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Automatic Pancreas Segmentation using A Novel Modified Semantic Deep Learning Bottom-Up Approach

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Abstract: Sharpe and smooth pancreas segmentation is a crucial and arduous problem in medical image analysis and investigation. A semantic deep learning bottom-up approach is the most popular and efficient method used for pancreas segmentation with a smooth and sharp result. The Automatic pancreas segmentation process is performed through semantic segmentation for abdominal computed tomography (CT) clinical images. A novel semantic segmentation is applied for acute pancreas segmentation with different angles of CT images. In the novel modified semantic approach, 12 layers are used. The proposed model is executed on a dataset of 80 patient single-phase CT images. For training purposes, 699 images and testing purposes 150 images are taken from a dataset with a different angle. The Proposed approach is used for many organs segmentation from CT scans clinical images with high accuracy. "transposedConv2dLayer" layer is used for up-sampling and down-sampling so the computation time period is reduced as related to the state-of-art. Bfscore, Dice Coefficient, Jaccard Coefficient are used to calculate similarity index values between test image and expected output image only. The proposed approach achieved a dice similarity index score upto 81±7.43%. The Class balancing process is executed with the help of class weight and data augmentation. In novel modified semantic segmentation, max-pooling layer, RELU layer, softmax layer, transposed conv2d layer and dicePixelClassification layer are used. DicePixelClassification is newly introduced and incorporated in a novel method for improved results. VGG-16, VGG-19 and RSnet-18 deep learning models are used for pancreas segmentation.

Keywords: *BFscore , Deep Learning, Dice Coefficient ,Visual Geometry Group(VGG)*

1. Introduction

Image splitting task is rigorously to act as a vital character in image investigation [1]. Image splitting task is beneficial for many applications like clinical image analysis, disease detection of crop, traffic control observation, metallic surface crack detection, and Aerospace image analysis. CT, MRI, PET, and supplementary images are used in the clinical image diagnosis and cure of illnesses. Pancreas segmentation is a challenging job in medical image investigation and analysis. Accurate organ segmentation and rapid processing are the major challenges in the result of medical images. Computerized segmentation of several image subsections is useful to analyse anatomical organization as well as the abdominal body. Segmentation is played a major role in the visualization and diagnosis of clinical images. Sub-grouping is an important subject to several image-processing research. Spleen, liver, kidney, pancreas is present in the abdominal CT images [2]. The Bottom-up approach and Top-down approach are applied to the image splitting process [3]. In top-down approach, medical image segmentation is performed within minimum time-period with less accuracy of segmentation. Bottom-Up approach is an efficient approach for medical image segmentation with high accuracy and minimum time period. Semantic segmentation is one approach of deep learning used for abdominal computed tomography. A Deep learning model is a popular approach to machine learning methods.

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The Deep learning model is dealing with algorithms with hierarchical procedure layers. It is experimenting with nonuniform transformations to view and gain datacharacteristics successfully [4]. Currently Deep learning model is popular in various domains such as medical image analysis, medical signal analysis, speech recognition, bioinformatics, computer vision [4]. Convolution neural networks, Generative Adversarial Networks, networks with auto-encoder, and recurrent neural networks are prominent deep learning approaches. These approaches are introduced and used in various tasks to be mapped with state-of-the-art results. In deep learning, network training is required with a dataset. For network training, a set of convolution networks, annotated dataset, optimizer, mini-batch size, epoch, the loss function is used. Dataset can be divided into training, validation and testing purposes also. The Fully convolution network (FCN) was introduced by Long et al. [5]. In FCN, fully convolution layer is used as the last fully convolution network layer. For more accuracy of dense pixel-wise predication, the network is used fully convolution network. Semantic segmentation can be performed by FCN. FCN architecture is built with pooling, upsampling, and convolution. FCN can perform the prediction of an image within on single forward pass.

2. Materials and Methods

In Computer-aided diagnosis (CAD), organ segmentation procedure is pivotal in CT scan images for detection of kidney, pancreas, and spleen from the abdominal body[6]. For this procedure, surgical assistance, qualitative and quantitative investigation are required. Accurate pancreas segmentation is very important for the pancreatic cancer detection process [7]. The size of pancreas is varying as per angle of computed tomography (CT) image. In some angles, the pancreas and right-side kidney may appear same so detection of pancreas should be correct and perfect.

