The Segmentation of Oral Cancer MRI Images using Residual Network

Varuna Shree. N.[1], TNR Kumar[2]
Research scholar[1], Associate Professor[2]
MSRIT, Bangalore

Abstract:- The segmentation of tumour from a cancer MRI images in image processing is classic research area of interest and a tedious task. Manually segmenting the MRI images is very time consuming and liable to errors. Many researchers have done investigation using deep neural network in segmenting the oral MRI images as they poses higher performance in segmenting the oral cancer images automatically. Owing to their gradient dissemination and complexity issues, the CNN takes more time and excess computational power in training the images. Our aim is build an automated technique for the segmentation of oral cancer images using Residual learning networks (ResNet) to render the complications of gradient dissemination caused by CNN. ResNet attains higher accuracy and trains the images faster compared to CNN. To accomplish this, ResNet counts a skip connection parallel to convolution neural network layers. The verification accuracy of the proposed technique has been carried out on oral cancer (lip and tongue) images dataset. The results of proposed technique shows a better accuracy, dice co-efficient, specificity and precision of 0.92, 0.95, 0.94, 0.96 respectively and computational time of 63 mins.

***Keywords:-** Oral cancer, Segmentation, DNN, ResNet.*

I. INTRODUCTION

In the present, Oral cancer is considered to be greatest threat to human beings. It is an uncontrollable growth of cells that starts from mouth and spreads to lips, tongue and other parts of the face. Squamous cell carcinoma is most deadly oral cancer where life span will be approximately for five years. Early stage diagnosis may help in curing the disease with less cost. Segmentation of the Oral cancer MRI images depicts a crucial role in deciding an exact location of the tumour. MRI (Magnetic resonance imaging) helps the physicians to explore the tissues and lesions of the tumours. Segmentation indicates the segregation of salient characteristics of the image background. It is representation and extracting of significant data from group pixels into similarity regions. Grouping of pixels takes place based on the change in their intensity accomplished by regions.

Segmenting of Oral images is a more complicated and tedious task as it has more complex appearance and structure of the tumors. They have a fuzzy borders and it may also have spread into other nearby areas of the lip and mouth. Manually recognizing the boundary of the Oral cancer tumor consumes of time and liable to lot more errors.

An automatic oral tumor segmentation using MRI images will be able to solve this issue which provides an early diagnosis and fast recovery. Early treatment can save the patient life by finding the exact tumor location and type.

In the recent years the deep leaning of neural network has gained the popularity and most of the researchers have an outstanding perseverance with a highest accuracy in segmenting the image. Convolution neural network is most important category of deep neural network which is capable of learning and extracting the features from the cancer MRI images.

In 2015(A.A Pereira et.al) the authors have designed an deep leaning CNN model containing an 3*3 convolution kernels that segments the tumors in cancer MRI images. They had employed a tiny kernel filters to obtain deeper CNN and cascaded few more convolution layers which had similar response in the bigger kernels. The algorithms of segmentation were proposed to overcome the issue of redundancy by allotting every pixel to a class label. The architecture of CNN was modified to a FCN (Fully Convolution Network). This classified each local block of an image into U-shaped model with expanding and contracting the paths. This model required a more number of training images to achieve a precise segmentation and suffered from more computational time.

To overcome the problem of gradient dissemination Convolution neural network (CNN) technique and to improve the computational power we have implied residual network (ResNet18).

In this research papers, section 2 contains literature survey regarding the research accomplished by the other researchers and outline information obtained by their work. Section 3 contains brief discussion of the proposed methodology; the proposed model using Resnet18 for segmentation. In section 4 simulation set up required is explained. The section 5 explains the performance evaluation with several parameters. The section 6 explains the result and comparison of ResNet with CNN. The conclusion is given in section 7.

II. LITERATURE SURVEY

In this paper we are mainly concentrating on segmentation of lesions from Oral cancer MRI images. It's very difficult to separate the tumour lesions from the normal lesions because of few similarity issues. There are many segmentation algorithms available in image processing such as Fuzzy C approach, histogram equalization, edge detection approach, clustering techniques, mathematical reconstruction and nearest neighbour, etc. But in the recent years deep neural network has been employed such as Convolution neural network, fully connected networks for the segmentation. Here we can see survey of few papers with different segmentation techniques used by the researchers and the result obtained.

