Liver Tumor Detection Model

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Introduction

Tumor detection is a critical task in medical diagnostics, as it plays a vital role in early intervention and treatment planning. With the large amounts of CT scans that radiologists must go through, we propose a program that helps detect liver tumors. The dataset we will be using is “Medical Image Segmentation: Evaluation” from Kaggle.

Aim

The aim of this project is to build a U-Net Model that will be able to predict tumors in the liver with a high accuracy. As well as create a GUI which allows anyone to input a CT scan as an image into a user interface to predict whether there is a tumor or not.

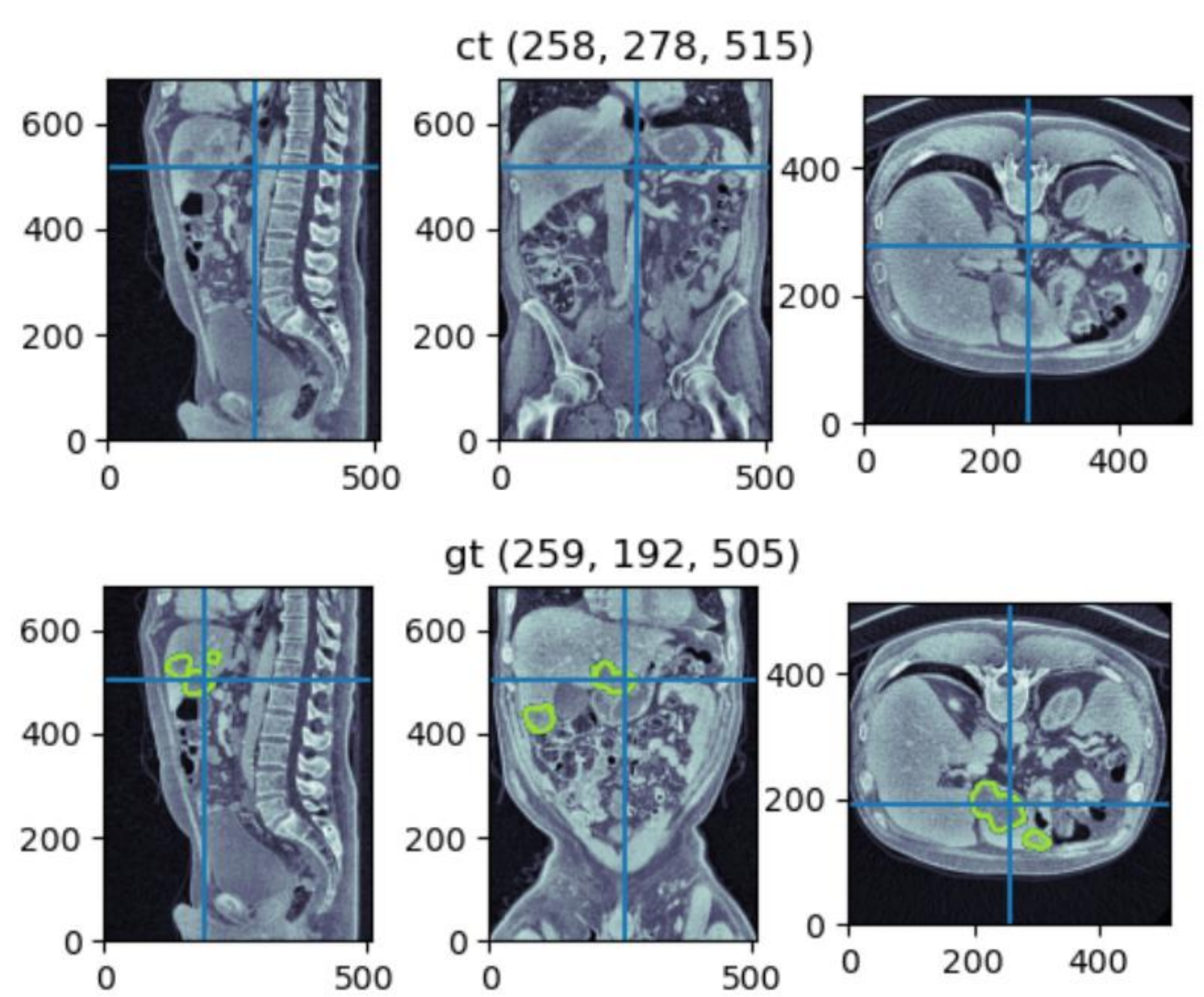
1. Data Collection and Preprocessing

We first gathered a dataset of medical images containing tumors from the liver from Kaggle (https://www.kaggle.com/datasets/modaresimr/medical-image-segmentation). In the dataset, it is separated into ground truth (GT) and raw CT scans as .nii files. The ground truth files are scans that radiologists have circled a tumor around.

