

Prognosis prediction based on estrogen receptor signaling activity from H&E staining by deep learning

```
In [14]: import sys
print("Python version:", sys.version)
!pip list | grep 'slideio\|pandas\|numpy\|matplotlib\|rpy2\|torch\|torchv
import slideio
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image
import os
import math
import rpy2
import json
import torch
torch.manual_seed(0)
from torch.utils.data import DataLoader, Dataset
import torch.nn as nn
import torch.optim as optim
from torch.optim import lr_scheduler
import torch.backends.cudnn as cudnn
import torchvision
from torchvision.models import ResNet50_Weights
from torchvision import datasets, models, transforms
import torchvision.transforms.functional as F
from PIL import Image
import matplotlib.pyplot as plt
import time
import os
import copy
from sklearn.model_selection import train_test_split
import scipy
from sklearn.model_selection import KFold
from sklearn.metrics import roc_auc_score, roc_curve, RocCurveDisplay
from scipy.stats import spearmanr, pearsonr
import kaplanmeier as km
import rpy2.robjects as ro
from rpy2.robjects.packages import importr
from rpy2.robjects import pandas2ri
import rpy2.robjects as robjects
from rpy2.robjects.conversion import importr
rinstalled = robjects.globalenv.find("installed.packages")
rversion = robjects.globalenv.find("R.Version")
rpkgs = rinstalled()
rvers = rpkgs.rx(robjects.StrVector(["GSVA"]), robjects.StrVector(["Versi
print(rversion().rx2("version.string"))
print("GSVA Version:", rvers)

def gsva(geneExpressionProfile, gene_sets):
    rbase = importr('base')
```

```

print("Converting df")
with localconverter(ro.default_converter + pandas2ri.converter):
    geneExpressionProfile_r = ro.conversion.py2rpy(geneExpressionProf
gene_sets_r = ro.ListVector(gene_sets)
gsvar = importr("GSVA")
es = gsvar.gsva(rbase.as_matrix(geneExpressionProfile_r), gene_sets_r
es_df = pd.DataFrame(np.array(es.transpose()), index=es.colnames, col
return es_df

def finding_best_threshold_with_FS_SS(fs_eeres_df, ss_eeres_df, survival_
bestp = 1
bestq = 0
for q in np.arange(q01, q09, 0.01):
    result1 = km.fit(fs_eeres_df[f'{survival_type[0]}_MONTHS'], fs_ee
    result2 = km.fit(ss_eeres_df[f'{survival_type[1]}_MONTHS'], ss_ee
    average_p = (result1["logrank_P"]+result2["logrank_P"])/2
    if (result1["logrank_P"]<0.05 or result2["logrank_P"]<0.05) and a
        bestp=average_p
        bestq=q
if bestp==1:
    print('not significant')
else:
    print(f"Best {value_name} threshold:", bestq)
    result = km.fit(fs_eeres_df[f'{survival_type[0]}_MONTHS'], fs_ee
    km.plot(result, title=f'{survival_type[0]} of ER+/HER2- stratifie
    plt.show()
    result = km.fit(ss_eeres_df[f'{survival_type[1]}_MONTHS'], ss_ee
    km.plot(result, title=f'{survival_type[1]} of ER+/HER2- stratifie
    plt.show()

```

Python version: 3.10.6 (main, Mar 10 2023, 10:55:28) [GCC 11.3.0]

```

kaplanmeier          0.1.8
matplotlib            3.5.1
matplotlib-inline     0.1.6
matplotlib-venn       0.11.9
numpy                 1.24.1
pandas                1.5.2
rpy2                  3.5.7
scipy                 1.8.0
sklearn               0.0.post1
slideio               2.0.0
torch                 1.13.1
torchaudio            0.13.1
torchvision           0.14.1
[1] "R version 4.2.3 (2023-03-15)"

```

GSVA Version: [1] "1.46.0"

Image resizing, annotating and cropping

```

In [ ]: meta = pd.read_table('File_metadata.txt', encoding='utf-8')
files = ("Images/" + meta_nondup["file_id"] + '/' + meta_nondup["file_name"])
for file in files:
    print(file)
    slide = slideio.open_slide(file, 'SVS')
    print("slide")
    num_scenes = slide.num_scenes
    print("num")
    scene = slide.get_scene(0)
    print("scene")
    rect = scene.rect
    print(rect)
    size=1024
    image = scene.read_block(size=(int(size*rect[2]/rect[3]) if rect[2]>rect[3] else int(size*rect[2]/rect[3])) if rect[2]>rect[3] else int(size*rect[2]/rect[3]))
    image_tr = scipy.ndimage.rotate(image, 180)
    print("image")
    block1 = image[0:size, 0:size, 0:3]
    block2 = image_tr[0:size, 0:size, 0:3]
    matplotlib.image.imsave(file+"-1.jpg", block1)
    matplotlib.image.imsave(file+"-2.jpg", block2)
    matplotlib.image.imsave(file+".jpg", image)
    print("save")

```

Loading TCGA Pan-Cancer BRCA level 3 gene expression data from cBioPortal

```

In [6]: brca_lv3 = pd.read_csv("brca_tcga_pan_can_atlas_2018/data_mrna_seq_v2_rse")
brca_lv3.index = [i[:12] for i in brca_lv3.index]
brca_lv3

```

Out[6]:

Hugo_Symbol	A1BG	A1CF	A2BP1	A2LD1	A2M	A2M-AS1	A2ML1	A4GALT
TCGA-3C-AAAU	197.090	0.0000	0.0000	102.9630	5798.37	32.2187	1.3786	68.2424
TCGA-3C-AALI	237.384	0.0000	0.0000	70.8646	7571.98	29.9782	4.3502	157.6940
TCGA-3C-AALJ	423.237	0.9066	0.0000	161.2600	8840.40	17.2620	0.0000	573.8890
TCGA-3C-AALK	191.018	0.0000	0.0000	62.5072	10960.20	17.8527	1.6549	506.4130
TCGA-4H-AAAK	268.881	0.4255	3.8298	154.3700	9585.44	31.5787	3.4043	342.1280
...	...	...	...	...	...	...	...	...
TCGA-WT-AB44	471.285	0.0000	0.0000	61.7308	5409.31	39.6823	6.5160	356.7500
TCGA-XX-A899	223.220	0.0000	0.3937	131.2280	20348.80	27.2283	0.3937	505.5120
TCGA-XX-A89A	255.135	2.3618	1.4171	79.9291	17094.80	31.7572	55.7393	615.4940
TCGA-Z7-A8R5	439.543	0.0000	0.5973	81.3010	36838.50	84.0964	2.3893	456.3510
TCGA-Z7-A8R6	248.327	0.0000	0.0000	25.1866	7339.17	8.3723	4.1757	768.6820

1082 rows × 20511 columns

Early Estrogen Response Enrichment Scores (EERES) by GSVA

```
In [3]: h_gs = json.loads(open("h.all.v2022.1.Hs.json", 'r').read())
early_es_gs = {'HALLMARK_ESTROGEN_RESPONSE_EARLY': h_gs['HALLMARK_ESTROGE
# brca_earlyes_es = gsva((brca_lv3+1).applymap(math.log2).transpose(), ea
# brca_earlyes_es.index = [i[:12] for i in brca_earlyes_es.index]
# brca_earlyes_es.to_csv("Table S1.csv")
brca_earlyes_es = pd.read_csv("Table S1.csv", index_col=0)
brca_earlyes_es
```

Out[3]:

HALLMARK_ESTROGEN_RESPONSE_EARLY	
TCGA-3C-AAAU	0.001404
TCGA-3C-AALI	-0.409362
TCGA-3C-AALJ	-0.038938
TCGA-3C-AALK	0.356928
TCGA-4H-AAAK	0.154434
...	...
TCGA-WT-AB44	-0.224513
TCGA-XX-A899	0.161219
TCGA-XX-A89A	-0.122835
TCGA-Z7-A8R5	-0.193181
TCGA-Z7-A8R6	0.209939

1082 rows × 1 columns

Loading TCGA BRCA IHC data from GDC Portal

```
In [7]: meta_erihc = pd.read_table("nationwidechildrens.org_clinical_patient_brca  
meta_erihc
```

```
# Joining IHC data with ESR1/EERES data
```

```
eeres_ihc_df = brca_earlyes_es.join(meta_erihc, how='inner')
```

```
eeres_ihc_df["Subtype"] = None
```

```
eeres_ihc_df["Subtype"][(eeres_ihc_df["er_status_by_ihc"]=="Positive") &
```

```
eeres_ihc_df["Subtype"][(eeres_ihc_df["er_status_by_ihc"]=="Negative") &
```

```
eeres_ihc_df_erposerb2neg = eeres_ihc_df[eeres_ihc_df["Subtype"]=="ER+/H
```

```
eeres_ihc_df_erposerb2neg
```

```
eeres_ihc_df_tnbc = eeres_ihc_df[eeres_ihc_df["Subtype"]=="TNBC"]
```

```
eeres_ihc_df["EERES"] = brca_earlyes_es.loc[eeres_ihc_df.index]
```

```
eeres_ihc_df["ESR1"] = brca_lv3.loc[eeres_ihc_df.index]["ESR1"]
```

```
eeres_ihc_df
```

```
/tmp/ipykernel_93586/3367593681.py:7: SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy
```

```
eeres_ihc_df["Subtype"][(eeres_ihc_df["er_status_by_ihc"]=="Positive")
```

```
& (eeres_ihc_df["her2_status_by_ihc"]=="Negative")] = "ER+/HER2-"
```

```
/tmp/ipykernel_93586/3367593681.py:8: SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy
```

```
eeres_ihc_df["Subtype"][(eeres_ihc_df["er_status_by_ihc"]=="Negative")
```

```
& (eeres_ihc_df["her2_status_by_ihc"]=="Negative") & (eeres_ihc_df["pr_s
```

```
tatus_by_ihc"]=="Negative")] = "TNBC"
```

