Pancreatic Adenocarcinoma Detection

About the model

The aim of this pancreatic adenocarcinoma detection is to develop an effective deep-learning based solution for identifying pancreatic cancer in abdomen in the CT – scan's of an individuals. The project utilizes the Ultralytics YOLO (You Only Look Once) model, a state-of-the-art real-time object detection algorithm, to accurately detect and localize **Malignant tumors** in CT scans. YOLO's speed and accuracy make it an ideal choice for real-time applications like this one.

The project involves setting up the environment, training the YOLO model on a custom dataset, evaluating its performance, and making predictions on test images. The ultimate goal is to enhance security and safety by automating the early stage detection of Malignant tumors in patients.

This command checks whether a compatible NVIDIA GPU is available for accelerated deep learning model training. GPUs are essential for efficiently training deep neural networks.



NVIDIA-SM		r Version: 535.104.05	
GPU Name Fan Temp	Persistence-M	Bus-Id Disp.A Memory-Usage 	Volatile Uncorr. ECC
0 Tesla N/A 36C	9W / 70W	-+====================================	
Processes: GPU GI ID	PID Type Proce	ess name	GPU Memory Usage

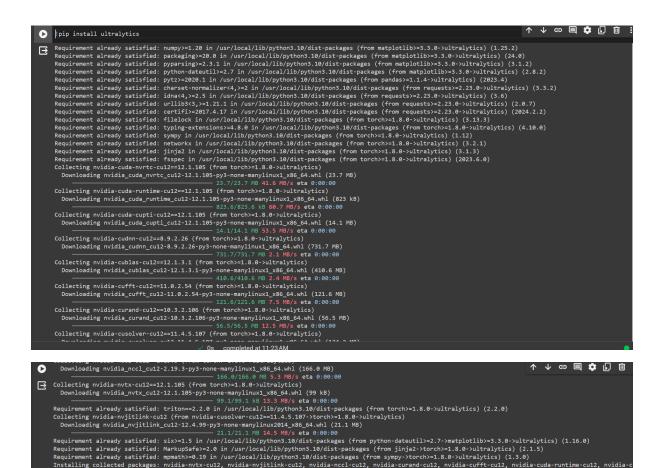
Setting Up the Environment

Here we get the current working directory and store it in the HOME variable. We then print the current working directory.

```
import os
HOME=os.getcwd()
print(HOME)
```

Installing Ultralytics

Here, we install the Ultralytics library, which is a popular framework for working with YOLO computer vision models. It provides tools and utilities for training and deploying object detection models.



Importing and Checking Ultralytics

In this part, we import the Ultralytics library and use the clear_output function to clear the current output. Then, we run checks to ensure that Ultralytics is correctly installed and configured.

```
from IPython import display display.clear_output()

import ultralytics
ultralytics.check()
```

Ultralytics YOLOv8.0.227

✓ Python-3.10.12 torch-2.1.0+cu121 CPU (Intel Xeon 2.20GHz)

Setup complete

✓ (2 CPUs, 12.7 GB RAM, 26.2/107.7 GB disk)

```
[8] import ultralytics
from ultralytics.utils.checks import check_pip_update_available

# Check for updates
update_available = check_pip_update_available()

if update_available:
    print("An update for ultralytics is available!")
else:
    print("ultralytics is up to date.")

ultralytics is up to date.
```

Importing YOLO from Ultralytics & Mounting Google Drive

We import the YOLO class from Ultralytics. This class is used for creating and managing YOLO models for object detection tasks.

In the next part we mount Google Drive into the Colab environment. It's a common practice for accessing data and project files stored in your Google Drive. We then navigate to the directory where your project files are located.

```
[1] from google.colab import drive drive.mount('/content/drive')

Mounted at /content/drive
```

Train / Val / Test Split

The dataset consists of 120 images for the training set, 30 images for the validation set and 5 images for the test set.

Hence, the data consists of a split of approximately 77% images in the train set, 20% in the validation set and 3% in the test set.

