Computational Biology Capstone Project

Sophia Judish

Paper:

"Brain tumor segmentation with self-ensembled, deeply-supervised 3D U-net neural networks: a BraTS 2020 challenge solution"

Authors:

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Brain tumor segmentation with self-ensembled, deeply-supervised 3D U-net neural networks: a BraTS 2020 challenge solution.

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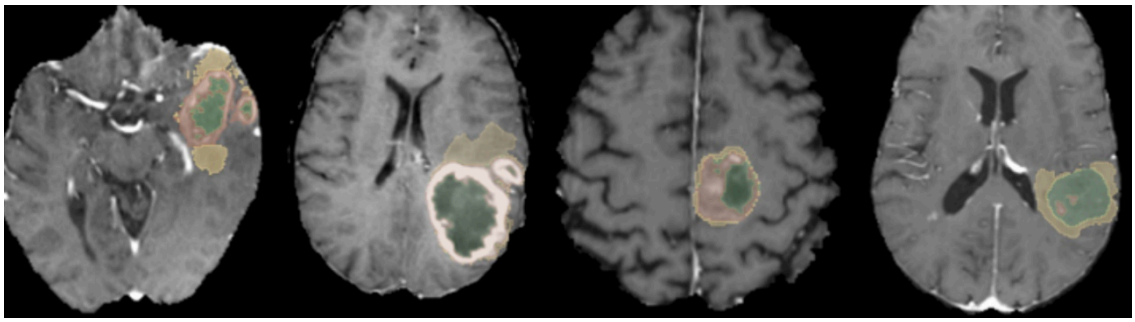
Literature Review

What does this paper accomplish?

- This paper trained U-net like neural networks to produce brain tumor segmentation maps from MRIs of brains with gliomas.
- The models were trained on the 2020 BraTS dataset, which provides specific sets of brain MRIs for training, testing, and validation.
- BraTS is a yearly competition where researchers build algorithms to detect and outline brain tumors from medical images.



Methods, Evaluation and Innovation

- The U-net like network used three rounds of downsampling and upsampling to capture features then reconstruct detailed tumor maps.
- Two different training pipelines were used to create models (different learning rates, epochs, etc.)
- The labelmap (scan where the tumor is labeled) from each pipeline was merged to created the final result.
- Pipeline B was found to be better at segmenting edema, so edema predictions from B were preferred, while predictions for other subregions like enhancing tumor (ET) and tumor core (TC) from Pipeline A were kept intact.
- The parameters used made this model a top 10 solution in the 2020 BraTS challenge.

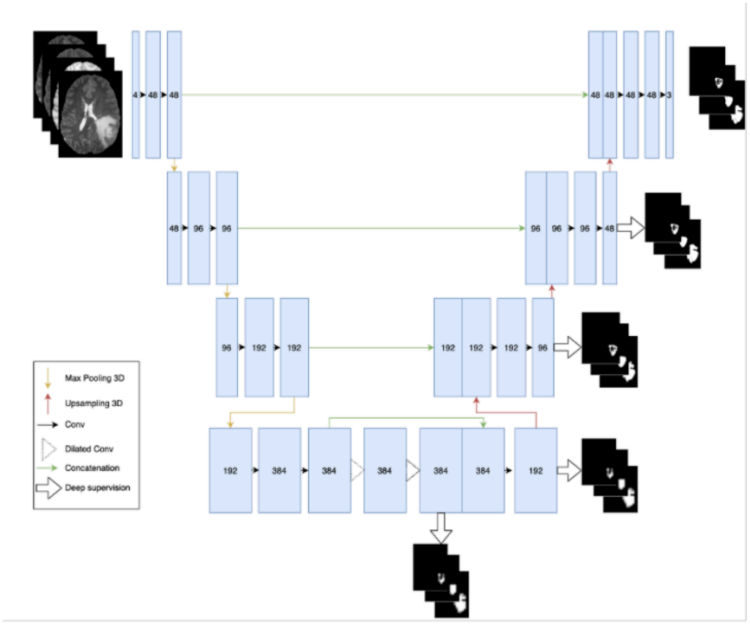


Fig. 2. Neural Network Architecture: 3D U-Net [35] with minor modifications

Why is this topic important?

- Gliomas, especially glioblastomas, are common and aggressive brain tumors in adults, with patients typically facing a poor prognosis.
- Tumor segmentation is important for gliomas as they are often heterogeneous tumors that must be classified into different regions.
- Accurate tumor segmentation is critical for patient treatment management and prognostic estimation.
- This research can support treatment for gliomas and improve patient outcomes.

Why am I interested in this project?

- I am majoring in Biochemistry and Computer Science and I am currently in the process of applying to medical school.
- I chose research on brain tumors specifically because I hope to eventually be a neurologist.
- I hope to use my computer science background to engage in research initiatives similar to this project to develop new treatments, medical tools, and improve patient outcomes in the field of neurology.

Expansion

- The paper includes multiple pipelines, but I focused on ‘Pipeline A’ as it has open-sourced code.

My Goals

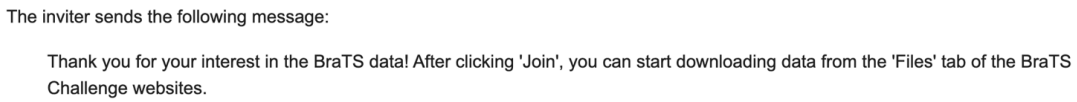
I aimed to evaluate per-case performance of the U-net to identify specific patient cases where the model performs poorly. I chose to use the Hausdorff Distance as my evaluation metric. This measures how far boundaries of segmentations are from each other. I wanted to analyze the poor performing cases in comparison with the best performing cases to gain insight into MRI characteristics that may be causing certain scans to be less successful in segmentation than others. I wanted to identify weak points in the model, as this could be useful in future model development

Input

I began my project using two key resources, the BraTS 2020 tumor dataset and the open-source segmentation model code provided by the paper I am focusing on.

Data

The first was MRI data from Brats2020 dataset (training and validation). I downloaded this data by making an account with Synapse, which is the official platform for requesting downloads of old BraTS data. To get this dataset, I needed to provide information on my intents for the data and my affiliated University, then wait to receive a response to my request.



Both the training and validation datasets had several MRI sequence types, including t2, t1ce, t1, and flair. Based on my research, each of these different sequences visualize brain tissues and tumors in different ways. I found that certain scans provided better segmentation of different tumor regions. For instance, .flair was described to be best for analyzing Whole Tumor (WT). The training dataset also included a ground truth segmentation file.

