A New Model for Image Segmentation Based on Deep Learning

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Abstract—Image segmentation is main point in computer vision (CV) and image processing (IP), that are used routinely in the fields of medicine and surgery training tools. Segmenting images and converting into a model that depends on work by the different algorithms from analysis DICOM files to convert to three-dimensional models. This paper describes a combination of two fields of solving segmentation problem to convert through the workflow of a hybrid algorithm structure Convolutional neural network (CNN, Active Contour & Deep Multi-Planar) based on seg3d2 to switch DICOM medical rays "Digital Imaging and Communications in Medicine" into a 3Dimintional model, using data from active contour to be the input of deep learning. the result of the pre-processing from DICOM raw images, each image contains edges and image size =256 X 256 pixel, which through adjustment and control we can create multiple results for output using Active Contour, by resizing the threshold frames and gray-scale image, and show liver 3D-model Deep architecture, it is through the CNN which the images of the three axes X, Y, and Z (three orthogonal) (coronal = X, sagittal = Y, axial = Z = 1) are determined and matched with a real image of the body, the area required to be determined, and edits the contrast using a histogram. This research will be using are human liver DICOM images and is divided into two stages (medical image segmentation - retinal model optimization), to help surgeons to study the patient's condition with accuracy and efficiency through the use of mixed reality technology in liver surgery [living donor liver transplantation (LDLT)], all implement by Seg3D2 and Python.

Keywords—Hybrid Algorithm, Convolutional neural network (CNN), Active Contour Model (ACM), Digital Imaging and Communications in Medicine (DICOM), living donor liver transplantation (LDLT), histogram equalization, Gaussian Equation Medical Image Processing, Image Segmentation

1 Introduction

1.1 DICOM & Big data classifications

DICOM files contain a lot of information storage known as BIG DATA, most of which is not required. We need to define the working area (the range of interest within the image) to get useful information. DICOM is closely used by hospitals and surgeons such as Brain and liver surgery clinics. DICOM consists of multi-layers images that are combined through a specific system to show radiograph results.

Big data (BD) [1] is a huge collection of information (either structured, semi-structured, or unorganized) on archival units. Big information creates an incentive to build systems of the store and prepares data that cannot be split using traditional processes [2]. Big information do not containing sample data only the same numbers, dates, and strings. BD is Bulky information, contains a Geographic Information System (GIS) 3D model, medical image information, audio, video, DICOM documents, networking documents, and online history [3]. Despite the huge volume of information stored on the electronic cloud that can reach a petabyte or and Exabyte of information, it is related to the process of stability and stability of information, the extent of its exchange, and the implementation of important activities on time, and the extent to which it is possible to analyze and display information in "DICOM" files with huge parameters and stored inside several Layers [4][5][6].

1.2 Medical Img.Seg. (Image-segmentation)

Img.Seg. is a complex part of the pattern recognition system and the main part & 1st step in image analysis is one of the most complicated steps in image processing and determines the goodness of the result of the analyses. Img.Seg. is an operation of cutoff an image to various areas, such that each region is similar to else [7] [8]. The segmentation model for monocular images can be expanded to color segmentation by using "RBG" or their conversion (linear/non-linear). Although, global surveys on color image segmentation are few [9]. Analyzed the issue when applying edge and area segmentation mode to color images with synthesis texture. [10]. Segmentation is a pertinent technique in image treatment. Various methods occur in multi-apps. Histograms are found to be very efficient in terms of calculation complexity when compared with other division methods. If identified low, High point is properly and proper threshold is fixed, this technique will show good output results [11] It was also implemented in converting DICOM files into a three-dimensional model. [6].

It can take advantage of a set of elements with high-resolution features, such as pixels, texture, and shape properties. Threshold nodes a very simple algorithm to perform hashing. This threshold optimum can be calculated by simulating a Gaussian normal distribution Equation 1 Figure 1, of two regions of the image and calculating the middle and norm deviations of the picture through classified region interest, edges, and background.[12][13].

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e - \frac{(x-\mu)2}{2\sigma^2} \tag{1}$$

Where, μ: Is expected or mean value, σ^2: Distribution data point (variance), When $\sigma > 0$.