Model Training

In this step, we start training a YOLO model. The command specifies various parameters, such as the training mode, the YOLO model architecture (yolov8s), the data configuration file (configdata.yaml), the number of training epochs (20), the input image size (imgsz), and whether to generate training plots (plots=True).

```
import os
from ultralytics import YOLO

# Load a model
model = YOLO("yolov8n.yaml") # build a new model from scratch

# Use the model
results = model.train(data=os.path.join(ROOT_DIR, "configdata.yaml"), epochs=20) # train the model
```

Epoch 4/10	GPU_mem 2.26G Class	box_loss 3.133 Images	cls_loss 4.959 Instances	dfl_loss 4.062 Box(P	Instances 11 R	Size 640: mAP50	100% 10/10 [00:02<00:00, 3.51it/s] mAP50-95): 100% 5/5 [00:01<00:00, 2.66it/s] all	
Epoch 5/10	GPU_mem 2.25G Class	box_loss 3.124 Images	cls_loss 4.848 Instances	dfl_loss 3.998 Box(P	Instances 13 R		100% 100%	
Epoch 6/10	GPU_mem 2.25G Class	box_loss 2.889 Images	cls_loss 4.671 Instances	dfl_loss 3.892 Box(P	Instances 11 R		100% 100% 10/10 [00:02<00:00, 4.05it/s] mAP50-95): 100% 5/5 [00:01<00:00, 2.63it/s] all	
Epoch 7/10	GPU_mem 2.25G Class	box_loss 2.951 Images	4.711	dfl_loss 3.795 Box(P	Instances 12 R		100% 100%	
Epoch 8/10	GPU_mem 2.25G Class	box_loss 2.925 Images	cls_loss 4.531 Instances	dfl_loss 3.635 Box(P	Instances 12 R		100% 100%	
Epoch 9/10	GPU_mem 2.25G Class	box_loss 2.812 Images	cls_loss 4.533 Instances	dfl_loss 3.551 Box(P	Instances 12 R		100% 100% 10/10 [00:04<00:00, 2.38it/s] mAP50-95): 100% 5/5 [00:02<00:00, 2.13it/s] all	

```
Optimizer stripped from runs/detect/train2/weights/last.pt, 6.2MB

Optimizer stripped from runs/detect/train2/weights/best.pt, 6.2MB

Validating runs/detect/train2/weights/best.pt...

Ultralytics YOLOV8.1.37  Python-3.10.12 torch-2.2.1+cu121 CUDA:0 (Tesla T4, 15102MiB)

YOLOV8N summary (fused): 168 layers, 3005843 parameters, 0 gradients, 8.1 GFLOPs

Class Images Instances Box(P R mAP50 mAP50-95): 100% 5/5 [00:05<00:00, 1.15s/it]

all 155 170 0.000436 0.118 0.000304 7.34e-05

Speed: 0.6ms preprocess, 4.9ms inference, 0.0ms loss, 7.5ms postprocess per image

Results saved to runs/detect/train2
```

- Data Augmentation
- **optimizer:** 'optimizer=auto' found, ignoring 'lr0=0.01' and 'momentum=0.937' and determining best 'optimizer', 'lr0' and 'momentum' automatically...
- optimizer: AdamW(lr=0.002, momentum=0.9) with parameter groups 57 weight(decay=0.0), 64 weight(decay=0.0005), 63 bias(decay=0.0)

```
optimizer: 'optimizer=auto' found, ignoring 'lr0=0.01' and 'momentum=0.937' and determining best 'optimizer', 'lr0' and 'momentum' automatically...
optimizer: AdamW(lr=0.002, momentum=0.9) with parameter groups 57 weight(decay=0.0), 64 weight(decay=0.0005), 63 bias(decay=0.0)

albumentations: Blur(p=0.01, blur_limit=(3, 7)), MedianBlur(p=0.01, blur_limit=(3, 7)), ToGray(p=0.01), CLAHE(p=0.01, clip_limit=(1, 4.0), tile_grid_size=(8, 8))
```

These are augmentation operations defined using the Albumentations library. Albumentations is a library for image augmentation, used to increase the diversity of training data.

Blur(p=0.01, blur_limit=(3, 7)):

This augmentation applies blur to the image with a probability of 0.01. The blur_limit parameter specifies the range of blur strength, which is a random value between 3 and 7. Blur is a common image processing operation that reduces image noise and detail.

