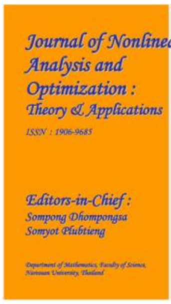
Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 15, Issue. 1, No.4 : 2024
ISSN : **1906-9685**



LIVER CT IMAGE NOISE REDUCTION USING ENHANCED FILTERING AND EDGE DETECTION TECHNIQUE FOR LIVER SEGMENTATION

Mrs. C. Clement Sherlin, Research Scholar, Department of Computer Science, Sri Krishna Arts& Science College, Bharathiar University, Coimbatore. Assistant Professor, Department of Computer Science, Nirmala College for Women, Coimbatore, India. clementsherlinc20rcs304@skasc.ac.in
Dr. N. A. Sheela Selvakumari, Associate Professor, Department of Computer Science, Sri Krishna Arts & Science College, Bharathiar University, Coimbatore, India. sheelana@skasc.ac.in

Abstract: The liver is the largest solid organ in the body. It does hundreds of other vital functions, such as clearing impurities from the bloodstream, controlling blood clotting, blood sugar, and much more. There are many different types of liver diseases and conditions. One of the most common diseases in India, cancer is estimated to cause 0.3 million deaths per year. Approximately 32% of Indians will have liver cancer at some point in their lives. The liver is the only organ capable of self-healing after injury. It can re-grow to its previous size even after having up to 90% of its liver removed. CT imaging technologies are currently used for both the diagnosis and treatment of liver cancer. CT scattering is the source of noise artifacts. Noise deteriorates image quality, alters how a clinician interprets a CT scan, and interferes with efficient health monitoring and assessment. A thorough CT scan preprocessing phase needs to be put in place if the system is to deliver information of higher quality. In such a way proposed SIGF-ED filter for enhanced preprocessing of Liver CT Images.

Keyword:
Liver Segmentation, Liver Cancer, Image Filter, Edge Detection, Deep Learning

1. Introduction

The largest solid organ in the body is the liver as shown in fig.1. In addition to hundreds of other essential tasks, it eliminates pollutants from the body's blood supply, keeps blood sugar levels in check, controls blood clotting, and much more. It secretes vital proteins and hormones, provides compartmentalized metabolism and directed transport of a vast array of substances, and purifies the blood. Almost every organ system in the body depends on the liver. It helps with digestion and metabolism, which interacts with the gastrointestinal and endocrine systems. The liver is responsible for maintaining cholesterol homeostasis and storing fat-soluble vitamins. It keeps copper and iron in storage. It contributes to protein synthesis and clotting factor in haematology. Heme is broken down by the liver into unconjugated bilirubin and then conjugated [1].

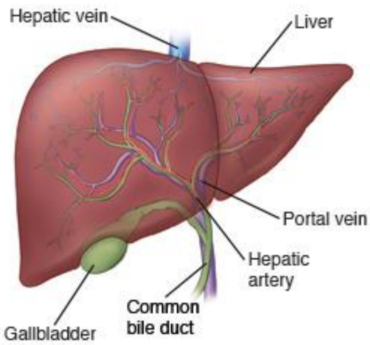


Figure: 1. Human Liver

Liver illnesses and ailments come in a variety of forms. Some are brought on by viruses, such as hepatitis. Others may be brought on by drug use or excessive alcohol consumption. Cirrhosis can be brought on by a persistent injury or scar tissue in the liver. One indicator of liver disease is jaundice, or yellowing of the skin. Liver diseases that can develop are cirrhosis and fatty liver disease. Hepatocellular carcinoma (HCC), often known as primary liver cancer is one of the main causes of death for those with chronic liver disease [2]. The frequency and etiological factors pertaining to HCC vary greatly throughout nations, which is indicative of regional variations. In the past, the most frequent causes of HCC on the Asian continent were chronic liver disorders linked to the hepatitis B and hepatitis C viruses. Cancer affects about 32% of Indians at some point in their lives. Approximately 0.3 million fatalities annually are attributed to cancer, one of the most prevalent diseases in India [3]. People's changing habits such as increasing their tobacco usage, changing their diets, engaging in less activity, and many more increase their risk of developing liver illness. The recent combined advances in engineering and medicine have raised the likelihood of a cancer cure.

