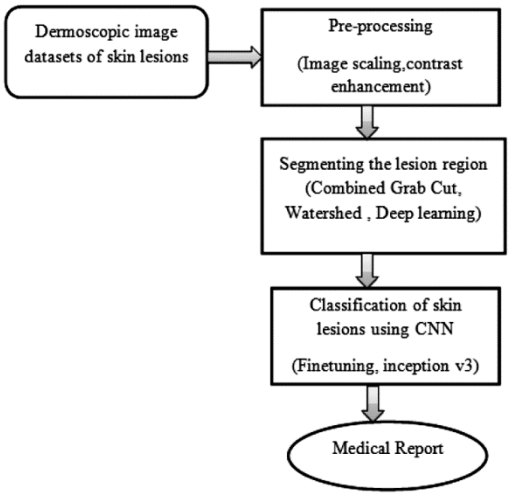


Fig. 2 — Work flow SLD model

Illumination Correction

It is useful to remove the inconsistent brightness of the scanned images induced by the sensor faults. First the down-scaled image is transformed into L colour space and then added to the contrast limited adaptive histogram equalization (CLAHE) algorithm with the L channel.[20] The upgraded variant of histogram equalization is CLAHE in form of tiles, which overrides the disadvantage of the traditional technique of histogram equalization. To each of these tiles, Histogram equalization is then added and to remove the noise on dermoscopic scans. Finally, using bilinear interpolation to delete objects at the borders, the adjacent tiles are combined. The outcome of applying this technique has limited the lesions on skin.

Image Segmentation

Segmentation of images is usually used in an image to locate objects and edges. The product of image segmentation is a collection of segments that collectively cover the entire image, or a collection of contours taken from the image. In relation to certain characteristics or computed properties, each pixel in a region is identical, such as colour, intensity and texture.

GrabCut Segmentation

To segment the foreground area of the image, the GrabCut segmentation method considers both the edges and region information.[21] So we have applied the GrabCut to locate the generic lesions in dermoscopic image-scans. It has two inputs, such as TB and TF, a set of background & foreground pixels. These pixels in the regions are linked to the sink nodes. The segmented region includes both the lesion region and some of the context information. It initiates by considering the pre-processed skin lesion image. This is generally achieved by drawing a rectangle around the object of interest and defining the unknown area inside that rectangle. Pixels are then labelled outer part as background or else foreground and it is modeled as Gaussian Mixture Models (GMMs) where every pixel is processed to Gaussian components results in set of pixels. Then a graph is created and newly identified pixels used to find Graph Cut these results in iterations until the classification converges. The existing GrabCut segmentation is time consuming in which for each image the boundary box has to be drawn manually. The proposed method automatically extract the region of interest that combines U-net segmentation with the watershed algorithm is proposed to address the limitations of GrabCut Segmentation.

Watershed Segmentation

Watershed transformation is a sort of statistical morphology-based segmentation method that can decompose the dermoscopic scans into many identical and non-overlapping regions. This method transformation is typically done via the processing of flooding stimulus.[22] In the entire process dermoscopic images are considered as a model of the peaks and troughs of the mountain, where each pixel grey value reflects the heights of the point. Here, not only low mountains (local minimum regions) and giant ridges (watershed) included in this landscape, but also the high or slow hillsides between the ridges and mountains. In different catchment basins, as the rising water is about to fuse, a dam is installed to avoid fusion. Eventually, the flood would hit a point where only the tops of the dams are visible above the water line. These dam boundaries refer to the line separating the watersheds. Before using the watershed for segmentation, the gradient scale is used to handle the input dermoscopic scans. Along the edges of the object, the image gradient scale the pixel values rises and pixel values fall in the surroundings. Along the edges of the entity, transformation creates watershed edge lines. This may issues the over segmentation. The topological gradient offers a complete image analysis, and then our approach to decrease unexpected contours may arise in the dermoscopic scan image due to noise.

U-Net Segmentation

The U-Net is a one type of Convolutional Network. It combines a convolutional system model (contract

section on the left side) with a deconvolutional system model (extended section on the right side) to achieve semantic segmentation.