Out[7]:	HALLMARK_ESTROGEN_RESPONSE_EARLY	her2_status_by_ihc	er_status_by_ihc	pr
TCGA-3C-AAAU	0.001404	Negative	Positive	
TCGA-3C-AALI	-0.409362	Positive	Positive	
TCGA-3C-AALJ	-0.038938	Indeterminate	Positive	
TCGA-3C-AALK	0.356928	Positive	Positive	
TCGA-4H-AAAK	0.154434	Equivocal	Positive	
...	...	...	...	
TCGA-WT-AB44	-0.224513	Negative	Positive	
TCGA-XX-A899	0.161219	Negative	Positive	
TCGA-XX-A89A	-0.122835	Negative	Positive	
TCGA-Z7-A8R5	-0.193181	Negative	Positive	
TCGA-Z7-A8R6	0.209939	Negative	Positive	

1081 rows × 7 columns

Loading file metadata and file locations

```
In [8]: meta = pd.read_table('File_metadata.txt', encoding='utf-8')
meta_nondup = meta[~meta['cases.0.submitter_id'].duplicated(keep='first')]
meta_nondup = meta_nondup.set_index('cases.0.submitter_id') # Get images
files = ("Images/" + meta_nondup["file_id"] + '/' + meta_nondup["file_name"])
meta_nondup.to_csv("Table S2.csv")
meta_nondup
```

Out[8]:	cases.0.case_id	cases.0.samples.0.sample_id	cases.0.samples.0.sample_name	cases.0.submitter_id
TCGA-AO-A1KQ	d2219a3f-4c55-4dee-9b08-	38c306c0-bd3f-41b6-bf2e-	Primary tumor	

c6f330dd1acf		c27f6df81567	
TCGA-D8-A1XU	332148f5-f070-4c20-8eb1-4d8c0673aa52	ba37ce51-fb89-4e7a-964c-e69538d69e66	Primary
TCGA-B6-A0IK	0491063c-14a7-4104-8002-1459126332f3	e84a2787-e329-4db4-b636-2b94ffc0289d	Primary
TCGA-BH-A18L	9ddc3e7b-8b54-4a83-8335-8053940f56c1	d5dc0fec-ff5e-4dea-82f6-a25f52342f94	Primary
TCGA-E9-A247	636b0a90-c8c2-4ad6-a77d-6cd428a826d1	d4054576-335d-4e27-b3a0-d041f07cd393	Primary
...	...	...	
TCGA-A2-A0T7	43d5632e-7272-4aad-9496-7f5a99671223	a79f80f7-5704-4eae-856b-9b3fd0ba26f1	Primary
TCGA-E9-A1RC	5cdae21d-eee5-478f-932a-0f51fcf5f031	d3393b43-a688-4de3-9d1f-11b76f69e32a	Primary
TCGA-A2-A4RY	5a53ec47-e63f-44a2-8078-87659544fb04	e742341b-0392-4f84-89c6-97264a235b2b	Primary
TCGA-AC-A3QP	6f4c8d30-47fb-47df-9eb7-4e5881e3711e	bbcb581f-1f71-4335-a552-e0eb49c8246a	Primary
TCGA-EW-A1IW	5e2cbc56-97f9-4b94-ade2-a3f739bcc7be	665bdee5-6983-45c8-b09f-e1898d65a380	Primary

1062 rows × 11 columns

Loading survival data from cBioPortal

```
In [9]: brca_clinical = pd.read_table("brca_tcga_pan_can_atlas_2018/data_clinical
brca_clinical = brca_clinical[["OS_STATUS", "OS_MONTHS", "PFS_STATUS", "PF
brca_clinical["OS_STATUS"] = [s[0] for s in brca_clinical["OS_STATUS"]]
brca_clinical["PFS_STATUS"] = [str(s)[0] for s in brca_clinical["PFS_STAT
brca_clinical["DFS_STATUS"] = [str(s)[0] for s in brca_clinical["DFS_STAT
brca_clinical["DSS_STATUS"] = [s[0] if str(s) != 'nan' else np.nan for s
```