2.1. Image Datasets and Ground Truth Labeling

Bottom-UP approaches are applied on a dataset of 80 patients,53 male and 27 female patients' high resolution (512*512) CT scan images of 3D abdominal with 1.5-2.5 mm slice thickness range using Philips and Siemens MDCT scanners [2]. The 63 patients CT scans abdominal images are erratic recommended by an expert radiologist from the Picture Archiving and Communications System (PACS). National Institutes of Health Clinical Center is providing a database of CT dicom images for abdominal.78 to 79 years patient age series with a mean of 46.8±16.7 are used dataset [8]. DICOM medical images are converted to PNG image format. The view of scans images was axial, sagittal and coronoal with 1.5 mm or 3 mm thickness available [9]. Human expert labeling was performed under the guideline of a certified radiologist. 3 labels are created for manual labelling like background, pancreas, and kidney. Medical images are selected with a different focal phase angle of CT. The size and shape of pancreas is varies in a different view of CT. Image input size is 255x255x3. 699 images are used for and 150 for testing.

2.2. Network of Proposed Methods

A novel modified semantic segmentation deep learning approach is used 12 layers for smooth and sharp abdominal organ segmentation. In the system, 3-Con2dLayer, 2-Relu layer, 2-droupoutLayer, imageinputlayer with 255*255*3 size image, maxpooling2d layer, transposedCov2dlayer and Dicepixelclassification layer are used. For Conv2dlayer, 3 label classes are used. 64 number of filters with size 3 and padding with 1 is used for same layer. Filters are used in proposed method to detect edges of images. The convolution process is applied on input image size 255x255x3 with filter size 3x3 and output image size is calculated by following equation

$$(M \times M)\times(F \times F) = (M - F + 1)\times(M - F + 1) \qquad (1)$$

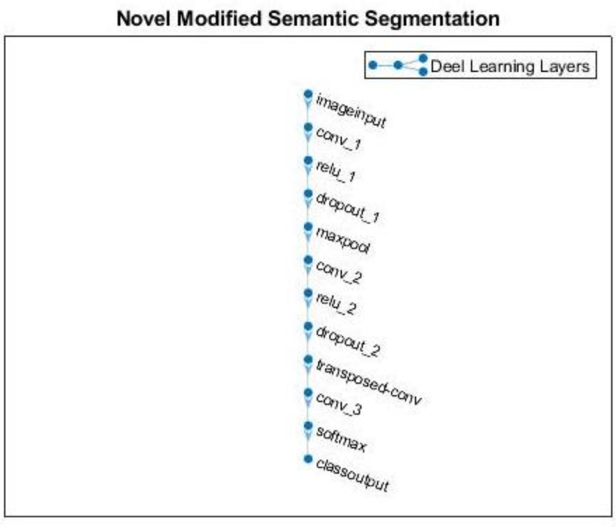

Fig.1. Layered Graph of Proposed Method

2.2.1. imageInputLayer Layer

2-D images with size *255*255*3* are passed to a network and apply data normalization.

imageInputLayer([255 255 3]) (2)

Where,

- 255, a positive integer value of input image which indicate height and width.
- 3, a positive integer value specified RGB image.

2.2.2. convolution2dLayer Layer

Sliding convolution filters are used to the input image. It convolves received input by handing the filters along with received input upright and horizontally, also evaluating the dot product of the weights,input, and lastly adding a bias term[9].

2.2.3. reluLayer Layer

Set any value is zero if pixel value less than zero,threshold operation for each and every pixel of input executed using reluLayer layer. Convolutional and batch normalization layers are regularly running by a nonuniform activation function like Rectified-Linear-Unit (ReLU), specified by a reluLayer layer.

$$f(x) = \begin{cases} x, & \text{ifx} \geq 0 \\ 0, & \text{x0} \end{cases} \qquad (3)$$

