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Research Article

An XAI-Driven Support System to Enhance the Detection and Diagnosis of Liver Tumor for Interventional Radiologist

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ABSTRACT

In healthcare, the use of opaque deep learning models often results in limited transparency, potential bias, and inaccuracies, leading to a lack of trust among healthcare providers and patients. To address these challenges, this work integrates Explainable Artificial Intelligence (XAI) methods to enhance the transparency and interpretability of AI models, particularly in liver tumor segmentation. By employing XAI techniques, such as GradCAM (Gradient-weighted Class Activation Mapping), the proposed approach provides visual explanations that highlight the most critical regions influencing the model's predictions. This study focuses on combining state-of-the-art deep learning models, achieving a high accuracy of 99%, to ensure precise and reliable segmentation of liver tumors. GradCAM further enhances this process by generating heatmaps that explain the AI's decision-making, fostering trust and reliability among medical professionals. Beyond segmentation, the framework extends to decision support systems that offer transparent insights into medical decision-making, predictive analytics for patient outcome forecasting, and natural language processing for analyzing medical data. This approach ultimately empowers interventional medical professionals with accurate, interpretable, and trustworthy AI solutions, transforming how liver tumors are analyzed and segmented.
Keywords: XAI, GradCAM, Deep learning models.

INTRODUCTION

Artificial Intelligence (AI) plays a crucial role in reshaping the healthcare sector, driving substantial advancements in healthcare delivery, diagnostics, treatment planning, and research. In the realm of personalized medicine, AI models utilize patient data, electronic health records, and genetic information to assess the risk of specific conditions and predict patient outcomes (Kalyanathaya et al.,2022). The early and accurate detection and diagnosis of liver tumors are crucial for successful treatment and improved patient outcomes. In recent years, advancements in medical imaging techniques, such as CT and MRI, have enabled more precise visualization of the liver and associated lesions. However, interpreting these complex medical images and accurately identifying and characterizing liver tumors remains a significant challenge for clinicians, particularly in the context of interventional radiology procedures. AI and deep learning technologies have shown great promise in medical image analysis and Computer-aided Diagnosis (CAD) systems. These techniques can assist clinicians by automating the liver and its vessels' segmentation and detecting liver lesions(Hille et al.,2023;Zbinden et al.,2022). The integration of explainable AI techniques into medical imaging-based decision support systems is an emerging area of research that aims to enhance the transparency and interpretability of AI models, ultimately improving clinician trust and facilitating informed decision-making.

This paper is organized as follows: related works are discussed next, followed by a description of the system design for Liver Tumor Detection and Diagnosis. The implementation and results are the presented, concluding with a discussion on the conclusion and future work.

RELATED WORK

Significant advancements have been made in the application of AI-driven medical image analysis, particularly in liver and liver lesion segmentation. Recent studies have highlighted the efficacy of hybrid CNN-transformer architectures and transfer learning approaches in segmenting liver and hepatic lesions using MRI data(Zbinden et al., 2022). These advancements aim to streamline clinical workflows by automating the labor-intensive tasks of segmenting complex anatomical structures, enabling clinicians to focus on higher-level diagnostic and therapeutic decisions(Anil et al.,2023;Fallahpoor et al.,2024)