Among the organs, the liver is the only one that can heal itself after harm. Even after up to 90% of its liver has been removed; it can still grow back to its original size. However, the liver is not unbeatable. There are numerous illnesses and exposures that can damage it irreversibly. The early identification and diagnosis of cancer are critical to its prognosis. The selection of the treatment of cancer fully depends on its level of aggressiveness. Medical practitioners employ numerous procedures for detection of cancer. Numerous imaging modalities, including X-rays, CT scans, PET scans, ultrasounds, and MRIs, as well as pathological testing like blood and urine tests, may be used in conjunction with these procedures [4]. In histopathology, classifying an image biopsy as either malignant or noncancerous is the typical step in the cancer diagnosis procedure. Physicians and pathologists identify numerous anomalies in CT image analysis and classify the sample according to the colour, shape, size, and ratio of the nucleus to the cytoplasm. Reliable information is provided by high resolution CT images to distinguish between diseased and normal tissues. Liver cancer is now diagnosed and treated via computer tomography (CT) imaging technologies. Noise artifacts are caused by CT scattering. Noise interferes with effective health monitoring and assessment, reduces picture resolution, and changes the way the doctor perceives the CT scan. In order to improve the quality of information provided by the system, a good preprocessing step for CT scans must be implemented. This can be achieved by applying techniques for noise reduction and enhancement to the images, which will improve their quality. Liver Resection performed on the Stage 1 and Stage 2 liver cancer. CT Image used for the analysis where liver part with single scare or primary cancer scare identified and highlighted to do Liver Segmentation.

The paper organized as below earlier studies are discussed in section 2, Materials and Methods of the proposed system depicted in section 3, Dataset used for this study with performance metrics are presented in section 4 and finally paper concluded in section 5.

2. Background Work

In [5] hybrid deep learning technique was used to remove local speckle noise from breast ultrasound images. Ultrasound imaging technology has improved its usefulness for breast screening and diagnosis. However, local speckle noise in ultrasound breast images can impair image quality and impact observation and diagnosis. The technique involved improving contrast, using guided filter algorithms, and spatial high-pass filtering to enhance clarity. Edge-sensitive terms were added to the Logical-Pool Recurrent Neural Network (LPRNN) to remove local speckle noise without sacrificing image edges. The LPRNN was trained properly, and ultrasound images with local speckle noise were better characterized by signal-to-noise ratios, edge preservation index values, and quick destruction times.

In [6] proposes a patch-based deep learning method for segmenting a liver from CT images using Stacked Auto Encoder (SAE). This method uses patches instead of pixel by pixel learning to learn representations and identify the liver area. The dataset is preprocessed to create enhanced images, which are then converted into overlapping patches. These patches are then inputted to SAE for unsupervised feature learning. The learned features with image labels are fine-tuned, and classification is performed to develop a supervised probability map. Experimental results show satisfactory results on test images, with a 96.47% dice similarity coefficient (DSC), which is better than other methods in the same domain.

In [7] focuses on deep learning algorithms for segmenting liver and tumors from abdominal CT scan images, aiming to minimize time and energy used for liver disease diagnosis. The algorithm uses a modified ResUNet architecture and an automatic method based on semantic segmentation Convolutional Neural Networks (CNNs) to segment liver from CT scans and lesions from the segmented liver part. The proposed system achieves Dice Similarity Coefficients (DSCs) of 96.35% and 89.28%, and accuracy of 99.71% and 99.72% for liver and tumor segmentations, respectively. Comparison with linked methods confirms the system's promise for liver and tumor segmentation.

