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SPECIAL SECTION ON EMERGING DEEP LEARNING THEORIES AND METHODS FOR BIOMEDICAL ENGINEERING

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Deep Semantic Segmentation and Multi-Class Skin Lesion Classification Based on Convolutional Neural Network

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ABSTRACT Skin cancer is developed due to abnormal cell growth. These cells are grown rapidly and destroy the normal skin cells. However, it's curable at an initial stage to reduce the patient's mortality rate. In this article, the method is proposed for localization, segmentation and classification of the skin lesion at an early stage. The proposed method contains three phases. In phase I, different types of the skin lesion are localized using tinyYOLOv2 model in which open neural network (ONNX) and squeeze Net model are used as a backbone. The features are extracted from depthconcat7 layer of squeeze Net and passed as an input to the tinyYOLOv2. The propose model accurately localize the affected part of the skin. In Phase II, 13-layer 3D-semantic segmentation model (01 input, 04 convolutional, 03 batch-normalization, 03 ReLU, softmax and pixel classification) is used for segmentation. In the proposed segmentation model, pixel classification layer is used for computing the overlap region between the segmented and ground truth images. Later in Phase III, extract deep features using ResNet-18 model and optimized features are selected using ant colony optimization (ACO) method. The optimized features vector is passed to the classifiers such as optimized (O)-SVM and O-NB. The proposed method is evaluated on the top MICCAI ISIC challenging 2017, 2018 and 2019 datasets. The proposed method accurately localized, segmented and classified the skin lesion at an early stage.

INDEX TERMS YOLOv2, ant colony optimization, squeeze Net, ResNet-18, SVM, ONNX.

I. INTRODUCTION

Skin cancer is a more aggressive and common in human beings. It's caused due to abnormal cells growth. These cells are developed through mitosis and replicate themselves. Melanoma is caused due to anomalous cell growth; these cells replicate themselves by migrating from bloodstream to other body organs and also infect the adjacent skin tissues. The basement membrane provides protection for epidermis. Cancerous cells grow and bypass the basement membrane and spread into the inner skin layers. Melanocytes create brown pigment known as melanin. Melanin is a protective pigment, which provides protection to the skin from ultra-violet rays. Skin cancer is commonly caused to those peoples who play or work outside and it is typical amongst sunbathers. Fair-skinned peoples are mostly affected by skin cancer due to less melanin production. However, skin cancer may also develop in dark skinned people, due to lack of exposure to sunlight [1]. From 2008- 2018 current news depicted that, 53% rise in new melanoma cases are diagnosed yearly [2], [3]. In the next 10 years the death rate of this disease is estimated to increase. If treated in later stages, less than 14% survival rate of this disease [4], [5]. Therefore, diagnosis of skin cancer at an earlier stage is necessary

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and a challenging task. The classified dermatologists mostly pursuits a sequence of steps for skin cancer diagnosis, first of all they do observation of suspected lesions with an naked eye, then microscopically magnifying lesions and monitored by biopsy. This is a time-consuming task and the patients are diagnosed too far ahead. Depending on the ability of the clinician, correct diagnosis/treatment is subjective. Dermatologists diagnose the skin lesion having accuracy less than 80% [6]. In health care centers, there are not many professional doctors available all around the world. Therefore computerized methods are implemented so far for detection of the skin cancer [7]. The machine learning algorithms such as decision tree [8] Bayesian classifiers [9], and SVM [10] are used to classify different grades of the skin cancer. However, accurate skin cancer detection still a intricate task due to several factors such as variability in texture, shape, color and size of the lesion, poor contrast/brightness, light/dark hairs, and irregular/unclear lesion boundaries. The optimized features extraction/selection is also a challenging task for accurate classification [11]. To overcome these challenging tasks, this article investigates a new methodology for the detection of eight types of skin cancer such as MN, BCC, AK, NV, BKL, DF, VL, and SCC. The foremost contribution steps are opted for accurate detection is as follows:

- YOLOv2-SqueezeNet model is used for localization of the infected region with locations, class label as well as prediction scores.
- The localized affected region is segmented using modified 13-layers semantic segmentation model.
- Deep features are extracted and selected using ResNet-18 and ACO respectively. The resultant features vector is passed to the O-SVM and O-NB for skin lesions classification.