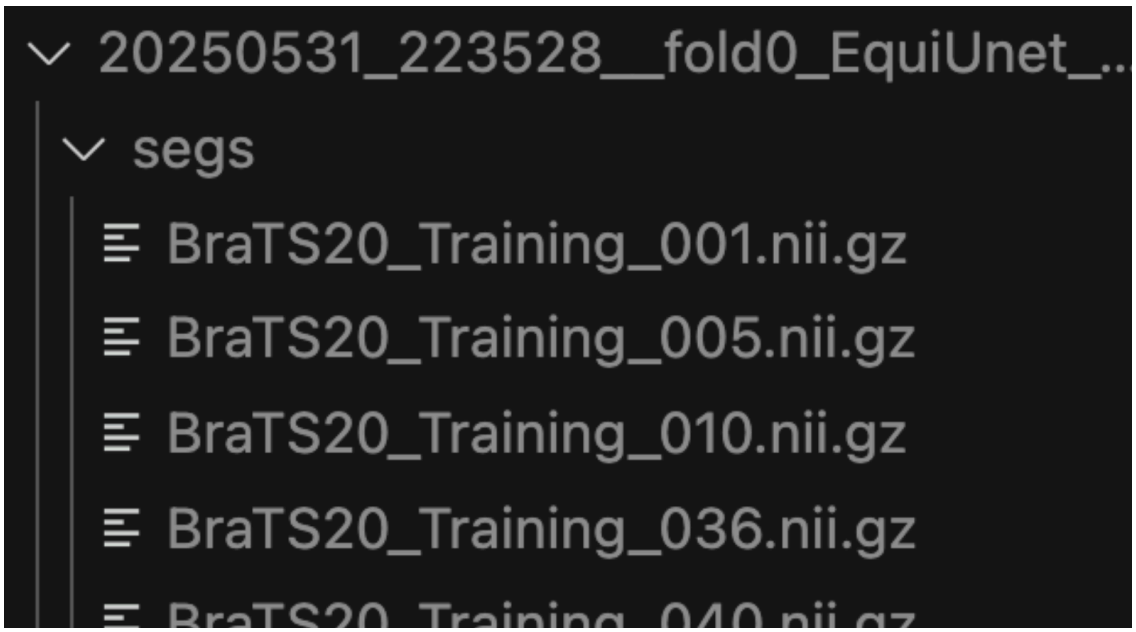
Code

I used open source code to train and validate a segmentation model. The code is located on GitHub at https://github.com/lescientifik/open_brats2020. Before I

could start training the model, I needed to upload my data and code onto the remote Hamachi server, as I needed more GPUs than were available on my Mac. Additionally, I needed to download the dependencies and change the directories of the training and validation data in the code.

Training Model

- Before I could start training the model, I needed to upload my data and code onto the remote Hamachi server, as I needed more GPUs than were available on my Mac. I logged into the Hamachi server with the following command: code --folder-uri "vscode-remote://ssh-remote+hamachi/homes/iws/sjudish/open_brats2020"
- Additionally, I needed to download the dependencies and change the directories of the training and validation data in the code. I had to troubleshoot this slightly as I had multiple versions of Python downloaded.
- I ran the model once with 10 epochs and once with 20 epochs in the interest of time, to keep the project moving forward. In the future, I would definitely train for more epochs to ensure convergence and achieve the best results.
- I began training using the command: python -m src.train --devices 0 --width 48 --arch EquiUnet --epochs 20
- Once training was complete for the first time, there was an output folder called "runs". This folder would create a new directory for each time trained the model with a new segmentation file for each patient and a .csv file called patients_indiv_perf.csv which contained a file with performance metrics for each patient, per patient & tumor subregion (WT, TC, ET).



```
patient_id,label,tta,haussdorf,dice,sens,spec
BraTS20_Training_001,ET,False,19.131126469708992,0.8835006049039822,0.9345036406892077,0.9994359714066716
BraTS20_Training_001,TC,False,22.516660498395403,0.9155218526116798,0.9868704411253908,0.999178598541444
BraTS20_Training_001,WT,False,21.283796653792763,0.9274178914897477,0.9403242774048373,0.9978717352792059
BraTS20_Training_005,ET,False,2.23606797749979,0.7007117252844304,0.6252549601335063,0.9998072267863034
```

Performance Metrics

The four performance metrics available were:

1. Dice coefficient (dice) What it is: Measures overlap between predicted and ground truth segmentation.

   Range: 0 (no overlap) to 1 (perfect match).

   Good value: High is good — closer to 1.0 is better.

   Target: ≥ 0.8 is generally considered good for medical segmentation.

2. Hausdorff distance (haussdorf) What it is: Measures the maximum distance between the predicted and true boundaries.

   Units: In voxels or mm, depending on dataset preprocessing.

   Good value: Low is good — a smaller distance means the boundaries are closely aligned.

   Target: < 10 is considered reasonable for many BraTS tasks, but varies.

3. Sensitivity (sens) What it is: True positive rate — how well the model finds the tumor.

   Formula: TP / (TP + FN)

   Good value: High is good — closer to 1.0 means fewer missed tumors.

4. Specificity (spec) What it is: True negative rate — how well the model avoids false alarms.

   Formula: TN / (TN + FP)

