A Novel Solution of Enhanced Refinement, Localization and Extraction using Deep Learning for Melanoma Segmentation and Detection.

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***Abstract*—To detect malignant melanoma which is a prominent form of skin cancer, deep Learning has not implemented measures to fully eliminate undesired artefacts from the skin lesion images neither incorporated adequate regression targets for precise lesion region localization. Similarly, pixel width and height information are left unconsidered in the activation function for melanoma detection. This research aims to lower the cases of false negatives in melanoma diagnosis and raise segmentation and detection accuracy. The proposed system is enhanced refinement, localization, and extraction for melanoma (ERLE). Enhanced refinement improves the image segmentation and feature recognition capability by performing the morphological operation. Lesion localization raises segmentation accuracy by minimizing lesion search space. Enhanced extraction improves accuracy by deriving information from the lesion pixel. ERLE improved the segmentation and detection accuracy by 2.27% and 2.04% than state of the art system on average. Likewise, the proposed system reduced the negative rate from state of the art 3.69% to 1.65% along with the processing time 5.05 to 4.74 seconds. The proposed ERLE system performs elimination of unnecessary artefacts from dermoscopic images for improved lesion segmentation, localizes the region of lesion in the dermoscopic images, and derives detailed pixel information for improved melanoma detection accuracy.**

Keywords—Malignant melanoma detection; Skin Lesion segmentation; Dermoscopic refinement; Lesion localization; Convolutional neural network.

I. INTRODUCTION

Dermatologists evaluated skin lesions in their patients by using visual examination assisted by hand-held dermoscopy under intense light and illumination, through either reflection or immersion solution. The ABCD (Asymmetry, Border irregularity, Color variation and Diameter property of lesion) criteria was used by dermatologists to diagnose the skin lesion and distinguish melanoma [1]. However, this manual analysis of dermoscopic images is complex, time consuming and dependent on dermatologist practice, clinical training and availability. It is also prone to diagnostic error even by an experienced dermatologist [2]. Skin lesion analysis is now performed by Deep learning methods which uses convolutional neural network (CNN) that increasingly exceeds dermatologists performance in detecting melanoma. CNNs use dermoscopic image patches to learn and execute lesion area segmentation depending on the learned model in the test pictures . The deep learning model focuses on input image pre-processing to extract features from the image and classify them to determine melanoma from non-melanoma images with higher rate of accuracy consistently in shorter period of time [3]. Skin cancer detection in the field of dermatology has been greatly enhanced by Deep learning technology [4]. Melanoma is one fatal kind of skin cancer and deep learning has the capacity to distinguish early malignant melanoma lesions from the non-malignant ones in dermoscopic images for its timely diagnosis and treatment [5]. However, to detect melanoma, deep Learning has not implemented measures to fully eliminate undesired artefacts such as non-uniform illumination, clinical gel, ink marks, air bubbles, and cutaneous elements that can affect border segmentation such as vessel lining, hairs, and skin texture from the skin lesion images, either it incorporated adequate regression targets for precise lesion region localization. Similarly, pixel width and height information are left unconsidered in the loss function which affects the recognition accuracy in melanoma detection. This research aims to raise segmentation and detection accuracy by lowering the rate of false negatives in melanoma diagnosis. To attain this goal, this study proposes integrating morphological transformation operation to along with fast local Laplacian filtering to eliminate undesired artefacts for improving the segmentation, feature extraction and subsequently melanoma detection accuracy. Secondly, regression targets are raised by narrowing down the search area around lesion for precise and robust melanoma detection. Thirdly, pixel width and height that raises the information from pixels corresponding to the skin lesion and its edges are taken into consideration in loss function as activation to improve recognition capability for melanoma.

II. LITERATURE REVIEW

Deep learning have been used to attain significant outputs in skin cancer analysis. Here we discuss the concept of deep learning in melanoma diagnosis.

A. Lesion segmentation

Nida, et al. [2] enhanced refinement and localization to detect lesion region. They offer the solution by fine tuning dermoscopic images for removal of clinical artefacts and integrating deep regional convolutional neural network (RCNN) and Fuzzy C-means (FCM) clustering to localize

the image and extract feature vectors. This provides average pixel level Specificity (SP) value as 0.9417, 0.9781 for Sensitivity (SE), 0.948, 0.94 for Dice Score (Di) and 0.948 for Accuracy (Ac). As a result, occluding clinical artefacts and lessening search space for lesion region segmentation is important for attaining higher segmentation accuracy. However, image fusion techniques are not carried out in this work which significantly highlights discriminative features for feature extraction and get better results [3]. Thus, we only adopt morphological operation and localization technique from this paper. Xie, et al. [6] enhanced spatial details in feature extraction while lowering unrepresentative features for segmentation. This was undertaken using high resolution feature block, which extracts the high resolution feature maps from CNN to preserve image details and then using attention branches for boosting the discriminative features. It provides 87.00% SE, 96.4% SP, 86.2 % DI and 93.8% Ac and is considerate of pixel information corresponding to the skin lesion in the loss function. As a result, the accuracy in terms of discriminative lesion features for improving segmentation is accepted. However, segmentation algorithms often gives inferior outcome when lesion with less contrast against the background is presented as in this paper [3]. Therefore, we adopt only loss function from this paper to enhance the pixel information from the skin lesion.

