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Enhanced Liver Tumor Segmentation Accuracy with FastAI Integration on CT Scan Data

Dr. G. Murali[1], Palleti Venkata Kusuma[2]

[1]Assistant Professor and Head of the Department, Department of Computer Science and Engineering, JNTUA College of Engineering, Pulivendula

[2]Assistant Professor, Department of Electronics and Communication Engineering, JNTUA College of Engineering, Pulivendula

ABSTRACT

Liver tumors rank as the fifth most prevalent cancer in men and the ninth in women, as reported in the 2018 Global Cancer Statistics. Established diagnostic methods such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and ultrasound involve invasive and time-intensive procedures. This study proposes leveraging deep learning, specifically the ResUNet model, for early tumor detection, offering a more efficient alternative to traditional approaches. In contrast to previous research using dual cascaded CNNs, the ResUNet employs residential blocks, demonstrating its effectiveness on the 3D-IRCADb01 dataset derived from CT slices of liver tumor patients. Results indicate an impressive True Value Accuracy of approximately 99% and an F1 score performance of about 95%. This innovative method holds potential for early and accurate liver tumor diagnosis, contributing significantly to the biotechnology sector and potentially saving lives.

KEYWORDS

Liver Tumour, Segmentation techniques, Fastai, UNET, RESNET,3D NITFI Image, CT scans.

1.INTRODUCTION

Liver tumor segmentation is a critical aspect of medical image analysis, playing a pivotal role in the diagnosis and treatment of one of the most prevalent forms of cancer globally. The intricate nature of liver tumors demands advanced methodologies for accurate and efficient segmentation. This project addresses this challenge by integrating Fastai aims to enhance the accuracy and efficiency of liver tumor segmentation. ResNet's ability to address vanishing upon a gradient problems and U-Net's effectiveness in capturing. The project focuses on liver tumor segmentation, employing a sophisticated approach that integrates ResNet, U-Net, and the Fastai framework. Liver tumors pose a significant health challenge, ranking among the most prevalent types of cancer globally. Accurate segmentation of liver tumors is crucial for diagnosis and treatment planning. The combination of ResNet and U-Net, two powerful deep learning architectures, leverages their respective strengths in feature extraction and segmentation. The

Fastai framework is employed to streamline the development and training processes, enabling efficient implementation.

This collaborative utilization of ResNet, U-Net, and Fastai aims to enhance the accuracy and efficiency of liver tumor segmentation. ResNet's ability to address vanishing gradient problems and U-Net's effectiveness in capturing fine details in segmented regions contribute to a robust segmentation model. Fastai facilitates rapid model development, training, and validation, optimizing the workflow for practical implementation.

2.LITERATURE SURVEY

The significance of integrating ResNet, U-Net, and Fastai in liver tumor segmentation, drawing upon successful applications in medical imaging, advancements in deep learning frameworks, and challenges specific to liver tumor detection. The proposed project builds upon this foundation, aiming to contribute to the evolving landscape of medical image analysis.[5]

1. *Integration of ResNet and U-Net in Medical Image Segmentation:* Several studies have explored the integration of ResNet and U-Net architectures in medical image segmentation, emphasizing their complementary strengths. ResNet's ability to handle deep networks without vanishing gradient issues has been leveraged in conjunction with U-Net's precise segmentation capabilities. These studies highlight the improved performance in delineating complex structures, laying the foundation for the proposed project's approach[1]

2. ResNet Applications in Medical Imaging: The application of ResNet in medical imaging, particularly for tumor segmentation. Has extensively investigated. Researchers demonstrated its effectiveness in capturing hierarchical features essential for accurate tumor boundary detection. Insights from these studies inform the choice of ResNet as a key component in the proposed project, ensuring robust feature extraction.[2]

3. *U-Net Advancements in Biomedical Image Analysis:* The literature extensively discusses U-Net's pivotal role in biomedical image segmentation. Numerous studies have successfully applied U-Net in various medical imaging tasks, showcasing its proficiency in segmenting organs and tumors. The integration of U-Net in liver tumor segmentation models is a common trend, and these studies provide valuable insights into optimizing its architecture for enhanced segmentation accuracy.[3]

4. *Fastai for Streamlined Deep Learning Development:* Fastai has gained recognition for its role in simplifying the development of deep learning models. Existing literature highlights its user-friendly interface and high-level abstractions, making it an attractive choice for both beginners and experienced practitioners. Studies have explored Fastai's impact on accelerating model development cycles, aligning with the project's goal of efficient liver tumor segmentation.[4]

