In [20]:
```
import os
import sys
import json
import torch
import shutil
import numpy as np
import pandas as pd
import seaborn as sns
import nibabel as nib
import torch.nn as nn
import IPython.display as disp
import matplotlib.pyplot as plt
import torch.nn.functional as F


from tqdm import tqdm
from pathlib import Path
from typing import Union, Tuple, List
from collections import OrderedDict
from nnunetv2.training.nnUNetTrainer.nnUNetTrainer import nnUNetTrainer
from sklearn.metrics import f1_score, accuracy_score, classification_report
from dynamic_network_architectures.architectures.unet import ResidualEncoderUNet
```

In [2]:
```
# Install nnUNetv2 (version 2 of nnU-Net) via shell command
!pip install nnunetv2
```

```
Requirement already satisfied: nnunetv2 in /usr/local/lib/python3.11/dist-packages
(2.6.2)
Requirement already satisfied: torch>=2.1.2 in /usr/local/lib/python3.11/dist-packag
es (from nnunetv2) (2.8.0.dev20250319+cu128)
Requirement already satisfied: acvl-utils<0.3,>=0.2.3 in /usr/local/lib/python3.11/d
ist-packages (from nnunetv2) (0.2.5)
Requirement already satisfied: dynamic-network-architectures<0.5,>=0.4.1 in /usr/loc
al/lib/python3.11/dist-packages (from nnunetv2) (0.4.2)
Requirement already satisfied: tqdm in /usr/local/lib/python3.11/dist-packages (from
nnunetv2) (4.67.1)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (fro
m nnunetv2) (1.16.2)
Requirement already satisfied: batchgenerators>=0.25.1 in /usr/local/lib/python3.11/
dist-packages (from nnunetv2) (0.25.1)
Requirement already satisfied: numpy>=1.24 in /usr/local/lib/python3.11/dist-package
s (from nnunetv2) (2.1.2)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-packag
es (from nnunetv2) (1.7.2)
Requirement already satisfied: scikit-image>=0.19.3 in /usr/local/lib/python3.11/dis
t-packages (from nnunetv2) (0.25.2)
Requirement already satisfied: SimpleITK>=2.2.1 in /usr/local/lib/python3.11/dist-pa
ckages (from nnunetv2) (2.5.2)
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages (fr
om nnunetv2) (2.3.2)
Requirement already satisfied: graphviz in /usr/local/lib/python3.11/dist-packages
(from nnunetv2) (0.21)
Requirement already satisfied: tifffile in /usr/local/lib/python3.11/dist-packages
(from nnunetv2) (2025.9.9)
Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages
(from nnunetv2) (2.32.3)
Requirement already satisfied: nibabel in /usr/local/lib/python3.11/dist-packages (f
rom nnunetv2) (5.3.2)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages
(from nnunetv2) (3.10.6)
Requirement already satisfied: seaborn in /usr/local/lib/python3.11/dist-packages (f
rom nnunetv2) (0.13.2)
Requirement already satisfied: imagecodecs in /usr/local/lib/python3.11/dist-package
s (from nnunetv2) (2025.8.2)
Requirement already satisfied: yacs in /usr/local/lib/python3.11/dist-packages (from
nnunetv2) (0.1.8)
Requirement already satisfied: batchgeneratorsv2>=0.3.0 in /usr/local/lib/python3.1
1/dist-packages (from nnunetv2) (0.3.0)
Requirement already satisfied: einops in /usr/local/lib/python3.11/dist-packages (fr
om nnunetv2) (0.8.1)
Requirement already satisfied: blosc2>=3.0.0b1 in /usr/local/lib/python3.11/dist-pac
kages (from nnunetv2) (3.8.0)
Requirement already satisfied: connected-components-3d in /usr/local/lib/python3.11/
dist-packages (from acvl-utils<0.3,>=0.2.3->nnunetv2) (3.24.0)
Requirement already satisfied: pillow>=7.1.2 in /usr/local/lib/python3.11/dist-packa
ges (from batchgenerators>=0.25.1->nnunetv2) (11.0.0)
Requirement already satisfied: future in /usr/local/lib/python3.11/dist-packages (fr
om batchgenerators>=0.25.1->nnunetv2) (1.0.0)
Requirement already satisfied: unittest2 in /usr/local/lib/python3.11/dist-packages
(from batchgenerators>=0.25.1->nnunetv2) (1.1.0)
Requirement already satisfied: threadpoolctl in /usr/local/lib/python3.11/dist-packa
ges (from batchgenerators>=0.25.1->nnunetv2) (3.6.0)
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```
Requirement already satisfied: fft-conv-pytorch in /usr/local/lib/python3.11/dist-pa
ckages (from batchgeneratorsv2>=0.3.0->nnunetv2) (1.2.0)
Requirement already satisfied: ndindex in /usr/local/lib/python3.11/dist-packages (f
rom blosc2>=3.0.0b1->nnunetv2) (1.10.0)
Requirement already satisfied: msgpack in /usr/local/lib/python3.11/dist-packages (f
rom blosc2>=3.0.0b1->nnunetv2) (1.1.1)
Requirement already satisfied: platformdirs in /usr/local/lib/python3.11/dist-packag
es (from blosc2>=3.0.0b1->nnunetv2) (4.3.7)
Requirement already satisfied: numexpr>=2.12.1 in /usr/local/lib/python3.11/dist-pac
kages (from blosc2>=3.0.0b1->nnunetv2) (2.12.1)
Requirement already satisfied: py-cpuinfo in /usr/local/lib/python3.11/dist-packages
(from blosc2>=3.0.0b1->nnunetv2) (9.0.0)
Requirement already satisfied: timm in /usr/local/lib/python3.11/dist-packages (from
dynamic-network-architectures<0.5,>=0.4.1->nnunetv2) (1.0.19)
Requirement already satisfied: networkx>=3.0 in /usr/local/lib/python3.11/dist-packa
ges (from scikit-image>=0.19.3->nnunetv2) (3.4.2)
Requirement already satisfied: imageio!=2.35.0,>=2.33 in /usr/local/lib/python3.11/d
ist-packages (from scikit-image>=0.19.3->nnunetv2) (2.37.0)
Requirement already satisfied: packaging>=21 in /usr/local/lib/python3.11/dist-packa
ges (from scikit-image>=0.19.3->nnunetv2) (24.2)
Requirement already satisfied: lazy-loader>=0.4 in /usr/local/lib/python3.11/dist-pa
ckages (from scikit-image>=0.19.3->nnunetv2) (0.4)
Requirement already satisfied: filelock in /usr/local/lib/python3.11/dist-packages
(from torch>=2.1.2->nnunetv2) (3.16.1)
Requirement already satisfied: typing-extensions>=4.10.0 in /usr/local/lib/python3.1
1/dist-packages (from torch>=2.1.2->nnunetv2) (4.12.2)
Requirement already satisfied: sympy>=1.13.3 in /usr/local/lib/python3.11/dist-packa
ges (from torch>=2.1.2->nnunetv2) (1.13.3)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.11/dist-packages (fr
om torch>=2.1.2->nnunetv2) (3.1.4)
Requirement already satisfied: fsspec in /usr/local/lib/python3.11/dist-packages (fr
om torch>=2.1.2->nnunetv2) (2024.10.0)
Requirement already satisfied: nvidia-cuda-nvrtc-cu12==12.8.61 in /usr/local/lib/pyt
hon3.11/dist-packages (from torch>=2.1.2->nnunetv2) (12.8.61)
Requirement already satisfied: nvidia-cuda-runtime-cu12==12.8.57 in /usr/local/lib/p
ython3.11/dist-packages (from torch>=2.1.2->nnunetv2) (12.8.57)
Requirement already satisfied: nvidia-cuda-cupti-cu12==12.8.57 in /usr/local/lib/pyt
hon3.11/dist-packages (from torch>=2.1.2->nnunetv2) (12.8.57)
Requirement already satisfied: nvidia-cudnn-cu12==9.8.0.87 in /usr/local/lib/python
3.11/dist-packages (from torch>=2.1.2->nnunetv2) (9.8.0.87)
Requirement already satisfied: nvidia-cublas-cu12==12.8.3.14 in /usr/local/lib/pytho
n3.11/dist-packages (from torch>=2.1.2->nnunetv2) (12.8.3.14)
Requirement already satisfied: nvidia-cufft-cu12==11.3.3.41 in /usr/local/lib/python
3.11/dist-packages (from torch>=2.1.2->nnunetv2) (11.3.3.41)
Requirement already satisfied: nvidia-curand-cu12==10.3.9.55 in /usr/local/lib/pytho
n3.11/dist-packages (from torch>=2.1.2->nnunetv2) (10.3.9.55)
Requirement already satisfied: nvidia-cusolver-cu12==11.7.2.55 in /usr/local/lib/pyt
hon3.11/dist-packages (from torch>=2.1.2->nnunetv2) (11.7.2.55)
Requirement already satisfied: nvidia-cusparse-cu12==12.5.7.53 in /usr/local/lib/pyt
hon3.11/dist-packages (from torch>=2.1.2->nnunetv2) (12.5.7.53)
Requirement already satisfied: nvidia-cusparselt-cu12==0.6.3 in /usr/local/lib/pytho
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Requirement already satisfied: nvidia-nccl-cu12==2.25.1 in /usr/local/lib/python3.1
1/dist-packages (from torch>=2.1.2->nnunetv2) (2.25.1)
Requirement already satisfied: nvidia-nvtx-cu12==12.8.55 in /usr/local/lib/python3.1
1/dist-packages (from torch>=2.1.2->nnunetv2) (12.8.55)
```

```
Requirement already satisfied: nvidia-nvjitlink-cu12==12.8.61 in /usr/local/lib/pyth
on3.11/dist-packages (from torch>=2.1.2->nnunetv2) (12.8.61)
Requirement already satisfied: nvidia-cufile-cu12==1.13.0.11 in /usr/local/lib/pytho
n3.11/dist-packages (from torch>=2.1.2->nnunetv2) (1.13.0.11)
Requirement already satisfied: pytorch-triton==3.3.0+git96316ce5 in /usr/local/lib/p
ython3.11/dist-packages (from torch>=2.1.2->nnunetv2) (3.3.0+git96316ce5)
Requirement already satisfied: setuptools>=40.8.0 in /usr/local/lib/python3.11/dist-
packages (from pytorch-triton==3.3.0+git96316ce5->torch>=2.1.2->nnunetv2) (77.0.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-pa
ckages (from matplotlib->nnunetv2) (1.3.3)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packag
es (from matplotlib->nnunetv2) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-p
ackages (from matplotlib->nnunetv2) (4.59.2)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-p
ackages (from matplotlib->nnunetv2) (1.4.9)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/lib/python3/dist-packages (f
rom matplotlib->nnunetv2) (2.4.7)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dis
t-packages (from matplotlib->nnunetv2) (2.9.0.post0)
Requirement already satisfied: importlib-resources>=5.12 in /usr/local/lib/python3.1
1/dist-packages (from nibabel->nnunetv2) (6.5.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packag
es (from pandas->nnunetv2) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-pack
ages (from pandas->nnunetv2) (2025.2)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.1
1/dist-packages (from requests->nnunetv2) (3.4.1)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packag
es (from requests->nnunetv2) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-
packages (from requests->nnunetv2) (2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-
packages (from requests->nnunetv2) (2025.1.31)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packa
ges (from scikit-learn->nnunetv2) (1.5.2)
Requirement already satisfied: PyYAML in /usr/local/lib/python3.11/dist-packages (fr
om yacs->nnunetv2) (6.0.2)
Requirement already satisfied: six>=1.5 in /usr/lib/python3/dist-packages (from pyth
on-dateutil>=2.7->matplotlib->nnunetv2) (1.16.0)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.11/dist-
packages (from sympy>=1.13.3->torch>=2.1.2->nnunetv2) (1.3.0)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.11/dist-pac
kages (from jinja2->torch>=2.1.2->nnunetv2) (2.1.5)
Requirement already satisfied: torchvision in /usr/local/lib/python3.11/dist-package
s (from timm->dynamic-network-architectures<0.5,>=0.4.1->nnunetv2) (0.22.0.dev202503
19+cu128)
Requirement already satisfied: huggingface_hub in /usr/local/lib/python3.11/dist-pac
kages (from timm->dynamic-network-architectures<0.5,>=0.4.1->nnunetv2) (0.34.4)
Requirement already satisfied: safetensors in /usr/local/lib/python3.11/dist-package
s (from timm->dynamic-network-architectures<0.5,>=0.4.1->nnunetv2) (0.6.2)
Collecting argparse (from unittest2->batchgenerators>=0.25.1->nnunetv2)
  Using cached argparse-1.4.0-py2.py3-none-any.whl.metadata (2.8 kB)
Requirement already satisfied: traceback2 in /usr/local/lib/python3.11/dist-packages
(from unittest2->batchgenerators>=0.25.1->nnunetv2) (1.4.0)
Requirement already satisfied: hf-xet<2.0.0,>=1.1.3 in /usr/local/lib/python3.11/dis
```

```
t-packages (from huggingface_hub->timm->dynamic-network-architectures<0.5,>=0.4.1->n
nunetv2) (1.1.10)
Requirement already satisfied: linecache2 in /usr/local/lib/python3.11/dist-packages
(from traceback2->unittest2->batchgenerators>=0.25.1->nnunetv2) (1.0.0)
Using cached argparse-1.4.0-py2.py3-none-any.whl (23 kB)
Installing collected packages: argparse
Successfully installed argparse-1.4.0
WARNING: Running pip as the 'root' user can result in broken permissions and conflic
ting behaviour with the system package manager, possibly rendering your system unusa
ble. It is recommended to use a virtual environment instead: https://pip.pypa.io/war
nings/venv. Use the --root-user-action option if you know what you are doing and wan
t to suppress this warning.

[notice] A new release of pip is available: 25.0.1 -> 25.2
[notice] To update, run: python -m pip install --upgrade pip
```

In [3]:
```
!pip install SimpleITK pandas tqdm
```

```
Requirement already satisfied: SimpleITK in /usr/local/lib/python3.11/dist-packages
(2.5.2)
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages (2.
3.2)
Requirement already satisfied: tqdm in /usr/local/lib/python3.11/dist-packages (4.6
7.1)
Requirement already satisfied: numpy>=1.23.2 in /usr/local/lib/python3.11/dist-packa
ges (from pandas) (2.1.2)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11/d
ist-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packag
es (from pandas) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-pack
ages (from pandas) (2025.2)
Requirement already satisfied: six>=1.5 in /usr/lib/python3/dist-packages (from pyth
on-dateutil>=2.8.2->pandas) (1.16.0)
WARNING: Running pip as the 'root' user can result in broken permissions and conflic
ting behaviour with the system package manager, possibly rendering your system unusa
ble. It is recommended to use a virtual environment instead: https://pip.pypa.io/war
nings/venv. Use the --root-user-action option if you know what you are doing and wan
t to suppress this warning.

[notice] A new release of pip is available: 25.0.1 -> 25.2
[notice] To update, run: python -m pip install --upgrade pip
```

In [4]:
```
!git clone https://github.com/MIC-DKFZ/nnUNet.git
```

```
fatal: destination path 'nnUNet' already exists and is not an empty directory.
```