Joining survival data with EERES_IHC data

Show the survival of ER+/HER2- and TNBC of all data

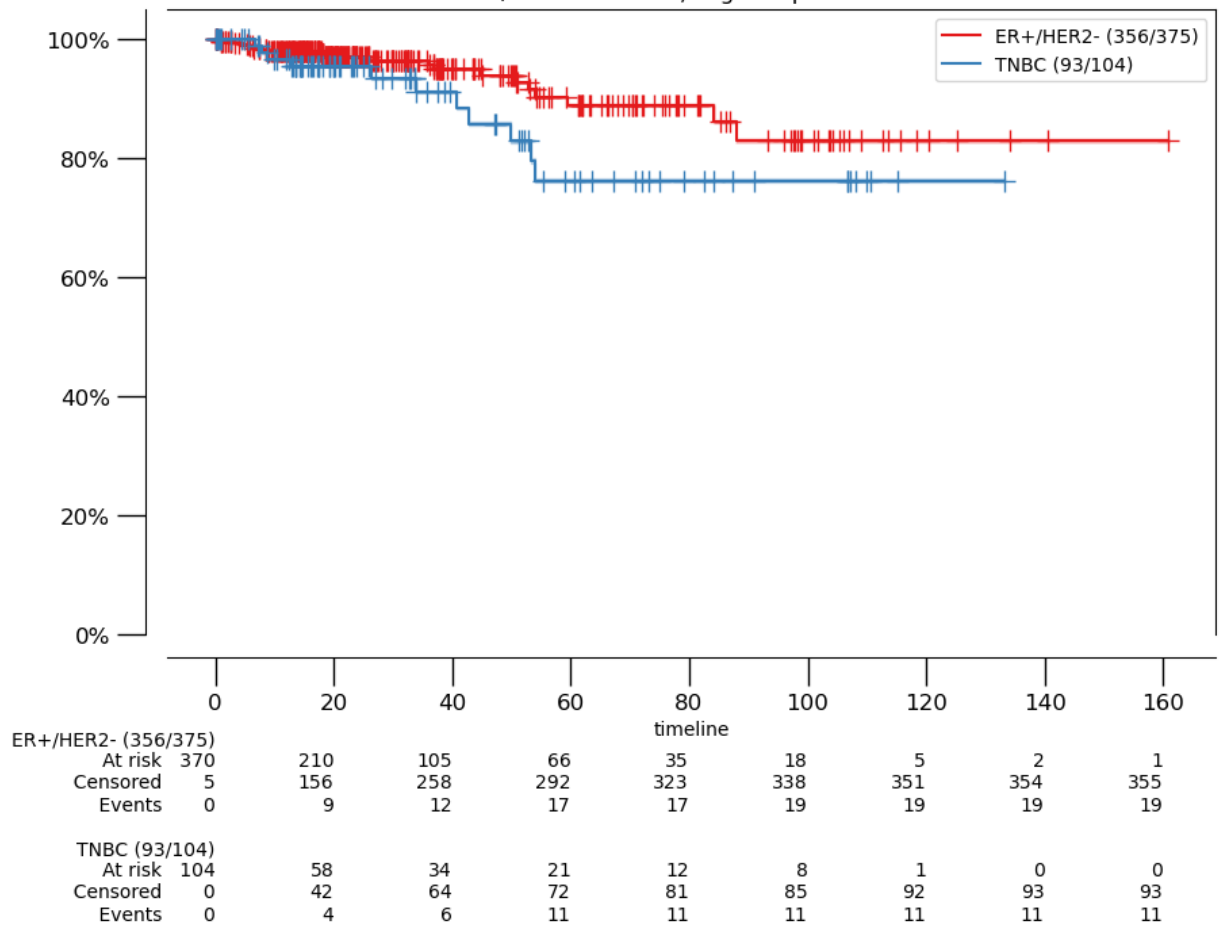
```
In [10]: brca_clinical_eeres_ihc_df = brca_clinical.join(eeres_ihc_df, how='inner'

brca_clinical_dfs = brca_clinical_eeres_ihc_df[["DFS_MONTHS", "DFS_STATUS
brca_clinical_dss = brca_clinical_eeres_ihc_df[["DSS_MONTHS", "DSS_STATUS
brca_clinical_pfs = brca_clinical_eeres_ihc_df[["PFS_MONTHS", "PFS_STATUS
brca_clinical_os = brca_clinical_eeres_ihc_df[["OS_MONTHS", "OS_STATUS",

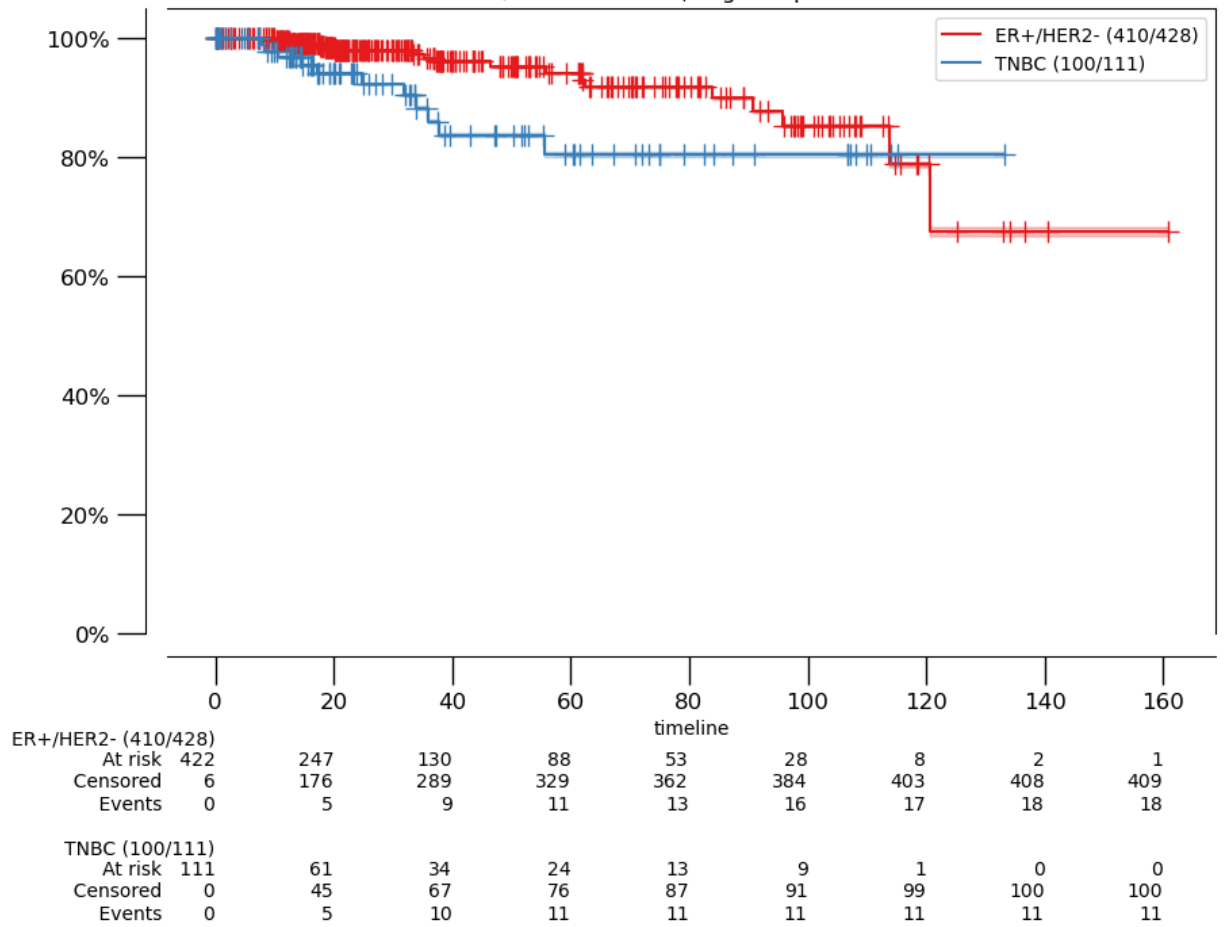
result = km.fit(brca_clinical_dfs['DFS_MONTHS'], brca_clinical_dfs['DFS_S
km.plot(result, title=f"DFS of ER+/HER2- vs TNBC, Logrank p-value={result
plt.show()
result = km.fit(brca_clinical_dss['DSS_MONTHS'], brca_clinical_dss['DSS_S
km.plot(result, title=f"DSS of ER+/HER2- vs TNBC, Logrank p-value={result
plt.show()
result = km.fit(brca_clinical_pfs['PFS_MONTHS'], brca_clinical_pfs['PFS_S
km.plot(result, title=f"PFS of ER+/HER2- vs TNBC, Logrank p-value={result
plt.show()
result = km.fit(brca_clinical_os['OS_MONTHS'], brca_clinical_os['OS_STATU
km.plot(result, title=f"OS of ER+/HER2- vs TNBC, Logrank p-value={result[
plt.show()
plt.scatter(eeres_ihc_df[eeres_ihc_df["Subtype"]=="ER+/HER2-"]["ESR1"].ap
# plt.scatter(eeres_ihc_df[eeres_ihc_df["Subtype"]=="ERBB2+"]["esr1"].app
plt.scatter(eeres_ihc_df[eeres_ihc_df["Subtype"]=="TNBC"]["ESR1"].apply(m

plt.legend(["ER+/HER2-", "TNBC"])
plt.xlabel("ESR1")
plt.ylabel("EERES")
plt.show()
```

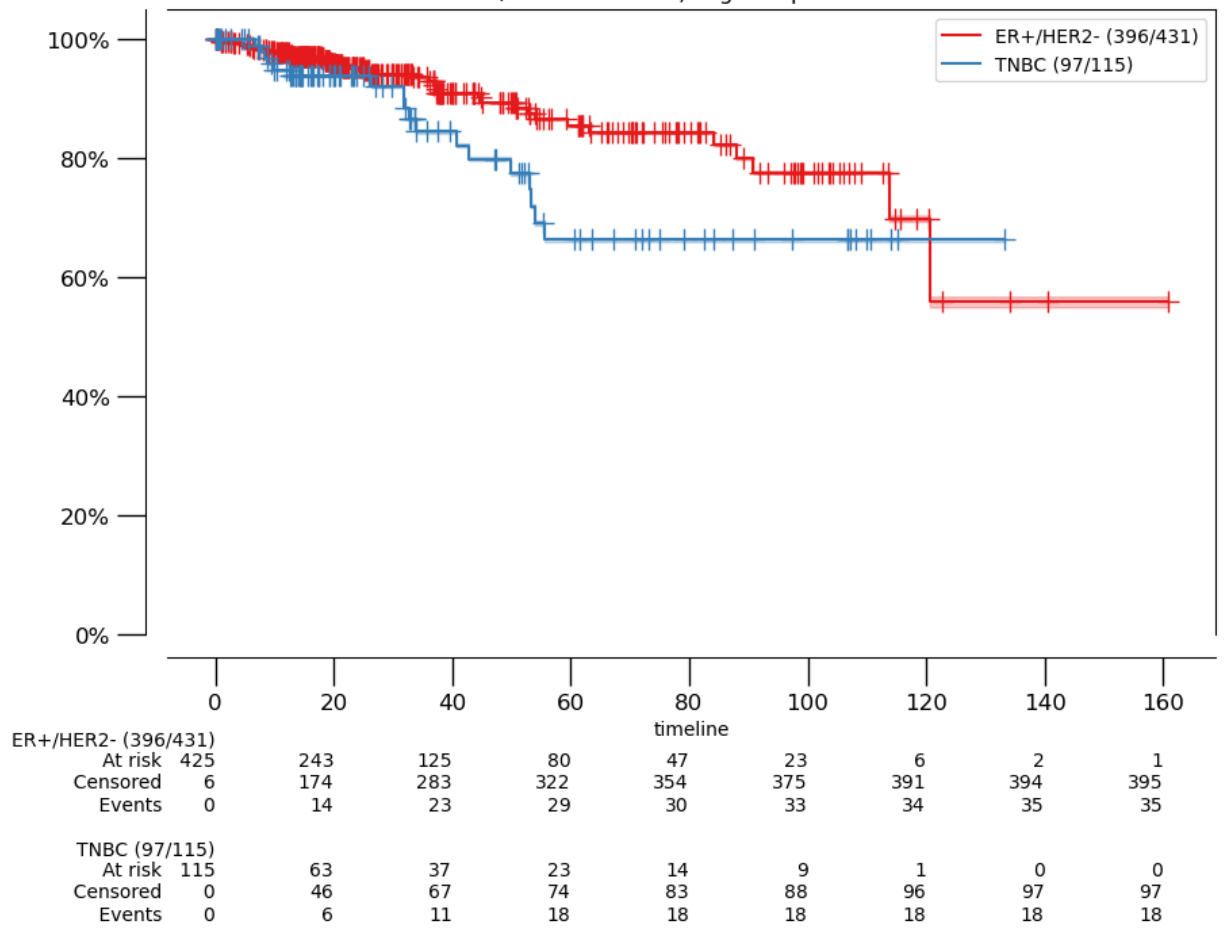
DFS of ER+/HER2- vs TNBC, Logrank p-value=7.360e-02



