ISSN 2278-3091
Volume 8, No.3, May - June 2019
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse02832019.pdf
https://doi.org/10.30534/ijatcse/2019/02832019

Recent advances and investigation of efficient Computer Aided Diagnosis systems for CT images in Liver cancer detection

Andrews Jose[1], Dr.D. Sujitha Juliet[2]
[1]Research Scholar, Computer Science Department, Karunya University, India, andrewsjoz@gmail.com
[2]Assistant Professor, Computer Science Department, Karunya University, India, sujitha@karunya.edu

ABSTRACT

Liver tumor identification and classification is a challenging task for radiologists. The Liver parenchyma must be segmented from the abdomen and the least variation found in the Liver cells must be accounted as benign or malignant tumor. CT images still remain one of the best modality of choice due to its better cross sectional view, clear spatial resolution, fast interpretation and high SNR. The other common Liver imaging modalities are MRI, PET and US. The CT images are preferred over the competitor MRI due to its low cost. Computer aided diagnosis (CAD) systems is the area of medical imaging that serves as the second opinion for medical practitioner during image interpretation. The CAD systems are interactive/semi automated and incorporates the findings of the medical practitioner before producing the final result. This is in contradictory with a fully automated system, where all decisions are taken by the computer software. The CAD systems can be either based on a single classifier or ensemble/hybrid model classifier. Ensemble models are preferred over single classifier models. The unavailability of public datasets resulted in classifiers which work alone with a specific dataset. Other CAD systems are also limited to small private datasets collected from hospitals and scanning centers. This means that more datasets should be made public for research and applied for classification. The different Liver cancer detection approaches can't be compared as the performance measure varies across the CAD systems. But we will make use of the final performance measure, accuracy used with the proposed CAD systems to evaluate classifiers. This paper also emphasis the proposed methods to improve the accuracy in the existing works.

Key words: CAD system, Computed tomography, Hepatocellular Carcinoma.

1.INTRODUCTION

The Liver plays an important role as the detoxification unit during metabolism, in which the biomolecules are changed inside the body [1] .It also, has 500 other different functions and is the only organ that can completely regenerate itself. A recent database GLOBOSCAN 2018 estimated the cancer mortality in 185 countries for 36 types of cancer. Liver cancer was found to be the second in mortality rates of men and third in mortality rates of women among the participating countries. There were over 840,000 new Liver cancer cases worldwide in 2018 [2]. Liver cancer rates in India increased by 32.2% since 1990 with about 30000 new cases being reported in 2016 [3]. These surveys show the relevance of Liver cancer detection and treatment at an earlier stage. Liver diseases are found to progress from fatty Liver, Fibrosis to Cirrhosis (Compensated, Decompensated, Cancer) [13]. A malignant Liver tumor (cancerous) can be classified as Liver metastatis, Hemangioma or three histological types of Hepatocellular Carcinoma (HCC) [4]. A Liver cancer will progress from stage 1 to the final stage 4, if left untreated. An early detection of Liver cancer, at a beginning stage using CAD systems is the effective way to treat the patient.

The CT scanner uses X-ray beams for scanning and produces DICOM image slices (CT images) of the scanned area [5]. These CT images are fed to the CAD system for further analysis, where it is converted to .PNG, .JPG or .BMP for CAD analysis [22] .Computer aided diagnosis (CAD) is a [28] semi-automated or interactive system designed to aid faster diagnosis and detect false negatives while physicians are interpreting medical images. [6,14]. CAD systems for any organ are different from fully automated computerized diagnosis systems as they aid physician/radiologists to examine and analyze the results before the final diagnosis [4]. These CAD systems have higher accuracy and are preffered over fully computerized systems. The Liver CAD systems has to overcome the challenges such as low contrast, high variability in Liver size and shape across patients[8] and CT image[29] segmentation from nearby structures such as vertebra ,ribs and abdomen area. The different techniques used with Liver cancer detection using CAD systems will be discussed in the following sections. Our study focuses on Liver cancer detection, Hepatocellular carcinoma (HCC) the commonly occurring cancer[20] and is the most critical stage and might even lead to death of the patient.