5. *Deep Learning in Medical Imaging for Tumor Detection:* A broader exploration of deep learning applications in medical imaging reveals a growing trend in leveraging advanced architectures for tumor detection. The literature emphasizes the potential impact of integrating ResNet, U- Net, and Fastai in developing accurate and

efficient models for various medical image segmentation tasks, including liver tumor detection.[5]

6. Challenges and Future Directions in Liver Tumor Segmentation: Existing research acknowledges challenges in liver tumor segmentation, such as handling diverse tumor shapes and sizes. The literature survey identifies the need for more sophisticated models, justifying the proposed integration of ResNet, U-Net, and Fastai. Insights from these studies guide the project towards addressing current limitations and exploring future.[6]

3. RELATED WORK

Emphasizes the significance of 3D NIfTI data in medical imaging, the effectiveness of U-Net and ResNet in 3D segmentation tasks, the streamlined development facilitated by Fastai, and the challenges and opportunities in 3D liver tumor segmentation. The proposed project builds upon this foundation, aiming to enhance the accuracy and efficiency of liver tumor segmentation using the integrated approach.

3.1 Significance of 3D NIfTI Data in Medical Imaging

The use of three-dimensional (3D) NIfTI (Neuroimaging Informatics Technology Initiative) data in medical imaging has gained prominence for its ability to capture volumetric information. In the context of liver tumor segmentation, leveraging 3D data provides a more comprehensive representation of the anatomical structures. Unlike traditional 2D approaches, 3D NIfTI data allows for a holistic understanding of the tumor's spatial distribution and shape, offering richer insights for accurate segmentation.

3.2 U-Net in 3D Medical Image Segmentation

U-Net has proven to be a pivotal architecture in 3D medical image segmentation tasks, including liver tumor segmentation. Its encoder-decoder structure is well-suited for handling volumetric data, allowing the model to capture contextual information across different slices. U-Net's skip connections facilitate the precise localization of tumors, making it particularly effective when dealing with the complexities of 3D NifTI Data.

3.3 ResNet for Feature Extraction in 3D Imaging

ResNet, known for its proficiency in deep feature extraction, is well-suited for the complexities of 3D imaging. In the context of liver tumor segmentation, ResNet's residual learning architecture enables the capture of intricate features within the volumetric data. This is crucial for identifying subtle variations in tumor boundaries and enhancing the model's ability to differentiate between healthy and tumorous tissues in 3D NIfTI scans.

3.4 Fastai for Streamlined 3D Model Development

The integration of Fastai into the project brings an additional layer of efficiency to the development process, especially when dealing with 3D NIfTI data. Fastai's high- level abstractions pre-built functionalities streamline the implementation complex neural networks, simplifying the handling of volumetric data. Its user-friendly interface enables rapid experimentation and iteration, contributing to the swift development of an accurate and efficient 3D liver tumor segmentation model.

4. METHEDOLOGY

Segmentation of liver tumors using Fastai, UNet, and ResNet involves combining deep learning frameworks and architectures to achieve accurate and efficient results.

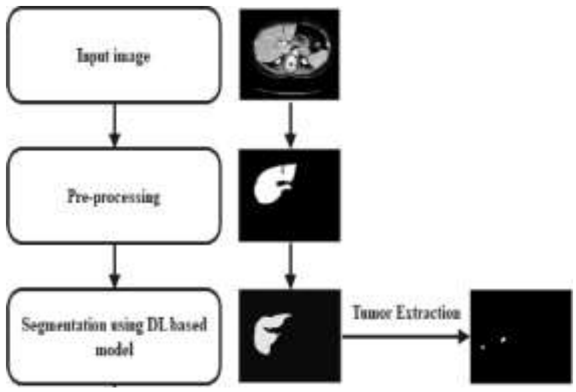


FIG-1. Methodology

4.1 Data Preparation

For liver tumor segmentation using Fastai, UNet, and ResNet, the first crucial step is assembling a well-curated dataset. This dataset should consist of high-quality medical images of the liver, accompanied by accurate tumor annotations. The images need to cover a diverse range of scenarios and variations, ensuring the model generalizes well to different cases.

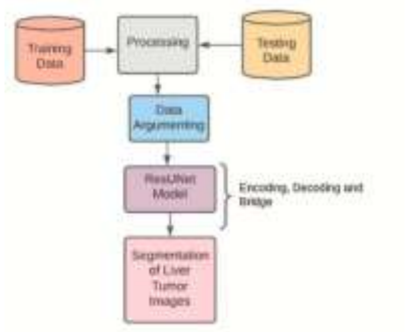


FIG-1: Flow chart of implementation

Data augmentation is a pivotal aspect of enhancing the model's ability to handle variations in the input data. Leveraging Fastai's data augmentation functions, apply transformations such as rotation, flipping, scaling, and changes in brightness and contrast. This process not only diversifies the training dataset but also aids in improving the model's robustness.