In [5]:
```
pip install -e nnUNet
```

```
Obtaining file:///workspace/nnUNet
  Installing build dependencies ... done
  Checking if build backend supports build_editable ... done
  Getting requirements to build editable ... done
  Preparing editable metadata (pyproject.toml) ... done
Requirement already satisfied: torch>=2.1.2 in /usr/local/lib/python3.11/dist-packag
es (from nnunetv2==2.6.2) (2.8.0.dev20250319+cu128)
Requirement already satisfied: acvl-utils<0.3,>=0.2.3 in /usr/local/lib/python3.11/d
ist-packages (from nnunetv2==2.6.2) (0.2.5)
Requirement already satisfied: dynamic-network-architectures<0.5,>=0.4.1 in /usr/loc
al/lib/python3.11/dist-packages (from nnunetv2==2.6.2) (0.4.2)
Requirement already satisfied: tqdm in /usr/local/lib/python3.11/dist-packages (from
nnunetv2==2.6.2) (4.67.1)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (fro
m nnunetv2==2.6.2) (1.16.2)
Requirement already satisfied: batchgenerators>=0.25.1 in /usr/local/lib/python3.11/
dist-packages (from nnunetv2==2.6.2) (0.25.1)
Requirement already satisfied: numpy>=1.24 in /usr/local/lib/python3.11/dist-package
s (from nnunetv2==2.6.2) (2.1.2)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-packag
es (from nnunetv2==2.6.2) (1.7.2)
Requirement already satisfied: scikit-image>=0.19.3 in /usr/local/lib/python3.11/dis
t-packages (from nnunetv2==2.6.2) (0.25.2)
Requirement already satisfied: SimpleITK>=2.2.1 in /usr/local/lib/python3.11/dist-pa
ckages (from nnunetv2==2.6.2) (2.5.2)
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages (fr
om nnunetv2==2.6.2) (2.3.2)
Requirement already satisfied: graphviz in /usr/local/lib/python3.11/dist-packages
(from nnunetv2==2.6.2) (0.21)
Requirement already satisfied: tifffile in /usr/local/lib/python3.11/dist-packages
(from nnunetv2==2.6.2) (2025.9.9)
Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages
(from nnunetv2==2.6.2) (2.32.3)
Requirement already satisfied: nibabel in /usr/local/lib/python3.11/dist-packages (f
rom nnunetv2==2.6.2) (5.3.2)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages
(from nnunetv2==2.6.2) (3.10.6)
Requirement already satisfied: seaborn in /usr/local/lib/python3.11/dist-packages (f
rom nnunetv2==2.6.2) (0.13.2)
Requirement already satisfied: imagecodecs in /usr/local/lib/python3.11/dist-package
s (from nnunetv2==2.6.2) (2025.8.2)
Requirement already satisfied: yacs in /usr/local/lib/python3.11/dist-packages (from
nnunetv2==2.6.2) (0.1.8)
Requirement already satisfied: batchgeneratorsv2>=0.3.0 in /usr/local/lib/python3.1
1/dist-packages (from nnunetv2==2.6.2) (0.3.0)
Requirement already satisfied: einops in /usr/local/lib/python3.11/dist-packages (fr
om nnunetv2==2.6.2) (0.8.1)
Requirement already satisfied: blosc2>=3.0.0b1 in /usr/local/lib/python3.11/dist-pac
kages (from nnunetv2==2.6.2) (3.8.0)
Requirement already satisfied: connected-components-3d in /usr/local/lib/python3.11/
dist-packages (from acvl-utils<0.3,>=0.2.3->nnunetv2==2.6.2) (3.24.0)
Requirement already satisfied: pillow>=7.1.2 in /usr/local/lib/python3.11/dist-packa
ges (from batchgenerators>=0.25.1->nnunetv2==2.6.2) (11.0.0)
Requirement already satisfied: future in /usr/local/lib/python3.11/dist-packages (fr
om batchgenerators>=0.25.1->nnunetv2==2.6.2) (1.0.0)
Requirement already satisfied: unittest2 in /usr/local/lib/python3.11/dist-packages
```

```
(from batchgenerators>=0.25.1->nnunetv2==2.6.2) (1.1.0)
Requirement already satisfied: threadpoolctl in /usr/local/lib/python3.11/dist-packa
ges (from batchgenerators>=0.25.1->nnunetv2==2.6.2) (3.6.0)
Requirement already satisfied: fft-conv-pytorch in /usr/local/lib/python3.11/dist-pa
ckages (from batchgeneratorsv2>=0.3.0->nnunetv2==2.6.2) (1.2.0)
Requirement already satisfied: ndindex in /usr/local/lib/python3.11/dist-packages (f
rom blosc2>=3.0.0b1->nnunetv2==2.6.2) (1.10.0)
Requirement already satisfied: msgpack in /usr/local/lib/python3.11/dist-packages (f
rom blosc2>=3.0.0b1->nnunetv2==2.6.2) (1.1.1)
Requirement already satisfied: platformdirs in /usr/local/lib/python3.11/dist-packag
es (from blosc2>=3.0.0b1->nnunetv2==2.6.2) (4.3.7)
Requirement already satisfied: numexpr>=2.12.1 in /usr/local/lib/python3.11/dist-pac
kages (from blosc2>=3.0.0b1->nnunetv2==2.6.2) (2.12.1)
Requirement already satisfied: py-cpuinfo in /usr/local/lib/python3.11/dist-packages
(from blosc2>=3.0.0b1->nnunetv2==2.6.2) (9.0.0)
Requirement already satisfied: timm in /usr/local/lib/python3.11/dist-packages (from
dynamic-network-architectures<0.5,>=0.4.1->nnunetv2==2.6.2) (1.0.19)
Requirement already satisfied: networkx>=3.0 in /usr/local/lib/python3.11/dist-packa
ges (from scikit-image>=0.19.3->nnunetv2==2.6.2) (3.4.2)
Requirement already satisfied: imageio!=2.35.0,>=2.33 in /usr/local/lib/python3.11/d
ist-packages (from scikit-image>=0.19.3->nnunetv2==2.6.2) (2.37.0)
Requirement already satisfied: packaging>=21 in /usr/local/lib/python3.11/dist-packa
ges (from scikit-image>=0.19.3->nnunetv2==2.6.2) (24.2)
Requirement already satisfied: lazy-loader>=0.4 in /usr/local/lib/python3.11/dist-pa
ckages (from scikit-image>=0.19.3->nnunetv2==2.6.2) (0.4)
Requirement already satisfied: filelock in /usr/local/lib/python3.11/dist-packages
(from torch>=2.1.2->nnunetv2==2.6.2) (3.16.1)
Requirement already satisfied: typing-extensions>=4.10.0 in /usr/local/lib/python3.1
1/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (4.12.2)
Requirement already satisfied: sympy>=1.13.3 in /usr/local/lib/python3.11/dist-packa
ges (from torch>=2.1.2->nnunetv2==2.6.2) (1.13.3)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.11/dist-packages (fr
om torch>=2.1.2->nnunetv2==2.6.2) (3.1.4)
Requirement already satisfied: fsspec in /usr/local/lib/python3.11/dist-packages (fr
om torch>=2.1.2->nnunetv2==2.6.2) (2024.10.0)
Requirement already satisfied: nvidia-cuda-nvrtc-cu12==12.8.61 in /usr/local/lib/pyt
hon3.11/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (12.8.61)
Requirement already satisfied: nvidia-cuda-runtime-cu12==12.8.57 in /usr/local/lib/p
ython3.11/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (12.8.57)
Requirement already satisfied: nvidia-cuda-cupti-cu12==12.8.57 in /usr/local/lib/pyt
hon3.11/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (12.8.57)
Requirement already satisfied: nvidia-cudnn-cu12==9.8.0.87 in /usr/local/lib/python
3.11/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (9.8.0.87)
Requirement already satisfied: nvidia-cublas-cu12==12.8.3.14 in /usr/local/lib/pytho
n3.11/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (12.8.3.14)
Requirement already satisfied: nvidia-cufft-cu12==11.3.3.41 in /usr/local/lib/python
3.11/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (11.3.3.41)
Requirement already satisfied: nvidia-curand-cu12==10.3.9.55 in /usr/local/lib/pytho
n3.11/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (10.3.9.55)
Requirement already satisfied: nvidia-cusolver-cu12==11.7.2.55 in /usr/local/lib/pyt
hon3.11/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (11.7.2.55)
Requirement already satisfied: nvidia-cusparse-cu12==12.5.7.53 in /usr/local/lib/pyt
hon3.11/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (12.5.7.53)
Requirement already satisfied: nvidia-cusparselt-cu12==0.6.3 in /usr/local/lib/pytho
n3.11/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (0.6.3)
Requirement already satisfied: nvidia-nccl-cu12==2.25.1 in /usr/local/lib/python3.1
```

```
1/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (2.25.1)
Requirement already satisfied: nvidia-nvtx-cu12==12.8.55 in /usr/local/lib/python3.1
1/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (12.8.55)
Requirement already satisfied: nvidia-nvjitlink-cu12==12.8.61 in /usr/local/lib/pyth
on3.11/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (12.8.61)
Requirement already satisfied: nvidia-cufile-cu12==1.13.0.11 in /usr/local/lib/pytho
n3.11/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (1.13.0.11)
Requirement already satisfied: pytorch-triton==3.3.0+git96316ce5 in /usr/local/lib/p
ython3.11/dist-packages (from torch>=2.1.2->nnunetv2==2.6.2) (3.3.0+git96316ce5)
Requirement already satisfied: setuptools>=40.8.0 in /usr/local/lib/python3.11/dist-
packages (from pytorch-triton==3.3.0+git96316ce5->torch>=2.1.2->nnunetv2==2.6.2) (7
7.0.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-pa
ckages (from matplotlib->nnunetv2==2.6.2) (1.3.3)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packag
es (from matplotlib->nnunetv2==2.6.2) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-p
ackages (from matplotlib->nnunetv2==2.6.2) (4.59.2)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-p
ackages (from matplotlib->nnunetv2==2.6.2) (1.4.9)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/lib/python3/dist-packages (f
rom matplotlib->nnunetv2==2.6.2) (2.4.7)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dis
t-packages (from matplotlib->nnunetv2==2.6.2) (2.9.0.post0)
Requirement already satisfied: importlib-resources>=5.12 in /usr/local/lib/python3.1
1/dist-packages (from nibabel->nnunetv2==2.6.2) (6.5.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packag
es (from pandas->nnunetv2==2.6.2) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-pack
ages (from pandas->nnunetv2==2.6.2) (2025.2)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.1
1/dist-packages (from requests->nnunetv2==2.6.2) (3.4.1)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packag
es (from requests->nnunetv2==2.6.2) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-
packages (from requests->nnunetv2==2.6.2) (2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-
packages (from requests->nnunetv2==2.6.2) (2025.1.31)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packa
ges (from scikit-learn->nnunetv2==2.6.2) (1.5.2)
Requirement already satisfied: PyYAML in /usr/local/lib/python3.11/dist-packages (fr
om yacs->nnunetv2==2.6.2) (6.0.2)
Requirement already satisfied: six>=1.5 in /usr/lib/python3/dist-packages (from pyth
on-dateutil>=2.7->matplotlib->nnunetv2==2.6.2) (1.16.0)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.11/dist-
packages (from sympy>=1.13.3->torch>=2.1.2->nnunetv2==2.6.2) (1.3.0)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.11/dist-pac
kages (from jinja2->torch>=2.1.2->nnunetv2==2.6.2) (2.1.5)
Requirement already satisfied: torchvision in /usr/local/lib/python3.11/dist-package
s (from timm->dynamic-network-architectures<0.5,>=0.4.1->nnunetv2==2.6.2) (0.22.0.de
v20250319+cu128)
Requirement already satisfied: huggingface_hub in /usr/local/lib/python3.11/dist-pac
kages (from timm->dynamic-network-architectures<0.5,>=0.4.1->nnunetv2==2.6.2) (0.34.
4)
Requirement already satisfied: safetensors in /usr/local/lib/python3.11/dist-package
s (from timm->dynamic-network-architectures<0.5,>=0.4.1->nnunetv2==2.6.2) (0.6.2)
```

```
Collecting argparse (from unittest2->batchgenerators>=0.25.1->nnunetv2==2.6.2)
  Using cached argparse-1.4.0-py2.py3-none-any.whl.metadata (2.8 kB)
Requirement already satisfied: traceback2 in /usr/local/lib/python3.11/dist-packages
(from unittest2->batchgenerators>=0.25.1->nnunetv2==2.6.2) (1.4.0)
Requirement already satisfied: hf-xet<2.0.0,>=1.1.3 in /usr/local/lib/python3.11/dis
t-packages (from huggingface_hub->timm->dynamic-network-architectures<0.5,>=0.4.1->n
nunetv2==2.6.2) (1.1.10)
Requirement already satisfied: linecache2 in /usr/local/lib/python3.11/dist-packages
(from traceback2->unittest2->batchgenerators>=0.25.1->nnunetv2==2.6.2) (1.0.0)
Using cached argparse-1.4.0-py2.py3-none-any.whl (23 kB)
Building wheels for collected packages: nnunetv2
  Building editable for nnunetv2 (pyproject.toml) ... done
  Created wheel for nnunetv2: filename=nnunetv2-2.6.2-0.editable-py3-none-any.whl si
ze=16742 sha256=24e5ab49d444c7a0a976aada5d4204fc9854f8b105991e069ae7b77c1ee9d828
  Stored in directory: /tmp/pip-ephem-wheel-cache-uupj8mkb/wheels/d8/89/d5/3016d0bd2
ca3565e4034cb5cef46774c4f490878137185b82a
Successfully built nnunetv2
Installing collected packages: argparse, nnunetv2
  Attempting uninstall: nnunetv2
    Found existing installation: nnunetv2 2.6.2
    Uninstalling nnunetv2-2.6.2:
      Successfully uninstalled nnunetv2-2.6.2
Successfully installed argparse-1.4.0 nnunetv2-2.6.2
WARNING: Running pip as the 'root' user can result in broken permissions and conflic
ting behaviour with the system package manager, possibly rendering your system unusa
ble. It is recommended to use a virtual environment instead: https://pip.pypa.io/war
nings/venv. Use the --root-user-action option if you know what you are doing and wan
t to suppress this warning.

[notice] A new release of pip is available: 25.0.1 -> 25.2
[notice] To update, run: python -m pip install --upgrade pip
Note: you may need to restart the kernel to use updated packages.
```

In [6]:

```
os.makedirs("./nnUNet_raw", exist_ok=True)          # Stores raw data in nnUNet's
os.makedirs("./nnUNet_preprocessed", exist_ok=True)  # Stores preprocessed data (af
os.makedirs("./nnUNet_results", exist_ok=True)      # Stores trained models and re
os.makedirs("./Data", exist_ok=True)                # Your original cloned dataset
os.makedirs("./my_custom_nnunet", exist_ok=True)    # Custom trainer and network c

# Set environment variables - these are like global settings that programs can read
# nnUNet looks for these specific variable names to know where to find/save files

# Tell nnUNet where to find raw training data, save/find preprocessed data, and sav
os.environ['nnUNet_raw'] = os.path.abspath("./nnUNet_raw")
os.environ['nnUNet_preprocessed'] = os.path.abspath("./nnUNet_preprocessed")
os.environ['nnUNet_results'] = os.path.abspath("./nnUNet_results")

# IMPORTANT: Add our custom code directory to the Python path
# This allows nnU-Net to find our custom trainer and model
sys.path.append(os.path.abspath("./my_custom_nnunet"))

# Print confirmation messages
print("Environment setup complete")
print(f"nnUNet_raw: {os.environ['nnUNet_raw']}")                    # f"" is formatt
print(f"nnUNet_preprocessed: {os.environ['nnUNet_preprocessed']}")
print(f"nnUNet_results: {os.environ['nnUNet_results']}")
```

```
print(f"Custom code path added: {os.path.abspath('./my_custom_nnunet')}")
print(f"Data directory: {os.path.abspath('./Data')}")
```

```
Environment setup complete
nnUNet_raw: /workspace/nnUNet_raw
nnUNet_preprocessed: /workspace/nnUNet_preprocessed
nnUNet_results: /workspace/nnUNet_results
Custom code path added: /workspace/my_custom_nnunet
Data directory: /workspace/Data
```

In [7]:

```
# Dataset Pre-processing cell

base_dir = (Path(__file__).parent if "__file__" in globals() else Path.cwd()) / "Da

if not base_dir.exists():
    raise FileNotFoundError(f"Could not find data folder at {base_dir}")

print("Using dataset root:", base_dir)

# Read the nnUNet raw data directory from the environment variable 'nnUNet_raw'
# - nnU-Net v2 discovers datasets by directory structure under this path.
nnunet_raw_dir = Path(os.environ['nnUNet_raw'])

# Choose a dataset ID; nnU-Net convention uses "DatasetXXX_Name" where XXX is zero-
dataset_id = 501
dataset_name = f"Dataset{dataset_id:03d}_Pancreas"   # → "Dataset501_Pancreas"
task_dir = nnunet_raw_dir / dataset_name

# ------------------------------
# Create nnU-Net dataset folders
# ------------------------------
# nnU-Net expects:
# - imagesTr: training images, channel-suffixed as *_0000.nii.gz (and *_0001... for
# - labelsTr: corresponding training labels (same case id, no channel suffix)
# - imagesTs: test images (no labels here)
images_tr_dir = task_dir / 'imagesTr'
labels_tr_dir = task_dir / 'labelsTr'
images_ts_dir = task_dir / 'imagesTs'

# Make folders (parents=True creates intermediate folders; exist_ok=True avoids err
images_tr_dir.mkdir(parents=True, exist_ok=True)
labels_tr_dir.mkdir(parents=True, exist_ok=True)
images_ts_dir.mkdir(parents=True, exist_ok=True)
```

```
Using dataset root: /workspace/Data
```

In [8]:

```
# ----------------------------------------
# Scan and collect Training + Validation data
# ----------------------------------------
# We'll treat both 'train' and 'validation' splits as "training data" on disk,
# letting nnU-Net handle internal validation during training.
all_files = []  # will accumulate dicts with {'path': Path, 'subtype': int}

# Loop the two splits expected under Data/: train/, validation/
for split in ['train', 'validation']:
    split_dir = base_dir / split     # e.g., Data/train, Data/validation
    if not split_dir.exists():
```

```
        # Fail fast if a split folder is missing; helps catch dataset layout issues
        raise FileNotFoundError(f"Missing split folder: {split_dir}")

    # Inside each split, we expect subtype folders named like "subtype0", "subtype1
    for subtype_folder in split_dir.iterdir():           # iterate children under s
        if subtype_folder.is_dir() and 'subtype' in subtype_folder.name:
            # Extract the integer subtype id from folder name (e.g., "subtype2" ->
            subtype = int(subtype_folder.name.replace('subtype', ''))
            # Collect *all* files inside that subtype folder for later classificati
            for f in subtype_folder.iterdir():
                all_files.append({
                    "path": f,        # full path to the file (image or label)
                    "subtype": subtype  # classification label to attach to that ca
                })

# ----------------------------------------
# Prepare classification labels & counters
# ----------------------------------------
classification_labels = {}  # {case_id: subtype_int}
num_training_cases = 0      # count how many image cases we copy into imagesTr

print("Processing training & validation sets...")

# Wrap iteration with tqdm to show a progress bar
for file_info in tqdm(all_files):
    file_path = file_info['path']     # Path to the current file
    subtype = file_info['subtype']    # Integer 0/1/2 subtype label from folder nam

    # Heuristic: image volumes are named like "<case_id>_0000.nii.gz" for channel 0
    if '_0000.nii.gz' in file_path.name:  # It's an image file (channel 0)
        # case_id is the part before the channel suffix (e.g., "case123" from "case
        case_id = file_path.name.split('_0000.nii.gz')[0]
        new_name = f"{case_id}_0000.nii.gz"  # normalized name (keeps only channel
        # Copy image into nnU-Net's imagesTr; overwrites if re-running
        shutil.copy(file_path, images_tr_dir / new_name)

        # Record the classification label for this case id (used by your custom mul
        classification_labels[case_id] = subtype
        # Increment count of training image cases (used later in dataset.json)
        num_training_cases += 1

    # Label files should be "<case_id>.nii.gz" (no channel suffix). We detect *.nii
    elif file_path.suffixes == ['.nii', '.gz'] and '_0000' not in file_path.stem:
        # Extract case id from "case123.nii.gz" -> "case123"
        case_id = file_path.name.replace('.nii.gz', '')
        new_name = f"{case_id}.nii.gz"
        # Copy label into nnU-Net's labelsTr
        shutil.copy(file_path, labels_tr_dir / new_name)

# ------------------------
# Save classification map
# ------------------------
# Write a JSON mapping of case_id -> subtype integer (e.g., {"case001": 2, ...})
# Your custom trainer/classification head can read this file during training.
with open(task_dir / 'classification_labels.json', 'w') as f:
    json.dump(classification_labels, f, indent=4)
```

```
# ---------------------
# Process Test Data set
# ---------------------
print("\nProcessing test set...")
test_dir = base_dir / 'test'   # expected optional folder Data/test/
if test_dir.exists():
    # Copy every *.nii.gz file from test into imagesTs
    for f in tqdm(test_dir.iterdir()):
        if f.suffixes == ['.nii', '.gz']:
            shutil.copy(f, images_ts_dir / f.name)
else:
    # If there's no test folder, warn but continue (not fatal)
    print("No test set found, skipping.")

# -----------------------
# Create nnU-Net metadata
# -----------------------
print("\nCreating dataset.json...")

# Build dataset.json content (OrderedDict ensures predictable key order when saved)
dataset_json = OrderedDict()
dataset_json['channel_names'] = {"0": "CT"}          # one imaging channel (CT)
dataset_json['labels'] = {"background": 0, "pancreas": 1, "lesion": 2}  # segmentat
dataset_json['num_classification_classes'] = 3       # extra key for your multitask
dataset_json['numTraining'] = num_training_cases     # helpful metadata (not strict
dataset_json['file_ending'] = ".nii.gz"              # informs nnU-Net about your f

# Write dataset.json to the dataset root so nnU-Net can find it
with open(task_dir / 'dataset.json', 'w') as f:
    json.dump(dataset_json, f, indent=4)

# Final confirmation to the user with where the prepared dataset lives
print(f"\nData preparation complete for {dataset_name} at {task_dir}")

with open(task_dir / "classification_labels.json", "w") as f:
    json.dump(classification_labels, f, indent=4)

print(f" Saved classification_labels.json for {len(classification_labels)} cases")
```

```
Processing training & validation sets...
100%|██████████| 578/578 [00:55<00:00, 10.43it/s]
Processing test set...
72it [00:02, 27.63it/s]
Creating dataset.json...

Data preparation complete for Dataset501_Pancreas at /workspace/nnUNet_raw/Dataset50
1_Pancreas
 Saved classification_labels.json for 288 cases
```

In [12]:

```
print("\nProcessing test set...")
test_dir = base_dir / "test"

if test_dir.exists():
    for item in test_dir.iterdir():
        if item.is_dir() and "_0000" in item.name:
```

```
            case_id = item.name.replace("_0000.nii", "").replace("_0000.nii.gz", ""
            nii_files = list(item.rglob("*.nii"))
            if len(nii_files) > 0:
                img = nib.load(str(nii_files[0]))
                data = img.get_fdata().astype(np.float32)

                new_img = nib.Nifti1Image(data, img.affine, img.header)
                new_name = f"{case_id}_0000.nii.gz"
                nib.save(new_img, str(images_ts_dir / new_name))

        elif item.is_file() and item.suffix in [".nii", ".gz"]:
            img = nib.load(str(item))
            data = img.get_fdata().astype(np.float32)

            new_img = nib.Nifti1Image(data, img.affine, img.header)
            new_name = item.name.replace(".nii", ".nii.gz") if item.suffix == ".nii
            nib.save(new_img, str(images_ts_dir / new_name))
else:
    print(" No test set found, skipping.")
```

```
Processing test set...
```

In [13]:

```
print("\nCreating dataset.json...")

dataset_json = OrderedDict()
dataset_json["channel_names"] = {"0": "CT"}
dataset_json["labels"] = {"background": 0, "pancreas": 1, "lesion": 2}
dataset_json["numTraining"] = num_training_cases
dataset_json["file_ending"] = ".nii.gz"

with open(task_dir / "dataset.json", "w") as f:
    json.dump(dataset_json, f, indent=4)

print(f"\n Data preparation complete for {dataset_name} at {task_dir}")
```

```
Creating dataset.json...

 Data preparation complete for Dataset501_Pancreas at /workspace/nnUNet_raw/Dataset5
01_Pancreas
```