2.LIVER CANCER CAD SYSTEMS

The CT scanner scans the abdomen area of the patient for Liver images. The inputs to a Liver CAD system are CT image slices. Around 150 DICOM image slices or more are taken as input to a CAD system. These images are converted to .PNG, .JPG or .BMP for CAD analysis. The middle slice is preferred and provides detailed information [18]. The CT images can be viewed in axial, coronal or saggital planes as shown in Figure 1. For example, a 3D CT image can be visualized by three orthogonal sections: an axial (z is constant), coronal (y is constant), and sagittal (x is constant). [12]

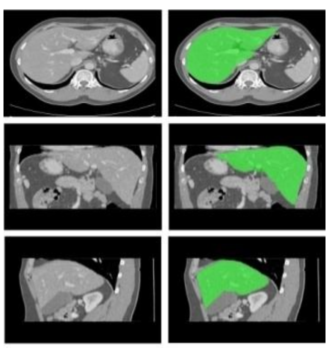

Figure 1 : Liver CT image views(Green appearance) : Axial, Coronal or Saggital [11]

A simple CAD system for Liver cancer detection is shown in Figure 2. This system aims to preprocess the abdomen CT image, Segment the Liver contour/parenchyma, Segment the Liver lesions/ROI – computerized or medical practioner assisted, Identify and select appropriate features of Liver cancer and classify the tumor as benign or malignant and cancer as primary or secondary. An optional classification is to identify the type(Type I to IV) of Liver cancer.

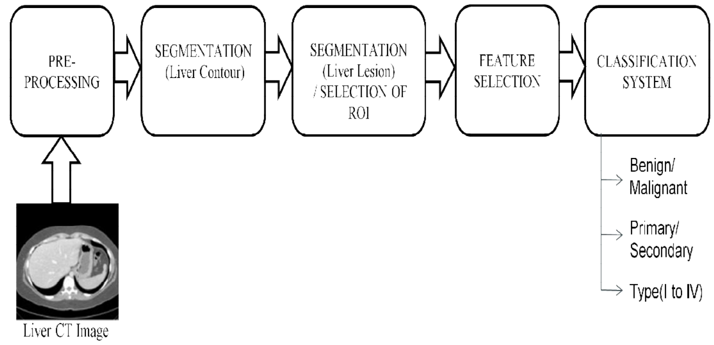

Figure 2: A simple Liver cancer CAD system

3.PREPROCESSING

The preprocessing step aims to turn off regions not of interest like suppressing low contrast structural background [8] or any annotations(film artifacts)[7] , enhance signal-to-noise ratio and reduce non-homogeneity of gray levels [8]. The preprocessing also aims in contrast enhancement. The preprocessing step should also aim at minimising the over segmentation problem [7]. John Stoitsis et al. as well as Vincey Jeba Malar.V et al. [10,20] proposed that the structural background can be suppressed Mean, Laplacian, and Gaussian filters. Ahmed M. Anter et al. [19] proposed that Grey scale and Noise removal to focus on Liver parenchyma can be performed by Adaptive threshold and morphological operators. Sonali Patil et al. as well as Ahmed M. Anter et al. [7,19] proposed that Contrast enhancement can be performed by Histogram equilization. They also proposed that Film artifacts can be removed by median filter. Vincey Jeba Malar.V et al. [20] proposed that Holes can be removed by Dilation and Erosion. Alaa Salah El-Din Mohamed et al. [8] proposed that Blur removal can be performed by Wiener filter. Aravinda H.L et al. [16] proposed that background equalization and image enhancement can be done by Applying threshold and top-hat algorithm. Jayanthi Muthuswamy et al. [18] proposed that smoothing and optimal threshold can be obtained using Bilateral filter and Swarm optimization algorithms such as Mean Grey Wolf Optimization technique (mGWO). Any appropriate Linear spatial filtering, Non-linear spatial filtering or multi resolution filters can even be applied to remove any further noise. The preprocessing phase should promote efficiency at both segmenting Liver contour as well as Liver lesions at later stages.