Pour and Seker [7] enhanced augmentation and pre-processing techniques to remove artefacts. They offer the solution by applying CIE (International Commission on Illumination)-Lab color space which provides the network with more information improving the segmentation metrics. The research is conducted by implementing image representations of the transform domain to Fully Convolutional Network (FCN). It provides AC of 0.971, 0.98 SP and. 0.88 SE. As a result, data augmentation is show to be suitable for small dataset as available for the melanoma to improve the algorithm performance by raising data variation for training models. However, the research did not undergo robust artefacts and noise removal and thus lagged in specificity, the segmentation gives less precise results because the noises and contours can also be segmented alongside the lesion boundary which gives imprecise results [2]. Goyal, et al. [1] enhanced the ensembled method with semantic and instance segmentation algorithm to downgrade the selection of noisy annotations in datasets. They offer the solution by using Ensemble-add and Ensemble-comparison to improve lesion region masking. This solution conducted research by using DeeplabV3+ and Mask Region CNN with Inception V2 and ensemble methods to produce final segmentation. It provides Se of 89.93%, 95% Sp and 94.08% Ac. As a result, legion region masking provides a good boundary overview for raising segmentation accuracy. However, this research lacks procedures such as artefacts elimination and the usage of data-augmentation strategies which would have yielded lesser false negatives and precise masking of lesion regions for melanoma detection [7]. Al-Masni, et al. [8] enhanced boundary segmentation algorithm to lower the consequential error in weighted prediction accuracy for melanoma detection. They offer solution by integrating 2-stage diagnostic network and multitude of classifiers for improved data normalization. The research is conducted by using full resolution convolutional network (FrCN) then, a convolutional neural network classifier (Inception-v3, ResNet-50, InceptionResNet-v2, and DenseNet-201). It provides SE of 81%, SP of 87.16 and ACC of 89.28%. As a result, it is shown that proper balancing of the data can raise lesion diagnostic efficiency and prevent bias against the dominant class and improve detection accuracy. However, omitting pre-processing methods like artefacts removal and data-augmentation results in higher false negatives likelihood because of imprecise boundary segmentation [7]. Majtner, et al. [5] enhances the efficacy of the set of features extracted to lower the dimensions of the features using linear discriminant analysis. They conducted research by using ImageNet. It provides acc of 0.85, Se of 0.52 and SP of 0.97. As a result, it provides ability to reduce feature effectively and increase the performance for better performance to make classification decision. However, where there is no discriminatory details in the means of classes, it can possess limitation for the dimensionality diminishing of deep learning characteristics for identification of melanoma [9].

B. Lesion classification

Amin, et al. [10] enhanced the Otsu algorithm to downgrade the negative rate in lesion segmentation. They offer the solution by incorporating Biorthogonal 2-Dimensional wavelet transform, serially fusing pre-trained Alex net and Visual Geometry Group-16 (VGG16) and applying Principle Component Analysis (PCA) for optimal selection of features for precise classification. It provides 0.9952 SE, 0.9841 SP and 0.9900 ACC. As a result, deep feature extraction using transfer learning is shown to be reliable for better accuracy and optimal performance. However, feature fusion using different kernels for extraction can lead to redundancy among elements and add irrelevant features. This makes the melanoma identification complicated [11]. Saba, et al. [3] enhanced deep features from the dermoscopic images by forming a single feature vector by fusing them in order to enhance significant image characteristics that leads to detect melanoma with more accuracy. They undertook this by using DCNN and incorporating local Laplacian filtering along with hue saturation value transformation for highlighting skin lesions, in-depth feature extraction using Inception V3, followed by hamming distance-fusing deep features to feed it to classifier and detect melanoma. Here, clustered controlled entropy is enacted to select the best features for classification. This provides accuracy of 95.1% on ISBI dataset, 94.8% on ISBI 2017 dataset 98.4% on PH2 datasets. As a result, feature fusion to improve accuracy is considered. However, this work has not considered removal of clinical artefacts, without which segmentation algorithms tend to conflate noise with lesion region and localization step for lessening search space for lesion region segmentation [2]. In addition, it is inconsiderate of pixel information corresponding to the skin lesion to refine the features for feature extraction [12].

