AI for Healthcare - Ex 2

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Matching Collab notebook:
https://drive.google.com/file/d/1BNuSAHgAMD1SJnOmXA8sHsY2SQjRmzLn/view?usp=sharing

Problem Formulation

Medical imaging plays a critical role in diagnosing and treating various diseases, including detecting tumors. Liver tumors, both primary and metastatic, are a significant concern in oncology, often requiring timely and accurate detection for effective intervention. In this project, I aimed to use an AI model capable of detecting liver tumors in contrast-enhanced CT images.

The dataset used in this study is derived from the Medical Decathlon challenge, explicitly focusing on liver tumors.

To tackle this problem, I employed the YOLOv7 architecture, a state-of-the-art object detection model known for its efficiency and effectiveness in detecting objects within images. YOLOv7, short for "You Only Look Once," is a popular deep learning-based approach that performs object detection by dividing the image into a grid and predicting bounding boxes and class probabilities for each grid cell.

The primary objective of this project was to develop an AI model capable of automating the detection of liver tumors in contrast-enhanced CT scans. The successful implementation of such a model could provide significant benefits to medical professionals by assisting in the early identification and characterization of liver tumors, ultimately leading to improved patient outcomes and treatment planning.
In this report, I present the Dataset, EDA and Preprocessing, experimental results, evaluation metrics to assess the performance of the AI model in liver tumor detection, and Limitations and Discussions.

Dataset Description

The dataset used in this Project is derived from the Medical Decathlon challenge, explicitly focusing on liver tumors. The dataset comprises 201 contrast-enhanced CT images obtained from patients with primary cancers and metastatic liver disease, resulting from colorectal, breast, and lung primary cancers. The corresponding target regions of interest (ROIs) include both liver segmentation and tumor segmentation within the liver. The availability of such annotated data allows us to train and evaluate our AI model's performance in accurately identifying tumors and delineating their boundaries.

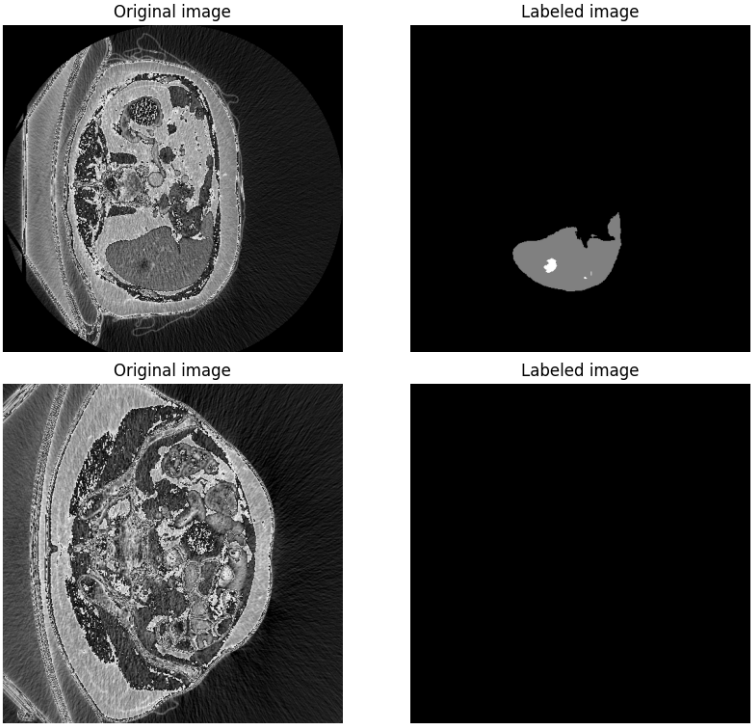
The dataset provides annotations for both the liver and tumor regions within the liver. The liver segmentation annotations define the boundaries of the liver, allowing for accurate localization and extraction of the liver region. The tumor segmentation annotations outline the boundaries of tumors present within the liver, enabling the identification and classification of tumor regions.

The annotations were created by expert radiologists with extensive experience in liver tumor diagnosis. The high-quality annotations serve as ground truth for training and evaluating our AI model's performance in liver tumor detection.

To ensure consistency and compatibility across the dataset, the images were preprocessed by normalizing the pixel intensities and rescaling them to a common resolution. The preprocessing step aimed to remove any variations in image quality and size, allowing for a standardized input for the AI model.

Exploratory Data Analysis (EDA) and Preprocessing

Before developing my AI model for liver tumor detection, I conducted an exploratory data analysis (EDA) to gain insights into the dataset and understand its characteristics. Additionally, I performed preprocessing steps to ensure data consistency and prepare the dataset for training the AI model.