2.2.4. dropoutLayer Layer

The Dropout layer is a regularization approach for minimizing over-fitting in deep neural networks by averting complex co-adaptations on training data[10]. A dropoutLayer layer arbitrary formulate input elements to zero with a said probability. Dropout term mention to arbitrary "dropping out", or leave out, units during training procedure of a network. Dropout is regularly divided into weak dilution and strong dilution. Weak dilution emphasizes the procedure in which the finite fraction of eliminated connections are small, and strong dilution refers to when this fraction is large[11]. These approaches are also in some cases referred to as arbitrary pruning of weights, but this is generally a non-recurring one-way operation[12]. The network is trim, and kept same if development against an older model. At training, layer arbitrary formulate input elements to zero assigned by the dropout mask *rand(size(X))<Probability*, where *X* is the layer input and then scales the remaining elements by *1/(1-Probability)*. This operation successfully modified the underlying network architecture between iterations and helps avoid the network from overfitting[13].

$$\hat{d}_j = \begin{cases} d_j, & \mathrm{P(c)} \\ 0, & \text{otherwise} \end{cases} \qquad (4)$$

where, *P(c)*: the probability *c* to keep a row in the weight matrix, d_j: real row in the weight matrix before dropout,$\hat{d}_j$: dropout row in the weight matrix.

2.2.5. maxPooling2dLayer Layer

A maxpooling2dlayer is responsible for partitioning downsampling. Rectangular pooling regions assimilate input with evaluated the maximum of respective region. A maxPooling2dlayer layers operate the convolution layers for down-sampling, hence, minimizing the number of connections to the connected layers[14]. Layers do not experiment with any learning within, but minimize the number of an attribute to be gained in the connected layers. It may also help to minimize over-fitting. A maxPooling2dLayer layer reverts the peak values of rectangular regions of its input. The Poolsize argument has calculated the size of the rectangular regions. For example, if poolSize equals(2,3), then the layer reverts the peak value in regions of height 2 and width 3.

maxpooling2dlayer layers scan through the input plane and upright in step sizes mentioned using the 'Stride' name-value pair argument. Pooling regions are not overlapping when the $poolsize \leq stride$[15]. Non-overlapping regions, if the input to the pooling layer is *m-by-m*, and the pooling region size is *t-by-t*, then the pooling layer down-samples the regions by *t [1]*[16]. That is, the output of a max or average pooling layer for one channel of a convolution layer is *m/t-by-m/t*[17]. For overlapping regions, the output of a pooling layer is

*(InputSize – PoolSize + 2*Padding)/Stride + 1* (5)

2.2.6. transposedConv2dLayer Layer

A transposedConv2dLayer layer is a convolution layer upsamples feature maps and transposes of convolution. The training time period is reduced by using these layers. Deconvolution function is not available in this layer[13].

transposedConv2dLayer(4,numFilters,'Stride',2,'Cropping',0)

(6)

where,

- 4 *filtersize* is specifies filter height 4 and width 5
- 64 *numFilters* are used.64 neurons is used.
- *Stride* is Up-sampling key of the input and having 2 positive integer related to the upright and plane stride.
- *Cropping* is output size reduction and integer(+) value trim data.

2.2.7. softmaxLayer Layer

A softmax function is used for input. It is also called softargmax which is a generalization of the logistic function to many dimensions[18]. For classification problems, a softmax layer and a classification layer are mandatory to follow the final fully connected layer.
The output unit activation function is the softmax function:

$$t_r(x) = \frac{exp(a_r(x))}{\sum_{j=1}^{k} exp(a_r(x))} \quad (7)$$

where $0 \leq t_r \leq 1$ and $\sum_{j=1}^{k} t_j = 1$

The last fully connect layer is used softmax function as the output unit activation function for multi-class classification:

$$P(c_r|x,\Theta) = \frac{P(x,\Theta|c_r)P(c_r)}{\sum_{j=1}^{k} P(x,\Theta|c_r)P(c_r)} \quad (8)$$

Where,$P(c_r)$is the class prior probability.