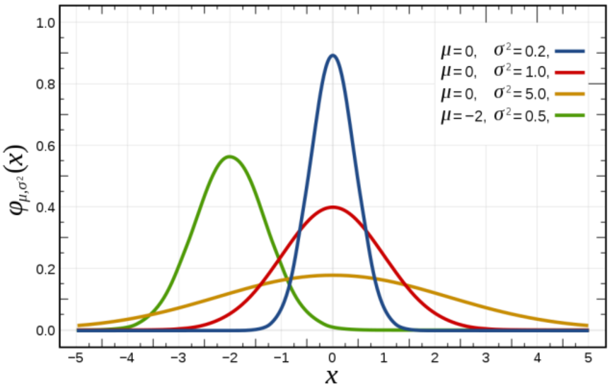


Fig. 1. Red Curve: Normal Distribution Probability Density Functions (PDFs)

1.3 Anatomical model & visualization system

A lot of applications working in surgical and medical image research called Anatomical models in the clinic's the body natural interaction with Virtual-Models simplify anatomy in training and different interactive structures spatially in the human body. Mixed reality is a part of a Visualization system called training Simulation with virtual models anatomy, where to reduces the surgical involvement which is linked to patient risk and cost of healthcare [14]. MR is part of the visualization systems, and it works to create a new reality by integrating a realistic environment with the virtual, which allows the integration of real models and virtual models, to enhance the positive indicators of the surgeon. Applied to liver surgeons during training, before, during, and after the surgical operation in terms of visualization techniques [15]. For example, using Mixed Reality (MR) is an advanced technology used to live in a real environment with fictional models, and it also helps the user to determine its location and medical model location information by Azure Spatial Anchors. Helps classify and store medical images by "Azure Cosmo DB", using Internet of Things services [16]. HOLOLENS devices can live in the real environment and recover 3D models by improving display speed during training in real-time, by increasing the accuracy of the intensity and degree of illumination while taking into account the degree of illumination distributed in the area to improve the display intensity [17].

1.4 CNN in medical segmentation

CNN: "Convolutional-Neural-Network", a part of ANN: "Artificial-Neural-Networks" has been prevailing in different computer vision objectives, benefits across a set of domains consist of radiology. CNN designed a spatial hierarchy of features through back-propagation out of a lot of building layers automatically [18]. CNN's hold three types of layers, A) convolution layers, where a kernel of weights is convolved to extract features; B) pooling layers, which replace a small district of a feature map with some statistical input (mean, max, etc.), and C) nonlinear layers, apply an activation duty on feature maps, to can the designing of non-linear duty by the network [19] [20] Figure 2.

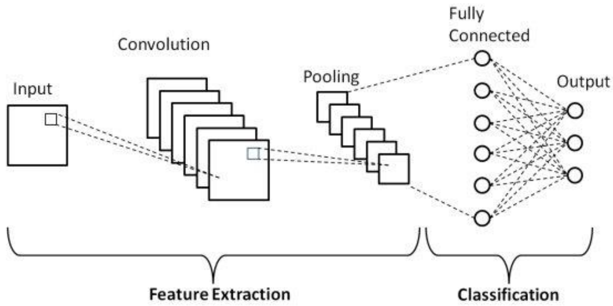


Fig. 2. Diagram Schema of a basic architecture CNN consists of two parts. Feature Extraction: Content 3 layers (Input, Convolution, and pooling layer). Classification: Content 2 layers (Fully Connected and Output layer).

2 Related Work

The researcher uses part of deep learning called a steady architecture CNN with input trip planar perpendicular patches while be used with advances in convolution kernels and deep networks The fulfillment of totally linked layers as 1×1 convolution layers and the skip from Shorthand layers pliable rapid diversion of full figures compared with more taking longer timing scanning Moreover Input 3D information patches force result in increased execution performance but require calculation the increased load of the parameter network [21] A new version method using deep learning techniques and dynamic random walker method has been proposed of MR brain image segmentation The hybrid method has shown that best execution as compared through another state methods [22]. The use of CNN and limitations of deep learning and all advantages is primary in a major of radiology research to improve performance radiologists and, patient care [23]. He used an automatic algorithm in liver segmentation to improve the accuracy of the segmentation problem, where it is based on combine between active area (contour) and collect data to use as input for deep learning networks [24]. Using the multi-view and the power of CNN to split, segment PPV and LA through cardiac-NET MRI. The method shown, a combination between different information inputs of MRI throw an adaptive combination planning and a new mission, improves damage segmentation and accuracy [25].

