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AN EFFICIENT DEEP LEARNING BASED SEGMENTATION AND CLASSIFICATION FRAMEWORK FOR SKIN LESION IMAGES

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Abstract: Skin lesion segmentation plays a significant part in the earlier and precise identification of skin cancer using computer aided diagnosis (CAD) models. But, the segmentation of skin lesions in dermoscopic images is a difficult process due to the constraints of artefacts (hairs, gel bubbles, ruler markers), unclear boundaries, poor and so on. This paper presents a new deep learning (DL) based skin lesion segmentation and classification model. The proposed model involves different stages namely pre-processing, segmentation, image enhancement, feature extraction and classification. The segmentation process is carried out using deep instance segmentation (DIS) technique. Then, the images get enhanced by removing the hair presented in the segmented lesion region. Afterwards, the features are extracted from the image using Inception ResNet v2 model. Finally, support vector machine (SVM) model gets executed to classify the images into respective classes. For examining the effective outcome of the proposed model, a detailed comparative analysis with earlier models takes place. The simulation results exhibited superior performance of the presented model under diverse aspects.

Keywords: Skincancer, Dermoscopic, Deep learning, SVM, Inception ResNet v2.

1. Introduction

At present days, skin canceris treated as a commonly occurring disease over the globe (Murugan. A et al. 2019). Various types of cancers exist namely melanoma, basal cell carcinoma, squamous cell carcinoma, intraepithelial carcinomaand so on(Gandhi, S.A.; Kampp, J. 2015). Skin of human contains three cells namely dermis, epidermis, and hypodermis. The epidermis comprises of melanocytes that generates melanin at imbalanced rate due to some reasons (Xiao, J. Et al.2021). For example, if there is the exposure of UV rays from sun for prolonged duration, then melanin gets produced. The abnormal development of melanocytes leads to melanoma refers todangerous skin cancer (Feng, J et al. 2013). By the survey of 2019 by American Cancer Society, it is measured as 96,480 novel cases of melanoma and maximum patients woulddie by this disease(Jemal, A. et al. 2019). Melanoma is referred as malignant type of cancer with the fatal rate of 1.62% compared to other cancers (Tarver, T.; 2012). Primary detection of this disease is mandatory to prolong the lifetime of a person by additional survival rate of 92% (Siegel, R et al. 2017). But, identifying the similarities among benign and malignant lesions isa complex task in predicting melanoma. It is complex to findmelanoma with naked eye and it is a challenging task even for a professional (Punj, R., et al. 2019).

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In order to overcome this complexity, a new technique has been established which is termed as Dermoscopy. This is a non-invasive imaging model which enables to view the skin surface with the help of immersion fluid and light enlarging device (Pellacani, G.; Seidenari, S 2002). It is a commonly applied image method in dermatology which has increased ability of diagnosing cancerous disease (Ali, A.-R.A.; Deserno, T.M 2012, Sinz, C et al. 2017). But, detecting melanoma with human eye may result in inaccuracy, confused solution since it is based on the experience of dermatologist (Bi, L et al. 2017). A specialist without any experience could diagnose melanoma and provide the results approximately 76% to 85% (Ali, A.-R.A.; Deserno, T.M 2012). To reduce these shortcomings involved in predicting melanoma, Computer-Aided Diagnosis (CAD) systems are required for efficient diagnosis. Four stages are involved in CAD system to find the lesion of skin: pre-processing, segmentation, feature extraction, and classification. To achieve the effective result in detection of melanoma, segmentation of lesion is a basic step in CAD. Thus, segmentation process is a problematic phase because of major variations in texture, colour, location and size of the lesion that is acquired from dermoscopic images. Besides, poor contrast of image avoids the differentiation of nearby cells. Additionally, some artefacts like air bubbles, hair, ebony frames, ruler marks, blood vessels, and color illumination tends to cause tedious segmentation of lesion.