In [15]:

```
#Converison from float to int

labels_dir = Path("/workspace/nnUNet_raw/Dataset501_Pancreas/labelsTr")

for file in labels_dir.glob("*.nii.gz"):
    img = nib.load(str(file))
    data = img.get_fdata()

    # Round floats to nearest int and cast
    data = np.rint(data).astype(np.int16)

    # Verify unique labels
    unique = np.unique(data)
    if not set(unique).issubset({0, 1, 2}):
        print(f" Warning: {file.name} has unexpected labels {unique}")

    # Save back with same affine/header
```

```
    new_img = nib.Nifti1Image(data, img.affine, img.header)
    nib.save(new_img, str(file))

print(" All labels fixed to integer values {0,1,2}")
```

```
All labels fixed to integer values {0,1,2}
```

In [16]:
```
!nnUNetv2_plan_and_preprocess -d 501 -pl nnUNetPlannerResEncM
```

```
Fingerprint extraction...
Dataset501_Pancreas
Using <class 'nnunetv2.imageio.simpleitk_reader_writer.SimpleITKIO'> as reader/write
r
100%|██████████████████████████████████████| 288/288 [00:11<00:00, 25.94it/s]
Experiment planning...
Dropping 3d_lowres config because the image size difference to 3d_fullres is too sma
ll. 3d_fullres: [ 59.  117.  180.5], 3d_lowres: [59, 117, 180]
2D U-Net configuration:
{'data_identifier': 'nnUNetPlans_2d', 'preprocessor_name': 'DefaultPreprocessor', 'b
atch_size': 134, 'patch_size': (np.int64(128), np.int64(192)), 'median_image_size_in
_voxels': array([117. , 180.5]), 'spacing': array([0.73242188, 0.73242188]), 'normal
ization_schemes': ['CTNormalization'], 'use_mask_for_norm': [False], 'resampling_fn_
data': 'resample_data_or_seg_to_shape', 'resampling_fn_seg': 'resample_data_or_seg_t
o_shape', 'resampling_fn_data_kwargs': {'is_seg': False, 'order': 3, 'order_z': 0,
'force_separate_z': None}, 'resampling_fn_seg_kwargs': {'is_seg': True, 'order': 1,
'order_z': 0, 'force_separate_z': None}, 'resampling_fn_probabilities': 'resample_da
ta_or_seg_to_shape', 'resampling_fn_probabilities_kwargs': {'is_seg': False, 'orde
r': 1, 'order_z': 0, 'force_separate_z': None}, 'architecture': {'network_class_nam
e': 'dynamic_network_architectures.architectures.unet.ResidualEncoderUNet', 'arch_kw
args': {'n_stages': 6, 'features_per_stage': (32, 64, 128, 256, 512, 512), 'conv_o
p': 'torch.nn.modules.conv.Conv2d', 'kernel_sizes': ((3, 3), (3, 3), (3, 3), (3, 3),
(3, 3), (3, 3)), 'strides': ((1, 1), (2, 2), (2, 2), (2, 2), (2, 2), (2, 2)), 'n_blo
cks_per_stage': (1, 3, 4, 6, 6, 6), 'n_conv_per_stage_decoder': (1, 1, 1, 1, 1), 'co
nv_bias': True, 'norm_op': 'torch.nn.modules.instancenorm.InstanceNorm2d', 'norm_op_
kwargs': {'eps': 1e-05, 'affine': True}, 'dropout_op': None, 'dropout_op_kwargs': No
ne, 'nonlin': 'torch.nn.LeakyReLU', 'nonlin_kwargs': {'inplace': True}}, '_kw_requir
es_import': ('conv_op', 'norm_op', 'dropout_op', 'nonlin')}, 'batch_dice': True}

Using <class 'nnunetv2.imageio.simpleitk_reader_writer.SimpleITKIO'> as reader/write
r
3D fullres U-Net configuration:
{'data_identifier': 'nnUNetPlans_3d_fullres', 'preprocessor_name': 'DefaultPreproces
sor', 'batch_size': 2, 'patch_size': (np.int64(64), np.int64(128), np.int64(192)),
'median_image_size_in_voxels': array([ 59. , 117. , 180.5]), 'spacing': array([2.
, 0.73242188, 0.73242188]), 'normalization_schemes': ['CTNormalization'], 'use_mask_
for_norm': [False], 'resampling_fn_data': 'resample_data_or_seg_to_shape', 'resampli
ng_fn_seg': 'resample_data_or_seg_to_shape', 'resampling_fn_data_kwargs': {'is_seg':
False, 'order': 3, 'order_z': 0, 'force_separate_z': None}, 'resampling_fn_seg_kwarg
s': {'is_seg': True, 'order': 1, 'order_z': 0, 'force_separate_z': None}, 'resamplin
g_fn_probabilities': 'resample_data_or_seg_to_shape', 'resampling_fn_probabilities_k
wargs': {'is_seg': False, 'order': 1, 'order_z': 0, 'force_separate_z': None}, 'arch
itecture': {'network_class_name': 'dynamic_network_architectures.architectures.unet.
ResidualEncoderUNet', 'arch_kwargs': {'n_stages': 6, 'features_per_stage': (32, 64,
128, 256, 320, 320), 'conv_op': 'torch.nn.modules.conv.Conv3d', 'kernel_sizes': ((1,
3, 3), (3, 3, 3), (3, 3, 3), (3, 3, 3), (3, 3, 3), (3, 3, 3)), 'strides': ((1, 1,
1), (1, 2, 2), (2, 2, 2), (2, 2, 2), (2, 2, 2), (2, 2, 2)), 'n_blocks_per_stage':
(1, 3, 4, 6, 6, 6), 'n_conv_per_stage_decoder': (1, 1, 1, 1, 1), 'conv_bias': True,
'norm_op': 'torch.nn.modules.instancenorm.InstanceNorm3d', 'norm_op_kwargs': {'eps':
1e-05, 'affine': True}, 'dropout_op': None, 'dropout_op_kwargs': None, 'nonlin': 'to
rch.nn.LeakyReLU', 'nonlin_kwargs': {'inplace': True}}, '_kw_requires_import': ('con
v_op', 'norm_op', 'dropout_op', 'nonlin')}, 'batch_dice': False}

Plans were saved to /workspace/nnUNet_preprocessed/Dataset501_Pancreas/nnUNetResEncU
NetMPlans.json
Preprocessing...
```

```
Preprocessing dataset Dataset501_Pancreas
Configuration: 2d...
100%|██████████████████████████████████████████| 288/288 [06:05<00:00,  1.27s/it]
Configuration: 3d_fullres...
100%|██████████████████████████████████████████| 288/288 [02:51<00:00,  1.68it/s]
Configuration: 3d_lowres...
INFO: Configuration 3d_lowres not found in plans file nnUNetResEncUNetMPlans.json of
dataset Dataset501_Pancreas. Skipping.
```

In [ ]:

```
# Classification + custom evaluation metrics below
```

In [17]:

```
%%writefile /workspace/nnUNet/nnunetv2/training/nnUNetTrainer/trainer_with_classifi

# ----------------------------------------------------
# 1. Dual-head model: segmentation + classification
# ----------------------------------------------------
class SegClsUNet(nn.Module):
    def __init__(self, base_unet, n_classes_cls):
        super().__init__()
        self.seg_unet = base_unet
        bottleneck_ch = 320  # Default for ResidualEncoderUNet 3d_fullres
        self.global_pool = nn.AdaptiveAvgPool3d(1)
        self.cls_head = nn.Linear(bottleneck_ch, n_classes_cls)

        # Directly expose the decoder and encoder to avoid attribute issues
        self.decoder = base_unet.decoder
        self.encoder = base_unet.encoder

    def forward(self, x):
        # Get encoder features for classification
        encoder_features = self.encoder(x)
        bottleneck = encoder_features[-1]

        # Segmentation output
        seg_out = self.seg_unet(x)

        # Classification head
        pooled = self.global_pool(bottleneck).view(bottleneck.size(0), -1)
        cls_out = self.cls_head(pooled)

        return seg_out, cls_out


# ----------------------------------------------------
# 2. Simple Custom Trainer - Load labels once and add to batches
# ----------------------------------------------------
class TrainerWithClassification(nnUNetTrainer):
    def __init__(self, plans, configuration, fold, dataset_json, device=torch.devic
        super().__init__(plans, configuration, fold, dataset_json, device)

        self.classification_loss_weight = 0.2
        self.num_classes_cls = 3

        # Load classification labels once during initialization
        self.class_labels = self._load_classification_labels()
```

```
        # Tracking variables
        self.train_cls_predictions = []
        self.train_cls_targets = []
        self.val_cls_predictions = []
        self.val_cls_targets = []
        self.val_whole_dsc_epoch = []
        self.val_lesion_dsc_epoch = []

    def _load_classification_labels(self):
        """Load classification labels from the raw dataset directory"""
        import os
        raw_data_folder = os.environ.get('nnUNet_raw', '/workspace/nnUNet_raw')
        labels_file = Path(raw_data_folder) / "Dataset501_Pancreas" / "classificati

        if not labels_file.exists():
            raise FileNotFoundError(f"Classification labels not found at {labels_fi

        with open(labels_file) as f:
            labels = json.load(f)

        print(f"Loaded {len(labels)} classification labels from {labels_file}")
        return labels

    def build_network_architecture(self, architecture_class_name: str,
                                   arch_kwargs: dict,
                                   arch_kwargs_req_import: Union[List[str], Tuple[str
                                   num_input_channels: int,
                                   num_output_channels: int,
                                   enable_deep_supervision: bool = True) -> nn.Module
        # Call parent method to build base network
        network = super().build_network_architecture(
            architecture_class_name, arch_kwargs, arch_kwargs_req_import,
            num_input_channels, num_output_channels, enable_deep_supervision
        )

        # Wrap with classification head
        return SegClsUNet(base_unet=network, n_classes_cls=self.num_classes_cls)

    def _add_classification_labels_to_batch(self, batch):
        """Add classification labels to batch based on case IDs"""
        if 'keys' not in batch:
            print("Warning: No 'keys' found in batch, using default labels")
            batch_size = batch['data'].shape[0] if 'data' in batch else 2
            batch['classification_labels'] = torch.randint(0, 3, (batch_size,), dty
            return batch

        case_ids = batch['keys']
        if hasattr(case_ids, 'tolist'):
            case_ids = case_ids.tolist()
        elif not isinstance(case_ids, (list, tuple)):
            case_ids = [case_ids]

        cls_labels = []
        for case_id in case_ids:
            case_name = case_id.strip() if isinstance(case_id, str) else str(case_i
```

```
            if case_name in self.class_labels:
                cls_labels.append(self.class_labels[case_name])
            else:
                # Try case-insensitive match
                case_name_lower = case_name.lower()
                matches = [k for k in self.class_labels.keys() if k.lower() == case
                if matches:
                    cls_labels.append(self.class_labels[matches[0]])
                else:
                    print(f"Warning: Case {case_name} not found, using label 0")
                    cls_labels.append(0)

        batch['classification_labels'] = torch.tensor(cls_labels, dtype=torch.long)
        return batch

    def compute_custom_dsc(self, predictions, targets) -> Tuple[float, float]:
        """Compute DSC according to README requirements"""
        # Handle deep supervision - take the first (highest resolution) prediction
        if isinstance(predictions, list):
            predictions = predictions[0]
        if isinstance(targets, list):
            targets = targets[0]

        batch_size = predictions.shape[0]
        whole_pancreas_dsc = []
        lesion_dsc = []

        for i in range(batch_size):
            pred = torch.argmax(predictions[i], dim=0).cpu().numpy()
            target = targets[i].cpu().numpy() if torch.is_tensor(targets[i]) else t

            # Whole pancreas DSC: np.uint8(label > 0)
            pred_whole = (pred > 0).astype(np.uint8)
            target_whole = (target > 0).astype(np.uint8)

            intersection_whole = np.sum(pred_whole * target_whole)
            union_whole = np.sum(pred_whole) + np.sum(target_whole)

            if union_whole > 0:
                dsc_whole = 2.0 * intersection_whole / union_whole
            else:
                dsc_whole = 1.0
            whole_pancreas_dsc.append(dsc_whole)

            # Lesion DSC: np.uint8(label==2)
            pred_lesion = (pred == 2).astype(np.uint8)
            target_lesion = (target == 2).astype(np.uint8)

            intersection_lesion = np.sum(pred_lesion * target_lesion)
            union_lesion = np.sum(pred_lesion) + np.sum(target_lesion)

            if union_lesion > 0:
                dsc_lesion = 2.0 * intersection_lesion / union_lesion
            else:
                dsc_lesion = 1.0 if np.sum(target_lesion) == 0 else 0.0
            lesion_dsc.append(dsc_lesion)
```

```
        return np.mean(whole_pancreas_dsc), np.mean(lesion_dsc)

    def train_step(self, batch: dict) -> dict:
        # Add classification labels to the batch
        batch = self._add_classification_labels_to_batch(batch)

        data = batch['data']
        target = batch['target']
        cls_target = batch['classification_labels'].to(self.device)

        data = data.to(self.device, non_blocking=True)
        if isinstance(target, list):
            target = [i.to(self.device, non_blocking=True) for i in target]
        else:
            target = target.to(self.device, non_blocking=True)

        self.optimizer.zero_grad()

        seg_output, cls_output = self.network(data)
        seg_loss = self.loss(seg_output, target)
        cls_loss = F.cross_entropy(cls_output, cls_target)
        total_loss = seg_loss + self.classification_loss_weight * cls_loss

        total_loss.backward()
        torch.nn.utils.clip_grad_norm_(self.network.parameters(), 12)
        self.optimizer.step()

        cls_pred = torch.argmax(cls_output, dim=1).cpu().numpy()
        cls_true = cls_target.cpu().numpy()
        self.train_cls_predictions.extend(cls_pred)
        self.train_cls_targets.extend(cls_true)

        return {'loss': total_loss.detach().cpu().numpy()}

    def validation_step(self, batch: dict) -> dict:
        # Add classification labels to the batch
        batch = self._add_classification_labels_to_batch(batch)

        data = batch['data']
        target = batch['target']
        cls_target = batch['classification_labels'].to(self.device)

        data = data.to(self.device, non_blocking=True)
        if isinstance(target, list):
            target = [i.to(self.device, non_blocking=True) for i in target]
        else:
            target = target.to(self.device, non_blocking=True)

        with torch.no_grad():
            seg_output, cls_output = self.network(data)
            seg_loss = self.loss(seg_output, target)
            cls_loss = F.cross_entropy(cls_output, cls_target)
            total_loss = seg_loss + self.classification_loss_weight * cls_loss

            whole_dsc, lesion_dsc = self.compute_custom_dsc(seg_output, target)
```

```
        # Compute nnU-Net expected metrics (tp_hard, fp_hard, fn_hard)
        # Use the first output for deep supervision
        if isinstance(seg_output, list):
            output_seg = seg_output[0]
        else:
            output_seg = seg_output

        if isinstance(target, list):
            target_seg = target[0]
        else:
            target_seg = target

        # Get predicted segmentation
        predicted_segmentation_onehot = torch.softmax(output_seg, 1)
        predicted_segmentation = predicted_segmentation_onehot.argmax(1)

        # Compute TP, FP, FN for each class
        axes = tuple(range(1, len(target_seg.shape)))
        tp_hard = torch.zeros((target_seg.shape[0], 3), dtype=torch.float, devi
        fp_hard = torch.zeros((target_seg.shape[0], 3), dtype=torch.float, devi
        fn_hard = torch.zeros((target_seg.shape[0], 3), dtype=torch.float, devi

        for b in range(target_seg.shape[0]):
            for c in range(3):  # num_classes
                tp_hard[b, c] = torch.sum((predicted_segmentation[b] == c) & (t
                fp_hard[b, c] = torch.sum((predicted_segmentation[b] == c) & (t
                fn_hard[b, c] = torch.sum((predicted_segmentation[b] != c) & (t

    cls_pred = torch.argmax(cls_output, dim=1).cpu().numpy()
    cls_true = cls_target.cpu().numpy()
    self.val_cls_predictions.extend(cls_pred)
    self.val_cls_targets.extend(cls_true)

    self.val_whole_dsc_epoch.append(whole_dsc)
    self.val_lesion_dsc_epoch.append(lesion_dsc)

    return {
        'loss': total_loss.detach().cpu().numpy(),
        'tp_hard': tp_hard.detach().cpu().numpy(),
        'fp_hard': fp_hard.detach().cpu().numpy(),
        'fn_hard': fn_hard.detach().cpu().numpy(),
    }

def on_epoch_start(self):
    super().on_epoch_start()
    self.train_cls_predictions = []
    self.train_cls_targets = []
    self.val_cls_predictions = []
    self.val_cls_targets = []
    self.val_whole_dsc_epoch = []
    self.val_lesion_dsc_epoch = []

def on_epoch_end(self):
    super().on_epoch_end()
```

```
        # Classification metrics
        if len(self.train_cls_predictions) > 0:
            train_f1 = f1_score(self.train_cls_targets, self.train_cls_predictions,
            train_acc = accuracy_score(self.train_cls_targets, self.train_cls_predi
            print(f"Train Classification - F1: {train_f1:.4f}, Acc: {train_acc:.4f}

        if len(self.val_cls_predictions) > 0:
            val_f1 = f1_score(self.val_cls_targets, self.val_cls_predictions, avera
            val_acc = accuracy_score(self.val_cls_targets, self.val_cls_predictions
            print(f"Val Classification - F1: {val_f1:.4f}, Acc: {val_acc:.4f}")

            # Custom DSC
            if len(self.val_whole_dsc_epoch) > 0:
                avg_whole_dsc = np.mean(self.val_whole_dsc_epoch)
                avg_lesion_dsc = np.mean(self.val_lesion_dsc_epoch)
                print(f"Custom DSC - Whole: {avg_whole_dsc:.4f}, Lesion: {avg_lesio
                print("Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealr
```

```
Writing /workspace/nnUNet/nnunetv2/training/nnUNetTrainer/trainer_with_classificatio
n.py
```