Modified architectures such as UNET-60 have demonstrated their applicability in classifying liver diseases while offering comparative insights into their performance against other classifiers. Challenges in accurately delineating lesions remain a focus of research, which provides a comparative analysis of different CNN architectures. (Jesi et al., 2024) propose Differential CNN to extracts the relevant features for improving the ability of a model to differentiate healthy and cancerous tissues. Integrating explainable AI (XAI) techniques into medical imaging decision-support systems is an emerging trend aimed at improving transparency and clinician trust. (Arrieta, A. B. et al. 2020) explore XAI taxonomies, emphasizing the dual objectives of model understanding and regulatory compliance. These studies underscore the value of explainability in machine learning (ML) models. (Chaddad et al.,2023) further investigate techniques such as saliency maps, Layer-wise Relevance Propagation (LRP), and SHAP to make AI models interpretable for clinicians. Specific methodologies have also been proposed for enhancing explainability. (Pfahler et al.,2021)present a method that interprets deep neural networks by analyzing intermediate layer representations, offering visual explanations through influential training instances and aggregated statistics. Similarly, (Alberto Lamas. et al.2020)propose the EXPLANet framework, which combines symbolic and deep learning for monument facade image classification using SHAP-Backprop for XAI-informed training.In liver tumor segmentation, (Alirr et al.,2024) propose an attention-based U-Net approach that uses hard and soft attention mechanisms, such as spatial and channel attention, to improve feature extraction from CT scans. (Bilic et al., 2017) analyze the performance of various deep learning models, including U-Net and ResNet50, on the LiTS17 dataset, demonstrating promising results for liver and tumor segmentation. Wang et al.emphasize preprocessing techniques and propose an efficient encoder-decoder architecture for U-Net, showcasing its advantages over contemporary designs(Wang et al.,2022).

The use of XAI tools in medical imaging has also been extensively studied in (Angelov et al.,2021). (Sun, Jia et al.,2020) applied SHAP, LIME, and SEG-GRAD-CAM for skin lesion classification using the HAM10000 dataset, finding LIME to provide the best local explanations. SEG-GRAD-CAM, while useful, was noted to be more challenging to interpret. (Selvaraju et al., 2017)proposed Grad-CAM as a visualization technique to highlight regions relevant to neural network decisions, showing its superiority over methods like Guided Backpropagation and Class Activation Mapping. Similarly, (Vinogradova, Kira et al.,2020). found SEG-GRAD-CAM to offer promising interpretability when applied to U-Net models for the CityShapes dataset. These studies demonstrate the potential of AI and XAI to revolutionize medical imaging by improving transparency, decision-making, and clinician trust. However, ensuring the ethical, transparent, and explainable implementation of these technologies remains critical for their broader adoption and success

SYSTEM DESIGN OF LIVER TUMOR DETECTION AND DIAGNOSIS

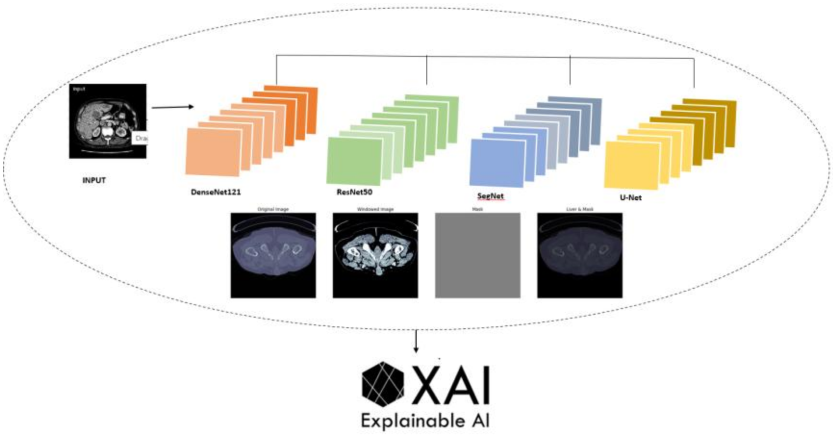

Figure 1. System Overview of Liver Tumor Detection and Diagnosis

The proposed Overview in Figure 1 consist of a multi-stage deep learning pipeline for liver tumor detection and diagnosis, coupled with an explainable AI component to provide clinicians with interpretable insights into the model's decision-making process.

1 Preprocessing

1.1 Histogram Equalization

Histogram Equalization is a technique in computer image processing designed to enhance image contrast. This is accomplished by evenly distributing the most common intensity values, thereby broadening the image's intensity range. In cases where the usable data in an image is characterized by closely distributed contrast values, this approach typically augments overall contrast. As a result, areas with initially low local contrast can experience an improvement in contrast(Fallahpoor et al.,2024).

