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Skin Lesion Segmentation Using Deep Learning Convolutional Neural Network

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***Abstract* —*Small blood vessels, thicker areas, ulcers, and bleeding are all indications of a skin lesion. We used Deep Learning Convolutional Neural Networks for image augmentation and model construction in Skin Lesion Segmentation (SLS) (DCNN). We used a database gathered at the Hospital Pedro Hispano's Dermatology Service in Matosinhos, Portugal (PH2 dataset). The model is trained on the PH2 dataset, it includes manually segmented images. Their masks are also included. SegNet V2 architecture is used to construct the model. The goal is to keep image pre- and post-processing to a minimum. After evaluation, the goal is to acquire a higher performance threshold and obtain 96% accuracy.*

Keywords*— *Segnetv2,Segmentation,Enhancement

I. INTRODUCTION

Skin is the body's largest organ it's natural that skin cancer is the most prevalent type of cancer in humans. Dermatology is one of medicine's most significant specialties, with skin problems like hypertension, obesity, and cancer combined.

Many machine learning and computer vision challenges have been solved successfully using Deep Convolutional Neural Networks. A DCNN's convolutional and pooling layers extract features that can be aapplied to a trainable classifier. The invariance of the features is said to be dependent on the network depth and pooling operators (sub-sampling, max pooling, or average pooling). The translation invariance property is determined by the network's depth, but vertical translation invariance requires pooling. Because DCNN contains a huge number of parameters, developing deep convolutional neural networks is ineffective without enough training examples[12,15,16,18].

The traditional approach of manual segmentation by the expert dermatologists has been already proposed to be replaced with computerized segmentation techniques in which machine assisted methods are used[7,11]. The previous manual approach was time-consuming, complex and dependent on the observer and his capabilities. The efficient approach of segmentation can save a lot of time and expertise required to complete the task with sufficient accuracy. The already proposed architectures involve some state-of- the-art neural networks like FCN[8,10], Fast-RCNN and U-Net[9]. Obtaining the image, preprocessing, data augmentation, implementing the SegNet V2 model, assessing the accuracy, precision, recall, intersection over union(IOU), and dice coefficient are the procedures followed in skin lesion segmentation. The final part is to save the trained model and make predictions.

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II. LITERATURE SURVEY

Researchers that specialise in the field of Skin Lesion Segmentation have done a lot of work in the past.

Tran-Dac-Thinh Phan , et al,[1] described a U-Net-based deep learning approach that accomplishes injury division, boundary separate outline relapse, and form location are the three assignments. On dataset, they attained an accuracy of 89.7%. Future study will combine that will identify the stages of skin lesions with precision.

Muhammad Attique Khan, et al, [2] described most discriminant features, an improved moth flame optimization (IMFO) technique was described. The generated features are merged using a multiset maximum correlation analysis (MMCA), and they are then classified using the Kernel Extreme Learning Machine (KELM) classifier. The HAM10000 dataset was 90.67% accurate

Cheng-Hong Yang et al, [3] described enhanced algorithm EfficientUNet++ adds the pre-trained EfficientNet model to speed up division handle, resulting in accurate, reliable skin cancer image segmentation. The accuracy rate was 89%. To boost performance in future.

Kashan Zafar et al, [4] described U-Net and ResNet architectures that are combined for segmenting lesion borders. The Jaccard Index of their proposed model was 0.772.

Vinicius Ribeiro et al, [5] described inter-annotator agreement in the context of training and grading automated skin lesions segmentation. For the entire ISIC Archive, the performance score was 0.72 kappa.

Md. Mostafa Kamal Sarker et al, [6] described encoder-decoder network that used to represent a deep learning SLS model. In terms of segmentation accuracy model exceeds current methods. To demonstrate its versatility, the proposed model will be tested on multiple color spaces and used to other medical applications in the future.