Steps we took for preprocessing:

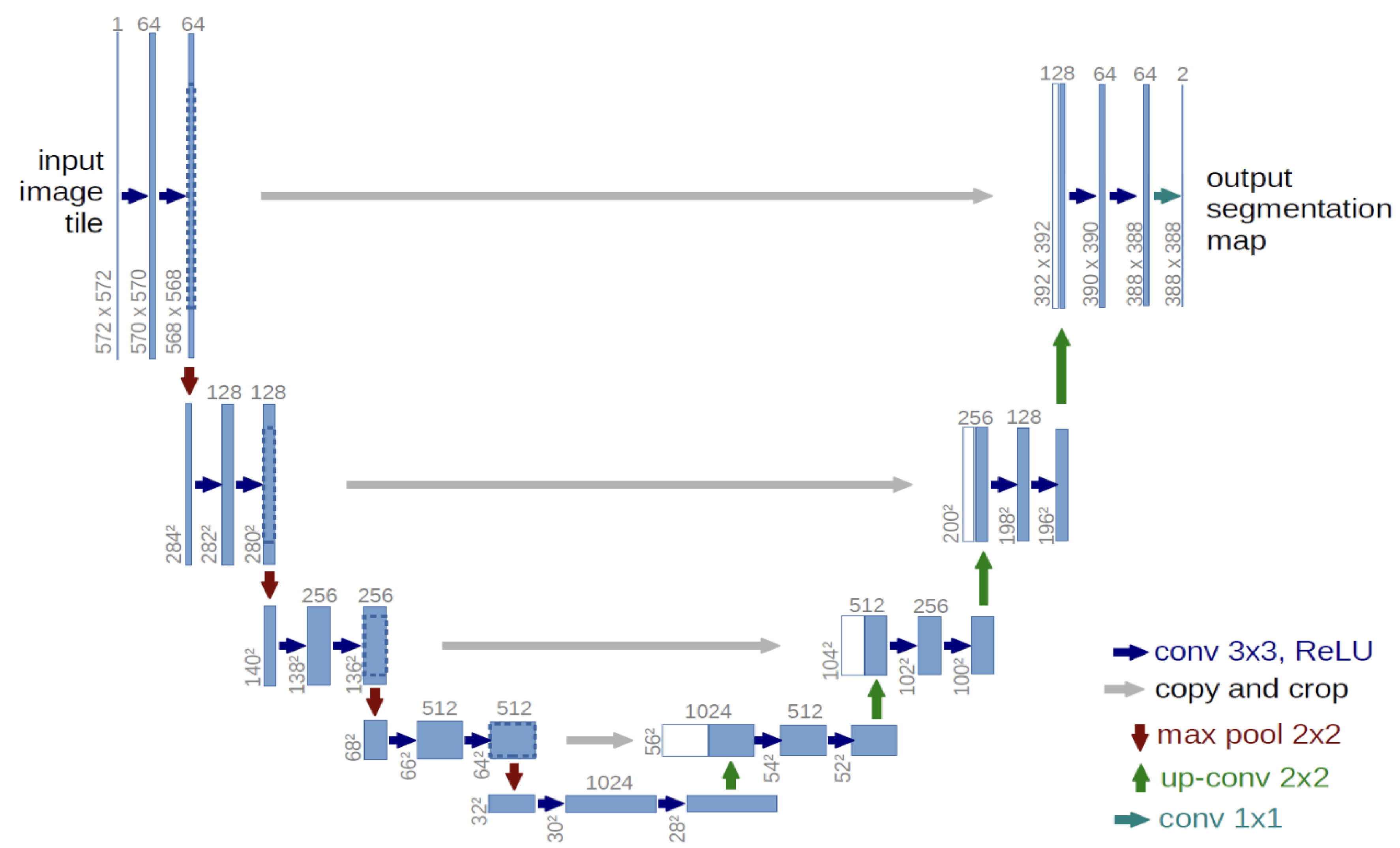
1. Conversion of medical image files (.nii) into slices of the CT scan as PNG files.
2. Ensure that the images had corresponding ground truth files.
3. Resize and ensure everything is the same between raw and GT files.

To achieve the steps, we converted the 3D CT scan into 2D image slices by utilizing Python’s libraries like numpy and the converting 3D arrays into 2D. Then we looped through the sizes of the files to ensure that they had the same size, if they did not, we would resize them into 512 by 512 images.