4.SEGMENTATION OF LIVER CONTOUR

Liver contour or Liver parenchyma segmentation is the next important step in a CAD system [19]. The major challenge is to segment adjacent organs such as pancreas and stomach as they have similar signal levels compared to Liver. The time delay in multi-phase CT image slice acquisition due to respiratory motion of patients also affects the image quality [14].Liver segmentation methods can be categorized into two: data-driven approaches and model-based approaches or region based and edge based approaches[14,21].In data-driven approach conventional methods such as thresholding are used to segment the Liver. Whereas, model-driven approach makes use of prior knowledge to segment the Liver. The Liver segmentation problem in CAD systems mainly performs model driven approach, when multiple datasets are involved [14]. The edge based approaches are difficult in Liver segmentation as we don't finally end up in a closed loop. Region based approaches work efficient as they take into account the characteristics of the nearby pixels. The best methods used here are region growing, merging/splitting, watershed algorithm, clustering and Level set algorithms [20,21]

Hussein Alahmer et al. [15] models the Liver as the largest organ in the abdomen CT slice. The Liver contour is separated by a binary mask as seen in model driven approach. Then a series of morphological operations are performed to segment the Liver contour. Ahmed M. Anter et al.[19] applied connected component algorithm to segment the Liver contour. Alaa Salah El-Din Mohamed et al. [8] applied marker-control watershed transform method to segment the Liver contour. This transform does edge preservation as well as non-overlapped regions. Aravinda H.L et al. [16] proposed segmentation of Liver portion using adaptive region growing. Jayanthi Muthuswamy et al. [18] applied Fuzzy C means clustering (FCM) for segmentation. Vincey Jeba Malar.V et al. as well as Abdalla Mostafa et. al [20,21] applied region growing techniques. Huiyan Jiang et al. [9] proposed that Registration Based Organ Positioning(ROP) serves as an improvement to the existing methods to identify Liver contour wherein a float image is taken as the reference image for image registration. This method will also account for the difference in physical shape of Liver images. The commonly used method for liver contour segmentation are bounding box approaches or depends on a good reference image to find the largest connected component.

5.SEGMENTATION OF LIVER LESION / SELECTION OF ROI

The Liver lesion can now be segmented from the Liver contour. The segmentation of Liver lesion will be either automatic or semi-automatic. Here automatic lesion segmentation doesn't require human intervention. The selection of ROI by a medical practitioner is a guided process and the lesions generated by the CAD system will be examined and lead to accurate lesion segmentation. The algorithms that work with segmentation of Liver Contour can also be applied to Liver lesion segmentation. Hussein Alahmer et al. [15] proposed that the segmented lesion can be divided into three areas, i.e. inside, outside (surrounding) and boundary areas. This selection of multiple ROI yields better results than single ROI selection. As seen in segmentation of Liver contour, region growing is applied to segment Liver lesions.The seed pont is selected by FCM clustering algorithm. Aravinda H.L et al.[16] proposed Adaptive Region Growing method with Simple Linear Iterative Clustering for Liver lesion detection. Jayanthi Muthuswamy et al. as well as Vincey Jeba Malar.V et al. [18,20] proposed largest connected region using Label Connected Component (LCC) algorithm to identify lesions.

6.FEATURE EXTRACTION

The entire image can't be fed to a classifier or clustering algorithm as there are plenty of CT image slices and are having high dimensions. So we select a subset of the CT image, best features as input to the the classifier for classifying the Liver Lesions. The commonly taken features are Shape, Intensity and texture [15][16]. Low-level features are usually used for understanding radiological images [15][17]. John Stoitsis et al. [10] proposed five texture features based on genetic algorithms for each tumor. Doron et al. [24] proposed a combination of texture features and intensity features. Hussein Alahmer et al. [15] proposed ROI (inside, boundary, and outside lesion) as the new feature vector. Aravinda H.L et al. [16] proposed that histogram features and Gray-Level Co-Occurrence Matrix as the features. The Liver lesions feature set can also be in terms of Morphological features like shape, size, edge, surface roughness, spiculation ; Gray level features like Contrast, density; and Texture features like Patterns, homogeneity, gradient, Wavelet features etc.