III. PROPOSED METHODOLOGY

3.1 Collection of data set and models

3.2 Detailed design

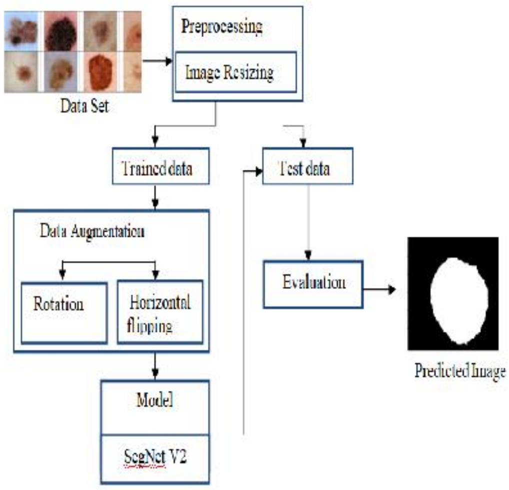

Fig.1. Detailed design

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A. *Dataset*

PH2 dermoscopic dataset which contains 200 dermoscopic images and their label masks. Each one is an RGB image and the fixed dimension of each image is 572 x 765.[14] The dataset has been provided publicly for experimental and studying purposes. For training purpose the dimensions of each image have been reduced to 192 x 256 before feeding it into the network. It largely reduces the parameters to be trained in the network as well as the training time and complexity without significantly affecting the results.

Fig.2. PH2 dataset

C. Model

SegNet V2

SegNet v2 is a pixel-wise segmentation deep neural network based on the encoder-decoder architecture, first proposed and constructed by members of the University of Cambridge. SegNet based on guideline of Semantic Pixel-Wise Labeling at first utilized for the division of street images which include a total of twelve different classes. Each pixel in the image is to be classified among one of the twelve classes as per the data. The architecture of SegNet has non-linear layer encoding sequences and decoders corresponding to each layer. There is a final classifier present for the pixel-wise classification. We have used it as the base architecture with varying hyper parameters and structural differences for our lesion segmentation problem.

Network Architecture

The proposed is a 64-layered network excluding the final activation layer. Every sequence of encoder has multiple convolutional layers, batch normalized with ReLU [13,17] followed maxpooling and sub-sampling. In between two dense layers present before the first up-sampling begins. Using max-pooling indices in decoders to accomplish upsampling of low-resolution feature maps is a distinguishing feature of SegNet. Which leads to retaining of the important detailed features in the image and non-useful features are dropped. SegNet provides smooth images without any post-processing technique involved.

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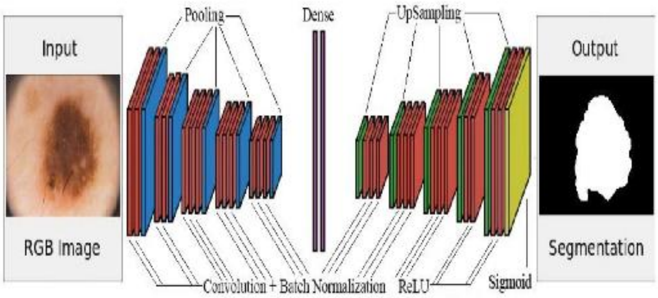

Fig.3. SegNet V2 Architecture

D. Evaluation matrices

Several evaluation metrics were used to assess the model's overall performance: accuracy and precision. The following mathematical equations were used to calculate the weighted average for Recall and Precision.

There are four key terms :

- **True Positives (TP):** The projected yield matching the actual yield.
- **True Negatives (TN):** We predict a false result and then got the same result.
- **False Positives (FP):** This is when we expect something to be true but it turns out to be false.
- **False Negatives (FN):** This is when we expect something to be false but it turns out to be true.

❖ Accuracy :

It refers to the number of valid predictions divided by the total number of input samples.

Accuracy = TP+TN/ (TP+TN+FP+FN)

❖ Precision:

It is found by dividing the number of valid positive outcomes by the number of correct results predicted by the classifier.[20]

Precision = TP/(TP+FP)

❖ Recall:

Recall measure which is targeted towards the actual or the true positives yielded by the model output. In the scenarios where the cost of the False Negatives is greater than recall is the better metric to choose the best model among the possible ones.