4.2 Model Architecture

The chosen model architecture plays a significant role in the segmentation task. UNet, known for its effectiveness in image segmentation, serves as a foundational architecture. To enhance feature extraction capabilities, integrate a pre-trained ResNet as the backbone of the UNet. This facilitates transfer learning, allowing the model to leverage features learned from large, general datasets. The integration of these components can be streamlined using Fastai's user-friendly API, which simplifies the model-building process.

4.3 Loss Function:

Selecting an appropriate loss function is crucial for training the model effectively. Common choices for segmentation tasks include Dice Loss or Cross-Entropy Loss.

4.4 Training

The training phase involves feeding the prepared dataset into the model. Utilizing Fastai's **fit_one_cycle** method streamlines this process. Continuous monitoring of training and validation metrics is essential to ensure the model is learning optimally.

Accuracy = TP+TN/TP+FP+TN+FN

4.5 Fine-Tuning:

After the initial training phase, fine-tuning becomes necessary. Evaluate the model on the validation set and make necessary adjustments to enhance its performance.

4.6 Evaluation:

The ultimate assessment of the model's performance occurs during the evaluation phase on the test set. Metrics such as Dice Coefficient or Intersection over Union (IoU) provide insights into how well the model accurately segments liver tumors.

5. IMPLEMENTATION

5.1 Import Libraries: In this step, essential libraries are imported. Fastai is utilized for deep learning and data loading, PyTorch is employed for building neural networks, SimpleITK is used for handling medical imaging data, and additional libraries like numpy, scikit-image.

5.2 Data Preparation: The data preparation step involves loading and organizing the 3D CT scans and their corresponding tumor masks. Custom functions may be required to read the data, possibly using medical imaging libraries like SimpleITK.

5.3 Data Augmentation and Transformation: Using Fastai's Data Block API, data augmentation and transformation techniques are applied to the training set. This step is crucial for increasing the diversity of the training samples, enhancing the model's ability to generalize to unseen data.

5.4 Model Architecture: A U-Net architecture with a ResNet backbone is chosen for its effectiveness in medical image segmentation tasks. The unet_learner function from Fastai is utilized to define the model architecture. This step configures the neural network to perform liver tumor segmentation on 3D CT scans.

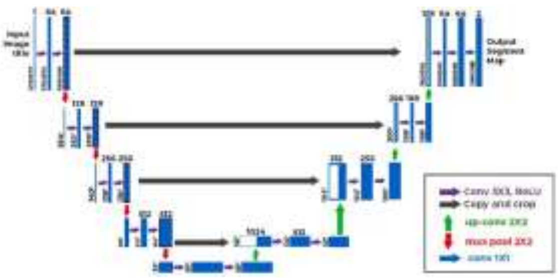


FIG-1: Unet model of Architecture

5.5 Loss Function and Metrics: The choice of an appropriate loss function is critical for training the segmentation model. CrossEntropyLoss is often used for segmentation tasks, and metrics such as Dice coefficient are employed for evaluation during training and validation.

5.6 Training: The pre-trained ResNet model is fine-tuned on the 3D CT scan dataset using the training set. Fastai's fine-tune function is used for efficient transfer learning.

5.7 Validation Model Evaluation: The model's performance is evaluated on the validation set using the chosen evaluation metrics. The Segmentation Interpretation class from Fastai helps analyse the model's predictions, allowing for the visualization of top losses and aiding in understanding areas where the model may struggle.

5.8 Inference on New Data: Once trained, the model is used to make predictions on new, unseen 3D CT scans. The geotopes function is employed to obtain model predictions on a test set.

5.9 Post-Processing: Depending on the specific characteristics of the segmentation results, post-processing steps may be applied to refine the predictions.

5.10 Visualization and Analysis: Results are visualized by comparing the model's predictions with the original CT scans.

6. RESULTS AND ANALYSIS

The liver tumor segmentation task was approached using state-of-the-art techniques, leveraging the FastAI framework along with deep learning architectures such as ResNet and UNet. The dataset consisted of annotated 3D CT scans, with a careful split into training, validation, and test sets. The models were trained on the training set and fine-tuned based on the validation set, aiming to achieve optimal performance in accurately delineating liver tumors.