Lesion images play a vital role in classifying melanoma. Proper classification could be performed only if the segmentation has done perfectly from the cells around. Segmentation of lesions from normal surrounding tissue and obtaining large number of features are the ingredients for accomplishing efficient diagnosis (Schaefer, G et al. 2014). Different models for segmentation have been developed for automatic segmenting of skin lesions. There are 5 types of segmenting techniques. Histogram threshold model is applied for searching threshold values to segment the lesion from surrounding cells. Unsupervised clustering techniques apply colour space properties of RGB dermoscopic images to acquire similar area.

Edge-based and region-based models considered the edge operators as well as diverse techniques to separate or combine the lesions. Active contour models apply meta-heuristic techniques, genetic algorithms and snake algorithms, etc. to partition the lesion area. The final model is supervised segmentation method. In this model, skin lesion is segmented using Decision Trees (DTs), Support Vector Machines (SVMs)and Artificial Neural Networks (ANNs) (Xie, F, Bovik, A.C 2013). A brief knowledge about these models could be attained from current reviews of segmentation process which is applied in skin lesions. Every method utilizes lower features based on pixel features. Hence, conventional segmentation methods are not capable of achieving convenient decision and disadvantages like fuzzy lesion boundaries, hair artifacts, poor contrast and alternate artifactsinvolved could not be rectified.

In recent times, Deep Learning (DL) models like convolution neural networks (CNNs)has major success in image classification process, segmentation issues andobject detection(Redmon, J et al. 2018). CNN is efficient because it is potential is learning hierarchical featuresandextractsmaximum robust features from original image. Different levels of CNN are applied in various operations like classification, segmentation, object detection and localization. Additionally, while classifying natural images, CNNaccomplish great success in different medical issues namely prediction of mitosis present in histological images, brain tumour segmentation by MR images, detecting breast cancer using mammography images. This work also utilizes DL models for segmentation and feature extraction.

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This paper presents a new deep learning based skin lesion segmentation and classification model. The presented model involves different stages namely pre-processing, segmentation, image enhancement, feature extraction and classification. The segmentation process is carried out using deep instance segmentation (DIS) technique. Then, the images get enhanced by removing the hair presented in the segmented lesion region. Afterwards, the features are extracted from the image using Inception ResNet v2 model. Finally, support vector machine (SVM) model gets executed to classify the images into respective classes. For examining the effective outcome of the presented model, a detailed comparative analysis with earlier models takes place. The simulation results exhibited superior performance of the presented model under diverse aspects.

2. Proposed method

The working process involved in the proposed model is shown in Fig. 1. As shown in figure, it comprises of two separate training phases and a testing phase. At the initial training phase, preprocessing and segmentation are carried out. In the subsequent training phase, image enhancement and feature extraction takes place. Finally, in the testing phase, classification of test images will be done. The different processes involved in this proposed work is clearly provided in Algorithms I-IV.