MedianBlur(p=0.01, blur_limit=(3, 7)):

This augmentation applies median blur to the image with a probability of 0.01. Similar to the Blur operation, the blur_limit parameter specifies the range of blur strength.

ToGray(p=0.01):

This augmentation converts the image to grayscale with a probability of 0.01. Grayscale images contain only shades of gray (black, white, and various gray levels), removing color information from the original image.

CLAHE(p=0.01, clip_limit=(1, 4.0), tile_grid_size=(8, 8)): This augmentation applies Contrast Limited Adaptive Histogram Equalization (CLAHE) to the image with a probability of 0.01. CLAHE enhances the image contrast by redistributing pixel intensities based on local histogram equalization. The clip_limit parameter controls the contrast, and it's a random value between 1 and 4.0. The tile_grid_size parameter specifies the size of the grid for histogram equalization.

These augmentations are applied to input images during the training phase to create variations of the original data. By applying random transformations to the images, the model is exposed to a broader range of scenarios, helping it generalize better to different conditions. The low probabilities (e.g., 0.01) indicate that these augmentations are applied infrequently to avoid overdoing the transformations.

```
TensorBoard: Start with 'tensorboard -logdir runs/detect/train', view at <a href="https://localbost:6005/">https://localbost:6005/</a>
Freezing Jayer 'mondal 27.6fl.comv.weight
Freezing Jayer 'mondal 27.6fl.comv.weight

ADB: numming Automatic Sites Precision (ADW) checks with YOLOy8n...
Downloading https://dithub.com/ultralyzis/assasts/releases/download/v8.1.0/yalov8n.pt'...

Downloading https://dithub.com/ultralyzis/assasts/releases/download/v8.1.0/yalov8n.pt'...

ADB: numming forter/ydrivv/loybriv-yeigh-generalyzis/assasts/releases/download/v8.1.0/yalov8n.pt'...

ADB: numming forter/ydrivv/loybriv-yeigh-generalyzis/assast/releases/download/v8.1.0/yalov8n.pt'...

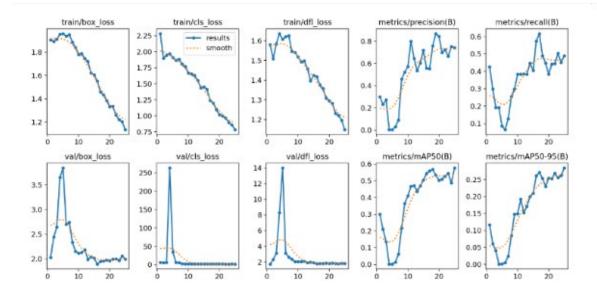
| ADB: numming forter/ydrivv/loybriv-yeigh-generalyzis/assast/releases/download/v8.1.0/yalov8n.pt'...
| ADB: numming forter/ydrivv/loybriv-yeigh-generalyzis/assast/releases/download/v8.1.0/yalov8n.pt'...
| ADB: numming forter/ydrivv/loybriv-yeigh-generalyzis/assast/releases/download/v8.1.0/yalov8n.pt'...
| ADB: numming forter/ydriv-yeigh-generalyzis/assast/releases/download/v8.1.0/yalov8n.pt'...
| ADB: numming forter/ydriv-yeigh-generalyzi
```