Albert [4] enhanced the melanoma diagnostics accuracy with Predict-Evaluate-Correct K-fold (PECK) and Synthesis and Convergence of Intermediate Decaying Omni-gradients (SCIDOG) algorithm to downgrade prediction layer error across the training period. They offer the solution by merging Inception V3 CNN, Support vector machine (SVM), and random forest with X trees and X random features with unlimited depth to achieve introspective learning. It provides 0.91 Ac, 0.89 True Negative rate and 0.93 True positive rate. As a result, the algorithm is shown to be a reliable for variable images quality as well as for large range of lesion appearances. However, intermediate degradation of image

resolution could diminish spatial information, resulting in incorrect boundary segmentation of the lesions in later stages [10]. Adegun and Viriri [13] enhanced semantic level of feature maps algorithm to downgrade the negative rate in melanoma detection. They offer a solution using lesion classifier that improves lesion classification into melanoma and non-melanoma. This solution conducted research by using encoder feature maps closer to that of the decoder feature map and softmax classifier for pixel-wise classification in D. It provides Ac of 95%, Di of 92% on ISIC dataset and 95% and 93% Ac and Di respectively in PH2 dataset. As a result, it is shown that factors present in the lesion has significance in the feature extraction transfer. However, without color enhancement, contrast adjustment and negating artefacts, negative rate is bound to be significant when lesion is processed against the background as presented in this paper [14]. Song, et al. [15] enhanced loss function on the basis of focal loss and the Jaccard distance to render lesser false positive in segmentation of melanoma region. They offer a solution to the problem by fine tuning melanoma features by Fuzzy C means (FCM) to extract feature vectors for increasing precision in detection and segmentation of melanoma. It provides 0.87 Di, 0.95 Ac, 0.83 Se and 0.98 Sp. As a result, loss function along with FCM tend to generate region of interest for localization and provides better precision in melanoma detection. However, it is inconsiderate of pixel information corresponding to the skin lesion in the loss function that results in inferior specificity [6].

C. *State of art:*

Saba, et al. [3] proposed a framework incorporating color transformation and enhancement for lesion boundary extraction and fusion method to raise detection accuracy of melanoma. It attained the best accuracy of 95.41% and 94.78% on PH2 dataset and ISBI 2017 dataset respectively for segmentation performance. This outperforms various existing methods. This model comprises of three prime stages (Fig. 1. State of art) i.e. Pre-processing, Boundary extraction and Feature recognition.

1) Pre-processing phase: Here, the datasets are rotated into different angles to streamline recognition accuracy of the skin lesions by raising data points for better CNN training. Color enhancement is carried out by fast local Laplacian filtering along with HSV(Hue Saturation Value) color transformation to find edges with rapid changes in the skin area and highlight it. The downside is that undesired artefacts sustain throughout the process that interferes with the segmentation and feature extraction processes and subsequently affects the melanoma detection accuracy [2].

2) Boundary extraction: The dataset is divided into 70:30 training and testing ratio. Exclusive-Or (XOR) operation is performed on enhanced images for range selection of the lesion pixels. The first channel of XOR image is extracted and nearest lesion pixel points are selected [3]. The pixels are then loaded into CNN model and from fine tuning, the model is trained using lesion and region pixel value. After this, activation is performed and lesion are identified. The limitation is that lesion pixel range selection operation has inadequate regression targets for localization of lesion regions [2]. Because of this, the affected skin regions are not narrowed down to enable higher and robust segmentation accuracy. Similarly, activation function is inconsiderate of pixel width and height that raises the information from pixels corresponding to the skin lesion [6].

3) Feature recognition: In this phase features are extracted by using activation of FC (Factorizing convolution) and AP (Average Pooling) layers of the V3 model. Then, extracted features are fused through Hamming distance to garner prominent features and eventually clustering controlled entropy (CCE) is used to concatenate all cluster features and classify thus formed image using Multilayer Perceptron classifier [3].