7.CLASSIFICATION

The features from lesion area can be classified as benign or a malignant tumor. The next step is to classify the tumor as primary or secondary tumor [22]. Cancers that originate in the Liver are called primary Liver cancer. Others which spread from adjacent organs are called secondary Liver cancer. [20]. The tumor stage(I to IV) and type can also be given as a precise output from the classifier. A common type of classification of a hepatic tissue is into types : Normal, HCC, and Hemangioma [23]. The comparison on major attributes such as features, classifier used, dataset, remarks and proposals from authors, year and accuracy is detailed in Table 1 from the research of recently proposed CAD systems.

Table 1: Comparison of classifier accuracy for Liver CT images

Sl. No	Author & Year	Features	Classifier	Dataset	Remarks and Proposal	Year	Accuracy (%)
1	Nanda N.[26]	Texture	CascadedConvolutionalNeuralNetworksandGeneticallyOptimised Classifier	Liver Tumor Segmentation Challenge dataset 131 CT scan images for training and 70 for testing	Predict whether lesion is malignant or benign and also other vital information about the tumor	2019	99.65 %
2	Feng X.,[27]	Spatial and context	Cascaded U-Net	3DIRCAD dataset	Tumor segmentation accuracy needs improvement	2019	91..3
3	Kakkar P. et al.[25]	Centeroid of the Liver	Artificial Neural Network(ANN)	Liver Tumor Segmentation Challenge dataset 131 CT scan images for training and 70 for testing	Not applied to Liver lesions	2018	98.11 %
4	Ahmed M. Anter et al.[19]	Intensity	Hybrid : Neutrosophic sets, Watershed algorithm, and Fast fuzzy c-means clustering algorithm (FFCM)	105 samples	Working around with Complex datasets	2018	95%
5	Jayanthi Muthuswamy et al.[18]	Intensity	Hybrid : FCM and Mean Grey Wolf Optimization Algorithm	20 Patients : The cancer Imaging Archive (TCIA)	Only Contour extracted. Comparison with other optimization algorithms	2018	91%
6	Aravinda H.L.[16]	Texture	Rough-set classifier	120 samples	More number of disease classes	2018	90%

8.CONCLUSION

The Liver cancer detection still remains a wide area of research, with much focus on the commonly occurring Liver cancer ,Hepatocellular Carcinoma. All research papers have come up with accuracy as the common performance evaluation. As we are dealing with medical images, ground truth images obtained from medical practioners must be used for comparisons . Our studies only considered the classifiers with more than 90% accuracy. The proposed CAD system is having segmentation process done as extraction of Liver contour and Liver tumour done at subsequent steps. The Liver tumor and lesion classification can either be fully automated or semi-automated system with manual intervention. The different levels of classification will also increase the complexity and selection of the classifier. The new set of classifiers like CNN, Neuro fuzzy sets must be focused. A classifier must be chosen based on accuracy, speed of diagnosis required, time to train the classifier, robustness in the presence of noise/outliers and should most importantly work with varied datasets.

