Deep Learning-Based Lesion Segmentation for Early Liver Tumor Detection in Rwanda

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ABSTRACT

This study presents a deep-learning model, based on a hybrid ResNet-UNet architecture, designed to automate liver lesion localization and enhance early detection. With an accuracy of 99.1% and an IoU of 0.96, the model proves effective for liver lesion detection in Rwanda's National Hospitals. Compared to prior research, our model's high IoU score underscores its capability for precise liver tumor segmentation, essential for accurate diagnosis and treatment planning.

PROBLEM STATEMENT/ MOTIVATION

Global Cancer Statistics 2020 emphasize that liver cancer accounts for 8.1% of cancer deaths in Africa[3]. In Rwanda, it was responsible for 1.22% of total deaths in 2020, with over 46,000 new cases reported annually and limited treatment options [1][2][3]. The delay between the disease onset and detection often results in postponed treatments and poor patient outcomes [4]. Driven by these challenges, our research introduced a deep-learning model for early liver lesion detection and precise tumour outcome prediction to ultimately enhance patient outcomes in Rwanda.

BODY ANATOMY (LIVER)

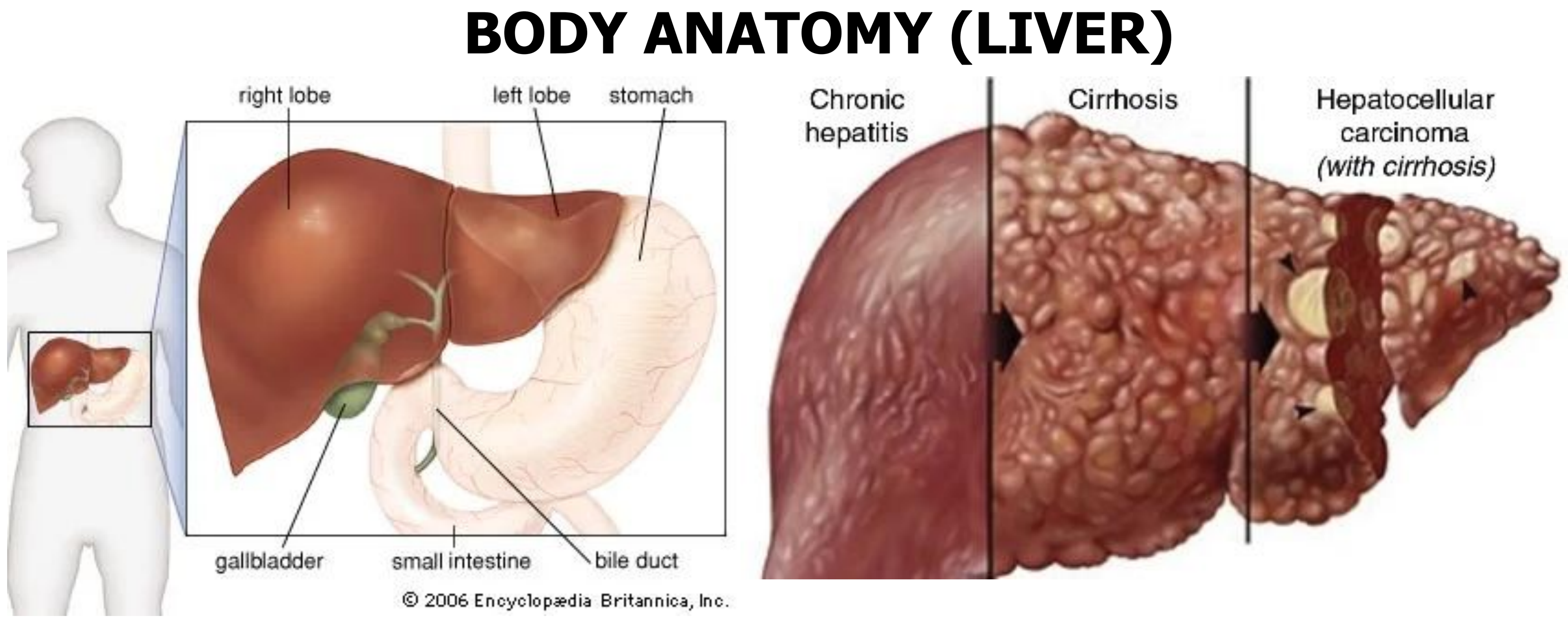

Figure 1: Body Anatomy (Liver)

