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LIVER CANCER IMAGE PREPROCESSING AND FEATURE SELECTION USING A HYBRID DEEP LEARNING NETWORK

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ABSTRACT

A liver's primary duties include producing bile, which is necessary for the breakdown of fats, filtering and changing potentially harmful compounds in the blood, and storing vitamins and nutrients. The diagnosis of malignant liver lesions can be made using a variety of techniques, including magnetic resonance imaging (MRI) and/or CT scanning with multiphase contrast agent injection. focuses on the methods for creating tumor and liver segmentation with the IVGG19-UNeT hybrid deep learning network. The suggested model's deep learning network scheme structure is made up of preprocessing, feature extraction, classification, and segmentation. With over 98% accuracy in tumor categorization, the suggested method accurately identifies the greatest number of tumor regions.

Keywords: Liver Segmentation, Deep Learning, VGG19, UNet, Liver Cancer

1. INTRODUCTION

The liver, the biggest gland in the body, is vital to human life. Among its essential functions are the removal and conversion of dangerous substances from the blood, the synthesis of bile, which is necessary for the digestion of fats, and the storage of vitamins and nutrients. Vitamins and carbohydrates are also stored in part by it. Globally, liver cancer is the sixth most frequent type of cancer. A direct outcome of changing lifestyles is an increase in cirrhosis and acute and chronic liver disease. In many areas, liver cancer is becoming the most common type of the disease as a direct result of these underlying disorders. When cancer is discovered early, there are more options for therapy. It is not possible to identify liver cancer physically; instead, imaging or radiology tests are the only methods available. Imagination tests are useful in the premature cancer detection with evaluating safety of therapy outcomes.

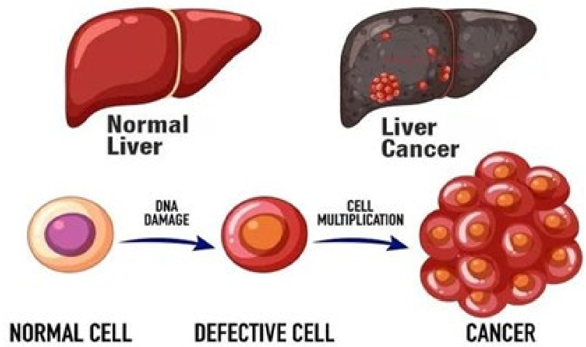

Figure: 1.1 Liver Cancer

The primary risk factors include alcoholism-induced liver cirrhosis and hepatitis B or C virus infections. With a rate of 15.5% and 6.5%, respectively, Males are more likely than females to experience it. (Men's 5th and Women's 9th in cancers) (Chidambaranathan et al., 2021). Developing malignant (cancer) cells in the liver's tissues is known as primary liver cancer as shown in fig.1.1. Liver cancer is not the same as cancer that starts in another place of the body and travels to the liver. Numerous cancers can start in the liver and spread. The most common type of liver cancer, called hepatocellular carcinoma, begins in the main hepatocyte form of the liver cell. Two less common types of liver cancer are intrahepatic cholangiocarcinoma and hepatoblastoma. The two forms of liver cancer that cause the most morbidity and death globally are CholangioCarcinoma (CCA) and HepatoCellular Cancer (HCC). While CCA starts in the bile ducts, HCC originates from hepatocytes, the major parenchymal cells of the liver. Over 80% of instances of primary liver cancer worldwide are HCC patients. When a tumor spreads to the liver from another area of the body, it results in secondary liver cancer. In around 70% of cases, liver cancer develops after colon cancer. Both Cholangio Carcinoma (CCA) and Hepato Cellular Cancer (HCC) are forms of liver cancer that need for exact staging and diagnosis. Estimating the Area of Interest is a really fascinating to improve Liver Segmentation. Early tumor discovery can reduce the danger of liver biopsy and surgery, increase long-term survival rates, and a critical part in the diagnosis of liver cancer.