II. RELATED WORK

Recently much work is carried out for discrimination of different kinds of skin lesions, some of which are discussed in this section [12]. Skin lesions are detected in four major steps i.e., preprocessing, segmentation, features extraction and finally classification. During image acquisition, dermoscopic images having certain artifacts such as thin/thick hair, low contrast image resolution, dark spots/bubbles around the infected skin region and irregular lesion boundary that ultimately minimize accuracy of skin lesion detection. To handle these challenging tasks preprocessing help in accurate detection of the skin lesion [13]. The high pass filter is used to highlight the edges; further illumination is removed by homomorphic filter [14]. Segmentation is a crucial step, provides significant information about lesion such as border, shape, asymmetry and the irregularity [15]. Morphological filtering with weight based features selection approach is used for detection of lesion boundary [16]. Star shape semantic segmentation method is used for skin lesion segmentation [17]. ABCD rule-based approach is used for skin lesion detection. In which total dermoscopic scores are also measured on the basis of asymmetry, lesion diameter and color [18]. Feature extraction is a third major step to extract meaningful information from the input images based on the certain characteristics such as shape, color and texture. However, best features selection is also a challenge for improved classification [18]. Hence after GLCM features extraction, GA is applied for the selection of optimum features [19]. PCA and PSO are also used for the selection of active features vectors [20]. After features extraction, classification is done to discriminate the affected skin region into benign/malignant. The KNN, decision tree [21] and SVM [22] are used for skin lesions classification. Deep learning methods [23]–[25] are mostly utilized for skin lesions detection [2]. Esteva et al developed GoogLeNet and Inception V3 CNN models for skin cancer classification. AlexNet [26] model is applied on the dermoscopic images to learn the pattern of the skin lesion. The extracted features pattern in the form of vector is passed to the multiclass SVM for discrimination among the healthy and infected skin region. Deep full resolution convolution network (DFRCN) with softmax layer [27] is used for classification of skin lesion.

III. PROPOSED METHODOLOGY

The proposed deep learning appraoch for skin lesion detection as shown in Fig 1, where ONNX [28] and squeeze Net [29] models are used as backbone of the YOLOv2 [30] model to localize the skin lesions more accurately. The semantic segmentation model is trained based on ground truth annotations to perform pixel wise classification. Later deep features are extracted using ResNet-18 model. The optimized features are selected using ACO which passed to the O-SVM [31] and O-NB [32] classifiers.

A. LOCALIZATION OF SKIN LESIONS

YOLOV2-squeezeNet model is proposed for localization of the actual skin lesions. In this model, pre-trained squeezeNet is used as a backbone of the open neural network (ONNX) model. The squeezeNet contains 68 layers such as 01 input, 26 convolutional, 26 ReLU, 03 maxpooling, 08 depth concatenation, 01 drop out, 01 average pooling, softmax and classification. The input images size of $300 \times 300 \times 3$ are used to train the network. The features are extracted from depth concatenation 'fire7-concat' layer of the squeezeNet model and passed as an input to the YOLOv2. YOLOv2-squeezeNet is trained on the selected hyperparameters as mentioned in Table 1.

TABLE 1. YOLOv2-SqueezeNet configuration parameters.

Number of Classes	08
Anchors	[43 59 18 22 23 29 84 109]
Rate of learning	0.001
Size of mini-batch	16
Number of Epochs	200
Verbose Frequency	30

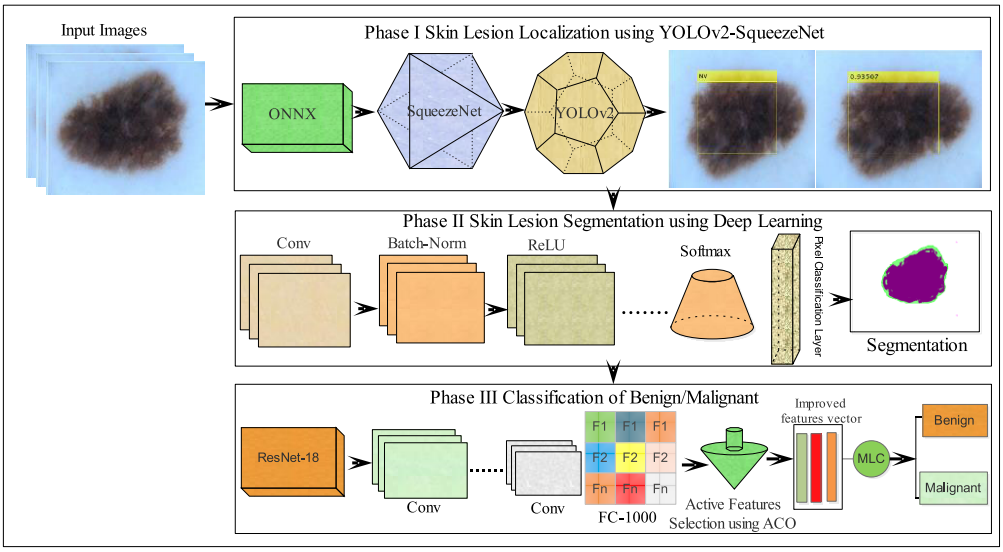

FIGURE 1. Proposed model architecture where MLC denote Machine learning classifier).

YOLO loss is computed into three major categories such as localization, confidence and classification. Localization loss computes the error between actual and predicted bounding box. While, confidence loss is measured through addition of the confidence scores when skin lesions are detected and when it is not detected in a bounding box of a grid cell. Whearse, classification loss compute squared error among conditional class probabilities for each class in the grid cell. The YOLO loss function is computed as shown below:

$$\begin{aligned}\text{Loss} = {} & A_1 \sum_{i=0}^{G^2} \sum_{j=0}^{B} 1_{ij}^{\text{Malignant}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] \\ & + A_1 \sum_{i=0}^{G^2} \sum_{j=0}^{B} 1_{ij}^{\text{Malignant}} \\ & \times \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right] \\ & + A_2 \sum_{i=0}^{Gl^2} \sum_{j=0}^{B} 1_{ij}^{\text{Malignant}} (s_i - \hat{s}_i)^2 \\ & + A_3 \sum_{i=0}^{G^2} \sum_{j=0}^{B} 1_{ij}^{\text{Benign}} (s_i - \hat{s}_i)^2 \\ & + A_4 \sum_{i=0}^{G^2} 1_i^{\text{Malignant}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2 \end{aligned} \tag{1}$$

where, G, B, h, w, p, and s denotes number of grid cells, number of the bounding box, height, width, probability, and confidence scores, respectively. The localization and classification losses are controlled using weight parameters A_1 and A_4, respectively. Similarly, A_2 and A_3 control the confidence loss.