RESULT AND DISCUSSION

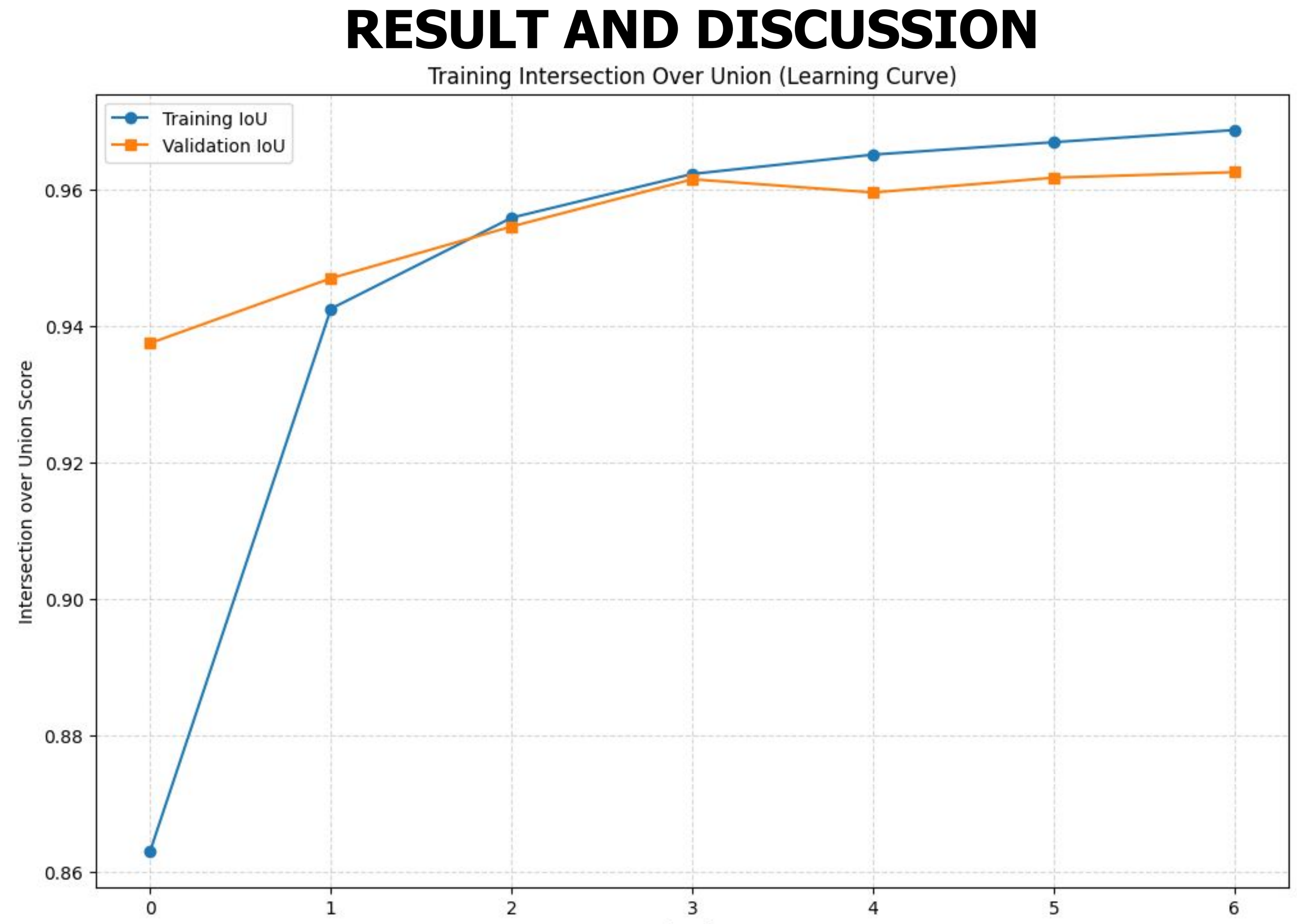

Figure 5: Training Data (Intersection Over Union)

Table II: Comparison with previous work

Citation	Training Data	Accuracy	Test Data
[5]	Chebyshev Graph Convolutional Layer	93%	0.908
[6]	ResNet-UNet	99%	-
Our Work	ResNet-UNet	99.1%	0.96

DATA REPRESENTATION

The dataset includes 1692 paired liver CT scans with corresponding segmentation masks.

