International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

# An uncertain Liver Segmentation in Computed Tomography Images with Enhanced generative Mask Region on CNN

**N Nanda Prakash[1*], V Rajesh[2] and Syed Inthiyaz[3]**

**Submitted:** 25/08/2022 **Accepted:** 20/11/2022

***Abstract:*** The ability to measure liver volume with a single device has emerged in medical practice. Images from CT & MRI are used to estimate the liver's total volume. After the liver and its peripherals are scanned using abdominal computed tomography, the PC-aided conclusion and remedial intervention may begin. This research presents a self-loader division technique based on the specific multivariable appropriation of Tissues in the Liver & sub-divisions of the graph cut. While it isn't wholly mechanized, the process negligibly includes human communications. Unequivocally, it comprises three primary stages. A subject-explicit probabilistic model, first and foremost, was worked from an inside fix encompassing a seed point determined by the client. Furthermore, a repeated task of pixel marks has been implemented to refresh the probabilistic guide of the tissues in light of spatial-logical data. The chart slice model was later upgraded to extricate the 3-dimensional Liver from the picture. In the post-handling, excessively fragmented nodal areas because of fluffy tissue division were eliminated, keeping up with their suitable life structures utilizing hearty bottleneck location with adjoining form imperatives. The proposed framework was carried out and approved on the MICCAI SLIVER07 dataset. Results were compared to cutting-edge techniques in light of critical clinical metrics. The visual and quantitative evaluations thus suggest that the proposed framework might function on the accuracy and dependability of asymptomatic liver division. Increasingly, the liver image division is being used for essential clinical objectives, such as liver evaluation, disease diagnosis, and therapy. Using GANs and veils local convolutional brain organizations, this study provides a liver picture division method (Mask R-CNN). We first looked at the combination of Mask R-CNN and GANs to improve pixel-wise characterization since that's how most incoming images contain uproarious parts. A GAN Mask R-CNN calculation was finally presented, and it outperformed the standard Mask R-CNN and Mask CNN calculations in terms of exhibition analysis. This includes measures for the Dice similitude coefficient (DSC) and MICCAI measurements. The proposed calculation additionally accomplished better execution analysis than ten advanced calculations concerning six Boolean markers.

***Keywords:*** *liver segmentation, CNN, uncertain dataset, CT scan.*

## 1. Introduction

The liver is the biggest organ in the mid-region, its capacities as a channel, keeping waste and different poisons from being delivered into the round framework. Since an unhealthy liver can't keep up with its exhibition, the earliest location of neurotic indications guarantees the viability of medicines, thus drawing out the patient's life. Besides, present-day improvements in remedial intercession and medical procedures have progressively depended on the electronic remaking of a subject-explicit liver, both for therapy arranging and the ensuing process. Registered “CT” is one of the important methods liked in following stages. This permits the doctor to imagine the physical construction of this organ and obsessive proof. Notwithstanding, prescient appraisal during treatment requires normalized conventions, which call for quantitating neurotic markers. They generally include depicting the liver, peripherals, and sores (if any) by an accomplished and gifted radiologist. The interaction is relentless, tedious, and inclined to between and intra-eyewitness fluctuations. As of late, it has been significantly more in this way, given a rising goal of a 3D network gained by an advanced CT. Subsequently, complete and self-loader frameworks have been essential in “CAD”. Unlike the other imaging conventions, Computed tomography liver is hard to portion because of acquiring difficulties [1].

[1]*Research Scholar, Department of ECE, Koneru Lakshmaiah Education Foundation, Guntur, AP, India-522302*
[2]*Professor, Department of ECE, Koneru Lakshmaiah Education Foundation, Guntur, AP, India-522302*
[3]*Associate Professor, Department of ECE, Koneru Lakshmaiah Education Foundation, Guntur, AP, India-522302*
**Corresponding Author: N Nanda Prakash. Email: nandaprakashnelaturi@gmail.com*

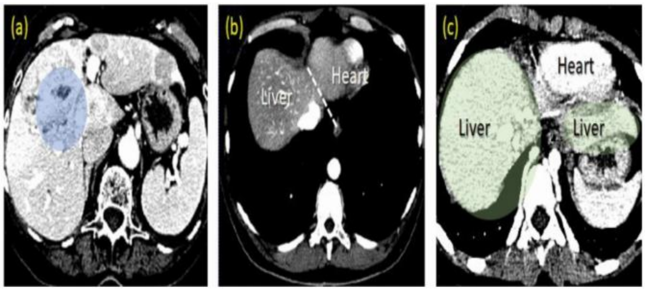


**Figure 1**: Issues related to liver division, i.e., in-homogeneity of force in the liver area (a), the fluffy partition among liver & heart (b), & the multi-portions calculation inside a solitary slide (c). Likewise, these cases show different power scopes of liver challenges.