The paper “Deep learning-based pixel wise lesion segmentation on oral cancer squamous cell carcinoma images” the author explains about the semantic segmentation used for separating the tumour cells from the normal cell. Performance analysis is done for deep learning pixel wise based for segmenting lesions. They had used dataset of Cancer Genome Atlas to create an Oral Cancer Annotated dataset.

The paper “Brain tumour detection using Convolution Neural network”, the author explains what will be the result of training large MRI brain tumour dataset using neural network models RESNET 50, U-NET and FPN. For the performance evaluation they have used IoU and Dice coefficient with 90% and 0.91 respectively with a loss value of 0.16. He concludes by saying that better accuracy is achieved using RESNET 50 in resemblance for U-Net and FPN for segmentation of brain tumour.

The paper “Deep learning model for tongue cancer diagnosis using endoscopic images”, the author has developed a model to rectify the tongue cancer related to Oral endoscopic images. Different types of convolution network techniques to calculate the probability of cancer. They have the compared model with CNN, VGG-16, VGG-19, Mobile Net V1, Mobile Net V2. The proposed methodology showed sensitivity of 91.7%, specificity of 90.9%, and accuracy of 91.7% respectively.

The paper “Deep learning for automatic segmentation of Oral and Oropharyngeal cancer using narrow banded imaging”, here the author test against FCNN techniques for segmenting semantically the oral squamous cell of the oropharynx and oral cavities. An OC dataset is poised with frames 110 and frames 116 with OP dataset. The FCCN’s U-Net 3, U-Net, and RESNET were employed for segmenting neoplastic images. The performance estimation was done on every tested network model and compared with golden standard. The FCCN segmentation on the OC dataset with median value of 0.655, and on the OP dataset with median value of 0.760. The tested FCCN’s shows better performance with high variance values and having all values minimum of all matric evaluation.

The paper “Brain Tumor Segmentation Using Convolution Neural Networks in MRI Images” the author explains an automated method for segmenting images using Convolution Neural networks (CNN) with tiny size of 3X3 kernels. The usage of tiny sized kernels helped in drafting an enhanced architecture which showed a reasonable effect contrary to over fitting giving lesser values of weights. They also inspected to use the normalization of intensities in the pre-processing stage. This was rare in segmentation of MRI image using CNN along with augmentation of data confirmed to be very efficient in segmenting the brain tumor images.

The paper “Brain image segmentation based on FCM clustering algorithm and rough set”, the author has employed Fuzzy C means clustering segmentation algorithm with rough set theory. Here the author constructs a feature weight value table from the results obtained from FCM with various clustering values and relating to identical relation of features the images is split-up in to several parts. Value reduction is done which is acquired by weight values of each feature and this act as foundation to estimate the dissimilarity among the regions and correlation is evaluated of every region that is analysed with equal relationship determined by difference in degrees. The equivalent regions are merged together based on relationship to complete the segmentation. This method showed lesser error rates and has achieved better accuracy in segmenting the image.

The paper “A novel region-based active contour model via local patch similarity measure for image segmentation”, the author has employed a novel method considering region as a base to build active contour model by measuring similarities of local patches through segmentation. They have used a restriction of spatial features on local regions which controlled amplitude of both centre to the neighbourhood pixels of the images. Firstly, they constructed similarity measures of local patches with the spatial restrictions; this balanced the suppression of noise that reserved the details of image. Secondly, they have constructed a new model combining the measures of similarity patches with region base active contour model. Thirdly, they have added regularized statistical terms for the object term ensuring the reliability of evolution of the curve and smoothness.

The paper “Deep Convolution Neural Network Using U-Net for Automatic Brain Tumor Segmentation in Multimodal MRI Images”, the author employs CNN and extracts automatically the tumor total part and inside tumor regions from 3D MRI. The modified version of U-Net was employed to segment MRI brain tumor images. The Cross Entropy and Dice loss were utilized to address the loss function to check the imbalance. The mean enhanced tumor, for whole the tumor, dice score of 0.783, 0.868 and 0.805 has been achieved correspondingly.