He worked on developing a framework to precisely segment all basic structures of the heart from calculating tomography and magnetic chest imaging together with high activity. Using multiple CNNs training from the start and permitting an adaptive information fusion strategy in the labeling of pixels was suggested despite data limitations. The results demonstrate a tool to accurately and efficiently identify cardiac structures called [MO-MP-CNN]. Instead of using 3D CNN which is a multi-level 2D CNNs. Thus, use a multi of 2D slides is more important than using a 3Dimentional model within the current setup. In the case of available a lot-of GPU processing and data 3D [26]. The author designed a framework called DMPCT for CT scan segmentation in multi-organ, which is Stimulate by the imitative co-exercise strategy to combine multi-planar input for the dummy data through training, without required a massive of 3D volumes labor from radiologists [27].

3 Methods

3.1 Proposed architecture

We propose a process to implement liver DICOM image segmentation, and use active contour technique as a method for segmentation as input data where use seg3D2 and CNN network of deep learning Figure 3.

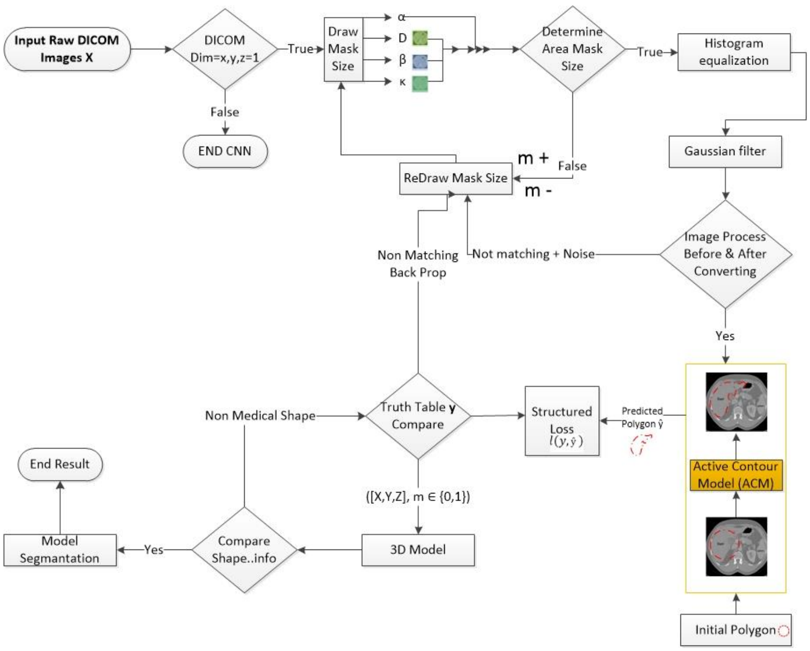
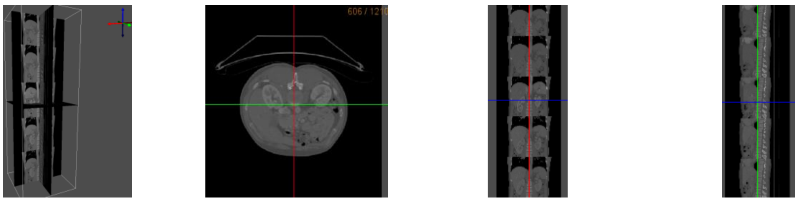


Fig. 3. Flow chart of our proposed DICOM Segmentation and convert to 3D-Model thought seg3D2 and (ACM) mean Active Contour Model, Wherever: a universal α for the extent punishment and local D maps, β: the bend penalization, and κ: the balloon term. Next step ACM deduction, a structured see is calculated and taken to the CNN, which parameters can already exit updated using back-propagation.

Since a DICOM image is usually of low contrast, and it is difficult to distinguish between each element and the other and the background, the image must be processed first before starting to split and segment. Due to the large size of the image data and its lack of arrangement, the processing of images plays a large role in defining each element and clarifying the data. As it is the first and required step to improve the quality of the images to obtain high accuracy in reading the data. DICOM images consist of many noises and lighting impurities. Before starting to analyse, segment, and object detection, all impurities must be removed through the processing procedures first.