The computed tomography (CT) component addresses tissues as its X-beam retention. It unavoidably doesn't separate well-adjoining organisms from the liver with comparable properties, like kidney, heart, and muscle. Moreover, there is no edge slope significant areas of strength for adequately distinguished as a limit isolating these items [2]. Inhomogeneity of liver inside is substantially more articulated than that against non-liver districts, prompting low dividing precision. Illness actuated changes and deformity1, 5, 6, ancient movement rarities, and between-subject inconstancy additionally demolish the results.

## 2. Literature survey

This segment centers on separating the liver from CT imaging. Existing methods varied in choice, how many clients' collaboration included, and demonstrating imperatives forced during the strategy. An outline of ongoing advancements can be found in [3]-[4]. While itemized assessments and their benchmarking, because of a typical dataset, are introduced in 3. In any case, a portion of the noticeable examinations is looked into here. They can be separated into those utilizing completely self-loader draws near.

### 2.1 Completely programmed Segmentation

Most mechanized division techniques depended on a factual design of liver shape, either utilizing instatement or as a limitation. Nonetheless, the degree to which a model could catch conceivable varieties found in normal conditions not entirely set in stone by the number and goal of preparing liver occurrences was accounted for. Using data from a dataset, a deformation model was fitted to a liver image. Models for the 20- and 112-liver studies were constructed using two million and two hundred thousand model boundaries, respectively. This study presented AAM, LW and chart cuts to learn text-based models, perceive the item of interest, and acquire its final bunching based on instances that were already known [5].

Likewise, Li et al. forced morphological imperatives on an underlying limit for a physically conceivable liver through head part examination (PCA) [6]. Deformable diagram cuts managed any unreasonable varieties left in inconspicuous cases. The latest and quick advancement of convolution brain organization (CNN) has empowered a lot of productive depictions of liver limits. Lu et al. assessed the a liver area utilizing a pixel-wise probabilistic model from 78 CT pictures prepared by CNN. Any varieties unrecoverable by CNN were comparably upgraded by using a diagram cut. Lu and Hu took a comparative methodology. The resulting probabilistic guidance, on the other hand, was used to speed up surface construction. 109 CT images were used to create the model in this study. The H-Dense UNet was used by Li et al. to segment progressively living growths in neurotic patients by crossbreeding (2D and 3D) thickly associated UNet (H-Dense UNet). When learning spatial data between consecutive ones, the 3D DenseNet was able to distinguish between 2D and 3D densities. DenseNet models were integrated and refined in order to gain the final liver and growing segment. It took nine hours to link and 30 hours total to construct these models, despite their reasonably good ratings in their category. When the pictures are done, another event might be fragmented in 30 to 200 seconds [7].

Resolving some problems in creating a real affected person who went thru a liver transfer, some other work proposed identical gaining and portioning of liver from belly CT angiography (CTA). CTA photos had been partitioned into low and excessive distinction bunches on this work. It applied records at the existence structures of kidneys, ribs and livers joined to the threshold procedure to put off unimportant elements and characteristic the vicinity of interest (ROI). Because of a programmed alternate system, k-Means an "MLP" categoration had been implemented with excessive and coffee differentiation records, separately, contingent upon their histogram appearances. Heuristic post-coping with became used to put off over-portions, even as incredible mistakes are probably bodily rectified [8]. Another later study via way of means of Zheng et al. fabricated a liver classifier from 12 text-primarily based totally highlights, decided from a darkish stage co-occasion network (GLCM). Moreover, the liver function became taken benefit of as applicable facts in some other classifier. Probabilities figured from those classifiers had been integrated into an arbitrary stroll version to get the final Segmentation. Eighteen cuts containing a subject`s maximum giant liver location had been organized of their trial, even as two CT volumes had been implemented for testing. Note that form facts of the liver became now no longer concept of. A few investigations depended completely on facts separated from CT photos without even a hint of a training set. In any case, a liver shape, therefore assessed in heterogeneity, became unsteady. This moreover applies to seed factor or marker, specifically whilst placed on a neurotic locale. Marcin19 evolved a 2D liver form via way of means of becoming a member of left and right-hand facet ones, characterized via way of means of five and three polylines, individually. Given a centroid of a picture, a starting level of a shape became first located via way of means of contrasting its pressure and that of the lumbar backbone vicinity [9]. The accompanying problems had been iteratively observed on a separate polyline in mild in their mathematical distance to an ongoing factor and its pressure inner discretized ranges. A weak spot of this approach became being reliant upon the lumbar backbone vicinity and the evenness of a records picture [10][11].

