

Automatic liver segmentation in computed tomography scans using deep semantic segmentation

Kadry Ali Ezzat¹, Lamia Nabil Omran¹, Ahmed Ibrahim Bahgat El Seddawy²

¹Department of Biomedical Engineering, Higher Technological Institute, Ash Sharqia Governorate, Egypt

²Computer Science and Information System, Arab Academy for Science, Technology and Maritime Transport, Giza, Egypt

Article Info

Article history:

Received Apr 30, 2022

Revised Aug 12, 2022

Accepted Sep 4, 2022

Keywords:

Computed tomography images

Convolution neural network

Deep learning

Liver

Segmentation

ABSTRACT

Division of the liver from figured computed tomography (CT) images is fundamental for the greater part of the PC supported clinical applications, for instance, the arranging period of a liver transfer, liver volume assessment, and radiotherapy. In this paper, a programmed liver location model from clinical CT filters utilizing profound semantic division convolutional neural organization will be introduced, this model will actually want to subsequently isolate the liver utilizing CT images. The proposed model presents simultaneously the liver ID and the probabilistic division utilizing a profound convolutional neural organization. The proposed approach was endorsed on 10 CT volumes taken from open data sets 3Dircadb1. The proposed model is totally programmed with no requirement for client mediation. Quantitative results show that proposed model is reliable and exact for hepatic volume assessment in a clinical course of action with testing exactness 98.8%.

This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.



Corresponding Author:

Kadry Ali Ezzat

Department of Biomedical Engineering, Higher Technological Institute

10th of Ramadan City, Next to Small Industries Complex, Industrial Area, Ash Sharqia Governorate, Egypt

Email: kadry_ezat@hotmail.com

1. INTRODUCTION

Medical professionals may develop accurate illness evaluations and treatment strategies with the use of precise liver segmentation from computed tomography (CT) or magnetic resonance imaging (MRI) images. Automatic liver segmentation techniques are thus substantially necessary in the clinical. However, automated segmentation of the liver from various types of medical imaging continues to be difficult because of the low contrast of soft tissue, the variable look of the liver, and its indistinct borders. The challenge for automated segmentation algorithms will be exacerbated by the fact that for many scans, the voxel space next to the z-axis vector spans from 0.4 mm to 6.5 mm [1]. Additionally, a frequent injection technique used by radiologists to enhance CT or MRI images to better see malignancies up close. Further liver damage and other artefacts may result from this [2].

Human health and lives are seriously threatened by liver diseases. According to statistics, liver cancer is the second most prevalent cause of cancer-related death in males and the sixth most important cause in women. Indeed, in 2008, about 696,000 people worldwide lost their lives to liver cancer and almost 750,000 people had the disease officially diagnosed [3]. CT with contrast enhancement is now routinely used to diagnose liver disease and plan surgical procedures. A few computer-assisted medical operations, such as surgical treatment planning for a liver transplant from a living donor, radiation, and quantity measurement, all need the segmentation of the liver from a CT scan. The standard medical procedure for the liver delineation remains to be guidance delineation on each slice by specialists. Guide segmentation takes time, is

subjective, and is not very repeatable. Expanding computerised methods is therefore essential to improve and ease prediction, treatment planning, and monitoring.

Due to the poor contrast between the liver and other surrounding organs, automatic liver segmentation from contrast-enhanced CT volume is a highly challenging process. Radiologists also frequently add an injection procedure to the CT image in order to clearly see the tumour. The liver area's imaging noise may rise as a result [4]. Automated segmentation techniques have extra difficulties since a lot of CT images have anisotropic dimensions with significant fluctuations along the Z axis (voxel spacing spans from 0.45 mm to 6.0 mm). Many segmentation techniques, including deformable models, region expansion, and strength thresholds, have been proposed to overcome these problems. However, these techniques rely on handcrafted characteristics and can only partially convey the features. Fully convolutional neural networks (FCNs) have recently achieved excellent results in a variety of cognitive difficulties [5], [6]. The literature may be generally separated into two groups since many researchers are advocating this collection of deep learning algorithms for issues with liver and tumour segmentation i) 2DFCN, including the UNet architecture [7], multi-channel FCN [8], and FCN built on VGG16 [9] and ii) 3D FCN [10], where 3D convolution with volume data input has been used in place of 2D convolution.