2.2.8. dicePixelClassificationLayer Layer

The pixelClassification layer supports a categorical label for every image pixel but dicePixelClassification layer is using generalized Diceloss function which supports pixel. The layer uses generalized Diceloss to reduced class imbalance problem in semantic segmentation. Generalized Dice loss controls the contribution that each class makes to the loss by weighting classes by the inverse size of the expected region. It generates Dicepixelclassification output layer for networks. The layer automatically omits unassigned pixel labels during training. The Dice loss function is based on the Sørensen-Dice similarity coefficient for measuring overlap between two segmented images[16]. The generalized Dice loss function *M* used by dicePixelClassificationLayer for the loss between one image*T* and the correlated ground truth *P* is:

$$M = 1 - \frac{2\sum_{k=1}^{K} w_K \sum_{i=1}^{I} T_{ki}P_{ki}}{\sum_{k=1}^{K} w_K \sum_{i=1}^{I} T_{ki}^2 + P_{ki}^2} \quad (9)$$

K:number of classes, *I*: number of elements along the first two dimensions of *T*, and wk:class specific weighting factor. *wk* contribute to control influence of larger patches on the Dice. *wk* is typically inverted of expected region.:

$$w_K = \frac{1}{(\sum_{i=1}^{I} P_{ki})^2} \quad (10)$$

There are several variations of generalized Dice Loss functions. The function used in dicePixelClassificationLayer has squared terms to ensure that the derivative is 0 when the prediction matches the ground truth.

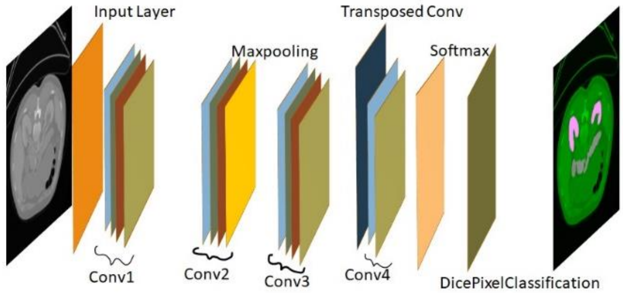

Fig.2 A Novel Modified Semantic Segmentation Method

2.3. Class Imbalance

The interest of anatomy in the small section of the scan medical images. Hence, background area is covered by the extracted patches and small organs are having a vital role in the analysis. In this condition, background data is taking the main lead role in training the network and is biased toward the background. Overcoming this drawback re-weighting of sample is the most acceptable solution by a trained network. Where peak weight is claimed to the foreground patches during training [17]. Dice coefficient value and DicelossLayer are used for automatic update of sample re-weighting. Proposed method is useful for detecting multi-organ from CT images like pancreas, right side kidney and left side kidney. 3 classes are derived for a dataset like background,pancreas and kidney with 0.0181,1.2519 and 1.0000 respectively class weights. The proposed method can be useful for other organ detection of abdominal computed tomography medical images. In this approach, pre-processing is required for creating class for each abdominal organ. Label *L*, is class name of training dataset and *n* number class can be defined in system as per requirement. Training dataset and Label dataset are required for segmentation process.

$$tb_1 = \sum L \quad (11)$$

Above equation for counts of label by class label.

$$t_p = \sum_{i=1}^{L} tp_L \quad (12)$$

Above equation for count of number of pixel in each class label.

$$f = \frac{\sum_{i=1}^{C} tp_C}{\sum_L tp_L} \quad (13)$$

Above equation for calculate frequency of input image.

$$C_w = \frac{|img_L|}{img} \quad (14)$$

Above equation for calculate median frequency of class weights and This class weights value is added into proposed network layer.