The variable with hat denote ground truth value in i^{th} grid cell. Whereas, the variable without hat and subscript i represent value of j^{th} bounding box in i^{th} grid cell. (x_i, y_i) and $(\hat{x}_i, \hat{y}_i)$ represent the center points of j^{th} bounding box and ground truth with respect to i^{th} grid cell, respectively. Skin lesions are localized using proposed YOLOV2-squeezeNet as shown in the Fig 2.

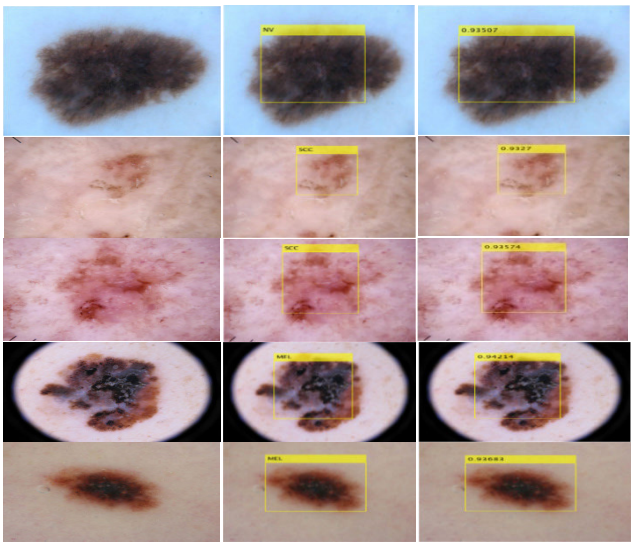

FIGURE 2. Localization results (a) input images (b) localized with class labels (c) localized with predicted scores.

B. SEGMENTATION OF SKIN LESIONS

In this work, 13-layer semantic segmentation model is proposed. The segmentation model consists of four blocks that are illustrated in Figure 3.

The dilated convolution layer might increase receptive field of layer without increase the number of the parameters or the computations. Therefore, in this model, two dilation convolution layers having dilation factor 1 and 2 are used.

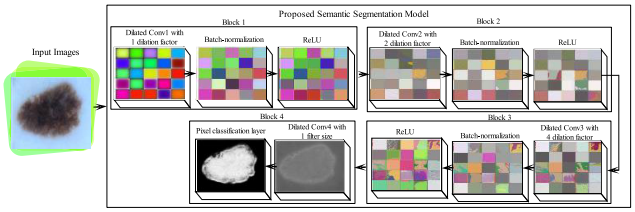

FIGURE 3. Proposed semantic segmentation model with activation units.

In which 3 × 3 filter size convolutional layer and pads the input size is same to the output size through setting [1111] padding option.

Two batch-normalization layers are used among the convolution and the ReLU layers to normalize the input x_i by measuring the μ_B and σ_B^2 over the mini-batch size to speed up the CNN training and also minimize the sensitivity of the network initialization.

The normalize activations are defined as:

$$\hat{x_i} = \frac{x_i - \mu_B}{\sigma_B^2 + e} \tag{2}$$

In the decoder section dilated convolution layer with 4 dilated factors is used. The last convolutional layer is applied with 1 × 1 filter size to squeeze down the number of channels related to the class labels. The mini-batch size of the proposed model is 16. The model is trained on maximum 300 epochs, with 1e-3 learning rate. The layered architecture of the segmentation model for training is mentioned in Table 2. The segmented lesion region is shown in Fig 4.

TABLE 2. Layered Architecture of the segmentation model.

Layer	Activation
Input image	300 × 300 × 3
Convolutional 1	300 × 300 × 32
Batch-normalization 1	300 × 300 × 32
ReLU1	300 × 300 × 32
Convolutional 2	300 × 300 × 32
Batch-normalization 2	300 × 300 × 32
ReLU2	300 × 300 × 32
Convolutional 3	300 × 300 × 32
Batch-normalization 3	300 × 300 × 32
ReLU3	300 × 300 × 32
Convolutional 4	300 × 300 × 2
Softmax	300 × 300 × 2
Pixel classification	-

C. CLASSIFICATION OF DIFFERENT KINDS OF SKIN LESIONS

In medical domain, different types of disease classification using machine learning approaches are helpful for medical specialists. The computerized approaches more computationally exhaustive due to increase the number of the patients slices. The deep convolutional neural networks perform better on large number of the input data as compared to classical methodologies [33]. In deep learning methodologies, features are extracted from input and integrated into single matrix to improve the performance. In this article, ResNet-18 model is applied for features extraction. The ResNet-18 model consists of 71 layers such as 01 input, 20 convolutional, 20 batch-normalization, 17 ReLU, 08 addition, 01 maxpooling, 01 average pool, fully connected (FC), softmax and classification. The extracted features are mapped using cross-entropy activation function that is defined as:

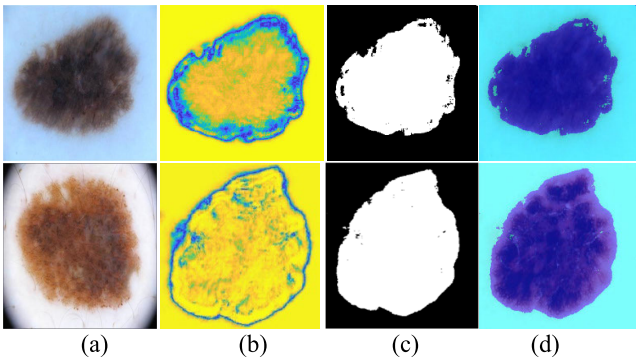

FIGURE 4. Shows lesion segmentation (a) input images (b) contour (c) binary segmentation (d) annotated lesion region.

$$H_C(f_i, L) = -\sum_c^C P_{(o,L)} LOG(P_{(o,L)}) \tag{3}$$

where P denote probability, f shows features vector, L represent class labels, o denote observation over the class.

Cross-entropy activation function is applied separately on training and testing images. The training and testing ratio is selected 50/50 that return two features vectors as output. Later active deep features are selected using ACO. The active selected features vector f_i fed to the O-SVM and O-NB for classification of different catagories of the skin disease. The features extraction/selection process for classification is visually presented in the Fig 5.

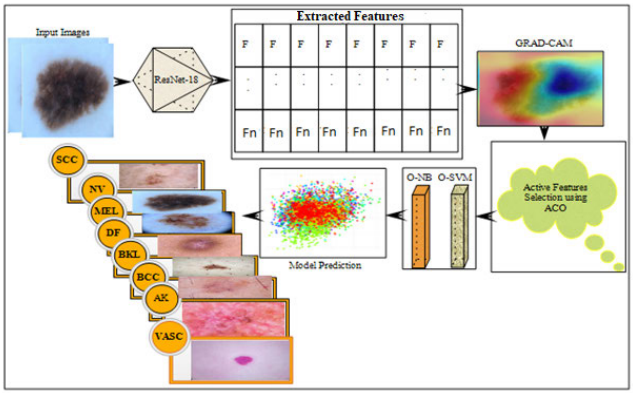

FIGURE 5. Classification using selected extracted features.

D. FEATURES ENGINEERING AND CLASSIFICATION

The features vectors are obtained in the previous section, in which prominent features selection from the pool of the features vectors is a challenging task. Therefore in this article features engineering is performed based on ant colony optimization [34]. ACO is a computational approach is utilized for problem optimization. In which problem is optimized by finding shortest path based on the phromone and heuristic exponential weights. The features vector length 1000 is passed to the ACO to find out the active deep features based on optimized cost function. In this approach features are optimized using selected parameters as mention in Table 3. The best cost function is graphically shown in Fig 6.

TABLE 3. Parameters of ACO.

Maximum iterations	20
Ants (size of population)	10
Phromone initial	1
Exponential weight phromone	α=1
Exponential weight heuristic	β=1
Rate of Evaporation	$\rho = 0.05$

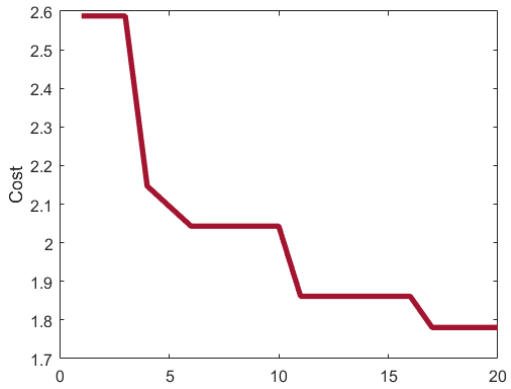

FIGURE 6. Best cost function using ACO.

Later optimized features vector is passed to the O-SVM and O-NB classifiers. The selected classifiers are optimized on 30 epochs for model training as graphically shown in Fig 7.

IV. MATERIAL FOR PERFORMANCE EVALUATION

The proposed method performance is evaluated on three latest challenging ISIC 2017 [35], 2018 [36] and 2019 [37] datasets. ISBI 2017 dataset having 2,750 images with two classes (2233 benign and 517 malignant).

The ISIC 2018 segmentation dataset contains 12,500 images with ground truth annotations. ISBI classification dataset contains 10,015 images with seven skin cancers classes such as Dermatofibroma (Der), Nevus(Nev), Melanoma(Mel), Pigmented Benign(Pig-Be), Keratoses(Ker), Pigmented Bowen's(Pig-Bo), Vascular and Basal Cell Carcinoma (BCC). ISBI 2019 dataset contains 25,331 images with 08 classes such as MN, BCC, AK, BKL, NV, DF, VL, and SCC. In this work ISBI 2019 training data is used for classification of the different types of the skin lesions. The ISIC 2020 dataset contains 33,126 training images of up to 2000 patients with 2 different classes such as benign and malignant [38]. The description about the dataset is mentioned in the Table 4.