Furthermore, searching at powers among makes a specialty of a polyline turned into sensitive to imaging commotion. Wu et al. registered the maximum sizeable energy projection (MIP) of three-D CT to decide the belly area. Edge & morpology strategies had been carried out to decide the extent of interest (VOI). At last, instantly iterative bunching and diagram slices had been used to phase the super-voxel liver. One greater traditional method turned into proposed through Kumar et.al [12][13]. They carried out locale outgrowing seed focuses clearly selected through thresholding [14][15]. A modified Fuzzy C-Mean computation was used to extract the injuries from the liver. Sub regions of a CT image have recently been decomposed using K-Mean, which is registered to an underlying cut [16]. Since then, a form has been regarded as walling one with the most no. of pixels. Chart cut with Gaussian boundaries and between cut slope integrated into area and limit terms, individually, were applied to gather little locales [17][18]. A rectangular layout confined Vena cava. Other over-sections were taken out if they were less covered with a predefined format and their typical powers dropped out of a predetermined reach. Inside void because of growth was disposed of by sunken filling, aside from those on the limit [19][20].

### 2.2 Self-loader Segmentation

The techniques in this classification require client cooperation either in introducing Segmentation or forcing limitations. A few models in which a level-set was utilized with client connection to a degree to finish the interaction were included. All the more explicitly, a client was approached to give an underlying liver form in sure cuts, although in 24 seed focuses on top and base parts in each projection of a liver were required. Minor source focuses physically instated on specific amounts were utilized to characterize an underlying region for the quick walking limit-based level set. Nonetheless, the low difference among the frontal area and foundation made it hard to stop the advancement of the level set. Moreover, the quantity of seed point could be ordinarily up to 10-15 focuses, indicated on 4-5 cuts, to catch their varieties adequately.

A seed factor turned into bodily positioned in IVC to take away gastric veins (ABV), which had been grouped into hepatic (HPV) and non-hepatic (non-HPV) veins. These vessels had been then used for the department of the liver. This approach finished the best rating of its group. However, if mistakes occurred, the client`s intercession turned into expected. These have protected re-deciding on the seeding factor, apart kidneys from a the liver, disentangling HBV from non-HBV, or putting off IVC from the segment & leaving the focus. Strategies additionally preferred the improvement of the district on this congregation. Lu et al.four used the quasi-Monte Carlo (QMC) approach to pick out a beginning factor. Because the low-degree highlights had been concept of separately, a non-direct channel and morph pastime turned into required for the evacuation of immoderate disturbances and fragments. Based on our written review, Chart Cut turned into additionally taken into consideration predominant. Peng et al. proposed a method primarily based totally on an look version wherein a liver turned into remoted in specific compartments. First, the beginning localities had been bodily decided withinside the shape of a chamber. The chart segment, whose enhancement trusted a geodesic space, turned into then implemented to segment a liver tissue Liao et al. have counseled a comparative study. A deformable version can be labored from bodily drawn contours in unique sections without a subject-unique guidance set. In this revision, a 3-d liver turned into approximated through including those shapes. Each vertex of this version has been assigned to a detail factor withinside the hidden image. A visible device enabled a client to modify cut up consequences for post-processing.

## 3. Materials and Techniques

### 3.1 The Original Mask R-CNN

In comparison to the RCNN, Fast-RCNN [9] & Faster RCNN [7] Frameworks, the MRCNN is a better variant. The MRCNN was swiftly overtaken by the Faster RCNN in terms of performance. When it comes to object detection and division, the R-CNN cover focuses on an adaptive and simple general method that creates top-notch division veil for image instances concurrently. In contrast to FrRCNN & MRCNN contains a third branch for forecasting division cover for every location of interest (RoI). Vessel branch is a small FCN that performs pixel-by-pixel division cover prediction on every ROI. When compared to R-CNN, the R-CNN veil is easier to construct and takes less computing effort.

Figure 1a diagrams the customary Mask-R-CNN system for picture division. Despite the fact that MRCNN & FrRCNN have comparative work processes, they actually have principal contrasts. From one viewpoint, the quicker R-CNN experiences loss of spatial data and subsequently shows less precise element extraction and RoI location. Then again, MRCNN utilizes a RPN (region proposal network) for highlight extraction and jumping box-changed confinement and grouping. Moreover, Mask R-CNN involves the RolPool technique for highlight extraction, RoI measurement, and treatment of multi-scale RoI highlights through greatest assembly. Likewise, MRCNN replaces Fr RCNN's RolPool layer with a RoI arrangement layer (RoIAlign) for the region of the covered article.