In [8] uses a Probabilistic Active Shape Model with an MR-specific preprocessing and appearance model to segment the liver in contrast-enhanced MR images, evaluated using 8 clinical datasets. The current standard for diagnosing liver tumors is contrast-enhanced multiphase computed tomography (CT), which has led to the development of numerous software tools and algorithms for measuring remnant liver volume, analyzing tumors, and planning resections. However, clinics are increasingly shifting towards magnetic resonance imaging (MR) as the gold standard for diagnosing liver diseases.

In [9] an enhanced approaches for segmenting liver tumors from Computerized Tomography (CT) images. It uses a two-class Convolutional Neural Network to discriminate tumor and liver from CT images. The network adjusts contrast and intensity values, removes high frequencies, and segments the liver tumor using multiple filters. The method is validated on CT images from the 3Dircadb and LiTS datasets. The results show that multiple filters extract local and global features simultaneously, minimize boundary distance errors, and show better performance in heterogeneous tumor regions.

In [10] propose effective image pre-processing techniques to improve accuracy and classification rates for Deep-CNN models. Breast cancer is the most diagnosed cancer in Australia, with crude incidence rates increasing from 62.8 to 271.4 cases per 100,000 women. Machine Learning and Convolutional Neural Networks have been proposed for assessing mammographic images, but these methods often produce detection and interpretation errors, leading to false-positive and false-negative cases. The proposed methods include background removal, pectoral muscle removal, noise addition, and image enhancements. The "Rolling Ball Algorithm" and "Huang's Fuzzy Thresholding" are used for background removal, while "Canny Edge Detection" and "Hough's Line Transform" are used for pectoral muscle removal. Image enhancements are done using Invert, CTI_RAS, and ISOCONTOUR lookup tables.

3. Materials and Methods

The proposed approach is to handle the artifacts of CT Images at the preprocessing stage. Enhancement performed in the preprocessing stage for reducing the noise and to retaining the edges of the image as explained in the fig. 2.

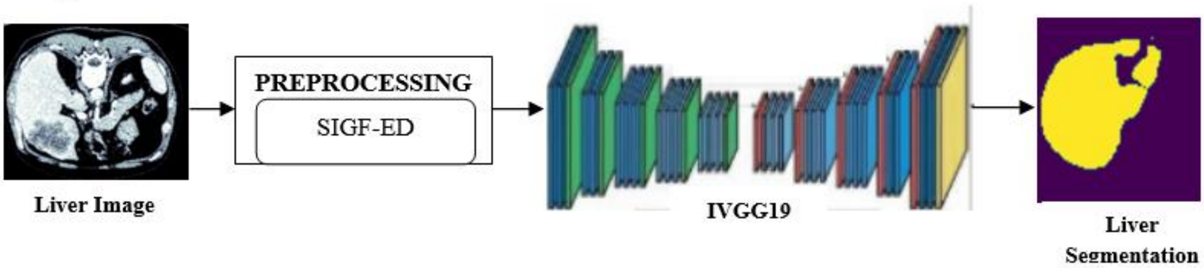


Figure: 2. Proposed Method

3.1. Preprocessing the Images

Preprocessing is used to remove noise from the CT picture in order to detect malignancy from liver CT images. Maintaining distinct edges in a CT scan is the aim. The primary purpose of filtering is to remove undesired distortion from the CT image that appears as noise. Preprocessing the Liver CT image for removing noise artifacts is the essential part of Liver Segmentation. Preprocessing, which creates processed pictures from raw CT scans that can distinguish the liver's attributes from those of other human organs, is an essential step in the image segmentation process. To perform the De-noising and preserving the edges of the CT image proposed Shift Invariant Gaussian Filter with Edge Detection (SIGF-ED) preprocessing technique. The CT Image is first smoothed using a SIGF in order to remove noise and identify the image's gradient of intensity. Same time preserves the Edges of the image using ED.