The paper “Brain Tumor Segmentation from MRI Images using Hybrid Convolutional Neural Networks” the author employs hybrid of three CNN techniques, Seg-UNet, Res-SegNet and U-SegNet for automatically segmenting MRI images. This model inherits salient features of U-Net, SegNet and Residual network for segmenting semantically. This hybrid technique was able to solve the issue of tiny minute tumor that are vanished during down sampling because of it skip connection. The three models achieved an accuracy of 93.3%, 91.6% and 93.1% respectively. These combined architectures were composed of too many layers and variables to train so longer period was required for training. The system automatically segments the images in few seconds.

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III. PROPOSED METHODOLOGY

The methodology includes the application of residual network for segmentation purpose. Here we are resizing the Oral cancer MRI data set into 128*128, 256*256 pixel size. The data collection was made from Radiopaedia squamous cell carcinoma tongue and digital imaging and communications in medicine dataset. The images were collected from https://radiopaedia.org/articles/squamous-cell-carcinoma-tongue and https://www.dicomstandard.org. We are enhancing the images based on their size, color and the texture features. After pre-processing we are using ResNet 18 for the segmentation of MRI images. The different section includes Pre-processing, Segmentation and Performance evaluation.

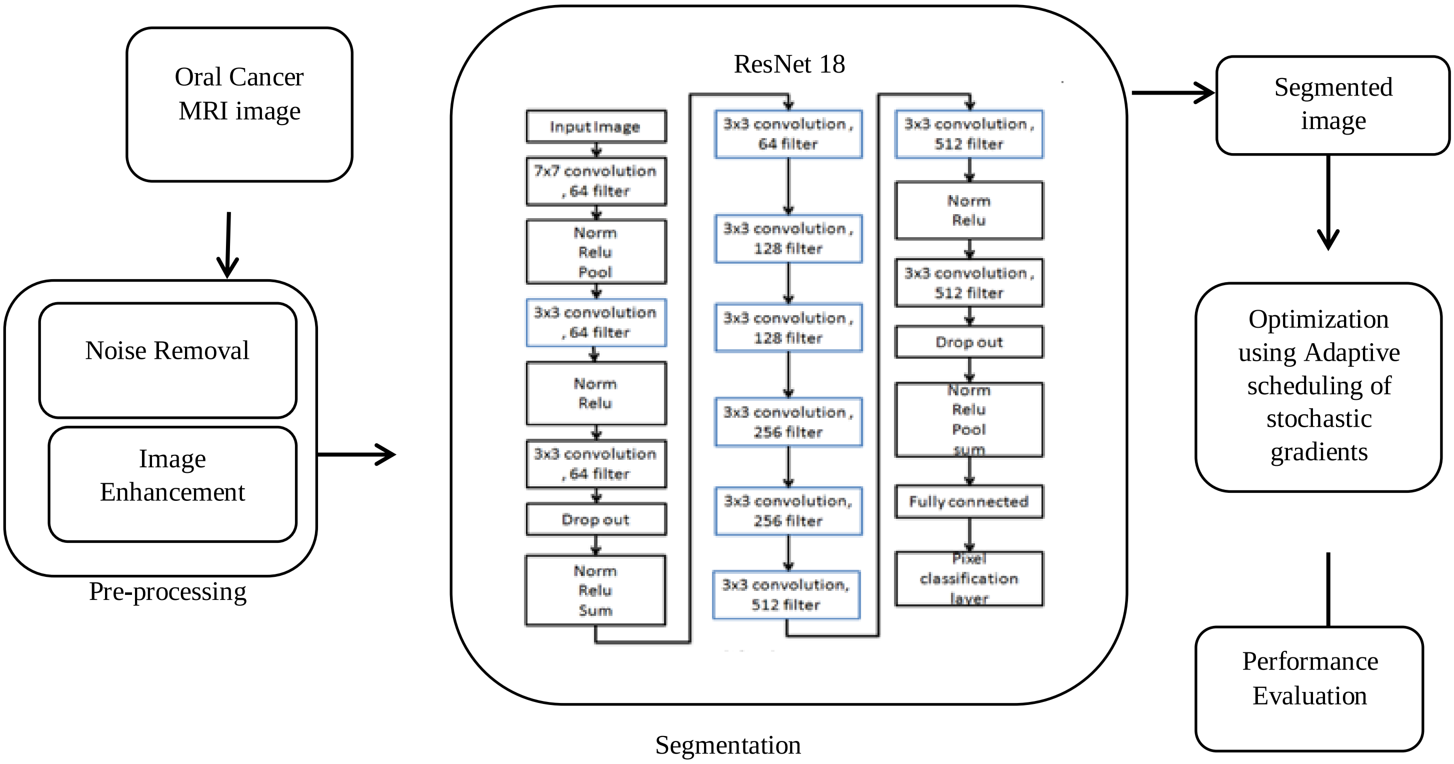

Fig. 1: Proposed methodology development and performance evaluation of Oral Cancer MRI images.

