A Deep Learning Model for Pancreatic Ductal Adenocarcinoma Chemotherapy Outcome Prediction

Nichol He, Connor Kamrowski, Thulasi Varatharajan, Amy Syzmoniak, Maulik K. Lathiya,
Dr. Rahul Gomes, Dr. Sushil Kumar Garg | Computer Science Department, UW-Eau Claire | Mayo Clinic Health System

University of Wisconsin Eau Claire

Introduction

Pancreatic Ductal Adenocarcinoma (PDAC)

- Pancreatic Cancer is the **fourth most deadly cancer in 2021**.
- PDAC accounts for **90% of Pancreatic Cancers**.
- PDAC has an overall **8.5% 5-Year Survival Rate**.

Patients diagnosed with PDAC **respond differently to surgery** or chemotherapy with unclear causes.

Ability to characterize PDAC tumors and predict response to chemotherapy becomes essential to comprehensive treatment planning.

Radiomics and Texture Analysis

Radiomic texture analysis is a tool that can quantify textural properties by analyzing pixel intensity and distributions. Advantages of Radiomics includes:

- **Detecting textures** too minute for the human eye.
- **Generating more information** about the tumor to help inform clinical decision making.
- **Non-invasive**, inexpensive, and faster than conventional lab-tests and biopsies

Radiomics has seen wide applications in recent studies. However, **Radiomics has poor reproducibility** and has not been applied to pancreatic cancer studies before.

Deep Learning

Deep learning is a type of Artificial Intelligence (AI) that **is effective in extracting patterns and trends hidden in data**. When working with images, a type of deep learning algorithm called Convolutional Neural Networks (CNN) is used due to its effectiveness

Project Goals

- **Generate a deep learning segmentation model** for Mayo Clinic PDAC patients with minimal Mayo Clinic data.
- **Apply Radiomic texture analysis** to generate radiomic textures on PDAC patients.
- Generate a deep learning model for **chemotherapy outcome prediction** and treatment suggestion.

Proof of Concept

For preliminary analysis, a CT scan dataset was collected from **420 CT scans of the pancreas**, processed and deidentified from The Medical Segmentation Decathlon. Each CT scan had a resolution of 512-by-512 with variable number of slices per patient.

Software Used for Analysis

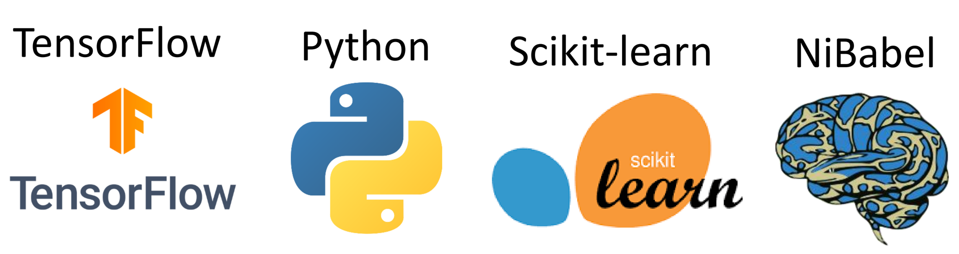

Fig 1. Python libraries utilized for Deep Learning and pre-processing.