It is easy to put into words. A weighted average of a pixel's neighbours is used to substitute each one. The size and contrast of the features to be preserved are the only two criteria that matter. A low pass filter called a Gaussian filter removes the high-frequency elements from the lever CT picture. Gaussian Filter applied through the following Equ. (1).

$$\boldsymbol{G(x,y)=\frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}}} \qquad \text{-- Equ. (1)}$$

where X and Y are the positions of the pixels within the Gaussian window, and σ is the standard deviation of the Gaussian distribution. To obtain the smooth boundaries in the CT image, the original image is convolved with a Gaussian filter with varying window sizes [11]. The improved image is then constructed by reconstructing the original images using the shift invariant wavelet transform. Using a method called "cycle spinning," one can also approach shift-invariance in the context of image denoising with the discrete wavelet transform. Shift invariance performed on the basis of below Equ. (2).

$$\mathbf{x[i,j]\rightarrow x[i-m,j-n] \quad \Rightarrow \quad y[i,j]\rightarrow y[i-m,j-n]} \qquad \text{-- Equ. (2)}$$

Where m,n of any shift of the input x that causes a matching shift in the output y is known as shift invariance. Finally, edge detection-based image fusion preserves the liver CT image textural information and edge quality. Any grayscale picture can be thought of as a tomographic surface with peak points standing in for high-intensity pixels and valley points for low-intensity values. Up until all of the peaks are covered, edges are located and borders are constructed. Raw image applied with proposed filtering techniques to enhance the quality and reduce the noise which is depicted in Fig.3 and 4 as well.

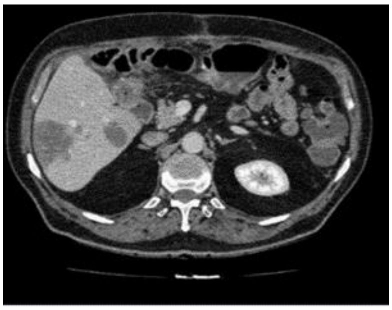


Figure: 3. Raw Ct Image

Figure: 3. SIGF-ED Filtered CT Image

3.2. Training the Deep Learning Model

For training the filter images used the Fine-tuned IVGG19 Model [12] which was earlier study proposed for the detection and classification of liver tumours. There are two phases to each neural network in the system: training and testing. Using the input CT images, a number of feature extraction strategies were obtained during the training phase. After that, the neural network system incorporates the enlarged information also referred to as input data to create an appropriate framework. The feature extraction process has tested several convention layers in an effort to find the best feature extraction network. By implementing smaller updates (i.e., high learning rates) for parameters linked to infrequent features and larger updates (i.e., low learning rates) for parameters associated with frequently occurring features, the earlier study improvises the optimizer and adjusts the learning rate to the parameters. It is therefore a sensible option for managing sparse data. t-Distributed Stochastic Neighbour Embedding is used to reduce the dimensionality.

The dimensionality of the present dataset is non-linearly reduced by this technique through the use of a randomized strategy. Through a comparison of the similarity between data points and features, the non-linear dimensionality reduction technique t-SNE finds patterns in the data. Filtered images passed into the model to identify the spots of tumor which are highlighted as Red and Green Lines and marked region further segmented for representing the Liver Segmentation as shown in Fig. 4.a) and b). Due to noise and uneven texture in the liver image, segmentation causes over segmentation. The foreground and background regions of the image are estimated via the marker-based watershed technique.