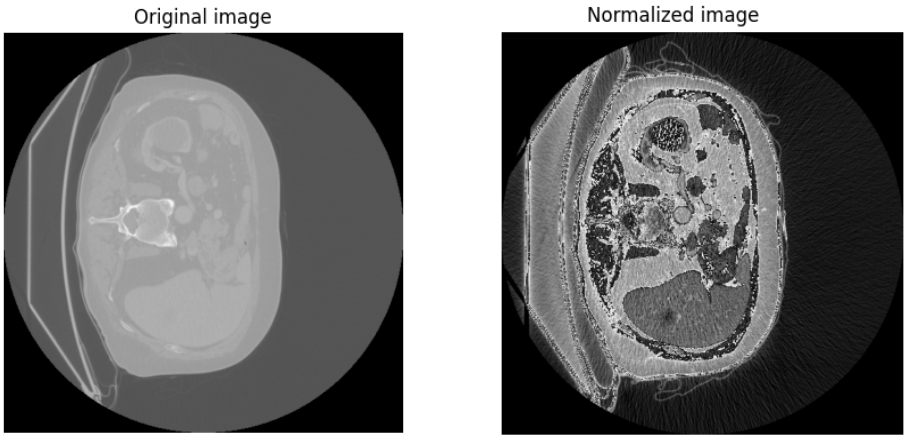


To begin my EDA, I converted the 3D CT images into 2D by taking each slice separately. Then, I examined the distribution of primary cancers in the dataset. I found that the dataset mostly consisted of unlabeled images. I decided to remove the unlabeled data due to a lack of computing power.

By visually inspecting the dataset, I observed that the internal organs in the contrast-enhanced CT images were challenging to discern, making it nearly impossible to accurately mark their boundaries. To address this issue and improve the visibility of the organs, I performed a normalization step on the images.

To enhance the contrast and facilitate better visualization, I normalized the pixel intensities of the CT scan images to a range between 0 and 255. This normalization process adjusted the intensity values of each pixel, stretching the dynamic range of the images while preserving the relative differences in intensities. As a result, the internal organs and their structures became more discernible, aiding in the subsequent annotation and detection tasks.

By transforming the pixel intensities to a standardized range, I aimed to create images that were visually consistent and easier to interpret for both human experts and the AI model. This normalization step played a crucial role in ensuring that the subsequent annotations and AI-based detection algorithms could accurately identify and delineate the liver and tumor regions within the images.

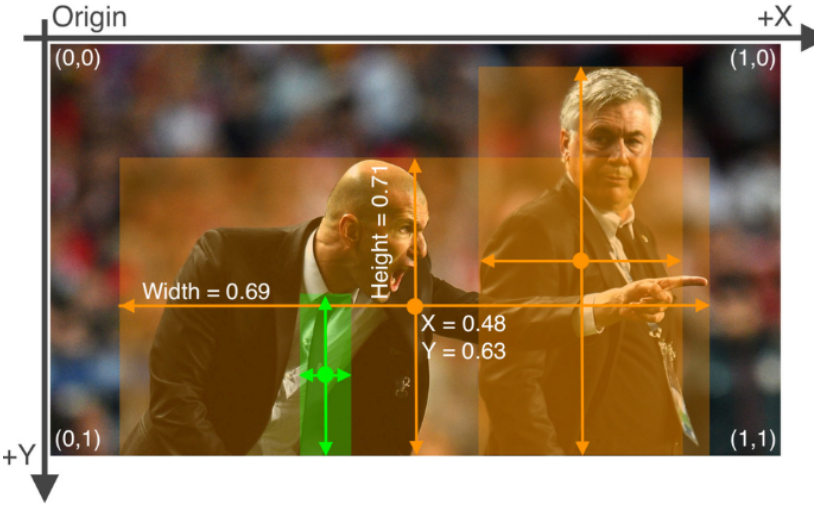


Initially, the task at hand involved liver and tumor segmentation within the CT scan images. However, to leverage the YOLOv7 architecture for liver tumor detection, it was necessary to convert the problem from segmentation to a detection format.

In the segmentation problem, the goal is to classify each pixel within the image and assign a corresponding class label, resulting in a pixel-wise segmentation map. On the other hand, the detection problem aims to identify and localize objects of interest within the image by predicting bounding boxes and associated class labels.

To convert the dataset from a segmentation problem to a detection problem, I followed a specific procedure. Firstly, I identified the tumor annotations within the images. Then, I transformed these annotations into bounding box representations that adhered to the requirements of YOLOv7.

