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## International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

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# Deep Multiclass Segmentation of Liver and Tumors in Abdominal CT Scans using U-Net

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**ABSTRACT:** Liver tumor segmentation in CT (Computed Tomography) scan images plays a critical role in diagnosis, treatment planning and monitoring of liver diseases. In recent years, deep learning techniques, particularly the U-Net architecture, have shown remarkable success in medical image segmentation tasks. However, segmenting both liver and tumor regions accurately in CT scans presents unique challenges due to variations in shape, size and intensity levels of lesions. This paper presents a novel multiclass U-Net architecture designed specifically for liver tumor segmentation in CT scan images. The proposed model integrates both liver and tumor classes into a unified segmentation framework, enabling simultaneous extraction of relevant anatomical structures and pathological regions.

**KEYWORDS:** Accuracy, Encoder, Decoder, Segmentation, Multiclass U-Net.

## I. INTRODUCTION

A liver tumor is an abnormal growth of cells within the liver, which can either be benign or malignant. Benign tumors are non-cancerous and typically do not spread to other parts of the body, whereas malignant tumors, also known as liver cancer, can metastasize to other organs and pose a significant health risk. The most common type of liver cancer is hepatocellular carcinoma (HCC), which originates from hepatocytes, the primary cell type in the liver. Liver tumors can arise due to various factors, including chronic liver disease (such as hepatitis B or C, cirrhosis), excessive alcohol consumption, genetic predisposition, and exposure to environmental toxins.

Liver tumors are dangerous primarily because they can impair the liver's crucial functions. The liver plays a vital role in detoxification, metabolism, and the production of essential proteins. When tumor develop within the liver, they can disrupt these functions, leading to a range of health complications. Additionally, malignant liver tumors have the potential to spread to other parts of the body, making them more challenging to treat and significantly reducing survival rates.

Hepatocellular carcinoma is the most common form of liver cancer, where the proliferation of cancer cells primarily happens in the hepatocytes. Hepatocellular carcinoma is chiefly correlated to cirrhosis of the liver and non-alcohol related fatty liver disease (NAFLD). People who are suffering from NAFLD should go for routine doctors consultations and checkups to look for signs of hepatocellular carcinoma so that it gets detected in the initial stage itself.

Liver tumors are identified through a combination of imaging tests and diagnostic procedures. Imaging techniques such as ultrasound, CT scan, MRI, and PET scan are commonly employed to visualize the liver and detect any abnormalities, including tumors. These imaging studies can provide detailed information about the size, location, and characteristics of the tumor, helping healthcare providers make an initial assessment. If a suspicious lesion is identified, a biopsy may be performed to obtain a sample of liver tissue for microscopic examination. During a biopsy, a small needle is inserted into the liver to collect cells or tissue, which are then analyzed by a pathologist to confirm the presence of cancerous cells and determine the type and stage of the tumor. This comprehensive approach to diagnosis enables healthcare



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professionals to accurately identify liver tumors and develop appropriate treatment plans tailored to the individual patient's needs. In our project we are taking computed tomography (CT) scans as our dataset to make the project.

### II. LITERATURE SURVEY

Liver tumor segmentation in CT scans has garnered significant attention in medical imaging due to its critical role in diagnosis, treatment planning, and monitoring of liver diseases. The utilization of deep learning techniques, particularly U-Net architectures, has shown promising results in automating liver tumor segmentation tasks. This literature review aims to summarize key findings and methodologies from relevant studies in this field.

Amir Zaghloul El-Sayed Gharib(2019)[1] proposed an improved U-Net architecture for liver and liver tumor segmentation with reduced false positives. Their work focused on enhancing the U-Net model's performance by addressing the challenge of false positives in liver tumor segmentation. By implementing novel features and modifications to the standard U-Net architecture, they achieved more accurate segmentation results which we considered as our existing model.

Alom et al. (2021)[2] conducted a comprehensive survey, offering insights into various deep learning-based approaches for liver tumor segmentation. Their review highlights the progress made in this field, discussing different methodologies and their effectiveness in segmenting liver tumors from medical images. Yan et al. (2018)[3] presented a study focusing on liver tumor segmentation specifically in CT images, employing deep learning methods. Their work demonstrates the applicability of CNNs in accurately delineating liver tumors, showcasing the potential of these techniques in clinical settings.

Zhu et al. (2018)[4] proposed a deep learning-based framework tailored for liver tumor segmentation in CT images. Their approach leverages CNNs to achieve precise segmentation results, offering a robust solution for automatic tumor delineation, which is crucial for various medical applications.

Christ et al. (2017)[5] introduced a cascaded fully convolutional neural network architecture for automatic liver and tumor segmentation in both CT and MRI volumes. Their method demonstrates promising results in accurate segmentation.

Litjens et al. (2017)[6] conducted a survey focusing on deep learning techniques for liver tumor segmentation on CT scans. Their reviews provides valuable insights into the state-of-the-art methodologies, discussing the strengths and limitations of different approaches, and highlighting potential avenues for future research in this domain.