The U-Net architecture is divided in three sections:

i. Contract/down sampling
ii Bottleneck
iii Extended/up sampling

i)Contract/down sampling

The contract is formed with four blocks. Each block has Convolution Layer (Conv Layer) and activation function (AF-with batch normalization)

a. 3x3 Conv Layer + AF
b. 3x3 Conv Layer + AF
c. 2x2 Max Pooling

At each pooling phase there is double increase in feature maps like 64, 128 etc. The down sampling is intended to capture the background of the input dermoscopic image so that segmentation can be done. This collected information is transferred to the up sampling.

ii)Bottleneck

This portion is between the layers of contract and expansion. The bottleneck is constructed with two Conv layers (with batch normalization), with one layer dropout.

iii) Extended/up sampling

The expand section is formed with four blocks. Each of these blocks is composed of

a. DeConv layer with stride 2
b. Concatenate with the equivalent cropped feature map from the contract section
c. 3x3 Conv Layer + AF
d. 3x3 Conv Layer + AF

The objective of the up sampling is to allow precise localization in combination with contextual information and contract path.

Modifications to existing architecture

i. Trained the model from scratch (generally pre-trained weights)
ii. Set the padding as same to avoid shrinking.
iii. Used ReLu activation function (generally linear)

The proposed model is explained in Algorithm I.

Algorithm I:
Proposed U-Net Segmentation with Watershed Transformation
Input: Pre-processed dataset
Output: Lesion segments

Procedure

Skin Lesion Segmentation (imageIn, colorSpace)

1. begin
2. for each preprocessed skin lesion images imageIn in training dataset
3. if (colorSpace is 'RGB') then
4. Convert RGB to HSV and YCbCrcolorSpace;
5. for each HSV and YCbCr images
6. Compute the histogram value v for the three channels;
7. If (v>threshold) then set region as foreground;
8. else set region as background;
9. Apply morphological operations such as dilation and erosion to background region B and foreground region A to remove noise.

Dilation: $\boldsymbol{A \oplus B = \{z|(B)_z \cap A \neq \phi\}}$ Eq. … (1)

Erosion: $\boldsymbol{A \ominus B = \{z|(B)_z \cap A \neq \phi\}}$ Eq. … (2)

10. combine foreground and background region to form the 'binary mask';
11. bitwise binary mask with original image to produce segmented image;
12. end for;
13. end if
14. Create a u-net model using preprocessed skin lesion image with its Corresponding binary mask;
15. Train U-Net with 300 epochs
16. Predict the test data set
17. end for; end

Feature Extraction

It involves extracting the features and classifying them using deep learning. Feature extraction methodology includes different features of pictures like colour, texture, edges, corner and spectral options. The handcrafted features are said to focus on spectral, colour, texture, shape and their combination. Whereas the unsupervised method uses principal component analysis, K-means cluster sparse coding and auto encoder to extract the features. In case of deep learning, this includes learning of both supervised and unsupervised learning method which is obtained using convolutional neural network methods.

Image Classification Using CNN

CNNs are more compatible for finding patterns in images and classify its features. A typical CNN has

two parts (Fig. 3): The convolutional base is to generate image features and then followed by classification.

The deep learning method CNN has given coherent performance in several applications such as classification of remote sensing images and analysis of satellite images using efficient feature learning methods. The standard design of a CNN is structured as a series of layers (Fig. 4) such as Conv layer, pool and fully connected layers.

Steps to perform CNN

i. The Convolutional Layer is implemented using the following formulae,

$$(\mathbf{fi} * \mathbf{gi})(\mathbf{t}) = \int_{-\infty}^{+\infty} \mathbf{fi}(\boldsymbol{\tau})\mathbf{gi}(\mathbf{t}-\boldsymbol{\tau})\mathbf{d}\boldsymbol{\tau}\text{Eq.} \quad \ldots (3)$$

$$(\mathbf{fi} * \mathbf{gi})(\mathbf{t}) = \int_{-\infty}^{+\infty} \mathbf{fi}(\mathbf{t}-\boldsymbol{\tau})\mathbf{gi}(\boldsymbol{\tau})\mathbf{d}\boldsymbol{\tau}\text{Eq.} \quad \ldots (4)$$

ii. This function is used to create the feature map.

iii. Apply the Rectified Linear Unit function to increase non-linearity in the CNN. This layer will increases in the positive layer and becomes zero for the negative values.

iv. Max pooling enables the CNN to detect features in various images. Max pooling is takes the higher values in feature matrix map.

v. Flatten the pooled feature map and softmax layer is applied.

vi. In Fully Connected layer the probability of each feature is identified and the output image is predicted.

vii. After this transfer learning (Inception V3) has to be performed by tuning the system to perform all similar secondary tasks without developing the extraction network from the scratch.