By performing these steps, I successfully transformed the segmentation labels into a detection format compatible with YOLOv7. This conversion facilitated the training and evaluation of the YOLOv7 architecture, which excels in object detection tasks.

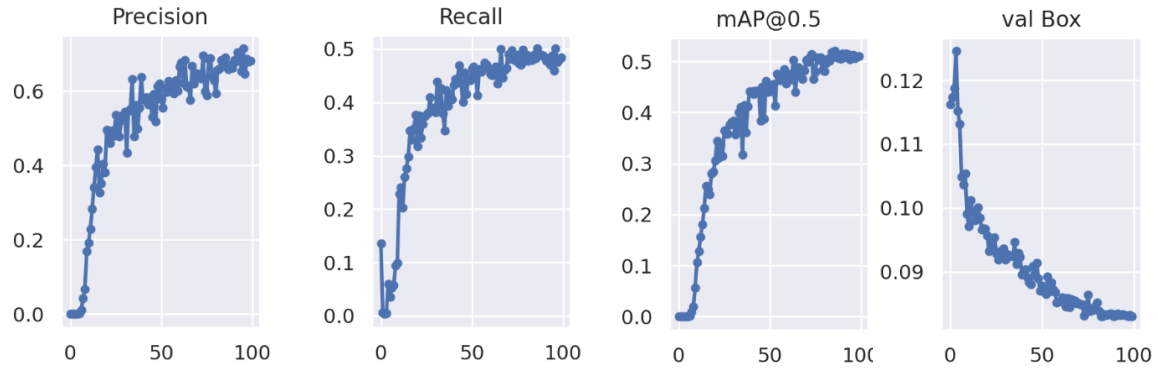


Experimental Results

In my liver tumor detection project, I employed the YOLOv7-tiny architecture for training the AI model. The model was trained for 100 epochs with a learning rate of 0.01. This section presents the experimental results obtained from training and evaluating the model.

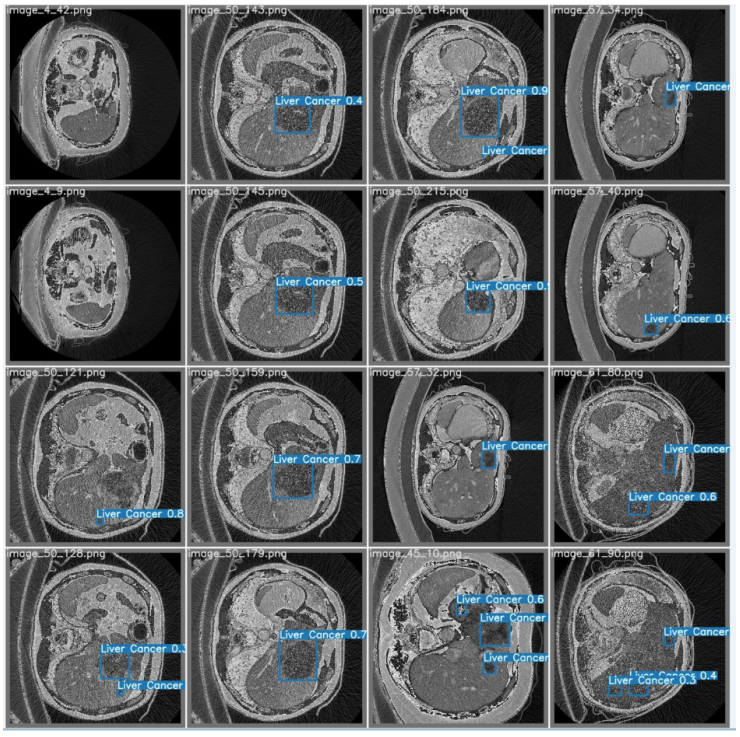
To evaluate the performance of my approach, I partitioned the dataset into train, validation, and test sets. The train set was utilized for model training, the validation set for hyperparameter tuning, and the test set for final evaluation.

During the training phase, I observed the convergence and improvement of the AI model's performance. The loss function (BCELoss) steadily decreased throughout the 100 epochs, indicating that the model effectively learned to detect liver tumors. The model monitored the training progress using metrics such as mean average precision (mAP), precision, recall, and F1-score.