For the most part, it has been seen that those with a more severe level of client association included outflanking their partners, unavoidably at the expense of more unimaginable tedious and try required. Then again, improving the dividing precision of completely programmed liver extraction frequently depended on directed AI (ML) methodologies and master frameworks that preparation of the model required. In this way, a lot of information isn't consistently available. Motivated by the problem, this paper considered the harmony between portioning precision and client connection reasonable for a run-of-the-mill clinical setting with a restricted space of specialists. Self-loading liver division from 3D CT images is proposed. We've made three kinds of commitments. First and foremost, collaboration is confined to just specifying a seed location inside a liver using the simple graphical UI (GUI). Besides, it guarantees strength by utilizing a probabilistic system in fundamental refining grouping. At long last, the rightness of liver life systems is stated by using bottleneck discovery and contiguous shape limitations to eliminate over-divided districts.

Proper best-in-class techniques in the field are checked. Multivariate pixel force display, a probabilistic tissue name calibration system, and physically required post-handling are all included in this itemized representation of the planned liver division. Emotional and quantitative examinations, as well as their dialogues, are presented in the following sections. In conclusion, closing comments on the proposed plot and its possibilities in modernized clinical frameworks are made. To wrap things up, as the liver calculation is highly mind-boggling yet independently associated, it might show up as discrete locales in specific cuts. Working on 3D division to 2D form following isn't paltry. Because of these difficulties, loyally portioning a liver from volumetric CT pictures generally stays an open examination region.

The MRCNN can be utilized for perform various tasks training with the accompanying misfortune work definition:

L = LClS + L bbox + L veil - - - - - - (3.1)

LClS is the accurate characterization of Lbbox misfortune, the relapse misfortune for the correct bounding box, and the objective division misfortune, characterized by the objective division necessities contrasted with the conventional location organization.

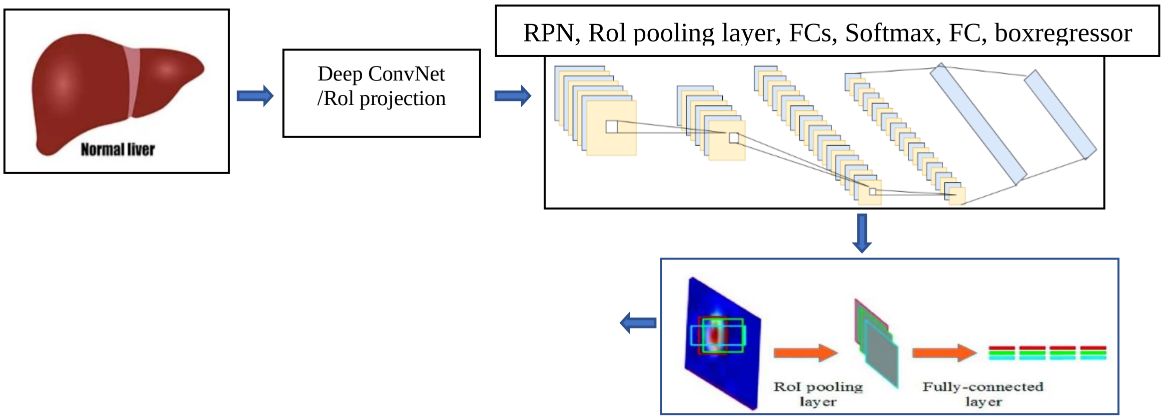


**Figure 2:** Structure of Mask R-CNN

## 4. Further Developed MRCNN

The MRCNN trains the worldwide highlights of liver image through extra preparation cycles (show is figure 2). The forecast box boundaries are iteratively changed until they are near the appropriate box boundaries. This paper endeavors to speed up the union and further develop the restriction accuracy for liver discovery & classification. We accomplish these objectives by breaking down the circulation of the viewpoint proportions of the liver pictures through - implied bunching. As additional preparation emphasis is acted in the organization preparing stage, the organization learns the worldwide liver attributes in the CT pictures; the forecast box boundaries are dynamically changed; lastly, the ground-truth boxes are drawn closer. The liver stage and width attributes are tested withinside the CT pix to hurry up the union pace and in addition increase the liver restrict exactness. Henceforth, - implies bunching is carried out to the dimensions and width statistics making use of the Euclidean distance. This grouping calculation estimates the space among designs the use of the Euclidean distance. It distinguishes the bunch groups via a given leaping container of anchors, in which the end result container is picked because the nearest 1 to an anchor. This cycle is rehashed till the anchors come to a prespecified number. Figure 3 suggest the shape of RoI Align with – implies bunching.