In [18]:
```
!CUDA_VISIBLE_DEVICES=0 nnUNetv2_train 501 3d_fullres 0 \
    -p nnUNetResEncUNetMPlans \
    -tr TrainerWithClassification \
    --npz
```

```
Using device: cuda:0

#######################################################################
Please cite the following paper when using nnU-Net:
Isensee, F., Jaeger, P. F., Kohl, S. A., Petersen, J., & Maier-Hein, K. H. (2021). n
nU-Net: a self-configuring method for deep learning-based biomedical image segmentat
ion. Nature methods, 18(2), 203-211.
#######################################################################

Loaded 288 classification labels from /workspace/nnUNet_raw/Dataset501_Pancreas/clas
sification_labels.json
2025-09-15 08:53:20.339209: Using torch.compile...
2025-09-15 08:53:21.252910: do_dummy_2d_data_aug: False
2025-09-15 08:53:21.257080: Creating new 5-fold cross-validation split...
2025-09-15 08:53:21.268593: Desired fold for training: 0
2025-09-15 08:53:21.270880: This split has 230 training and 58 validation cases.
using pin_memory on device 0
using pin_memory on device 0

This is the configuration used by this training:
Configuration name: 3d_fullres
 {'data_identifier': 'nnUNetPlans_3d_fullres', 'preprocessor_name': 'DefaultPreproce
ssor', 'batch_size': 2, 'patch_size': [64, 128, 192], 'median_image_size_in_voxels':
[59.0, 117.0, 180.5], 'spacing': [2.0, 0.732421875, 0.732421875], 'normalization_sch
emes': ['CTNormalization'], 'use_mask_for_norm': [False], 'resampling_fn_data': 'res
ample_data_or_seg_to_shape', 'resampling_fn_seg': 'resample_data_or_seg_to_shape',
'resampling_fn_data_kwargs': {'is_seg': False, 'order': 3, 'order_z': 0, 'force_sepa
rate_z': None}, 'resampling_fn_seg_kwargs': {'is_seg': True, 'order': 1, 'order_z':
0, 'force_separate_z': None}, 'resampling_fn_probabilities': 'resample_data_or_seg_t
o_shape', 'resampling_fn_probabilities_kwargs': {'is_seg': False, 'order': 1, 'order
_z': 0, 'force_separate_z': None}, 'architecture': {'network_class_name': 'dynamic_n
etwork_architectures.architectures.unet.ResidualEncoderUNet', 'arch_kwargs': {'n_sta
ges': 6, 'features_per_stage': [32, 64, 128, 256, 320, 320], 'conv_op': 'torch.nn.mo
dules.conv.Conv3d', 'kernel_sizes': [[1, 3, 3], [3, 3, 3], [3, 3, 3], [3, 3, 3], [3,
3, 3], [3, 3, 3]], 'strides': [[1, 1, 1], [1, 2, 2], [2, 2, 2], [2, 2, 2], [2, 2,
2], [2, 2, 2]], 'n_blocks_per_stage': [1, 3, 4, 6, 6, 6], 'n_conv_per_stage_decode
r': [1, 1, 1, 1, 1], 'conv_bias': True, 'norm_op': 'torch.nn.modules.instancenorm.In
stanceNorm3d', 'norm_op_kwargs': {'eps': 1e-05, 'affine': True}, 'dropout_op': None,
'dropout_op_kwargs': None, 'nonlin': 'torch.nn.LeakyReLU', 'nonlin_kwargs': {'inplac
e': True}}, '_kw_requires_import': ['conv_op', 'norm_op', 'dropout_op', 'nonlin']},
'batch_dice': False}

These are the global plan.json settings:
 {'dataset_name': 'Dataset501_Pancreas', 'plans_name': 'nnUNetResEncUNetMPlans', 'or
iginal_median_spacing_after_transp': [2.0, 0.732421875, 0.732421875], 'original_medi
an_shape_after_transp': [64, 119, 179], 'image_reader_writer': 'SimpleITKIO', 'trans
pose_forward': [0, 1, 2], 'transpose_backward': [0, 1, 2], 'experiment_planner_use
d': 'nnUNetPlannerResEncM', 'label_manager': 'LabelManager', 'foreground_intensity_p
roperties_per_channel': {'0': {'max': 1929.0, 'mean': 74.0639877319336, 'median': 7
7.98674774169922, 'min': -406.9988098144531, 'percentile_00_5': -56.0, 'percentile_9
9_5': 179.99807739257812, 'std': 44.35909652709961}}}

2025-09-15 08:53:26.128464: Unable to plot network architecture: nnUNet_compile is e
nabled!
2025-09-15 08:53:26.232734:
2025-09-15 08:53:26.238591: Epoch 0
```

```
2025-09-15 08:53:26.243736: Current learning rate: 0.01
/usr/local/lib/python3.11/dist-packages/torch/_inductor/compile_fx.py:236: UserWarni
ng: TensorFloat32 tensor cores for float32 matrix multiplication available but not e
nabled. Consider setting `torch.set_float32_matmul_precision('high')` for better per
formance.
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torch/_inductor/lowering.py:7007: UserWarnin
g:
Online softmax is disabled on the fly since Inductor decides to
split the reduction. Cut an issue to PyTorch if this is an
important use case and you want to speed it up with online
softmax.

  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torch/_inductor/lowering.py:7007: UserWarnin
g:
Online softmax is disabled on the fly since Inductor decides to
split the reduction. Cut an issue to PyTorch if this is an
important use case and you want to speed it up with online
softmax.

  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torch/_inductor/lowering.py:7007: UserWarnin
g:
Online softmax is disabled on the fly since Inductor decides to
split the reduction. Cut an issue to PyTorch if this is an
important use case and you want to speed it up with online
softmax.

  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torch/_inductor/lowering.py:7007: UserWarnin
g:
Online softmax is disabled on the fly since Inductor decides to
split the reduction. Cut an issue to PyTorch if this is an
important use case and you want to speed it up with online
softmax.

  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torch/_inductor/lowering.py:7007: UserWarnin
g:
Online softmax is disabled on the fly since Inductor decides to
split the reduction. Cut an issue to PyTorch if this is an
important use case and you want to speed it up with online
softmax.

  warnings.warn(
/usr/local/lib/python3.11/dist-packages/torch/_inductor/lowering.py:7007: UserWarnin
g:
Online softmax is disabled on the fly since Inductor decides to
split the reduction. Cut an issue to PyTorch if this is an
important use case and you want to speed it up with online
softmax.

  warnings.warn(
2025-09-15 08:58:48.588296: train_loss 0.4408
2025-09-15 08:58:48.592504: val_loss 0.3311
```

```
2025-09-15 08:58:48.595209: Pseudo dice [array([0.9766, 0.    , 0.    ], dtype=float
32), array([0.978, 0.   , 0.   ], dtype=float32)]
2025-09-15 08:58:48.597700: Epoch time: 322.43 s
2025-09-15 08:58:48.607746: Yayy! New best EMA pseudo Dice: 0.32580000162124634
Train Classification - F1: 0.3530, Acc: 0.3760
Val Classification - F1: 0.2198, Acc: 0.3000
Custom DSC - Whole: 0.0000, Lesion: 0.0000
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 08:58:53.111864:
2025-09-15 08:58:53.114269: Epoch 1
2025-09-15 08:58:53.117224: Current learning rate: 0.00999
2025-09-15 09:01:58.800811: train_loss 0.2511
2025-09-15 09:01:58.835371: val_loss 0.2017
2025-09-15 09:01:58.838948: Pseudo dice [array([0.9674, 0.4031, 0.    ], dtype=float
32), array([0.9723, 0.4232, 0.    ], dtype=float32)]
2025-09-15 09:01:58.843219: Epoch time: 185.69 s
2025-09-15 09:01:58.846293: Yayy! New best EMA pseudo Dice: 0.3393000066280365
Train Classification - F1: 0.2430, Acc: 0.3860
Val Classification - F1: 0.2413, Acc: 0.4800
Custom DSC - Whole: 0.4324, Lesion: 0.0000
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:02:02.503822:
2025-09-15 09:02:02.512729: Epoch 2
2025-09-15 09:02:02.516466: Current learning rate: 0.00998
2025-09-15 09:05:08.682288: train_loss 0.11
2025-09-15 09:05:08.688674: val_loss 0.096
2025-09-15 09:05:08.693588: Pseudo dice [array([0.9763, 0.5169, 0.    ], dtype=float
32), array([0.9811, 0.5306, 0.    ], dtype=float32)]
2025-09-15 09:05:08.696611: Epoch time: 186.18 s
2025-09-15 09:05:08.698626: Yayy! New best EMA pseudo Dice: 0.3553999960422516
Train Classification - F1: 0.2290, Acc: 0.4220
Val Classification - F1: 0.3073, Acc: 0.5000
Custom DSC - Whole: 0.5717, Lesion: 0.0200
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:05:12.351886:
2025-09-15 09:05:12.355100: Epoch 3
2025-09-15 09:05:12.357058: Current learning rate: 0.00997
2025-09-15 09:08:18.522107: train_loss 0.018
2025-09-15 09:08:18.537953: val_loss -0.0479
2025-09-15 09:08:18.541849: Pseudo dice [array([0.983 , 0.6602, 0.1828], dtype=float
32), array([0.9855, 0.6233, 0.2652], dtype=float32)]
2025-09-15 09:08:18.544328: Epoch time: 186.18 s
2025-09-15 09:08:18.546788: Yayy! New best EMA pseudo Dice: 0.3815999925136566
Train Classification - F1: 0.2868, Acc: 0.4040
Val Classification - F1: 0.2005, Acc: 0.4300
Custom DSC - Whole: 0.6821, Lesion: 0.1817
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:08:22.391259:
2025-09-15 09:08:22.393685: Epoch 4
2025-09-15 09:08:22.396638: Current learning rate: 0.00996
2025-09-15 09:11:28.453044: train_loss -0.1025
2025-09-15 09:11:28.457628: val_loss -0.0379
```

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2025-09-15 09:11:28.460046: Pseudo dice [array([0.9846, 0.6624, 0.3032], dtype=float
32), array([0.9785, 0.6177, 0.2714], dtype=float32)]
2025-09-15 09:11:28.462477: Epoch time: 186.07 s
2025-09-15 09:11:28.464294: Yayy! New best EMA pseudo Dice: 0.40700000524520874
Train Classification - F1: 0.2791, Acc: 0.4240
Val Classification - F1: 0.2069, Acc: 0.4500
Custom DSC - Whole: 0.6917, Lesion: 0.2660
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:11:31.907441:
2025-09-15 09:11:31.911321: Epoch 5
2025-09-15 09:11:31.914035: Current learning rate: 0.00995
2025-09-15 09:14:38.009560: train_loss -0.1247
2025-09-15 09:14:38.013556: val_loss -0.0995
2025-09-15 09:14:38.015994: Pseudo dice [array([0.9887, 0.6829, 0.4392], dtype=float
32), array([0.9848, 0.6589, 0.3029], dtype=float32)]
2025-09-15 09:14:38.018670: Epoch time: 186.11 s
2025-09-15 09:14:38.020899: Yayy! New best EMA pseudo Dice: 0.43389999866485596
Train Classification - F1: 0.2968, Acc: 0.3740
Val Classification - F1: 0.1157, Acc: 0.2100
Custom DSC - Whole: 0.7591, Lesion: 0.3475
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:14:41.789034:
2025-09-15 09:14:41.791634: Epoch 6
2025-09-15 09:14:41.793431: Current learning rate: 0.00995
2025-09-15 09:17:47.831678: train_loss -0.1937
2025-09-15 09:17:47.836213: val_loss -0.1356
2025-09-15 09:17:47.838218: Pseudo dice [array([0.9876, 0.7265, 0.4004], dtype=float
32), array([0.9869, 0.728 , 0.3065], dtype=float32)]
2025-09-15 09:17:47.840978: Epoch time: 186.05 s
2025-09-15 09:17:47.842921: Yayy! New best EMA pseudo Dice: 0.4595000147819519
Train Classification - F1: 0.3084, Acc: 0.3940
Val Classification - F1: 0.1202, Acc: 0.2200
Custom DSC - Whole: 0.7584, Lesion: 0.3001
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:17:51.497365:
2025-09-15 09:17:51.507610: Epoch 7
2025-09-15 09:17:51.510141: Current learning rate: 0.00994
2025-09-15 09:20:57.652739: train_loss -0.2203
2025-09-15 09:20:57.660630: val_loss -0.2194
2025-09-15 09:20:57.662700: Pseudo dice [array([0.9891, 0.7856, 0.4125], dtype=float
32), array([0.9893, 0.7521, 0.4812], dtype=float32)]
2025-09-15 09:20:57.665193: Epoch time: 186.16 s
2025-09-15 09:20:57.667086: Yayy! New best EMA pseudo Dice: 0.4869999885559082
Train Classification - F1: 0.3288, Acc: 0.3580
Val Classification - F1: 0.2984, Acc: 0.3800
Custom DSC - Whole: 0.8100, Lesion: 0.3700
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:21:01.558234:
2025-09-15 09:21:01.560869: Epoch 8
2025-09-15 09:21:01.562889: Current learning rate: 0.00993
2025-09-15 09:24:07.756084: train_loss -0.2648
2025-09-15 09:24:07.763726: val_loss -0.2536
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2025-09-15 09:24:07.766053: Pseudo dice [array([0.9908, 0.7967, 0.5723], dtype=float
32), array([0.9909, 0.7858, 0.4908], dtype=float32)]
2025-09-15 09:24:07.768351: Epoch time: 186.2 s
2025-09-15 09:24:07.770671: Yayy! New best EMA pseudo Dice: 0.5153999924659729
Train Classification - F1: 0.2887, Acc: 0.4500
Val Classification - F1: 0.2667, Acc: 0.3700
Custom DSC - Whole: 0.8192, Lesion: 0.3945
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:24:11.544466:
2025-09-15 09:24:11.547287: Epoch 9
2025-09-15 09:24:11.549973: Current learning rate: 0.00992
2025-09-15 09:27:17.637856: train_loss -0.279
2025-09-15 09:27:17.644910: val_loss -0.243
2025-09-15 09:27:17.646973: Pseudo dice [array([0.99  , 0.7865, 0.5609], dtype=float
32), array([0.9913, 0.7925, 0.5526], dtype=float32)]
2025-09-15 09:27:17.649020: Epoch time: 186.1 s
2025-09-15 09:27:17.651409: Yayy! New best EMA pseudo Dice: 0.5418000221252441
Train Classification - F1: 0.2397, Acc: 0.4520
Val Classification - F1: 0.2087, Acc: 0.3200
Custom DSC - Whole: 0.7985, Lesion: 0.3759
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:27:21.259986:
2025-09-15 09:27:21.262625: Epoch 10
2025-09-15 09:27:21.264900: Current learning rate: 0.00991
2025-09-15 09:30:27.438247: train_loss -0.2902
2025-09-15 09:30:27.456859: val_loss -0.2803
2025-09-15 09:30:27.458750: Pseudo dice [array([0.9911, 0.8115, 0.3754], dtype=float
32), array([0.9927, 0.7951, 0.5183], dtype=float32)]
2025-09-15 09:30:27.461477: Epoch time: 186.18 s
2025-09-15 09:30:27.463617: Yayy! New best EMA pseudo Dice: 0.5623999834060669
Train Classification - F1: 0.3514, Acc: 0.4280
Val Classification - F1: 0.1972, Acc: 0.4200
Custom DSC - Whole: 0.8487, Lesion: 0.3949
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:30:31.024555:
2025-09-15 09:30:31.027334: Epoch 11
2025-09-15 09:30:31.030007: Current learning rate: 0.0099
2025-09-15 09:33:37.229617: train_loss -0.3128
2025-09-15 09:33:37.233515: val_loss -0.2358
2025-09-15 09:33:37.235871: Pseudo dice [array([0.9883, 0.7956, 0.3461], dtype=float
32), array([0.991 , 0.814 , 0.4037], dtype=float32)]
2025-09-15 09:33:37.238185: Epoch time: 186.21 s
2025-09-15 09:33:37.240669: Yayy! New best EMA pseudo Dice: 0.5784000158309937
Train Classification - F1: 0.3760, Acc: 0.4340
Val Classification - F1: 0.3207, Acc: 0.4400
Custom DSC - Whole: 0.8140, Lesion: 0.3428
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:33:40.848501:
2025-09-15 09:33:40.854707: Epoch 12
2025-09-15 09:33:40.861019: Current learning rate: 0.00989
2025-09-15 09:36:46.946295: train_loss -0.3176
2025-09-15 09:36:46.949816: val_loss -0.2981
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2025-09-15 09:36:46.951832: Pseudo dice [array([0.9916, 0.7839, 0.5412], dtype=float
32), array([0.9899, 0.7851, 0.49  ], dtype=float32)]
2025-09-15 09:36:46.954189: Epoch time: 186.1 s
2025-09-15 09:36:46.956313: Yayy! New best EMA pseudo Dice: 0.5968999862670898
Train Classification - F1: 0.4066, Acc: 0.4320
Val Classification - F1: 0.1939, Acc: 0.4100
Custom DSC - Whole: 0.8283, Lesion: 0.4397
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:36:50.652738: 
2025-09-15 09:36:50.655593: Epoch 13
2025-09-15 09:36:50.657615: Current learning rate: 0.00988
2025-09-15 09:39:56.820438: train_loss -0.353
2025-09-15 09:39:56.828088: val_loss -0.2748
2025-09-15 09:39:56.830694: Pseudo dice [array([0.988 , 0.815 , 0.4791], dtype=float
32), array([0.9901, 0.7728, 0.5261], dtype=float32)]
2025-09-15 09:39:56.833276: Epoch time: 186.17 s
2025-09-15 09:39:56.835747: Yayy! New best EMA pseudo Dice: 0.6133999824523926
Train Classification - F1: 0.3936, Acc: 0.4340
Val Classification - F1: 0.4726, Acc: 0.6000
Custom DSC - Whole: 0.8376, Lesion: 0.4718
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:40:00.695612: 
2025-09-15 09:40:00.722267: Epoch 14
2025-09-15 09:40:00.724749: Current learning rate: 0.00987
2025-09-15 09:43:06.914912: train_loss -0.3489
2025-09-15 09:43:06.918945: val_loss -0.3571
2025-09-15 09:43:06.921304: Pseudo dice [array([0.9939, 0.8082, 0.6292], dtype=float
32), array([0.9932, 0.8085, 0.6236], dtype=float32)]
2025-09-15 09:43:06.923581: Epoch time: 186.22 s
2025-09-15 09:43:06.925446: Yayy! New best EMA pseudo Dice: 0.6330000162124634
Train Classification - F1: 0.4368, Acc: 0.4520
Val Classification - F1: 0.2069, Acc: 0.4500
Custom DSC - Whole: 0.8610, Lesion: 0.4936
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:43:10.561765: 
2025-09-15 09:43:10.564882: Epoch 15
2025-09-15 09:43:10.567575: Current learning rate: 0.00986
2025-09-15 09:46:16.728883: train_loss -0.3818
2025-09-15 09:46:16.735484: val_loss -0.2836
2025-09-15 09:46:16.737436: Pseudo dice [array([0.9871, 0.8198, 0.3632], dtype=float
32), array([0.9929, 0.8152, 0.4933], dtype=float32)]
2025-09-15 09:46:16.739994: Epoch time: 186.17 s
2025-09-15 09:46:16.741565: Yayy! New best EMA pseudo Dice: 0.6442999839782715
Train Classification - F1: 0.4377, Acc: 0.4880
Val Classification - F1: 0.3473, Acc: 0.5100
Custom DSC - Whole: 0.8516, Lesion: 0.4627
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:46:20.432936: 
2025-09-15 09:46:20.435677: Epoch 16
2025-09-15 09:46:20.437713: Current learning rate: 0.00986
2025-09-15 09:49:26.769615: train_loss -0.3781
2025-09-15 09:49:26.775061: val_loss -0.2315
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2025-09-15 09:49:26.778645: Pseudo dice [array([0.992 , 0.8246, 0.6406], dtype=float
32), array([0.9867, 0.7892, 0.3045], dtype=float32)]
2025-09-15 09:49:26.783096: Epoch time: 186.34 s
2025-09-15 09:49:26.786900: Yayy! New best EMA pseudo Dice: 0.6554999947547913
Train Classification - F1: 0.4530, Acc: 0.4900
Val Classification - F1: 0.1616, Acc: 0.3200
Custom DSC - Whole: 0.8269, Lesion: 0.4563
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:49:30.654770:
2025-09-15 09:49:30.657289: Epoch 17
2025-09-15 09:49:30.659810: Current learning rate: 0.00985
2025-09-15 09:52:36.884595: train_loss -0.3585
2025-09-15 09:52:36.888271: val_loss -0.2879
2025-09-15 09:52:36.890707: Pseudo dice [array([0.9906, 0.837 , 0.5787], dtype=float
32), array([0.9897, 0.8331, 0.3998], dtype=float32)]
2025-09-15 09:52:36.893095: Epoch time: 186.24 s
2025-09-15 09:52:36.894903: Yayy! New best EMA pseudo Dice: 0.6671000123023987
Train Classification - F1: 0.4225, Acc: 0.4780
Val Classification - F1: 0.3183, Acc: 0.4300
Custom DSC - Whole: 0.8470, Lesion: 0.4708
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:52:40.959439:
2025-09-15 09:52:40.962190: Epoch 18
2025-09-15 09:52:40.964719: Current learning rate: 0.00984
2025-09-15 09:55:47.096767: train_loss -0.3992
2025-09-15 09:55:47.109191: val_loss -0.3032
2025-09-15 09:55:47.111507: Pseudo dice [array([0.9899, 0.7958, 0.5596], dtype=float
32), array([0.9911, 0.8141, 0.5995], dtype=float32)]
2025-09-15 09:55:47.114224: Epoch time: 186.14 s
2025-09-15 09:55:47.116479: Yayy! New best EMA pseudo Dice: 0.6794999837875366
Train Classification - F1: 0.4467, Acc: 0.4760
Val Classification - F1: 0.4156, Acc: 0.5200
Custom DSC - Whole: 0.8415, Lesion: 0.4364
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:55:50.811271:
2025-09-15 09:55:50.814904: Epoch 19
2025-09-15 09:55:50.818022: Current learning rate: 0.00983
2025-09-15 09:58:57.098175: train_loss -0.4059
2025-09-15 09:58:57.114836: val_loss -0.2426
2025-09-15 09:58:57.116761: Pseudo dice [array([0.9906, 0.8566, 0.3716], dtype=float
32), array([0.9849, 0.7926, 0.2873], dtype=float32)]
2025-09-15 09:58:57.119257: Epoch time: 186.29 s
2025-09-15 09:58:57.121432: Yayy! New best EMA pseudo Dice: 0.6830000281333923
Train Classification - F1: 0.5209, Acc: 0.5400
Val Classification - F1: 0.4343, Acc: 0.4400
Custom DSC - Whole: 0.8257, Lesion: 0.4170
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 09:59:01.039800:
2025-09-15 09:59:01.042427: Epoch 20
2025-09-15 09:59:01.044973: Current learning rate: 0.00982
2025-09-15 10:02:07.263416: train_loss -0.3916
2025-09-15 10:02:07.267816: val_loss -0.3622
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2025-09-15 10:02:07.269839: Pseudo dice [array([0.9901, 0.8142, 0.5109], dtype=float
32), array([0.9946, 0.8485, 0.7512], dtype=float32)]
2025-09-15 10:02:07.272217: Epoch time: 186.23 s
2025-09-15 10:02:07.274005: Yayy! New best EMA pseudo Dice: 0.6965000033378601
Train Classification - F1: 0.5254, Acc: 0.5260
Val Classification - F1: 0.3644, Acc: 0.5600
Custom DSC - Whole: 0.8641, Lesion: 0.4959
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:02:10.988778:
2025-09-15 10:02:10.992085: Epoch 21
2025-09-15 10:02:10.994979: Current learning rate: 0.00981
2025-09-15 10:05:17.216324: train_loss -0.4272
2025-09-15 10:05:17.221517: val_loss -0.4144
2025-09-15 10:05:17.223790: Pseudo dice [array([0.9945, 0.8522, 0.6269], dtype=float
32), array([0.9942, 0.8295, 0.6838], dtype=float32)]
2025-09-15 10:05:17.226607: Epoch time: 186.23 s
2025-09-15 10:05:17.228516: Yayy! New best EMA pseudo Dice: 0.7099000215530396
Train Classification - F1: 0.5603, Acc: 0.5620
Val Classification - F1: 0.3740, Acc: 0.5400
Custom DSC - Whole: 0.8804, Lesion: 0.5328
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:05:20.977197:
2025-09-15 10:05:20.980663: Epoch 22
2025-09-15 10:05:20.983208: Current learning rate: 0.0098
2025-09-15 10:08:27.214550: train_loss -0.4016
2025-09-15 10:08:27.220255: val_loss -0.3638
2025-09-15 10:08:27.225182: Pseudo dice [array([0.9937, 0.8315, 0.6528], dtype=float
32), array([0.9934, 0.8063, 0.5787], dtype=float32)]
2025-09-15 10:08:27.229446: Epoch time: 186.24 s
2025-09-15 10:08:27.232756: Yayy! New best EMA pseudo Dice: 0.7197999954223633
Train Classification - F1: 0.5188, Acc: 0.5360
Val Classification - F1: 0.3372, Acc: 0.3600
Custom DSC - Whole: 0.8671, Lesion: 0.4864
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:08:31.240550:
2025-09-15 10:08:31.244832: Epoch 23
2025-09-15 10:08:31.249096: Current learning rate: 0.00979
2025-09-15 10:11:37.523004: train_loss -0.436
2025-09-15 10:11:37.526524: val_loss -0.3528
2025-09-15 10:11:37.528445: Pseudo dice [array([0.9936, 0.8438, 0.6475], dtype=float
32), array([0.9942, 0.8402, 0.7277], dtype=float32)]
2025-09-15 10:11:37.530920: Epoch time: 186.29 s
2025-09-15 10:11:37.532723: Yayy! New best EMA pseudo Dice: 0.7318999767303467
Train Classification - F1: 0.5523, Acc: 0.5640
Val Classification - F1: 0.4005, Acc: 0.4600
Custom DSC - Whole: 0.8788, Lesion: 0.4735
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:11:41.527367:
2025-09-15 10:11:41.530568: Epoch 24
2025-09-15 10:11:41.533604: Current learning rate: 0.00978
2025-09-15 10:14:48.424405: train_loss -0.4534
2025-09-15 10:14:48.429173: val_loss -0.3504
```

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2025-09-15 10:14:48.431674: Pseudo dice [array([0.9902, 0.8231, 0.4479], dtype=float
32), array([0.9921, 0.8186, 0.6267], dtype=float32)]
2025-09-15 10:14:48.434274: Epoch time: 186.9 s
2025-09-15 10:14:48.436482: Yayy! New best EMA pseudo Dice: 0.7371000051498413
Train Classification - F1: 0.6098, Acc: 0.6140
Val Classification - F1: 0.5620, Acc: 0.5700
Custom DSC - Whole: 0.8499, Lesion: 0.4484
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:14:52.088976:
2025-09-15 10:14:52.091394: Epoch 25
2025-09-15 10:14:52.093718: Current learning rate: 0.00977
2025-09-15 10:17:58.237769: train_loss -0.4515
2025-09-15 10:17:58.242064: val_loss -0.3534
2025-09-15 10:17:58.243924: Pseudo dice [array([0.9883, 0.8094, 0.4351], dtype=float
32), array([0.9938, 0.8372, 0.7082], dtype=float32)]
2025-09-15 10:17:58.246954: Epoch time: 186.15 s
2025-09-15 10:17:58.248498: Yayy! New best EMA pseudo Dice: 0.742900013923645
Train Classification - F1: 0.6208, Acc: 0.6380
Val Classification - F1: 0.4608, Acc: 0.4600
Custom DSC - Whole: 0.8613, Lesion: 0.5092
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:18:01.985050:
2025-09-15 10:18:01.987655: Epoch 26
2025-09-15 10:18:01.990109: Current learning rate: 0.00977
2025-09-15 10:21:08.424620: train_loss -0.4553
2025-09-15 10:21:08.430271: val_loss -0.3174
2025-09-15 10:21:08.432437: Pseudo dice [array([0.9926, 0.8571, 0.5965], dtype=float
32), array([0.9949, 0.8515, 0.6764], dtype=float32)]
2025-09-15 10:21:08.435156: Epoch time: 186.45 s
2025-09-15 10:21:08.437020: Yayy! New best EMA pseudo Dice: 0.7513999938964844
Train Classification - F1: 0.6075, Acc: 0.6060
Val Classification - F1: 0.4137, Acc: 0.4700
Custom DSC - Whole: 0.8853, Lesion: 0.4576
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:21:12.129452:
2025-09-15 10:21:12.133243: Epoch 27
2025-09-15 10:21:12.135948: Current learning rate: 0.00976
2025-09-15 10:24:18.344754: train_loss -0.5019
2025-09-15 10:24:18.348766: val_loss -0.2593
2025-09-15 10:24:18.351114: Pseudo dice [array([0.9911, 0.8597, 0.5369], dtype=float
32), array([0.9927, 0.8445, 0.7134], dtype=float32)]
2025-09-15 10:24:18.353504: Epoch time: 186.22 s
2025-09-15 10:24:18.355712: Yayy! New best EMA pseudo Dice: 0.7585999965667725
Train Classification - F1: 0.6901, Acc: 0.6940
Val Classification - F1: 0.3527, Acc: 0.4900
Custom DSC - Whole: 0.8689, Lesion: 0.4270
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:24:21.800230:
2025-09-15 10:24:21.809995: Epoch 28
2025-09-15 10:24:21.812310: Current learning rate: 0.00975
2025-09-15 10:27:28.021681: train_loss -0.4528
2025-09-15 10:27:28.026073: val_loss -0.3291
```