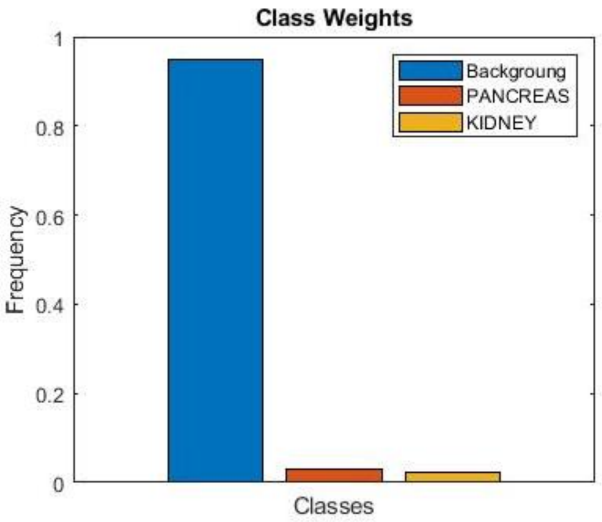

Figure 3. Class Weights of Label Class

2.4. Data Augmentation

Class imbalance is a problem in semantic segmentation. To overcome this drawback, novel semantic segmentation is using data augmentation and class weights. Semantic segmentation is having data overfitting and less accuracy of image segmentation. A novel modified semantic segmentation is using data augmentation to solve class imbalance problems for more accuracy. An image data augmenter setup to examine of pre-processing choices for image augmentation, such as resizing, rotation, and reflection. Data augmentation is beneficial to enhance output and results of deep learning approaches using set novel and discrete examples to datasets. If dataset in a deep learning approach is ample and sufficient, the model execution most accurate. For deep learning models, collecting and labeling data can be time consuming and expensive processes. Transformations in datasets by using data augmentation approaches authorize companies to minimize these experimental costs. In the system, data augmentation is using reflection, translation and rotation to improve model prediction accuracy and reduce overfitting of data.

3. Result

3.1. Hardware and Software Requirement

Table 1. Hardware and Software for Proposed Approach

Hardware/Software	**Requirements**
Processor	Intel i3,M-1.90 GHz
Operating System	Ubuntu 18 or Microsoft Windows 8
RAM	Minimum 8GB
Software	MATLAB 2019a onward
Tool	1. Image Processing 2. Computer Vision 3. Deep Learning

3.2. Metrics for Image Segmentation Approaches

Performance of image segmentation using various deep learning approaches are measured using following parameter.

• Global Accuracy(GA)

GA is the ratio of perfectly segmented pixels divided by the total number of pixels[19].

$$GA = \frac{\sum_{i=0}^{C} p_i}{\sum_{i=0}^{C} \sum_{j=0}^{C} p_{ij}} \tag{15}$$

where p_{ij} is the number of pixels of class *i* segmented as belonging to class *j*.

• Mean Accuracy(MA)

Mean Accuracy is an next step of Global Accuracy, in which the ratio of match pixels are computed in a per-class pattern and then averaged over the total number of classes[19].

$$MA = \frac{1}{C+1} \sum_{i=0}^{C} \frac{p_{ii}}{\sum_{j=0}^{C} p_{ij}} \tag{16}$$

• Intersection of Union(IoU)

Jaccard index alias IoU,It is correlation between segmented image(S) and annotated image(B). The value of IoU lies between 0 to 1[20].

$$Jaccard(S,B) = IoU = \frac{|S \cap B|}{|S \cup B|} \tag{17}$$

• Mean Intersection of Union(MIoU)

Mean IoU is calculated by the average IoU value of all classes.

$$MIoU = \frac{\sum_C IoU}{C} \tag{18}$$

Where,Total number of classes value is denoted by *C*. 3 classes are used like pancrea,kidney and background.

• Weighted Intersection of Union(W-IoU)

$$WIoU = \frac{\sum_C IoU * \sum_{i=0}^{C} p_i}{C} \tag{19}$$

Weight value is number pixel in class. Average IoU of each class[19].

• bfscore

The bf score measure how close to the segmented boundary of an input image matched with the annotated image. The BF score is calculated with the help of the harmonic mean of the precision and recall values with a distance error tolerance to decide whether a point on the segmented boundary has a correlated to annotated boundary or not[20].

$$score = \frac{2 * precision * recall}{(recall + precision)} \tag{20}$$

• dice coefficient

It is correlation between segmented image(S) and annotated image(B). The value of dice coefficient lies between 0 to 1 and easily converted into % for understanding purpose[20].

$$dice(S,B) = 2 * \frac{|S \cap B|}{(|S| + |B|)} \tag{21}$$

• Sensitivity

$$Sensitivity = \frac{TP}{FN + TP} \tag{22}$$

Where,*TP* is true positive, *FN* is false negative[20].

• Specificity

$$Specificity = \frac{TN}{FP + TN} \tag{23}$$

Where,*TN* is true negative, *FP* is false positive[20].

3.3. Experiment Result

The proposed method is trained on same dataset for 699 images and tested on 150 images.RSnet-18, VGG-16 and VGG-19 matlab deep learning model are using same dataset.

Table 2 gives a detail performance of proposed method. The Proposed method achieved closer performance value towards other approaches. MA and M-bscore value is more than other.