Recall = TP/(TP+FN)

❖ Intersection Over Union:

Intersection over Union is another name for the Jaccard index. A statistical similarity measure to check the diversity among the sample sets.

$$J(A, B) = |A \cap B|/ |A \cup B| = |A \cap B|/ |A| + |B| - |A \cap B|$$

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❖ Dice Coefficient

The Dice score is like precision. It measures the positives as well as it applies penalty to the false positives given by the model. It is more similar to precision than accuracy.[19]

$$Dice = 2 \times TP/\,(TP + FP) + (TP + FP)$$

IV. IMPLEMENTATION

Step 1: Collecting Dataset from Kaggle

Step 2: Data cleaning

Step3:Data Augmentation by applying different augmentations image rotation and horizontal flipping

Step 4: Training the model.

Step 5: Validation of model.

Step 6: Evaluation matrices.

Step 7: Finding the best possible accuracy, precision, recall, IoU and dice-coefficient of the model by increasing the epochs.

Step 8: The final part is to save the trained model and make prediction to the actual ground truth lesion mask images

V. RESULTS

A. Loading image dataset

We can observe that the images are of dimensions **(572, 765)** so we will scale down the images.

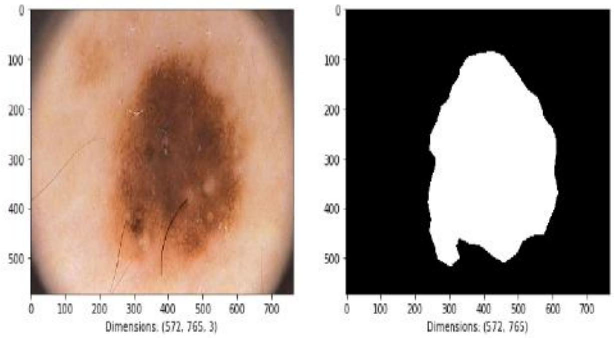

Fig.4. Loading image from dataset

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B. Resizing image

Resizing of image into dimensions size of (192,256) so that when data fetched to the network during, training happens more precisely.

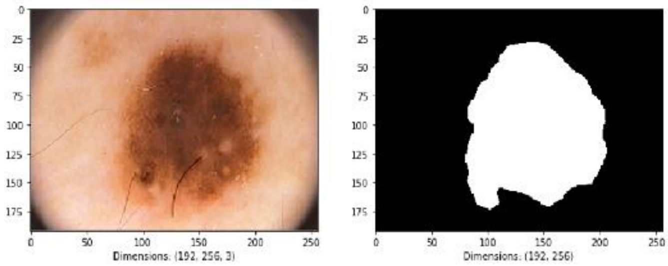

Fig.5. Resizing of image

C. Separating the dataset among train and test images

To test our model, we separate the dataset

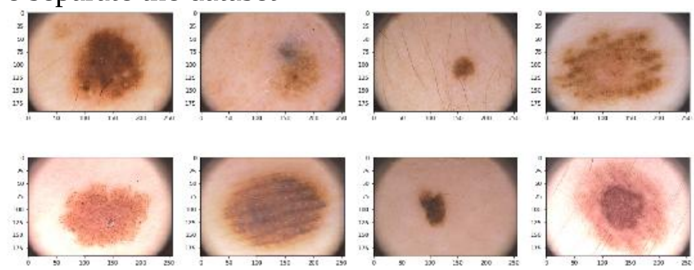

Fig.6. Separating the dataset

D. Model

TABLE II denotes the statistical analysis of train data

Table II: Performance statistics after training for epoch 40

Dataset	Accuracy	Precision	Recall	IOU	Dice-coffct	Loss
Train	96%	96%	93%	94%	77%	17%
Test	93%	89%	90%	92%	74%	22%
Validation	94%	92%	90%	93%	74%	21%

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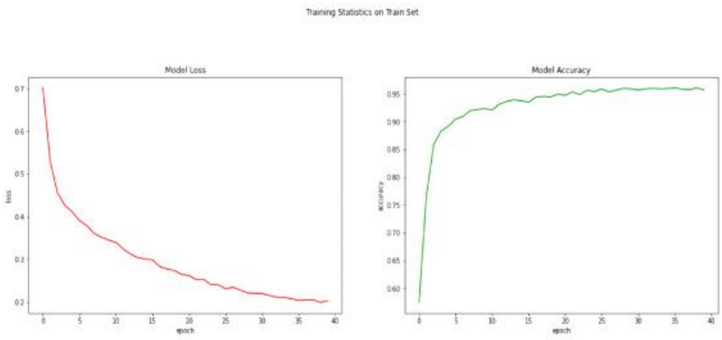
E. Plotting Training Statisctis

i. Training Statistics on train set

In the fig.12(a) where x axis depicts number of epochs and y axis denotes the train failure and in fig.12(b) where x axis denotes number of epochs and y axis depicts the train accuracy gain.