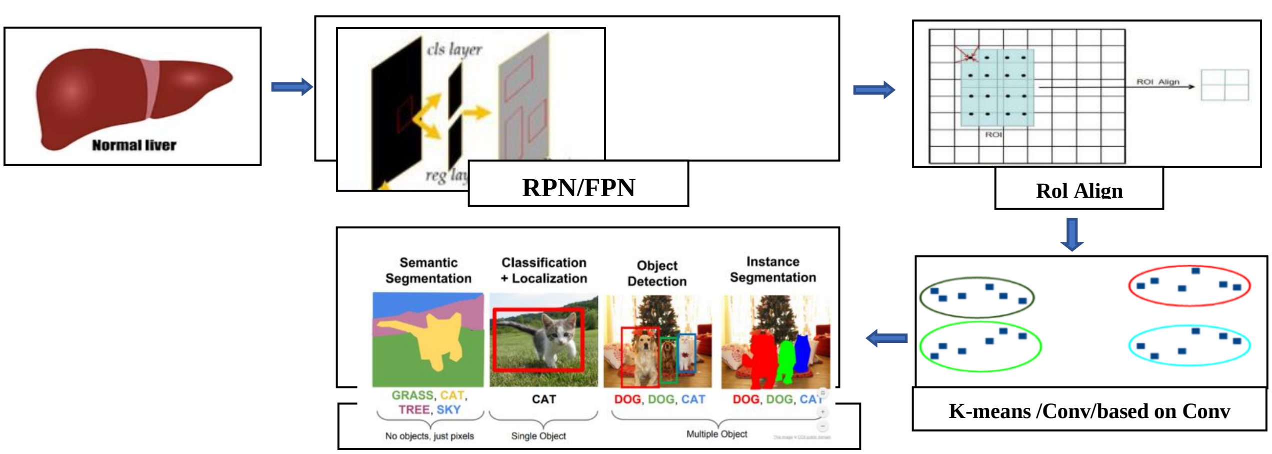


**Figure 3:** Structure of RoI Align with mean bunching

Wherein the 2 methods, D& G, have interaction via a 2-participant minimax aggressive recreation with the goal feature V

(G, D):

### 4.1 Generative Adversarial Networks and Algorithm

Good fellow et al. first proposed GANs, or generative antagonistic organisations, in 2014. An information appropriation model, known as a generative model, looks for evidence that a test's information derives more from the preparatory tests than any other source. This methodology is set up to increase the probability that the preparation and received assessments will be correctly identified. GAN MRCNN engineering for liver picture division is shown in Figure 4.

Whenever the commotion z is inspected from the dormant space & took care of into the produced model G, an example x = G(z) is delivered. The likelihood dissemination PG(x) of the produced tests could be considerably more convoluted for brain organizations. The generative model G is prepared to match the likelihood dispersions PG(x) and Pdata(x) as intently as could really be expected. The useful model G attempts to produce bogus information to befuddle the discriminator model (D), while the discriminator D attempts to separate among genuine and misleading information tests. This inconsistent learning powers the dispersion delivered by G to rough the specific information dissemination.

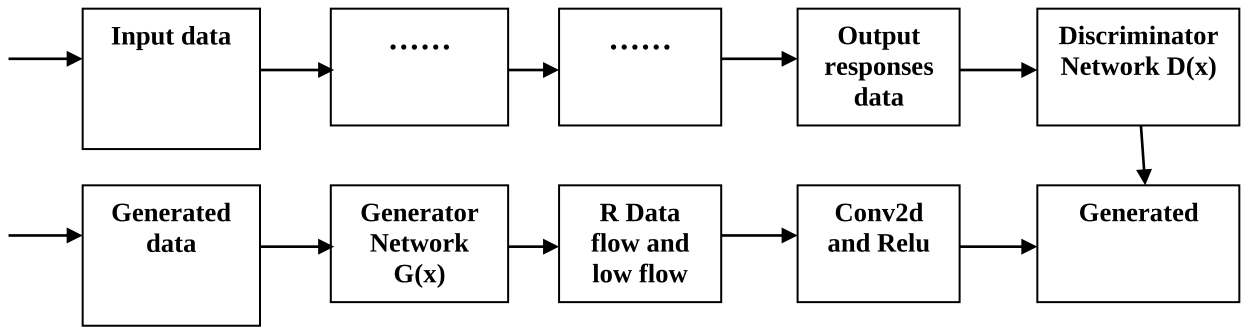


**Figure 4:** Block diagram of GAN MRCNN

The ill-disposed learning plan can be formed as the accompanying enhancement issue:

G = arg minG Div (PG(x), PData (x)) ----- (4.1)

Div denotes the variations among PData(x) and PG(x). The discriminator feature D may be described mathematically as

1.1.1.1.1

D = arg max V (G, D) ------- (4.2)

In which the 2 fashions D and G engage with the goal feature V (G, D) via a -participant minimax aggressive game.