To address these issues of programmed liver segmentation from 3D studies, other research has been offered, including diagram cut procedures, deformable models, level-set, and chart book approaches. The majority of these tactics are appropriate for the physical highlight former footing class. However, as the precise liver component extraction process is difficult to demonstrate, these methodologies are not often used for low complexity real centre information. Recent research has shown that convolutional neural network (CNN)-based techniques are extremely strong to image appearance variability, which has prompted fresh interest in segmentation problems [11].

A planned liver tumour segmentation method in CT stomach area images was suggested by Lu *et al.* [12] using cascaded FCNs and thick 3D dependent irregular fields (CRFs). They first developed an FCN to fragment the liver as a contribution to the second FCN's return on investment (ROI). Only damage from the projected stage 1 liver ROIs is segmented by the second FCN. The segmentation results were then improved using a thick 3D CRF that depicts both spatial rationality and appearance. The liver segmentation findings were produced by Peng *et al.* [13] using a deep image to-image to organise (DI2IN) procedure. Convolutional encoder-decoder technology was combined with staggered include connectivity, intense supervision, and convolutional encoding. The segmentation findings are then presented in a more elevated manner as a result of the preparation operations, which included the usage of an unfavourable method to separate the yield of DI2IN from the ground truth.

To tackle the challenge of liver segmentation, Dou *et al.* [14] created a 3D profoundly controlled system (3D deeply supervised network (also known as DSN)). They provided a significant supervision component during the learning process to overcome probable enhancement obstacles, assisting the model in achieving a faster intermingling rate and exceptional separation capacity. They further improved the segmentation results by using a dependent irregular field model. All of the aforementioned tactics made use of FCNs using varied systems. However, they don't take into account 3D logical data and instead focus on individual 2D cuts. There are now two major groups of methods often used for programmed liver segmentation: methods that are hostile to learning-based strategies and methods that are learning-based. The earlier version includes diagram cutting [15] and area growing [16]. In order to suggest neighborhood-associated area development for programmed 3D liver segmentation, Ruskó *et al.* [17] connected the neighbourhood around the voxel. Level set approaches are appealing in liver segmentation because they have the ability to capture objects with complicated form and regulate shape regularity.

In order to construct liver boundaries that have the same amount of variability as those obtained manually, particularly for some challenging clinical instances, Peng *et al.* [18] proposed a shape-power early level set model. The expansion of the illustrative chart cut provided, graph cut-based approaches are widely used in liver segmentation. In order to identify the liver, Linguraru *et al.* [19] used a non-exclusive affine invariant shape parameterization approach with a geodesic dynamic form, followed by graph-cut liver tumour segmentation. By using statistical shape models (SSMs), ASMs first construct an earlier state of the liver and then coordinate it with the objective image. A probabilistic active shape model was put out by Heimann *et al.* [20] that incorporated boundary, location, and shape data into a single level set equation. For the segmentation of the liver, Erdt *et al.* [21] presented a multitiered factual shape model. Recently, Wang *et al.* [22] used the insufficient shape arrangement (SSC) to create a robust form earlier for the liver in order to segment the liver, portal veins, hepatic veins, and malignancies precisely all at once.

2. METHOD

As shown in Figure 1, the proposed architecture consists of three phases the first phase is the preprocessing phase based on data augmentation techniques, then dividing the dataset so that 80% is used for

training and 20% is used for testing. The second step is the deep CNN training phase, and the third phase is the testing of the trained model.