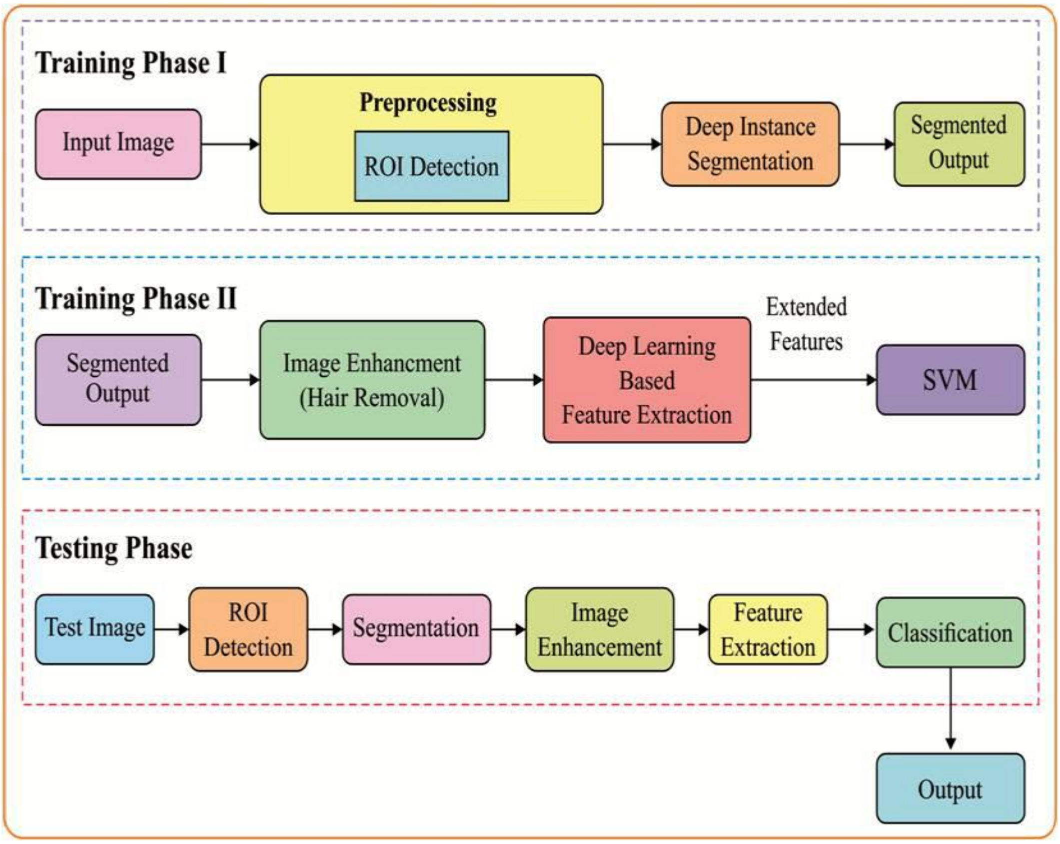

Fig. 1. Working process of proposed model

2.1. Preprocessing

The input images are pre-processed in two levels. In the first level, images which are in PNG or in any other formats will be transformed to JPEG format for further processing. Afterwards, region of interest (ROI) detection, i.e. lesion area detection process will be executed to detect the lesion region from the input image accurately. The input image database holds input images along with its corresponding ground truth images. At the pre-processing step, a bit-wise OR operation is performed between the original input image and

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ground truth image to detect the ROI accurately. Fig. 2 shows the ROI extraction process where the input and ground truth images undergo bit-wise OR operation and generates the lesion region detected image.

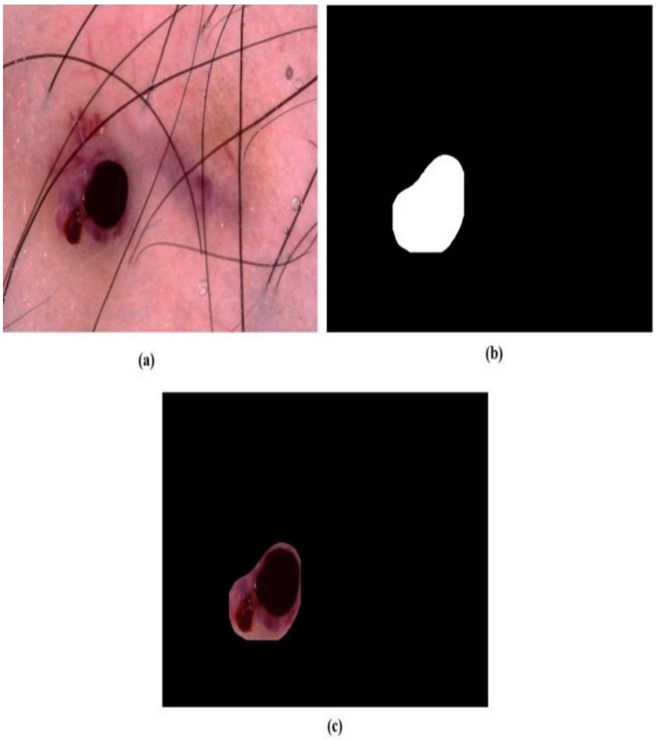

Fig. 2. ROI extraction process (a) input image,(b) ground truth image, (c) ROI extracted image