First of all, we must use the point of convergence and intersection of the DICOM files for the three images (three orthogonal) where (coronal=X, sagittal=Y, axial=Z =0) figure 4 as input data and compare them with the 3D model or real images to detect a liver object, Scientific Steps [1]. where the three images are the general shape of the model, and since the images are of low contrast, we should start Convolutional Layer then the histogram equation figure 5 for the raw images must be used as a technique for adjusting the image intensity to improve contrast as shown below figure 6.

The results show that the images with high noise use the Gaussian Blur technique, while the Gaussian function, in contrast, small and large. We, therefore, recommend Gaussian use, with alpha = 1.



DICOM Volume | Top: axial=Z | Front: coronal=X | Side: sagittal=Y

Fig. 4. Three Orthogonal

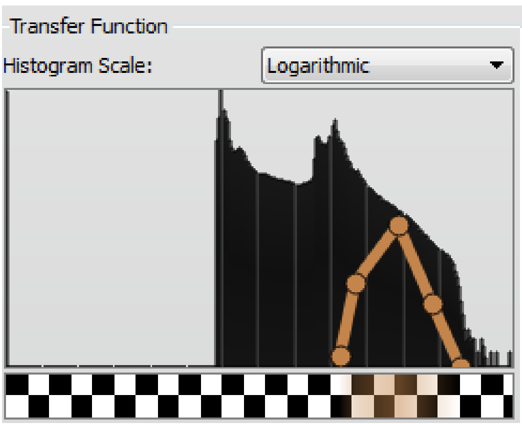


Fig. 5. Data Histogram Transfer

Scientific Steps [1] for Read & Write 3Axis and 3D Volume by Python language

```
Input: Path of DICOM Files as P
        Axial → Z
        Sagittal → Y
        Coronal → X
Output: Draw Active Contours → ACM & Read 3D Volume
→3DV
Process:
DICOM File request read = R;
Slices → sl
If (p == true)
{       sl ←  CT Images
        sl ←  Patient CT Position
        sl [0]←  Pixel Spacing
        sl [0]←  Slice Thickness
}
End if
   1. While (R=0)
      Calculate CT Images positions ();
      Calculate CT Images Aspect Ratio();
      Calculate Pixel Spacing == [0] ();
      Calculate slice thickness ();
      If (X=0,Y=0,Z=0)
          {
              print(pixel spacing="")
              print(slice thickness="")
              print(X aspect ratio="")
              print(Y aspect ratio="")
              print(Z aspect ratio="")
              update();
          }
      End if
   2. Read 3D_Volume as 3DV;
      If (3DV Slice Position == X,Y,Z < 0)
          Update Position (X,Y,Z == 0);
          Image Shape Append(len(sl));
          3DV Position == 0;
      End IF
   3. Plotting Images
            for I,S in enumerate(sl):
                array2d=S pixel  array
                3DV[:,:,I]=array2d
            print(array2d.shape)
            print(3DV.shape)
```

```
              DICOM = nm zeros((255, 255),
              Data Type=nm.uint8)
              DICOM[50:150, 50:150] = 150#
      4. Apply Threshold & Draw Active Contours Model as
         ACM
               If(threshold == cv2 filter(DICOM, 127, 255,
             0))
               {
               Contours Hierarchy = cv2 filter Contours()
               color = cv2.cvtColor(DICOM,
             cv2.COLOR_GRAY2BGR)
               DICOM = cv2.drawContours(color, contours, -
             1, (0, 255, 0), 2)
               cv2.imshow("contours", color)
               cv2.waitKey()
               cv2.destroyAllWindows()
               }
      5.  End For
      6. End While
   Return to R
```