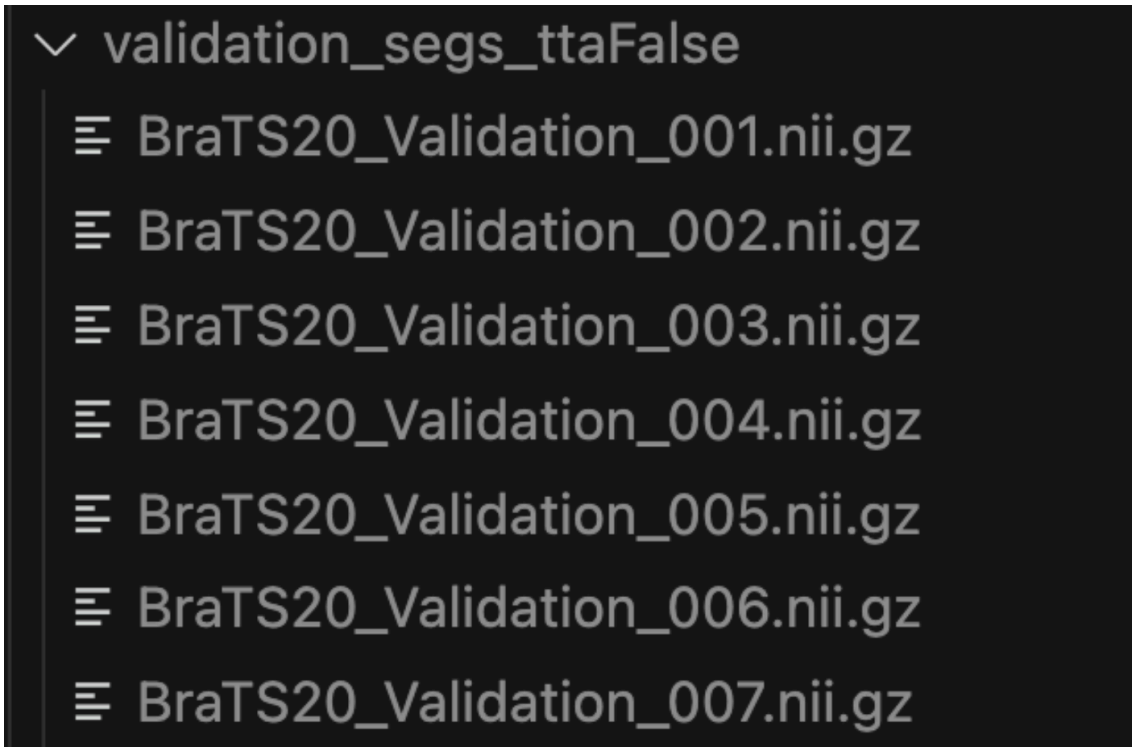
   Good value: High is good — closer to 1.0 means fewer false positives.

Inference on Validation Set

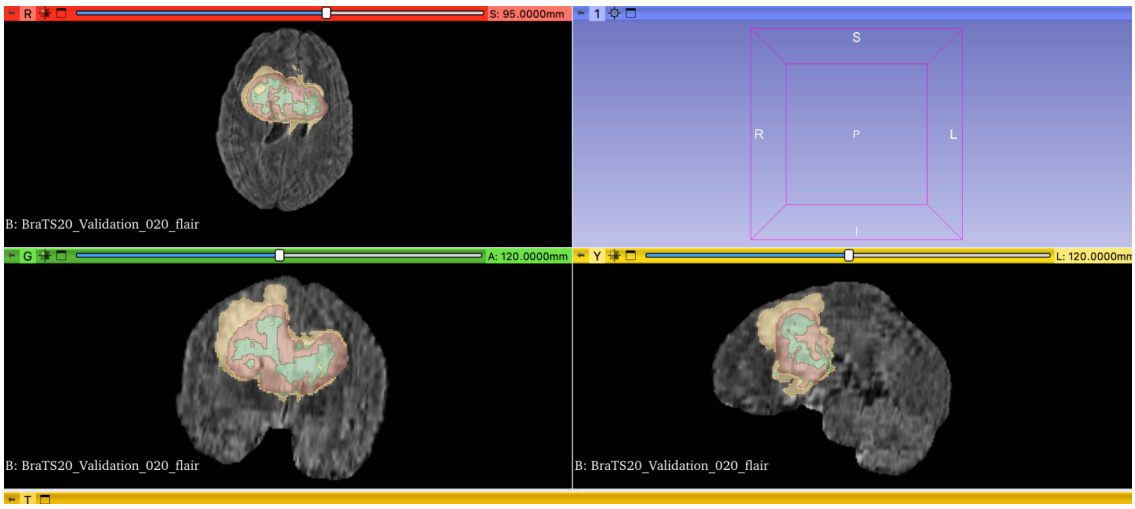
- Next, I performed inference using a specific training run. To do this, I copied the path to the desired run's configuration file from the runs/ directory and used it in the following command: python -m src.inference --config

runs/20250531_223528__fold0_EquiUnet_48_batch1_optimranger_ranger_lr0.0
wd0.0_epochs10_deepsupFalse_fp16_warm0__normgroup_dropout0.0_warm_re
wd0.0_epochs10_deepsupFalse_fp16_warm0__normgroup_dropout0.0_warm_re
--devices 0 --on val

- This command ran inference on the validation set using the specified training configuration. The output was saved in the /preds/ directory, with one segmentation result file generated per patient in the validation set.



- I explored the segmentation results using 3D Slicer, which allows overlaying multiple .nii files and visualizing segmentation regions in color. This helped me verify that the outputs were reasonable.



Data Analysis

- In my data analysis, I chose to consider only WT (whole tumor cases) because radiomic features extracted from the entire tumor volume tend to be more comprehensive.
- I chose to study the Hausdorff distance first, but the remaining process could be completed with any of these four metrics.
- I sorted the patient cases in a table and extracted those with the 20 best and 20 worst Hausdorff scores.
- My raw data before sorting or filtering was as follows:

Results

```
patient_id      label   tta     haussdorf       dice
sens    spec
BraTS20_Training_325    WT      FALSE
94.94208761134340       0.27610567750141800
0.9403465636342350      0.9906621293114810
BraTS20_Training_275    WT      FALSE
76.68115805072330       0.29669589617678000
0.6094236311239190      0.9902507505650320
BraTS20_Training_268    WT      FALSE   98.5393322486001
0.32611712461837400     0.9330333509793540
0.9919660886440960
BraTS20_Training_061    WT      FALSE
48.692915295759400      0.3602400547493290
0.9833780417704540      0.9918527012759670
BraTS20_Training_079    WT      FALSE
114.31972708155000      0.4039252088582420
0.836238846945779       0.9981182001666910
BraTS20_Training_340    WT      FALSE
59.87486951969080       0.4853750838512070
0.9865963467970160      0.98174087540931
BraTS20_Training_005    WT      FALSE
88.87631855561980       0.5646674501523810
0.6453581022628970      0.9984206218770480
BraTS20_Training_297    WT      FALSE   65.1536645170477
0.6458794361117940      0.8420778457510750
0.9935269250414600
BraTS20_Training_303    WT      FALSE
52.20153254455280       0.6465354178729980
0.9343393489721350      0.9961458135710500
BraTS20_Training_048    WT      FALSE
70.51950084905590       0.6549355495251020
0.7924005608946960      0.9979385894283490
BraTS20_Training_086    WT      FALSE
```

