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# Deep Learning for Liver Segmentation

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**Abstract- Liver cancer is becoming a huge threat to global health health, where early detection and accurate diagnosis are crucial for effective treatment [1]. Our research on deep learning- A based learning system for automatic segmentation of the liver and The tumor from computed tomography (CT) images is highlighted, using a U-Net model integrated with ResNet-34, which acts as a backbone [2]. This model is trained on the Liver Tumor Segmentation Challenge (LiTS) dataset, which is a standard for This type of problem [2]. Training a high-performance model, The project itself differentiates with the development of a user- friendly GUI with the help of the Python package PyQt5, making It is possible to achieve real- time visualization and user-friendly interaction for the end users like radiologists, students, and researchers [10] . This interface helps in taking input as an image in the form of a JPG, predicts segmentation tasks, and compares the results With the grayscale liver anatomy structures. Our model delivers high accuracy in segmentation, obtaining a high accuracy Dice coefficient of 98.20% with an extraordinary precision, recall, and f-score up to 99.89%, making it usable for real-time scenarios like clinical and research purposes Index Terms—Liver Segmentation, Deep Learning, U-Net, ResNet-34, FastAI, PyQt5**

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## I. INTRODUCTION

Medical image segmentation, especially liver and its related tumors, plays a crucial role in the diagnosis, prediction, treatment, and planning of hepatocellular carcinoma (HCC) [1]. Manual segmentation by radiologists is a time-consuming process, and there is also the probability of getting human error through various factors, mainly when the tumor is present at unclear boundaries [3]. By using several deep learning al- gorithms, mainly Convolution Neural Networks (CNNs) have been shown to produce real-time results in automating medical analysis [4]. Most deep learning models require technical experts or certified professionals due to their complexity [5]. This model helps to develop a user-centric solution that has a user-friendly GUI with real-time usage [10]. The model is trained on the Liver Tumor Segmentation Challenge (LiTS) dataset and deployed with the help of FastAI's deep learning framework, along with PyQt5 GUI, offering a good and efficient model and interface for liver and tumor segmentation extracted from CT scans [2].

## II. RELATED WORK

Over the years, several ways have been discovered for medical image segmentation, especially in the area of the liver [2]. Several research studies were conducted by MICCAI, like the Liver Tumor Segmentation Challenge (LiTS) [2]. U-Net, which is proposed by Ronneberger et al, remains a crucial architecture for biomedical imaging [6]. It is famous for its similar encoder-decoder structure and several skip connections that help in preserving spatial information [6]. Several studies have helped U-Net to integrate several attention mechanisms, 3D connections, and residual connections to improve seg- mentation quality to a greater extent [7]. Christ et al. have introduced a cascaded U-Net, which helps with segmentation and tumor findings in the liver [8]. In the same way, due to its ability to extract hierarchical features, ResNet has become popular [9].

Despite high accuracy, most of these models are not ac- cessible for end users like radiologists due to their complex command line interface, and also require high-end GPUs to yield the required results [11]. There are tools like 3D slicer and MITK that have some good segmentation capabilities, but they lack real-time inference and practical deployment, whereas our system mainly focuses on reliability, usability, and real-time deployment [12]. For that, we required a lightweight model, so we use ResNet 34 as a backbone integrated with PyQt5 GUI [13]. This design enables fast, efficient, and reliable CPU-based systems by giving a user-friendly interface.

## III. DATASET DESCRIPTION

We used the Liver Tumor Segmentation Challenge (LiTS) as an input dataset for training, testing, and validating the model [2]. This dataset consists of 130 3D enhanced CT scan images taken from several institutions [2]. Each scan consists of 70 to 400 axial slices, labeled at the smallest 3D units known as voxels, which helps differentiate liver, tumor, and the remaining background [14]. These were generated by certified radiologists, making them more accurate and reliable in real-time [15].