TABLE I: Data Composition

State	Training Data	Validation Data	Test Data
No. of Dataset	1354	169	169
Dim.	128 * 128	128 * 128	128 * 128
No. of Channels	Image: RGB (3) Mask: Grayscale (1)	Image: RGB (3) Mask: Grayscale (1)	Image: RGB (3) Mask: Grayscale (1)

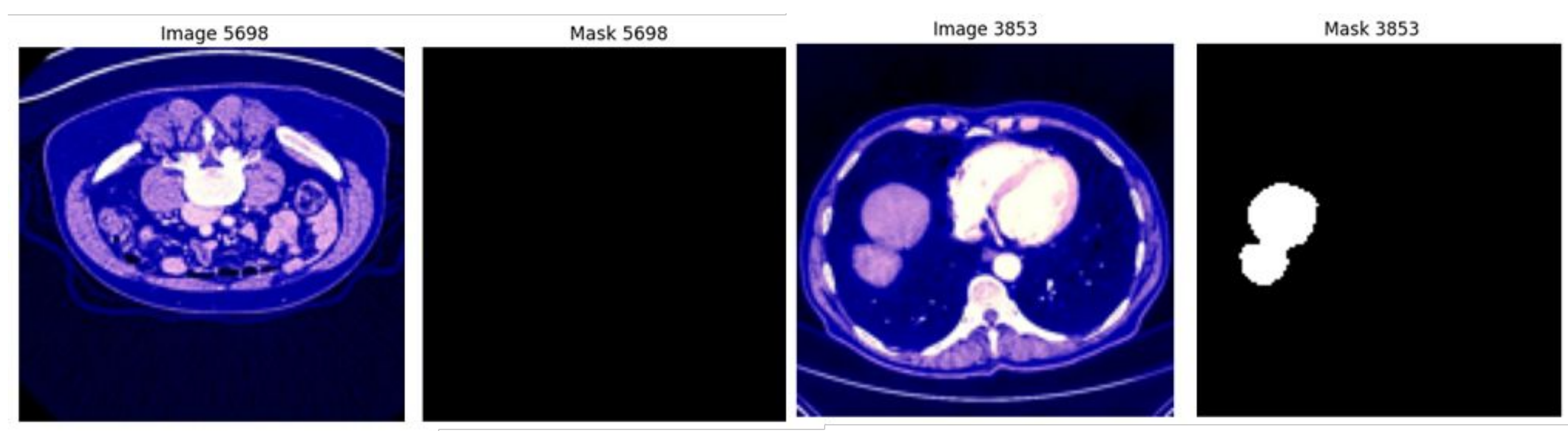

Figure 4: Data Representation Overview

METHODOLOGY

The methodology pipeline is illustrated in Figure 3.