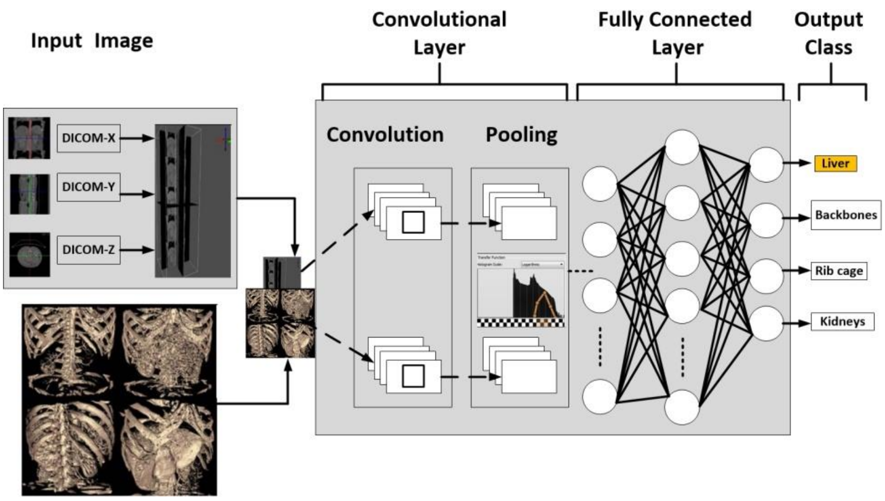


Fig. 6. CNN architecture

3.2 Comparative process of medical image

Growing the number of point light [brightness and contrast] Fig.7 (b) to improve image Accuracy & density, as it becomes higher image quality to make it easier to convert into a 3D-model. In Scientific Steps [2] present image processing result of

DICOM image before and after increasing point light on the image through using python and specializes in image-processing, data-visualize and data-analysis called openCV and NumPy library, to ensure DICOM empty from impurities and prepared to Convert.

There are no differences in the details and content of the image before and after increasing the brightness and width ratio Fig. 7, the appearance of impurities only in the borders Fig. 7(C) of the image, but it does not affect the conversion process in the three-dimensional model. The impurities are removed and the model is purified with MESHMIXER.

Scientific Steps [2] for Comparison between Medical image before and after increasing the rate of illumination

```
import cv2 as cv
import numpy as num
pic1 = cv.imread("DICOM_Before_Light.JPG")
pic2 = cv.imread("DICOM_After_Light.JPG")
difference = cv.subtract(pic1, pic2)
result = not num.any(variation)
if result is True:
    print " There are no variation "
else:
cv.imwrite("DICOM_DIFF_Result.jpg", difference)
    print "There Are Variation Data"
```

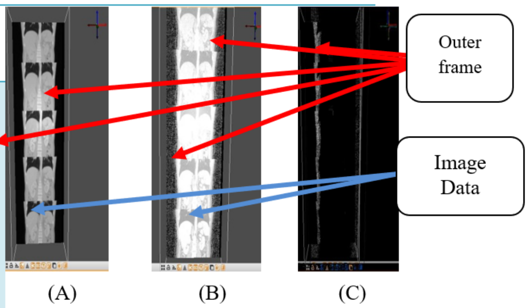


Figure 7 A result of DICOM image processing:
(A) Medical image before increasing the rate of illumination
(B) Medical image after increasing the rate of illumination
(C) The result of the medical image after increased lighting and the appearance of impurities on the borders of the image

Fig. 7. A result of DICOM image processing

3.3 Active Contour Model (ACM)

ACM is the practical framework [28] [29] of a two-dimensional potential image diagram called the snake model and is widely used in tracking objects, recognizing shapes, image segmentation, and defining edges. A true image, knowing that snakes do not solve the problem because of the clarity of the image's features, as the best way to know in advance the shape of the contour required so that the user can interact with the user with the highest-level images, or from all other information from the surrounding image data, time and place.

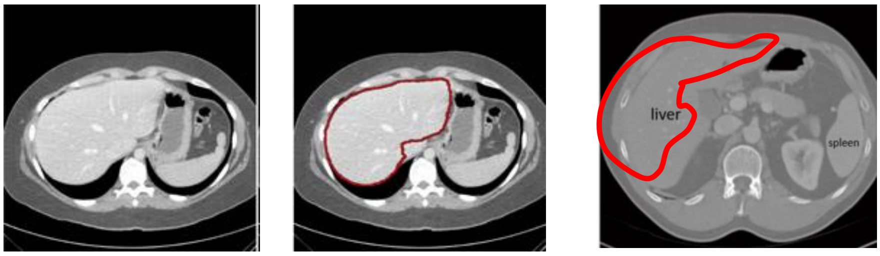
To obtain a good training result, the entire liver and its surrounding pixel units must be preserved, with the missing pixel versions eliminated and the liver frame deformed so as not to cause a bad prediction if versions of many good cases are available Figure 8.