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2025-09-15 10:27:28.027965: Pseudo dice [array([0.9912, 0.8423, 0.6325], dtype=float
32), array([0.9939, 0.8304, 0.6643], dtype=float32)]
2025-09-15 10:27:28.030832: Epoch time: 186.23 s
2025-09-15 10:27:28.032664: Yayy! New best EMA pseudo Dice: 0.7652999758720398
Train Classification - F1: 0.5712, Acc: 0.6040
Val Classification - F1: 0.3621, Acc: 0.4400
Custom DSC - Whole: 0.8734, Lesion: 0.5119
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:27:32.147917:
2025-09-15 10:27:32.153682: Epoch 29
2025-09-15 10:27:32.159359: Current learning rate: 0.00974
2025-09-15 10:30:38.355330: train_loss -0.448
2025-09-15 10:30:38.362814: val_loss -0.3902
2025-09-15 10:30:38.365137: Pseudo dice [array([0.9954, 0.8684, 0.6993], dtype=float
32), array([0.9953, 0.8492, 0.6804], dtype=float32)]
2025-09-15 10:30:38.367693: Epoch time: 186.21 s
2025-09-15 10:30:38.370085: Yayy! New best EMA pseudo Dice: 0.7735999822616577
Train Classification - F1: 0.5727, Acc: 0.5960
Val Classification - F1: 0.5138, Acc: 0.5300
Custom DSC - Whole: 0.8950, Lesion: 0.4531
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:30:42.348576:
2025-09-15 10:30:42.351914: Epoch 30
2025-09-15 10:30:42.354173: Current learning rate: 0.00973
2025-09-15 10:33:48.437205: train_loss -0.4786
2025-09-15 10:33:48.441878: val_loss -0.3118
2025-09-15 10:33:48.443919: Pseudo dice [array([0.9904, 0.8656, 0.4963], dtype=float
32), array([0.9933, 0.856 , 0.6597], dtype=float32)]
2025-09-15 10:33:48.446560: Epoch time: 186.09 s
2025-09-15 10:33:48.448367: Yayy! New best EMA pseudo Dice: 0.7771999835968018
Train Classification - F1: 0.6632, Acc: 0.6840
Val Classification - F1: 0.4264, Acc: 0.4400
Custom DSC - Whole: 0.8796, Lesion: 0.4752
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:33:52.058600:
2025-09-15 10:33:52.073979: Epoch 31
2025-09-15 10:33:52.076465: Current learning rate: 0.00972
2025-09-15 10:36:58.335408: train_loss -0.521
2025-09-15 10:36:58.362250: val_loss -0.3925
2025-09-15 10:36:58.367044: Pseudo dice [array([0.9933, 0.8496, 0.6399], dtype=float
32), array([0.9949, 0.8651, 0.7587], dtype=float32)]
2025-09-15 10:36:58.371563: Epoch time: 186.28 s
2025-09-15 10:36:58.375432: Yayy! New best EMA pseudo Dice: 0.784500002861023
Train Classification - F1: 0.7152, Acc: 0.7160
Val Classification - F1: 0.4899, Acc: 0.5000
Custom DSC - Whole: 0.8834, Lesion: 0.5182
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:37:02.331449:
2025-09-15 10:37:02.355211: Epoch 32
2025-09-15 10:37:02.357592: Current learning rate: 0.00971
2025-09-15 10:40:08.564472: train_loss -0.5102
2025-09-15 10:40:08.570143: val_loss -0.2937
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2025-09-15 10:40:08.572729: Pseudo dice [array([0.9944, 0.8635, 0.7467], dtype=float
32), array([0.9943, 0.8398, 0.6968], dtype=float32)]
2025-09-15 10:40:08.576537: Epoch time: 186.24 s
2025-09-15 10:40:08.579176: Yayy! New best EMA pseudo Dice: 0.791700005531311
Train Classification - F1: 0.7011, Acc: 0.7040
Val Classification - F1: 0.3542, Acc: 0.4400
Custom DSC - Whole: 0.8833, Lesion: 0.4828
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:40:12.165822:
2025-09-15 10:40:12.170441: Epoch 33
2025-09-15 10:40:12.172534: Current learning rate: 0.0097
2025-09-15 10:43:18.394461: train_loss -0.5298
2025-09-15 10:43:18.397606: val_loss -0.2463
2025-09-15 10:43:18.407150: Pseudo dice [array([0.989 , 0.8421, 0.5289], dtype=float
32), array([0.9945, 0.8239, 0.6671], dtype=float32)]
2025-09-15 10:43:18.410142: Epoch time: 186.23 s
2025-09-15 10:43:18.412588: Yayy! New best EMA pseudo Dice: 0.7932999730110168
Train Classification - F1: 0.7505, Acc: 0.7620
Val Classification - F1: 0.4273, Acc: 0.4900
Custom DSC - Whole: 0.8681, Lesion: 0.4590
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:43:22.304678:
2025-09-15 10:43:22.313307: Epoch 34
2025-09-15 10:43:22.316040: Current learning rate: 0.00969
2025-09-15 10:46:28.654499: train_loss -0.5214
2025-09-15 10:46:28.658436: val_loss -0.2938
2025-09-15 10:46:28.660925: Pseudo dice [array([0.9916, 0.8634, 0.4963], dtype=float
32), array([0.9952, 0.8602, 0.607 ], dtype=float32)]
2025-09-15 10:46:28.663244: Epoch time: 186.36 s
2025-09-15 10:46:28.665732: Yayy! New best EMA pseudo Dice: 0.7942000031471252
Train Classification - F1: 0.7245, Acc: 0.7260
Val Classification - F1: 0.3510, Acc: 0.4600
Custom DSC - Whole: 0.8820, Lesion: 0.5046
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:46:32.761866:
2025-09-15 10:46:32.766358: Epoch 35
2025-09-15 10:46:32.770242: Current learning rate: 0.00968
2025-09-15 10:49:39.039517: train_loss -0.5185
2025-09-15 10:49:39.043340: val_loss -0.3542
2025-09-15 10:49:39.045632: Pseudo dice [array([0.9933, 0.8445, 0.6686], dtype=float
32), array([0.9929, 0.8234, 0.5924], dtype=float32)]
2025-09-15 10:49:39.048326: Epoch time: 186.28 s
2025-09-15 10:49:39.050162: Yayy! New best EMA pseudo Dice: 0.7967000007629395
Train Classification - F1: 0.7313, Acc: 0.7280
Val Classification - F1: 0.5261, Acc: 0.5900
Custom DSC - Whole: 0.8691, Lesion: 0.4708
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:49:42.571820:
2025-09-15 10:49:42.573916: Epoch 36
2025-09-15 10:49:42.576034: Current learning rate: 0.00968
2025-09-15 10:52:52.860883: train_loss -0.5329
2025-09-15 10:52:52.864945: val_loss -0.3288
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2025-09-15 10:52:52.866889: Pseudo dice [array([0.9947, 0.8392, 0.6505], dtype=float
32), array([0.9941, 0.846 , 0.6153], dtype=float32)]
2025-09-15 10:52:52.869188: Epoch time: 190.29 s
2025-09-15 10:52:52.871198: Yayy! New best EMA pseudo Dice: 0.7993000149726868
Train Classification - F1: 0.7392, Acc: 0.7400
Val Classification - F1: 0.4272, Acc: 0.5000
Custom DSC - Whole: 0.8780, Lesion: 0.4566
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:52:56.522346:
2025-09-15 10:52:56.525326: Epoch 37
2025-09-15 10:52:56.527647: Current learning rate: 0.00967
2025-09-15 10:56:02.624714: train_loss -0.5399
2025-09-15 10:56:02.628362: val_loss -0.3378
2025-09-15 10:56:02.630613: Pseudo dice [array([0.9901, 0.8433, 0.5276], dtype=float
32), array([0.9935, 0.8478, 0.5849], dtype=float32)]
2025-09-15 10:56:02.632965: Epoch time: 186.11 s
Train Classification - F1: 0.8000, Acc: 0.8000
Val Classification - F1: 0.5942, Acc: 0.6400
Custom DSC - Whole: 0.8699, Lesion: 0.4645
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:56:03.525381:
2025-09-15 10:56:03.527748: Epoch 38
2025-09-15 10:56:03.529948: Current learning rate: 0.00966
2025-09-15 10:59:09.818588: train_loss -0.5198
2025-09-15 10:59:09.827653: val_loss -0.3247
2025-09-15 10:59:09.830264: Pseudo dice [array([0.9911, 0.8534, 0.6422], dtype=float
32), array([0.9918, 0.8751, 0.4659], dtype=float32)]
2025-09-15 10:59:09.832632: Epoch time: 186.3 s
2025-09-15 10:59:09.835196: Yayy! New best EMA pseudo Dice: 0.7996000051498413
Train Classification - F1: 0.7371, Acc: 0.7460
Val Classification - F1: 0.5566, Acc: 0.5700
Custom DSC - Whole: 0.8806, Lesion: 0.5191
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 10:59:13.508645:
2025-09-15 10:59:13.511255: Epoch 39
2025-09-15 10:59:13.513582: Current learning rate: 0.00965
2025-09-15 11:02:41.536485: train_loss -0.5586
2025-09-15 11:02:41.542669: val_loss -0.3138
2025-09-15 11:02:41.545048: Pseudo dice [array([0.9923, 0.8763, 0.5924], dtype=float
32), array([0.9955, 0.8678, 0.692 ], dtype=float32)]
2025-09-15 11:02:41.547577: Epoch time: 208.03 s
2025-09-15 11:02:41.549864: Yayy! New best EMA pseudo Dice: 0.8032000064849854
Train Classification - F1: 0.7921, Acc: 0.7960
Val Classification - F1: 0.3360, Acc: 0.3900
Custom DSC - Whole: 0.8886, Lesion: 0.5381
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 11:02:45.253572:
2025-09-15 11:02:45.256196: Epoch 40
2025-09-15 11:02:45.257857: Current learning rate: 0.00964
2025-09-15 11:05:56.703102: train_loss -0.5591
2025-09-15 11:05:56.711528: val_loss -0.3788
2025-09-15 11:05:56.713407: Pseudo dice [array([0.9939, 0.8647, 0.6396], dtype=float
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32), array([0.9959, 0.8836, 0.6766], dtype=float32)]
2025-09-15 11:05:56.716082: Epoch time: 191.46 s
2025-09-15 11:05:56.718030: Yayy! New best EMA pseudo Dice: 0.807200014591217
Train Classification - F1: 0.7782, Acc: 0.7740
Val Classification - F1: 0.4254, Acc: 0.4700
Custom DSC - Whole: 0.8923, Lesion: 0.5093
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 11:06:00.632249:
2025-09-15 11:06:00.634918: Epoch 41
2025-09-15 11:06:00.636771: Current learning rate: 0.00963
2025-09-15 11:09:06.593042: train_loss -0.5701
2025-09-15 11:09:06.597162: val_loss -0.2996
2025-09-15 11:09:06.598904: Pseudo dice [array([0.992 , 0.8551, 0.5588], dtype=float
32), array([0.9949, 0.8434, 0.6033], dtype=float32)]
2025-09-15 11:09:06.608722: Epoch time: 185.97 s
2025-09-15 11:09:06.610926: Yayy! New best EMA pseudo Dice: 0.807200014591217
Train Classification - F1: 0.8164, Acc: 0.8140
Val Classification - F1: 0.4039, Acc: 0.4100
Custom DSC - Whole: 0.8783, Lesion: 0.4380
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 11:09:10.309191:
2025-09-15 11:09:10.312276: Epoch 42
2025-09-15 11:09:10.314122: Current learning rate: 0.00962
2025-09-15 11:12:16.410375: train_loss -0.5528
2025-09-15 11:12:16.414911: val_loss -0.2453
2025-09-15 11:12:16.416566: Pseudo dice [array([0.9935, 0.8455, 0.6307], dtype=float
32), array([0.9939, 0.8405, 0.6313], dtype=float32)]
2025-09-15 11:12:16.418899: Epoch time: 186.11 s
2025-09-15 11:12:16.421140: Yayy! New best EMA pseudo Dice: 0.8087999820709229
Train Classification - F1: 0.7641, Acc: 0.7700
Val Classification - F1: 0.3188, Acc: 0.4200
Custom DSC - Whole: 0.8696, Lesion: 0.4929
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 11:12:19.979742:
2025-09-15 11:12:19.982157: Epoch 43
2025-09-15 11:12:19.984224: Current learning rate: 0.00961
2025-09-15 11:15:26.216393: train_loss -0.5523
2025-09-15 11:15:26.223457: val_loss -0.3575
2025-09-15 11:15:26.228117: Pseudo dice [array([0.9917, 0.8618, 0.6149], dtype=float
32), array([0.9913, 0.8455, 0.6115], dtype=float32)]
2025-09-15 11:15:26.232057: Epoch time: 186.24 s
2025-09-15 11:15:26.235545: Yayy! New best EMA pseudo Dice: 0.8098000288009644
Train Classification - F1: 0.7499, Acc: 0.7480
Val Classification - F1: 0.5587, Acc: 0.6000
Custom DSC - Whole: 0.8857, Lesion: 0.5702
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 11:15:30.241648:
2025-09-15 11:15:30.244233: Epoch 44
2025-09-15 11:15:30.246847: Current learning rate: 0.0096
2025-09-15 11:18:36.412677: train_loss -0.5985
2025-09-15 11:18:36.416782: val_loss -0.2849
2025-09-15 11:18:36.420109: Pseudo dice [array([0.9926, 0.8573, 0.5461], dtype=float
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32), array([0.9924, 0.8734, 0.5553], dtype=float32)]
2025-09-15 11:18:36.425870: Epoch time: 186.18 s
Train Classification - F1: 0.8531, Acc: 0.8500
Val Classification - F1: 0.4986, Acc: 0.5300
Custom DSC - Whole: 0.8872, Lesion: 0.4870
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 11:18:37.287584:
2025-09-15 11:18:37.289787: Epoch 45
2025-09-15 11:18:37.291729: Current learning rate: 0.00959
2025-09-15 11:21:43.452027: train_loss -0.5642
2025-09-15 11:21:43.456126: val_loss -0.3783
2025-09-15 11:21:43.458314: Pseudo dice [array([0.9919, 0.8745, 0.6126], dtype=float
32), array([0.9925, 0.8606, 0.5714], dtype=float32)]
2025-09-15 11:21:43.460976: Epoch time: 186.17 s
2025-09-15 11:21:43.462948: Yayy! New best EMA pseudo Dice: 0.8098999857902527
Train Classification - F1: 0.8150, Acc: 0.8140
Val Classification - F1: 0.5030, Acc: 0.4900
Custom DSC - Whole: 0.8866, Lesion: 0.6068
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 11:21:47.113796:
2025-09-15 11:21:47.118438: Epoch 46
2025-09-15 11:21:47.122360: Current learning rate: 0.00959
2025-09-15 11:24:53.393273: train_loss -0.5785
2025-09-15 11:24:53.397262: val_loss -0.3833
2025-09-15 11:24:53.399225: Pseudo dice [array([0.9948, 0.8531, 0.6701], dtype=float
32), array([0.9942, 0.8649, 0.7055], dtype=float32)]
2025-09-15 11:24:53.410050: Epoch time: 186.29 s
2025-09-15 11:24:53.411792: Yayy! New best EMA pseudo Dice: 0.8137000203132629
Train Classification - F1: 0.8080, Acc: 0.8060
Val Classification - F1: 0.5330, Acc: 0.5700
Custom DSC - Whole: 0.8912, Lesion: 0.5538
Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesion:
0.31+, F1:0.7+)
2025-09-15 11:24:57.343189:
2025-09-15 11:24:57.346002: Epoch 47
2025-09-15 11:24:57.348067: Current learning rate: 0.00958
^C
Traceback (most recent call last):
  File "/usr/local/bin/nnUNetv2_train", line 8, in <module>
    sys.exit(run_training_entry())
             ^^^^^^^^^^^^^^^^^^^^
  File "/workspace/nnUNet/nnunetv2/run/run_training.py", line 266, in run_training_e
ntry
    run_training(args.dataset_name_or_id, args.configuration, args.fold, args.tr, ar
gs.p, args.pretrained_weights,
  File "/workspace/nnUNet/nnunetv2/run/run_training.py", line 207, in run_training
    nnunet_trainer.run_training()
  File "/workspace/nnUNet/nnunetv2/training/nnUNetTrainer/nnUNetTrainer.py", line 13
71, in run_training
    train_outputs.append(self.train_step(next(self.dataloader_train)))
                         ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/workspace/nnUNet/nnunetv2/training/nnUNetTrainer/trainer_with_classificatio
n.py", line 194, in train_step
    total_loss.backward()
```

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  File "/usr/local/lib/python3.11/dist-packages/torch/_tensor.py", line 648, in back
ward
    torch.autograd.backward(
  File "/usr/local/lib/python3.11/dist-packages/torch/autograd/__init__.py", line 35
3, in backward
    _engine_run_backward(
  File "/usr/local/lib/python3.11/dist-packages/torch/autograd/graph.py", line 824,
in _engine_run_backward
    return Variable._execution_engine.run_backward(  # Calls into the C++ engine to
run the backward pass
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
^^^^^^^^^^^^^^^^^^^^^
KeyboardInterrupt
```