2.2. Deep Instance based segmentation (DIS) method

The main goal of segmentation involves in the portioning of image into tiny areas which is identical with respect to pixel intensity. Segmentation plays a significant role in the field of medical imaging. In order to extract features and estimate the image classification, segmentation is used effectively. The tumour classification is based on the accuracy rate that is obtained while filtering the tumour region. In this work, DIS model is applied for segmenting lesion present in the skin. This technique depends upon DL that works on the basis of Inception v2 model. The DIS technique automatically identifies the lesion region upon providing the input images with no extra processing. It is actually based on the DL based Inception model.

Inception structural developments are modified for feature elimination in CNN model. Inception v2 performs feature removal portion in order to obtain concat layer. Some merits of Inception design is that consists of significant gain from gradual increase in performance which is to estimate corresponding narrow and thick networks without executing bounding box decay (Ali, A.-R.A.; Deserno, T.M 2012). The intention of Inception design is to reduce the block as well as to build efficient performance by means of computation complexity with the help of factorization approaches. By using Inception v2, 5x5 pixel convolution layer could be reduced to 3x3 pixel convolution to improve the speed of computation. There is a correlation among current structure and ILSVRC 2012 categorized framework. Three conventional parts for35×35 is reduced by 288 filters. It could be minimized into 17 × 17 grid using 768 filters by reducing the grid. Also, it is lowered to 8 × 8 × 1280 grid with the application of grid reduction technique. At 8 × 8 level, 2 Inception areasare presented through concatenated result withfilter bank of 2048 in all surfaces. The network is combined

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to extract banks from inception parts which are named as supplementary material fixed in model.txt which is a tar-file. If network has the depth of 42 layers, then processing rate is 2.5 % better than Google Net and VGGNet should be effective than above model. At the end of this model, the segmented images from the preprocessed images will be generated.

2.3. Image enhancement

Elimination of hair is a mandatory process in dermoscopy image pre-processing step as it affects the segmentation as well as feature extraction processes. Initially, dermoscopic RGB image is transformed to grayscale. Afterwards, black top-hat transformation named asmorphological image processing is applied to the grayscale image. This technique find helpful in detecting thick and dark hairs. The result obtained from above process has major variation among closing task and incoming image:

$$Z_w(P) = P \circ b - P, \tag{2}$$

where $\circ$ indicates closing operation, P represent grayscale input image, b implies grayscale designing component. Finally, inpainting process gets executed where the pixel value of the hair line pixel is substituted with value measured based on neighbourhood pixels. Fig. 3 shows the input image and the hair-removed image.

(a) (b)

Fig. 3. Image enhancement: (a) input image, (b) hair removed image

2.4. Inception-ResNet v2 based feature extractor

For the residual version of the Inception network, simpler Inception block is employed compared to the classical Inception. Every Inception block is trailed by filter-expansion layer (1 × 1 convolution without activation) that is employed to increase the dimension of the filter bank prior to appending it to map the depthness of the input. It is required to give back the dimensionality minimization generated by the Inception block. The structure of Inception-ResNet v2 model is shown in Fig. 4.A small difference between the residual and non-residual Inception model is to utilize batch-normalization in traditional layers, but not to use in summations. If batch-normalization is applied then it should be more beneficial; thus each method has to be maintained using separate GPU. By removing batch normalization, inception block could be enhanced.