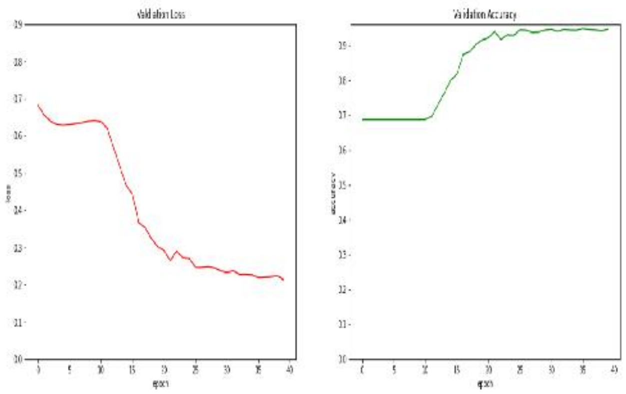


(a) *(b)*

Fig.9. Training Statistics on train set

ii. Training Statistics on validation set

In the fig13(a) where x axis depicts number of epochs and y axis denotes the validation failure and in fig13(b) where x axis depicts number of epochs and y axis denotes the validation accuracy gain.



(a) (b)

Fig.10. Training Statistics on validation set

G. Visualizing Predicted Lesions

The final part is to save the trained model and make predictions. The predictions are compared visually to the actual ground truth lesion mask images. The predicted outputs are initially slightly blurry at the edges and do not give a precise prediction towards the boundaries however, it still performs considerably well.

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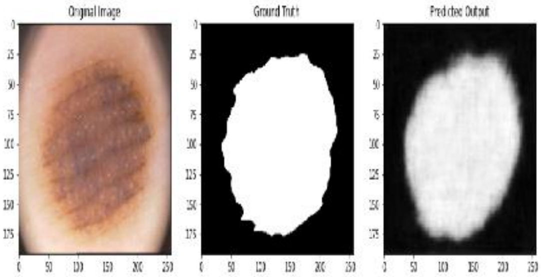

Fig.11. Predicted output

The threshold that we have used is 0.2, every pixel having a prediction value of greater than 0.2 will be rounded up to 1. After performing this technique, the sharp boundaries around lesion and the predicted masks can be observed.

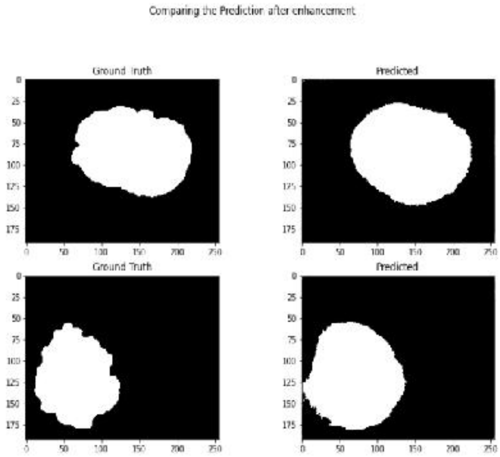

Fig.11. Predicted output after enhancement

VI. CONCLUSION

Skin cancer is a growing disease that claims the lives of a large number of people. There is no issue if it is detected earlier. If it is identified at its peak, the chance of survival lower from 91% to 15% The suggested study employed the SegNet architecture to solve the skin lesion segmentation problem and effectively presented the results of the experiment on the PH2 dataset with appropriate accuracy. Before feeding the training dataset to the network for training, two picture augmentation techniques, image rotation and horizontal flipping, are performed on it. Following the training phase, the model is evaluated for statistical measures. To reduce the blurry edges around the projected lesions, the model predictions on test images were post-processed using the thresholding technique. The aim is to achieve the performance threshold after evaluation where accuracy is 96%.

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