1.2 Image Windowing

Windowing is an image processing technique applied to CT scans to emphasize crucial anatomy, facilitating easier analysis of the images. Hounsfield windowing used here to isolate the intensity range corresponding to the liver tissue in the CT scan. Adjusting the windowing settings enhances the contrast of relevant structure while suppressing irrelevant information(Alirr et al.,2024). The image after equalization and windowing is shown in Figure 2. The CT slice is shown in grayscale (bone colormap) to look like traditional medical images.

Figure. 2. CT scan after equalization and Windowing

2 Methodologies used in ML Model

2.1 UNet

UNet stands out as a widely adopted deep learning framework employed in semantic segmentation tasks across diverse domains, particularly in medical imaging. Engineered to harness the complete resolution of the input image for segmentation, UNet achieves this by concurrently incorporating context information through both a contracting path and a symmetrical expanding path.

2.2 ResNet 50:

ResNet50, a prevalent deep learning framework, finds extensive application in diverse computer vision assignments, such as image classification and object detection. U-Net model with ResNet-50 as the encoder backbone for liver and tumor segmentation from medical images. The images and corresponding masks are preprocessed using transformations like resizing, normalization, and conversion to tensors. A DataBlock pipeline is used to map input images to masks and generate a DataLoader for training. The model is trained with a cross-entropy loss function and metrics such as foreground accuracy, custom accuracy, Dice and Jaccard for prioritizing tumor detection. After fine-tuning, the best model is saved, and the segmentation results are visualized, ensuring an efficient workflow for liver segmentation tasks.

2.3 DenseNet-121

U-Net model with DenseNet-121 as the encoder backbone for liver and tumor segmentation. Images and masks are preprocessed efficiently using multithreading to resize and standardize input data. The model is trained using a DataBlock pipeline that pairs images with their corresponding masks, applying transformations like normalization and resizing. DenseNet-121, pre-trained on ImageNet, extracts rich features for U-Net's decoder, which generates pixel-wise segmentation masks. The model is fine-tuned using CrossEntropy loss, with performance evaluated using

Dice and Jaccard metrics. The trained model is saved for deployment, ensuring efficient segmentation for medical imaging tasks.

3 XAI-GradCAM

The interpreting of model's focus areas during segmentation tasks has been analysed by Grad-Cam visualization. It extracts the activations and gradients from a specified layer in the model (default layer_name='0') after making predictions on the input image (x_b) and its corresponding mask (y_b). The code calculates class-specific heatmaps by weighting the activations with the gradients, then applies a color map to highlight the regions of interest. The final blended image is generated by overlaying the heatmap on the original image. The class_indices and weights allow customization for different classes (e.g., liver or tumor) in segmentation tasks is expressed in the Equation 1, where w_c represents the weights associated with different classes which is calculated by the mean of gradients across spatial dimensions. A_c represents the activation of the feature map from the convolution layer(Bilic et al.,2017)