V (G, D) =Ex˜ Pdata [log D(x)] + Ex ˜ Pdata[log(1-D(G(z)))] -------(4.3)

Therefore, the GAN parameter optimization hassle may be formulated as

G = arg minG max V (G, D) ----- (4.4)

The fashions G & D are up to date THROUGH ALTERNATING OPTIMIZATION. As the opposed getting to know system evolves, Model G generates a record that step by step resembles the precise records. The workflow of the schooling set of rules is proven withinside the following set of rules.

### 4.2 Stochastic gradient descent learning for GANs in a small batch

#### 4.2.1 GAN Training:

Stage 1: A mastering hyper-parameter is the quantity of discriminator steps, I. for the amount of MRCNN getting ready cycles do

Stage 2: Implement k-implies bunching to bolt the picture perspective proportion, & diminish secures. For 1 step, do

Stage 3: Select a minibatch of m commotion tests (z(1) . . . , z(m)) following the commotion earlier pg(z).

Stage 4: Take a small group of m models (x(1). . . x(m)) following the information conveyance pdata(x).

Stage 5: Implement the stochastic slope climb to refresh the discriminator:

## 5. Results and Discussions

Tests were directed to examine three plans: the traditional MRCNN, the MRCNN with - implies grouping (for the advancement of the completely associated layer boundaries) [10], and the GAN MRCNN, which supports the division execution with ill-disposed learning abilities. Eight cuts of liver pictures (with typical and obsessive cases) were gathered and used to research the impact of the - implies grouping and GAN modules on the MRCNN division yields. Figure 5 thinks about the outcomes, which are displayed in red forms.

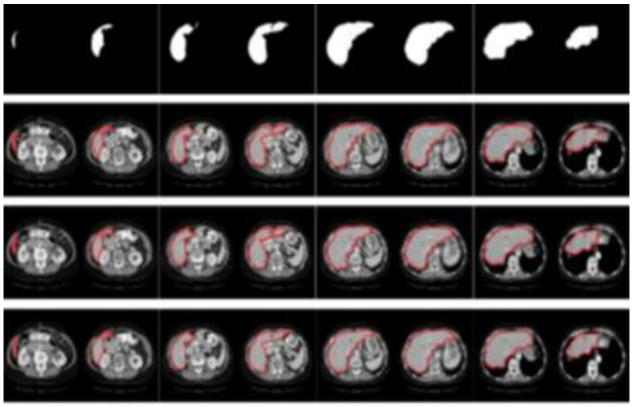

**Figure 5:** Original MRCNN, MRCNN with K. means, and R-CNN mask with GAN information

**Liver Volumes:** volumes and determine liver segments in general, so we have a case right here which is a male or female that has metastases from colorectal cancer in his/her liver. These are the only metastases, and they are considering doing a right hepatectomy, so they have asked to calculate the volumes of the right lobe and the left lobe with the caudate to determine. The percentages of the liver would remain, and whether or not they can make a right-hand attack on me, so the first thing to do is to find the sequence where you think you can see the tumor. The best general is best to do these on the third sequence, which are our post-contrast sequences.

We will check the postponed arrangement and see them and work out the volume off, so you want to right-click, and if this isn't your right snap and go to send series, then, at that point, you are sending discourse box will come up. You want to ensure that the objective is tera recon and afterward hit send chosen series; after you have sent that, you want to send off a fear-based workstation by adding the AQI button to your toolbar; after you are laid out PACs then, at that point, you can open the patients. Find the patient's test and open it, which we wiiillll show straightaway. All right, and open it, which we will show straightaway — looking for the patient utilizing the hunt box, which you can see here. We will stack it, and we will do it as a general after that is stacked, you ought to have the option to see what you imported here or the above figures for other developments. Things to be aware of tera recon is the window and level is the point at which you suitable and left click simultaneously so you can change your window level we can do that both. To define your boundaries now, your sections of the Liver are characterized by where your hepatic veins are.

Fragment 2 to L entryway v. superior, Fragment 3 to L entryway v. inferior, Fragment 4a to L entryway v.right, superior, Fragment 4b to L entryway v. right, substandard, Fragment 5 to R entryway v. Anterior, mediocre, Fragment 6 to R entryway v. posterior, mediocre, Fragment 7 to R entryway v. posterior, prevalent, Fragment 8 to R entryway v. Foremost, prevalent.

MRCNN vs. the more traditional MRCNN classification outcomes. Traditional MRCNN techniques overlooked parts with insignificant liver districts when cutting, resulting in division errors, as seen in Figure 6. The MRCNN with - implies bunching amended these division mistakes by consolidating the perspective proportion data of the liver picture arrangement. Notwithstanding, there are as yet apparent division mistakes in minor liver areas. For each successive cut, the suggested GAN MRCNN improved accuracy and robustness of division. Over the other MRCNN versions, this is a clear advantage.