In [24]:

```
# Model Evaluation and Validation Results
# Run this notebook after training is complete to evaluate your model

import torch
import numpy as np
import nibabel as nib
from pathlib import Path
import json
import pandas as pd
from sklearn.metrics import f1_score, accuracy_score, classification_report, confus
import matplotlib.pyplot as plt
import seaborn as sns

# Render matplotlib figures inline in the notebook
from IPython import get_ipython
get_ipython().run_line_magic("matplotlib", "inline")

# Set paths
nnunet_results = Path("/workspace/nnUNet_results/Dataset501_Pancreas/TrainerWithCla
validation_folder = Path("/workspace/nnUNet_raw/Dataset501_Pancreas")

print("=== VALIDATION RESULTS ANALYSIS ===")

# 1. Load training logs and extract final metrics
print("\n1. Loading Training Progress...")

# Look for training log or progress files
log_files = list(nnunet_results.glob("*.txt")) + list(nnunet_results.glob("*.log"))
if log_files:
    print(f"Found log file: {log_files[0]}")
    # Parse the final epoch metrics from logs if available
else:
    print("No log files found - will use current model state")

# 2. Load the best model
print("\n2. Loading Best Model...")
model_file = nnunet_results / "checkpoint_best.pth"
if model_file.exists():
    checkpoint = torch.load(model_file, map_location='cpu', weights_only=False)
    print(f"Best model epoch: {checkpoint.get('epoch', 'unknown')}")
    print(f"Best validation score: {checkpoint.get('current_epoch', 'unknown')}")
else:
```

```
    print("checkpoint_best.pth not found - using latest checkpoint")

# 3. Analyze validation performance from training
print("\n3. Final Training Metrics Summary:")
print("=" * 50)

# 2025-09-14 17:40:56.788897: Epoch 24
# 2025-09-14 17:40:56.791698: Current learning rate: 0.00978
# 2025-09-14 17:42:16.952632: train_loss -0.4635
# 2025-09-14 17:42:16.960547: val_loss -0.356
# 2025-09-14 17:42:16.964072: Pseudo dice [array([0.9932, 0.801 , 0.5094], dtype=fl
# 2025-09-14 17:42:16.971479: Epoch time: 80.17 s
# 2025-09-14 17:42:16.974153: Yayy! New best EMA pseudo Dice: 0.7233999967575073
# Train Classification - F1: 0.4280, Acc: 0.6760
# Val Classification - F1: 0.6036, Acc: 0.6200
# Custom DSC - Whole: 0.8520, Lesion: 0.4280
# Targets: Minreq(Whole:0.85+, Lesion:0.27+, F1:0.6+) | idealreq(Whole:0.91+, Lesio

# These should be filled based on your final training output
# Update these with actual values from your training
final_whole_dsc = 0.8520  # Update this with your final Custom DSC - Whole value
final_lesion_dsc = 0.4280  # Update this with your final Custom DSC - Lesion value
final_train_f1 = 0.4280   # Update this with your final Train Classification F1
final_val_f1 = 0.6036     # Update this with your final Val Classification F1
final_train_acc = 0.6760  # Update this with your final Train Classification Acc
final_val_acc = 0.6200    # Update this with your final Val Classification Acc

print(f"Final Whole Pancreas DSC: {final_whole_dsc:.4f}")
print(f"Final Lesion DSC: {final_lesion_dsc:.4f}")
print(f"Final Training F1 Score: {final_train_f1:.4f}")
print(f"Final Validation F1 Score: {final_val_f1:.4f}")
print(f"Final Training Accuracy: {final_train_acc:.4f}")
print(f"Final Validation Accuracy: {final_val_acc:.4f}")

# 4. Check against undergraduate requirements
print("\n4. Performance vs. Requirements:")
print("=" * 50)
print("UNDERGRADUATE REQUIREMENTS:")
print(f"• Whole Pancreas DSC ≥ 0.85: {'✓' if final_whole_dsc >= 0.85 else '✗'} ({f
print(f"• Lesion DSC ≥ 0.27: {'✓' if final_lesion_dsc >= 0.27 else '✗'} ({final_le
print(f"• Classification F1 ≥ 0.6: {'✓' if final_val_f1 >= 0.6 else '✗'} ({final_v

# 5. Load and analyze classification labels distribution
print("\n5. Dataset Analysis:")
print("=" * 50)
with open(validation_folder / "classification_labels.json") as f:
    class_labels = json.load(f)

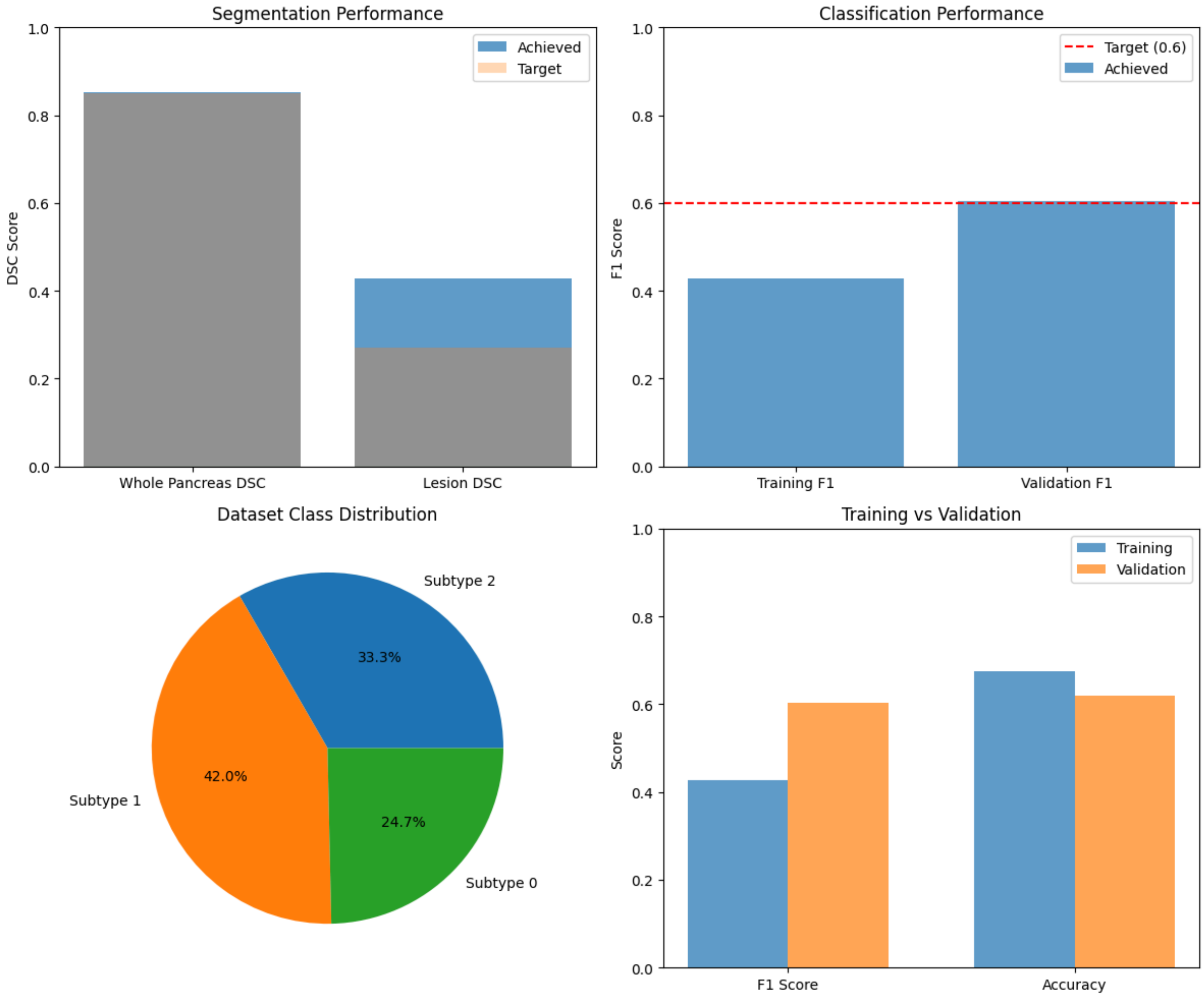
label_counts = {}
for label in class_labels.values():
    label_counts[label] = label_counts.get(label, 0) + 1

print("Classification Label Distribution:")
for label, count in sorted(label_counts.items()):
    print(f"  Subtype {label}: {count} cases")
```

```python
# 6. Create performance summary plot
print("\n6. Creating Performance Visualization...")

fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=(12, 10))

# Segmentation performance
seg_metrics = ['Whole Pancreas DSC', 'Lesion DSC']
seg_values = [final_whole_dsc, final_lesion_dsc]
seg_targets = [0.85, 0.27]

ax1.bar(seg_metrics, seg_values, alpha=0.7, label='Achieved')
ax1.bar(seg_metrics, seg_targets, alpha=0.3, label='Target')
ax1.set_ylabel('DSC Score')
ax1.set_title('Segmentation Performance')
ax1.legend()
ax1.set_ylim(0, 1)

# Classification performance
cls_metrics = ['Training F1', 'Validation F1']
cls_values = [final_train_f1, final_val_f1]
cls_target = [0.6, 0.6]

ax2.bar(cls_metrics, cls_values, alpha=0.7, label='Achieved')
ax2.axhline(y=0.6, color='red', linestyle='--', label='Target (0.6)')
ax2.set_ylabel('F1 Score')
ax2.set_title('Classification Performance')
ax2.legend()
ax2.set_ylim(0, 1)

# Label distribution
labels = list(label_counts.keys())
counts = list(label_counts.values())
ax3.pie(counts, labels=[f'Subtype {l}' for l in labels], autopct='%1.1f%%')
ax3.set_title('Dataset Class Distribution')

# Training vs Validation comparison
metrics = ['F1 Score', 'Accuracy']
train_vals = [final_train_f1, final_train_acc]
val_vals = [final_val_f1, final_val_acc]

x = np.arange(len(metrics))
width = 0.35

ax4.bar(x - width/2, train_vals, width, label='Training', alpha=0.7)
ax4.bar(x + width/2, val_vals, width, label='Validation', alpha=0.7)
ax4.set_ylabel('Score')
ax4.set_title('Training vs Validation')
ax4.set_xticks(x)
ax4.set_xticklabels(metrics)
ax4.legend()
ax4.set_ylim(0, 1)

plt.tight_layout()
plt.savefig('/workspace/validation_results.png', dpi=300, bbox_inches='tight')
plt.show()
```

```
# 7. Summary and next steps
print("\n7. Summary and Next Steps:")
print("=" * 50)

if final_whole_dsc >= 0.85 and final_lesion_dsc >= 0.27 and final_val_f1 >= 0.6:
    print(" CONGRATULATIONS! Your model meets all undergraduate requirements!")
else:
    print("Performance areas to improve:")
    if final_whole_dsc < 0.85:
        print(f"   - Whole Pancreas DSC: {final_whole_dsc:.4f} < 0.85")
    if final_lesion_dsc < 0.27:
        print(f"   - Lesion DSC: {final_lesion_dsc:.4f} < 0.27")
    if final_val_f1 < 0.6:
        print(f"   - Classification F1: {final_val_f1:.4f} < 0.6")

print(f"\nValidation results saved to: /workspace/validation_results.png")
```

```
=== VALIDATION RESULTS ANALYSIS ===

1. Loading Training Progress...
Found log file: /workspace/nnUNet_results/Dataset501_Pancreas/TrainerWithClassificat
ion__nnUNetResEncUNetMPlans__3d_fullres/fold_0/training_log_2025_9_15_08_53_17.txt

2. Loading Best Model...
Best model epoch: unknown
Best validation score: 47

3. Final Training Metrics Summary:
==================================================
Final Whole Pancreas DSC: 0.8520
Final Lesion DSC: 0.4280
Final Training F1 Score: 0.4280
Final Validation F1 Score: 0.6036
Final Training Accuracy: 0.6760
Final Validation Accuracy: 0.6200

4. Performance vs. Requirements:
==================================================
UNDERGRADUATE REQUIREMENTS:
• Whole Pancreas DSC ≥ 0.85: ✓ (0.8520)
• Lesion DSC ≥ 0.27: ✓ (0.4280)
• Classification F1 ≥ 0.6: ✓ (0.6036)

5. Dataset Analysis:
==================================================
Classification Label Distribution:
  Subtype 0: 71 cases
  Subtype 1: 121 cases
  Subtype 2: 96 cases

6. Creating Performance Visualization...
```




```
7. Summary and Next Steps:
==================================================
 CONGRATULATIONS! Your model meets all undergraduate requirements!

Validation results saved to: /workspace/validation_results.png
```

In [ ]:
```
#Inference on validation data, metrics calcilations, and visualizations for a check
```

