Using 3D Deep Learning for Detecting of Inferior Vena Cava Filters

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ABSTRACT

Inferior vena cava filters (IVCF), shown in Figure 1, are placed to keep blood clots from travelling up to the heart, and they are (usually) designed to be removed.

However, it is very common that IVCF retrieval doesn't occur, which puts the patient at risk of potential complications.

This research aims to propose an automated 3D deep learning algorithm which can detect IVCF from CT scans and alert healthcare professionals.

Data augmentation will be utilized to increase model prediction accuracy and reduce overfitting before scans are fed to the 3D UNet model.

By utilizing different filters to extract relevant information from the scans such as texture, shape, and contrast we will enable a real-time detection IVCF detection model ready for use by interventional radiologists.

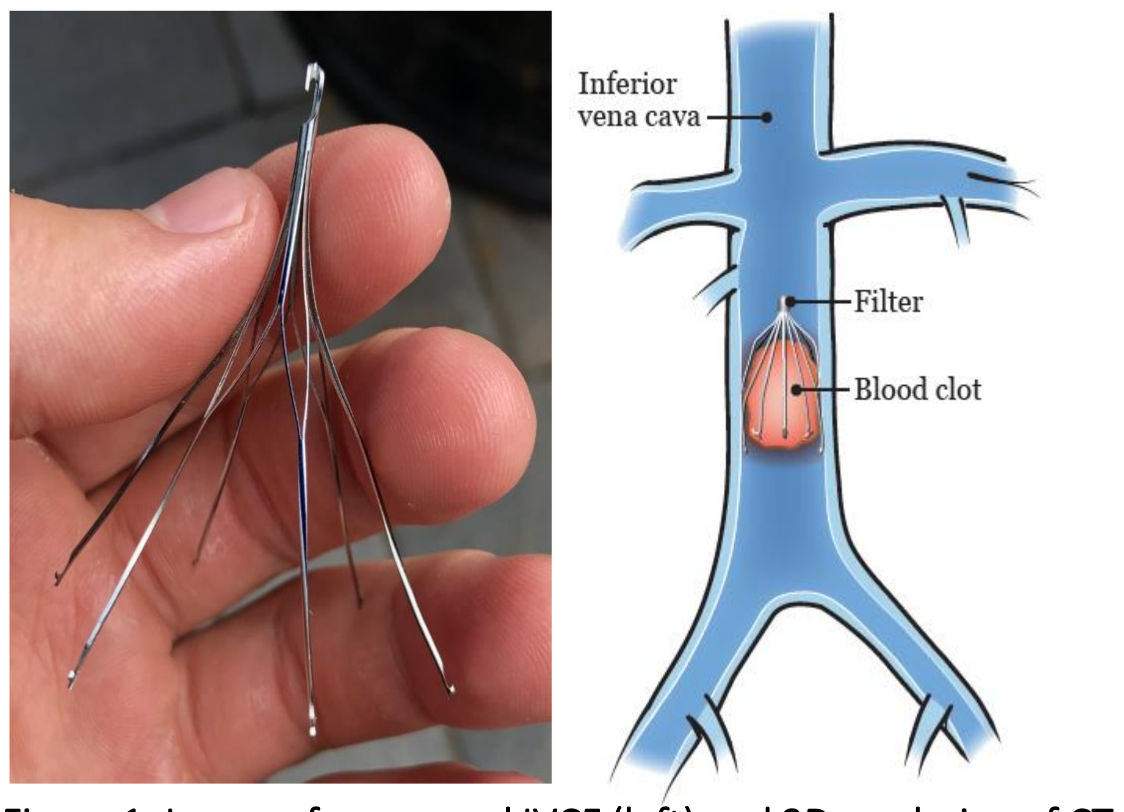

Figure 1: Image of an unused IVCF (left) and 3D rendering of CT scan showing IVC filter (right)