$$Heatmap_i = ReLU(\textstyle\sum_c w_c \cdot A_c) \qquad \text{--(1)}$$

IMPLEMENTATION AND RESULT OF LIVER LESION SEGMENTATION

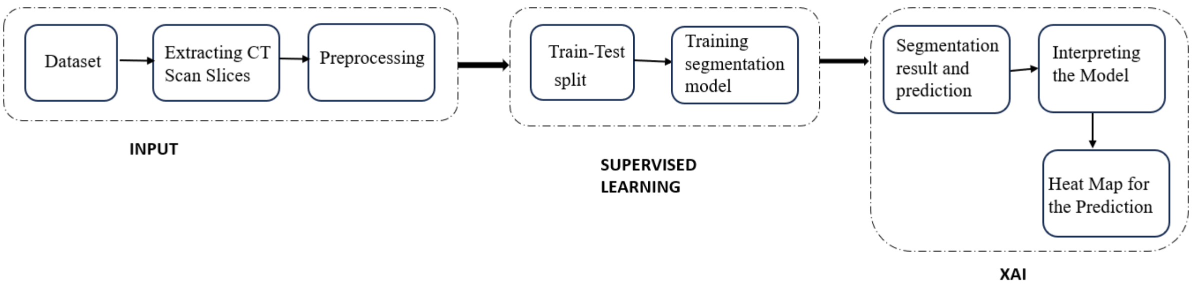

Figure 3: Workflow of Liver Lesion detection

Colab, a cloud-based platform, is utilized to execute Python code in a Jupyter Notebook environment. The hardware accelerator v2-8 TPU (Tensor Processing Unit) available in Colab is employed for model training. FastAI, an open-source library, is used for preprocessing with its *DataBlock API* and training using the *unet_learner* on TPU. It also provides built-in support for metrics such as Dice and Jaccard to evaluate model performance. NiBabel, another Python library, is employed for handling neuroimaging data. Additionally, libraries like NumPy, Pandas, and Matplotlib are utilized for data processing and exploratory data analysis. The LiTS17 training dataset used in this study comprises 131 abdominal CT scans, with in-plane resolutions ranging from 0.55 mm to 1.0 mm and inter-slice spacings varying from 0.45 mm to 6.0 mm. Each scan contains between 75 and 987 slices, with each slice having dimensions of 512x512 pixels (Bilic et al.,2017). The workflow of Liver Tumor detection is illustrated in Figure 3.

Pseudo Code for Liver Lesion Segmentation and Interpretation:

Input
C_i: set of CT scans where i=1,2.....130
S_j: Slices of each CT scan where j=0,1....9
M_j : Corresponding Masks
Windowing(w,l) \\ w= window width; l=anatomical region
From Pixcel (px-px_min) / (px_max-px_min) \\ to normalize[0,1]
For each S_j do begin
Step1(train);
Use S_j: labels as [0-background, 1-liver, 2-Tumor]
e = Epos , wt_delay=0.1
Savemodel()
Step2(test):
Evaluation Metrics=M_1, M_2, M_3
End
Gradcam(learn,x_b, y_b, layername)
learn = trained model
x_b = Input image batch
y_b= Target labels
Learn specified layer(h_a, h_g) where h_a = *activation*, h_g = *gradients*
Forward pass:
Make Prediction with model x_b
Backward pass:
compute gradients w.r.t. the feature map of the target layer.
Weighted Sum(Feature map with h_a, h_g)
Normalize and convert heatmap to RGB format
Return *: blended image showing the Grad-CAM overlay*

From the pseudocode , it is ensured that for each input CT scan available for training, there is a corresponding mask so the model can train upon it. If there is any ct scan that misses its mask, that should be weeded out from being used for training. CT Scan of the liver of each person is given in the form of .nii files and each file contains image slices. The slices are extracted for processing and training in upcoming steps. The extracted image slice is processed in order to emphasize over liver and lesion areas. At first, image windowing is applied followed by histogram equalization. Further, a color map is applied over the processed image for further improved visibility. (Window Length - 150 Hounsfield Units, Window Width - 30 Hounsfield Units). As illustrated the processed dataset is provided to models such as DenseNet121, ResUnet50, SegNet and U-Net for training.

Finally, the model and an additional sample input, along with the corresponding output, are evaluated using the metrics summarized in Table 1. The number of epochs for each model varies based on the performance achieved. The epochs used for the respective models are as follows: DenseNet121 - 2 epochs, ResUnet50 - 5 epochs, SegNet - 5 epochs, and U-Net - 5 epochs. Figure 4 shows the graph of number of eposes of each models attained the coreesponding evaluation metrics.