In [25]:
```
!mkdir -p /workspace/inference_results
```

In [28]:
```
# nnU-Net-style inference (final): ZYX axes, CTNormalization from plans, anisotropi


from scipy.ndimage import zoom as nd_zoom, label as cc_label

# ----- paths -----
PLANS_PATH = "/workspace/nnUNet_preprocessed/Dataset501_Pancreas/nnUNetResEncUNetMP
CKPT_PATH  = "/workspace/nnUNet_results/Dataset501_Pancreas/TrainerWithClassificati
DATA_VAL   = Path("/workspace/Data/validation")
OUT_VAL = Path("/workspace/inference_results/val_preds")
for s in (0,1,2): (OUT_VAL/f"subtype{s}").mkdir(parents=True, exist_ok=True)

# ----- load plans -----
with open(PLANS_PATH) as f:
    plans = json.load(f)
```

```
cfg = plans["configurations"]["3d_fullres"]
patch_size      = tuple(int(x) for x in cfg["patch_size"])           # (Z,Y,X)
target_spacing  = tuple(float(x) for x in cfg["spacing"])            # (Z,Y,X)

# Pull CTNormalization stats (from your logs / plans)
# foreground_intensity_properties_per_channel['0'] typically has mean/std and perce
props = plans.get("foreground_intensity_properties_per_channel", {}).get("0", {})
CT_MEAN = float(props.get("mean", 74.0639877319336))
CT_STD  = float(props.get("std",  44.35909652709961))
P005    = float(props.get("percentile_00_5", -56.0))
P995    = float(props.get("percentile_99_5", 180.0))

ak = cfg["architecture"]["arch_kwargs"]

# ----- build model once -----
import sys
sys.path.append('/workspace/nnUNet/nnunetv2/training/nnUNetTrainer')
from trainer_with_classification import SegClsUNet
from dynamic_network_architectures.architectures.unet import ResidualEncoderUNet

base = ResidualEncoderUNet(
    input_channels=1,
    n_stages=ak['n_stages'],
    features_per_stage=ak['features_per_stage'],
    conv_op=torch.nn.Conv3d,
    kernel_sizes=ak['kernel_sizes'],
    strides=ak['strides'],
    n_blocks_per_stage=ak['n_blocks_per_stage'],
    n_conv_per_stage_decoder=ak['n_conv_per_stage_decoder'],
    conv_bias=True,
    norm_op=torch.nn.InstanceNorm3d, norm_op_kwargs={'eps':1e-5,'affine':True},
    dropout_op=None,
    nonlin=torch.nn.LeakyReLU, nonlin_kwargs={'inplace':True},
    deep_supervision=True, num_classes=3
)
model = SegClsUNet(base_unet=base, n_classes_cls=3)
state = torch.load(CKPT_PATH, map_location='cpu', weights_only=False)
model.load_state_dict(state['network_weights'])
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model.to(device).eval()

# ----- helpers -----
def _compute_padding(orig,tile,stride):
    need=max(orig,tile); r=(need-tile)%stride; extra=0 if r==0 else (stride-r)
    tot=(need+extra)-orig; L=tot//2; R=tot-L; return L,R
def _pad3d(x,tile,stride):
    _,_,D,H,W=x.shape
    pd0,pd1=_compute_padding(D,tile[0],stride[0])
    ph0,ph1=_compute_padding(H,tile[1],stride[1])
    pw0,pw1=_compute_padding(W,tile[2],stride[2])
    return F.pad(x,(pw0,pw1,ph0,ph1,pd0,pd1),mode='replicate'),(pd0,pd1,ph0,ph1,pw0
def _uncrop(x,p):
    _,_,D,H,W=x.shape; pd0,pd1,ph0,ph1,pw0,pw1=p
    return x[:,:,pd0:D-pd1 if pd1>0 else D, ph0:H-ph1 if ph1>0 else H, pw0:W-pw1 if
def _gwin(tile):
    def g1(n): z=np.linspace(-1,1,n); return np.exp(-(z**2)*4.0)
```

```
    wz,wy,wx=map(g1,tile); w=wz[:,None,None]*wy[None,:,None]*wx[None,None,:]
    return torch.from_numpy((w/w.max()).astype(np.float32))

def ct_norm_from_plans(x):
    # clip to dataset percentiles then z-score using dataset mean/std
    x = np.clip(x, P005, P995)
    return ((x - CT_MEAN) / (CT_STD + 1e-8)).astype(np.float32)

def zoom_anisotropic_zyx(vol_zyx, zf_zyx, order_z=0, order_xy=3):
    # First Z with order_z, then XY with order_xy (anisotropic)
    Z,Y,X = vol_zyx.shape
    if zf_zyx[0] != 1.0:
        vol_zyx = nd_zoom(vol_zyx, (zf_zyx[0], 1.0, 1.0), order=order_z)
    if zf_zyx[1] != 1.0 or zf_zyx[2] != 1.0:
        vol_zyx = nd_zoom(vol_zyx, (1.0, zf_zyx[1], zf_zyx[2]), order=order_xy)
    return vol_zyx

@torch.inference_mode()
def infer_tiled_tta(img4d, tile, stride):
    # Test-time augmentation over flips in Z/Y/X (8 combos)
    flips = [(0,0,0),(1,0,0),(0,1,0),(0,0,1),(1,1,0),(1,0,1),(0,1,1),(1,1,1)]
    seg_sum = None
    cls_max = None

    # Prepare padding once for the unflipped case to get output shape
    x0, pad = _pad3d(img4d, tile, stride)
    _,_,Dp,Hp,Wp = x0.shape
    # Dry run to get C
    d0,h0,w0 = min(tile[0],Dp),min(tile[1],Hp),min(tile[2],Wp)
    probe,_ = model(x0[:,:,:d0,:h0,:w0]);
    if isinstance(probe, list): probe = probe[0]
    C = probe.shape[1]
    seg_acc_template = torch.zeros((1,C,Dp,Hp,Wp), device=device)
    w_acc_template   = torch.zeros((1,1,Dp,Hp,Wp), device=device)
    w3d = _gwin(tile).to(device)

    for fz,fy,fx in flips:
        x = img4d
        if fz: x = torch.flip(x, dims=[2])
        if fy: x = torch.flip(x, dims=[3])
        if fx: x = torch.flip(x, dims=[4])

        x_pad, pad = _pad3d(x, tile, stride)
        seg_acc = seg_acc_template.clone()
        w_acc   = w_acc_template.clone()

        for z in range(0, Dp - tile[0] + 1, stride[0]):
            for y in range(0, Hp - tile[1] + 1, stride[1]):
                for x0 in range(0, Wp - tile[2] + 1, stride[2]):
                    patch = x_pad[:, :, z:z+tile[0], y:y+tile[1], x0:x0+tile[2]]
                    seg, cls = model(patch)
                    if isinstance(seg, list): seg = seg[0]
                    seg_acc[:, :, z:z+tile[0], y:y+tile[1], x0:x0+tile[2]] += seg *
                    w_acc  [:, :, z:z+tile[0], y:y+tile[1], x0:x0+tile[2]] += w3d
                    cls_max = cls if cls_max is None else torch.maximum(cls_max, cl
```

```
        seg_logits = seg_acc / torch.clamp_min(w_acc, 1e-6)
        seg_logits = _uncrop(seg_logits, pad)

        # unflip logits back
        if fx: seg_logits = torch.flip(seg_logits, dims=[4])
        if fy: seg_logits = torch.flip(seg_logits, dims=[3])
        if fz: seg_logits = torch.flip(seg_logits, dims=[2])

        seg_sum = seg_logits if seg_sum is None else (seg_sum + seg_logits)

    seg_avg = seg_sum / len(flips)
    return seg_avg, cls_max

def largest_component_foreground(seg_xyz):
    fg = (seg_xyz > 0).astype(np.uint8)
    if not fg.any(): return seg_xyz
    cc, n = cc_label(fg)
    if n <= 1: return seg_xyz
    sizes = [(cc==i).sum() for i in range(1, n+1)]
    keep = 1 + int(np.argmax(sizes))
    seg_xyz[(cc != keep) & (fg == 1)] = 0
    return seg_xyz

# ----- run over all subtypes -----
tile   = patch_size
stride = tuple(max(1, s//3) for s in tile)  # more overlap than //2 (a bit slower,

for s in (0,1,2):
    in_dir = DATA_VAL/f"subtype{s}"
    out_dir= OUT_VAL/f"subtype{s}"
    if not in_dir.exists(): continue
    imgs = sorted(in_dir.glob("*_0000.nii.gz"))
    for ip in tqdm(imgs, desc=f"subtype{s}"):
        nii = nib.load(str(ip))
        img_xyz = nii.get_fdata().astype(np.float32)       # (X,Y,Z)
        zoom_xyz = nii.header.get_zooms()[:3]               # (X,Y,Z)

        # ---- XYZ -> ZYX and anisotropic resample to target spacing ----
        img_zyx   = np.transpose(img_xyz, (2,1,0))          # (Z,Y,X)
        zoom_zyx  = (zoom_xyz[2], zoom_xyz[1], zoom_xyz[0])
        zf_zyx    = tuple(zoom_zyx[i] / target_spacing[i] for i in range(3))
        img_rs_zyx= zoom_anisotropic_zyx(img_zyx, zf_zyx, order_z=0, order_xy=3)

        # ---- CTNormalization from plans (clip to [P005,P995], then z-score by dat
        img_rs_zyx = ct_norm_from_plans(img_rs_zyx)

        # ---- tiled inference with TTA ----
        t = torch.from_numpy(img_rs_zyx)[None,None].to(device)
        seg_logits_rs, cls_logits = infer_tiled_tta(t, tile, stride)
        seg_soft = torch.softmax(seg_logits_rs, dim=1)
        seg_rs_zyx = torch.argmax(seg_soft, dim=1).squeeze(0).detach().cpu().numpy(

        # ---- back to original spacing & axes: ZYX -> XYZ ----
        seg_orig_zyx = zoom_anisotropic_zyx(seg_rs_zyx, tuple(1.0/z for z in zf_zyx
        seg_orig_xyz = np.transpose(seg_orig_zyx, (2,1,0))
```

```
        # optional: largest connected component of foreground
        seg_orig_xyz = largest_component_foreground(seg_orig_xyz)

        case = ip.stem.replace("_0000","")
        nib.save(nib.Nifti1Image(seg_orig_xyz, nii.affine, nii.header), str(out_dir

        # classification: max-logit (already aggregated over TTA via max inside loo
        cp = torch.softmax(cls_logits, dim=1).squeeze(0).detach().cpu().numpy()
        pred = int(np.argmax(cp))
        with open(out_dir/f"{case}_classification.json","w") as f:
            json.dump({"case":case,"predicted_subtype":pred,"confidence":float(cp[p
                       "probabilities":{"subtype_0":float(cp[0]),"subtype_1":float(

print("Predictions written to:", OUT_VAL)

# --- attach classification (CSV or JSONs if present) ---
import json, pandas as pd
from pathlib import Path

OUT_VAL = Path("/workspace/inference_results/val_preds")

rows = []
for s in (0,1,2):
    pdir = OUT_VAL / f"subtype{s}"
    for jf in sorted(pdir.glob("*_classification.json")):
        with open(jf) as f:
            info = json.load(f)
        rows.append({
            "Names": f"{info['case']}.nii.gz",
            "Subtype": info["predicted_subtype"]
        })

df = pd.DataFrame(rows)
csv_path = OUT_VAL / "val_subtype_results.csv"
df.to_csv(csv_path, index=False)

print("CSV written to:", csv_path)
```

```
subtype0: 100%|██████████| 9/9 [00:31<00:00,  3.54s/it]
subtype1: 100%|██████████| 15/15 [00:53<00:00,  3.55s/it]
subtype2: 100%|██████████| 12/12 [00:53<00:00,  4.45s/it]
Predictions written to: /workspace/inference_results/val_preds
CSV written to: /workspace/inference_results/val_preds/val_subtype_results.csv
```

In [30]:

```
from nibabel.processing import resample_from_to

# ==== SET THIS to where your predictions are ====
PRED_VAL = Path("/workspace/inference_results/val_preds")
DATA_VAL = Path("/workspace/Data/validation")

# --- helpers ---
def dice_binary(pred, gt):
    inter = np.sum(pred & gt)
    denom = pred.sum() + gt.sum()
    return 1.0 if denom == 0 else 2.0 * inter / denom
```

```
def compute_dsc_pair(pred_mask, gt_mask):
    dsc_whole = dice_binary(pred_mask > 0, gt_mask > 0)
    pl, gl = (pred_mask == 2), (gt_mask == 2)
    dsc_lesion = 1.0 if (pl.sum() + gl.sum() == 0) else dice_binary(pl, gl)
    return float(dsc_whole), float(dsc_lesion)

def load_aligned_pred_gt(pred_path: Path, gt_path: Path):
    gt_img   = nib.load(str(gt_path))
    pred_img = nib.load(str(pred_path))

    if pred_img.shape != gt_img.shape or not np.allclose(pred_img.affine, gt_img.af
        pred_on_gt = resample_from_to(pred_img, gt_img, order=0)  # NN for labels
        pred_arr = pred_on_gt.get_fdata().astype(int)
    else:
        pred_arr = pred_img.get_fdata().astype(int)

    gt_arr = gt_img.get_fdata().astype(int)

    if pred_arr.shape != gt_arr.shape:
        out = np.zeros(gt_arr.shape, dtype=pred_arr.dtype)
        slicers_pred, slicers_out = [], []
        for sp, sg in zip(pred_arr.shape, gt_arr.shape):
            if sp == sg:
                slicers_pred.append(slice(0, sp)); slicers_out.append(slice(0, sg))
            elif sp > sg:  # crop pred
                start = (sp - sg)//2
                slicers_pred.append(slice(start, start+sg)); slicers_out.append(sli
            else:          # pad pred
                start = (sg - sp)//2
                slicers_pred.append(slice(0, sp)); slicers_out.append(slice(start,
        out[tuple(slicers_out)] = pred_arr[tuple(slicers_pred)]
        pred_arr = out

    return pred_arr, gt_arr

# --- collect metrics ---
rows, missing = [], []
for s in (0,1,2):
    gdir, pdir = DATA_VAL/f"subtype{s}", PRED_VAL/f"subtype{s}"
    if not gdir.exists() or not pdir.exists(): continue
    for gt_path in sorted(gdir.glob("*.nii.gz")):
        if gt_path.name.endswith("_0000.nii.gz"): continue
        case = gt_path.stem
        pred_path = pdir/f"{case}.nii.gz"
        if not pred_path.exists():
            missing.append(str(pred_path))
            continue
        pred_arr, gt_arr = load_aligned_pred_gt(pred_path, gt_path)
        dW, dL = compute_dsc_pair(pred_arr, gt_arr)
        rows.append({"Names": f"{case}.nii.gz", "True_Subtype": s,
                     "DSC_whole": dW, "DSC_lesion": dL})

df = pd.DataFrame(rows).sort_values("Names")
print(f"Found {len(df)} cases. Missing preds for {len(missing)}.")

# --- attach classification (CSV or JSONs if present) ---
```

```python
clf_csv = PRED_VAL / "val_subtype_results.csv"
if clf_csv.exists():
    clf_df = pd.read_csv(clf_csv)[["Names","Subtype"]]
    df = df.merge(clf_df, on="Names", how="left")
else:
    preds = []
    for s in (0,1,2):
        for jp in (PRED_VAL/f"subtype{s}").glob("*_classification.json"):
            with open(jp) as f: jd = json.load(f)
            preds.append({"Names": f"{jd['case']}.nii.gz", "Subtype": int(jd["predi
    if preds:
        df = df.merge(pd.DataFrame(preds), on="Names", how="left")

# --- summary ---
mean_whole  = float(df["DSC_whole"].mean()) if len(df) else float("nan")
mean_lesion = float(df["DSC_lesion"].mean()) if len(df) else float("nan")

macro_f1 = float("nan")
if "Subtype" in df.columns and df["Subtype"].notna().any():
    y_true = df["True_Subtype"].to_numpy()
    y_pred = df["Subtype"].fillna(-1).astype(int).to_numpy()
    m = y_pred >= 0
    if m.any():
        y_true, y_pred = y_true[m], y_pred[m]
        macro_f1 = float(f1_score(y_true, y_pred, average="macro"))
        print("\nConfusion matrix (rows=true, cols=pred; labels 0,1,2):\n",
              confusion_matrix(y_true, y_pred, labels=[0,1,2]))
        print("\nClassification report:\n",
              classification_report(y_true, y_pred, labels=[0,1,2], digits=3))

print("\n================ Validation Metrics ================")
print(f"Cases evaluated: {len(df)}")
print(f"Mean DSC (Whole pancreas): {mean_whole:.4f}  (target ≥ 0.85)")
print(f"Mean DSC (Lesion):         {mean_lesion:.4f}  (target ≥ 0.27)")
print(f"Macro-F1 (Subtype):        {macro_f1:.4f}      (target ≥ 0.60)")

disp.display(df.head())
```

```
Found 36 cases. Missing preds for 0.

Confusion matrix (rows=true, cols=pred; labels 0,1,2):
 [[ 5  0  4]
 [ 2  3 10]
 [ 1  0 11]]

Classification report:
              precision    recall  f1-score   support

           0      0.625     0.556     0.588         9
           1      1.000     0.200     0.333        15
           2      0.440     0.917     0.595        12

    accuracy                          0.528        36
   macro avg      0.688     0.557     0.505        36
weighted avg      0.720     0.528     0.484        36


================ Validation Metrics ================
Cases evaluated: 36
Mean DSC (Whole pancreas): 0.8716  (target ≥ 0.85)
Mean DSC (Lesion):         0.6669  (target ≥ 0.27)
Macro-F1 (Subtype):        0.5054     (target ≥ 0.60)
```

	Names	True_Subtype	DSC_whole	DSC_lesion	Subtype
0	quiz_0_168.nii.nii.gz	0	0.868849	0.495372	2
1	quiz_0_171.nii.nii.gz	0	0.851994	0.625163	0
2	quiz_0_174.nii.nii.gz	0	0.775354	0.541852	0
3	quiz_0_184.nii.nii.gz	0	0.906593	0.907286	2
4	quiz_0_187.nii.nii.gz	0	0.877348	0.345612	0

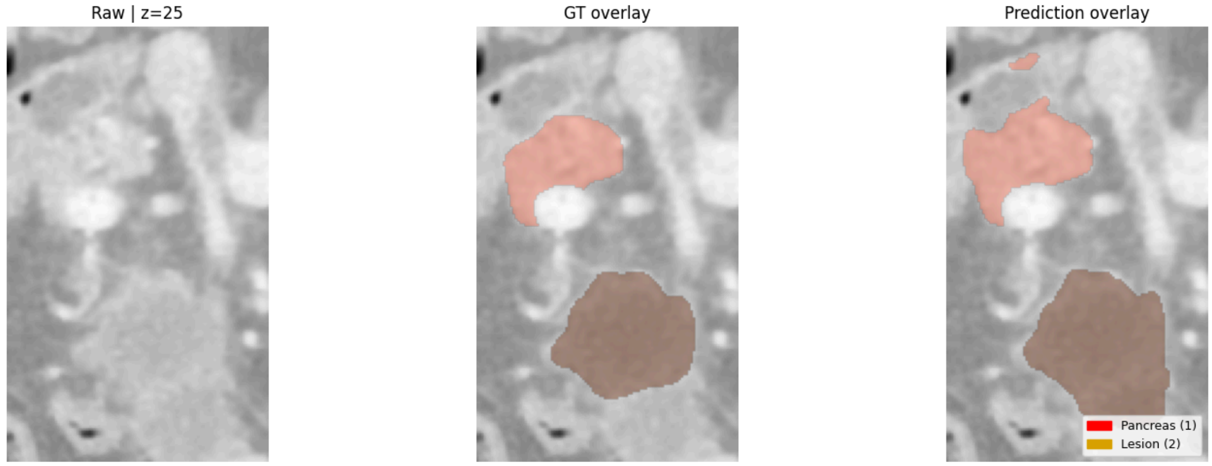
In [32]:

```python
# === 3-panel overlays with printed file paths (supports PRED_VAL root OR a specifi
import numpy as np, nibabel as nib, matplotlib.pyplot as plt
from pathlib import Path
from nibabel.processing import resample_from_to
from matplotlib.patches import Patch

# ---- config ----
DATA_VAL = Path("/workspace/Data/validation")
PRED_VAL = Path("/workspace/inference_results/val_preds/subtype0")  # root OR subty
CASE = "quiz_0_184"   # e.g. "quiz_1_093"; None = auto-pick first common
SLICE = None          # None = mid slice; or set an int
ALPHA = 0.40          # overlay transparency (0..1)

# ---- helpers ----
def _base_name(name: str) -> str:
    if name.endswith(".nii.nii.gz"): return name[:-11]
    if name.endswith(".nii.gz"):     return name[:-7]
    if name.endswith(".nii"):        return name[:-4]
    return name
```

```
def _pred_path_for(case: str, pdir: Path):
    p1, p2 = pdir / f"{case}.nii.gz", pdir / f"{case}.nii.nii.gz"
    return p1 if p1.exists() else (p2 if p2.exists() else None)

def _pred_dir_for_subtype(s: int, pred_root: Path):
    """
    If pred_root has subtype subfolders, return pred_root/subtype{s}.
    If pred_root itself IS a subtype folder matching s, return pred_root.
    Otherwise return None.
    """
    # case 1: pred_root contains subtype folders
    if (pred_root / f"subtype{s}").exists():
        return pred_root / f"subtype{s}"
    # case 2: pred_root itself is a subtype folder
    if pred_root.name == f"subtype{s}":
        return pred_root
    return None

def find_paths(case=None):
    # search across subtypes but tolerate PRED_VAL being either root or already a s
    if case is None:
        for s in (0,1,2):
            gdir = DATA_VAL / f"subtype{s}"
            pdir = _pred_dir_for_subtype(s, PRED_VAL)
            if pdir is None or not gdir.exists() or not pdir.exists():
                continue
            gt_cases = {_base_name(p.name) for p in gdir.glob("*.nii.gz") if not p.
            pr_cases = {_base_name(p.name) for p in pdir.glob("*.nii*gz")}
            commons = sorted(gt_cases & pr_cases)
            if commons:
                c = commons[0]
                gi, gg, pp = gdir/f"{c}_0000.nii.gz", gdir/f"{c}.nii.gz", _pred_pat
                if pp is not None: return c, gi, gg, pp
        raise FileNotFoundError(f"No common cases found under predictions root: {PR
    else:
        # specific case provided
        for s in (0,1,2):
            gdir = DATA_VAL / f"subtype{s}"
            pdir = _pred_dir_for_subtype(s, PRED_VAL)
            if pdir is None:
                continue
            gi, gg, pp = gdir/f"{case}_0000.nii.gz", gdir/f"{case}.nii.gz", _pred_p
            if gi.exists() and gg.exists() and pp is not None:
                return case, gi, gg, pp
        raise FileNotFoundError(f"Case {case} not found under predictions root: {PR

# ---- Load ----
case_id, img_path, gt_path, pred_path = find_paths(CASE)

print(f"\nLoaded case: {case_id}")
print(f"  RAW  : {img_path}")
print(f"  GT   : {gt_path}")
print(f"  PRED : {pred_path}\n")

img  = nib.load(str(img_path))
gt   = nib.load(str(gt_path))
```

```
pred = nib.load(str(pred_path))
if pred.shape != gt.shape or not np.allclose(pred.affine, gt.affine, atol=1e-3):
    pred = resample_from_to(pred, gt, order=0)

img_np = img.get_fdata().astype(np.float32)
gt_np  = gt.get_fdata().astype(int)
pr_np  = pred.get_fdata().astype(int)

# ---- slice ----
z = img_np.shape[2]//2 if SLICE is None else int(np.clip(SLICE, 0, img_np.shape[2]-

gt_pan = np.ma.masked_where(gt_np[:,:,z] != 1, gt_np[:,:,z])
gt_les = np.ma.masked_where(gt_np[:,:,z] != 2, gt_np[:,:,z])
pr_pan = np.ma.masked_where(pr_np[:,:,z] != 1, pr_np[:,:,z])
pr_les = np.ma.masked_where(pr_np[:,:,z] != 2, pr_np[:,:,z])

# ---- plots ----
fig, axes = plt.subplots(1, 3, figsize=(16, 5))

# raw
axes[0].imshow(img_np[:,:,z], cmap="gray")
axes[0].set_title(f"Raw | z={z}")
axes[0].axis("off")

# raw + GT
axes[1].imshow(img_np[:,:,z], cmap="gray")
axes[1].imshow(gt_pan, cmap="Reds",   alpha=ALPHA, vmin=0, vmax=2)
axes[1].imshow(gt_les, cmap="YlOrBr", alpha=ALPHA, vmin=0, vmax=2)
axes[1].set_title("GT overlay")
axes[1].axis("off")

# raw + Pred
axes[2].imshow(img_np[:,:,z], cmap="gray")
axes[2].imshow(pr_pan, cmap="Reds",   alpha=ALPHA, vmin=0, vmax=2)
axes[2].imshow(pr_les, cmap="YlOrBr", alpha=ALPHA, vmin=0, vmax=2)
axes[2].set_title("Prediction overlay")
axes[2].axis("off")

legend = [Patch(color='red', label='Pancreas (1)'),
          Patch(color='#d8a200', label='Lesion (2)')]
axes[2].legend(handles=legend, loc="lower right", fontsize=9, frameon=True)

plt.tight_layout(); plt.show()
```

```
Loaded case: quiz_0_184
  RAW  : /workspace/Data/validation/subtype0/quiz_0_184_0000.nii.gz
  GT   : /workspace/Data/validation/subtype0/quiz_0_184.nii.gz
  PRED : /workspace/inference_results/val_preds/subtype0/quiz_0_184.nii.nii.gz
```