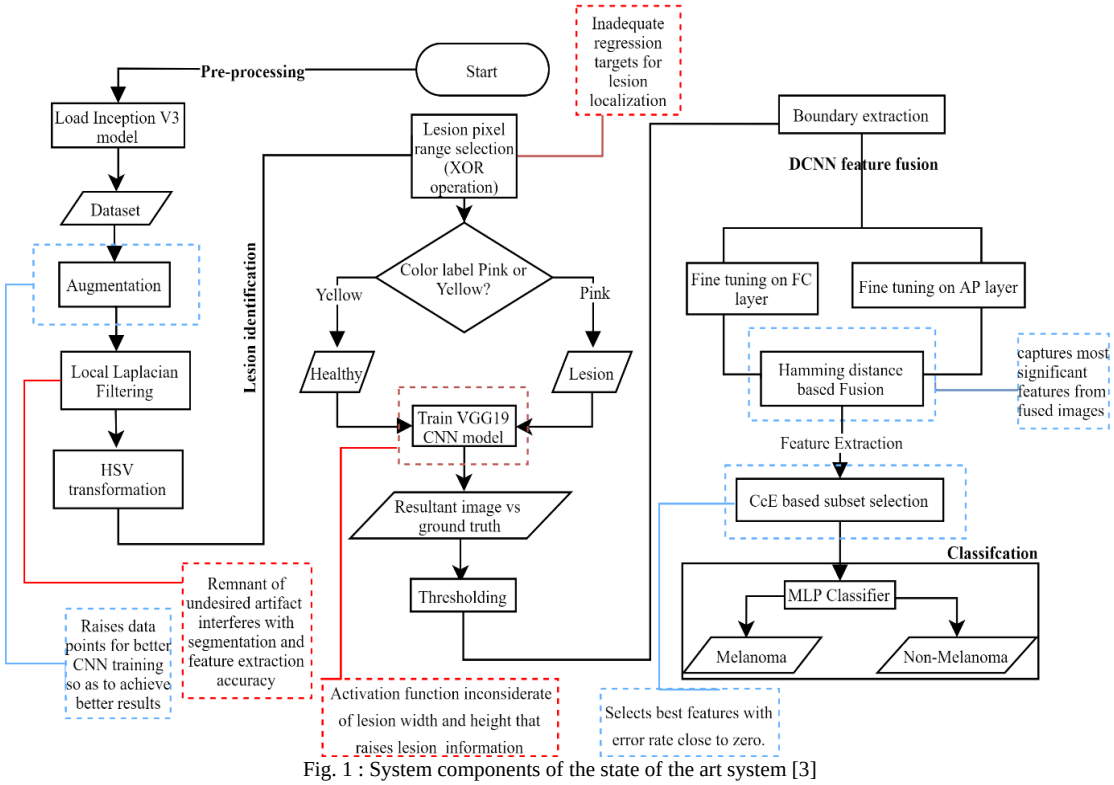

Fig. 1 : System components of the state of the art system [3]
[blue border indicates good features of the state of the art solution whereas the border red refers to the limitation]

III. PROPOSED SYSTEM

A. Proposed ERLE system:

The proposed system is shown in Fig. 2 and comprises of three main parts as follow:

1) Pre-processing phase: The dataset are rotated into 4 separate angles (45, 60, 135, 270 degrees) to streamline recognition accuracy of the skin lesions. Morphological operation is integrated to remove unnecessary artefacts like hair and blood vessel artefacts. Color enhancement is carried out by fast local Laplacian filtering with Hue Saturation Value color transformation to find edges with rapid changes in the skin area and highlight it.

2) Boundary extraction: The dataset is divided into training and testing into 70:30 ratio. Exclusive-Or (XOR) operation is performed on enhanced images for selection of range in the lesion pixels. The first channel of XOR image is extracted and nearest lesion pixel points are selected. Probability is calculated to determine exact lesion pixel values (to be used for CNN training); probability value is shown to be pixel in range of 0-0.4, these showcase lesion pixels and pixels higher than this range signify healthy skin region or background. The pixels are loaded into VGG19 (Visual Geometry Group 19) and from fine-tuning, the CNN model is trained using lesion and healthy region pixel value. After this, activation is performed by modified loss function and Otsu threshold operation is done and then refined via morphological operation like closing, filling, removal of area. The lesion are identified by trained Inception V3 CNN model.

3) Feature recognition: Trained inception V3 DCNN model is used and features are extracted by using activation of FC and AP layers of the model. The features are then corresponded to the dataset by fine tuning. The extracted features are then fused through Hamming distance. Dependent on the mean threshold value and measured entropy value, the fused CNN features are split into dual clusters. Instead, for each cluster the posterior probability values are determined. The original likelihood values are then modified until the risk of error is near zero. This method decreases the amount of feature by about 60 percent. Eventually, after clustering controlled entropy (CCE) is done, concatenate all cluster features and classify using MLP classifier.

B. Proposed Equation

We proposed Enhanced Refinement, Localization, and Extraction (ERLE) equation to remove undesired artefact in the dermoscopic image that raises the regression target for improved localization and enhance it for precise segmentation and feature extraction that leads to higher detection accuracy.

Equation (1) is used to remove undesired artefact in the dermoscopic image and enhance it for precise segmentation and feature extraction that leads to higher detection accuracy.

$$MPI_j(\mathrm{x,y}) = I_s(\mathrm{x,y}) - 4\sum_{m=-2}^{2}\sum_{n=-2}^{2} I_s\left(\frac{x-m}{2}, \frac{y-n}{2}\right) \quad (1)$$

Where,
MPIj = Modified localization operation (j subscript = levels of image pyramid)
(x, y) = Image coordinates
Is(x,y)= image on position (x, y)
m = melanoma region
n = background (normal skin region)

Equation (2) is used to raise the regression target for improved localization :

$$M\xi_L^l(\mathrm{i}) \cup \xi_{HSV}(\mathrm{j}) = \xi_L^l(\mathrm{i}) \cup \xi_{HSV}(\mathrm{j}) \cap MPI_j(\mathrm{x,y}) \quad (2)$$

Where,
$M\xi_L^l(\mathrm{i})$= Modified Exclusive Or operation
ξ_{HSV}= Enhanced image
$\xi_L^l(\mathrm{i})$= Local Laplacian filtering
(i, j) = pixel position

Activation is performed on basis of modified Loss function using the following equation:

$$ML = -\frac{1}{WH}\sum_{i=1}^{H}\sum_{j=1}^{W} [(y_{i,j} lnp(w|\xi_{i,j}) + (1-y_{i,j})\ln(1-p(w|\xi_{i,j})] \quad (3)$$

Where,
ML =Modified loss function
W = width of pixel
H = height of pixel
$y_{i,j}$ = class labels (background, lesion)
$\xi_{i,j}$ = actual image pixel
w = hyperparameter
i and j are positions of pixels in the image.