A. Pre-processing

This stage will remove unwanted data present in MRI images which helps the clinical researchers to diagnose properly so that tumor can be identified in early stage itself and also makes images suitable for further processing. The pre-processing involves mainly converting the image into grey scale, image noise removal and reconstruction of image. The criterions considered to improve are signal noise ratio, getting rid of unwanted noise and noise present in background and keeping all the relevant data.

B. Segmentation

This section contains detailed explanation of the different steps carried out to segment the Oral cancer MRI images. Here we have explained the two different sections of Residual Network and ResNet 18.

➢ *Residual Network*

The gradients dissemination issue occurs in deep CNN while training the process. As the training process continues the gradients values ultimately will be lowered to zero. To overcome this issue, Residual Network Learning (ResNet) was introduced. The RESNET model was proposed by He.et al.to to solve the issue related to accuracy training. The results obtained from the remaining layer were coiled with input which had to be the next layers input. Let P(z) represents the remaining layers aligning to build up residual block for learning as described in **Fig.2**. The residual network gives the value approximately to $P(z) = Q(z) + z$. These formulations are recognised by the feed forward neural network system with shortcut connections. These connections integrate the inside and outside of the gathered layers into the similar bounding operations involving no extra variables. This helps gradients to transfer effortlessly back, which results in rapid training and numerous layers.

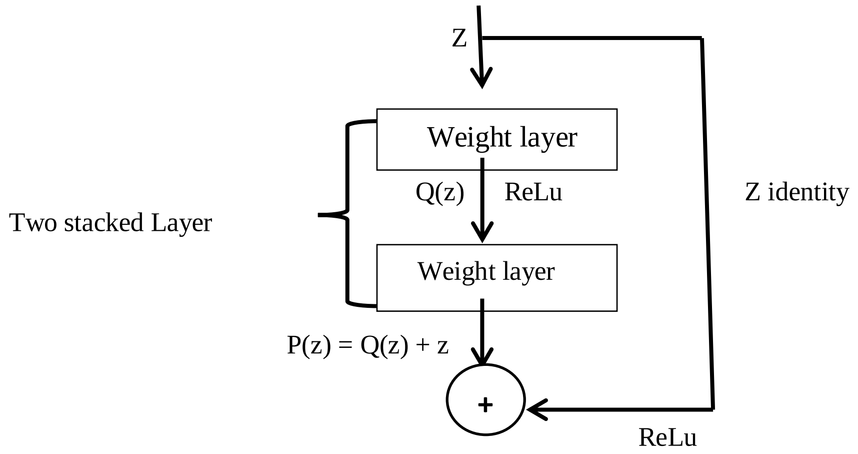

Fig. 2: Building block of Residual Network

There are two major blocks in the model of RESNET which is explained below:

C. Identity block

The identity block is described as $m = Q(z, \{Ki\}) + z$ .... (1)

The z and m represents the input and output layers and $Q(z, \{Ki\})$ function defines the bounding of residual network. The identity block consists of same dimension of x and Q. Fig. 3(a) explains the design of identity block composed of three constituents as shown below:

- 2D convolution layer is the first constituent with 1*1 size filter, a pace of (1, 1). Batch normalization is carried out to normalise the channels and rectified linear activation unit is applied for nonlinear activation units.
- The second element is same as the first one but with the change in size of filter $(q * q)$.
- The third element same as the first element but it will not contain ReLU activation function.

Finally, before applying the activation function the shortcut and inputs are integrated together.