In the conclusion, the studies collectively contribute to the advancement of liver tumor segmentation in CT scans through the utilization of deep learning techniques, particularly U-Net architectures.

### III. PROPOSED METHODOLOGY

The U-Net architecture was originally designed for biomedical image segmentation, particularly for tasks like segmenting cells or organs within medical images. It's a convolutional neural network (CNN) architecture that consists of a contracting path to capture context and a symmetric expanding path that enables precise localization. The original

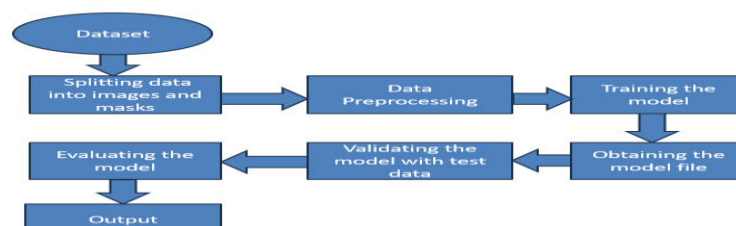


Figure 1: Block diagram for proposed methodology



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U-Net typically ends with a single-channel output layer using a sigmoid activation function, where each pixel is classified as either part of the object of interest or not. For multiclass segmentation, the output layer needs to be adjusted to accommodate multiple classes. You can use a softmax activation function with multiple channels. Below is the proposed flow chart of our proposed model.

### 1. Dataset preparation

The researchers worked with medical professionals to generate masks for segmentation of liver and tumor for each CT scan slice in the dataset, they made this dataset available in LITS challenge2017 competition. We obtained the dataset from the Kaggle datasets. This dataset contains 130 CT Scan volumes and each volume contains 400 image slices in every angle of view. The dataset also contains mask for each slice named to each corresponding image slice. Thus, it contains 52000 image slices among which 85 percent are used for training purpose and 15 percent are used for testing purpose.

### 2. Preprocessing and Augmentation

Preprocessing of image data is made easier by utilizing the Keras Image Data Generator. Each pixel value in the training set is normalized because the generator is configured with the rescale parameter set to 1/255, which results in the range [0, 1]. To provide consistent input data for both the training and assessment phases, the testing set also goes through the same rescaling process. The generated normalized images are used as the basis for abdomen CT scan dataset analysis and efficient model training.

Keras Image Data Generator facilitates augmentation in the training set. To improve dataset variety, it adds shear and zoom transformations, with training parameters set at 0.2. We lower the possibility that the model may focus too much on particular details by improving its adaptability to various types of input data. As the model's flexibility increases through modifications, so does its capacity to analyze images.

### 3. Experiment and result

This model was trained and validated for 5 consecutive epochs as part of the experimental work. According to the obtained csv file, the proposed approach has a training accuracy of 98.5% and validation accuracy of 98%. For the loss metric, in training we have obtained a loss of 0.03 % and in testing we obtained a loss of 0.33%. We have also calculated dice coefficient metric.

**Dice-coefficient:** The Dice coefficient is a measure of the overlap between two sets, A and B. In the context of image segmentation, A represents the ground truth segmentation mask and B represents the segmentation produced by the algorithm being evaluated.

In liver tumor segmentation project, a high Dice coefficient indicates that the algorithm's segmentation closely matches the manually annotated ground truth, which suggests that the algorithm is accurately identifying and delineating liver tumors in medical images. Therefore, researchers and developers often strive to achieve higher Dice coefficients as a measure of the algorithm's performance and accuracy in medical image segmentation tasks and its value ranges from 0 to 1.

#### Epochs vs Accuracy:

The below graph shows the relation between the epochs and the accuracy. If the number of epochs is increased then the accuracy may increase. But, increasing of accuracy stops if it is overfitted, to reduce overfitting we used early stopping which stops the increase of epochs if there is no increase in accuracy.

### 4. Deployment and Practical Applications

To ensure practical usability, the detection model was equipped with several important functionalities. It provided a real-time preview of detected number plates, enabling immediate analysis and quick verification of results. This feature allowed users to monitor the detection process as it happened, enhancing the model's effectiveness in real-world scenarios.



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Additionally, the model included a mid-process stopping option, giving users the flexibility to halt the detection process at any point while securely storing intermediate results. It also ensured that all detected frames and extracted number plate information were automatically saved for future analysis and reference, making the system reliable and user-friendly for post-processing tasks.