The final proposed equation is Enhanced Refinement, Localization, and Extraction (ERLE) as given in equation (4):

$$ERLE = ML(x,y) + M\xi_L^l(\mathrm{i}) \cup \xi_{HSV}(\mathrm{j}) + ML \quad (4)$$

Where,
(x, y) = Image coordinates
ML(x, y) = modified fast local Laplacian filter
$M\xi_L^l(\mathrm{i}) \cup \xi_{HSV}(\mathrm{j})$ = Modified exclusive-Or operation
i and j = positions of pixels in the image.
ML= Modified loss function

The pseudocode to implement the proposed system is descripted in Table 1.

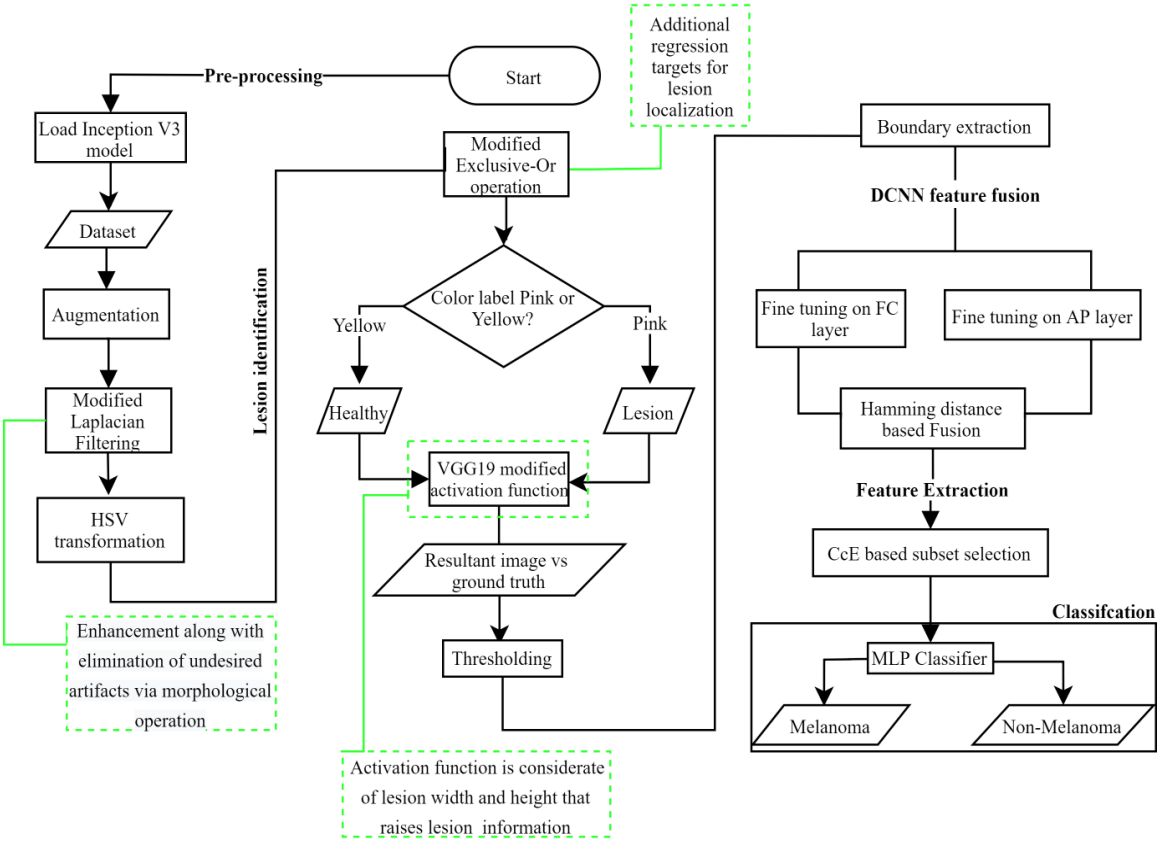

Fig. 2: Architectures of the proposed system for segmentation and detection of melanoma.
[Green border indicates features of the proposed model]

C. *Area of Improvement*

The modified fast local Laplacian filtering removes undesired artefacts that can potentially heighten the rate of false negative by impacting segmentation accuracy. Secondly, modified exclusive-Or operation adds to the precision of lesion segmentation from the lesion area against the background by localizing the information from lesion pixels. Thirdly, modified loss function solves the limitation by consideration of lesion pixel width and height that raises the information from pixels and correlates it with melanoma features contributing to detection accuracy while reducing the negative rate for melanoma detection.

TABLE 1. PSEUDO-CODE FOR PROPOSED SYSTEM FOR SEGMENTATION AND DETECTION OF MELANOMA.

Input: Dermoscopic image
Output: Segmented image
1. Input dermoscopic color images.
2. Perform image data augmentation.
3. Enhance image by Equation (1)
4. Enhance image by Hue Saturation and Value Color transformation.
5. Perform Equation (2)
6. Perform region selection for lesion and healthy pixels.
7. Load VGG19 pretrained CNN model.
8. Fine tune the model as:
   Padding mode: Set to manual
   Pooling size: 2*2
   Maximum epochs: 200
   Minimum batch size: 64
   Learning rate: 0.2
9. Activation by Equation (3)
10. Perform Otsu threshold operation.
11. Refine images via morphological operations.
12. Train model using lesion and background pixel values.
13. Extract boundary against segmented and ground truth image.