For the research, 3D scans were decomposed into 2D axial slices, making it compatible with the U-Net model architecture [16]. Several preprocessing steps were involved, normalizing intensity values, standardizing image resolutions, and converting of gray scale to the required three-channel RGB inputs [17]. Windowing and histogram equalization are the preprocessing techniques done on the original nii images to identify the liver and tumor using the masks given in the dataset, and these nii files are converted into RGB windowed JPG files, which were then fed into the training model and improved the model performance [18]. The dataset was divided into a training, testing, and validation ratio of 80:10:10, which helps in maintaining balance between tumor and liver volume across all samples.

## IV. METHODOLOGY

The proposed methodology has several steps, like data preprocessing, training, and integration with a GUI application [10]. There are several steps involved in converting grayscale axial slices into RGB images using histogram scaling and windowing [19]. There are different settings which are used to highlight various tissues, like liver tumor, and the final version with adjusted brightness, when added, creates a three-layer image [20].

The segmentation mode was done with the U-Net architecture implemented through the FastAI framework [2]. Predefined ResNet 34 weights, which are pretrained on ImageNet, act like an encoder that helps in obtaining the required features from the required input image [9]. For U-Net, which also acts as a decoder, it consists of a series of transposed convolutions and generates the required segmentation mask [6]. Using softmax activation and 1x1 convolution, which gives the required output, which are liver, tumor, and background.

Training was done over 8 epochs using the U-Net learner API with a loss function that is CrossEntropyLossFlat [2]. Several metrics, like dice coefficient and foreground accuracy, were tracked [2]. SaveModelCallback guarantees that the best model is saved based on its performance on validation [2]. The model was saved in .pkl format and integrated with a GUI using PyQt5 [10].

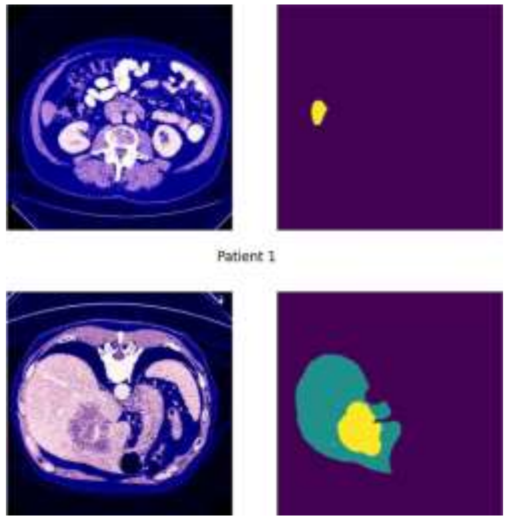


Fig. 1. Dataset Images (a): Original CT Scan (b): Mask

## V. EXPERIMENTS

On the LiTS dataset, extensive trials were done [2]. For checking various parameters, the training dataset has been aug- mented in several ways, like flipping, rotation, and brightness adjustments were done to improve the model's adaptability [2]. Model trained with one cycle learning policy to get real- time performance by optimizing the model [2]. Validation was done and tracked at every epoch [2].

Through epoch-wise metrics, we can observe that there is a gradual decrease in training and validation loss [2]. Our model has achieved 98.5% accuracy on training dice and 98.20% on validation dice [2]. Throughout the training accuracy metric of the model remained consistently at 99.89% [2]. The final model has been tested on different ages to ensure that the model works perfectly and making sure that the GUI works in real time and making it reliable.

## VI. MODEL ARCHITECTURE

The model that is used for segmentation is a U-Net with a ResNet encoder [9]. This ResNet-34 is a pretrained model on the ImageNet [9]. This model architecture has three components:

1. **Encoder –** ResNet-34 balances the depth and efficiency so that it is suitable for deployment on CPUs [9].
2. **Decoder –** It is crucial for preserving the edge information. It upsamples the feature maps and uses skip connections to integrate the low-level encoder features. [6]

3. **Output Layer –** A 1×1 convolutional layer maps the features to a three-class probability distribution: {0: background, 1: liver, 2: tumor} [6].