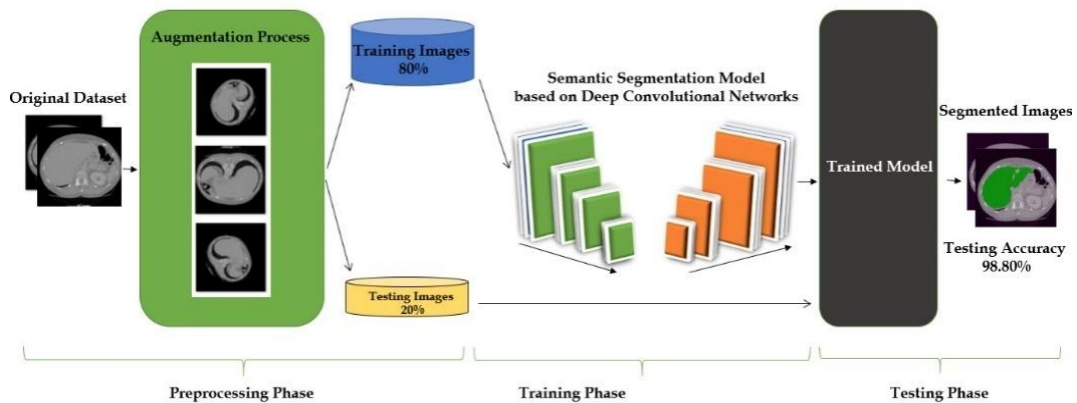


Figure 1. Proposed architecture for semantic segmentation model

2.1. Preprocessing phase

The preprocessing phase is based on the augmentation process. To avoid and overcome over fitting, label-preserving transformations are applied to increase the images. The medical scanning process may face some kinds of transformation during the process, so data augmentation is used to help the model become more resilient and invariant. The rotation approach at various angles was used as the augmentation strategy in this study. In (1) and (2) are used to compute the image transformation using the rotation approach.

$$a2 = \cos(\phi) * (a1 - a0) + \sin(\phi) * (b1 - b0) \quad (1)$$

$$b2 = -\sin(\phi) * (a1 - a0) + \cos(\phi) * (b1 - b0) \quad (2)$$

Where the coordinates of a point $(a1, b1)$ in the augmented image become $(a2, b2)$ when rotated by an angle around $(a0, b0)$. The dataset now contains 9 times more images than it did before the chosen augmentation procedure was used. 8000 photos are included in the dataset, which is utilised for both training and testing. The suggested model will become more resilient for any form of rotation as a result, which will significantly increase the accuracy of CNN testing. Examples of various rotation angles for the images in the dataset are shown in Figure 2.

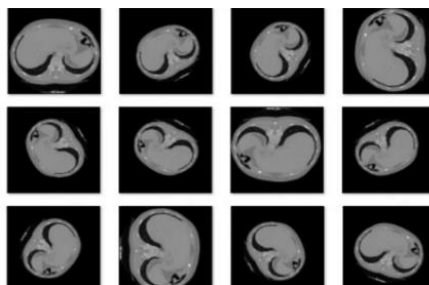


Figure 2. Rotated images for a sample image in the dataset applying 30, 60... 270 angles

2.2. Semantic segmentation model

Deep CNN provide the foundation of the suggested semantic segmentation paradigm. It has ten convolutional layers, thirteen ReLU layers, four max-pooling layers, four de-convolution layers, one soft-max layer, and lastly a layer for pixel categorization. The model's input layer is a 128*128-pixel medical image, followed by the layers stated above. The first and second convolutional layers each have 64 filters, the third

and fourth convolutional layers have 128 filters, the fifth and sixth layers have 256 filters, the seventh and eighth layers have 512 filters, and the ninth and tenth layers have 1,024 filters. All convolutional layers have windows that are 3 by 3 pixels in size. ReLU layer comes after each convolutional layer. Additionally, there is a max pool layer between every two convolutional layers that cuts the image size in half. The deconvolutional component consists of four deconvolutional layers, the first of which has 1,024 filters, the second of which has 512 filters, the third of which has 256 filters, and the fourth of which has 128 filters. The ReLU layer comes after each deconvolutional layer. The soft-max layer and the pixel categorization layer are the final two layers to be shown in the model. A visual depiction of the suggested model is shown in Figure 3.