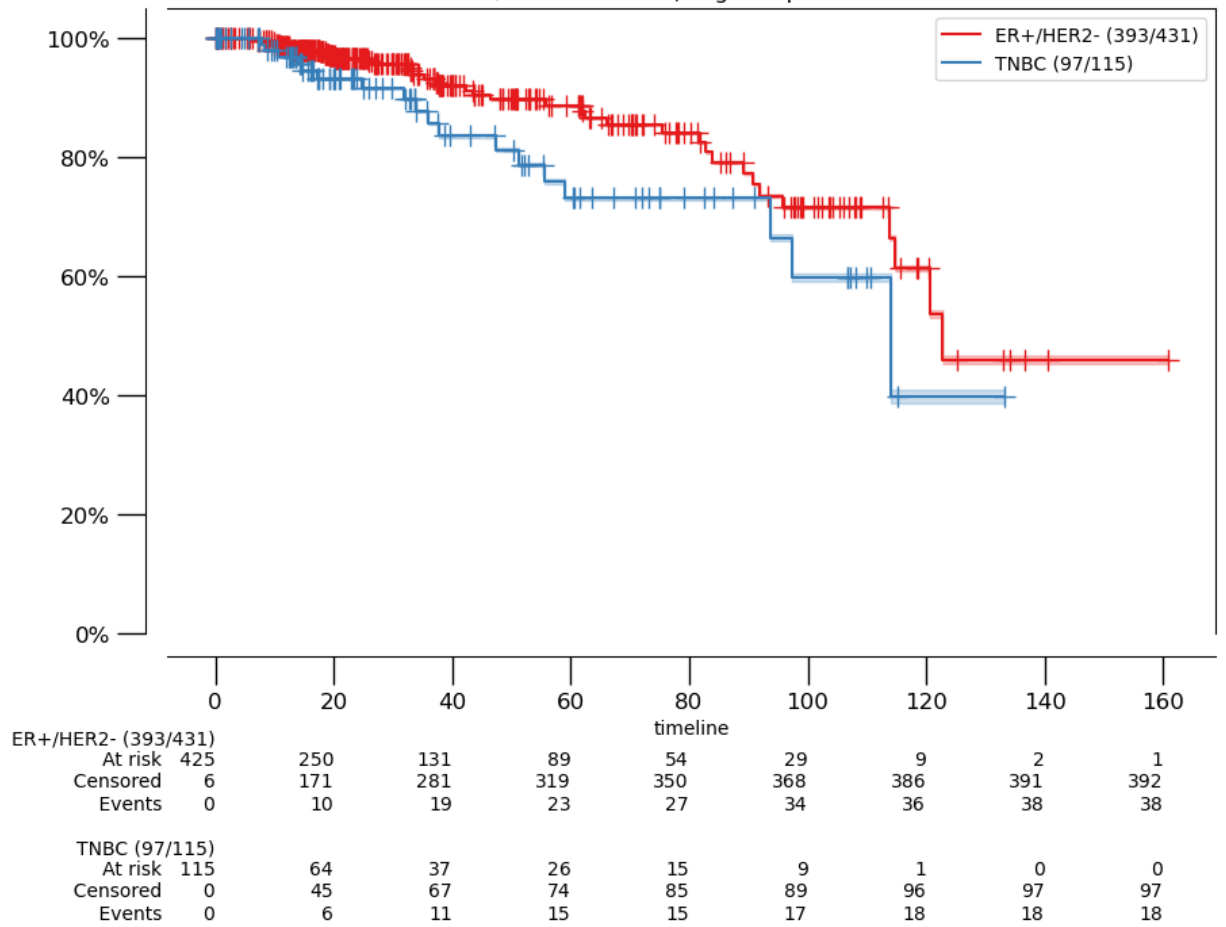
DSS of ER+/HER2- vs TNBC, Logrank p-value=1.594e-02