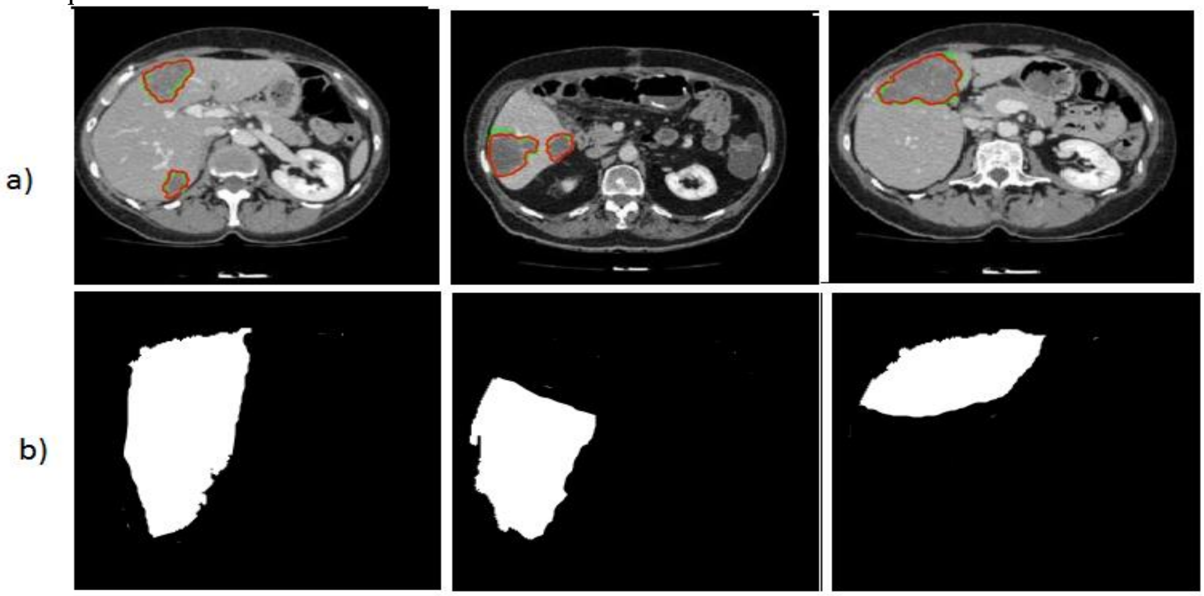


Figure: 4. Liver Tumor Identification and Segmentation

4. Experimentation

4.1. Dataset

The dataset used for this study taken from kaggle website LiST [13]. There are 194 CT scans with lesions out of 201 computed tomography pictures of the abdomen in the LiTS benchmark dataset. Every piece of information has been anonymised, and a visual assessment of the images has removed any possibility of identifying personal information.

4.2. Performance Metrics

The performance metrics used for evaluating the models are Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR).

- **Mean Square Error (MSE):**

The average squared difference between estimated and actual values is measured by the Mean Squared Error (MSE), a risk function. It is a gauge for prediction algorithms' inaccuracy [14]. The formula to calculate the MSE is given in Equ. (3).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \quad \text{-- Equ. (3)}$$

Where n is no of data points, Y_i and $\hat{Y}_i$ are observed values and predicted values respectively.

- **Peak Signal to Noise Ratio (PSNR):**

Peak signal-to-noise ratio (PSNR) is the ratio of a signal's maximum possible value (power) to the strength of noise that distorts it and degrades the quality of its representation. The formula to calculate the PSNR is given in Equ. (4).

$$PSNR = 10.\log_{10}\left(\frac{2^n - 1}{MSE}\right) \quad \text{-- Equ. (4)}$$

Where MSE is Mean Square Error and n is no of data points.

4.3. Result & Discussion

A Gaussian filter and a bilateral filter are compared with the proposed SIGF-ED filter based on the above stated performance metrics. Table 1 presented the comparison of Filters based on the performance metrics PSNR and MSE. Based on the resultant data obtained in the table it is clear that the proposed method SIGF-ED filter performs better compare to Gaussian Filter and Bilateral Filter.

Table: 1 Comparison of Filters based on the Performance Metrics PSNR and MSE

Filtering Techniques	**Performance Metrics**	
	MSE	**PSNR**
Gaussian Filter	0.78	48.08
Bilateral Filter	0.67	50.67

SIGF-ED Filter	0.53	51.34

Fig 5 shows the pictorial representation of the comparison of various filter techniques that adopted for Pre-processing the Liver CT images based on the performance metrics MSE. Among the results the proposed SIGF-ED shows minimum MSE values such as 0.53 while comparing with value of Gaussian Filter and Bilateral Filter such as 0.78 and 0.67 respectively.