The model is implemented using FastAI and fine-tuning is performed with automatic model checkpointing via SaveModelCallback.

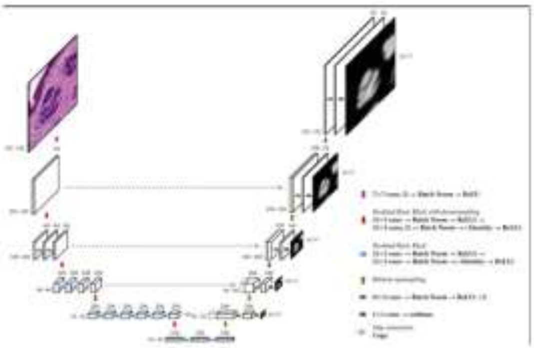

Fig. 2. Model Architecture

**Graphical User Interface (Gui)**
To enhance the usability, a desktop application using PyQt5 is developed, enabling real-time interaction with the trained deep learning model [10] . The GUI consists of a single-window interface which allows users to:

- Browse and upload the CT scan in .jpg format. [10]
- Run segmentation predictions using the pretrained model. [10]
- Visualise the results that include:
- Original RGB CT scan,
- Grayscale anatomical reference,
- Predicted segmentation output. [10]


Fig. 3. GUI

Matplotlib plots are embedded for seamless data visualization. [10]
A custom QThread is used for handling the model inference to keep the GUI responsive [10]. This enables the user interface to remain active and interactive even during heavy computational operations [10] .
A Go back button resets the interface, providing navigation and allowing users to test multiple images without restarting the application.
A contact information toggler is embedded for educational aid.

The application runs on local machines without GPU dependency, making it suitable for academic labs and offline use.
The framework and dependencies used in this GUI include: Pillow (PIL), FastAI, Torch, NumPy, and the Qt application framework.

## VII. EVALUATION METRICS AND RESULTS

The performance of the segmentation model was evaluated using the following metrics:

- **Dice Coefficient:** Measures the overlap between the predicted mask and the ground truth. The best model achieved a training dice of 98.50% and a validation dice of 98.20%. [2]
- **Precision and Recall:** Both scored 98.89%, indicating excellent balance between false positives and false negatives. [2]
- **F1 Score:** Achieved up to 98.89%, confirming robust segmentation performance. [2]
- **Hausdorff Distance (95%):** Achieved a value of 1.00, signifying high boundary accuracy. [2]
- **Inference Time:** Around 2.1 seconds per image on CPU, suitable for real-time use. [2]

| | |
|---|---|
| Accuracy: | 99.89% |
| Precision: | 99.89% |
| Recall: | 99.89% |
| F1 Score: | 99.89% |
| Hausdorff (95): | 1.00 |
| Best Dice: | 98.20% |

Fig. 4. Evaluation Metrics

The GUI application allows the user to visualise their uploaded CT scan image alongside the predicted segmentation mask [10]. This visualization aids in interpretability and allows quick validation of the model output [10]. Visual inspection of the produced masks closely aligning with the ground truth confirms that liver and tumor segmentation was smooth and complete [2].

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This model was evaluated in real-time settings and maintained performance across diverse image inputs, validating its robustness.


Fig. 5. Model Segmentation Output

## VIII. CONCLUSION

This study presents a complete deep learning-based liver and tumor segmentation system, from data preprocessing and model training to real-time GUI deployment [1]. Trained on the LiTS dataset and powered by a U-Net with a ResNet- 34 backbone, the model achieved high accuracy and usability [2]. We achieved a Dice score of 98.20% and accuracy metrics with near perfection [2].

The intuitive PyQt5 interface provided real-time inference, a user-friendly GUI, and easy-to-understand visualizations [10]. With a CPU-compatible design, this system is deploy- able in various healthcare environments, including those with limited resources [10].

Future expansions will focus on 3D analysis, DICOM compatibility, and integration with hospital systems for end-to-end clinical support [1].

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