IV. RESULT

Python 3.7.3 on Jupyter NoteBook with NumPy, SciPy, Tensorflow, keras and Matplotlib libraries were used for implementation of Enhanced Refinement, Localization and Extraction on four digital image datasets namely International Symposium on Biomedical Imaging (ISBI) 2016, ISBI 2017, International Skin Imaging Collaboration (ISIC) 2018 and Hospital Pedro Hispano 2 (PH2). The results are calculated by computing the ground truth with segmented area of the lesion in the segmentation phase and the prediction label are compared with the actual label to determine accuracy for melanoma detection in skin cancer diagnosis. These values were then compared between state of the art and proposed solution.

Samples were compared between state of the art method and the proposed solutions with the aid of graphs and data reports. Ten samples were compared between proposed method solution with the state of the art for lesion segmentation and melanoma detection accuracy (Fig 4). The segmentation accuracy is calculated using Equation (5) and detection accuracy is calculated using Equation (6) [3].

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad (5)$$

Where,

TP = True positive pixel
TN = True negative pixel
FP = False positive pixel

FN = False negative pixel

In equation (5), melanoma area pixel is regarded as true positive pixel if it is detected to be melanoma, else it is considered false negative pixel. A normal skin pixel is a true negative pixel if detected as background pixel, else it is referred to as a false positive pixel. The segmented images are compared with ground truth to determine the values [3].

$$\text{Accuracy} = \frac{\text{True positives} + \text{True negatives}}{\text{number of samples}} \qquad (6)$$

The accuracy was calculated using Equation (6). Accurately detected melanoma is regarded as true positive; else it is considered false negative pixel. The normal skin is true negative if detected as background, else it is referred to as a false positive pixel. Actual labels of the images is compared with predicted label to determine the values.

The results were compared in segmentation and detection stages with accuracy in terms of negative rate. Segmentation is vital as selection of lesion region is critical for relevant feature extraction whereas detection is responsible for determining whether the lesion is melanoma or not, thus we divided accuracy in terms of segmentation and detection. The proposed solution has improved the accuracy of the segmentation and detection of melanoma by refining the dermoscopic images and ridding it of undesired artefacts and localizing the lesion region for melanoma detection. This has raised the accuracy by lowering the rate of false negatives in melanoma detection as depicted in Fig. 4 and Fig. 5, while also lowering the processing time as shown in Fig. 6. The average segmentation and detection accuracy for state of art and proposed model is shown in Fig. 3.

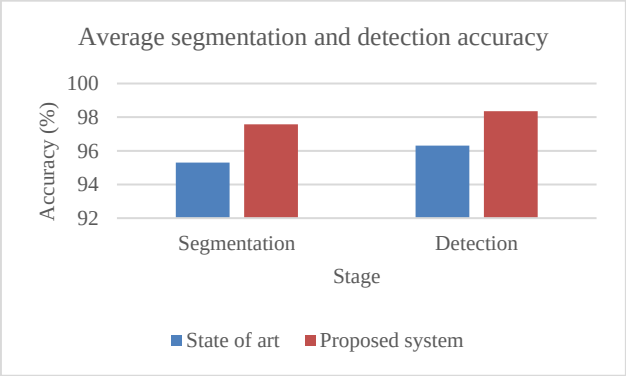

Fig. 3: Average segmentation and detection accuracy for State of the art and Proposed solution. a) First bar shows average segmentation accuracy for state of the art system. b) Second bar shows average detection accuracy for state of the art system. c) Third bar shows average segmentation accuracy for proposed system. d) Fourth bar shows average detection accuracy for proposed system. Blue bar indicates segmentation and detection accuracy in state of the art [3].Red bar indicates segmentation and detection accuracy in proposed solution.

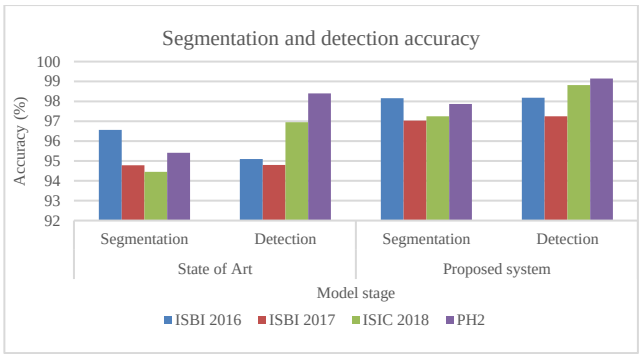

Fig. 4**:** Segmentation and detection accuracy for State of the art and Proposed solution on ISBI 2016, ISBI 2017, ISIC 2018 and PH2 Datasets. a) First set of bars shows segmentation accuracy for state of the art system. b) Second set of bars shows detection accuracy for state of the art system. c) Third set of bars shows segmentation accuracy for proposed system. d) Fourth set of bars shows detection accuracy for proposed system.