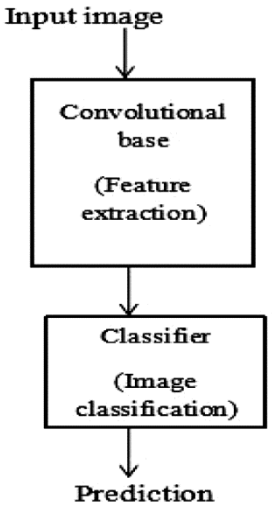


Fig. 3 — Architecture model based on CNN

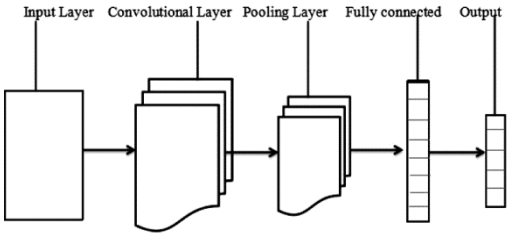


Fig. 4 — Representation to convolutional Network

Results Analysis

The proposed algorithm was implemented using ISIC dermoscopic image datasets which consist of 23000 images.[23] Out of these total images 2000 images were used which consists of 500 benign skin lesions, 500 melanoma skin lesions for training and 500 benign, 500 melanoma for testing. The model is trained in Keras and tensorflow using Python programming language. All the algorithm models experimented using Intel (R) CoreTM i7-4790 3.60 GHz and16 GB RAM. The sample results is shown in the Fig. 5

Performance Analysis of Segmentation

Using several parameters like JSC (Jaccard Similarity Coefficient), DSC (Dice Similarity Coefficient) and execution time the segmentation efficiency is evaluated.

DSC measures the correlation of two sets.

$$DSC(A_i,B_i) = 2(A_iB_i) / |A_i||B_i|\text{Eq.} \quad \ldots (5)$$

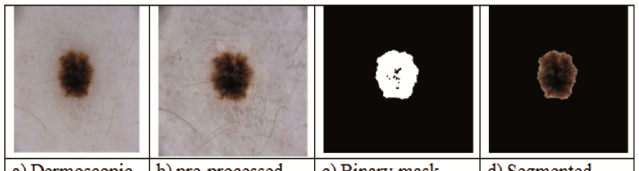
where A_i and B_i are two compare images.

JSC calculates the degree of the correspondence between two segmentations. The greater value of JSC indicates a better segmentation.

$$JSC\ (A_i, B_i) = (A_i \cap B_i) / (A_i \cup B)\text{Eq.} \quad \ldots (6)$$

Jaccard Similarity can also be obtained from dice coefficient.

$$JSC\ (A, B) = DSC / (2\text{-}DSC)\text{Eq.} \quad \ldots (7)$$



a) Dermoscopic image of a skin lesion	b) pre-processed Dermoscopic image	c) Binary mask from watershed algorithm	d) Segmented lesion region using U-net Algorithm

Fig. 5 — Sample results of the SLD Proposed system on Dermoscopic images

The proposed SLD system achieved higher values. Relative values of the proposed GrabCut and watershed segmentation algorithm are shown in Table 1.