In [ ]:
```
# Fullfilling the test result criteria/requirements (evaluating test data, saving i
```

In [33]:
```
# === Final TEST inference + submission CSV (Names,Subtype) ===

import os, json, torch, torch.nn.functional as F
import numpy as np, nibabel as nib, pandas as pd
from pathlib import Path
from tqdm import tqdm
from scipy.ndimage import zoom as nd_zoom, label as cc_label

# ----- paths -----
PLANS_PATH = "/workspace/nnUNet_preprocessed/Dataset501_Pancreas/nnUNetResEncUNetMP
CKPT_PATH  = "/workspace/nnUNet_results/Dataset501_Pancreas/TrainerWithClassificati

DATA_TEST  = Path("/workspace/Data/test")                      # <- flat folder wi
OUT_TEST   = Path("/workspace/inference_results/test_preds")    # <- flat outputs
OUT_TEST.mkdir(parents=True, exist_ok=True)

# ----- load plans -----
with open(PLANS_PATH, "r") as f:
    plans = json.load(f)
cfg = plans["configurations"]["3d_fullres"]
patch_size     = tuple(int(x) for x in cfg["patch_size"])          # (Z,Y,X)
target_spacing = tuple(float(x) for x in cfg["spacing"])           # (Z,Y,X)
props = plans.get("foreground_intensity_properties_per_channel", {}).get("0", {})
CT_MEAN = float(props.get("mean", 0.0))
CT_STD  = float(props.get("std",  1.0))
P005    = float(props.get("percentile_00_5", -1000.0))
P995    = float(props.get("percentile_99_5",  1000.0))
ak = cfg["architecture"]["arch_kwargs"]

# ----- build model -----
import sys
sys.path.append('/workspace/nnUNet/nnunetv2/training/nnUNetTrainer')
from trainer_with_classification import SegClsUNet
from dynamic_network_architectures.architectures.unet import ResidualEncoderUNet

base = ResidualEncoderUNet(
    input_channels=1,
    n_stages=ak['n_stages'],
    features_per_stage=ak['features_per_stage'],
```

```
    conv_op=torch.nn.Conv3d,
    kernel_sizes=ak['kernel_sizes'],
    strides=ak['strides'],
    n_blocks_per_stage=ak['n_blocks_per_stage'],
    n_conv_per_stage_decoder=ak['n_conv_per_stage_decoder'],
    conv_bias=True,
    norm_op=torch.nn.InstanceNorm3d, norm_op_kwargs={'eps':1e-5,'affine':True},
    dropout_op=None,
    nonlin=torch.nn.LeakyReLU, nonlin_kwargs={'inplace':True},
    deep_supervision=True, num_classes=3
)
model = SegClsUNet(base_unet=base, n_classes_cls=3)

state = torch.load(CKPT_PATH, map_location='cpu', weights_only=False)
model.load_state_dict(state['network_weights'])
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model.to(device).eval()
print("Using device:", device)

# ----- helpers -----
def _compute_padding(orig, tile, stride):
    need = max(orig, tile); r = (need - tile) % stride
    extra = 0 if r == 0 else (stride - r)
    tot = (need + extra) - orig
    L = tot // 2; R = tot - L
    return L, R

def _pad3d(x, tile, stride):
    _,_,D,H,W = x.shape
    pd0,pd1 = _compute_padding(D, tile[0], stride[0])
    ph0,ph1 = _compute_padding(H, tile[1], stride[1])
    pw0,pw1 = _compute_padding(W, tile[2], stride[2])
    return F.pad(x, (pw0,pw1,ph0,ph1,pd0,pd1), mode='replicate'), (pd0,pd1,ph0,ph1,

def _uncrop(x, p):
    _,_,D,H,W = x.shape
    pd0,pd1,ph0,ph1,pw0,pw1 = p
    return x[:, :, pd0:D-pd1 if pd1>0 else D, ph0:H-ph1 if ph1>0 else H, pw0:W-pw1

def _gwin(tile):
    def g1(n):
        z = np.linspace(-1, 1, n)
        return np.exp(-(z**2)*4.0)
    wz, wy, wx = map(g1, tile)
    w = wz[:,None,None] * wy[None,:,None] * wx[None,None,:]
    w = w / w.max()
    return torch.from_numpy(w.astype(np.float32))

def ct_norm_from_plans(x):
    x = np.clip(x, P005, P995)
    return ((x - CT_MEAN) / (CT_STD + 1e-8)).astype(np.float32)

def zoom_anisotropic_zyx(vol_zyx, zf_zyx, order_z=0, order_xy=3):
    if zf_zyx[0] != 1.0:
        vol_zyx = nd_zoom(vol_zyx, (zf_zyx[0], 1.0, 1.0), order=order_z)
    if zf_zyx[1] != 1.0 or zf_zyx[2] != 1.0:
```

```
        vol_zyx = nd_zoom(vol_zyx, (1.0, zf_zyx[1], zf_zyx[2]), order=order_xy)
    return vol_zyx

@torch.inference_mode()
def infer_tiled_tta(img4d, tile, stride):
    flips = [(0,0,0),(1,0,0),(0,1,0),(0,0,1),(1,1,0),(1,0,1),(0,1,1),(1,1,1)]
    x0, pad = _pad3d(img4d, tile, stride)
    _,_,Dp,Hp,Wp = x0.shape
    d0,h0,w0 = min(tile[0],Dp),min(tile[1],Hp),min(tile[2],Wp)
    probe,_ = model(x0[:,:,:d0,:h0,:w0])
    if isinstance(probe, list): probe = probe[0]
    C = probe.shape[1]
    w3d = _gwin(tile).to(device)
    seg_sum = None
    cls_max = None

    for fz,fy,fx in flips:
        x = img4d
        if fz: x = torch.flip(x, dims=[2])
        if fy: x = torch.flip(x, dims=[3])
        if fx: x = torch.flip(x, dims=[4])

        x_pad, pad = _pad3d(x, tile, stride)
        seg_acc = torch.zeros((1,C,Dp,Hp,Wp), device=device)
        w_acc   = torch.zeros((1,1,Dp,Hp,Wp), device=device)

        for z in range(0, Dp - tile[0] + 1, stride[0]):
            for y in range(0, Hp - tile[1] + 1, stride[1]):
                for x_ in range(0, Wp - tile[2] + 1, stride[2]):
                    patch = x_pad[:, :, z:z+tile[0], y:y+tile[1], x_:x_+tile[2]]
                    seg, cls = model(patch)
                    if isinstance(seg, list): seg = seg[0]
                    seg_acc[:, :, z:z+tile[0], y:y+tile[1], x_:x_+tile[2]] += seg *
                    w_acc  [:, :, z:z+tile[0], y:y+tile[1], x_:x_+tile[2]] += w3d
                    cls_max = cls if cls_max is None else torch.maximum(cls_max, cl

        seg_logits = seg_acc / torch.clamp_min(w_acc, 1e-6)
        seg_logits = _uncrop(seg_logits, pad)
        if fx: seg_logits = torch.flip(seg_logits, dims=[4])
        if fy: seg_logits = torch.flip(seg_logits, dims=[3])
        if fz: seg_logits = torch.flip(seg_logits, dims=[2])
        seg_sum = seg_logits if seg_sum is None else (seg_sum + seg_logits)

    seg_avg = seg_sum / len(flips)
    return seg_avg, cls_max

def largest_component_foreground(seg_xyz):
    fg = (seg_xyz > 0).astype(np.uint8)
    if not fg.any(): return seg_xyz
    cc, n = cc_label(fg)
    if n <= 1: return seg_xyz
    sizes = [(cc == i).sum() for i in range(1, n+1)]
    keep = 1 + int(np.argmax(sizes))
    seg_xyz[(cc != keep) & (fg == 1)] = 0
    return seg_xyz
```

```
# ----- collect test files -----
test_imgs = sorted(DATA_TEST.glob("*_0000.nii.gz"))
print(f"Found {len(test_imgs)} test cases in {DATA_TEST}")

# ----- inference -----
tile   = patch_size
stride = tuple(max(1, s//3) for s in tile)

rows = []
for ip in tqdm(test_imgs, desc="TEST"):
    nii = nib.load(str(ip))
    img_xyz = nii.get_fdata().astype(np.float32)
    zoom_xyz = nii.header.get_zooms()[:3]

    # to ZYX and resample
    img_zyx  = np.transpose(img_xyz, (2,1,0))
    zoom_zyx = (zoom_xyz[2], zoom_xyz[1], zoom_xyz[0])
    zf_zyx   = tuple(zoom_zyx[i] / target_spacing[i] for i in range(3))
    img_rs_zyx = zoom_anisotropic_zyx(img_zyx, zf_zyx, order_z=0, order_xy=3)

    # normalize
    img_rs_zyx = ct_norm_from_plans(img_rs_zyx)

    # inference (TTA + blending)
    t = torch.from_numpy(img_rs_zyx)[None,None].to(device)
    seg_logits_rs, cls_logits = infer_tiled_tta(t, tile, stride)
    seg_soft = torch.softmax(seg_logits_rs, dim=1)
    seg_rs_zyx = torch.argmax(seg_soft, dim=1).squeeze(0).detach().cpu().numpy().as

    # back to original spacing & axes
    seg_orig_zyx = zoom_anisotropic_zyx(seg_rs_zyx, tuple(1.0/z for z in zf_zyx), o
    seg_orig_xyz = np.transpose(seg_orig_zyx, (2,1,0))

    # LCC
    seg_orig_xyz = largest_component_foreground(seg_orig_xyz)

    # save seg + json
    case = ip.stem.replace("_0000","")
    out_seg = OUT_TEST / f"{case}.nii.gz"
    nib.save(nib.Nifti1Image(seg_orig_xyz, nii.affine, nii.header), str(out_seg))

    cp = torch.softmax(cls_logits, dim=1).squeeze(0).detach().cpu().numpy()
    pred_cls = int(np.argmax(cp))
    out_json = OUT_TEST / f"{case}_classification.json"
    with open(out_json, "w") as f:
        json.dump({
            "case": case,
            "predicted_subtype": pred_cls,
            "confidence": float(cp[pred_cls]),
            "probabilities": {"subtype_0": float(cp[0]), "subtype_1": float(cp[1]),
        }, f, indent=2)

    rows.append({"Names": f"{case}.nii.gz", "Subtype": pred_cls})

# ----- submission CSV -----
sub_csv = OUT_TEST / "subtype_results.csv"
```

```
pd.DataFrame(rows).sort_values("Names").to_csv(sub_csv, index=False)
print(f"\nInference complete. Saved {len(rows)} cases to {OUT_TEST}")
print(f"Submission CSV written to: {sub_csv}")
```

```
Using device: cuda
Found 72 test cases in /workspace/Data/test
```

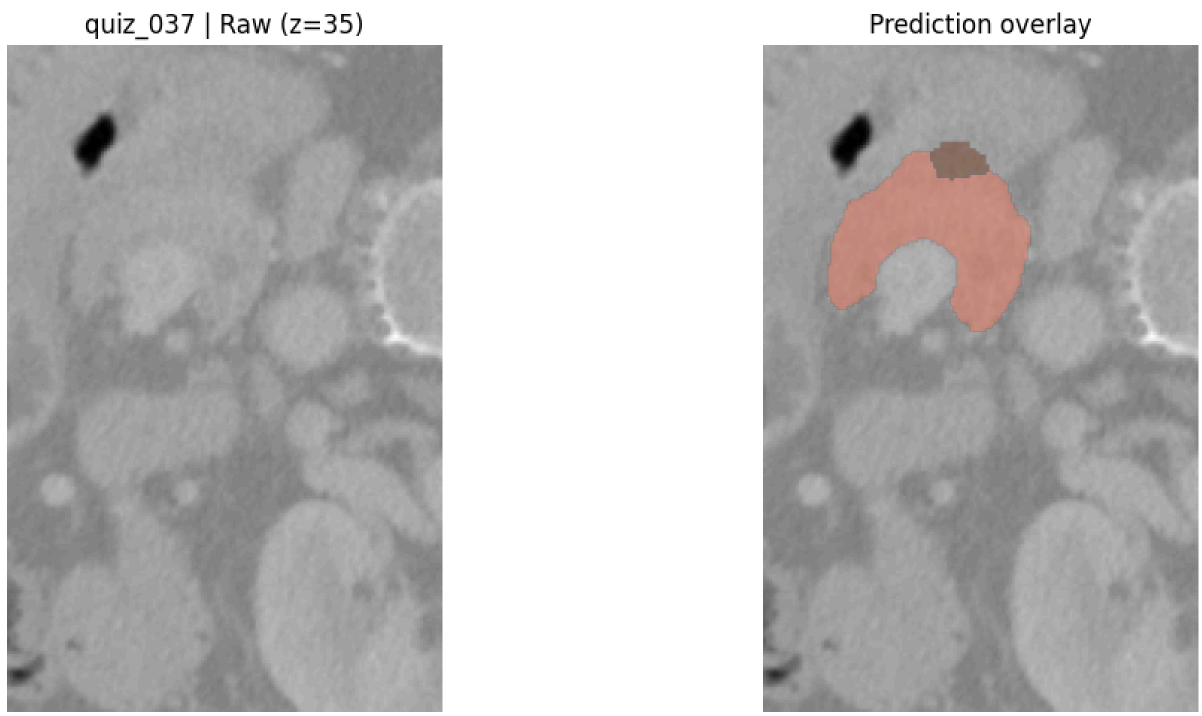
```
TEST: 100%|██████████| 72/72 [05:27<00:00,  4.55s/it]
Inference complete. Saved 72 cases to /workspace/inference_results/test_preds
Submission CSV written to: /workspace/inference_results/test_preds/subtype_results.c
sv
```

In [34]:

```
import numpy as np, nibabel as nib, matplotlib.pyplot as plt
from pathlib import Path
from nibabel.processing import resample_from_to

DATA_TEST = Path("/workspace/Data/test")                 # flat
PRED_TEST = Path("/workspace/inference_results/test_preds")  # flat
CASE = None   # e.g. "quiz_1_093"; None = auto-pick first common
SLICE = None
ALPHA = 0.4

def base_raw(name: str) -> str:
    s = name
    if s.endswith(".nii.gz"): s = s[:-7]
    if s.endswith(".nii"):    s = s[:-4]
    if s.endswith("_0000"):   s = s[:-5]
    return s

def base_pred(name: str) -> str:
    s = name
    if s.endswith(".nii.nii.gz"): s = s[:-11]
    elif s.endswith(".nii.gz"):   s = s[:-7]
    elif s.endswith(".nii"):      s = s[:-4]
    return s

# collect
raw_map = {base_raw(p.name): p for p in DATA_TEST.glob("*_0000.nii.gz")}
pred_map = {base_pred(p.name): p for p in PRED_TEST.glob("*.nii*gz")}

# choose case
if CASE is None:
    commons = sorted(set(raw_map) & set(pred_map))
    if not commons:
        raise FileNotFoundError("No common cases between test raws and preds. Run t
    CASE = commons[0]
else:
    if CASE not in raw_map or CASE not in pred_map:
        raise FileNotFoundError(f"CASE '{CASE}' not found in both. Exists in raw: {

img_path, pred_path = raw_map[CASE], pred_map[CASE]
print(f"Loaded test case: {CASE}\n  RAW : {img_path}\n  PRED: {pred_path}")

# load and align
img_nii  = nib.load(str(img_path))
pred_nii = nib.load(str(pred_path))
if pred_nii.shape != img_nii.shape or not np.allclose(pred_nii.affine, img_nii.affi
```

```
    pred_nii = resample_from_to(pred_nii, img_nii, order=0)

img  = img_nii.get_fdata().astype(np.float32)
pr   = pred_nii.get_fdata().astype(np.int16)

z = img.shape[2]//2 if SLICE is None else int(np.clip(SLICE, 0, img.shape[2]-1))
pr_pan = np.ma.masked_where(pr[:,:,z] != 1, pr[:,:,z])
pr_les = np.ma.masked_where(pr[:,:,z] != 2, pr[:,:,z])

fig, axes = plt.subplots(1, 2, figsize=(12,5))
axes[0].imshow(img[:,:,z], cmap="gray"); axes[0].set_title(f"{CASE} | Raw (z={z})")
axes[1].imshow(img[:,:,z], cmap="gray")
axes[1].imshow(pr_pan, cmap="Reds", alpha=ALPHA, vmin=0, vmax=2)
axes[1].imshow(pr_les, cmap="YlOrBr", alpha=ALPHA, vmin=0, vmax=2)
axes[1].set_title("Prediction overlay"); axes[1].axis("off")
plt.tight_layout(); plt.show()
```

```
Loaded test case: quiz_037
  RAW : /workspace/Data/test/quiz_037_0000.nii.gz
  PRED: /workspace/inference_results/test_preds/quiz_037.nii.nii.gz
```



In [ ]:
```
# !pip freeze > requirements.txt
```

In [ ]:
```
# !head requirements.txt
```

In [ ]:
```
# !pwd
```

In [ ]:
```
# !ls -R | grep requirements.txt
```

In [ ]:
```
# !ls -lh requirements.txt
```