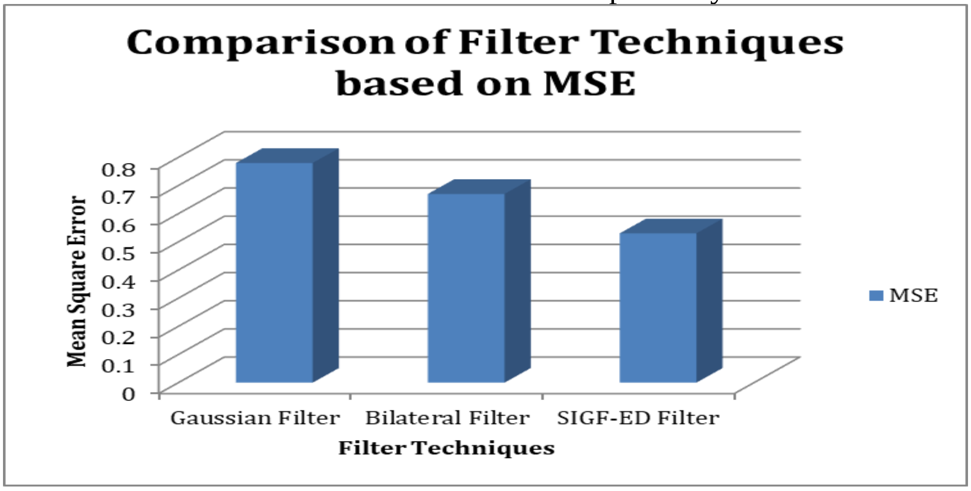


Figure: 5 Comparison of Filter Techniques based on MSE

Fig 6 shows the pictorial representation of the comparison of various filter techniques that adopted for Pre-processing the Liver CT images based on the performance metrics PSNR. Among the results the proposed SIGF-ED shows higest PSNR values such as 51.34 while comparing with value of Gaussian Filter and Bilateral Filter such as 50.67 and 48.08 respectively.

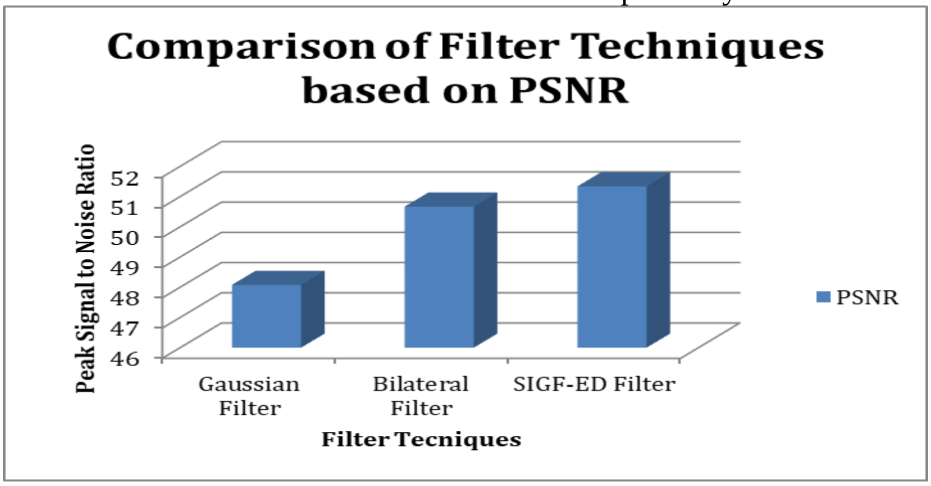


Figure: 6 Comparison of Filter Techniques based on PSNR

5. Conclusion

Liver CT images processed through and utilised using an SIGF-ED with IVGG19 improves clinical objectivity and manipulation significantly. This work uses a set of procedures to perform, an IVGG19, and high-pass filtering of a Shift invariant technique to eliminate noise in CT images. Consequently, marker-controlled wavelet transform-based automatic edge detection for liver segmentation is presented in this study. The liver segmentation on the CT images has improved, according to the SIGF-ED filter at preprocessing stage. Improved performance in liver segmentation from noisy and intricately structured abdominal CT images has been demonstrated by the suggested system. When compared to baseline techniques, the liver segmentation performance of the SIGF-ED has improved. With the suggested approach, the resulting MSE is 0.53, and the PSNR is 51.34. The suggested approach can also be expanded to detect liver tumors.