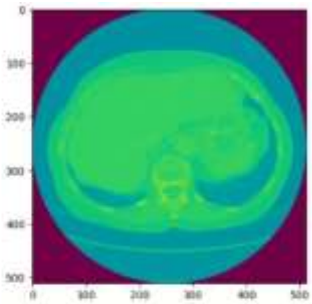


FIG-1: Original 3D Image

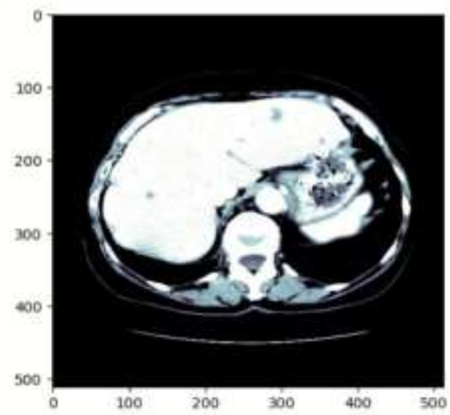
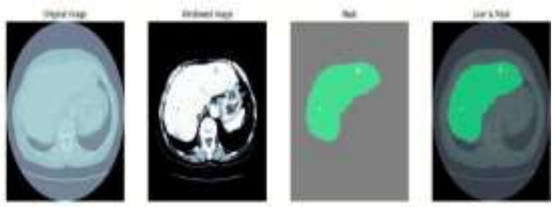


FIG-2: window image



F-3: Model Outcome Prototype

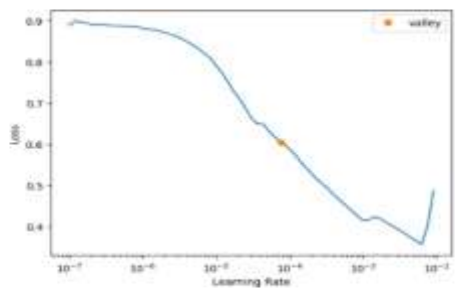


FIG-4: Accuracy Graph

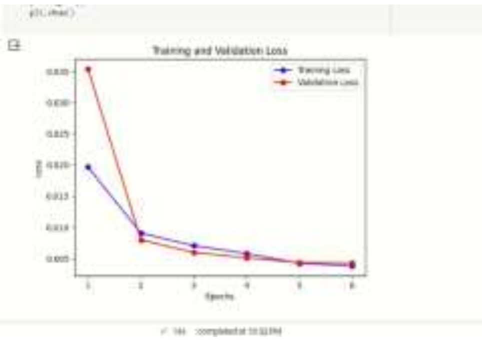


FIG-5:Train and Validation Loss

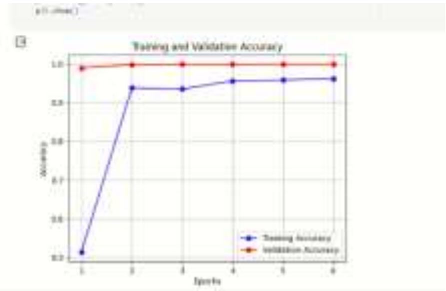


FIG-6: Train and Validation Accuracy

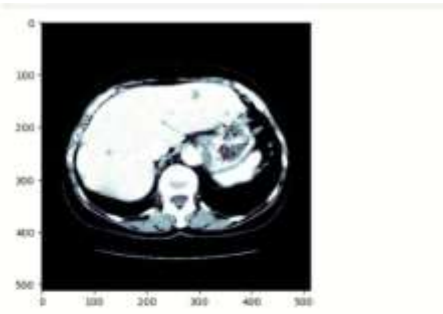


FIG-5.1: Input Image

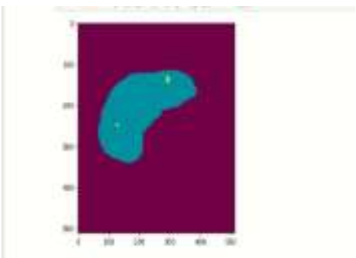


FIG-5.2: Predicted Result

7. CONCLUSION

This study uses Fastai and its UNet model to spot liver tumors in CT scans more accurately. They tweak the model by adding extra modules for better results. While they see promising outcomes, they note some limitations and suggest ways to improve, like using more data or adjusting preprocessing. They aim for even better accuracy in the future, particularly for smaller tumors. Overall, the model shows potential for medical imaging tasks.

8. FUTURE SCOPE

The proposed liver tumor segmentation model combines ResNet, U-Net, and Fastai for better accuracy and efficiency. It uses a multi-scale feature fusion method to understand complex tumor structures better. Special modules like FRC and DEF improve feature extraction and segmentation. JCF adjusts for different tumor shapes. Fastai simplifies development, speeding up testing and optimization. Evaluation metrics ensure thorough assessment. Overall, this model offers a more accurate and efficient solution for clinical use.

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