ACM conclusion modified dependent on image and local point sentence equation terms, and expected loss that is used to train CNN to create these sanctions maps, the following Figure 8 is designed in Python to display the field of masks on the images. The proposed system of framework diagram is shown in Figure 3.

Fig. 8. Active Contour Model Mask

3.4 Medical 2D image structure generator

A single image is just a two-dimensional plane depicted through a projection of a three-dimensional object. Because some data is lost through the dimensions and area of the image that represent the lowest (2D) dimension from the top (3D), so no data available to originate a model-3Dimensional from 2Dimensional images Figure 9. But should generate a standard 2D CNN Structure include shape prior knowledge of the 3D object. from a single to multiple 2D-image projection mapping Figure 10, with definition a viewpoint: projection 2D Equal projection 3D-axis (x,y,z) & binary mask (m).



a) Full Image Without Object Detection

b) Liver Surrounding Pixel Units

c) Single-View that's not enough data to build 3D-Model

Fig. 9. Liver Active Contour

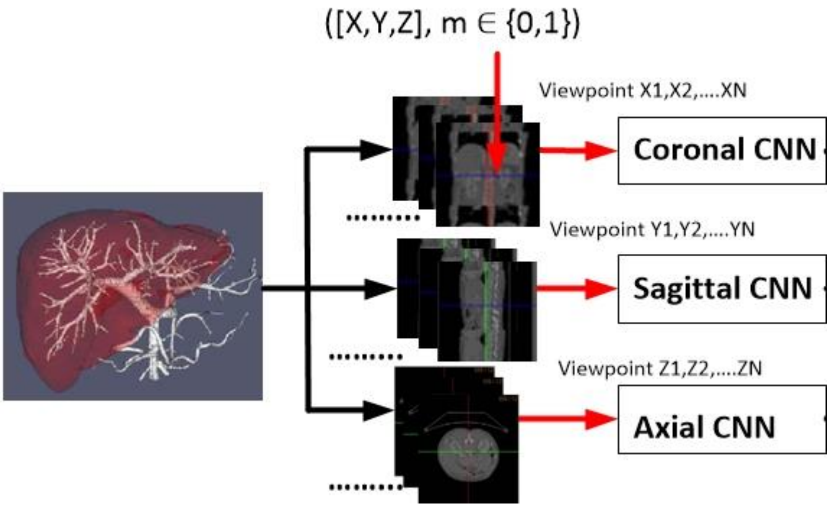
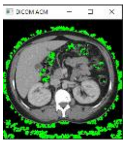
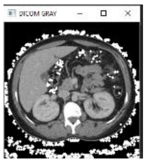
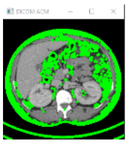
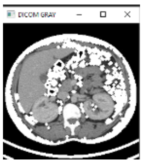
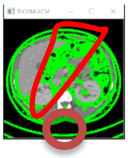
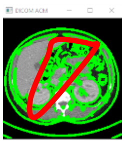
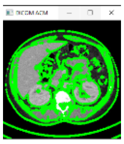
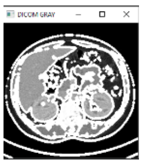
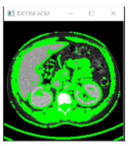
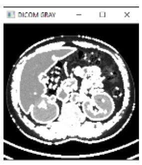


Fig. 10. 2D-Image Projection Mapping

4 Results

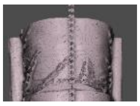
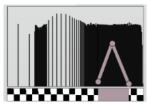
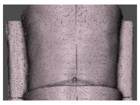
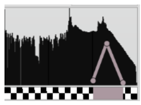
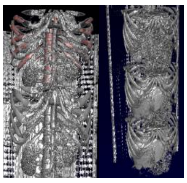
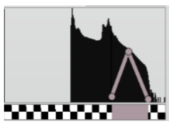
This section shows the result of active contour images from the DICOM raw image to the 3D-model. First, we show the result of the pre-processing from DICOM raw images. Each image contains edges and image size =256 X 256, which through adjustment and control we can create multiple results for output using Active Contour, by resizing the threshold frames and gray-scale image, shown below in table 1.