Table 1. Evaluation Metrics Analysis

Model	Dice similarity Coefficient	Jaccard Index	Accuracy
DenseNet121	97.41%	94.95%	99.83%
ResUnet50	88.53%	78.66%	99.79%
SegNet	89.38%	88.12%	99.01%
U-Net	83.80%	80.99%	98.49%

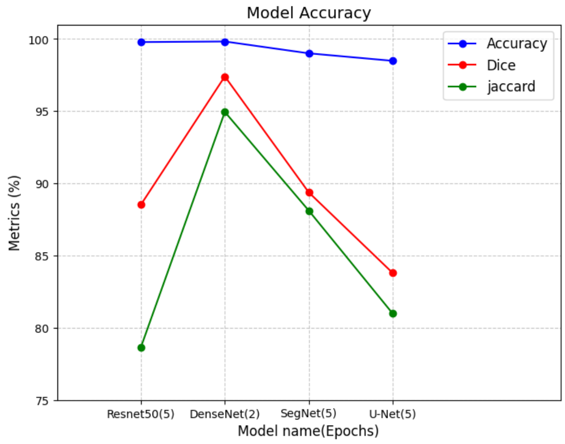

Figure 4. Epos vs Metrics

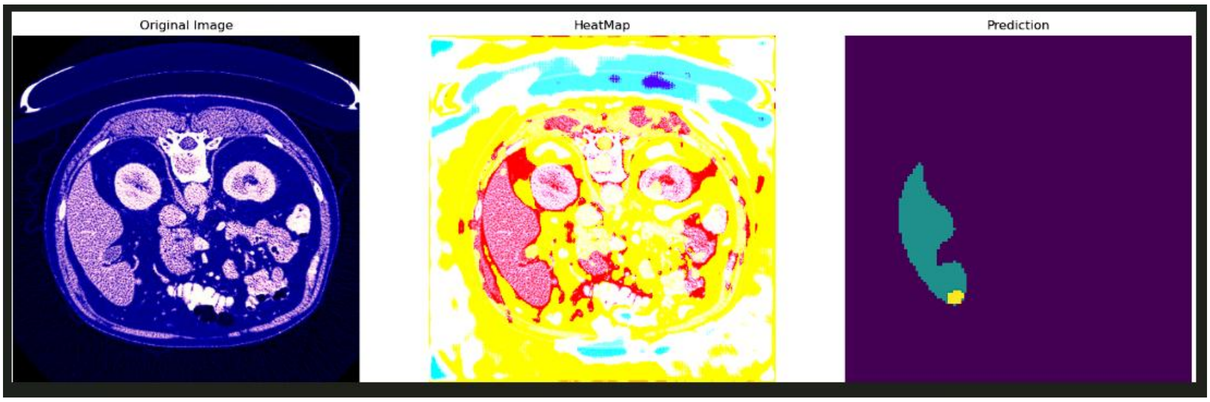

Figure 4: Heatmap I of ResUnet50

In Figure 4, the prediction given by the model of the processed CT scan i.e classification of liver and lesion is present on the right side. But, the model came to this conclusion on the left by considering various parts of the input. The very important parts are represented with red and white dots whereas the less important parts are represented with yellow and the least with light blue and white. Similarly in Figure 5, on the right side is the prediction supplied by the model of the processed CT scan, i.e. classification of liver and lesion.

However, the model on the left arrived at this conclusion by taking into account various parts of the input. The most significant elements are represented by red and white dots, while the less important parts are represented by yellow dots and the least important by light blue and white dots. It is to be noted that only a small percent is predicted and liver is not present in the prediction because of the slice and the angle of the CT scan considered as input. Finally in

Figure 6, under the right angle, the liver and lesion is very much visible and the explanation follows the same pattern as followed in previous images.