101.7742600071350 0.6636552872606160
0.7681669236700080 0.9987260936262240
BraTS20_Training_010 WT FALSE
76.42643521714200 0.6952231940561380
0.9119599838499840 0.9964290771862810
BraTS20_Training_295 WT FALSE
78.03204469959760 0.6988795130723480
0.9987348278179730 0.9975584954104410
BraTS20_Training_265 WT FALSE
39.71145930332960 0.7255762510442530
0.9987043695138150 0.9947479510512560
BraTS20_Training_036 WT FALSE
80.77747210701760 0.7406917935293670
0.9826028320971000 0.9988842353506100
BraTS20_Training_129 WT FALSE
74.39085965358920 0.7470221213840050
0.9988202578579250 0.9954818453510200
BraTS20_Training_315 WT FALSE
92.00543462209180 0.7525539409951560
0.9986852100742130 0.9974776737074720
BraTS20_Training_107 WT FALSE
56.73623181001710 0.7635349961936320
0.9938795138585290 0.9976486697477280
BraTS20_Training_080 WT FALSE
67.47592163134940 0.7645504082260720
0.9716777102889750 0.9972107716148600
BraTS20_Training_158 WT FALSE
74.20916385460760 0.7681286968624000
0.979537505872527 0.9975393956546950
BraTS20_Training_169 WT FALSE
29.30870177950570 0.7752760064050340
0.9894946307882610 0.996459510298382
BraTS20_Training_209 WT FALSE
55.47972602672080 0.7812162427575370
0.989028237524671 0.9960580586807720
BraTS20_Training_278 WT FALSE
37.107950630558900 0.7968925890715560
0.9286601646517840 0.995083295767775
BraTS20_Training_122 WT FALSE
78.45380806563820 0.7999610582422660
0.9908953873982510 0.9990946443409940
BraTS20_Training_361 WT FALSE
102.57192598367300 0.8009288800092050
0.9747800735846420 0.9959227979227190
BraTS20_Training_345 WT FALSE
49.02040391510460 0.8056686803960550
0.8715601119138100 0.9968330696772220
BraTS20_Training_134 WT FALSE
85.65628990331070 0.8067072194653430
0.7495352123150150 0.9990085130883730

BraTS20_Training_090 WT FALSE
50.78385570237850 0.8072262612910330
0.971458872703453 0.9984307449880790
BraTS20_Training_298 WT FALSE
87.80091115700340 0.8083963876006830
0.9785948785292190 0.9977239029036370
BraTS20_Training_052 WT FALSE
69.49100661236680 0.81692060730524
0.9912080259406760 0.9977470288668750
BraTS20_Training_130 WT FALSE
13.564659966250500 0.8179529736183550
0.9902975188858260 0.9945368089656000
BraTS20_Training_185 WT FALSE
34.322004603461000 0.8185430082244890
0.9621428329704790 0.9961015237430890
BraTS20_Training_076 WT FALSE
62.65780079128220 0.8215818763950750
0.96370012321107 0.9981844057639860
BraTS20_Training_184 WT FALSE
75.67033764957050 0.8324694978104130
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BraTS20_Training_250 WT FALSE
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BraTS20_Training_359 WT FALSE
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0.9823678472508690 0.9965588073487350
BraTS20_Training_144 WT FALSE
63.54525946126900 0.8553872163339620
0.9931200048315990 0.9925133813585220
BraTS20_Training_239 WT FALSE
44.83302354291980 0.8608343957981300
0.9396950123193710 0.997934578610548
BraTS20_Training_171 WT FALSE 37.3496987939662
0.8610578502904800 0.9211844853714150
0.9963554087419630
BraTS20_Training_266 WT FALSE
82.42572413997950 0.872687209849963
0.9738897022938020 0.9984509944307010
BraTS20_Training_348 WT FALSE
65.80273550544840 0.8747603272469810
0.9943368737663310 0.99731411276497
BraTS20_Training_186 WT FALSE
47.38143096192850 0.8774479741608410
0.9917437481227040 0.9960334883695560
BraTS20_Training_197 WT FALSE
61.45730225123780 0.8852185597709570
0.9962534862336520 0.9961911738776190
BraTS20_Training_338 WT FALSE
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0.9934060378448650 0.9960943348571140
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BraTS20_Training_306 WT FALSE
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BraTS20_Training_179 WT FALSE
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BraTS20_Training_363 WT FALSE
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BraTS20_Training_361 TC FALSE
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BraTS20_Training_275 TC FALSE
53.907327887774200 0.018057203110583900
0.012977171544946500 0.9994976138339210
BraTS20_Training_325 TC FALSE
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BraTS20_Training_250 TC FALSE
35.45419580247170 0.18477261865372600
0.7696784073506890 0.9975995925929450
BraTS20_Training_086 TC FALSE
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0.9999367663407340
BraTS20_Training_129 TC FALSE 16.0312195418814
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BraTS20_Training_303 TC FALSE
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0.9999061484337330
BraTS20_Training_133 TC FALSE
7.874007874011810 0.6611902516503700
0.5295146480104940 0.9993845826429940
BraTS20_Training_345 TC FALSE
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BraTS20_Training_261 TC FALSE
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BraTS20_Training_050 TC FALSE
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BraTS20_Training_239 TC FALSE
25.25866188063020 0.7607793037368250
0.7972332236291630 0.9993992192881020
BraTS20_Training_216 TC FALSE
7.874007874011810 0.7655772961754220
0.6510628501266210 0.9997810754460590
BraTS20_Training_005 TC FALSE
1.7320508075688800 0.7768222426317110
0.6456627342123530 0.9999730748217050
BraTS20_Training_294 TC FALSE
12.36931687685300 0.7770986253836920
0.8059461853615330 0.9989100162890260
BraTS20_Training_076 TC FALSE 3.0
0.7825958177833070 0.6943291112629420
0.9998289365115370
BraTS20_Training_080 TC FALSE
27.712812921102000 0.7964053833254500
0.8769886363636360 0.9996146876233540
BraTS20_Training_097 TC FALSE
13.45362404707370 0.8198289204192660
0.7138292206639450 0.9998072419503780
BraTS20_Training_160 TC FALSE
11.74734012447070 0.8225834457519130
0.7509205745360550 0.9993061259649290
BraTS20_Training_340 TC FALSE
71.05631569396210 0.8333599446484650
0.8271526677231910 0.9991582847024580
BraTS20_Training_207 TC FALSE 9.0
0.8343289171020490 0.8509438766231400
0.9994165500909110
BraTS20_Training_036 TC FALSE
7.874007874011810 0.8430081441691220
0.8459398365501650 0.9998962145082480
BraTS20_Training_244 TC FALSE
9.486832980505140 0.8478838805638430
0.7928190043802160 0.9994546241666800
BraTS20_Training_184 TC FALSE