Table 2. Detail performance of deep learning model on dataset. GA:Global Accuracy, MA:Mean Accuracy,MIoU: Mean Intersection of Union,WIoU: Weighted Intersection of Union,M-bfscore ,Bf score(%)

Approach	GA(%)	MA(%)	MIoU(%)	WIoU(%)	M-bfscore(%)	Bf(%)
Proposed Method	94.391	42.549	33.114	80.296	24.132	64.10±9.31
RS-18	94.339	42.160	32.871	80.183	23.785	84.06±3.96
VGG-16	94.408	42.439	33.129	80.534	24.055	84.05±4.02
VGG-19	94.331	42.170	32.832	80.56	23.973	56.62±2.48

Table 3. Detail execution of proposed approach with state-of-art on manually segmented CT images

Method	IOU(%)	Dice(%)	Sensitivity(%)	Precision(%)
Proposed Method	69.82±11.52	82.57±07.48	98.66±00.02	68.22±00.12
RS-18	96.63±01.25	98.29±00.63	96.78±00.03	96.64±00.12
VGG-16	96.63±01.24	98.27±00.64	95.79±00.03	96.63±00.01
VGG-19	95.52±01.23	97.70±00.64	96.60±00.01	98.84±00.00
Atlas(Wolz et.al,2013)	55.50±17.10	69.60±16.70	67.90±18.20	74.10±17.10
U-net Single Model(Oktay et.al,2018)	-	74.10±00.13	74.30±00.17	78.90±00.13
Frame-1(Amal et.al,2017)	57.2±25.40	68.80±25.60	72.50±27.20	71.50±30.00
Frame-2(Amal et.al,2017)	57.9±13.60	70.70±1300	74.40±15.10	71.60±10.50

Table 3 is consist information of proposed method and state-of-art. Proposed method is achieved dice value 82.57±07.48 which higher than state-of-art. Proposed method having improved value than state-of-art for evaluation parameter like Jaccard index,Sensitivity and Precision. Atlas(Wolz et.al,2013) is working on 150 scan images, U-net single Model(Oktay et.al,2018) is working on 150 scan images in which 30 images uses for training and 120 for testing images. Frame-1(Amal et.al,2017) and Frame-2(Amal et.al,2017) is working on 80 patients image dataset.

4. Discussion and Conclusion

Amal et.al,2017, patch labeling is used so 64*64 patch channel used so only one organ segmentation can be performed. In proposed method, manually annotation process is performed by medical practitioner and two classes is generated for pancrea and kidney. With the help of proposed method many abdominal organ segmentations can be performed. Input image size is 255*255*3 used so maximum pixel information is available in convolution network. Noisy pixel image information can be easily omitted during dropout network layer.

Table 4. Detail summary of Convolution Layer of Proposed Method

Name	**Output Size**	**Proposed Method Layer**
CONV1	112×112	7×7,64 Stride,2
CONV2	56×56	3×3 max pool, stride 2 $\begin{bmatrix} 3\times3,64 \\ 3\times3,64 \end{bmatrix}\times2$
CONV3	28×28	$\begin{bmatrix} 3\times3,128 \\ 3\times3,128 \end{bmatrix}\times2$
CONV4	14×14	$\begin{bmatrix} 3\times3,256 \\ 3\times3,256 \end{bmatrix}\times2$

In Table 5, Number of layers used in this approach is less as compared to other so training time of model is reduced. With minimum number of layers, proposed approach is achieving high accuracy in mentioned evaluation matrix parameter for segmentation. TransposedCov2dLayer is used in network, so it handles up-sampling and down-sampling process at same time. Training time is reduced due to TransposedConv2dLayer only. No separate layers are used for up-sampling and downs-sampling. TransposedCov2dLayer is playing vital role in minimization of time of training network. dicePixelClassificationLayer layer are used in proposed network for classification purpose. In this layer, dice loss is calculated so unlabeled pixel are omitted for next classification process. This layer is used for achieving high accuracy as compared to another model. With the help of equation 9, generalized dice loss value is calculated and control the effect of imbalance class effect on the segmentation.

Table 5. Proposed Deep Learning Model Performance analysis using Time, count of number layer parameter and count of convolution layer.