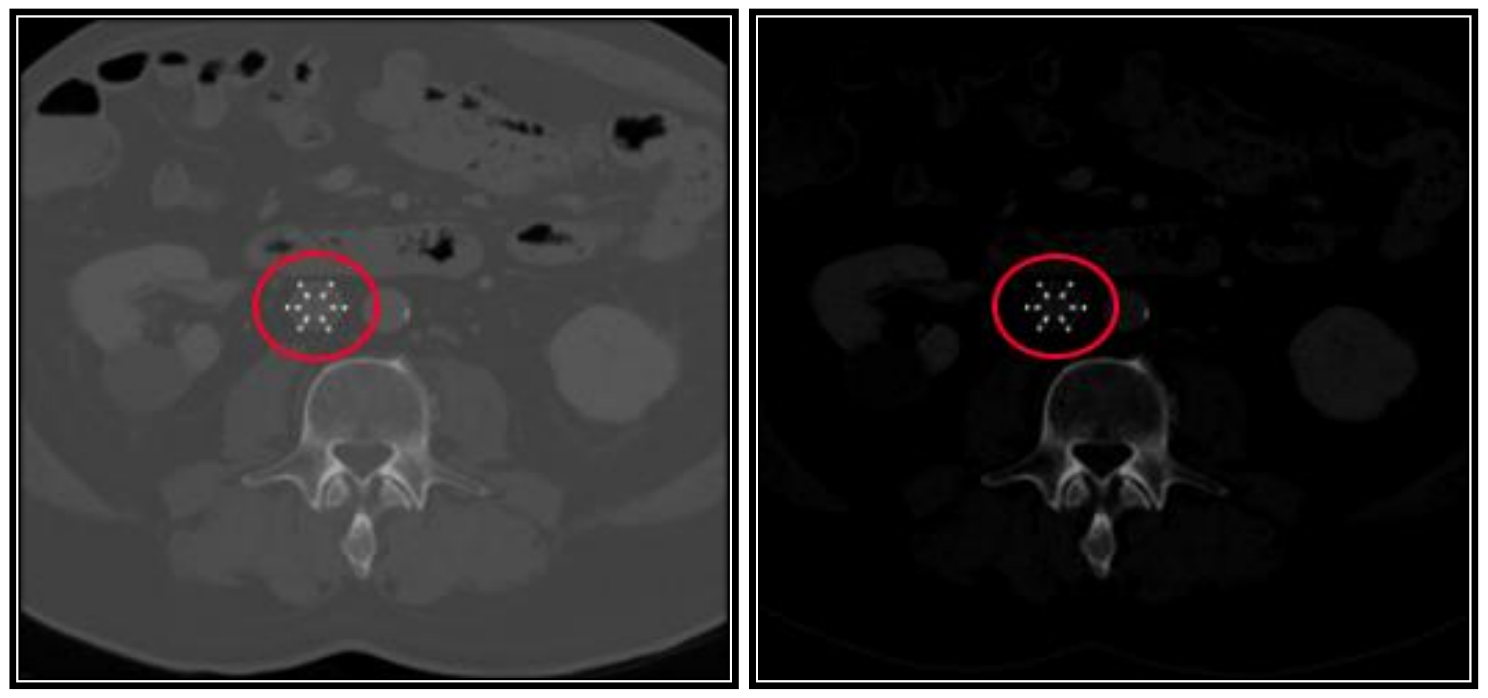

Figure 2: IVCF before normalization (left) and after normalization (right)

DATA OVERVIEW

DATASET INFORMATION

A CT scan dataset was collected for the purpose of this research from the Mayo Clinic Health System. Scans were collected from radiology report texts, deidentified, and manually verified.

The final dataset contains 90 scans with IVC filters and 90 normal scans.