TABLE 4. ISBI 2019 dataset description.

Types of the skin lesions	Total slices	Total slices after rotation
Melanocytic (MEL)	4522	4522
NV	12875	12875
BCC	3323	3232
AK	867	3470
BKL	2624	3200
DF	239	3232
VASC	253	2240
SCC	628	3200
Total number of images	**25331**	**35971**

In Table 4, second column shows total skin lesion slices that are already available in dataset. To increase the size and complexity of dataset, the rotation is applied with different angles such as 30°, 60°, 90°, 120°, 180°, and 270°. In this process we observe that number of images of MEL and NV are sufficient as compared to other types of the lesions. Therefore, we used number of images of MEL and NV without augmentation for experimentation. The 25331 slices are available but after the rotation with different angles numbers of slices are increased up to 35971. Three experiments are implemented to compute the proposed method performance on MATLAB 2020a toolbox with 740K Nvidia Graphic Card.

A. EXPERIMENT #1 LOCALIZATION OF THE SKIN LESIONS

In this experiment, YOLOv2-squeezeNet model is applied to localize the skin lesions with class labels as well as predicted scores. The model performance is evaluated with different performance measures such as average precision, Recall, IoU and average log miss rate (am) as mentioned in the Table 5.

TABLE 5. Performance evaluation of the proposed localization method.

ISIC Datasets	mAP	am	IoU
2017	0.95	0.50	0.92
2018	0.96	0.40	0.93
2019	1.00	0.00	0.94
2020	0.94	0.60	0.91

The localization results in the Table 5 shows that, methods achieved mAP of 0.95 on ISBI 2017, 0.96 on ISBI 2018, 1.00 on ISBI 2019 and 0.94 on ISIC 2020 datasets. The graphical representation of the mAP with respect to am and IoU is shown in the Fig 8.

The localization results with respect to the class labels and predicted scores are also visually shown in the Figure 9.

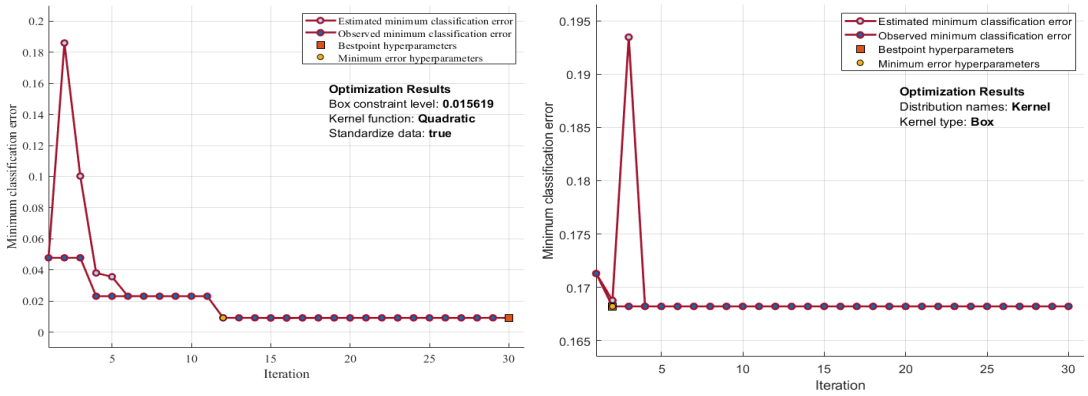

FIGURE 7. Graphically representation of classifiers training (a) O-SVM (b) O-NB.

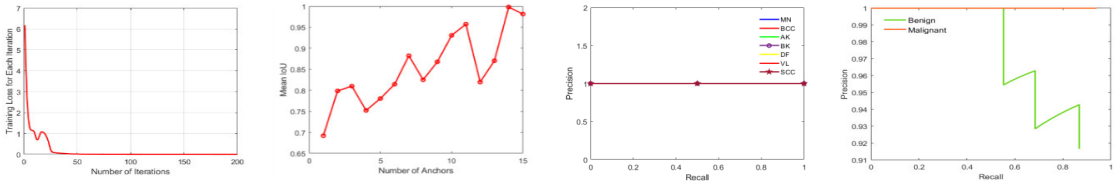

FIGURE 8. Graphically representation of the localization results (a) training loss (b) mean IoU/number of anchors (c) mAP of 8 classes of the skin lesions (d) mAP of two classes (benign and malignant).

B. EXPERIMENT #2 PIXEL BASED CLASSIFICATION

In this experiment, localized infected region is segmented using proposed segmentation model. The segmentation results are also evaluated with pixel by pixel with ground truth annotations in term of performance measures such as IoU, and accuracy as mentioned in Table 6.

TABLE 6. Segmentation results of the proposed method.