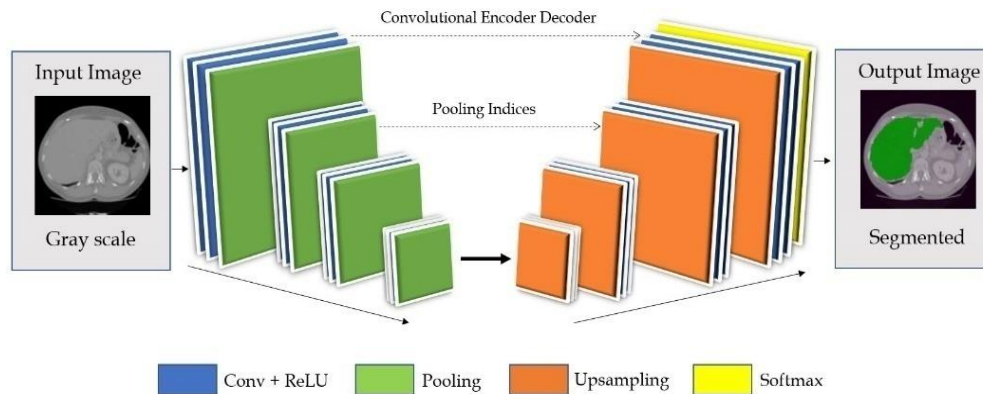


Figure 3. Graphical representation for the semantic segmentation model

3. RESULTS AND DISCUSSION

Using a piece of software, the suggested paradigm was put into practise (MATLAB). The solution was used using NVIDIA Titan Xp GPUs, which have 3,840 NVIDIA CUDA cores and 12 GB of GDDR5X standard memory. On a machine with an intel Core i9 running at 2 GHz and 32 GB of RAM, all trials were conducted. The dataset includes 8,106 photos following the augmentation procedure, as was indicated in the part before. After the augmentation procedure, the dataset was split into two halves. the first section is for instruction, and the second section is for testing. Divided by two, it is 80% and 20%. based on the random data splitting approach, 80% for the training phase and 20% for the testing phase. While 1,622 photos were utilised in total during the testing phase, 6,484 images were used in total during the training phase. The suggested model's total testing accuracy, measured across the testing pictures, is 98.80%. The result of the suggested model for four distinct patients is shown in Figure 4. Where Figure 4(a) show the original image, Figure 4(b) show the ground truth of segmented liver, Figure 4(c) show the output segmented image of the proposed model over the original image, and Figure 4(d) show the difference image between the result segmented image and the ground truth image. It displays the initial image, the initial manual segmented image (the ground truth image), the resulted segmented image using the proposed model, and the difference between the resulted image and the ground truth image, which contains red pixels that reflect the incorrect segmented pixel images and is caused by a summation error for all testing images that is 1.20% error in all segmented output images. A selection of rotated medical photos were taken from the testing dataset to see how well the proposed model could find and segment the liver in each situation of rotation. This was done to assess the proposed model's robustness and resilience. Figure 5 shows test results for four patients with variously rotated angles and varying liver size, structure, and texture. Where Figure 5(a) show the original image, Figure 5(b) show the ground truth of segmented liver, Figure 5(c) show the output segmented image of the proposed model over the original image, and Figure 5(d) show the difference image between the result segmented image and the ground truth image. The outcome was rather intriguing, with an average mistake rate of 1.2% and the ability of the suggested model to properly identify the liver regardless of its position, size, or colour in the picture. Table 1 compares the testing accuracy of its results to those of comparable works.