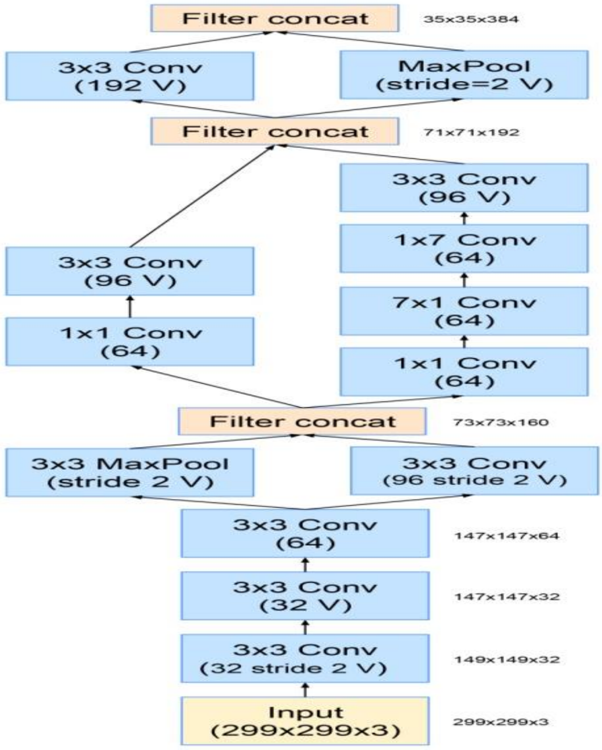

Fig. 4.Inception-ResNet-v2 network

Algorithm: Pre-processing of Proposed Method

Input: Dataset X, i=1, 2…n
Output: Pre-Processed Output
For Each X_i Є X do
Step 1: Detect Region of Interest in an Image Using Ground Truth
Step 2: Return ROI Masked Image
End For

Algorithm: Deep Instance Segmentation

Input: Dataset X, i=1, 2…n
Output: Extracted region from X_i
For Each X_i Є X do
Step 1: Compute Features Correlated with Masked Region
Step 2: Extract the Correlated Region
Step 3: Return Segmented Image
End For

Algorithm: Image Enhancement with Feature Extraction
Input: Segmented Image of X **Output:** Extracted Features **For** Each X_i Є X do

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Step 1: Convert Segmented Colour Image to Grayscale Image Step 2: Apply Morphological Operation Based on Black Top-Hat Transformation Step 3: Extract Features from the Enhanced Image using Inception ResNet V2 Step 4: Return Extracted Features **End For**
Algorithm: Classification Using SVM
Input: Extracted Features **Output:** Classified Skin Lesion Images / Validation using Confusion Matrix Step 1**:**Set Number of Samples (X), Number of Class Labels Y=7 Step 2**:For**Each X_i € X do Step 2.1: Train the Features Obtained from Feature Extraction Phase Step 2.2: Return Trained Model End For Step 3: Construct New Label Vector V for Prediction Step 4: Apply Trained Model to New Vector V_i for Prediction Step 5:Return Predicted Output and Confusion Matrix Step 6: Calculate Sensitivity, Specificity, Accuracy

2.5. SVM Classification

After the group of discriminate features have been chosen by the previous model, a classifier will be applied to classify the different types of skin lesions. SVM is a supervised learning concept utilized for data testing, model identification, classification, and regression testing. An SVM trained technique creates a concept that allocates a new example with connected class. The SVM concept is illustration of examples as views in space; a linear operation is utilized so that the instances of the separates class are divided with a clear gap.Provided a train group of example label pairs $(l_p, m_p), p = 1$,where $l_p$and

$m \in \{1,,$ the SVM needs the solution of the subsequent optimization problem:

$$\min_{w,b,\xi} \frac{1}{2} w^Z w + C \sum_{p=1}^{n} \xi_p \qquad (1)$$

$$subject\ to\ m_p\left(w^Z \phi(l_p) + b\right) \geq 1 - \xi_p$$

$$\xi_p \geq 0,$$

where training vectors are mapped into a maximum dimensional space with the function ϕ.

The SVM discovers a linear dividing hyper plane by the maximal margin in this maximum dimensional space. C is the punishment attribute of the mistake term.Also,

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$K(l_p, l_q) \equiv \phi(l_p)^z$ is known as the kernel function. We utilize the generally executed Radial Basis Function (RBF) described as

$$K(l_p, l_q) = \exp\left(-\gamma \| l_p, -l_q \|^2\right), \gamma > 0 \qquad (2)$$

During the testing process, the input test image will be segmented and the hair removal process takes place. Then, features are extracted from the image and subsequently classification process is carried out where the input images are classified into diverse classes.