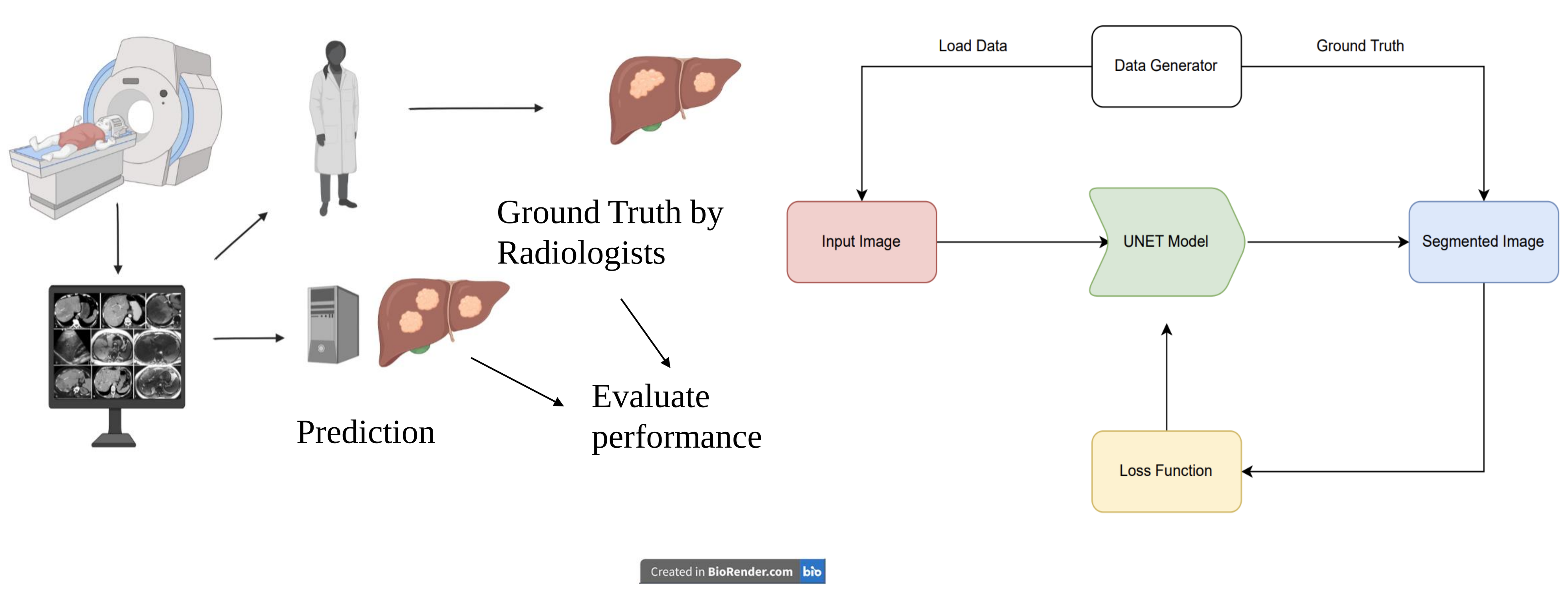
2. Model Selection

We had to explore different models to use for representation learning for medical images and the one that worked the best for this that we found was the U-Net Model. From, Olaf Ronneberger, Philipp Fischer, and Thomas Brox’s paper’s “U-Net: Convolutional Networks for Biomedical Image Segmentation”, we found that this model has been proven to be effective and reliable model utilizing advantages of CNN. U-Shaped skip connections also makes it a good choice for medical image segmentation. The model has been used before to identify the boundaries of tumors in other body parts and can perform well with limited training data.