The diagnosis of Cancer liver lesions can be made using a variety of techniques, including Magnetic Resonance Imaging (MRI) and/or CT scan. These are the two examinations that provide accurate tumor images and enable the detection of any potential extension to the liver's blood vessels. On the other hand, manually interpreting a numerous medical photographs leads to laborious and extended time, and it can easily result in mistakes being made by the radiologist when visually interpreting the image. Computer based automated detection of tumor region and suggests the best solutions are highly recommended now. Such systems are mostly based on Machine Learning and Medical Imaging methods, have proven to be quite reliable and are now practically required for use in clinical diagnosis, categorization, and plan the treatment procedures (Mizouri, 2022). This is particularly relevant in light of digitization, significant advancements in Medical Imaging, and significant advancements in Machine Learning, particularly in its Deep Learning (DL) version. Precise cancer diagnosis and staging are essential for enhancing patient longevity and therapeutic results.

This study evaluates a DL framework on a large dataset in an effort to close a gap in the prior research. Main objective is to develop a strong and capable DL model that can identify the Region of Interest (ROI) and complete the segmentation. Both automated feature extraction and feature categorization can be accomplished with deep learning systems. This is the arrangement of the paper further. The existing works are explored in Section 2 with reference to the available datasets. Section 3 gives deep insight of the suggested model. Section 4 offers an assessment of IVGG19-UNeT. Ultimately, Section 5 presents the limitations of the suggested methodology, while Section 6 concludes with recommendations for further research.

2. RELATED WORKS

A hybrid model called ResUNet, which combines the ResNet and UNet models, is proposed by (Rahman et al. 2022) to effectively segment tumors and the liver from CT image volumes. The 9th most prevalent cancer in women is liver cancer, because of the tumor's overlapping intensity and the soft tissue placements' unpredictability, liver and tumor segmentation is difficult. Using the dataset IRCADB01 as a test, the model produced true value accuracy results of 99.55%, 97.85%, and 98.16% along with a higher dice coefficient authentication rate.

In order to detect liver organs in computed tomography images and segment liver tumors, (Khoshkhabar et al., 2023) introduces a deep learning-based method. Based on the LiTS17 database, the approach consists of four Chebyshev graph convolution layers and a fully connected layer. It attains around 99.1%, 99.4%, 90.8%, 91.1%, 99.4%, and 91.2% Accuracy, Precision, Mean IoU, Dice coefficient, Sensitivity, and Recall, respectively. In the near future, radiologists and specialty physicians should find the model useful.

. A DL-based technique for segmenting liver tumors in dynamic contrast-enhanced MRI during the late hepatocellular phase (DCE-MRI) is presented by (Hansch et al. in 2022). In comparison to 2D U-Net, segmentation performance is enhanced by the 3D and a Multi-Model training approach. While the lesion identification performance is enhanced by the multi-model training technique, there is still room for improvement in the detection of smaller lesions. The study found that liver lesions in late-phase DCE-MRI data could generally be segregated with good accuracy.

The Adding Inception Module-Unet (AIM-Unet) model is presented by (Ozcan et al., 2023) as a hybridization of the Unet and Inception models based on convolutional neural networks for automated segmentation of the liver and liver tumors from CT scans of the abdomen with computer assistance. The CHAOS, LIST, and 3DIRCADb liver CT imaging datasets were used for experimental investigations. The outcomes demonstrated the best liver segmentation performance metrics for DSC, JSC, and ACC on the CHAOS dataset, with respective values of 97.86%, 96.10%, and 99.75%. On the LiST and 3DIRCADb datasets, the model also attained 75.6% and 65.5% of DSC scores, respectively. The study indicates that the AIM-Unet model can be helpful for medical pictures and applications in a variety of medical sectors by serving as an additional tool for doctors' decision-making processes when it comes to liver segmentation and tumor identification...