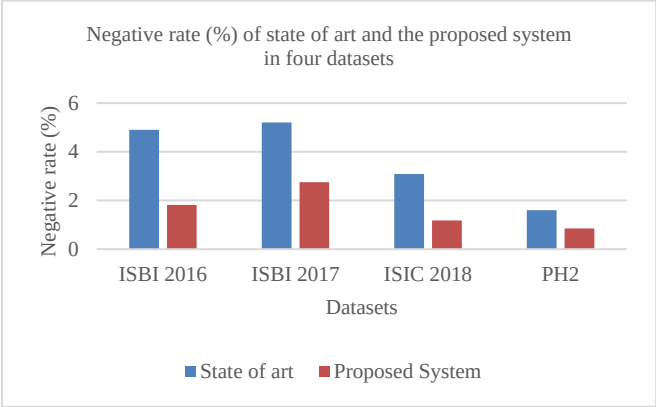

Fig. 5: Negative rate for State of the art and Proposed solution on ISBI 2016, ISBI 2017, ISIC 2018 and PH2 Datasets. a) First set of bars shows Negative rate for state of the art system and proposed system on ISBI 2016. b) Second set of bars shows Negative rate for state of the art system and proposed system on ISBI 2017. c) Third set of bars shows Negative rate for state of the art system and proposed system on ISIC 2018. d) Fourth set of bars shows Negative rate for state of the art system and proposed system on PH2.

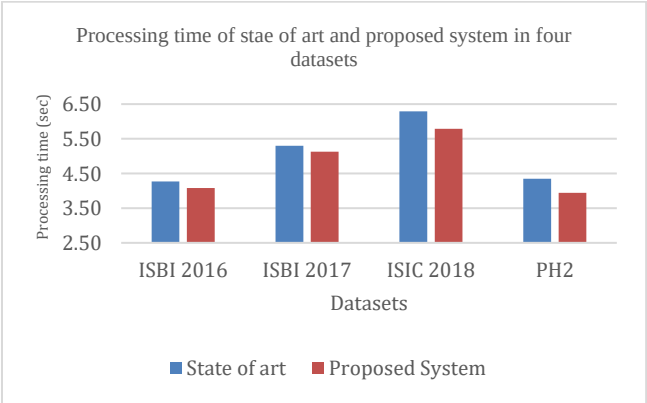

Fig. 6: Processing time for State of the art and Proposed solution on ISBI 2016, ISBI 2017, ISIC 2018 and PH2 Datasets. a) First set of bars shows Processing time for state of the art system and proposed system on ISBI 2016. b) Second set of bars shows Processing time for state of the art system and proposed system on ISBI 2017. c) Third set of bars shows Processing time for state of the art system and proposed system on ISIC 2018. d) Fourth set of bars shows Processing time for state of the art system and proposed system on PH2.

V. Discussion

The results shows difference in segmentation and detection accuracy between current and the proposed solution with respect to negative rate. The proposed method shows overall improvement in the segmentation and recognition accuracy by 2.27% and 2.04% respectively as shown in Fig. 3. Likewise, there was decrement in negative rate from 3.69% to 1.65% as shown in Fig. 5, along with processing time 5.05 secs to 4.74 seconds from state of the art to proposed system as shown in Fig. 6. The segmentation and detection accuracy is calculated by Equation (2) and Equation (3) respectively. We quantify these degree of improvement by running the state of the art and proposed algorithm in the boundary extraction and classification phases of both systems.

The enhanced refinement method is responsible for removal of unnecessary artefacts from dermoscopic images and color enhancement for improved lesion segmentation. The enhanced localization is implemented to detect region of lesion pixels in the dermoscopic images within bounded search space and enhanced extraction operation is performed for improved binary classification of the image. In conclusion, the combination of these measures improves the lesion segmentation and detection accuracy of melanoma.

For the modelling of the melanoma detection system, a range of techniques has been utilized with fine-tuning the existing system to attain higher accuracy and lesion segmentation and melanoma detection. This research has accomplished the goal of overcoming the limitation in the state of the art solution by raising the segmentation accuracy from 94.78% - 96.56% to 97.03% - 98.16% in ISBI 2016, ISBI 2017, ISIC 2018 and PH2 datasets. In terms of detection accuracy, it was raised from 94.80% - 98.40% to 97.25% - 99.15%. Likewise, the proposed system reduced the negative rate from state of the art 1.60% - 5.20% to 0.85% - 2.75% along with processing time 4.35 secs - 6.29 secs to 3.94 secs – 5.79 secs. The given results are supported by enhanced refinement which refines the skin from undesired artefacts and enhances image color. Likewise, enhanced localization adds regression targets for lesion localization and bounds the lesion area for segmentation. Furthermore, enhanced extraction integrates lesion pixel information in the loss function for activation which categorizes melanoma from non-melanoma with higher detection accuracy.