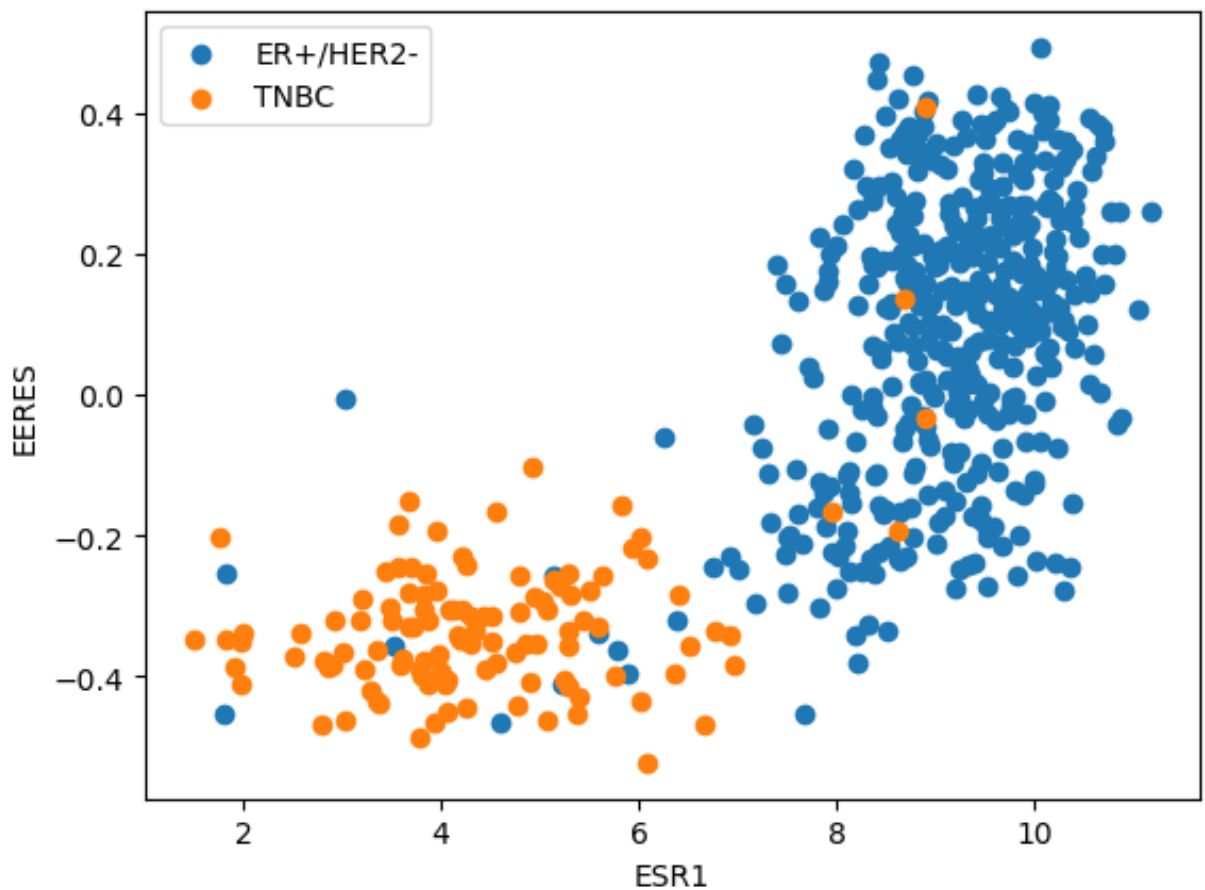


PFS of ER+/HER2- vs TNBC, Logrank p-value=2.916e-02



OS of ER+/HER2- vs TNBC, Logrank p-value=3.937e-02





Getting the best threshold of EERES for ER+/HER2- and TNBC patients

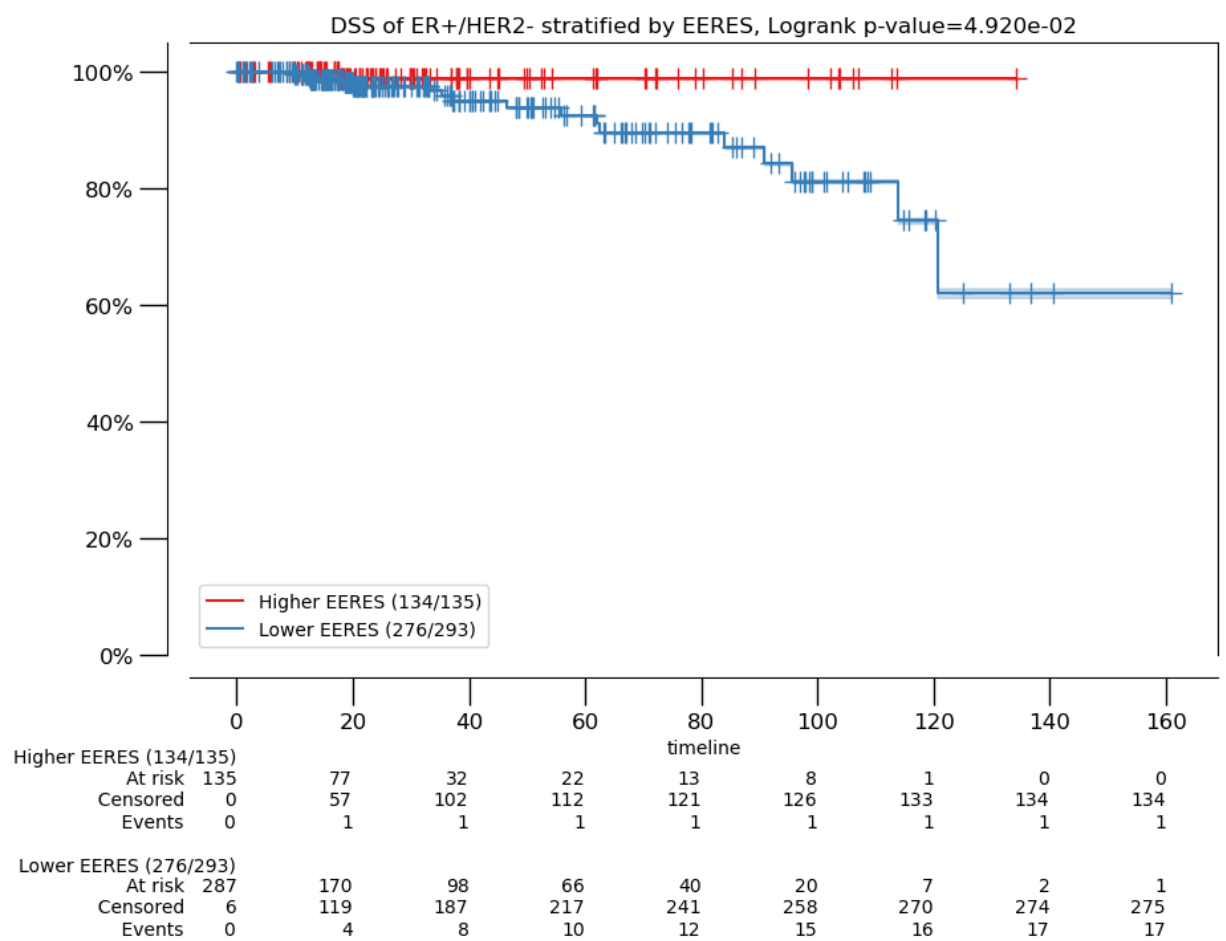
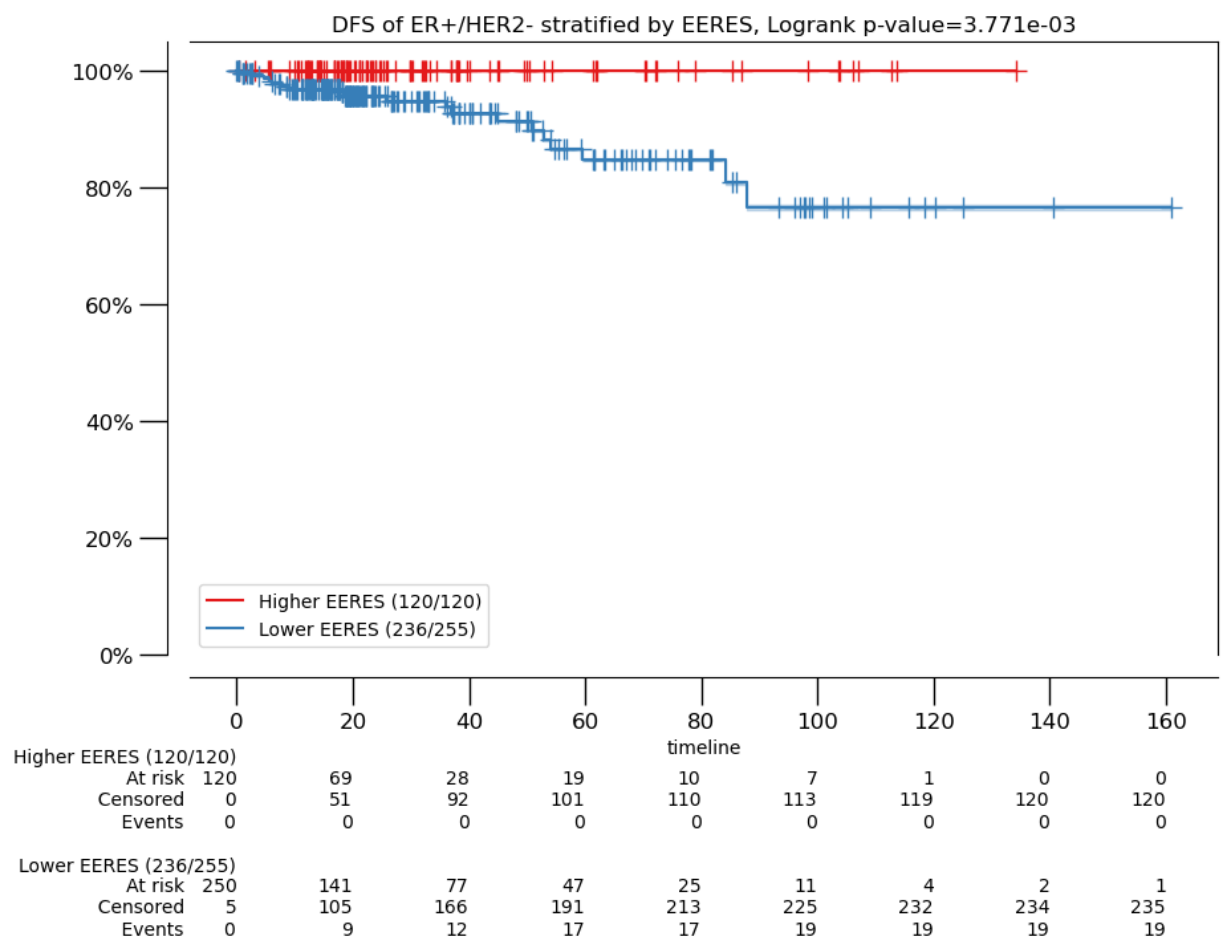
```
In [11]: brca_clinical_erposerbb2neg = brca_clinical_eeres_ihc_df[brca_clinical_eer
brca_clinical_erposerbb2neg_dfs = brca_clinical_erposerbb2neg[["DFS_MONTH
brca_clinical_erposerbb2neg_dss = brca_clinical_erposerbb2neg[["DSS_MONTH
brca_clinical_erposerbb2neg_pfs = brca_clinical_erposerbb2neg[["PFS_MONTH
brca_clinical_erposerbb2neg_os = brca_clinical_erposerbb2neg[["OS_MONTHS"
```

ER+/HER2-

```
In [15]: print("DFS/DSS")
finding_best_threshold_with_FS_SS(brca_clinical_erposerbb2neg_dfs, brca_c
print("PFS/OS")
finding_best_threshold_with_FS_SS(brca_clinical_erposerbb2neg_pfs, brca_c
```