DATA PREPROCESSING

Before being used in the model following steps were used to prepare CT images:

- 40 cm were cropped from the base of the lung. Followed by 20.31% crop on all four sides of each 2D slice
- Each scan was resized to a shape of 128 x 128 x 64 pixels.
- The intensity was cropped to a range of 1 to 2500 Hounsfield units(HU).
- Normalization also occurs, shown in Figure 2. With hard normalization, more techniques are used to increase the size of the filter as well as select only denser materials in the image (including metals, bones, etc.)

DATA AUGMENTATION

Data augmentation techniques were utilized to reduce any bias brought by the dataset. The technique used was a left/right flip, as seen below in Figure 3.

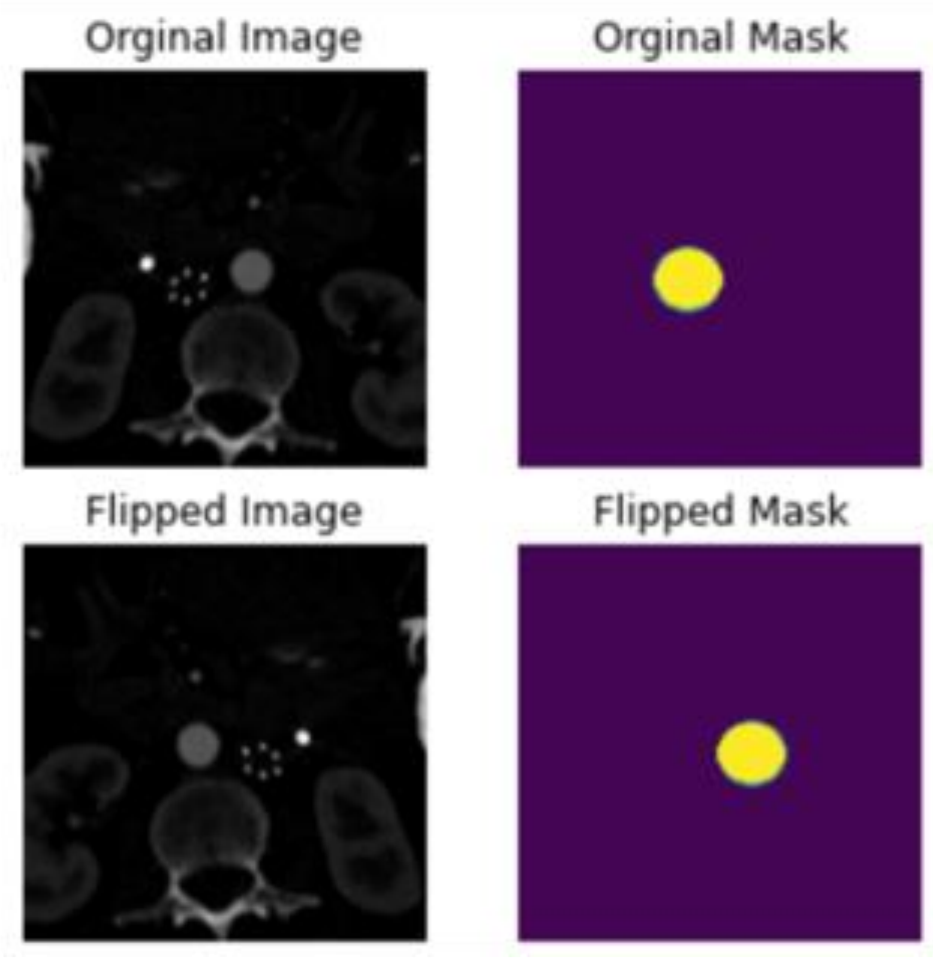

Figure 3: Image augmentation while model training

Figure 4: Architecture of the UNet model used for detection of IVCF

MODEL OVERVIEW

A deep learning UNet model was determined to be best suited for this application.

A deep learning model offers a higher overall accuracy when compared to machine learning approaches. This is necessary for the medical field as patient safety is a top priority.