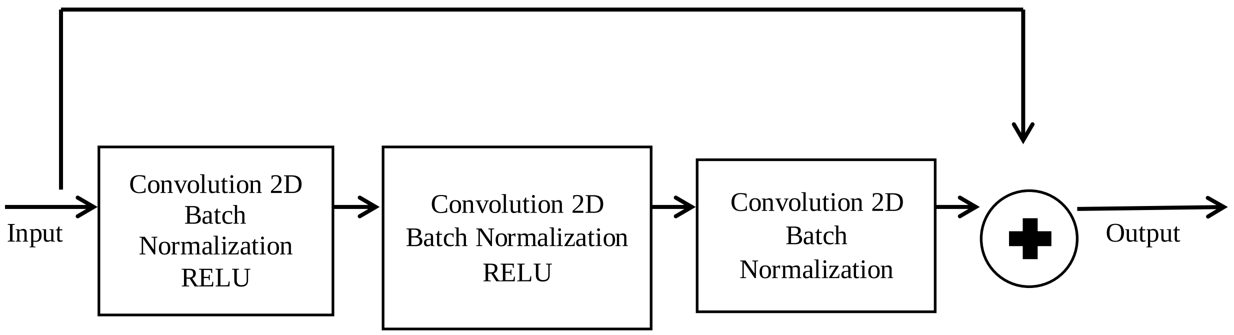

Fig. 3(a): Represents an Identity Block of ResNet.

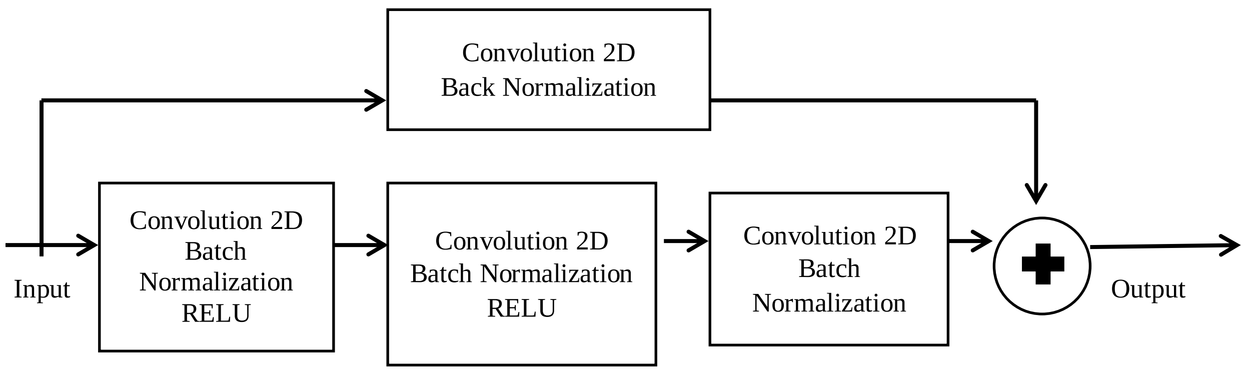

Fig. 3(b): Represents a Convolution Block of ResNet.

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D. Convolution block

In this block the shortcut connections carries out the linear projection Ks to size up the dimension between z and Q. Here the input and output of the elements are not matched. The equation is explained as follows:

$$m = Q(n, \{Ki\}) + Ks\ n) \ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

Where Q is the output obtained from the stacked layer, m and n are the inputs and merged output vectors obtained of the convolution block is shown in fig. 3(b). The design of convolution block is same as identity block but with addition of 2D convolution layer with a short cut way. The input is matched with the main path with a filter size of 1*1 of 2D convolution layer and stride (s,s) which depends on the output layer. The shortcut altered is merged with main path output. The major advantage of this altered shortcut was to control the issue of dissemination of gradients. This enables the process to gain knowledge that the identity function assures that the higher layers will carry out an event same as that of the lower classes.

➢ *ResNet 18*

Many different models of ResNet are proposed by the authors such as ResNet with 18, 34, 50, 101, 152 and 1202 layers. Each layer consists of various blocks and in these the identity and convolution blocks are defined in section (2.3). In this proposed methodology, we have used ResNet 18 for segmenting MRI images which is good compensation between performance and depth. Since it has less number of parameters comparing to other ResNets this leads to faster and accurate training period. The architecture of ResNet 18 is shown in **fig.4.**