23.706539182259400 0.8505997818974920
0.9451097569583320 0.9986744691940140
BraTS20_Training_048 TC FALSE
7.0710678118654800 0.8529817568603400
0.8038139266108060 0.999968625830421
BraTS20_Training_355 TC FALSE
7.810249675906650 0.8537529292020740
0.7795139451702490 0.999512192858345
BraTS20_Training_265 TC FALSE
8.366600265340760 0.8653194779963450
0.7798461042252220 0.9998895841498220
BraTS20_Training_348 TC FALSE
15.556349186104000 0.8658924081527400
0.7828925454666580 0.9998280325251950
BraTS20_Training_079 TC FALSE 3.0
0.8662790697674420 0.8669991687448050
0.9999455425025640
BraTS20_Training_198 TC FALSE
18.138357147217100 0.8748925151927960
0.8181308951609990 0.9996749564786560
BraTS20_Training_122 TC FALSE 19.1049731745428
0.8807995449744050 0.9552344025378920
0.9998640489038400
BraTS20_Training_363 TC FALSE
11.180339887498900 0.8863195444020280
0.8043675810757090 0.999914875092181
BraTS20_Training_061 TC FALSE
13.784048752090200 0.8899058866949620
0.8990305741983590 0.9998172658529440
BraTS20_Training_010 TC FALSE 9.1104335791443
0.9007358462231570 0.8575922219044900
0.9999634570361240
BraTS20_Training_339 TC FALSE
11.224972160321800 0.9039661075241920
0.9033870766154230 0.9993115968516220
BraTS20_Training_098 TC FALSE
59.61543424315550 0.9098808437343340
0.9503262358027010 0.9994195094973350
BraTS20_Training_151 TC FALSE
26.94438717061500 0.9112236562653160
0.8799141793399380 0.9996326968399750
BraTS20_Training_001 TC FALSE
22.516660498395400 0.9155218526116800
0.9868704411253910 0.999178598541444
BraTS20_Training_179 TC FALSE
18.384776310850200 0.9166840949492840
0.9558663177407040 0.9994652085248120
BraTS20_Training_107 TC FALSE
11.832159566199200 0.9171998494542720
0.9617205998421470 0.9998461514999560

BraTS20_Training_315 TC FALSE
73.00684899377590 0.9191028054339690
0.898700492304963 0.99985593096724
BraTS20_Training_090 TC FALSE
13.076696830622000 0.9201898960945900
0.9769388046217490 0.9996543156263370
BraTS20_Training_271 TC FALSE 10.0
0.9217005023456640 0.9482338871567080
0.9997125077221440
BraTS20_Training_185 TC FALSE
6.324555320336760 0.9229098156452420
0.9253626953359180 0.9995493333038970
BraTS20_Training_338 TC FALSE
10.198039027185600 0.9235316960287840
0.9123177853977800 0.9995432153375860
BraTS20_Training_197 TC FALSE
6.164414002968980 0.9240297335573870
0.8731866973622170 0.9998634807507860
BraTS20_Training_359 TC FALSE
2.8284271247461900 0.9258108791446940
0.8717520163249440 0.9999335326976880
BraTS20_Training_144 TC FALSE
5.744562646538030 0.9284901042412340
0.9367992406003660 0.9993342978016240
BraTS20_Training_052 TC FALSE
11.874342087037900 0.9310131613815030
0.9362785739666000 0.9998578180012060
BraTS20_Training_124 TC FALSE
16.06237840420900 0.9312701879595160
0.9392856256360610 0.999290302060735
BraTS20_Training_175 TC FALSE
7.810249675906650 0.9322286293644260
0.9289322472690530 0.999311557212075
BraTS20_Training_130 TC FALSE
4.358898943540670 0.9330432638105980
0.9027337491904420 0.9997863422767410
BraTS20_Training_337 TC FALSE 8.12403840463596
0.9389468460178460 0.90994168453538
0.9998410695803240
BraTS20_Training_209 TC FALSE
3.1622776601683800 0.9443203224251980
0.9755832635604530 0.9995491798619260
BraTS20_Training_351 TC FALSE
35.185224171518400 0.9451136535456880
0.9659008962604310 0.9998298270904050
BraTS20_Training_169 TC FALSE
9.899494936611670 0.9460899440366110
0.975156310518453 0.9996492295082670
BraTS20_Training_336 TC FALSE
13.152946437965900 0.9476840598805120

0.9207374492378320 0.9998282174022770
BraTS20_Training_093 TC FALSE
14.071247279470300 0.955135000311779
0.9694927054653630 0.9997848568201910
BraTS20_Training_040 TC FALSE
17.916472867168900 0.9557249700425600
0.9558632090091950 0.9997578721125550
BraTS20_Training_186 TC FALSE
22.64950330581230 0.957883972535641
0.9471644885542890 0.9997979514851300
BraTS20_Training_270 TC FALSE
1.7320508075688800 0.9617129619350020
0.9519267399267400 0.9997864499562630
BraTS20_Training_298 ET FALSE
2.8284271247461900 0.07920792079207920
0.0425531914893617 0.9999996639749570
BraTS20_Training_315 ET FALSE
97.02061636580140 0.3669724770642200
0.3669724770642200 0.9999922714110200
BraTS20_Training_048 ET FALSE 1.0
0.4204502098435710 0.2699657030867220
0.999996751049383
BraTS20_Training_303 ET FALSE
20.12461179749810 0.42629904559915200
0.30362537764350500 0.9999820761949910
BraTS20_Training_158 ET FALSE
15.297058540778400 0.4508870618779750
0.3134777376654630 0.9999856604130380
BraTS20_Training_086 ET FALSE
14.071247279470300 0.48484848484848500
0.5283018867924530 0.9999922714136170
BraTS20_Training_271 ET FALSE
3.605551275463990 0.4934210526315790
0.33482142857142900 0.9999994399501060
BraTS20_Training_250 ET FALSE
26.30589287593180 0.5534000408413310
0.42106898694841500 0.9999636965922530
BraTS20_Training_261 ET FALSE 19.8997487421324
0.5665442573129040 0.4686779803058870
0.999801086600884
BraTS20_Training_309 ET FALSE
16.76305461424020 0.6001333629695490
0.6831983805668020 0.9998685865061530
BraTS20_Training_134 ET FALSE
3.4641016151377500 0.630993795502636
0.47929606625258800 0.9999178418536490
BraTS20_Training_079 ET FALSE
5.477225575051660 0.6409469530907500
0.9945578231292520 0.9998173982499360
BraTS20_Training_160 ET FALSE