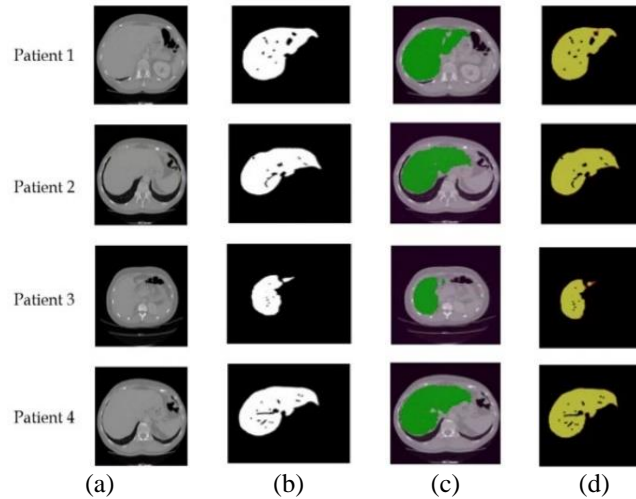


Figure 2. Samples images for 4 different patients (a) the original image, (b) the ground truth of segmented liver, (c) the output segmented image of the proposed model over the original image, and (d) the difference image between the result segmented image and the ground truth image

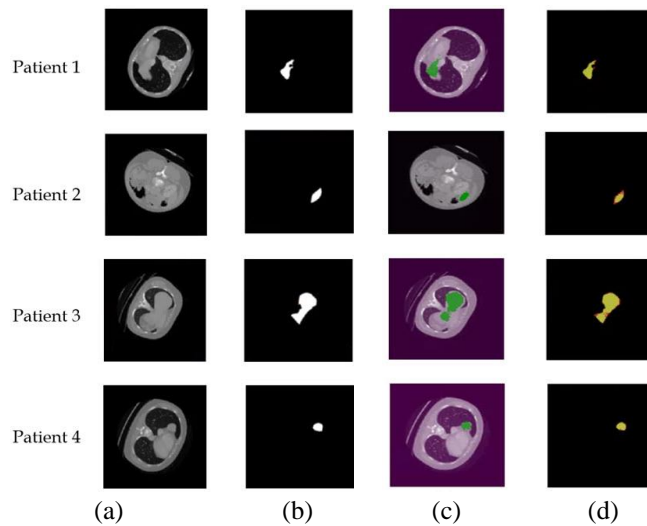


Figure 5. Samples of rotated images for 4 different patients (a) the original image, (b) the ground truth of segmented liver, (c) the output segmented image of the proposed model over the original image, and (d) the difference image between the result segmented image and the ground truth image

Table 1. Comparison of this study against the related works according to the testing accuracy

Author(s)	Year	Method	Network size	dataset	Compute resource	Traning time	Testing acc (%)
Chlebus <i>et al.</i> [23]	2017	Fully CNN in two dimensions with object-based post processing.	4 convolutional layers	179 liver CT volumes	GeForce GTX 1080	8 hours	96.00
Nanda <i>et al.</i> [24]	2019	Cascaded CNN and genetically optimized classifier	13 convolutional layers	131 CT scan images	Nvidia GTX 750 Ti	Not mentioned	95.57
Liu <i>et al.</i> [25]	2018	CNN and SVM	12 convolutional layers	5500 liver images	NVIDIA GeForce GTX 960	38sec/slice	97.43
Presented model	2022	Deep semantic segmentation CNN	10 convolutional layers	8106 liver images	NVIDIA Titan Xp	4 hours	98.80

4. CONCLUSION

In this study, the automated segmentation of the liver in abdominal CT images is performed using a deep semantic segmentation CNN. For the creation of CT images of the liver, a generative deep semantic CNN model was trained. To create an initial segmentation, a liver probability map was acquired in the meanwhile. The key benefit of the suggested solution is that there is no user input necessary for startup. As a result, amateurs can use the suggested approach. The suggested model is also one of the early attempts to separate the liver using deep semantic segmentation and CNN. On the medical image computing and computer-assisted intervention (MICCAI)-Sliver07 and 3Dircadb1 public datasets, the suggested model was assessed. Our model's segmentation accuracy was higher when compared to cutting-edge automated liver segmentation techniques. The suggested model has 98.8% testing accuracy and has practical application for liver segmentation based on the good correlation between our segmentation and manual reference. Future study will involve applying our approach to medical image segmentation problems including kidney and spleen segmentation.