MODEL DESIGN

- The model uses convolution blocks: two sets of 3D convolution and batch normalization
- The model is made of 4 encoding blocks (32, 64, 128, and 256 filters), 4 decoding blocks (256, 128, 64, and 32 filters), and a bridge.
- Each encoding block is composed of a convolution block and a max-pooling layer.
- Each decoding block uses 3D convolution transposed, concatenation, and a convolution block.
- The bridge is a convolution block with 512 filters
- Each input to the model is a 3D image in the shape (128, 128, 96).
- **The model returns a (128, 128, 96) predicted mask, outlining the location of the IVCF**

MODEL TRAINING

A total of 144 CT images were used for training and 36 for validation. The training process is depicted in Figure 4. The model was trained for 100 epochs without early stopping.

Deep learning models are computationally intensive, and all experiments were conducted using the computing resources available through the **Blugold Center for High-Performance Computing**.

RESULTS

The highest dice coefficient achieved was 0.9707 on the training dataset and 0.9704 on the validation dataset. But the model was not very accurate when making predictions. It had a mean intersection over union of 0.49922752 when predicting on a test image. Figure 5 shows how the accuracy of the model increases with the number of epochs when the model is trained using 144 CT images.

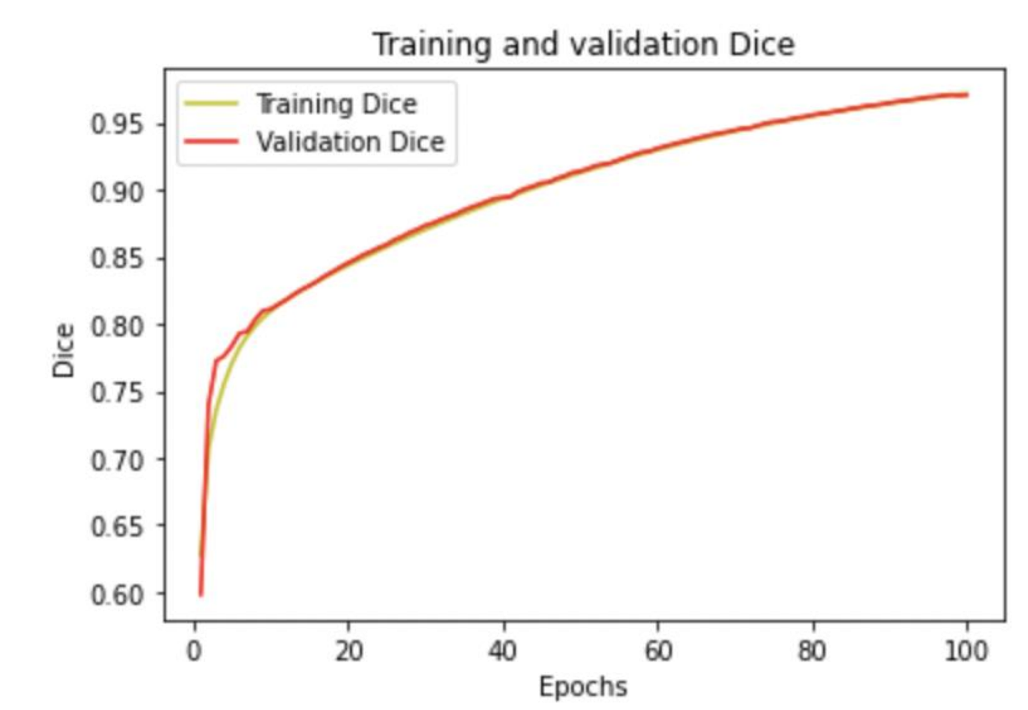

Figure 5: Training dice coefficient of deep learning model

FUTURE WORK

- The model will be improved upon to increase the mean intersection over union for test images.
- The model will be compared to 2D UNet Model for image segmentation.
- The model will be deployed in the Mayo Clinic Health System to provide immediate results after a patient receives a CT scan.

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