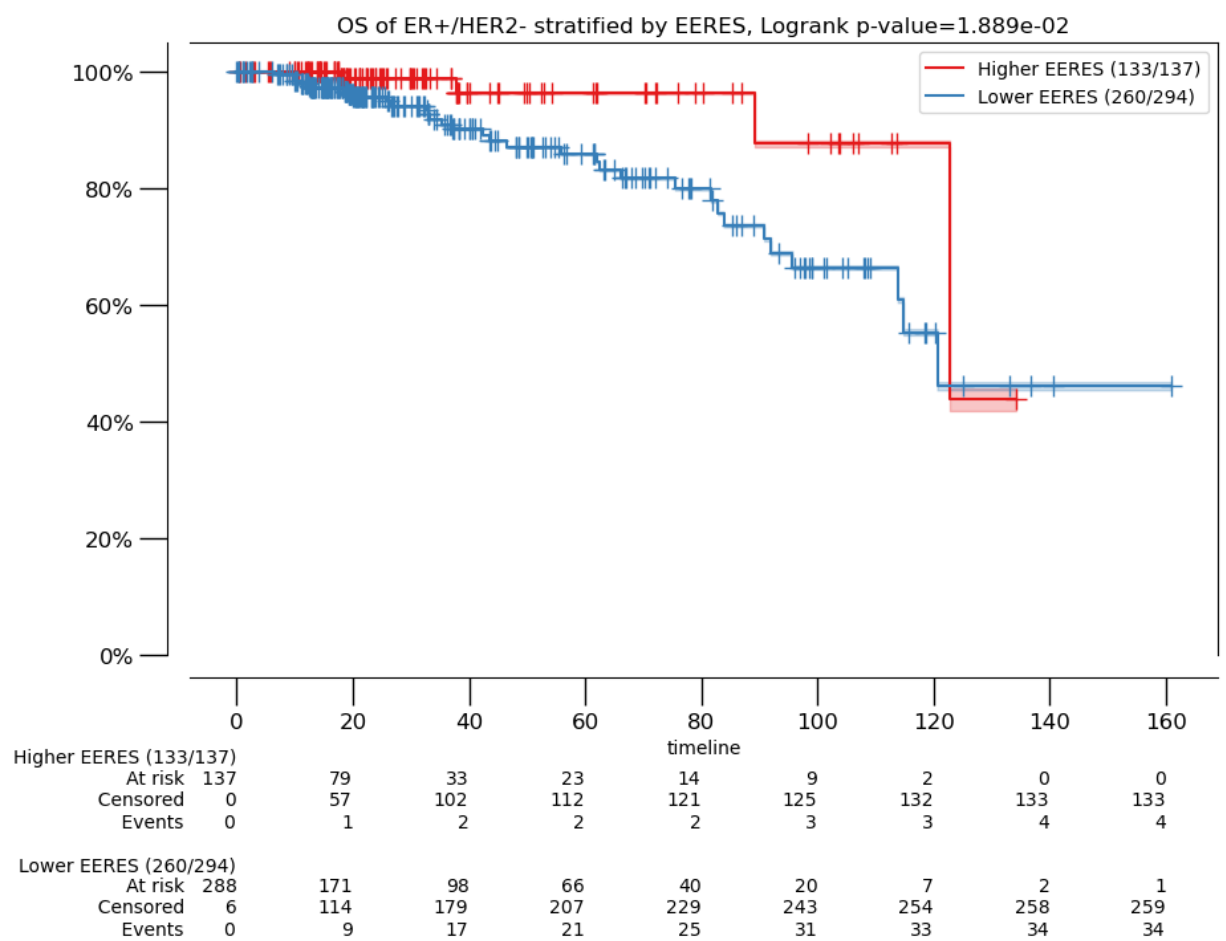
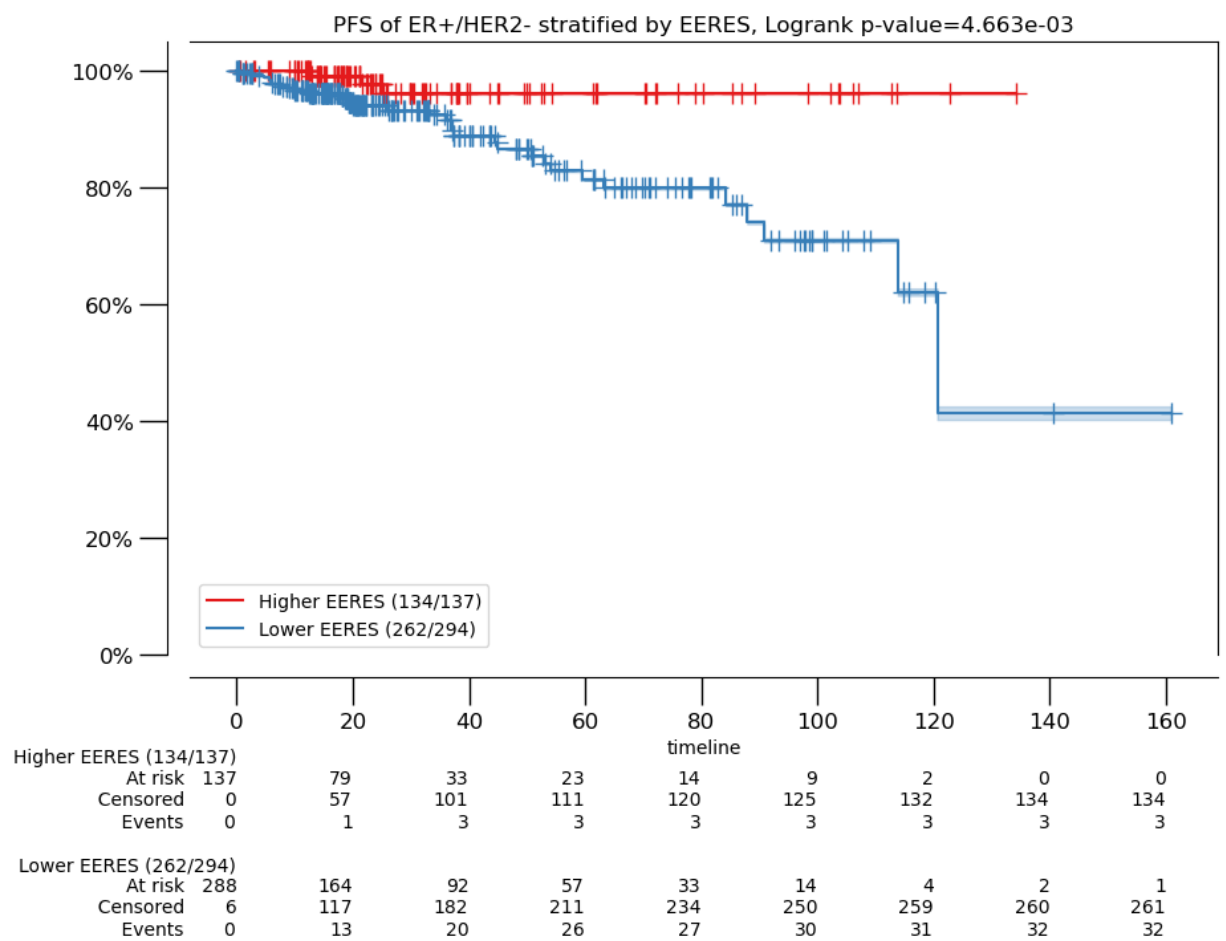
DFS/DSS

Best HALLMARK_ESTROGEN_RESPONSE_EARLY threshold: 0.2020931077758909



PFS/OS

Best HALLMARK_ESTROGEN_RESPONSE_EARLY threshold: 0.2020931077758909



TNBC

```
In [16]: brca_clinical_tnbc = brca_clinical_eeres_ihc_df[brca_clinical_eeres_ihc_d

brca_clinical_tnbc_dfs = brca_clinical_tnbc[["DFS_MONTHS", "DFS_STATUS",
brca_clinical_tnbc_dss = brca_clinical_tnbc[["DSS_MONTHS", "DSS_STATUS",
brca_clinical_tnbc_pfs = brca_clinical_tnbc[["PFS_MONTHS", "PFS_STATUS",
brca_clinical_tnbc_os = brca_clinical_tnbc[["OS_MONTHS", "OS_STATUS", 'HA

print("DFS/DSS")
finding_best_threshold_with_FS_SS(brca_clinical_tnbc_dfs, brca_clinical_t
print("PFS/OS")
finding_best_threshold_with_FS_SS(brca_clinical_tnbc_pfs, brca_clinical_t

DFS/DSS
not significant
PFS/OS
not significant
```

Preparing trainig and testing data

In [17]: *# Data augmentation and normalization for training*

```
class MyData_train(Dataset):
    def __init__(self, X, y):
        self.X = X
        self.classes = np.unique(y)
        self.y = np.array(y)
        self.tumorid = y.index

    def __len__(self):
        return len(self.X)

    def __getitem__(self, index):
        transform = transforms.Compose([
            transforms.RandomRotation(360),
            transforms.RandomHorizontalFlip(),
            transforms.RandomVerticalFlip(),
            transforms.Normalize([0.485, 0.45
#         print(Image.open(self.X[index]))
        image = transform(torch.tensor(np.moveaxis(np.array(Image.open(se
        label = self.y[index]).astype(float)

        return image, label

class MyData_test(Dataset):
    def __init__(self, X, y):
        self.X = X
        self.classes = np.unique(y)
        self.y = np.array(y)
        self.tumorid = y.index

    def __len__(self):
        return len(self.X)

    def __getitem__(self, index):
        transform = transforms.Compose([
            transforms.Normalize([0.485, 0.45
        ])
        image = transform(torch.tensor(np.moveaxis(np.array(Image.open(se
        label = self.y[index]).astype(float)

        return image, label
```

```

In [18]: eeres_threshold = brca_earlyes_es["HALLMARK_ESTROGEN_RESPONSE_EARLY"].qua
print("EERES threshold:", eeres_threshold)
y_eeres = (brca_earlyes_es>eeres_threshold).applymap(lambda x: 1 if x els
meta_y = y_eeres.join(meta_nondup, how='inner')

files = ("Images/" + meta_y["file_id"] + '/' + meta_y["file_name"] + "-1.

X_train, X_test, y_train, y_test = train_test_split(files, meta_y['HALLMA
print("Total number of data:", len(files))
# 5-fold CV with X_train/y_train
train_dataset = MyData_test(X_train, y_train)
train_dataloader = DataLoader(train_dataset, batch_size=1, shuffle=False)

cv_files = {}
dataset_sizes = {}
kf = KFold(n_splits=5, random_state=0, shuffle=True)
for i, (train_index, val_index) in enumerate(kf.split(X_train)):
    # Double training dataset with cropped and augmented images
    print(f"Fold {i} train data: {len(train_index)}, val data: {len(val_i
    train_file_2 = [file.replace('-1.jpg', '-2.jpg') for file in files[tr
    X_train_double = np.concatenate([files[train_index], train_file_2])
    y_fold_train = meta_y['HALLMARK_ESTROGEN_RESPONSE_EARLY'].iloc[train_
    y_train_double = pd.concat([y_fold_train, y_fold_train])
    X_val = files[val_index]
    y_val = meta_y['HALLMARK_ESTROGEN_RESPONSE_EARLY'].iloc[val_index]
    train_dataset = MyData_train(X_train_double, y_train_double)
    val_dataset = MyData_test(X_val, y_val)
    cv_files[i] = {'train': DataLoader(train_dataset, batch_size=2, shuffle
    dataset_sizes[i] = {'train': len(train_dataset), 'val': len(val_datas
# Testing data with X_test/y_test
print(f"Test data: {len(X_test)}")
test_dataset = MyData_test(X_test, y_test)
test_dataloader = DataLoader(test_dataset, batch_size=1, shuffle=False)

EERES threshold: 0.0225090214649534
Total number of data: 1046
Fold 0 train data: 627, val data: 157
Fold 1 train data: 627, val data: 157
Fold 2 train data: 627, val data: 157
Fold 3 train data: 627, val data: 157
Fold 4 train data: 628, val data: 156
Test data: 262

```

Training

```

In [ ]: folder = "Output"
!mkdir "Output"