3. Performance Validation

A wide range of experiments were carried out to examine the superior characteristics of the presented model. The dataset used, measures and the results are explained in the following sections.

3.1. Dataset used

For validation purposes, a benchmark skin lesion dataset is employed. A set of seven classes exist in the dataset. Besides, some of the sample test images are provided in Fig. 5. For every image present in the dataset, a corresponding ground truth image is also present.

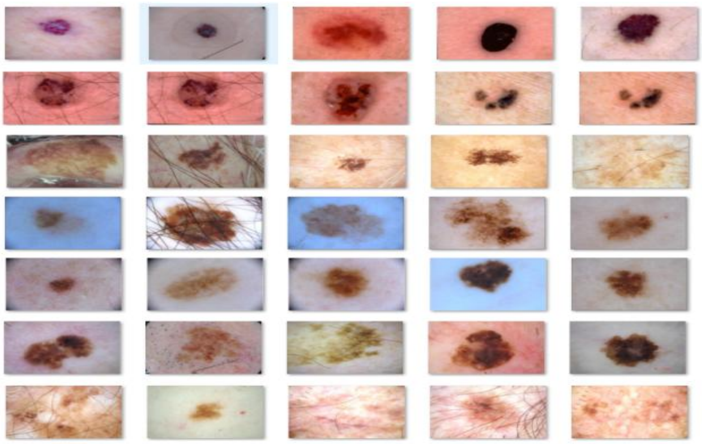
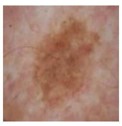
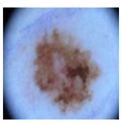
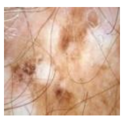
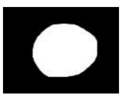
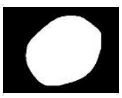
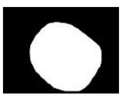


Fig. 5. Sample Test Images

3.2. Results analysis

An extensive visualization of the results attained by various subprocesses involved in the presented model is shown in Fig. 6.

Skin Cancer Classes **DIS-ResNetV2-SVM**	**Angioma**	**Basal Cell Carcinoma**	**Lentigo NOS**	**Melanoma**	**Nevus**	**Seborrheic Keratosis**	**Solar Lentigo**
Original Image							
Ground truth Image							

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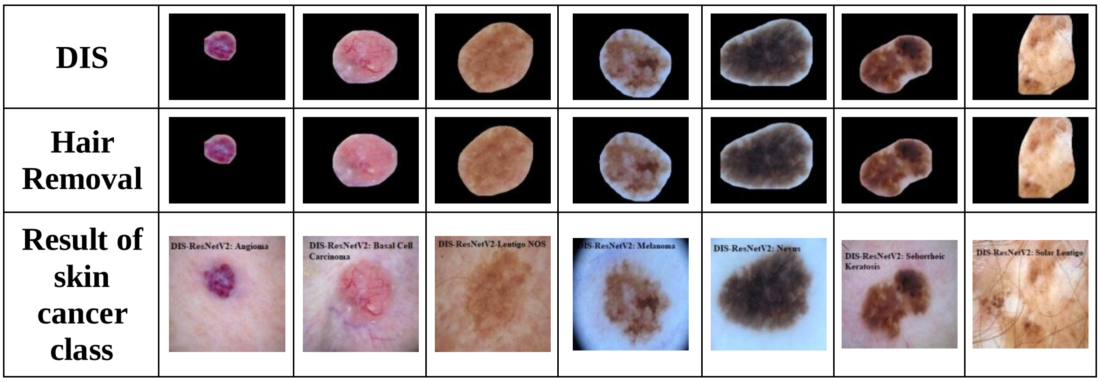

Fig. 6. Outcome of subprocesses involved in proposed model

A detailed experimental validation takes place interms of sensitivity, specificity and accuracy.

