FINAL PROJECT: CHAOS

Liver Segmentation

Group 2 - Deep Learning Methods for Medical Image Analysis
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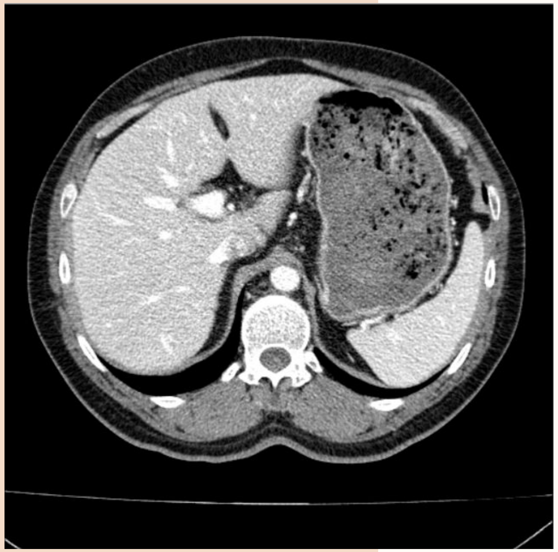
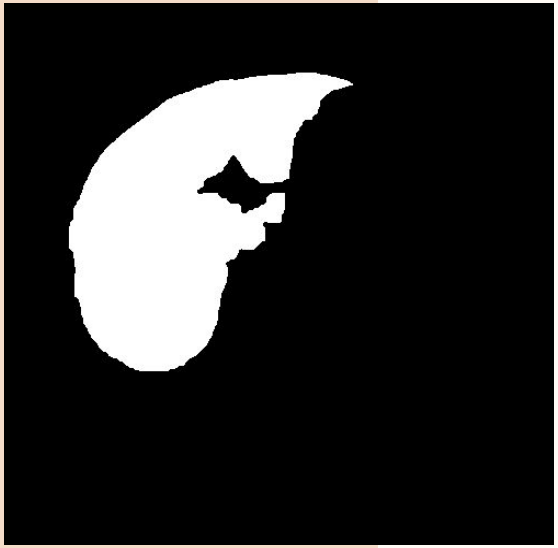




Steps followed to solve the challenge

1. Analyzing the data to work with
2. Data loading
3. Data generator function
4. Training the model
5. Obtaining the predicted masks
6. Calculating the dice scores
7. Conclusions

Data structure

- Data
  - Train_sets
    - CT
      - 1
        - **DICOM_anon:** *.dcm files* containing the CT images for all the slices
        - **Ground:** *.jpg files* containing the masks for each slice
      - 2
        - DICOM_anon
        - Ground
      - 3
        - ...
        - ...
      - 4
      - ...
    - MR
  - Test_sets

- **20 patients in Train_sets**
  - **15 train, 4 validation, 1 test**
- **Around 90 slices per patient.**

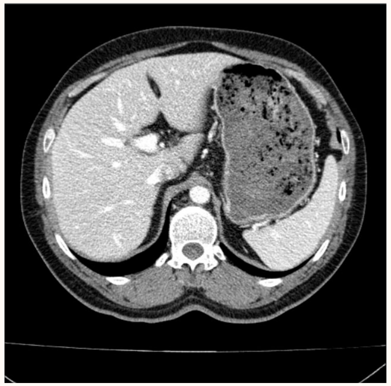


Figure 1: Dicom_anon file

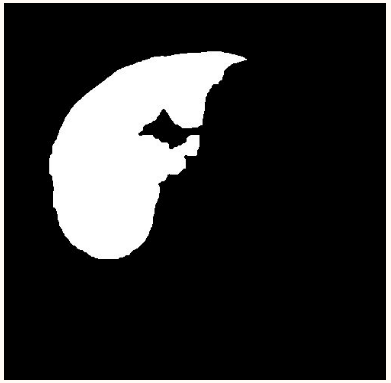


Figure 2: Ground file

Data loading

Images: *.dcm files*

1. dcmread
2. pixel_array
3. apply_modality_LUT

np.unique(dicom_array)
array([-1024., -1023., -1022., ..., 1183., 1187., 1211.])