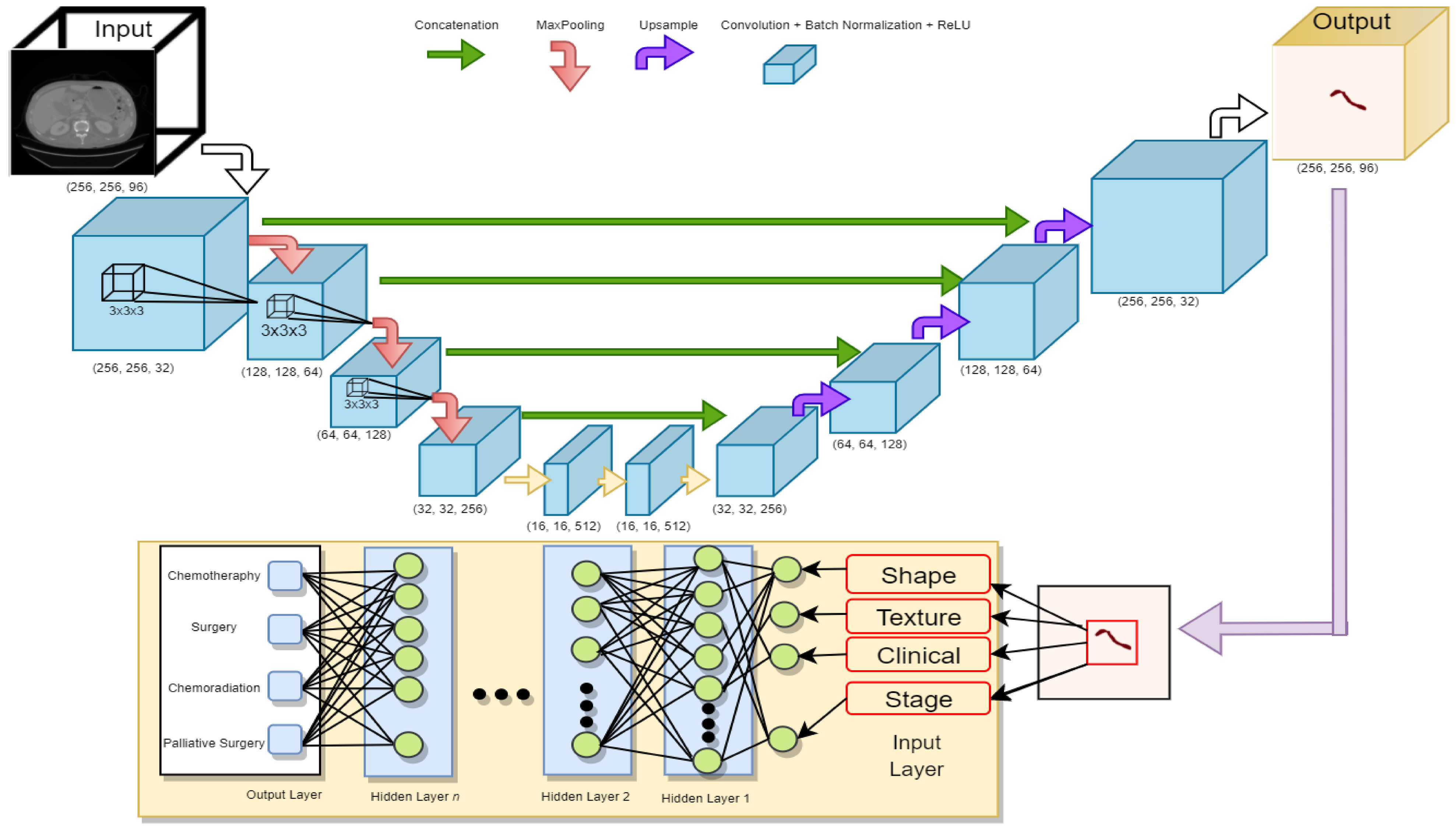

Fig 2. Visual representation of proposed model to achieve PDAC outcome prediction

Proposed Model

The proposed model describes a three-step process:

- A customized CNN will be applied on the abdominal CT Scans of a PDAC patient to automatically **generate a segmentation of the pancreas**.
- The generated segmentation will be re-applied to the CT Scan as a mask for Radiomic texture analysis. **Radiomic features** summarizing the PDAC texture **will be generated**.
- The radiomic features will be combined with **clinical factors** such as patient demographics, blood antigens, and other relevant data in order to **generate recommendations for treatment**

Preliminary Analysis

Dataset Preprocessing and Augmentation

Each CT scan was resized to (256, 256, 96). 256 is the slice width, and the height has the same value. 96 is the depth of the slices. The final dataset from all scans contained **19584 scans** with segmented masks of the pancreas.

Before being used in the model, the following steps were used to prepare CT images and create four variants of the dataset:

- **Original dataset** with only normalization.
- **Cropped version** of original dataset to focus more on pancreas.
- **Addition of window/level** to filters out with Hounsfield Units (HU) not corresponding to structures of interest and increase expression of pancreas.
- Addition of **window/level** and **crop** during preprocessing before normalization.

Each dataset was subjected to random rotation while training to reduce any bias caused by position of pancreas in the dataset.

Results

- Four variants of a 2D-Unet model was **trained on 15667** images and **validated on 3917** images over **50 epochs**. A segmentation result is shown in Figure 3.
- **Addition of window/level and crop** during preprocessing **improved model performance** reaching a Jaccard Score of 0.64. Results of 4 models shown in Figure 4.