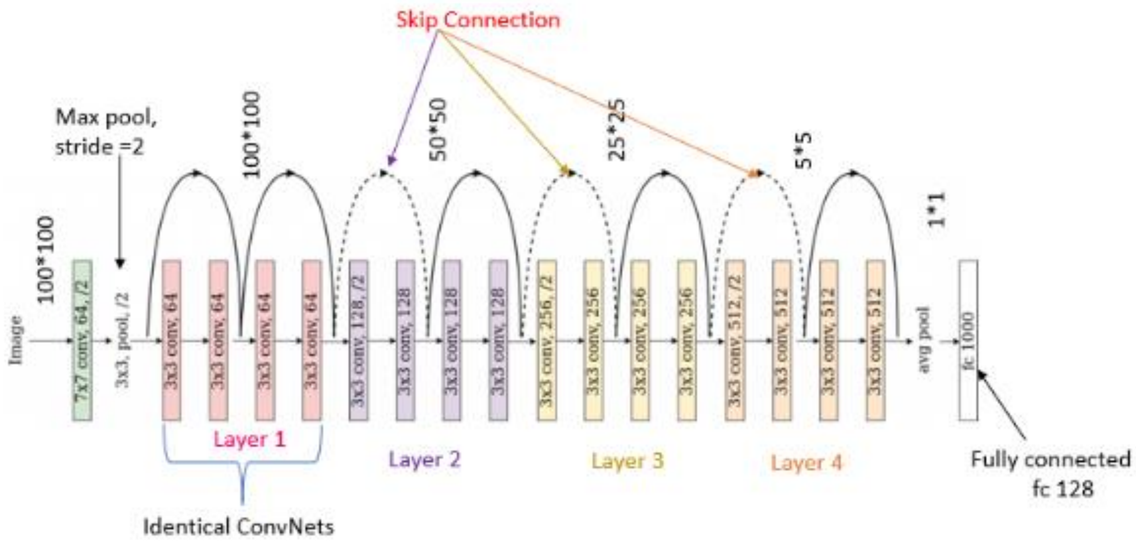


Fig. 4: ResNet-18 Architecture

The ResNet 18 contains 4 convolution layers in each of the module (first convolution layer and fully connected layer = 18 layers) and is composed of 5 stages with every layer having convolution and identity blocks to persist:

- Stage 1: Contains 2D Convolution layer with a shape of (7*7) size, 64 filters and a stride (2, 2). Similarities of the channels are performed by batch normalisation and activation function ReLU. Max pooling is combined at end with stride (2, 2).
- Stage 2: Contains two identity blocks with one 2D convolution block, both the blocks uses 3 filter sets (56, 56, 64), with kernel size (3 * 3) and (2, 2) stride.
- Stage 3: Contains three identity blocks with one convolution block, both uses 3 filter set (28, 28, 128) with kernel size - (3 * 3) , (2, 2) stride.
- Stage 4: Contains four identity blocks with one convolution block, both uses 3 filter sets (14, 14, 256) with kernel size - (3 * 3) , (2, 2) stride.
- Stage 5: Contains five identity blocks and one convolution block and both uses 3 filters set (7, 7, 512) and with the size (3 * 3) and (2 * 2) stride.
- Stage 6: An Average pooling of size 7*7 is used, the obtained output is smashed and the fully connected layer is declined its input to several numbers of classes employs activation unit "softmax'.

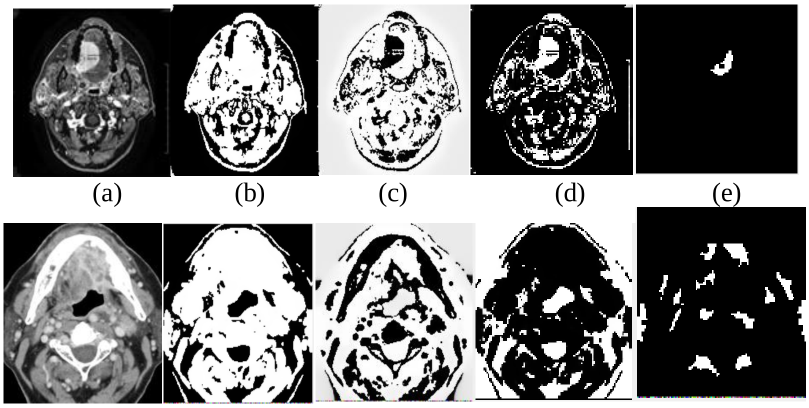
E. Simulation set up

In this section, we are explaining in detail our simulations to verify the performance of deep residual network ResNet 18 in segmenting the oral cancer MRI images. We have employed tensor flow for our model.