Dataset	Global ACC	Mean ACC	IoU (Mean)	IoU (Weighted)	BF Score (Mean)
ISBI 2017	0.93	0.94	0.80	0.83	0.85
ISBI 2018	0.95	0.92	0.87	0.86	0.89

The segmentation result in Table 6 shows that, a proposed segmentation method achieves global accuracy of 0.93 on ISBI 2017 and 0.95 on ISBI 2018. Whereas, in this experiment, mean accuracy of 0.94 and 0.92 on ISBI 2017-2018 datasets respectively. The segmented skin lesions are visually shown in Fig 10.

C. EXPERIMENT #3 CLASSIFICATION OF DERMOSCOPIC IMAGES INTO DIFFERENT CATEGORIES

This experiment is performed to classify the skin lesions into different catagories such as AK, MEL, SCC, BCC, BKL, NV, VL, and DF. In this experiments deep features vectors are extracted by cross entropy activation function using ResNet-18 model. The optimum features are selected using ACO. The selected features vector is obtained after applying the ACO, fed to machine learning classifiers with 0.5 hold out cross-validation approach. The proposed method classify the input images into benign/malignant on ISBI2017, 2020 datasets, 7 and different categories on ISBI-2018, ISBI-2019 datasets respectively. The classification results with corresponding classes are plotted in the form of confusion matrix as shown in Figure 11.

The discrimination outcomes are computed using different metrics as mentioned in the Table 7-15.

TABLE 7. Classification results on ISBI-2017 using O-SVM.

Total accuracy 97.8%				
Classes	ACC	PPV	Recall/Sensitivity	F1Score
Benign	97.89%	0.99	0.98	0.98
Malignant	97.89%	0.96	0.98	0.97

TABLE 8. Classification results on ISBI-2017 using O-NB.

Total accuracy 99.1%				
Classes	ACC	PPV	Recall	F1Score
Benign	99.03%	1.0	0.99	0.99
Malignant	99.03%	0.98	0.99	0.99

The classification results in Table 7-15, shows that, proposed method classifies the input images into two classes

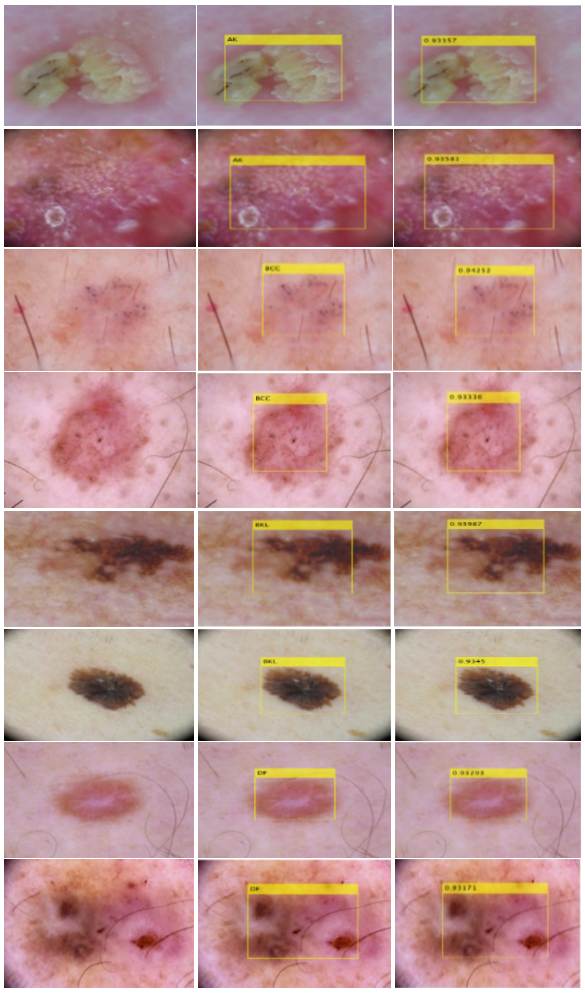

FIGURE 9. Localization of different types of skin lesions (a) input images (b) localized lesion region (c) predicted scores.

TABLE 9. Classification results on ISBI-2018 using O-SVM.

Total accuracy 97.9%				
Classes	ACC	PPV	Recall	F1Score
Der	99.09%	0.97	0.98	0.97
Nev	99.96%	1.0	1.0	1.0
Mel	99.64%	1.0	0.98	0.99
Pig- Be	98.81%	0.97	0.95	0.96
Ker	99.13%	0.95	0.96	0.96
Pig- Bo	99.21%	0.96	0.98	0.97
BCC	99.96%	1.0	1.0	1.0

benign and malignant on ISBI 2017, ISIC 2020 datasets, however, it classify the images into seven and eight classes on ISBI 2018 and 2019 datasets respectively.

The proposed method result in term of accuracy is 97.8%, 99.1% on ISBI 2017 dataset and 99.07%, 83.18% on ISIC 2020 dataset using O-SVM and O-NB respectively. Similarly, 97.9% and 98% accuracy achieved on ISBI 2018 dataset

TABLE 10. Classification results on ISBI-2018 using O-NB.

Total accuracy 98 %				
Classes	ACC	PPV	Recall	F1Score
Der	99.3%	0.95	0.98	0.97
Nev	99.93%	1.0	1.0	1.0
Mel	99.51%	1.0	0.98	0.99
Pig- Be	98.95%	0.98	0.97	0.98
Ker	99.23%	0.94	0.96	0.95
Pig- Bo	99.16%	0.95	0.97	0.96
BCC	99.93%	1.0	0.99	1.0

TABLE 11. Classification results on ISBI 2019 using O-SVM.