8.246211251235320 0.6410967344423910
0.4983834271344750 0.9997881859951820
BraTS20_Training_076 ET FALSE
5.477225575051660 0.6457097874573600
0.5806512505899010 0.9997411803097430
BraTS20_Training_129 ET FALSE 14.7648230602334
0.6480147428379960 0.5422683302958080
0.9998949653660350
BraTS20_Training_171 ET FALSE
31.89043743820400 0.6644971224993150
0.572415014164306 0.9997139508493720
BraTS20_Training_113 ET FALSE
30.14962686336270 0.6702089119671540
0.652787579393084 0.9998593640408310
BraTS20_Training_005 ET FALSE 2.23606797749979
0.7007117252844300 0.6252549601335060
0.9998072267863030
BraTS20_Training_197 ET FALSE
6.164414002968980 0.7100500668741940
0.5548054158034920 0.9999517688655860
BraTS20_Training_061 ET FALSE 9.9498743710662
0.7169602654238090 0.69473361910594
0.9998218902987710
BraTS20_Training_133 ET FALSE 21.0
0.7271386948432620 0.5813313875168390
0.9999647594258440
BraTS20_Training_216 ET FALSE 3.0
0.7356235486955330 0.6299935661227120
0.9998410935457380
BraTS20_Training_244 ET FALSE
9.433981132056600 0.7408010484719710
0.6924676096076030 0.999464221295816
BraTS20_Training_080 ET FALSE
17.72004514666940 0.7788622420524260
0.8352272727272730 0.9997679713477120
BraTS20_Training_239 ET FALSE
19.209372712298500 0.7822950819672130
0.8130025896142840 0.999781630580597
BraTS20_Training_036 ET FALSE
7.0710678118654800 0.7853184147234130
0.7268679829655440 0.9999280497653550
BraTS20_Training_050 ET FALSE
7.874007874011810 0.7950157512242290
0.7873779809712100 0.9992961711078750
BraTS20_Training_100 ET FALSE
12.328828005938000 0.8107273707898600
0.7261702482092290 0.9997799501797320
BraTS20_Training_348 ET FALSE
13.379088160259700 0.811017658548252
0.6973858598784330 0.9998896922842450

BraTS20_Training_345 ET FALSE 1.0
0.818880567599527 0.6992595085829690
0.9999942838300310
BraTS20_Training_052 ET FALSE
8.774964387392120 0.836378548320955
0.8422501605946590 0.9997900663477810
BraTS20_Training_130 ET FALSE 4.69041575982343
0.8401680966555770 0.7619818961410200
0.9998163325751710
BraTS20_Training_359 ET FALSE
6.4031242374328500 0.8418022482555070
0.7326060759814800 0.9999717865498500
BraTS20_Training_179 ET FALSE
18.384776310850200 0.8432091372486020
0.8242953825066390 0.9994847621961630
BraTS20_Training_207 ET FALSE
5.744562646538030 0.8440194191010300
0.7920119388917250 0.9997575971883070
BraTS20_Training_337 ET FALSE
9.273618495495700 0.8550736171906090
0.7611221309152740 0.9999393242610370
BraTS20_Training_336 ET FALSE
11.704699910719600 0.868033290128931
0.7909065481555150 0.9998864635683510
BraTS20_Training_097 ET FALSE
12.767145334803700 0.8692425973732840
0.82835479794585 0.9996755075214210
BraTS20_Training_090 ET FALSE
10.723805294763600 0.8711198589412390
0.9688070047427950 0.9996858821698150
BraTS20_Training_010 ET FALSE
5.385164807134500 0.8796357615894040
0.8207940676656880 0.999967046000085
BraTS20_Training_198 ET FALSE
17.944358444926400 0.8797647137017710
0.8713669727790400 0.9996259673514900
BraTS20_Training_363 ET FALSE
8.774964387392120 0.880459688238297
0.7967383597258330 0.999931430185063
BraTS20_Training_040 ET FALSE
16.73320053068150 0.8816507378519900
0.8537035067191430 0.9997372973788050
BraTS20_Training_001 ET FALSE
19.131126469709000 0.8835006049039820
0.9345036406892080 0.9994359714066720
BraTS20_Training_209 ET FALSE 2.0
0.8869342223361970 0.888734710658855
0.9997481069292820
BraTS20_Training_124 ET FALSE
16.06237840420900 0.8905634240129930

0.8724350125178410 0.9995822294921890
BraTS20_Training_185 ET FALSE
7.483314773547880 0.8914332759067560
0.9353703407454810 0.9994266442389890
BraTS20_Training_339 ET FALSE
11.874342087037900 0.8927768730737660
0.8609921345689590 0.9997061694405640
BraTS20_Training_122 ET FALSE
10.862780491200200 0.892787014007069
0.9443367488230410 0.9999307515618160
BraTS20_Training_340 ET FALSE 68.7749954561976
0.8967593293308440 0.8620109925638540
0.9997897060492950
BraTS20_Training_175 ET FALSE
3.7416573867739400 0.8968250292753610
0.8578516371552610 0.9995068364291480
BraTS20_Training_098 ET FALSE
59.481089431852200 0.9004952924902950
0.9151550879738800 0.9997092954057220
BraTS20_Training_338 ET FALSE 9.1104335791443
0.9070416871453470 0.8615413996519970
0.9997976550506180
BraTS20_Training_151 ET FALSE
3.605551275463990 0.9154132423631570
0.9296118415872770 0.9995653492948230
BraTS20_Training_186 ET FALSE
21.77154105707720 0.9194400589411640
0.872094880600591 0.9998594264690050
BraTS20_Training_270 ET FALSE 2.0
0.9236608801826190 0.865837272953471
0.999939104944171
BraTS20_Training_093 ET FALSE
21.470910553583900 0.924310224163892
0.8954267165221680 0.999884991154764
BraTS20_Training_355 ET FALSE
6.164414002968980 0.9244120321969210
0.9017179053493850 0.9996655274753500
BraTS20_Training_184 ET FALSE 2.0
0.929593817462765 0.9511099561957090
0.9997119444848270
BraTS20_Training_169 ET FALSE
7.681145747868610 0.9307446474424100
0.9600243893144320 0.9996966891599740
BraTS20_Training_351 ET FALSE 35.4400902933387
0.9327407020066670 0.8850161250310100
0.9999771091967620
BraTS20_Training_144 ET FALSE
3.4641016151377500 0.934888160351911
0.9234149300716500 0.9996420438955230
BraTS20_Training_107 ET FALSE 11.0

```
0.9455419113721300      0.9280997798972850
0.9999625495839580
```