REFERENCES

1. DM Grant. Detoxification pathways in the liver, *Journal of Inherited Metabolic Disease 14*, pp. 421–430, 1991. https://doi.org/10.1007/BF01797915
2. Freddie Bray , Jacques Ferlay, Isabelle Soerjomataram, Rebecca L. Siegel, Lindsey A. Torre, Ahmedin Jemal. **A Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries**, *CA- A Cancer Journal for Clinicians*, Volume 68, Issue 6, pp. 394 424, 2018. https://doi.org/10.3322/caac.21492
3. Abantika Ghosh, **Cervical and oesophageal cancer down, increase in breast and liver cancer, finds Lancet Oncology study**, NICPR, Updated September 13, 2018 *http://cancerindia.org.in/cervical-oesophageal-cancer-increase-breast-Liver-cancer-finds-lancet-oncology-study/*
4. Katsutoshi Sugimoto, Junji Shiraishi, Fuminori Moriyasu, Kunio Doi. **Computer-aided diagnosis for contrast-enhanced ultrasound in the liver**, *World Journal of Radiology*, Volume 2, Issue 6, pp. 215-223, 2010. https://doi.org/10.4329/wjr.v2.i6.215
5. Imasato Y. , **CT Scanner**. In: Takahashi S., Sakuma S., Kaneko M. (eds) Illustrated Computer Tomography. Springer, Berlin, Heidelberg, 1983 https://doi.org/10.1007/978-3-642-81814-1_4
6. Castellino RA, **Computer aided detection (CAD): an overview** ,Cancer Imaging 5, 17–19 ,2005 https://doi.org/10.1102/1470-7330.2005.0018
7. Sonali Patil, Dr. V. R. Udupi. **Preprocessing To Be Considered For MR and CT Images Containing Tumors**, *IOSR Journal of Electrical and Electronics Engineering*, Volume 1, Issue 4, PP 54-57, 2012. https://doi.org/10.9790/1676-0145457
8. Alaa Salah El-Din Mohamed, Mohammed A.-M. Salem, Doaa Hegazy, Howida A. Shedeed., **Improved Watershed Algorithm for CT Liver Segmentation Using Intraclass Variance Minimization**,

Communications in Computer and Information Science 756, pp. 164–176, 2017.
https://doi.org/10.1007/978-3-319-67642-5_14