Results saved to runs/detect/train3

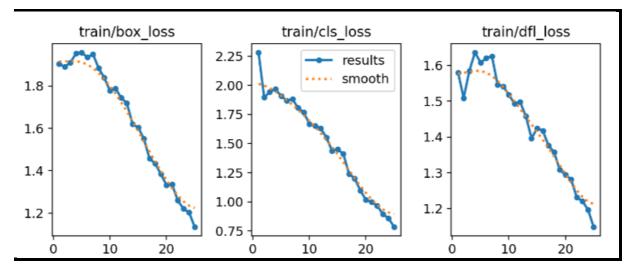
Listing Training Results

After training the model, we list the contents of the "runs/detect/train6/" directory. This contains various training-related files and artifacts, such as model weights, logs, and metrics.

```
train batch2.jpg
args.yaml
                                                       P_curve.png
                                                                         train_batch420.jpg
confusion matrix normalized.png
                                                       PR_curve.png
confusion_matrix.png R_curve.png
events.out.tfevents.1702648999.75cd95999981.6856.0 results.csv
                                                                         train batch421.jpg
                                                                        train batch422.jpg
                                                       results.png
F1_curve.png
                                                                        val_batch0_labels.jpg
labels_correlogram.jpg
                                                       train_batch0.jpg val_batch0_pred.jpg
                                                       train_batch1.jpg weights
labels.jpg
```



- Accuracy Metric Curves
- **box_loss:** This curve represents the error in predicting the bounding boxes around detected pancreas. The y-axis shows the magnitude of loss, and x-axis indicates epochs or iterations. A lower value indicates that the model is getting better at accurately drawing boxes around the desired.
- **cls_loss:** This curve illustrates classification loss, indicating how well the model is classifying objects within those predicted bounding boxes as cancer or not. A decrease in this value over epochs (x-axis) means improved accuracy in classification.
- **dfl_loss:** This curve represents the focal loss, which is a modification of the standard crossentropy loss that is used to address class imbalance in object detection tasks. The y-axis shows the magnitude of loss, and x-axis indicates epochs or iterations. A lower value indicates that the model is getting better at detecting cancer.

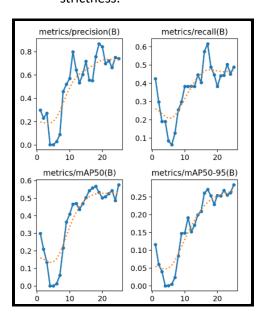


Precision Curve (Top Left): This graph shows how precise the model is, meaning how many
of the detected objects are actual pancreas. A higher precision indicates fewer false
positives.

• **Recall Curve (Top Right):** This curve represents the recall rate, indicating how many actual pancreas in the images were detected by the model. A higher recall means that the model is good at identifying pancreas but may also include some false positives.

Recall =
$$TP / (TP + FN)$$

- mAP50 Curve (Bottom Left): mAP50 stands for mean Average Precision at 50% IoU
 (Intersection over Union). It gives us an idea about the accuracy of our model; higher values
 indicate better performance in terms of both precision and recall but only considering
 detections as true positives if they have an IoU above 50% with ground truths.
- mAP50-95 Curve (Bottom Right): This is a metric which takes into account detections as true
 positives only if they have an IoU between 50% and 95% with ground truths. It provides a
 broader perspective on the model's performance across different levels of detection
 strictness.



Programmatic Predictions

In the final step, we load the YOLO model using the YOLO class and make predictions on a specific image programmatically.

```
Speed: 1.5ms preprocess, 163.1ms inference, 6.1ms postprocess per image at shape (1, 3, 224, 224) Results saved to runs/detect/predict2

1 label saved to runs/detect/predict2/labels
[ultralytics.engine.results.Results object with attributes:
```

boxes: ultralytics.engine.results.Boxes object

keypoints: None masks: None

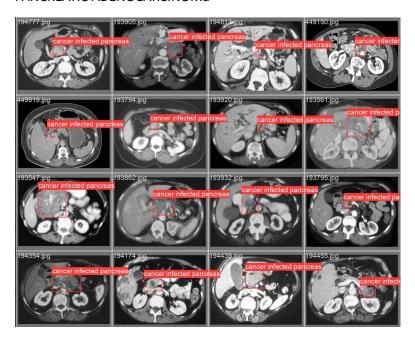
```
orig_img: array([[[255, 255, 255],
                                                                                                  [[202, 208, 213],
[202, 208, 213],
[202, 208, 213],
              [255, 255, 255],
               [255, 255, 255],
                                                                                                    [223, 231, 231],
[223, 231, 231],
[223, 231, 231]],
               [255, 255, 255],
               [255, 255, 255],
                                                                                                   [[202, 208, 213],
[202, 208, 213],
               [255, 255, 255]],
                                                                                                     [202, 208, 213],
            [[255, 255, 255],
                                                                                                    [223, 231, 231],
[223, 231, 231],
[223, 231, 231]],
              [255, 255, 255],
[255, 255, 255],
                                                                                                   [[202, 208, 213],
[202, 208, 213],
[202, 208, 213],
               [255, 255, 255],
               [255, 255, 255],
                                                                                                     [223, 231, 231],
              [255, 255, 255]],
                                                                                          [223, 231, 231],
[223, 231, 231]]], dtype=uint8)
orig_shape: (460, 460)
```