VI. Conclusion and Future work

From our research for melanoma segmentation and detection, it can be deemed that image data augmentation raises the data points for better CNN training and obtain better segmentation and detection accuracy. Similarly, fusing images is bound to capture more significant features from the lesion and aid in recognition accuracy. Likewise, clustering controlled entropy is robust for best feature selection with error rate close to zero for melanoma detection. However, limitations in the state of the art model are confronted as retention of undesired artifact that contributes to misidentifying lesions and lead to higher negative rate in melanoma detection. Likewise, inadequate regression targets make the range selection of lesion tedious and prone to error. Also, loss function as activation is not considerate about pixel width and height for raising the lesion information to attain a higher accuracy rate in its extraction. Thus, in this model, enhancement of skin refinement is carried out to remove undesired artefacts like hair, blood vessel, skin texture, ink markings, intrinsic and cutaneous elements, this integration enables the system to segment the lesion precisely and identify melanoma features with better accuracy. Similarly, lesion localization is carried out to raise the regression target by narrowing down the search area around lesion for robust and better lesion area segmentation. Likewise, boundary extraction with modified loss function which raises lesion information and raises accuracy by adding to the reduction in false negative instances. The main purpose of the proposed system is to improve the information derivation from the relevant skin lesion. The experiment results shows that the proposed system is effectual and robust in comparison to state of art model in terms of segmentation as well as detection accuracy and processing time for diagnosing melanoma using deep learning.

The future research includes examination of high resolution feature block, such as semantic segmentation for certain forms of clinical images, and investigate certain processes such as integration of multi normalization in the proposed framework to further enhance feature extraction functionality.

References

[1] M. Goyal, A. Oakley, P. Bansal, D. Dancey, and M. H. Yap, "Skin Lesion Segmentation in Dermoscopic Images With Ensemble Deep Learning Methods," *IEEE Access*, vol. 8, pp. 4171-4181, 2020.

[2] N. Nida, A. Irtaza, A. Javed, M. H. Yousaf, and M. T. Mahmood, "Melanoma lesion detection and segmentation using deep region based convolutional neural network and fuzzy C-means clustering," *International Journal of Medical Informatics*, vol. 124, pp. 37-48, 2019.

[3] T. Saba, M. Khan, A. Rehman, and S. Marie-Sainte, "Region Extraction and Classification of Skin Cancer: A Heterogeneous framework of Deep CNN Features Fusion and Reduction," *Journal of Medical Systems*, vol. 43, no. 9, pp. 1-19, 2019.

[4] B. A. Albert, "Deep Learning From Limited Training Data: Novel Segmentation and Ensemble Algorithms Applied to Automatic Melanoma Diagnosis," *IEEE Access*, vol. 8, pp. 31254-31269, 2020.

[5] T. Majtner, S. Yildirim-Yayilgan, and J. Hardeberg, "Optimised deep learning features for improved melanoma detection," *Multimedia Tools and Applications*, vol. 78, no. 9, pp. 11883-11903, 2019.

[6] F. Xie, J. Yang, J. Liu, Z. Jiang, Y. Zheng, and Y. Wang, "Skin lesion segmentation using high-resolution convolutional neural network," *Computer Methods and Programs in Biomedicine*, vol. 186, 2020.

[7] M. Pour and H. Seker, "Transform domain representation-driven convolutional neural networks for skin lesion segmentation," *Expert Systems With Applications*, vol. 144, 2020.

[8] M. A. Al-Masni, D. H. Kim, and T. S. Kim, "Multiple skin lesions diagnostics via integrated deep convolutional networks for segmentation and classification," *Comput Methods Programs Biomed*, vol. 190, p. 105351, Jan 23 2020.

[9] T. Y. Tan, L. Zhang, and C. P. Lim, "Adaptive melanoma diagnosis using evolving clustering, ensemble and deep neural networks," *Knowledge-Based Systems*, vol. 187, 2020.

[10] J. Amin *et al.*, "Integrated design of deep features fusion for localization and classification of skin cancer," *Pattern Recognition Letters*, vol. 131, pp. 63-70, 2020.

[11] K. Zafar *et al.*, "Skin Lesion Segmentation from Dermoscopic Images Using Convolutional Neural Network," *Sensors (Basel, Switzerland)*, vol. 20, no. 6, 2020.

[12] Y. Yuan and Y. Lo, "Improving Dermoscopic Image Segmentation With Enhanced Convolutional-Deconvolutional Networks," *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 2, pp. 519-526, 2019.

[13] A. A. Adegun and S. Viriri, "Deep Learning-Based System for Automatic Melanoma Detection," *IEEE Access*, vol. 8, pp. 7160-7172, 2020.
[14] X. Wang, X. Jiang, H. Ding, and J. Liu, "Bi-Directional Dermoscopic Feature Learning and Multi-Scale Consistent Decision Fusion for Skin Lesion Segmentation," *IEEE Transactions on Image Processing*, vol. 29, pp. 3039-3051, 2020.
[15] L. Song, J. P. Lin, Z. J. Wang, and H. Wang, "An End-to-end Multi-task Deep Learning Framework for Skin Lesion Analysis," *IEEE Journal of Biomedical and Health Informatics*, pp. 1-1, 2020.