9. Huiyan Jiang, Shaojie Li, Siqi Li. **Registration-Based Organ Positioning and Joint Segmentation Method for Liver and Tumor Segmentation**, *Hindawi BioMed Research International*, Volume 2018, Article ID 8536854.
https://doi.org/10.1155/2018/8536854
10. Stoitsis, John, Ioannis Valavanis, Stavroula G. Mougiakakou, Spyretta Golemati, Alexandra Nikita, and Konstantina S. Nikita. , **Computer aided diagnosis based on medical image processing and artificial intelligence methods**, *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment* 569, no. 2. 2006; p.591-595.
https://doi.org/10.1016/j.nima.2006.08.134
11. D. A. Oliveira, R. Q. Feitosa and M. M. Correia. **Segmentation of Liver, Its Vessels and Lesions from CT Images for Surgical Planning**, *BioMedical Engineering OnLine*, Vol. 10, pp. 30, 2011.
https://doi.org/10.1186/1475-925X-10-30
12. László Ruskó, **Automated segmentation methods for liver analysis in oncology applications** , *Ph.D. dissertation , University of Szeged, Department of Image Processing and Computer Graphics*, 2014.
13. Dimitrios N Samonakis, Mairi Koulentaki, **Constantina Coucoutsi, et al. Clinical outcomes of compensated and decompensated cirrhosis: A long term study, World Journal of Hepatology;** 6(7), pp. 504– 512, July 2014.
https://doi.org/10.4254/wjh.v6.i7.504
14. Y. Masutani, K. Uozumi, Masaaki Akahane, Kuni Ohtomo. **Liver CT image processing: A short introduction of the technical elements**, *European Journal of Radiology 58*, pp. 246–251, 2006.
https://doi.org/10.1016/j.ejrad.2005.11.044
15. Hussein Alahmer, Amr Ahmed. **Computer-Aided Classification of Liver Lesions from CT Images Based on Multiple ROI**, *Procedia Computer Science* ***90***, pp. 80–86, 2016.
https://doi.org/10.1016/j.procs.2016.07.027
16. Aravinda H.L, M.V. Sudhamani. **Liver tumour classification using average correction higher order local autocorrelation coefficient and legendre moments**, *International Journal of Engineering & Technology*, Vol 7, No 2.6, pp. 306-310, 2018.
https://doi.org/10.14419/ijet.v7i2.6.11269
17. El-gayar M., Soliman H. **A comparative study of image low level feature extraction algorithms**, *Egyptian Informatics Journal*, Vol.14, Number 2, pp. 175-181, 2013.
https://doi.org/10.1016/j.eij.2013.06.003
18. Jayanthi Muthuswamy, B. Kanmani. **Optimization Based Liver Contour Extraction of Abdominal CT Images**, *International Journal of Electrical and Computer Engineering*, Vol.8, No.6, pp. 5061~5070, December 2018.
https://doi.org/10.11591/ijece.v8i6.pp5061-5070
19. Ahmed M. Anter, Aboul Ella Hassenian. ,**CT Liver tumor segmentation hybrid approach using neutrosophic sets, fast fuzzy c-means and adaptive watershed algorithm**, Journal of Artificial Intelligence In Medicine , December 2018.
20. Vincey Jeba Malar.V, Saravana Kumar. E. **Computer Aided Diagnosis for Liver Cancer using Statistical Model**, *International Journal of Research in Engineering and Technology*, Volume: 02 Issue: 12, pp. 84~89, Dec-2013.
https://doi.org/10.15623/ijret.2013.0212014
21. Abdalla Mostafa, Ahmed Fouad, Mohamed Abd Elfattah, Aboul Ella Hassanien, Hesham Hefny, Shao Ying Zhu, Gerald Schaefer., **CT Liver Segmentation using Artificial Bee Colony Optimisation**, *Procedia Computer Science 60*, pp. 1622–1630, 2015
https://doi.org/10.1016/j.procs.2015.08.272
22. Nazish Khan, Mehreen Kiran, Imran Ahmed, Awais Adnan. Overview of Technical Elements of Liver Segmentation, *International Journal of Advanced Computer Science and Applications*, Vol. 7, No. 12, pp. 271~278, 2016
https://doi.org/10.14569/IJACSA.2016.071235
23. Luyao Wang, Zhi Zhang, Jingjing Liu, Bo Jiang, Xiyao Duan, Qingguo Xie, Daoyu Hu and Zhen Li. **Classification of Hepatic Tissues from CT Images Based on Texture Features and Multiclass Support Vector Machines**, *Proceedings of the 6th International Symposium on Neural Networks: Advances in Neural Networks* **-** Part II. 2009, pp. 374-381
https://doi.org/10.1007/978-3-642-01510-6_43
24. Doron, Yeela, Nitzan Mayer-Wolf, Idit Diamant, and Hayit Greenspan. **Texture feature based Liver lesion classification**, *proceedings of SPIE- International Society for Optics and Photonics*, Volume 9035, 2014; pp. 90353K-90353K.
https://doi.org/10.1117/12.2043697
25. Kakkar P., Nagpal S., Nanda N. , **Automatic Liver Segmentation in CT Images Using Improvised Techniques**. In: Chen H., Fang Q., Zeng D., Wu J. (eds) Smart Health. ICSH 2018. Lecture Notes in Computer Science, vol 10983. Springer, Cham, 2018
https://doi.org/10.1007/978-3-030-03649-2_4
26. Nanda N., Kakkar P. & Nagpal S. , **Computer-Aided Segmentation of Liver Lesions in CT Scans Using Cascaded Convolutional Neural Networks and Genetically Optimised Classifier**, *Arabian Journal for Science and Engineering*, Volume 44, Issue 4, pp 4049–4062 ,2019
https://doi.org/10.1007/s13369-019-03735-8
27. Feng X., Wang C., Cheng S., Guo L., **Automatic Liver and Tumor Segmentation of CT Based on Cascaded U-Net.** In: Jia Y., Du J., Zhang W. (eds) Proceedings of 2018 Chinese Intelligent Systems Conference. Lecture

Notes in Electrical Engineering, vol 529. Springer, Singapore, 2019. https://doi.org/10.1007/978-981-13-2291-4_16

28. Amir Hesam Yaribakht, Mohd Shahidan Abdullah, Alireza Ghobadi "**A Novel Color Image Watermarking Method based on Digital Wavelet Transform and Hungarian Algorithms**" International Journal of Advanced Trends in Computer Science and Engineering. Volume 8, No.2, March - April 2019. https://doi.org/10.30534/ijatcse/2019/09822019
29. B. Buvaneswari , T. Kalpalatha Reddy "**ELSA- A Novel Technique to Predict Parkinson's Disease in Bio-Facial Recognition System"** International Journal of Advanced Trends in Computer Science and Engineering, Volume 8, No.1, January – February 2019. https://doi.org/10.30534/ijatcse/2019/03812019