probs: None

save_dir: 'runs/detect/predict2'

speed: {'preprocess': 1.5411376953125, 'inference': 163.100004196167, 'postprocess': 6.129026412963867}]

PANCREATIC ADENOCARCINOMa



Healthy pancreas



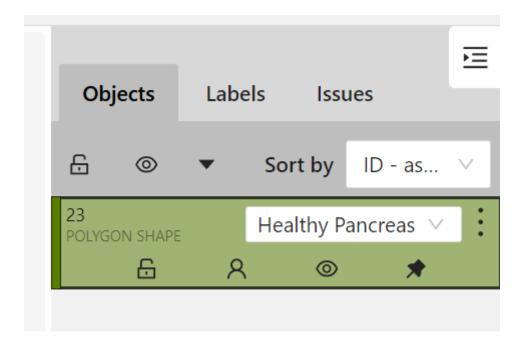


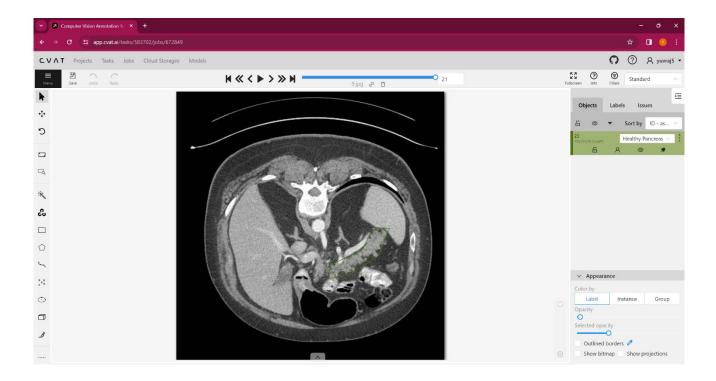
DATA USED – (Private and confidential)

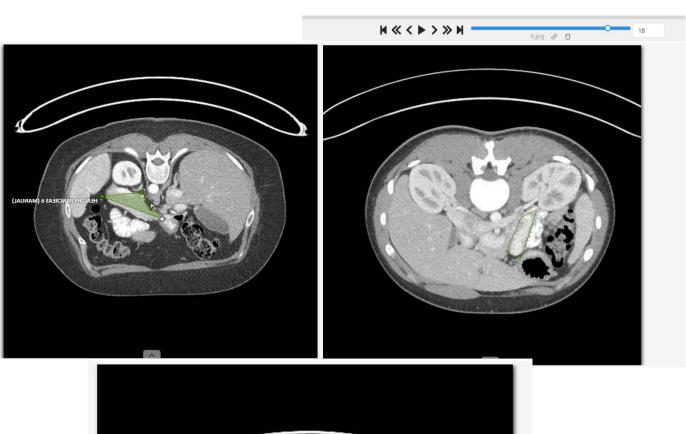
- 133 CT images of cancer patients
- 22 healthy patients

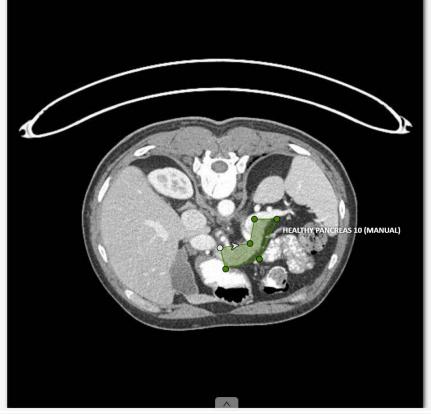
Annotations of data

HEALTHY PANCREAS









CANCER – Pancreatic adenocarcinoma