An automated technique to identify malignancies in every slice of volumetric CT liver images is presented by Anwar et al. (2018). For the diagnosis of liver cancer and computer-aided diagnosis (CAD), tumor segmentation is essential. An automated test for comparing liver lesion segmentation methods is provided by the Liver Tumor Segmentation Challenge (LiTS). However, because tumor forms and textures vary, segmenting tumors in CT volumes is challenging. Manual segmentation can be imprecise and time-consuming. The LiTS 2017 dataset is used to evaluate the algorithm, which makes use of CT volume sequence information. With an average dice score of 0.60 and a slice time of 34 seconds, the method outperforms cutting-edge CAD system segmentation techniques by a wide margin.

3. PROPOSED METHODOLOGY

The primary focus of this section is the techniques applied to the hybrid DL network IVGG19-UNeT to achieve liver and tumour segmentation. Fig. 3.1 illustrates the components of the DL network scheme pattern of the proposed model, which include segmentation, classification, feature extraction, and pre-processing.

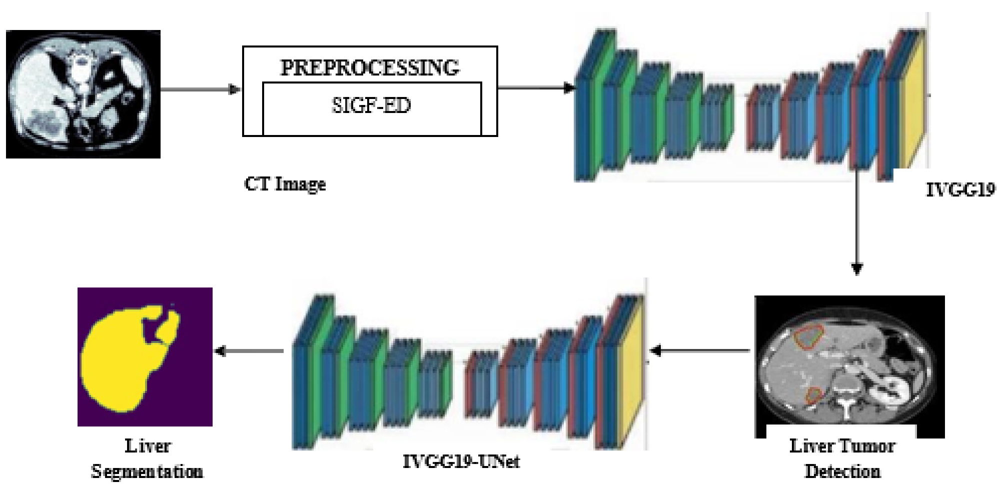

Figure: 3.1 Proposed Methodology

3.1. DATASET

The datasets LiST17 and 3DIRCADb were utilized for model training, validation, and testing based on existing research. The patient three-dimensional (3D) CT scans that make up the 3DIRCADb dataset have been organized and made publicly accessible by the IRCAD. Each picture has dimensions of 512 × 512 pixels for both width and height. Ten women and ten men with hepatic tumors whose 3D CT scans comprise the 3D-IRCADb-01 database in 75% of instances. Each of the 20 folders—which can be downloaded individually or collectively—relates to 20 different patients. The table below displays the image's width, depth, and height as well as the tumor sites determined using Couninaud's segmentation. It also emphasizes the serious difficulties that liver segmentation algorithms may encounter due to the liver's unusual form or density, close proximity to other organs, or even image artifacts.

3.2. CT IMAGE PREPROCESSING

In order to identify cancer from liver CT images, preprocessing is done to eliminate noise from the image. The goal is to keep the boundaries of a CT scan distinct. Filtering is mostly used to eliminate unwanted distortion from CT images that appears as noise. The most important step in liver segmentation is preprocessing the liver CT picture to eliminate noise artifacts. Preprocessing creates processed pictures from raw CT scans that can distinguish the features of the liver from those of other human organs, making it an essential step in the image segmentation process (Clement Sherlin et al 2023). The Shift Invariant Gaussian Filter with Edge Detection (SIGF-ED) preprocessing approach was suggested in order to denoise and preserve the edges of the CT image.