After filtering by WT and sorting by Hausdorff, I found the 20 worst performers as follows (the first is the worst, with the highest Hausdorff score):

```
BraTS20_Training_079
114.31972708155000

BraTS20_Training_361
102.57192598367300

BraTS20_Training_086
101.7742600071350

BraTS20_Training_268
98.5393322486001

BraTS20_Training_325
94.94208761134340

BraTS20_Training_315
92.00543462209180

BraTS20_Training_207
90.77995373429090

BraTS20_Training_005
88.87631855561980

BraTS20_Training_298
87.80091115700340

BraTS20_Training_134
85.65628990331070

BraTS20_Training_359
85.53946457629950

BraTS20_Training_266
82.42572413997950

BraTS20_Training_036
80.77747210701760

BraTS20_Training_336
79.71198153351850
```

```
BraTS20_Training_122
78.45380806563820

BraTS20_Training_337
78.06407624509500

BraTS20_Training_295
78.03204469959760

BraTS20_Training_275
76.68115805072330

BraTS20_Training_010
76.42643521714200

BraTS20_Training_184
75.67033764957050
```

Similarly, I found the 20 best performers as follows (the last in the table is the absolute best, with the lowest Hausdorff score):

```
BraTS20_Training_171
37.3496987939662

BraTS20_Training_278
37.107950630558900

BraTS20_Training_160
35.22782990761710

BraTS20_Training_093
34.84250278036870

BraTS20_Training_185
34.322004603461000

BraTS20_Training_100
31.559467676119

BraTS20_Training_169
29.30870177950570

BraTS20_Training_040
29.223278392404900

BraTS20_Training_244
28.861739379323600
```