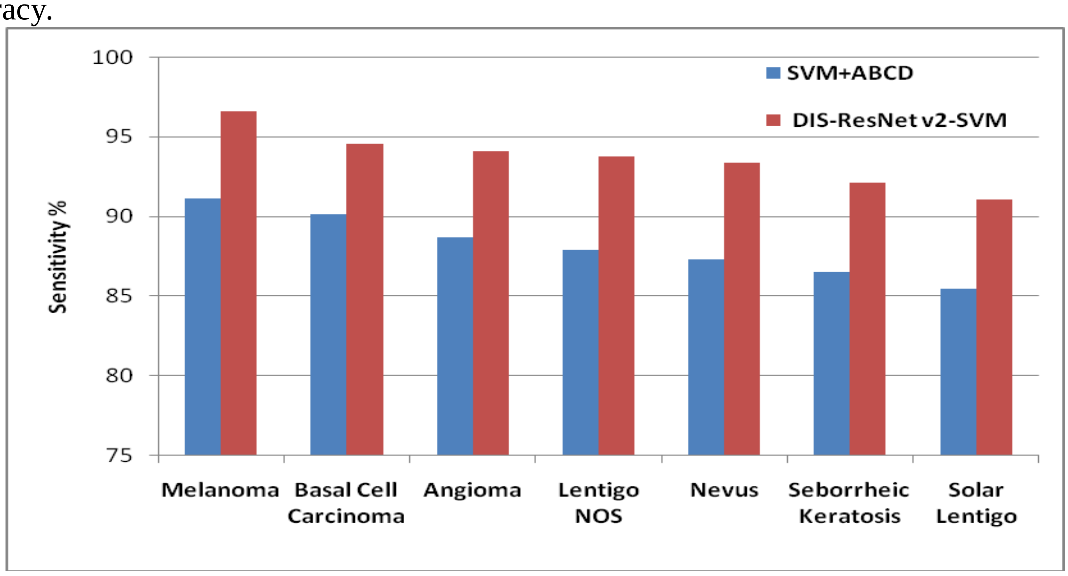

Fig.7.Sensitivity analysis of proposed model

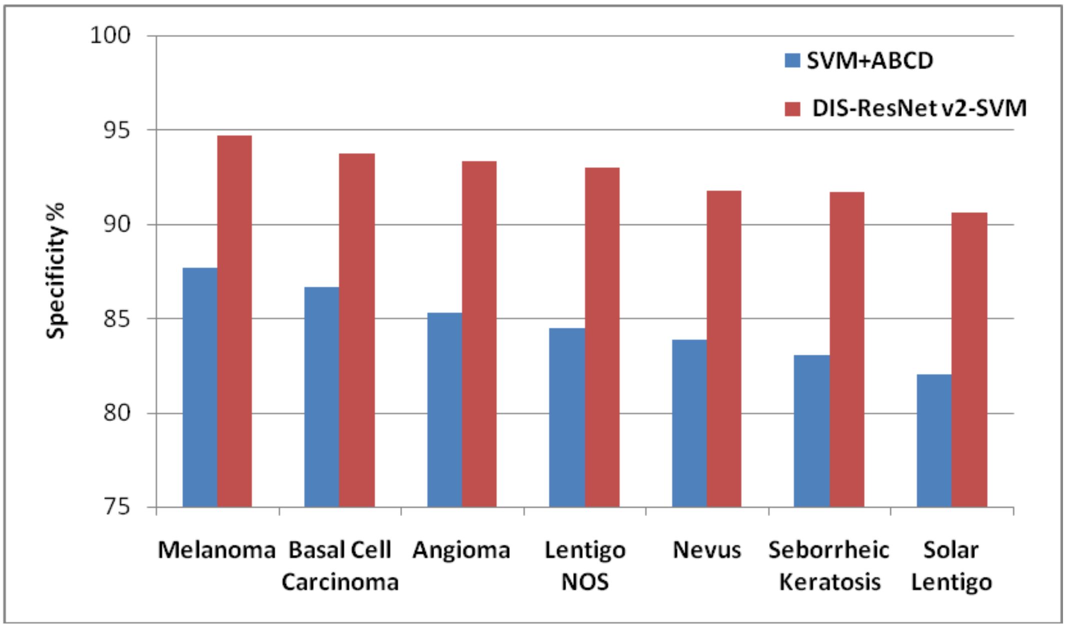

Fig.8.Specificity analysis of proposed model

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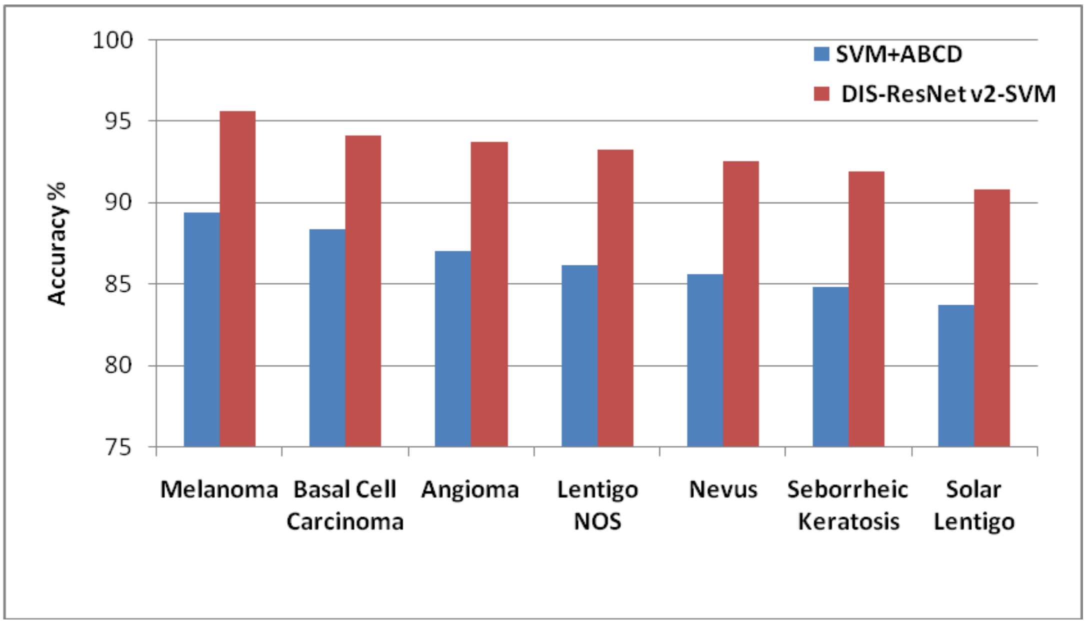

Fig. 9.Accuracy analysis of proposed model

Comparative results of the classification performance of the proposed model while classifying the seven types of skin lesion images are provided in Figs. 7-9. Fig.7 shows that the proposed DIS-ResNet v2-SVM provided 96.58% sensitivity therefore proposed DIS-ResNet v2-SVM classifier is better than SVM classifier with ABCD feature. Fig.8 shows that the proposed DIS-ResNet v2-SVM provided 94.72% specificity therefore proposed DIS-ResNet v2-SVM classifier is better than SVM classifier with ABCD feature. Fig.9 shows that the proposed DIS-ResNet v2-SVM provided 95.65% accuracy therefore proposed DIS-ResNet v2-SVM classifier is better than SVM classifier with ABCD feature.

4. Conclusion

This paper has presented a novel DL based skin lesion segmentation and classification model. The presented model operates on two training phases and a testing phase. At the initial training phase, preprocessing and segmentation using DIS method are carried out. In the subsequent training phase, image enhancement and IncpetionResNet v2 based feature extraction takes place. Finally, in the testing phase, classification of test images using SVM is done. For validation purposes, a benchmark skin lesion dataset consists of seven types of skin lesions is employed. The experimental values stated that the proposed model offered extraordinary classifier outcome with the maximum with the sensitivity of 96.58%, specificity of 94.72% and accuracy of 95.65%. The detailed simulation experiments evidently showed the superior characteristics of the presented model over the compared methods.

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