Using a variety of indices, including general exactness, responsiveness, particularity, accuracy, FOR, and false discovery rate (FDR), the exploratory impacts of the GAN Mask R-CNN were evaluated. The suggested GAN-based computation has high assessment accuracy and a low overlook rate. This exhibition can be attributed to the result limit's preparation ampleness and relative strength. However, missegmentation or over-division mistakes exist (seen in Table 1).

**Table 1:** Comparisons of Segmentation algorithms

| Algorithm type | Performance levels/ DSC | Recall /VOE | Specificity/RVD | Precision/ ASSD | FOR/ RMSD | FDR/ MSDD |
|---|---|---|---|---|---|---|
| Mask R-CNN | 93.2 | 9.44 | 0.61 | 3.46 | 6.05 | 21.22 |
| Mask R-CNN +R-means | 91.7 | 92.5 | 92.7 | 92.9 | 13.5 | 7.9 |
| GAN MRCNN | 92.0 | 92.5 | 92.7 | 92.8 | 13.4 | 07.6 |
| Improved mask R-CNN | 96.1 | 09.54 | 00.39 | 02.63 | 02.44 | 21.67 |

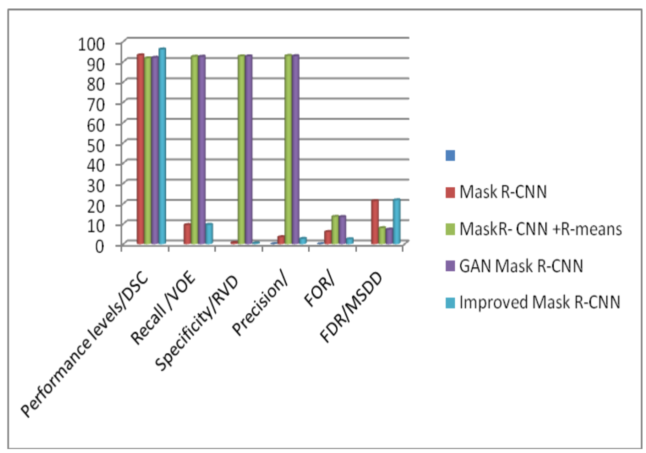


**Figure 6:** Performance levee DSC to MSDD-FDR of GAN Mask R-CNN

## 6. Conclusion and Future Scope

In this work, another CT-based system for picture division of the liver was proposed. In the first place, we attempt to get more significant anchors (along these lines further developing the division results) by utilizing a media binning calculation to lock the angle proportion and lessen excess and pointless anchors. Second, the issues of loud elements in liver pictures, which normally don't have picture upgrade applied, delivering many pictures unusable and lessening division precision. In particular, we executed a GAN design in our division structure and showed commendable execution across six measurements: DSSC, VOE, RVD, ASSD, RMSD, and MSSD. Contrast it with FCN-8s, U-

Net and FCN2 and 2D-FCN1 as well as FCN, H-dense UNet as well as IU-Net as well as G-dense U-Net. Red. Six criteria were used to score this test: overall correctness, responsiveness, explicitness, accuracy, FOR, and the false discovery rate (FDR). Our superior GAN MRCNN engineering showed the most excellent generally speaking exhibition. This work can assist radiologists with further developing analysis, early discovery and therapy of liver infection and lessen the gamble of death from liver malignant growth.

## References


Girshick, R. (2015). Fast r-cnn. In Proceedings of the IEEE international conference on computer vision (pp. 1440-1448).

J. Jin, S., Su, Y., Gao, S., Wu, F., Hu, T., Liu, J., ... & Guo, Q. (2018). Deep learning: individual maize segmentation from terrestrial lidar data using faster R-CNN and regional growth algorithms. Frontiers in plant science, 9, 866..

Bürgel, U., Mädler, B., Honey, C. R., Thron, A., Gilsbach, J., & Coenen, V. A. (2009). Fiber tracking with distinct software tools results in a clear diversity in anatomical fiber tract portrayal. Central European Neurosurgery-Zentralblatt für Neurochirurgie, 70(01), 27-35.

Virzì, A., Muller, C. O., Marret, J. B., Mille, E., Berteloot, L., Grévent, D., ... & Bloch, I. (2020). Comprehensive review of 3D segmentation software tools for MRI usable for pelvic surgery planning. Journal of digital imaging, 33(1), 99-110.

Ananth, C., & Jain, R. (2020). Enhancing Segmentation Approaches from Oaam to Fuzzy KC-Means. The Journal of Research on the Lepidoptera, 51(2), 1086-1108.

Sanai, F. M., & Bzeizi, K. I. (2005). Systematic review: tuberculous peritonitis–presenting features, diagnostic strategies and treatment. Alimentary pharmacology & therapeutics, 22(8), 685-700.