BraTS20_Training_133
28.722813232690100

BraTS20_Training_216
27.80287754891570

BraTS20_Training_001
21.283796653792800

BraTS20_Training_261
15.684387141358100

BraTS20_Training_355
14.7648230602334

BraTS20_Training_098
13.92838827718410

BraTS20_Training_179
13.74772708486750

BraTS20_Training_130
13.564659966250500

BraTS20_Training_124
12.328828005938000

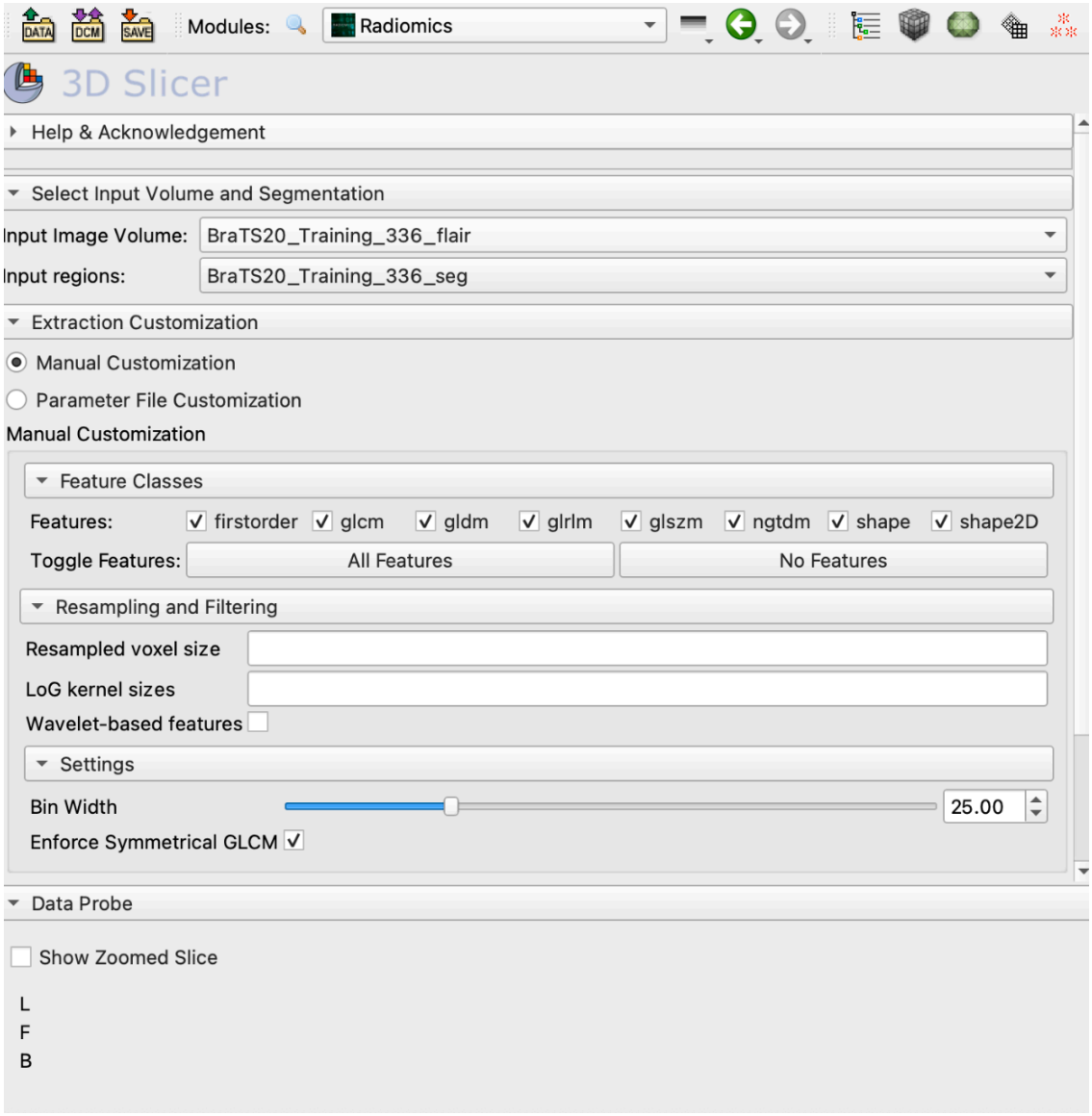
BraTS20_Training_363
9.848857801796100

BraTS20_Training_306
9.273618495495700

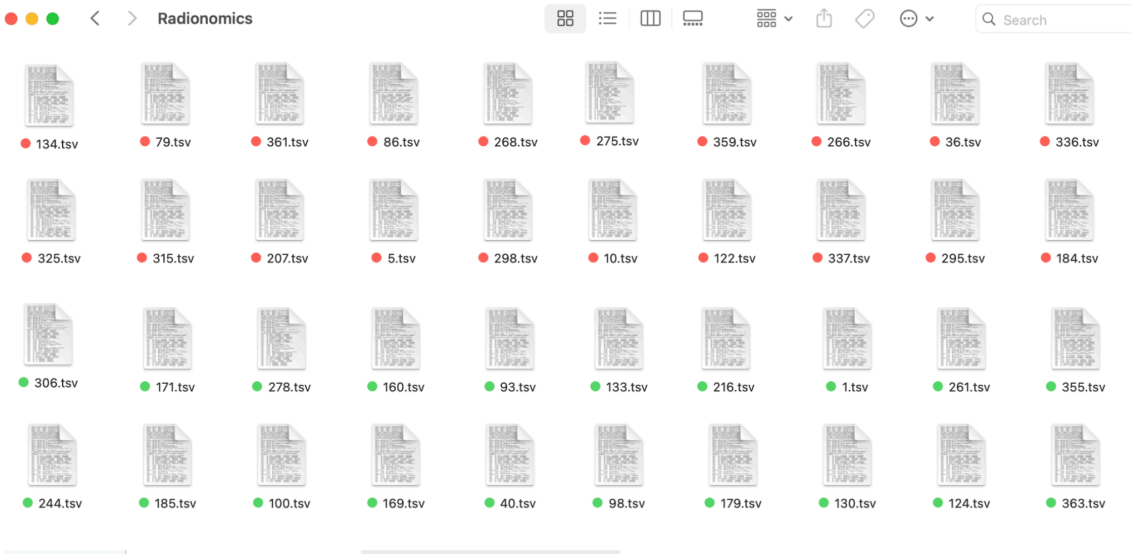
BraTS20_Training_198
7.810249675906650

Data Analysis - Radiomics

- Now that I identified the 20 best and 20 worst cases, my next step was to extract Radiomics information for best & most poorly performing cases.
- Radiomics extracts 100+ quantitative metrics from medical images that capture information about tumors or other lesions (i.e. shape, texture, intensity, spatial arrangement, etc)
- I used 3D Slicer's SlicerRadiomics extension which encapsulates the pyRadiomics library. The newest version of 3D Slicer currently has a bug so SlicerRadiomics does not work on Mac, so I downloaded 3D Slicer Version 5.2.2, which had a SlicerRadiomics that worked on my computer. https://www.slicer.org
- I needed to input a raw scan & a segmentation file for it to extract information about the scans and tumor.



- I chose to Use .flair MRI scans for raw scan because they work best for WT (whole tumor) according to my research
- My goal with Radiomics was to extract quantitative information about the tumors/scans into tables that could be analyzed by LLMs or statistical methods
- I entered the .flair and .seg files for each of the 20 best and 20 worst cases, and ran the feature extraction on each. The output of this was a .tsv file with quantitative values for each feature it can analyze.



Data Analysis - LLM

- Now that I had the best & worst case radiomics data files, I was able to provide them to LLMs to run data analysis. I chose to use the ChatGPT with GPT-4o.
- For each of these 40 cases, I provided ChatGPT with the patient ID number, its Hausdorff score, if it was a good or bad case, and its .tsv Radiomics file. I directed it to compare the different features of each tumor/scan to see what features were associated with a difference in high versus low performance.
- In response, it outputed the 20 most differentiating radiomics features in a table. It was comparing the average of each metric for the 'best cases' to the average of each metric for the 'worst cases'. And using Cohen's D as a statistical analysis metric. A large positive Cohen’s D indicates that the feature is higher in worst-segmented tumors, while a large negative Cohen’s D means the feature is higher in best-segmented tumors.

Top Differentiating Radiomic Features

	mean worst	mean best	Cohen's D
VoxelNum	15484.133333333300	41009.0	-1.2636048728406600
Idmn	0.9945461763222280	0.9974033610355680	-1.1534056562821300
RunLengthNonUniformity	6930.059632848790	14962.875066676000	-0.9464509216618370
Idn	0.9581874480920000	0.9686642353720480	-0.9279794412336950
GrayLevelNonUniformity	55.765863273394700	104.15138599650300	-0.8170928832750870
VolumeNum	17.666666666666700	46.9375	-0.7434347315864150
InverseVariance	0.3758810081939860	0.43080971592616100	-0.6360272908422310
LowGrayLevelEmphasis	0.03241320268164100	0.0064199690549399800	0.6307772882225410
LowGrayLevelRunEmphasis	0.02742345835770900	0.006746681729842410	0.6303948994806060
ShortRunLowGrayLevelEmphasis	0.018226453077957800	0.005032112087128590	0.607135979280792
SmallDependenceLowGrayLevelEmphasis	0.0015098278761101200	0.0004707476862361610	0.6026855935946840
LongRunLowGrayLevelEmphasis	0.293476401378383	0.02738612762747390	0.5850525412698460
Minimum	333.06666666666700	103.0625	0.5640566604492650
LargeDependenceLowGrayLevelEmphasis	8.559870776116880	0.8729156203168560	0.5335211686244110
LargeAreaHighGrayLevelEmphasis	16941937.21576950	49953148.73135880	-0.49066564837776500
ZonePercentage	0.12988510670041500	0.05528938494990860	0.4906090745814930
SmallAreaLowGrayLevelEmphasis	0.01754494934778400	0.007000230978190190	0.48778330831105600
LowGrayLevelZoneEmphasis	0.04107725760521820	0.01288200990137280	0.48776302468394300
MCC	0.8743047873305660	0.9064096725831870	-0.4864064436130230
SmallDependenceEmphasis	0.12996712046349100	0.06326727860784550	0.4712217664903020

Results

- I converted the table provided by ChatGPT into a graphical representation to compare the Cohen's d values for each feature. Additionally, I categorized each feature into broader groups based on what they describe, such as shape, texture homogeneity, size, or gray-level distribution.