Reference:-

1. Kalra A, Yetiskul E, Wehrle CJ, et al. Physiology, Liver. [Updated 2023 May 1]. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; Available: https://www.ncbi.nlm.nih.gov/books/NBK535438/
2. Shi, J.-H. and Line, P.-D. (2014) 'Effect of liver regeneration on malignant hepatic tumors', World Journal of Gastroenterology, 20(43), p. 16167. doi:10.3748/wjg.v20.i43.16167.
3. Ali I., Wani W. A., Saleem K. Cancer scenario in India with future perspectives. *Cancer Therapy*. 2011; 8:56–70.
4. Kumar, R., Srivastava, R. and Srivastava, S. (2015) 'Detection and classification of cancer from microscopic biopsy images using clinically significant and biologically interpretable features', Journal of Medical Engineering, 2015, pp. 1–14. doi:10.1155/2015/457906.
5. Vimala, B.B.; Srinivasan, S.; Mathivanan, S.K.; Muthukumaran, V.; Babu, J.C.; Herencsar, N.; Vilcekova, L. "Image Noise Removal in Ultrasound Breast Images Based on Hybrid Deep Learning Technique", Sensors 2023, 23, 1167. https://doi.org/10.3390/s23031167.
6. Mubashir Ahmad, Syed Furqan Qadri, M. Usman Ashraf, Khalid Subhi, Salabat Khan, Syeda Shamaila Zareen, Salman Qadri, "Efficient Liver Segmentation from Computed Tomography Images Using Deep Learning", Computational Intelligence and Neuroscience, vol. 2022, Article ID 2665283, 12 pages, 2022.
7. Manjunath, R.V. and Kwadiki, K. (2022) 'Automatic liver and tumour segmentation from CT images using Deep Learning algorithm', Results in Control and Optimization, 6, p. 100087. doi:10.1016/j.rico.2021.100087.
8. Drechsler, K. et al. (2014) 'Liver segmentation in contrast enhanced MR Datasets using a probabilistic active shape and appearance model', 2014 IEEE 27th International Symposium on Computer-Based Medical Systems [Preprint]. doi:10.1109/cbms.2014.120.
9. Thi-Tuong, V.V. et al. (2021) 'Effects of multiple filters on liver tumor segmentation from CT images', Frontiers in Oncology, 11. doi:10.3389/fonc.2021.697178.
10. Beeravolu, A.R. et al. (2021) 'Preprocessing of breast cancer images to create datasets for deep-CNN', IEEE Access, 9, pp. 33438–33463. doi:10.1109/access.2021.3058773.
11. Napte, K.M. and Mahajan, A. (2023) 'Liver segmentation using marker controlled watershed transform', International Journal of Electrical and Computer Engineering (IJECE), 13(2), p. 1541. doi:10.11591/ijece.v13i2.pp1541-1549.
12. C.Clement Sherlin and Sheela Selvakumari N.A (2023) 'Liver Cancer segmentation through Enhanced Feature Extraction and Mapping Using Improved Transfer Learning Techniques'International Journal on Recent and Innovation Trends in Computing and Communication (IJRITCC),11(11) pp38-43 doi.org/10.17762/ijritcc. v11i11.9085.
13. Larxel (2020) Liver and liver tumor segmentation, Kaggle. Available at: https://www.kaggle.com/datasets/andrewmvd/lits-png (Accessed: 28 January 2024).
14. Rekha Gautam, Ms. Rupali Bharti . (2018) 'Liver Ultrasound Image Enhancement Using Bilateral Filter', International Journal of Engineering and Technical Research (IJETR) 8(4),pp. 69-75.
15. Anastácio, R. et al. (2015) 'Preprocess enhancement of CT image for liver segmentation with region growing algorithm', IFMBE Proceedings, pp. 134–137. doi:10.1007/978-3-319-11128-5_34.