Approach	Time	Number of Layer	Convolution Layer
Proposed Method	158 min 19 sec	12	4
RS-18	242 min 42 sec	18	17
VGG-16	522 min 7 Sec	16	13
VGG-19	632 min 44 sec	19	16

In this paper, we proposed a novel semantic segmentation method for automatic pancreas segmentation from CT scan images. 12 layers architecture is used for multiple organ segmentation from CT scan images. In VGG-16 method, 16 convolution layers are used, in VGG-19, 19 convolution layers are used and in RSnet-18, 18 convolution network layers are used. In deep learning, training of network layer is time-consuming task. Proposed method takes a very less time period as compared to other deep learning method. Bfscore value of proposed method is superior from VGG-19 method for same dataset. Sensitivity, Mean Accuracy, and Mean-bfscore value are superior to other methods. Dice coefficient,jaccard Index are high as compared to state-of-art. Proposed method values as per evaluation matrix parameters are high as compared to state-of-art. Dice loss function is used as loss function in the last network layer in proposed method. Due to last network layer, accuracy is improved and minimizes loss of network.

Training validation accuracy of proposed approach is less. In future work, training validation accuracy and loss value will improve as compared to state-of-art. Training validation accuracy will not effect on accuracy of detection of accurate pancreas sharpe. Accurate pancreas shape and size is detected by proposed method but it fails to detect pancreas cancer affected areas in percentage. Pancreas size and shape is available in 2D image using proposed method. 3D pancreas image detection is a future scope for the proposed method.

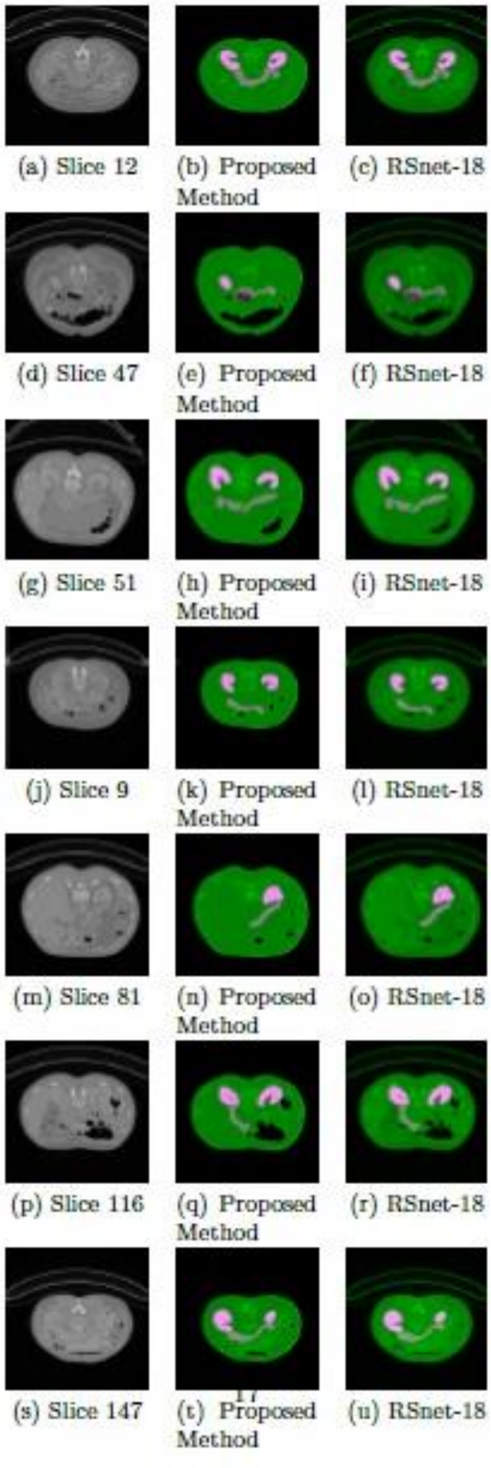

Fig. 4. sub-figure (a),(d),(g),(j),(m),(p),(s) are original image slices,(b),(e),(h),(k),(n),(q),(t) are Segmentation Output using Proposed Method,(c),(f),(i),(l),(o),(r),(u) are Segmentation Output using RSnet-18 Approach

Competing Interests

The Authors have declared that no competing interest exits.

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