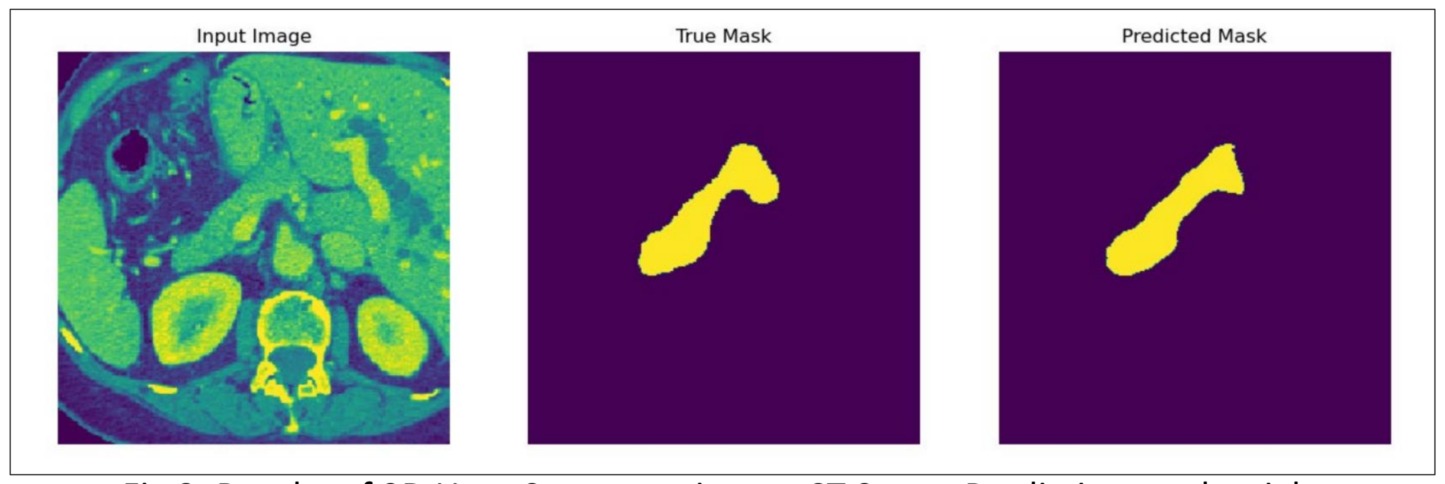

Fig 3. Results of 2D Unet Segmentation on CT Scans. Prediction on the right.

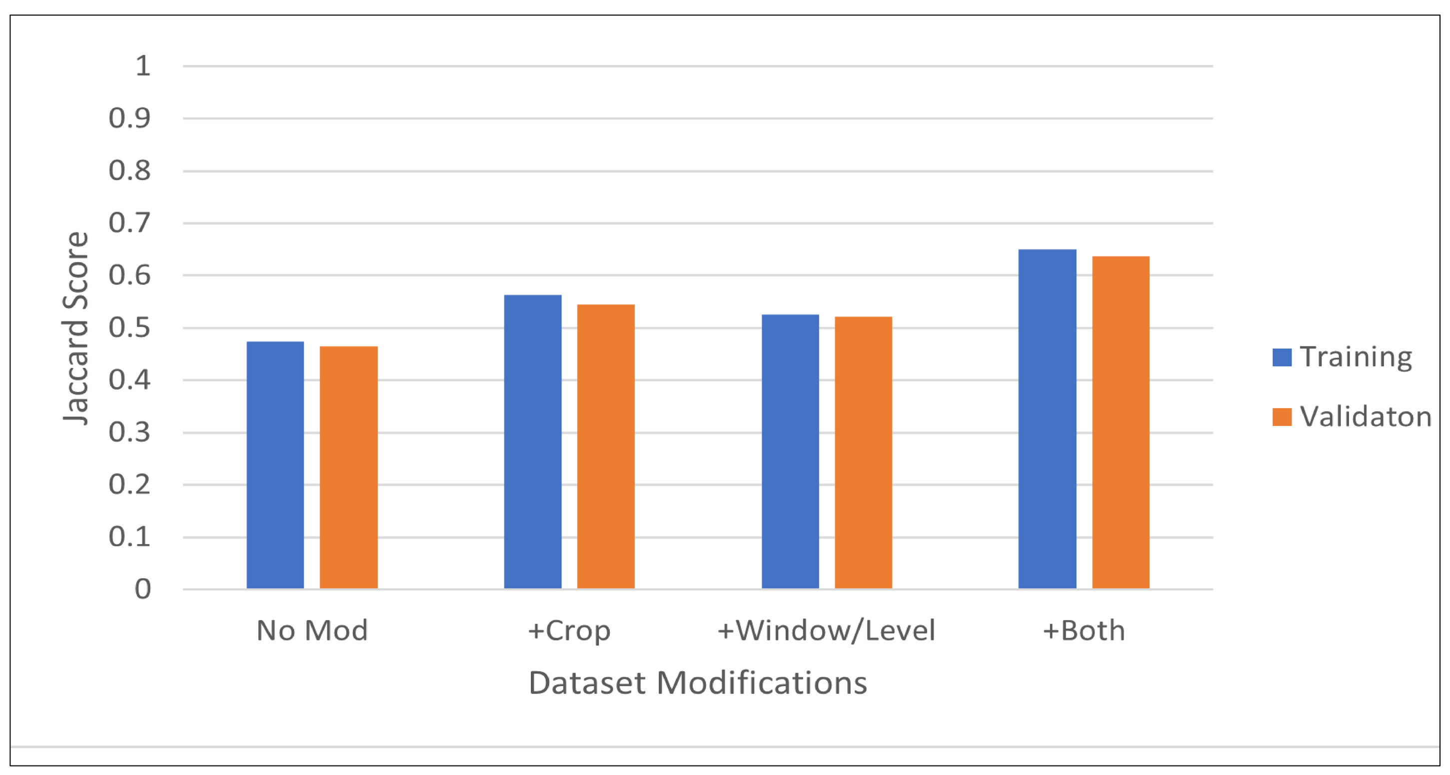

Fig 4. IoU segmentation metrics for Unet segmentation models.

Future Direction

- Development of **Transfer Learning model** adjusted for Mayo Clinic Data.
- Validating and implementing Radiomic texture Analysis.
- Outcome prediction and treatment recommendation.

Acknowledgements

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