REFERENCES

- [1] X. Li, H. Chen, X. Qi, Q. Dou, C. W. Fu, and P. A. Heng, "H-DenseUNet: hybrid densely connected UNet for liver and tumor segmentation from CT volumes," *IEEE Transactions on Medical Imaging*, vol. 37, no. 12, pp. 2663–2674, 2018, doi: 10.1109/TMI.2018.2845918.
- [2] M. Moghbel, S. Mashohor, R. Mahmud, and M. I. Saripan, "Review of liver segmentation and computer assisted detection/diagnosis methods in computed tomography," *Artificial Intelligence Review*, vol. 50, no. 4, pp. 497–537, Dec. 2018, doi: 10.1007/s10462-017-9550-x.
- [3] A. Jemal, F. Bray, M. M. Center, J. Ferlay, E. Ward, and D. Forman, "Global cancer statistics," *CA: A Cancer Journal for Clinicians*, vol. 61, no. 2, pp. 69–90, Mar. 2011, doi: 10.3322/caac.20107.
- [4] J. Wang, Y. Cheng, C. Guo, Y. Wang, and S. Tamura, "Shape-intensity prior level set combining probabilistic atlas and probability map constrains for automatic liver segmentation from abdominal CT images," *International Journal of Computer Assisted Radiology and Surgery*, vol. 11, no. 5, pp. 817–826, May 2016, doi: 10.1007/s11548-015-1332-9.
- [5] Y. A. Ayalew, K. A. Fante, and M. A. Mohammed, "Modified U-Net for liver cancer segmentation from computed tomography images with a new class balancing method," *BMC Biomedical Engineering*, vol. 3, no. 1, pp. 1–13, Dec. 2021, doi: 10.1186/s42490-021-00050-y.
- [6] X. Wei, X. Chen, C. Lai, Y. Zhu, H. Yang, and Y. Du, "Automatic liver segmentation in CT images with enhanced GAN and mask region-based CNN architectures," *BioMed Research International*, vol. 2021, pp. 1–11, Dec. 2021, doi: 10.1155/2021/9956983.
- [7] B. Qian, D. Kyuno, M. Schäfer, W. Gross, A. Mehrabi, and E. Ryschich, "Liver segment imaging using monocyte sequestration: a potential tool for fluorescence-guided liver surgery," *Theranostics*, vol. 8, no. 22, pp. 6101–6110, 2018, doi: 10.7150/thno.29223.
- [8] M. Y. Ansari *et al.*, "Practical utility of liver segmentation methods in clinical surgeries and interventions," *BMC Medical Imaging*, vol. 22, no. 1, p. 97, May 2022, doi: 10.1186/s12880-022-00825-2.
- [9] C. Sun *et al.*, "Automatic segmentation of liver tumors from multiphase contrast-enhanced CT images based on FCNs," *Artificial Intelligence in Medicine*, vol. 83, pp. 58–66, Nov. 2017, doi: 10.1016/j.artmed.2017.03.008.
- [10] O. I. Alirir, "Deep learning and level set approach for liver and tumor segmentation from CT scans," *Journal of Applied Clinical Medical Physics*, vol. 21, no. 10, pp. 200–209, Oct. 2020, doi: 10.1002/acm2.13003.
- [11] F. Isensee, P. F. Jaeger, S. A. A. Kohl, J. Petersen, and K. H. M. -Hein, "nnU-Net: a self-configuring method for deep learning-based biomedical image segmentation," *Nature Methods*, vol. 18, no. 2, pp. 203–211, Feb. 2021, doi: 10.1038/s41592-020-01008-z.