Total accuracy 98.1%				
Classes	ACC	PPV	Recall	F1Score
AK	99.52%	0.98	0.99	0.99
BCC	99.82%	1.0	0.99	0.99
BKL	99.85%	1.0	0.99	1.0
DF	99.36%	0.98	0.98	0.98
MEL	99.44%	0.99	0.97	0.98
NV	99.66%	0.99	0.97	0.98
SCC	99.39%	0.95	0.97	0.96
VASC	99.55%	0.96	1.0	0.98

TABLE 12. Classification results on ISBI 2019 using O-NB.

Total accuracy 97.1%				
Classes	ACC	PPV	Recall	F1Score
AK	99.51%	0.98	0.99	0.99
BCC	99.8%	1.0	0.98	0.99
BKL	99.4%	1.0	0.97	0.98
DF	99.32%	0.98	0.97	0.98
MEL	99.02%	0.96	0.97	0.96
NV	99.59%	0.98	0.97	0.97
SCC	99.38%	0.95	0.97	0.96
VASC	99.56%	0.96	1.0	0.98

TABLE 13. Classification results on ISIC-2020 using O-SVM.

Total accuracy 99.07%				
Classes	ACC	PPV	Recall/Sensitivity	F1Score
Benign	99.07%	1.0	0.98	0.99
Malignant	99.07%	0.98	1.0	0.99

TABLE 14. Classification results on ISIC-2020 using O-NB.

Total accuracy 83.18%				
Classes	ACC	PPV	Recall	F1Score
Benign	83.18%	0.89	0.83	0.86
Malignant	83.18%	0.74	0.83	0.78

using O-SVM and O-NB classifiers. The 98.1% and 97.1% accuracy is achieved on ISBI-2019 dataset using O-SVM and O-NB classifiers respectively.

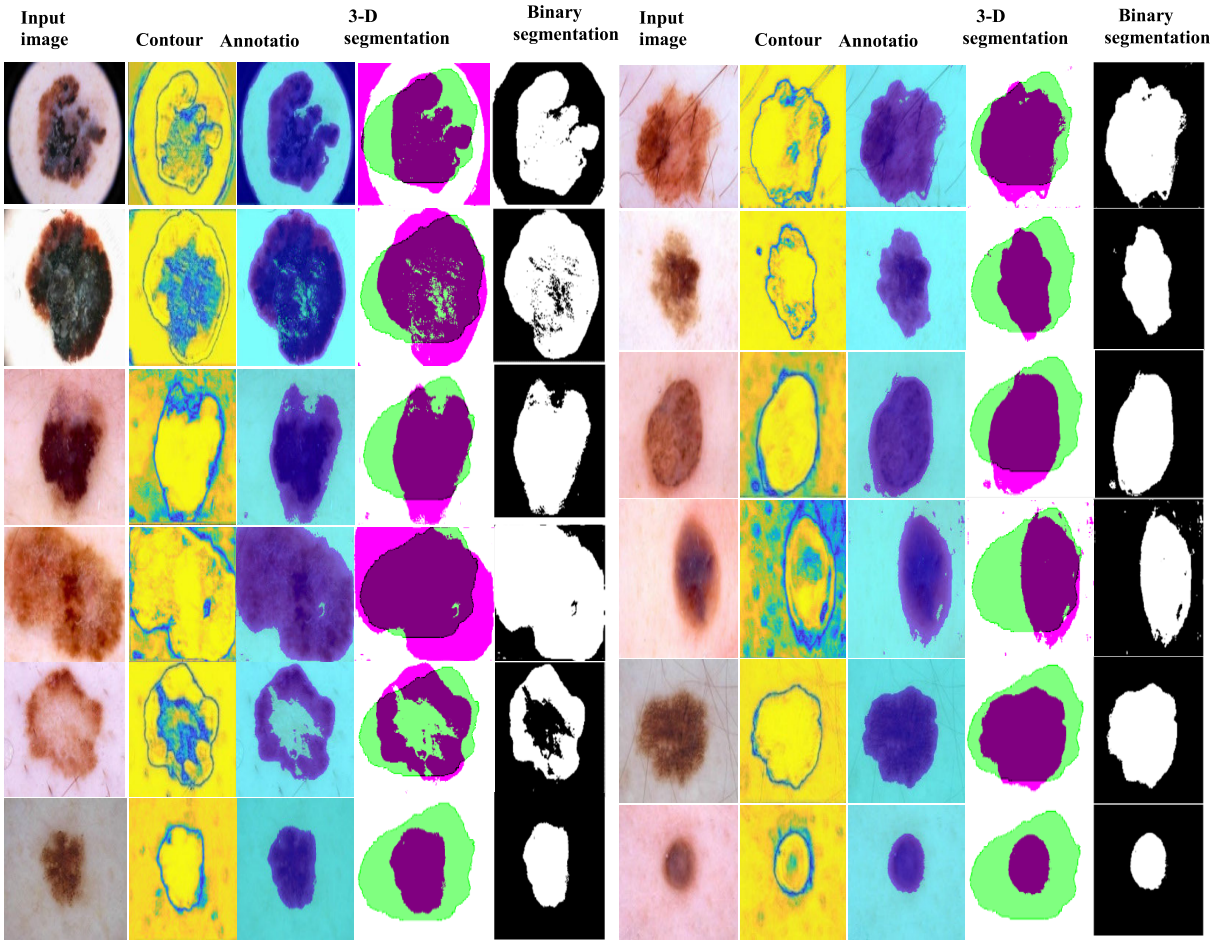

FIGURE 10. Proposed method segmentation results.