Table 1. Results of Active Contour Model (ACM) With Threshold Mask Size

#	Threshold (ACM) Color Image	Threshold (ACM) Gray Scale	Explain
1	(imgray, 25, 256,20) 		Threshold ACM = [X=25, Y=256, X=20] Not determined of liver pixel
2	(imgray, 25, 256,256) 		Threshold ACM = [X=25, Y=256, X=256] Determined outer body, Lost all of liver pixel
3	(imgray, 50, 256,256) 		Threshold ACM = [X=50, Y=256, X=256] Determined outer body, Lost Some of liver pixel outer
4	(imgray, 75, 256,256) 		Threshold ACM = [X=75, Y=256, X=256] Not determined all of the liver pixel & Non-Liver
5	(imgray, 100, 256,256) 		Threshold ACM = [X=100, Y=256, X=256] determined all of liver pixel & Non-Liver
6	(imgray, 125, 256,256) 		Threshold ACM = [X=125, Y=256, X=256] determined all of the liver, Outer Non-Liver & Lost Outer Body pixel

Second, we can generate a lot of versions of active contour 3D-model output result, by changing the Histogram and Gaussian equation, and many of transfer function. will show all functions as shown below “table 2”.

Table 2. Layers of Active Contour 3D-Model By Histogram & Gaussian Equation

#	Active Contour 3D-Model	Target	Histogram Scale	Frame Count
1		Set1_Histogram & Gaussian Equ.		(Axial) Z=1210 (Coronal) X=512 (Sagittal) Y=512
2		Set2_Histogram & Gaussian Equ.		(Axial) Z=1210 (Coronal) X=512 (Sagittal) Y=512
3		Set1_HistogramEqu.		(Axial) Z=1210 (Coronal) X=512 (Sagittal) Y=512
4		Set2_HistogramEqu.		(Axial) Z=1210 (Coronal) X=512 (Sagittal) Y=512
5		Set1_Gaussian Equ.		(Axial) Z=1210 (Coronal) X=512 (Sagittal) Y=512
6		Set2_ Gaussian Equ.		(Axial) Z=1210 (Coronal) X=512 (Sagittal) Y=512

Now we can show 3D-model Deep architecture, it is through the CNN, through which the images of the three axes X, Y, and Z are determined and matched with a real image of the body shown above Figure 6, and the area required to be determined as shown above Figure 9 and edits the contrast using a histogram. Therefore, its prior knowledge and identification of the three dimensions of the images (three orthogonal) (coronal = X, sagittal = Y, axial = Z = 1) to intersect them at one point and determine the liver area and convert to the 3D shape model Figure 11, Figure 12.

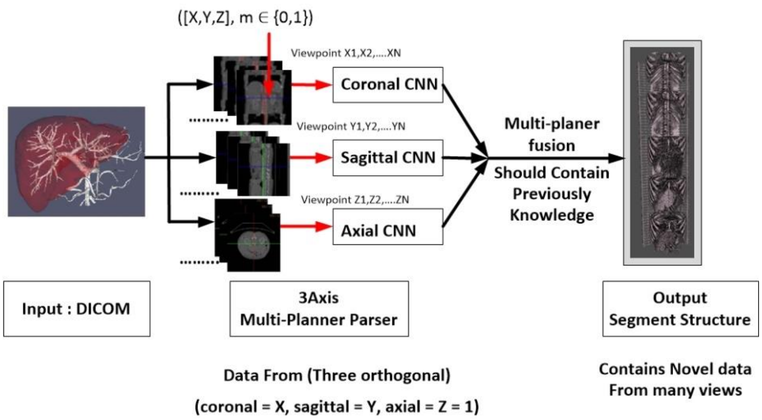


Fig. 11. Illustration of converting multi-planner to 3D-model, where the input DICOM file content 3sets of 3Axis (sagittal), corona, axial. The final 3D-model from the individual plane

```
#Read Axial Axis
axial=plt.subplot(2,2,1)
plt.title("Axial")
plt.imshow(volume3d[:,:,image_shape[2]//2])
axial.set_aspect(axial_aspect_ratio)

#Read Sagital Axis
sagital=plt.subplot(2,2,2)
plt.title("Sagital")
plt.imshow(volume3d[:,:,image_shape[2]//2,:])
sagital.set_aspect(sagital_aspect_ratio)

#Read Coronal Axis
coronal=plt.subplot(2,2,1)
plt.title("Coronal")
plt.imshow(volume3d[:,:,image_shape[2]//2,:,:])
coronal.set_aspect(coronal_aspect_ratio)
```

Fig. 12. Read 3-Axis [Axial, Sagital, Coronal]

To receive grate experience and training result, we should to keep versions of the active contour 3D-model which include full pixels knowledge of the liver and delete other versions which the lost pixel of a liver model, because other versions will be made more distortion when re- Sculpting & Trimming 3D-liver model by 3d programs Figure 13.