The model proposed is examined and evaluated using MRI Oral cancer images dataset. The training set compromises of 100 patients suffering from Oral Squamous cell Carcinoma. In the dataset we have every patient 10 samples so total number of 1000 images having image size of 225*225. We have resized the image into 128*128. The hyper-parameters used in this proposed models is described in table 1.

Table 1: Hyper parameters used for the training purpose

Hyper parameters	values
Optimizer	ADAS
Loss function	0.121
Initial learning rule	0.0001
No. of epochs	32



(a) (b) (c) (d) (e)

(a) (b) (c) (d) (e)

Fig. 5: Represents the Oral MRI images (a), the different stages of segmentation is represented by (b), (c) and (d), here (e) represents the segmented image.

F. Performance Evaluation

The methodology proposed for Oral cancer MRI segmentation is calculated using evaluation metrics. The segmentation output is assessed by its contrast and the segmentation of ground truth images having similar features that are given by the dialogists.

To compare the two MRI images we have used Dice Similarity Coefficient (DSC), Specificity (rate of true negative), Sensitivity (rate of true positive), and Accuracy (A) and Precision (P) values.

- *Dice Similarity Coefficient*

The Dice similarity Coefficient calculates the overlap that occurs between the main Oral cancer MRI segmented images and ground truth images. It is gives us shown below:

$$DSC = \frac{2TP}{FP+2TP+FN} \quad \ldots\ldots\ldots\ldots \text{(3)}$$

TP (true positive) – this precisely identifies pixels of tumor.

FP (false positive) – this precisely distinguishes the pixels of non-tumor.

FN (false negative) - this inaccurately identifies non-tumor pixels.

The efficiency evaluator's specificity and sensitivity examine the robustness of our proposed methodology for segmenting MRI tumor images.

- *Specificity*

$$Specificity = \frac{TN}{TN+FP} \quad \ldots\ldots\ldots\ldots \text{(4)}$$

- *Accuracy*

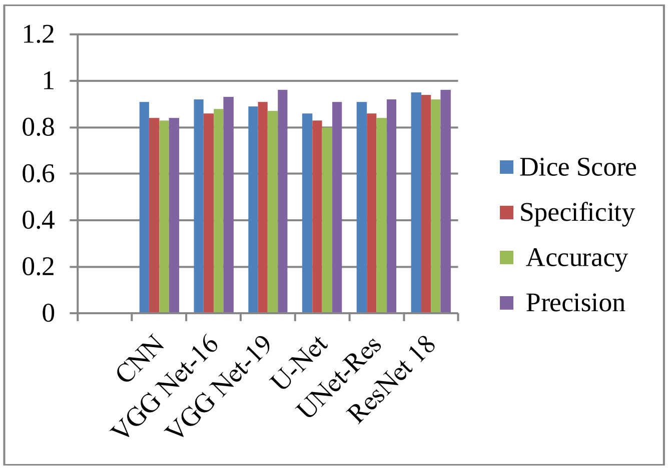
$$Accuracy = \frac{(TP+TN)}{TP+FN+TN+FP)} \quad \ldots\ldots\ldots\ldots \text{(5)}$$

- *Precision*

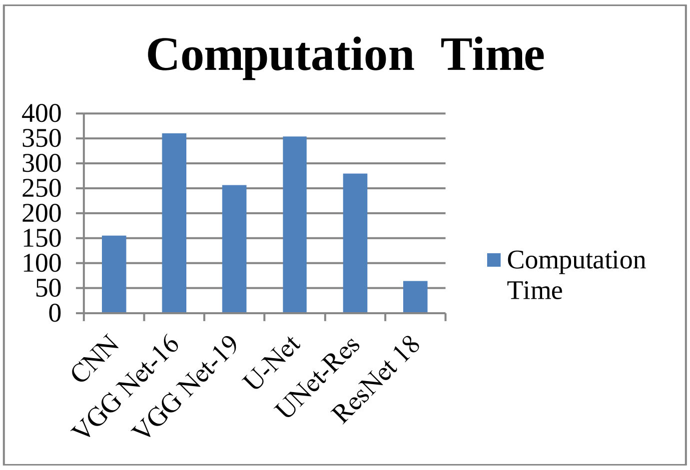
$$Precision = \frac{TP}{(TP+FP)} \quad \ldots\ldots\ldots\ldots \text{(6)}$$