Figure: 3.2. Preprocessed CT Image

The liver CT image textural information and edge quality are lastly preserved using edge detection-based image fusion as shown in Fig. 3.2. A grayscale image can be conceptualized as a tomographic surface, where high-intensity pixels are represented by peak points and low-intensity values by valley points. Edges are found and borders are built until all of the peaks are covered.

3.3. FEATURE EXTRACTION & FEATURE MAPPING USING IVGGG19

From the previous work (Clement Sherlin et al 2023) suggests IVGG19 model for the detection and classification of liver cancer. Every neural network in the system has two stages: testing and training.

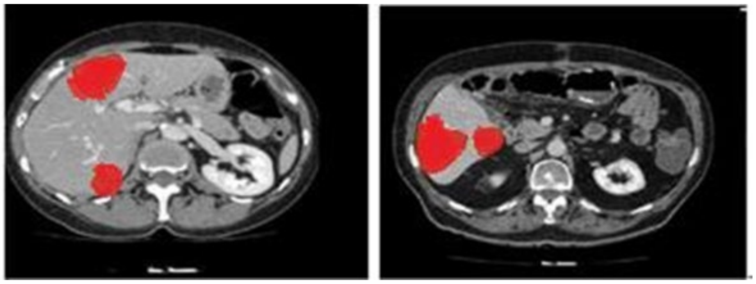

Figure: 3.3. Tumor Identification

Using the input CT images, a number of feature extraction strategies were obtained during the training phase as in Fig. 3.3. After that, the neural network incorporates the enlarged information—also referred to as input data—to create an appropriate framework. Feature extraction process has tested several convention layers in an effort to find the best feature extraction network. Without the top layer, the VGG19 Pre-Trained model allows for performance fine-tuning. The model was redefined by adding new top layers such as Fatten, 256-Dense (ReLU), Dropout (0.5), and 8-Dense (Softmax). Stochastic gradient descent (SGD) is used by the model to update a parameter for each training using the Improved Optimizer ISDG.

While other dimensionality reduction algorithms seek to minimize dimensionality by maximizing data variance, t-SNE seeks to minimize dimensionality in higher and lower dimensions by grouping like data points together (and dissimilar data points apart). Due to these variables, t-SNE performs substantially better in terms of dimensionality reduction than the other method.

3.4. LIVER SEGMENTATION USING IVGG19-UNET

The target region or item of interest must be taken out of the larger context before it can be ready for feature extraction. ROI stands for region of interest, and this process is used in it. ROI in medical imaging can be ascertained manually, semi-automated, or automatically. Generally speaking, it separates pixels into two groups: those that fall inside a given intensity range and those that fall outside of it.

Figure: 3.4. Liver Segmentation

By using a closed parametric surface that changes or deforms in response to the internal force of the model and the external force of the picture, models are able to extract area boundaries. With liver masks and CT images, IVGG19-UNet was able to differentiate the ROI from the surrounding organs, as shown in Fig. 3.4. After the ROI was divided and trained using liver CT scan data, IVGG19-UNet was employed to segment liver tumours. By merging the most advantageous aspects of both models, IVGG19-UNet substitutes convolution patches for any remaining portions. Eliminating connections between the high and low levels of the network is made simple by the presence of residuals in each block throughout the DL preparation process. It also increases the constraints on the trainable parameters of each surviving unit.

4. RESULT & ANALYSIS

4.1. PERFORMANCE METRICS

The accuracy and dice similarity coefficient (DSC), also known as the F1-score, were calculated to assess each analyzed network's performance (Hossain et al., 2023). DSC, and accuracy can all be stated as

- Accuracy: The frequency with which the suggested model accurately predicts the result is measured by its accuracy. Equ. (2) used to calculate it.

$$Accuracy = \frac{TP+TN}{2(TP+TN+FP+FN)}$$ --- Equ. (2)

- Dice Similarity Coefficient: The DSC measures the degree of overlapping between two segmentations, the A and B target regions. DSC measured using below Equ. (1)

$$DSC = \frac{2(A \cap B)}{(A+B)}$$ --- Equ. (1)

4.2. RESULTS

Based on the performance metrics Accuracy and DSC the proposed model compared with above mentioned literature works.