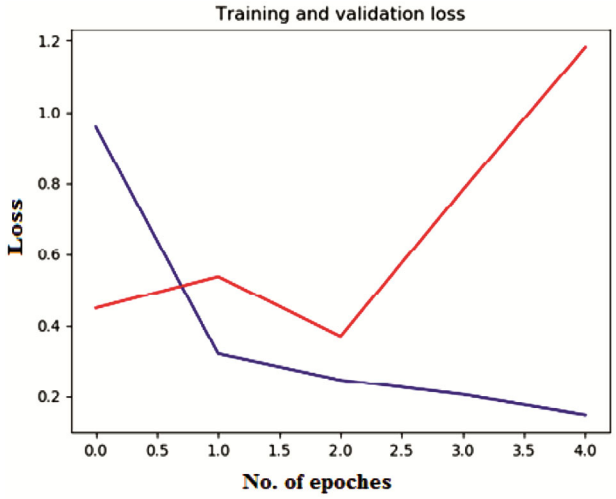


Fig. 6 — Training loss function graph of transfer learning model

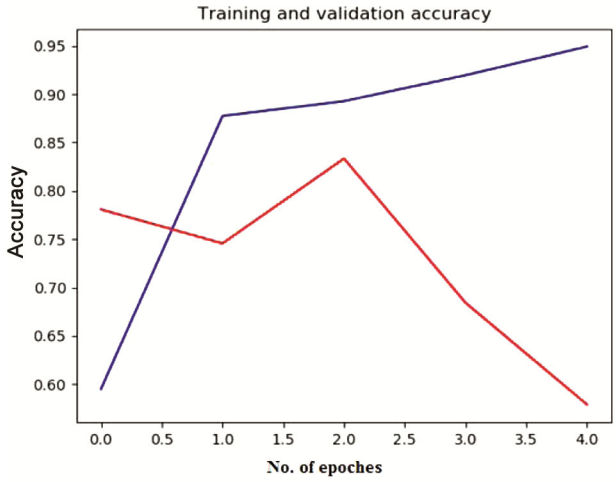


Fig.7— Training accuracy graph of transfer learning model

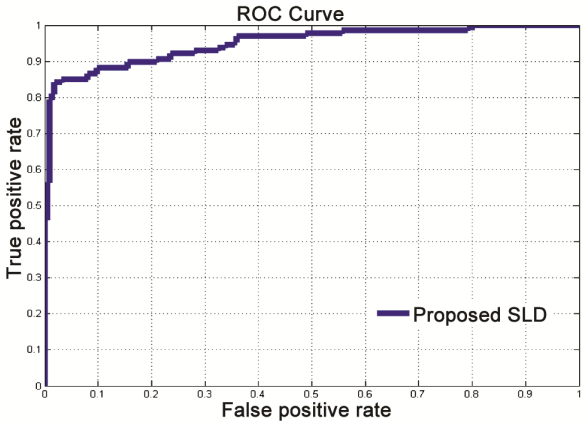


Fig. 8 — ROC Curve of Proposed SLD

The segmented binary mask is trained using U-net model for about 300 epochs which produces 69.4% accuracy and validation loss 69.7% loss for training inputs.

Result Analysis of Classification Using CNN

The CNN is trained using benchmark model with added transfer learning model. The accuracy of benchmark model is shown in Table 2 for 5 epochs.

The graph for the transfer learning model is shown in the Fig. 6. The graph is plotted by taking epoch in x-axis and loss in y-axis. This graph shows a training loss value of 0.14% and a validation loss of 1.18% from the Transfer learning model for 5 epochs.

The transfer learning model utilizes the weights obtained from benchmark model. A training accuracy of 0.94% is obtained using Inception v3 model as shown in Table 3.

The accuracy graph of the transfer learning model is shown in the Fig. 7. The graph shows accuracy 0.57% at validation phase and training accuracy of 0.94% from the Transfer learning for 5 epochs.

The final weights obtained from the fine tuning model obtained an accuracy of 95.7% for the training datasets as shown in Table 4. The overall accuracy of the proposed CNN method for skin disease is shown in Table 5.

The predicted true or false positive and negative values obtained by applying confusion matrix for the proposed Skin Lesion Diagnosis System is shown in Table 6

The predicted performance values for the proposed Skin Lesion Diagnosis System is shown in Table 7.

The performance can be examined by observing the ROC Curve shown in the above Fig. 8, this curve mainly used to visualize the quality. The accuracy of

Table 1 — Performance Metrics of segmentation methods

METHOD	DSC	JSC
Existing GrabCut Segmentation	0.9089	0.8330
Proposed Skin Lesion Diagnosis System (Watershed Segmentation+U-net Segmentation)	0.9665	0.9353

Table 2 — Accuracy of benchmark model of CNN

Epoch No	Validation loss	Validation accuracy	Training loss	Training accuracy
1	0.8692	0.4607	0.6338	0.5573
2	0.7076	0.5610	0.6330	0.6073
3	0.7425	0.5393	0.7123	0.5836
4	0.8452	0.4756	0.6212	0.6146
5	0.7787	0.5169	0.6553	0.5934