```

```

In [20]: # Training function

def train_model(model, criterion, optimizer, scheduler, num_epochs=25, fo
    device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu
    since = time.time()
    checkpoint = torch.load(folder+"/model_initial.pt", map_location=torch

```

```

for fold in folds:
    best_auroc = 0.0
    best_average_loss = 100
    model.load_state_dict(checkpoint['model_state_dict'], strict=False)
    model.to(device)
    optimizer.load_state_dict(checkpoint['optimizer_state_dict'])
    folder_fold = folder+"/"+str(fold)
    !mkdir "{folder_fold}"
    for epoch in range(num_epochs):
        print(f'Epoch {epoch}/{num_epochs - 1}')
        print('-' * 10)

        # Each epoch has a training and validation phase
        train_epoch_loss = 100
        val_epoch_loss = 100
        for phase in ['train', 'val']:
            if phase == 'train':
                model.train() # Set model to training mode
            else:
                model.eval() # Set model to evaluate mode

            running_loss = 0.0
            running_corrects = 0
            running_scores = []
            running_golds = []
            # Iterate over data.
            for inputs, labels in cv_files[fold][phase]:
                inputs = inputs.to(device)
                labels = labels.reshape(-1,1).to(device)

                # zero the parameter gradients
                optimizer.zero_grad()

                # forward
                # track history if only in train
                with torch.set_grad_enabled(phase == 'train'):
                    outputs = model(inputs)
                    running_scores += torch.flatten(outputs[:,1]).tolist()
                    running_golds += torch.flatten(labels).tolist()
                    _, preds = torch.max(outputs, 1)
                    preds = torch.reshape(preds, (-1,1)).float()
                    gold = torch.tensor([[1,0] if label==0 else [0,1]])
                    loss = criterion(outputs.float(), gold.float())

                    # backward + optimize only if in training phase
                    if phase == 'train':
                        loss.backward()
                        optimizer.step()

                # statistics
                running_loss += loss.item() * inputs.size(0)
                running_corrects += torch.sum(preds == labels.data)
            if phase == 'train':
                scheduler.step()

        epoch_loss = running_loss / dataset_sizes[fold][phase]
        epoch_auroc = roc_auc_score(running_golds, running_scores)

```

```

    if phase == 'train':
        train_epoch_loss = epoch_loss
    elif phase == 'val':
        val_epoch_loss = epoch_loss
        average_loss = (train_epoch_loss+val_epoch_loss)/2
        print(f'{phase} Average Loss: {average_loss}')

    print(f'{phase} Loss: {epoch_loss:.4f} AUROC {epoch_auroc:.4f}')

    # Save the model with highest val AUROC
    if phase == 'val' and best_auroc < epoch_auroc:
        best_average_loss = average_loss
        best_auroc = epoch_auroc
        torch.save({
            'epoch': epoch,
            'model_state_dict': model.state_dict(),
            'optimizer_state_dict': optimizer.state_dict(),
            'loss': loss,
        }, folder_fold+str(epoch)+"_auroc_"+str(epoch_auroc))

    print()

time_elapsed = time.time() - since
print(f'Training complete in {time_elapsed // 60:.0f}m {time_elapsed % 60:.0f}s')
print(f'Best val AUROC: {best_auroc:.4f}')

```

```

In [21]: device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Transfer learning with ResNet50 and followed by 3 fc layers

model_ft = models.resnet50(weights='DEFAULT').to(device)
import torch.nn.functional as F
class net(nn.Module):
    def __init__(self):
        super(net, self).__init__()
        self.fc1 = nn.Linear(1000, 128)
        self.fc2 = nn.Linear(128, 32)
        self.fc3 = nn.Linear(32, 2)
        self.m = nn.Dropout(p=0.2)

    def forward(self, x):
        x = self.m(x)
        x = F.relu(self.fc1(x))
        x = self.m(x)
        x = F.relu(self.fc2(x))
        x = self.m(x)
        x = F.softmax(self.fc3(x), dim=1)
        return x

net_add = net()

model_ft = nn.Sequential(model_ft, net_add).to(device)

# Observe that all parameters are being optimized
optimizer_ft = optim.SGD(model_ft.parameters(), lr=0.01, momentum=0.9)

# Decay LR by a factor of 0.1 every 7 epochs
exp_lr_scheduler = lr_scheduler.StepLR(optimizer_ft, step_size=7, gamma=0.1)

# Save initial model parameters for each fold of CV
torch.save({
    'model_state_dict': model_ft.state_dict(),
    'optimizer_state_dict': optimizer_ft.state_dict(),
}, folder+"/model_initial.pt")

criterion = nn.CrossEntropyLoss()

In [ ]: train_model(model_ft, criterion, optimizer_ft, exp_lr_scheduler,
                    num_epochs=25, folder=folder, folds=[0,1,2,3,4])

```

Evaluation with unseen testing data

```

In [22]: cv_test_index = y_test.index
cv_predicted_df_dict = {}

for fold in range(5):
    cv_test_predicted_df = pd.DataFrame(np.zeros((len(cv_test_index),2)),
    file = np.sort(os.listdir(f"{folder}/{str(fold)}"))[-1] # Get the last
    print(f"Fold {fold} model:", file)
    model_path = f"{folder}/{str(fold)}/{file}"
    checkpoint = torch.load(model_path, map_location=torch.device('cpu'))
    model_ft = models.resnet50().to(device)
    model_test = nn.Sequential(model_ft, net_add).to(device)
    model_test.load_state_dict(checkpoint['model_state_dict'])
    model_test.cuda()
    criterion = nn.CrossEntropyLoss()
    epoch_test = checkpoint['epoch']
    loss_test = checkpoint['loss']
    model_test.eval()

    loss_epoch_test=[]
    y_proba = []
    y_gold = []
    y_pred = []
    with torch.no_grad():
        for b, (X, y) in enumerate(test_dataloader):
            outputs = model_test(X.cuda())
            _, preds = torch.max(outputs, 1)
            y_proba += torch.flatten(outputs[:,1]).cpu().tolist()
            y_gold += y.data.cpu().tolist()
            y_pred += preds.cpu().tolist()
        # loss = criterion(outputs.float(), torch.tensor([[1,0] if la
        # loss_epoch_test.append(loss.item())

    auc=roc_auc_score(y_gold,y_proba)
    print(f"Fold {fold} AUROC: {auc}")
    cv_test_predicted_df.loc[cv_test_index,'score'] = y_proba
    cv_test_predicted_df.loc[cv_test_index,'gold'] = y_gold
    cv_predicted_df_dict[fold] = cv_test_predicted_df

# Average the scores of the 5 folds
cv_test_predicted_df["score"] = (cv_predicted_df_dict[0]["score"]+\
                                cv_predicted_df_dict[1]["score"]+\
                                cv_predicted_df_dict[2]["score"]+\
                                cv_predicted_df_dict[3]["score"]+\
                                cv_predicted_df_dict[4]["score"])/5

Fold 0 model: epoch_21_loss_0.617512_auroc_0.729207.pt
Fold 0 AUROC: 0.7536934306569344
Fold 1 model: epoch_9_loss_0.674120_auroc_0.596405.pt
Fold 1 AUROC: 0.7063941605839417
Fold 2 model: epoch_6_loss_0.676420_auroc_0.628654.pt
Fold 2 AUROC: 0.6602043795620438
Fold 3 model: epoch_9_loss_0.650217_auroc_0.667819.pt
Fold 3 AUROC: 0.728992700729927
Fold 4 model: epoch_8_loss_0.667883_auroc_0.647039.pt
Fold 4 AUROC: 0.7028321167883211

```

Examine the Survival of the testing data (ER+/HER2- vs TNBC)

```
In [23]: cv_test_predicted_df_ihc = cv_test_predicted_df.join(meta_erihc, how='inner')
cv_test_predicted_df_ihc["Subtype"] = None
cv_test_predicted_df_ihc["Subtype"][(cv_test_predicted_df_ihc["er_status_"] == "ERBB2+")] = "ERBB2+"
cv_test_predicted_df_ihc["Subtype"][(cv_test_predicted_df_ihc["er_status_"] == "ERBB2-")] = "ERBB2-"
cv_test_predicted_df_ihc["EERES"] = brca_earlyes_es.loc[cv_test_predicted_df_ihc["ESR1"]]
cv_test_predicted_df_ihc["ESR1"] = brca_lv3.loc[cv_test_predicted_df_ihc["ESR1"]]

brca_clinical_testing = brca_clinical.join(cv_test_predicted_df_ihc, how='inner')
brca_clinical_testing_dfs = brca_clinical_testing[["DFS_MONTHS", "DFS_STATUS"]]
brca_clinical_testing_dss = brca_clinical_testing[["DSS_MONTHS", "DSS_STATUS"]]
brca_clinical_testing_pfs = brca_clinical_testing[["PFS_MONTHS", "PFS_STATUS"]]
brca_clinical_testing_os = brca_clinical_testing[["OS_MONTHS", "OS_STATUS"]]

result = km.fit(brca_clinical_testing_pfs['PFS_MONTHS'], brca_clinical_testing_pfs['PFS_STATUS'])
km.plot(result, title=f"PFS of ER+/HER2- vs TNBC, Logrank p-value={result.pval}")
plt.show()
result = km.fit(brca_clinical_testing_os['OS_MONTHS'], brca_clinical_testing_os['OS_STATUS'])
km.plot(result, title=f"OS of ER+/HER2- vs TNBC, Logrank p-value={result.pval}")
plt.show()
result = km.fit(brca_clinical_testing_dfs['DFS_MONTHS'], brca_clinical_testing_dfs['DFS_STATUS'])
km.plot(result, title=f"DFS of ER+/HER2- vs TNBC, Logrank p-value={result.pval}")
plt.show()
result = km.fit(brca_clinical_testing_dss['DSS_MONTHS'], brca_clinical_testing_dss['DSS_STATUS'])
km.plot(result, title=f"DSS of ER+/HER2- vs TNBC, Logrank p-value={result.pval}")
plt.show()

plt.scatter(cv_test_predicted_df_ihc[cv_test_predicted_df_ihc["Subtype"] == "ERBB2+"]["ESR1"],
            cv_test_predicted_df_ihc[cv_test_predicted_df_ihc["Subtype"] == "ERBB2+"]["EERES"],
            label="ER+/HER2-")
plt.scatter(cv_test_predicted_df_ihc[cv_test_predicted_df_ihc["Subtype"] == "ERBB2-"]["ESR1"],
            cv_test_predicted_df_ihc[cv_test_predicted_df_ihc["Subtype"] == "ERBB2-"]["EERES"],
            label="TNBC")
plt.legend(["ER+/HER2-", "TNBC"])
plt.xlabel("ESR1")
plt.ylabel("EERES")
plt.show()
```

```
/tmp/ipykernel_93586/4221478194.py:3: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame
```