Masks: *.png files*

1. Image.open
2. Array

np.unique(ground_array)
array([False, True])

patient_data = {'patient id' : [image,mask] for all the slices, 'patient id' : [image,mask], ...}

To maintain order in the slices: ***sorted()*** *when loading the images*

- 15 patients to train_data
- 4 patients to val_data
- 1 patient to test _data

Dictionary to list

- train_pairs
- val_pairs
- test_pairs

Data generator function

- Data augmentation

  Parameters:
  ImageDataGenerator(rotation_range=5, fill_mode='nearest')

- Image normalization
  - Dividing each image array by 1400
    - To have all values in the range [-1,+1]

- Mask normalization
  - Make sure masks are all boolean (True/False)

Training the model

➢ Implement U-Net Model

➢ Compile Model

- Adam optimizer
- x3 Loss average dice score for all patients:
    - Binary cross-entropy loss → 0.908
    - Dice loss → 0.928
    - **IoU loss → 0.933**
- Evaluation metrics: binary accuracy, precision, recall and dice coefficient

➢ Training

- Data obtained with data generator function (training / validation)
- num_epochs = 400
- batch_size = 8

<u>Parameters used:</u>

base = 8
img_h = 512
img_w = 512
img_ch = 1
learning_rate = 1e-5
dropout = True
dr = 0.2
batch_norm = True
img_size= 512