Table 3 — Accuracy of Inception V3 model using transfer learning

Epoch No	Validation loss	Validation accuracy	Training loss	Training accuracy
1	0.4488	0.7807	0.9532	0.5962
2	0.5373	0.7456	0.3203	0.8774
3	0.3696	0.8333	0.2463	0.8927
4	0.7815	0.6842	0.2058	0.9190
5	1.1818	0.5789	0.1485	0.9493

Table 4 — Accuracy of fine tuning model with proposed Skin Lesion Diagnosis System

Epoch No	Validation loss	Validation accuracy	Training Loss	Training accuracy
1	0.7485	0.6180	0.1413	0.9394
2	0.6123	0.6463	0.1676	0.9295
3	0.5918	0.6854	0.1492	0.9445
4	0.6338	0.6951	0.1323	0.9541
5	0.6671	0.7079	0.1251	0.9579

Table 5 — Accuracy of CNN models for training

Models	Validation loss	Validation accuracy	Training loss	Training accuracy
Benchmark	0.7787	0.5169	0.6553	0.5934
Transfer learning	1.1818	0.5789	0.1485	0.9493
Proposed SLD model	0.6671	0.7079	0.1251	0.9579

Table 6 — Confusion Matrix of Skin Lesion Diagnosis System

N=165	Predicted benign	Predicted Malignant	
Actual benign	100	5	105
Actual malignant	10	50	60
	110	55	

Table 7— Performance Metrics

Performance metric	Equation	Relative Value (%)
Accuracy	(TP+FN)/ Total Number of Samples	0.91
Sensitivity	True Positive/ (False Negative + True Positive)	0.66
Specificity	False Positive /(False positive + True Negative)	0.66
Precision	True Positive / Predicted Yes	0.91

the proposed Skin Lesion Diagnosis System is 95% which is comparatively high than the existing traditional works.[15,19,24,25]

Conclusions

Based on the importance of early and quick melanoma diagnosis, the goal is to develop an automatic diagnosis model for melanoma classifications. It is important to examine skin lesion regions from dermoscopic images and to provide good lesion segmentation. Automatic skin cancer diagnosis is therefore a challenging task. This work provides a new methodology for segmenting skin lesions and classifying them. The skin datasets are obtained as dermoscopic images. Since the dermoscopic images are taken with increased contrast the skin lesion data set obtained as dermoscopic images are first preprocessed to limit the contrast of the dermoscopic images using CLAHE algorithm better classification. Then the lesion on skin region is segmented using a proposed method which combines with U-net segmentation model with watershed algorithm result. Then the segmented lesion region is processed and trained using Convolutional Neural Network classifier with added transfer learning models such as inception v3 and fine tuning which is used to predict the lesions. The proposed Skin Lesion Diagnosis System will provide a medical report by diagnosing image of the lesion as benign or malignant with its cancer probability rate. The SLD model has attained a better classification precision rate of 95%. The proposed Skin Lesion Diagnosis System is based on Computer-Aided-Diagnosis model. It is important to be more specific to diagnosis the diseases. For that, more tests and analysis using larger datasets are binding. The proposed system achieves only a moderate result for U-net segmentation. In future, additional models are added to the U-net architecture for better segmentation result.

References

1 Aberg P, Nicander I, Hansson J, Geladi P, Holmgren U & Ollmar S, Skin cancer identification using multi-frequency electrical impedance-a potential screening tool, *IEEE Trans Biomed Eng*, **51(12)** (2004) 2097–2102.

2 Abuzaghleh O, Barkana B D & Faezipour M, Non-invasive real-time automated skin lesion analysis system for melanoma early detection and prevention, *IEEE J Transl Eng Health Med*, **3** (2015) 1–12.

3 Rajinikanth V & Satapathy S C, Segmentation of ischemic stroke lesion in brain MRI based on social group optimization and Fuzzy-Tsallis entropy, *Arabian J Sci Eng*, **43(8)** (2018) 4365–4378.

4 Rajinikanth V, Satapathy S C, Dey N, Fernandes S L & Manic K S, Skin melanoma assessment using Kapur's entropy & level set—A study with bat algorithm, *Smart Intell Comput Appl*, (2019) 193–202.

5 Barata C, Marques J S & Rozeira J, A System for the detection of pigment network in dermoscopy images using directional filters, *IEEE Trans Biomed Eng*, **59(10)** (2012) 2744–2754.