- [12] F. Lu, F. Wu, P. Hu, Z. Peng, and D. Kong, "Automatic 3D liver location and segmentation via convolutional neural network and graph cut," *International Journal of Computer Assisted Radiology and Surgery*, vol. 12, no. 2, pp. 171–182, 2017, doi: 10.1007/s11548-016-1467-3.
- [13] J. Peng, F. Dong, Y. Chen, and D. Kong, "A region-appearance-based adaptive variational model for 3D liver segmentation," *Medical Physics*, vol. 41, no. 4, pp. 1–11, Mar. 2014, doi: 10.1118/1.4866837.
- [14] Q. Dou, H. Chen, Y. Jin, L. Yu, J. Qin, and P. A. Heng, "3D deeply supervised network for automatic liver segmentation from CT volumes," *Computer Vision and Pattern Recognition*, pp. 149–157, 2016, doi: 10.1007/978-3-319-46723-8_18.
- [15] S. Pan and B. M. Dawant, "Automatic 3D segmentation of the liver from abdominal CT images: a level-set approach," *Medical Imaging 2001: Image Processing*, vol. 4322, pp. 128–138, 2001, doi: 10.1117/12.431019.
- [16] K. Ni, X. Bresson, T. Chan, and S. Esedoglu, "Local histogram based segmentation using the wasserstein distance," *International Journal of Computer Vision*, vol. 84, no. 1, pp. 97–111, Aug. 2009, doi: 10.1007/s11263-009-0234-0.
- [17] L. Ruskó, G. Bekes, and M. Fidrich, "Automatic segmentation of the liver from multi- and single-phase contrast-enhanced CT images," *Medical Image Analysis*, vol. 13, no. 6, pp. 871–882, Dec. 2009, doi: 10.1016/j.media.2009.07.009.
- [18] J. Peng, Y. Wang, and D. Kong, "Liver segmentation with constrained convex variational model," *Pattern Recognition Letters*, vol. 43, no. 1, pp. 81–88, Jul. 2014, doi: 10.1016/j.patrec.2013.07.010.
- [19] M. G. Linguraru, W. J. Richbourg, J. M. Watt, V. Pamulapati, and R. M. Summers, "Liver and tumor segmentation and analysis from CT of diseased patients via a generic affine invariant shape parameterization and graph cuts," in *Abdominal Imaging. Computational and Clinical Applications*, 2012, pp. 198–206.
- [20] T. Heimann *et al.*, "Comparison and evaluation of methods for liver segmentation from CT datasets," *IEEE Transactions on Medical Imaging*, vol. 28, no. 8, pp. 1251–1265, Aug. 2009, doi: 10.1109/TMI.2009.2013851.
- [21] M. Erdt, S. Steger, M. Kirschner, and S. Wesarg, "Fast automatic liver segmentation combining learned shape priors with observed shape deviation," in *2010 IEEE 23rd International Symposium on Computer-Based Medical Systems (CBMS)*, Oct. 2010, pp. 249–254, doi: 10.1109/CBMS.2010.6042650.
- [22] G. Wang, S. Zhang, F. Li, and L. Gu, "A new segmentation framework based on sparse shape composition in liver surgery planning system," *Medical Physics*, vol. 40, no. 5, pp. 1–11, Apr. 2013, doi: 10.1118/1.4802215.
- [23] G. Chlebus, H. Meine, J. H. Moltz, and A. Schenk, "Neural network-based automatic liver tumor segmentation with random forest-based candidate filtering," *Arxiv-Computer Vision and Pattern Recognition*, pp. 5–8, 2017, [Online]. Available: <http://arxiv.org/abs/1706.00842>.