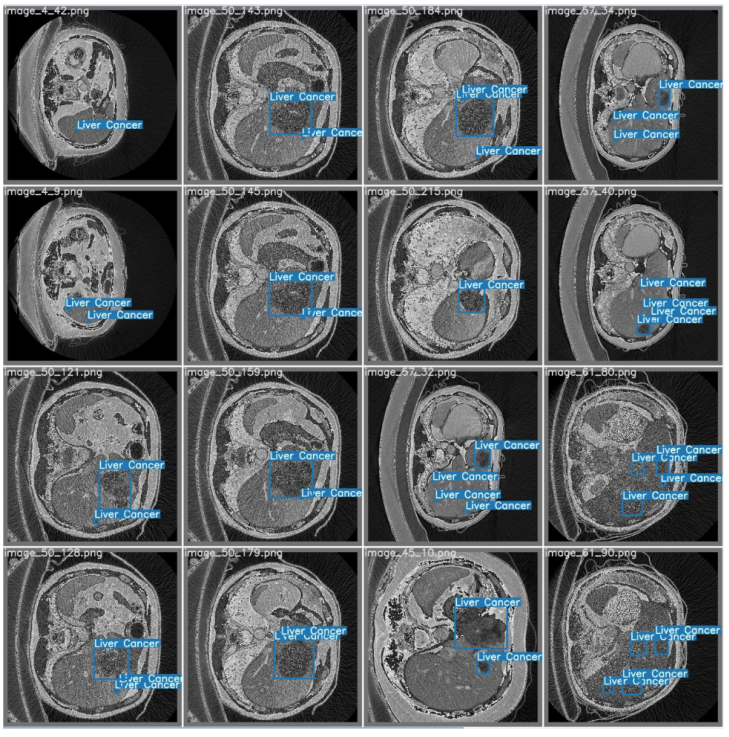


Additionally, I showcase some visual results obtained from the model's predictions on a set of test images. The images depict the CT scans with overlaid bounding boxes representing the detected liver tumors. These visualizations provide a qualitative understanding of the model's performance and its ability to accurately localize tumors of different sizes and locations within the liver.

Predictions



Labels



The visual results obtained from the model's predictions on the test images further support its capability to accurately identify and delineate liver tumors of varying sizes and locations. The overlaid bounding boxes showcased the model's ability to highlight the regions of interest and provide valuable information for clinicians and researchers.

However, it is worth noting that the detection of small tumors remains a challenging aspect. Due to their size and limited visibility, small tumors may not be as easily detected by the model. This limitation poses an area for improvement, and future iterations of the model could be enhanced to specifically address the detection of small tumors.

Overall, my experimental results demonstrate the potential of AI models, particularly the YOLOv7-tiny architecture, in the detection of liver tumors. The model's ability to detect larger tumors with high precision and recall provides valuable assistance to medical professionals, aiding in early diagnosis and treatment planning.

Limitations and Discussions

While my trained AI model has shown promising results in the detection of liver tumors, there are several limitations and areas for further improvement that should be considered:

1. **Difficulty in Detecting Small Tumors**: One notable limitation of the model is its challenge in accurately detecting small tumors. The visibility and distinct characteristics of small tumors within the CT scan images present a complex detection task. Enhancing the model's sensitivity to small tumors would greatly benefit its overall performance and clinical applicability.
2. **Leveraging Liver Labels for Improved Detection**: To address the aforementioned limitation, one potential improvement is to leverage the liver segmentation labels available in the dataset. By incorporating liver segmentation information, the model can gain valuable contextual cues and improve its ability to distinguish between liver tissues and tumors. Utilizing this additional information during training could lead to more precise and reliable tumor detection.
3. **Exploring Different YOLOv7 Architectures**: Another avenue for improvement is exploring different variants of the YOLOv7 architecture. While I used the YOLOv7-tiny architecture for my experiments, there are different versions and configurations available. Exploring these variations, such as YOLOv7 with different backbone architectures or modifications, may yield improved performance and address the challenge of detecting small tumors.
4. **Further Training and Fine-tuning**: Increasing the training duration or conducting additional training cycles could potentially enhance the model's performance. Extending the number of training epochs allows the model to learn more intricate tumor patterns and refine its detection capabilities. Additionally, fine-tuning the model on a larger and more diverse dataset can contribute to improved generalization and robustness.

5. **Utilizing Ensemble Models**: Ensemble learning, where multiple models are combined, can be an effective approach to boost the performance of liver tumor detection. By training multiple models with different initializations, architectures, or data augmentation techniques, and combining their predictions, I can leverage the collective intelligence of the ensemble to enhance detection accuracy and mitigate individual model biases.

In summary, while the trained AI model demonstrates promising results in liver tumor detection, it has certain limitations, particularly in detecting small tumors. Incorporating liver labels, exploring different YOLOv7 architectures, conducting further training and fine-tuning, and utilizing ensemble models are potential avenues for improving the model's performance. These enhancements can contribute to more accurate and robust liver tumor detection, ultimately benefiting healthcare professionals in clinical decision-making and patient care.