6 Glaister J, Wong A & Clausi D A, Segmentation of skin lesions from digital images using joint statistical texture distinctiveness, *IEEE Trans Biomed Eng*, **61(4)** (2014) 1220–1230.

7 Rajesh, Classification of malignant melanoma and Benign Skin Lesion by using back propagation neural network and ABCD rule, *IEEE Int Conf Electrical, Instrumentation Commun Eng (ICEICE)*, Karur, 2017, 1–8.

8 Amelard R, Glaister J, Wong A & Clausi D A, High-level intuitive features (HLIFs) for intuitive skin lesion description, *IEEE Trans Biomed Eng*, **62(3)** (2015)820–831.

9 Kharazmi P, AlJasser M I, Lui H, Wang Z J & Lee T K, Automated detection and segmentation of vascular structures of skin lesions seen in dermoscopy, with an application to basal cell carcinoma classification, *IEEE J Biomed Health Inform*, **21(6)** (2017) 1675–1684.

10 Agarwal, Issac A, Dutta M K, Riha K & Uher V, Automated skin lesion segmentation using K-Means clustering from digital dermoscopic images, *Int Conf Telecomm Signal Process (TSP)*, Barcelona, 2017, 743–748.

11 Nezhadian F K & Rashidi S, Melanoma skin cancer detection using color and new texture features, *Artif Intell Signal Process Conf (AISP)*, Shiraz, 2017, 1–5.

12 Priya H, Anitha J & Poonima J, Identification of melanoma in dermoscopy images using image processing algorithms, *Int Conf Control Power Commun Comput Technol (ICCPCCT)*, Kannur, 2018, 553–557.

13 Pereira, Pedro M M, Rui Fonseca-Pinto, Rui Pedro Paiva, Pedro A A Assuncao, Luis M N Tavora, Lucas A Thomaz, & Sergio M M Faria, Skin lesion classification enhancement using border-line features–The melanoma vs nevus problem, *Biomed Signal Process Control*, 57, 2020, 101765.

14 Sachdev J, Shekhar S & Indu S, Melanoma screening using deep neural networks, *3rd Int Conf Converg Tech (I2CT)*, Pune, 2018, 1–5.

15 Shahin H, Kamal A, Elattar M A, Deep ensemble learning for skin lesion classification from dermoscopic images, *9th Cairo Int Biomed Eng Conf (CIBEC)*, Egypt, 2018, 150–153.

16 Thao L T & Quang N H, Automatic skin lesion analysis towards melanoma detection, *21st Asia Pacific Symp Intell Evolut Syst (IES)*, Hanoi, 2017, 106–111.

17 Singh V & NwoguI, Analyzing skin lesions in dermoscopy images using convolutional neural networks, *IEEE Int Conf Syst Man Cybernetics (SMC)*, Miyazaki, Japan, 2018, 4035–4040.

18 Xie F, Fan H, Li Y, Jiang Z, Meng R & Bovik A , Melanoma classification on dermoscopy images using a neural network ensemble model, *IEEE Trans Med Imag*, **36(3)** (2017) 849–858.

19 Yang J, Xie F, Fan H, Jiang Z & Liu J, Classification for dermoscopy images using convolutional neural networks based on region average pooling, *IEEE Access*, **6** (2018) 65130–65138.

20 Zuiderveld & Karel, Contrast limited adaptive histograph equalization, graphic gems IV, San Diego: Academic Press Professional, 1994, 474–485.

21 Orchard M T & A B, Bouman Color quantization of images, *IEEE Trans Signal Process*, **39(12)** (1991) 2677–2690.

22 Beucher S, The watershed transformation applied to image segmentation, *Scanning Microsc*, (1991) 299–314.

23 International Skin Imaging Colloboration "https://www.isdis.net/isic-project/"

24 Hameed N, Shabut A & Hossain M A , A Computer-aided diagnosis system for classifying prominent skin lesions using machine learning", *2018 10th Comutp Sci Electron Eng (CEEC)*, Colchester, United Kingdom, 2018, 186–191.

25 Lynn N C & Kyu Z M, Segmentation and classification of skin cancer melanoma from skin lesion images, *18th Int Conf Parall Distribut Comput Appl Technol (PDCAT)*, Taipei, 2017, 117–122.