Table 2: This shows comparison of different techniques with proposed methodology- performance evaluated for Dice score, Specificity, Accuracy, Precision and computation time in minutes

Techniques	**Dice Score**	**Specificity**	**Accuracy**	**Precision**	**Computation Time**
CNN	0.91	0.84	0.83	0.84	156 mins
VGG Net-16	0.92	0.86	0.88	0.93	360 mins
VGG Net-19	0.89	0.91	0.87	0.96	256 mins
U-Net	0.86	0.83	0.80	0.91	354 mins
UNet-Res	0.91	0.86	0.84	0.92	280 mins
ResNet 18	0.95	0.94	0.92	0.96	63 mins



Graph 1: Represents the performance Evaluation



Graph 2: Represents the Computational time

IV. RESULT AND DISCUSSION

This section contains the comparing of the results of our proposed methodology of segmenting Oral cancer MRI images with 3 segmentation techniques: CNN, VGG Net-16, VGG Net-19, U-Net and UNet-Res (residual block).

The data collection was made from Aster CMI Hospital Hebbal, MRI Oral cancer images related to lip and mouth cancer. Few images were taken from Radiopaedia squamous cell carcinoma tongue and digital imaging and communications in medicine database.

from : https://radiopaedia.org/articles/squamous-cell-carcinoma-tongue and https://www.dicomstandard.org.

A. Dataset Training

The proposed methodology is compared with CNN, VGG Net-16, VGG Net-19, U-NET and UNet-Res over all the process of training. Each and every sequence in the model is normalised as discussed in the pre-processing stage. Adaptive scheduling of stochastic gradients optimization algorithm is employed to restrict the optimization. It is faster comparing to other optimization at attaining convergence. It displays low level loss with outlined features helping in optimization. The performance of training of the model compared with CNN, VGG Net-16, VGG Net-19, U-Net and UNet-Res are shown in **Graph 1**. It shows that ResNet 18 has lesser error while training and shows high accuracy comparing to various techniques.

The validation of proposed model uses over 32 epochs for the process of training. This exhibits that the errors decreases rapidly over the training period and accuracy of the training rises after every epoch.

B. Dataset Testing

In this process, the data is tested over the model in segmenting the tumors in Oral MRI images. The model is evaluated against the techniques using performance metrics as defined in section 5 along with the computational time this gives us the results of the segmentation. We have calculated the evaluation metrics on each patient dataset and the average value of each data is estimated. **Graph 2** displays the segmented image that displays the performance of the proposed methodology. To represent the viability, the average computational time is calculated in segmenting the data. The average computational time is calculated defined as the processing time that is required for segmenting the Oral MRI images. **Table2** also shows that the proposed model has minimal average computational comparing to the other techniques. This aptly shows that the proposed methodology has higher accuracy and minimal average computational time period.

The ResNet model accomplishes identity mapping and these outputs get connected to the corresponding stacked layers without any addition of extra parameters. This mechanism show that the layers of ResNet model will try to learn the leftover inputs and outputs while the layers of CNN, VGG-16, VGG-19, U-Net and UNet-Res learns exclusively the true outputs. The gradients flow backwards without any effort which results in quick processing in comparison with other techniques. The ResNet has power of short connections which helps in solving the issue related to dissemination the gradients. ResNet also guarantees that the higher layers execute as good as that of the lower layers.

V. CONCLUSION AND FUTURE SCOPE

Oral cancer MRI tumor segmentation is one of the needed requirements in the early treatment of Oral cancers. Though the Deep neural networks are important strength of image segmentation they have one drawback of dissemination of gradients which arises during the process of training. We have used Residual Network – ResNet to come out of this problem. In residual network we have employed ResNnet 18 in our proposed methodology since it has fewer errors while training and also high accuracy as it contains lesser number of layers. The proposed methodology performs well compared to CNN, VGG 16, VGG 19, U-Net, UNet-Res models relating to computation time. We have employed Adaptive scheduling of stochastic gradients optimization technique. It has minimal computing execution time comparing to all other techniques mentioned above. Our proposed methodology achieves shows a better accuracy, dice co-efficient, specificity and precision of 0.92, 0.95, 0.94, 0.98 respectively and computational time of 63 mins.

In the future we can modify the Resnet 18 with different number of filter sizes or we can make hybrid models with Residual Networks which improves the efficiency of segmenting the tumors in Oral cancer MRI images.

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