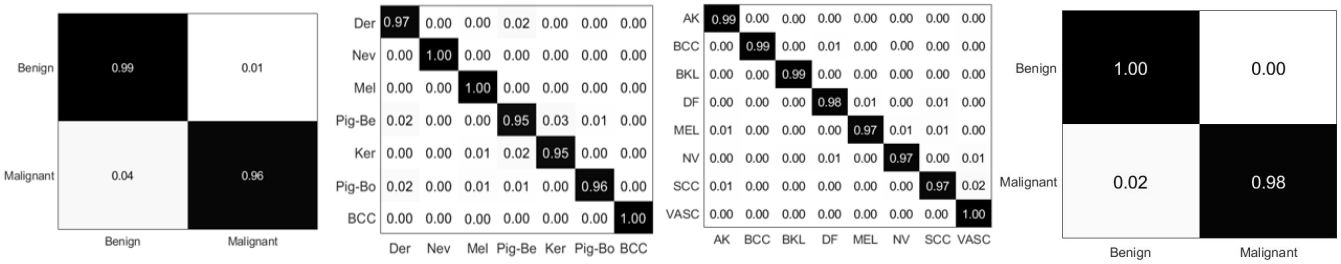

FIGURE 11. Confusion matrix (a) ISBI 2017(b) ISBI 2018 (c) ISBI 2019 (d) ISIC 2020.

The quantative results comparison is performed with existing works in term of different performance metrics as mentioned in Table 15.

The classification results compared recent work [39]–[43]. The focus net model is utilized for segmentation, in which encoding layers encode the data properly that helps in the prediction of lesion segmentation. However, focus Net has less sensitive for lesion detection with 0.76 sensitivity [39]. Unet with FCN8s method is used for lesion segmentation with 0.87 sensitivity and 0.95 specificity on ISIC 2017 dataset [40]. Similarly, ensemble approach, in which combination of the transfer learning models are used for segmentation of the skin lesions with 0.76 validation score [41]. Another existing method used pre-trained model i.e., DenseNet-201, ResNet-50, Inception-v3, Inception-ResNet-v2 models with are used with FrCN for detection of the skin lesions with 0.88 accuracy [42]. Transfer learning models such as VGG16, Densenet201, InceptionResNetV2,

TABLE 15. Existing method comparison.

Ref	Dataset	Year	Results
[39]	ISBI 2017	2019	76% Sensitivity
[40]		2020	87% Sensitivity, 95% Specificity
[41]	ISBI 2018	2019	0.76 Validation score
[42]		2020	88% Accuracy
[43]	ISBI 2019	2020	94.92% Accuracy
Proposed Method			99.1% Accuracy on ISBI 2017 , 98.0% Accuracy on ISBI 2018 and 98.1% on ISBI 2019 Accuracy

Google net is used for skin lesion detection on ISBI 2019 dataset with 94.92% accuracy [43].

In this work, two proposed end to end deep models i.e., YOLOv2-SqueezeNet and 3-D semantic segmentation model are fine-tine by the selected configuration parameters that provide accurate localization and segmentation of lesion region. Furthermore, data augmentation is implemented to balance the slices of the different kinds of lesions. After data augmentation, deep features are extracted using cross entropy function and optimum features are selected using ACO. The data augmentation approach with optimized features vector provides higher classification accuracy. The proposed method achieves up to 98% accuracy on ISBI 2018, 2019 and 99% accuracy on ISBI 2017 datasets.

The results comparison, prove that proposed work performed better as compared to latest work published.

V. CONCLUSION

In this research, ensemble CNN models are proposed for skin lesion detection. In the localization method, ONNX and squeeze Net model is used as a backbone of the YOLOv2 model. In addition, depthconcat7 layer is passed as an input to YOLO model. The method localizes the infected skin lesion more accurately. The method achieves mAP of 0.95, 0.96, 1.00 and 0.94 on ISBI 2017, ISBI 2018, ISBI 2019 and ISIC 2020 datasets respectively. The 3D-segmentation method is also proposed based on CNN. The configuration parameters of the segmentation model are selected after the extensive experiment for accurate lesion segmentation. The segmentation method achieves Global Accuracy of 0.93, 0.95 on ISBI 2017, and ISBI 2018 respectively. The skin lesion classification is performed by applying ResNet-18 model and deep features are extracted by cross entropy activation function. Later, extracted features vectors are enhanced by using ACO method. The hybrid classification approach provides good classification results compared to the recent existing work. In future this work, further enhance to apply the re-enforcement learning for accurately classify the skin lesion.

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