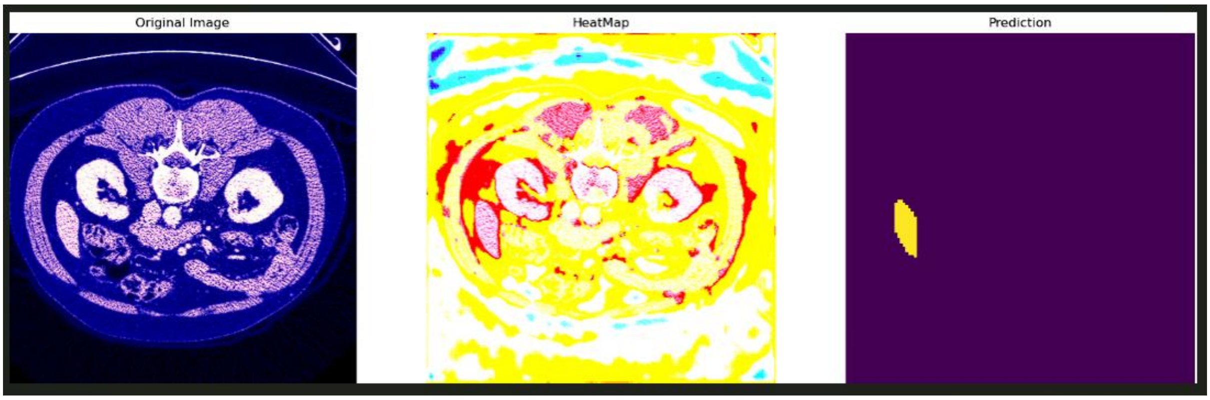

Figure 5: Heatmap II of ResUnet50

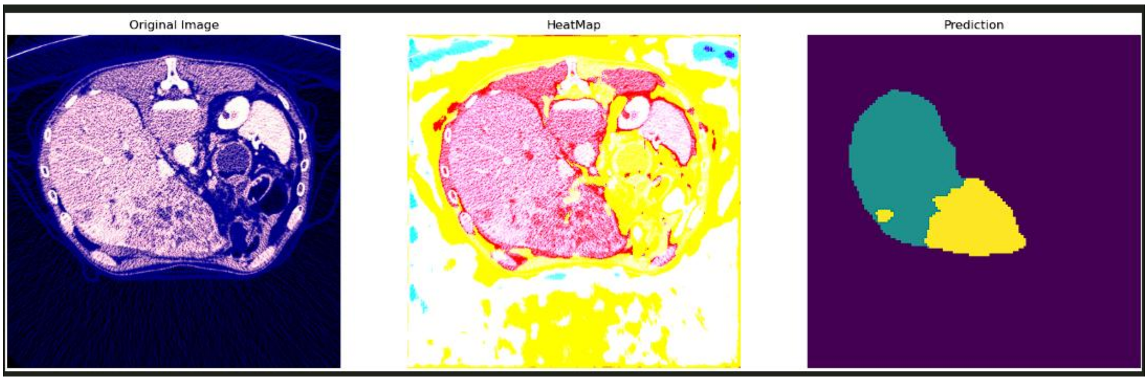

Figure 6: Heatmap III of ResUnet50

CONCLUSION AND FUTURE WORK

In the context of liver segmentation modeling, the integration of Grad-CAM could yield valuable insights into the liver regions utilized by the model for segmentation decisions. Specifically, it aids in pinpointing accurately or inaccurately segmented portions of the liver. Analysis of the Grad-CAM heatmap enables the identification of liver regions that the model either neglects or overly focuses on, potentially resulting in segmentation inaccuracies. These insights offer guidance for refining the model's architecture or optimizing the training dataset to enhance segmentation precision. In essence, the incorporation of Grad-CAM within a liver segmentation model facilitates a deeper understanding of the model's decision-making process, highlighting avenues for enhancement and ultimately leading to improved segmentation accuracy and more dependable diagnoses. In the future, the integration of multiple explanation tools such as SHAP or Seg-Grad-CAM could offer deeper insights into the model's underlying principles. Furthermore, concerning the segmentation model, additional training could enable it to predict optimal incision points in three dimensions, thereby minimizing damage to arteries and preserving liver volume. Presently, the model is tailored to a single use case, but efforts can be made to develop a model-agnostic system capable of providing interpretations for similar models.

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