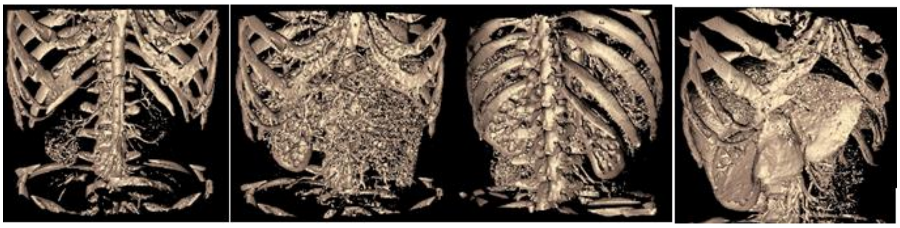


Fig. 13. 3D-liver model after re- Sculpting & Trimming

This significant step will be to test the final simulation through a 3D-model and converted the OBJ file to a low poly object by the modeling process steps sculpt, smooth, and test the model motion in the graphics programs such as using "Adobe MESHMIXER". Therefore, in this status can be estimated outer perimeter shape stabilization and mass the liver and kidneys volume, wherever can evaluate the internal mass (Volume) by mm3 and the external perimeter (Surface Area) by mm2 Figure 14.

Now can be compared through the combination of hybrid algorithm structure (CNN, Active Contour & Deep Multi-Planar) and seg3d2, the use of Python programming language and open-source libraries OPENCV, CV2, and NUMPY, and real results through the liver volume analysis report from MeVis Distant Services (1731 ml), where the volume of the liver is measured in milliliters ML, and our results are MM3 (1.73059e+06 mm^3)as shown Figure 14, so the final results were converted into milliliters ML to ensure the correct size of the liver as shown Figure 15.

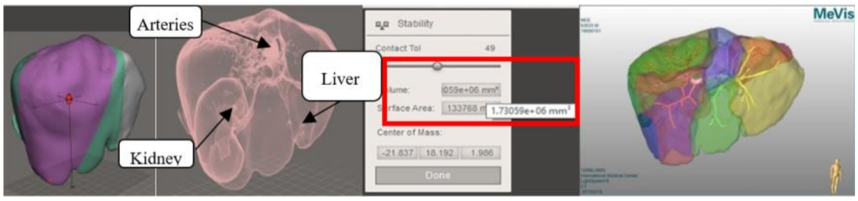


Fig. 14.OBJ file to a low poly object

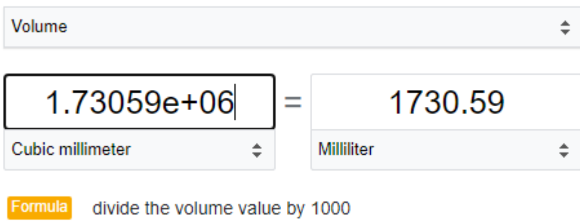


Fig. 15. Liver Volume 1731Ml (Convert from mm^3 to ml)

5 Conclusion

We proposed in this research a simple efficient hybrid technique based on two algorithms "ACM and CNN", which has applied the power of deeply CNN to DICOM image and enhancement segmentation data files. The system achieved a high result of segmentation, each image contains edges and image size =256p X 256p, using Active Contour Model can generate multiple results for output, by resizing the threshold frames and gray-scale image and adjustment control, and generate a multi 3D model as output by changing the Histogram and Gaussian equation. In the future work, the proposed system could be utilized for detecting the Cancer and position accuracy in the Liver CT images.

6 Abbreviations

CNN: Convolutional Neural Networks
MR: Mixed Reality
CV: computer vision
IP: image processing
LDLT: living donor liver transplantation
DICOM: Digital Imaging and Communications in Medicine
GIS: Geographic information system
MM^3: Cubic millimeter
Ml: Milliliter

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