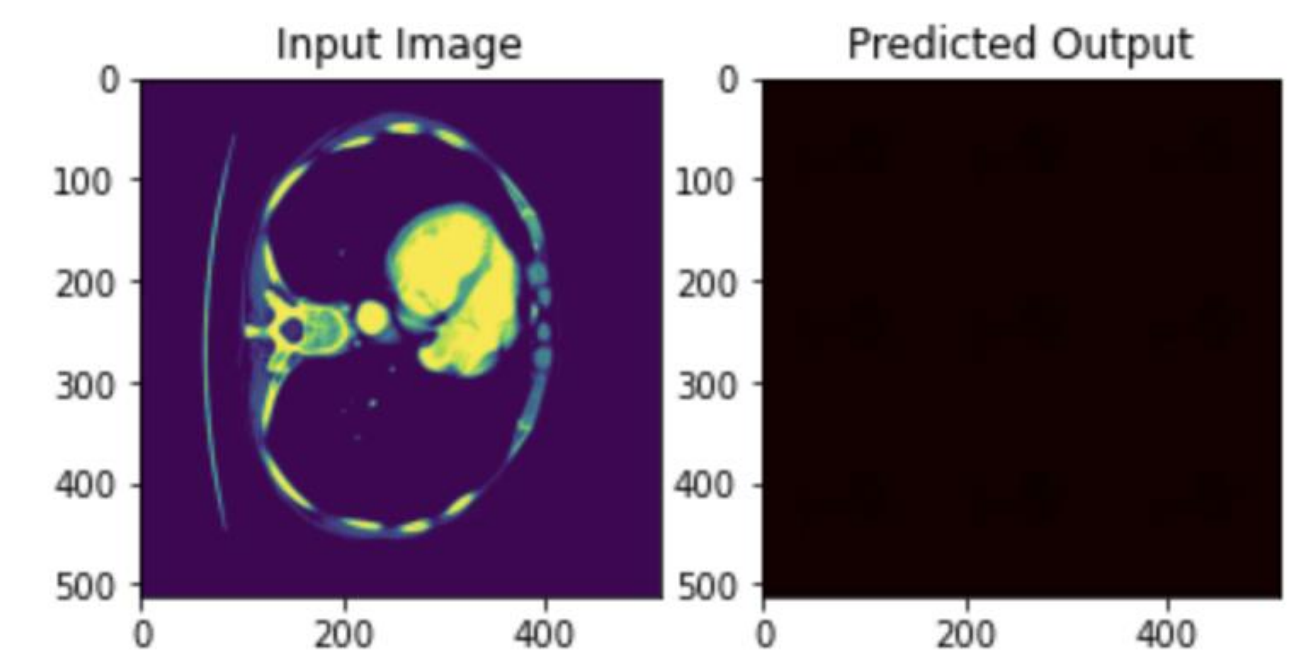
3. Model Training and Validation

For this we had split our dataset into training and validation. We stored images into folders of pairs containing the raw CT scan and corresponding GT file for that CT scan. Then trained our U-Net model using the training set and validate its performance on the validation set. Also applying an appropriate loss function (Mean Squared Error) and optimization techniques to optimize the model's parameters and improve its liver tumor detection accuracy.



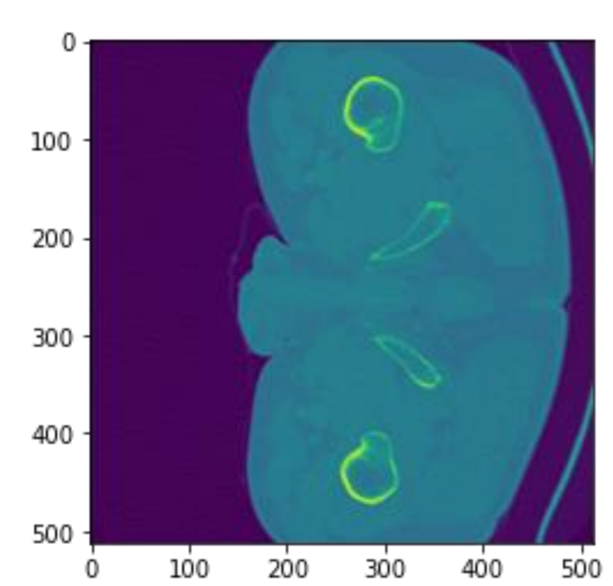
Results

The liver tumor detection model achieved an overall accuracy of 68% on the evaluation dataset. While the accuracy indicates that the model performs better than random guessing, it falls short of meeting the desired level of performance for clinical deployment. Several factors might contribute to the lower accuracy of the model. The limited size of the training dataset may not have provided sufficient diversity and representation of different tumor types and imaging conditions. In addition, the short of computing power during our model training process also limit the performance of our model. Additionally, the complexity and heterogeneity of liver tumors pose significant challenges for accurate detection and segmentation.



Conclusion

In this project, we developed a liver tumor detection model using the U-Net architecture to accurately identify and segment tumors in liver images. The model achieved a 68% accuracy on the evaluation dataset, demonstrating a moderate ability to detect liver tumors. Although the model's performance is not yet optimal, it lays the foundation for future advancements. Addressing limitations, such as the limited training dataset and complex liver tumors, is crucial for enhancing accuracy and robustness. Our next steps involve expanding the dataset, incorporating advanced deep learning techniques, refining the model architecture, and improving preprocessing and augmentation methods. Despite limitations, the model can serve as a valuable supporting tool when used alongside expert radiologists' assessments, potentially reducing workload and providing additional insights. Future work aims to extend the study to other anatomical regions, such as the brain and pancreas, using the U-Net model, to improve results and achieve higher accuracy in tumor detection, ultimately contributing to enhanced clinical decision-making and patient care.



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