Wang, K., Lu, X., Zhou, H., Gao, Y., Zheng, J., Tong, M., ... & Zheng, R. (2019). Deep learning Radiomics of shear wave elastography significantly improved diagnostic performance for assessing liver fibrosis in chronic hepatitis B: a prospective multicentre study. Gut, 68(4), 729-741.

Loffroy, R., Favelier, S., Chevallier, O., Estivalet, L., Genson, P. Y., Pottecher, P., ... & Cercueil, J. P. (2015). Preoperative portal vein embolization in liver cancer: indications, techniques and outcomes. Quantitative imaging in medicine and surgery, 5(5), 730. [9] L. Lenchik, L., Heacock, L., Weaver, A. A., Boutin, R. D., Cook, T. S., Itri, J., ... & Narayana, P. A. (2019). Automated segmentation of tissues using CT and MRI: a systematic review. Academic radiology, 26(12), 1695-1706.

Guo, X., Schwartz, L. H., & Zhao, B. (2019). Automatic liver segmentation by integrating fully convolutional networks into active contour models. Medical physics, 46(10), 4455-4469.

Lu, F., Wu, F., Hu, P., Peng, Z., & Kong, D. (2017). Automatic 3D liver location and segmentation via convolutional neural network and graph cut. International journal of computer assisted radiology and surgery, 12(2), 171-182.

Saikumar, K., Rajesh, V., Babu, B.S. (2022). Heart disease detection based on feature fusion technique with augmented classification using deep learning technology. Traitement du Signal, Vol. 39, No. 1, pp. 31-42. https://doi.org/10.18280/ts.390104 .

Kailasam, S., Achanta, S.D.M., Rama Koteswara Rao, P., Vatambeti, R., Kayam, S. (2022). An IoT-based agriculture maintenance using pervasive computing with machine learning technique. International Journal of Intelligent Computing and Cybernetics, 15(2), pp. 184–197.

Saikumar, K. (2020). RajeshV. Coronary blockage of artery for Heart diagnosis with DT Artificial Intelligence Algorithm. Int J Res Pharma Sci, 11(1), 471-479.

Saikumar, K., Rajesh, V. (2020). A novel implementation heart diagnosis system based on random forest machine learning technique International Journal of Pharmaceutical Research 12, pp. 3904-3916.

Raju K., Chinna Rao B., Saikumar K., Lakshman Pratap N. (2022) An Optimal Hybrid Solution to Local and Global Facial Recognition Through Machine Learning. In: Kumar P., Obaid A.J., Cengiz K., Khanna A., Balas V.E. (eds) A Fusion of Artificial Intelligence and Internet of Things for Emerging Cyber Systems. Intelligent Systems Reference Library, vol 210. Springer, Cham. https://doi.org/10.1007/978-3-030-76653-5_11

Sankara Babu B., Nalajala S., Sarada K., Muniraju Naidu V., Yamsani N., Saikumar K. (2022) Machine Learning Based Online Handwritten Telugu Letters Recognition for Different Domains. In: Kumar P., Obaid A.J., Cengiz K., Khanna A., Balas V.E. (eds) A Fusion of Artificial Intelligence and Internet of Things for Emerging Cyber Systems. Intelligent Systems Reference Library, vol 210. Springer, Cham. https://doi.org/10.1007/978-3-030-76653-5_12.

Kiran Kumar M., Kranthi Kumar S., Kalpana E., Srikanth D., Saikumar K. (2022) A Novel Implementation of Linux Based Android Platform for Client and Server. In: Kumar P., Obaid A.J., Cengiz K., Khanna A., Balas V.E. (eds) A Fusion of Artificial Intelligence and Internet of Things for Emerging Cyber Systems. Intelligent Systems Reference Library, vol 210. Springer, Cham. https://doi.org/10.1007/978-3-030-76653-5_8.

Shravani, C., Krishna, G. R., Bollam, H. L., Vatambeti, R., & Saikumar, K. (2022, January). A Novel Approach for Implementing Conventional LBIST by High Execution Microprocessors. In 2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT) (pp. 804-809). IEEE.

Rao, K. S., Reddy, B. V., Sarada, K., & Saikumar, K. (2021). A Sequential Data Mining Technique for Identification of Fault Zone Using FACTS-Based Transmission. In Handbook of Research on Innovations and Applications of AI, IoT, and Cognitive Technologies (pp. 408-419). IGI Global..

Raju, K., Pilli, S. K., Kumar, G. S. S., Saikumar, K., & Jagan, B. O. L. (2019). Implementation of natural random forest machine learning methods on multi spectral image compression. Journal of Critical Reviews, 6(5), 265-273.