- [24] N. Nanda, P. Kakkar, and S. Nagpal, "Computer-aided segmentation of liver lesions in CT scans Using cascaded convolutional neural networks and genetically optimised classifier," *Arabian Journal for Science and Engineering*, vol. 44, no. 4, pp. 4049–4062, Apr. 2019, doi: 10.1007/s13369-019-03735-8.
- [25] X. Liu *et al.*, "Automatic organ segmentation for CT scans based on super-pixel and convolutional neural networks," *Journal of Digital Imaging*, vol. 31, no. 5, pp. 748–760, Oct. 2018, doi: 10.1007/s10278-018-0052-4.

BIOGRAPHIES OF AUTHORS






Kadry Ali Ezzat    He received B.Sc degree in biomedical engineering from the higher technological institute, Cairo, Egypt in 2004 and the M.Sc. and PhD degree in biomedical engineering from Cairo University, Egypt, in 2011 and 2017 respectively. In 2004 he joined the Department of Biomedical Engineering in the higher technological institute as researcher assistant then he promoted as assistant Lecturer in 2011 and then he promoted to be Lecturer in 2017. His current research interests are: diagnostic imaging, robotics, satellite communications, artificial intelligence, image processing, expert systems, biomechanics, data transmission, data structures, biomedical instrumentation and electronics, pattern recognition, microcontrollers, modeling and simulation. He is now Lecturer in Department of Biomedical Engineering at Higher Technological Institute in 10th of Ramadan city since 2017, Member in Scientific Research Group in Egypt (SRGE), Consultant member of the Egyptian Remote Sensing and Space Science Authority (Satellite Alliance Project), Instructor in High Technology Center, Faculty of Engineering, Cairo University. He is reviewer for papers in many international conferences: Cairo International Biomedical Engineering Conference (CIBEC), International Undergraduate Research Conference in Military Technical College (IUGRC). He is reviewer in Australasian Physical and Engineering Sciences in Medicine (APES) journal. He can be contacted at email: kadry_ezat@hotmail.com.



Lamia Nabil Omran    She received B.Sc degree in biomedical engineering from Helwan University, Cairo, Egypt in 2004 and the M.Sc. and PhD degree in biomedical engineering from Cairo University, Egypt, in 2009 and 2016 respectively. In 2004 she joined the Department of Biomedical Engineering in the higher technological institute as researcher assistant then she promoted as assistant Lecturer in 2009 and then she promoted to be Lecturer in 2016. Her current research interests are: diagnostic imaging, robotics, hospital design, artificial intelligence, reproductive surgery, image processing, expert systems, biomechanics, computer programming, data transmission, data structures, biomedical instrumentation and electronics, pattern recognition, microcontrollers, modeling and simulation, internet of things (IoT). She is now Lecturer (PhD) in Department of Biomedical Engineering at Higher Technological Institute in 10th of Ramadan city since 2016, member in Scientific Research Group in Egypt (SRGE), Head of Bright Minds students (BMS) Research Group in Higher Technological Institute; she supervised on more than 13 under graduate bachelor projects. She can be contacted at email: englamia_82@yahoo.com.



Ahmed Ibrahim Bahgat El Seddawy    He is Associated Professor, Vice Dean of Educational Affairs, and Head of Business Department of Information System. He received his bachelor from Business Administration, MIS department and M.Sc. degree in college of Computer Science and Information Systems, Department of Information Systems 2008 from, both from AASTMT. Cairo, Egypt. On December 2014, he received his doctoral degree from the Department of Information Systems, College of Computer Science, and Department of Information Systems, Helwan University. Working as visitor professor in Ludwigsburg university in Germany and Proto University Italy. He has authored/co-authored several research publications in selected fields such as, knowledge discovery, data science, data analytics decision support systems, knowledge base systems, project management, and leadership management using ERP. He can be contacted at email: ahmed.bahgat@aast.edu.