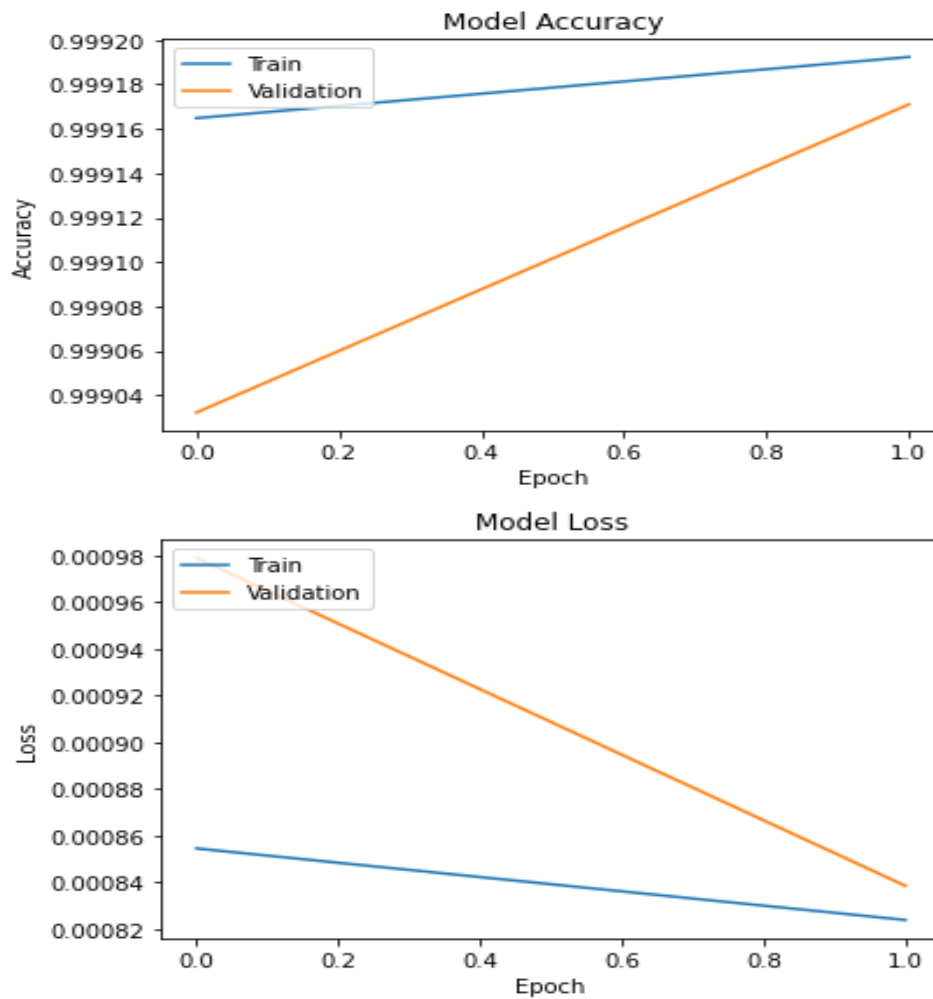


Figure: Epochs vs Accuracy graph

### IV. TESTING AND RESULTS

Testing results gives the visualized capability of the proposed model by giving us the original CT scan image and the ground truth mask along with the generated mask which is generated with the trained model which is build upon the proposed methodology. The ground truth mask and the generated mask should be almost similar then only it can be said that our model is giving the results relevant and accurately



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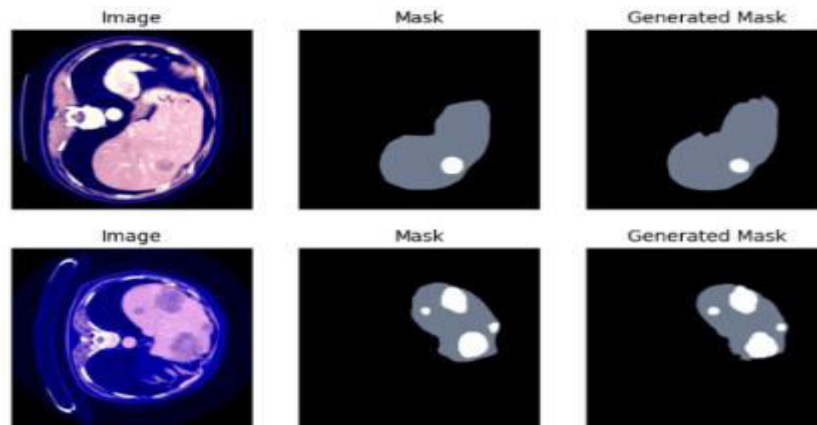


Figure: Testing results

### V. CONCLUSION

Our proposed methodology demonstrates the effectiveness of employing Convolutional Neural Networks, specifically a multi-class U-Net architecture, for liver tumor segmentation in CT scan images. Through rigorous Evaluation using metrics such as Dice coefficient and Accuracy, we have shown that our approach achieves accurate and robust segmentation results, providing valuable assistance to radiologists in diagnostics, treatment planning and monitoring for liver tumors. Our method exhibits promising computational efficiency and generalization capability across diverse datasets, laying the groundwork for its potential clinical adoption. While further research is warranted to address challenges and enhance the model's performance, our findings underscore the significant contribution of deep learning techniques to advancing medical image analysis and improving patient care in oncology.

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