Table: 1 Comparison of Proposed model with earlier studies on Liver Segmentation based on Accuracy and Dice Similarity Coefficients

Authors	Methodology and Approach	Metrics	
		Accuracy	DSC
Hansch et al., 2022	3D Architectured model with dynamic contrast enhanced	91.1%	70.60%
Ozcan et al., 2023	Unet and Inception Based on Convolutional Neural Networks	90.36%	75.60%
Khoshkhabar et al., 2023	Graph Convolution with fully connected Network	93.06%	91.10%
Hossain et al., 2023	Cascaded Network for Handling Anatomical Ambiguity	96.12%	95.15%
Proposed	IVGG19-UNet for Liver Segmentation	98.23%	96.87%

From the Table: 1 comparison of proposed model with the literature studies conducted on Liver Segmentation using DL Techniques based on Accuracy and Dice Similarity Coefficients (DSC) is presented. With the representation it is clear that the proposed model IVGG19-UNet yields highest accuracy and similarity score of 98.23% and 96.87% respectively compare to existing studies.

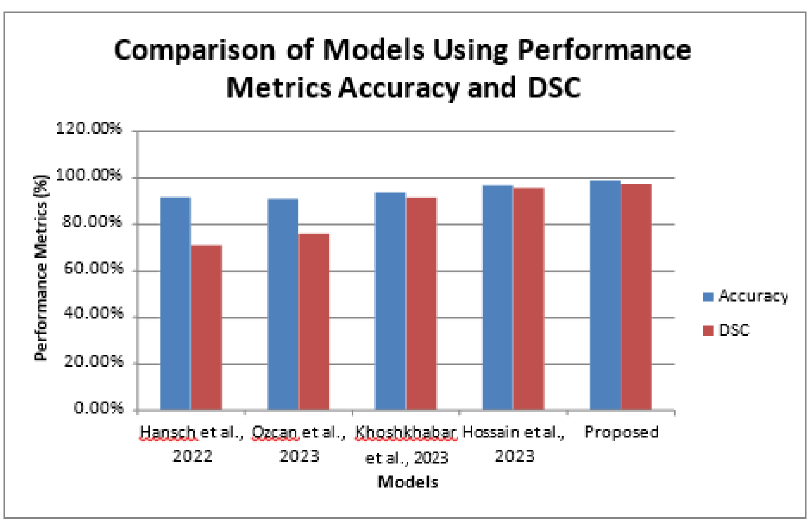

Figure: 4.1. Comparison of Proposed model with earlier studies on Liver Segmentation based on Accuracy and Dice Similarity Coefficients.

From the fig. 4.1 shows pictorial representation of proposed model with the existing studies conducted on Liver Segmentation using DL Techniques based on Accuracy and Dice Similarity Coefficients (DSC) is presented. With the representation it is clear that the proposed model IVGG19-UNet yields highest accuracy and similarity score of 98.23% and 96.87% respectively compare to existing studies.

5. CONCLUSION

The DL model for liver tumour segmentation in CT images is presented in this paper. Therefore, compared to baseline procedures, IVGG19-UNet produces substantially better outcomes in terms of training time, memory use, and accuracy. In order to expedite the processing of medical CT images, the binary segmentation by classification structure was developed. The suggested model was trained and assessed using the dataset. The suggested method successfully detects the greatest number of tumour sites and has a tumour classification accuracy of above 98%. By utilizing false positive filters and training the model on a larger dataset, the small percentage of false positives that were found after the data was evaluated may be reduced. IVGG19-UNet performed quite well in terms of giving a precise and prompt diagnosis. The results show that DL neural networks helped us accomplish our objectives and might be the most effective method for liver tumour classification.

CONFLICT OF INTERESTS

None.

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