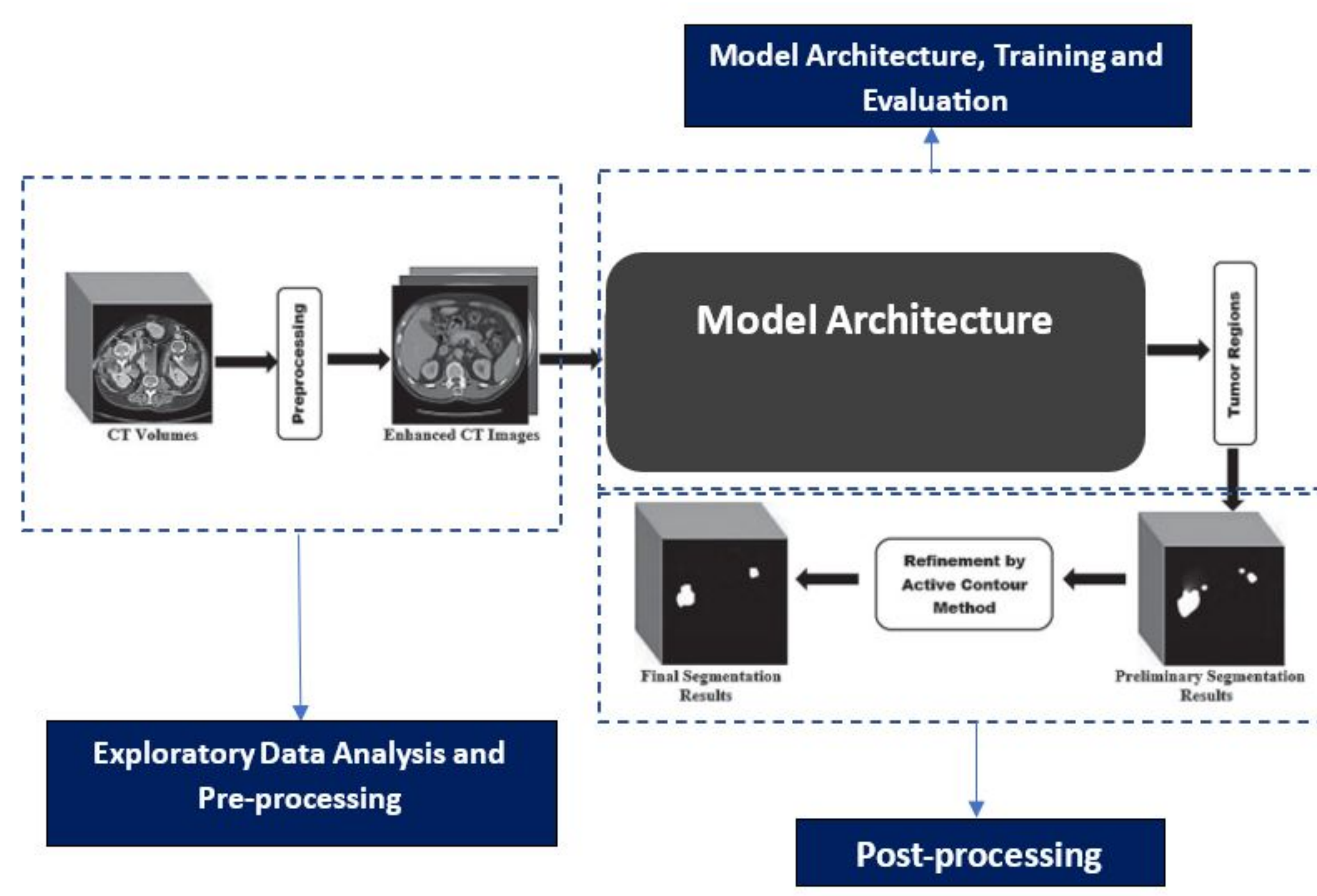

Figure 3: Methodology Pipeline

Result Inference

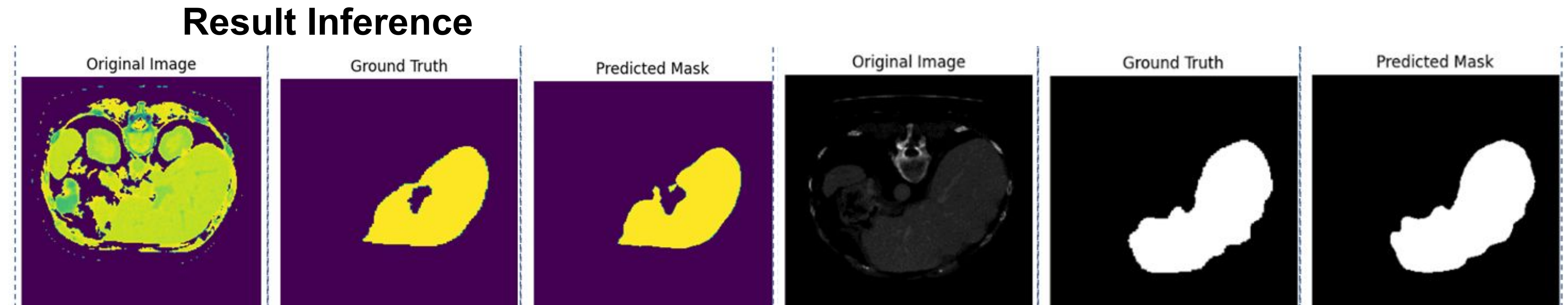

Figure 6: Result Inference – Ground Truth vs Predicted Mask

REFERENCES.

1. R. Ibrahim, S. Samian, M. Mazli, M. Amrizal, and S. M. Aljunid, "Cost of Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scan in UKMMC," BMC Health Serv. Res., vol. 12, no. Suppl 1, p. P11, Nov. 2012, doi: 10.1186/1472-6963-12-S1-P11.
2. M. Y. Ansari et al., "Practical utility of liver segmentation methods in clinical surgeries and interventions," BMC Medical Imaging, vol. 22, no. 1, May 2022, doi: https://doi.org/10.1186/s12880-022-00825-2.
3. "Liver Cancer in Rwanda," World Life Expectancy. https://www.worldlifeexpectancy.com/rwanda-liver-cancer#:~:text=Rwanda%3A%20Liver%20Cancer&text=According%20to%20the%20latest%20WHO (accessed Mar. 28, 2024).
4. Anatomy and Function of the Liver." Accessed: Jun. 05, 2024. [Online]. Available: https://www.stanfordchildrens.org/en/topic/default?id=anatomy-and-function-of-the-liver-90-P03069

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