Loss curve

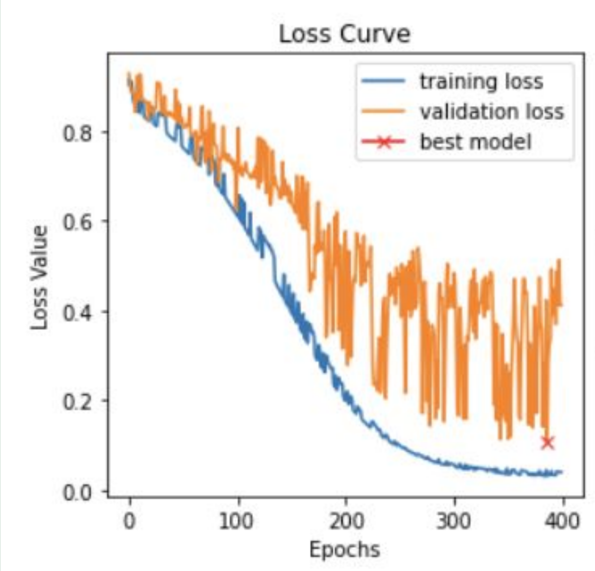


Figure 3: Graph of loss curve

Plot curves

Accuracy curve

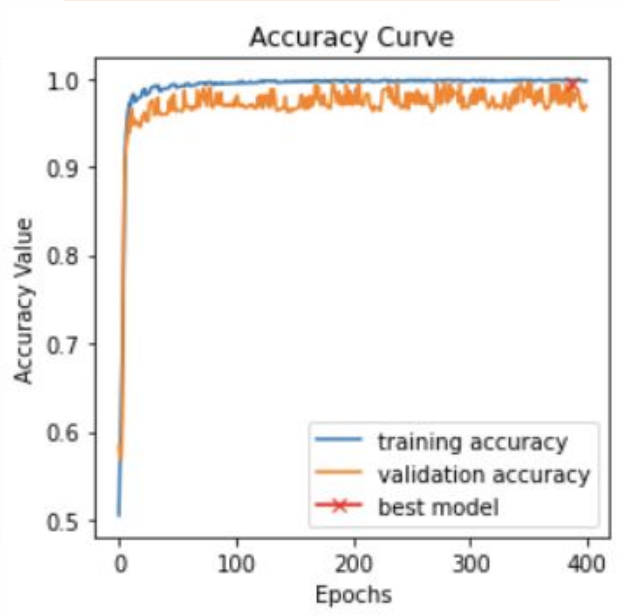


Figure 3: Graph of accuracy curve

Evaluation metrics

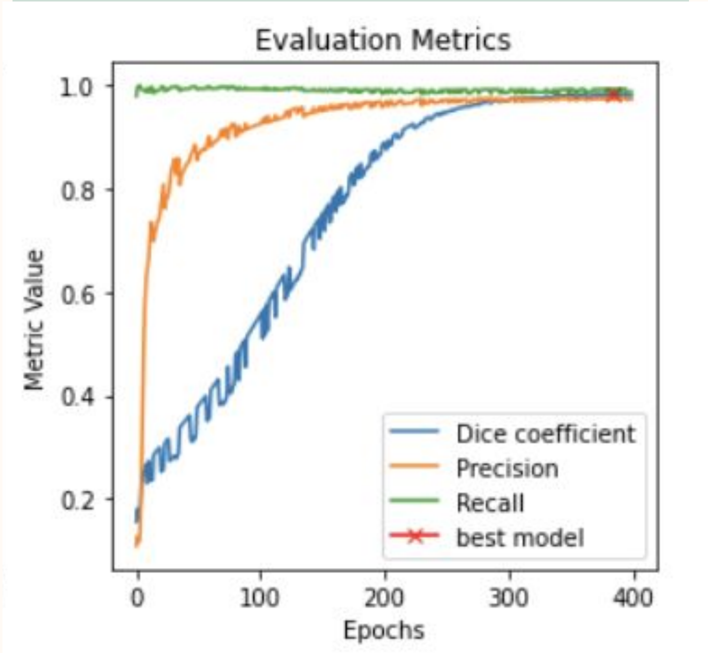


Figure 3: Graph with metrics

Obtaining the predicted masks

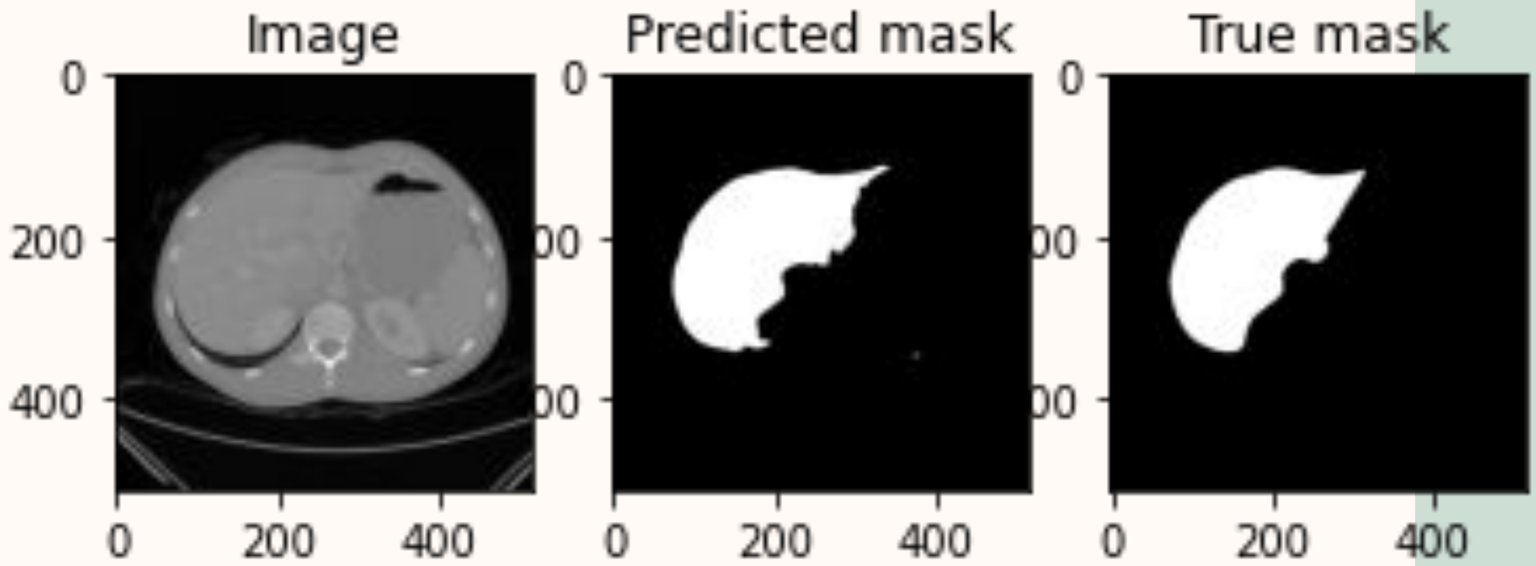
test_pairs =*{'patient id' : [image,mask]...}*

Dictionary to list

- test_images
- test_masks

test_images → model.predict → Binary → Predicted mask

threshold=100



Dice coefficient= 0.957

Calculating the dice scores

Function → calculate_dice_coefficient(true_mask, predicted_mask_binary)

patient_dice_scores = *{'patient id' : [dice_score]...}*

average_patient_dice_scores= *{'patient id' : [average_score]...}*

Total average = 0,936

Train data

Patient id	30	28	24	27	8	22	23	21	10	6	2	14	19	18	1	Average
Average dice score	0,963	0,959	0,950	0,964	0,952	0,980	0,965	0,945	0,977	0,960	0,969	0,951	0,965	0,972	0,973	0,965

Validation data

Patient id	16	25	5	26	Average
Average dice score	0,867	0,845	0,939	0,943	0,899

Test data

Patient id	29
Average dice score	0,944

Conclusions

- Knowledge application
- Model Performance
- Intersection over Union (IoU) loss
  - Accurate object localization
  - Delineate boundaries accurately
- Final Result

Thanks!

Do you have any questions?