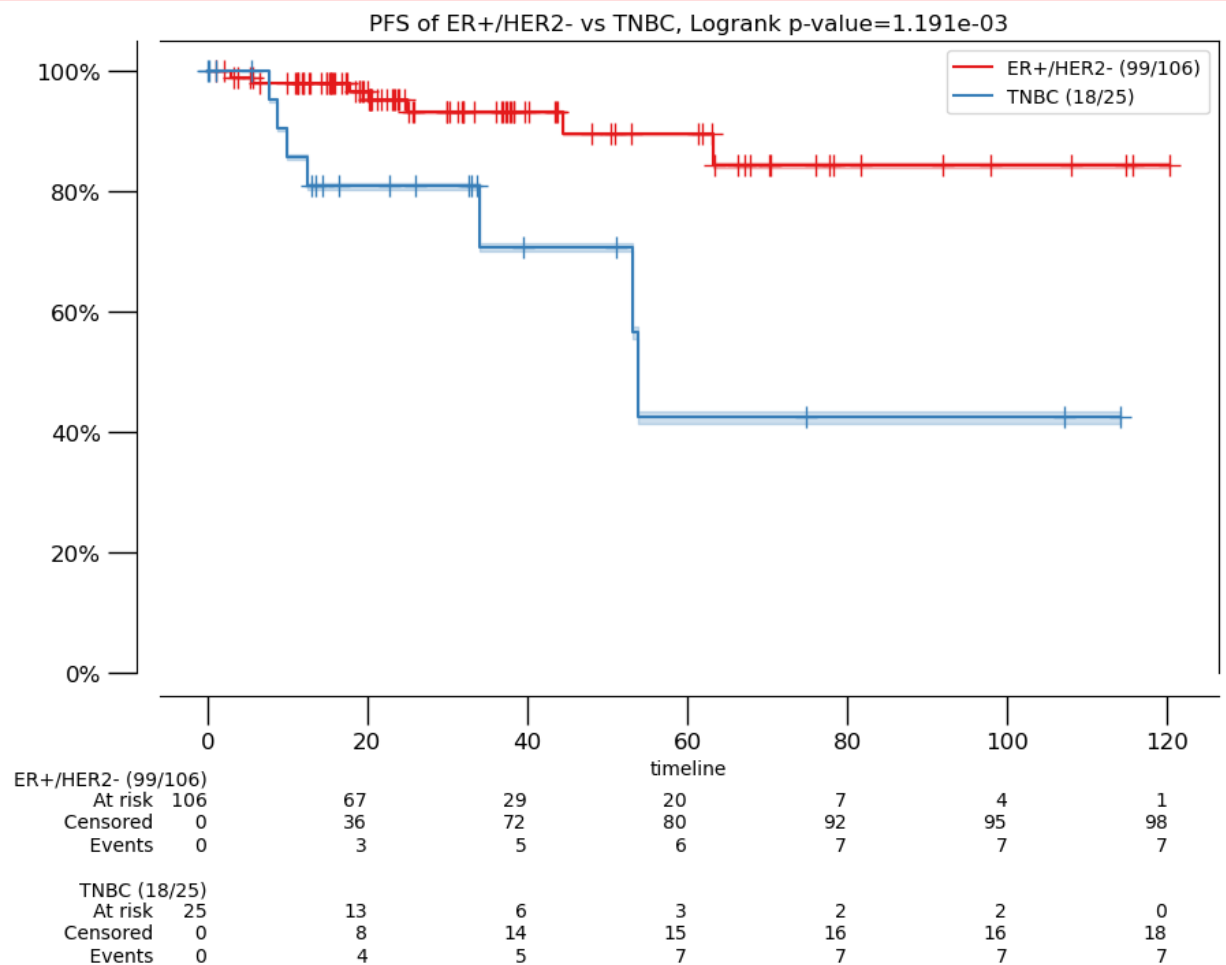
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

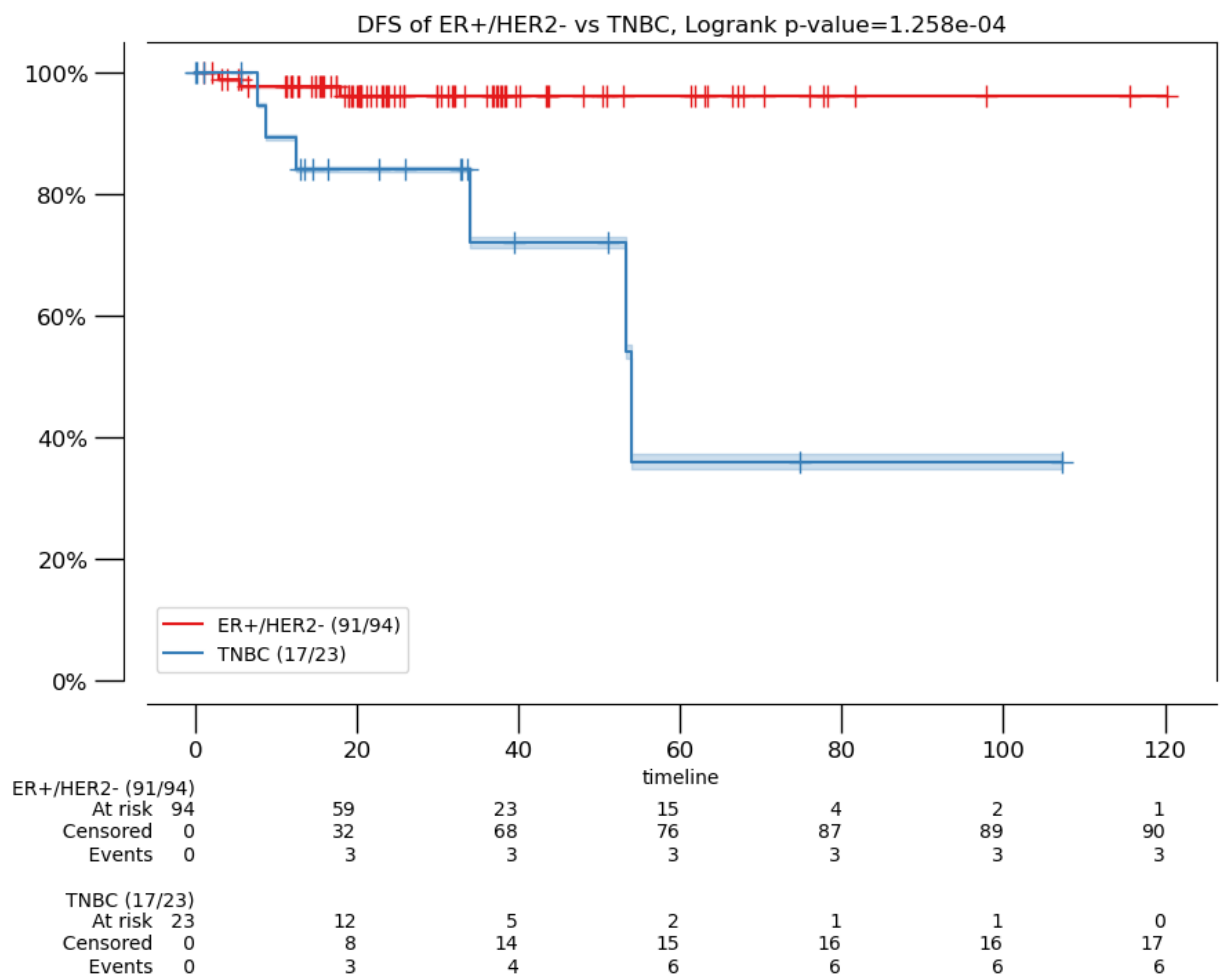
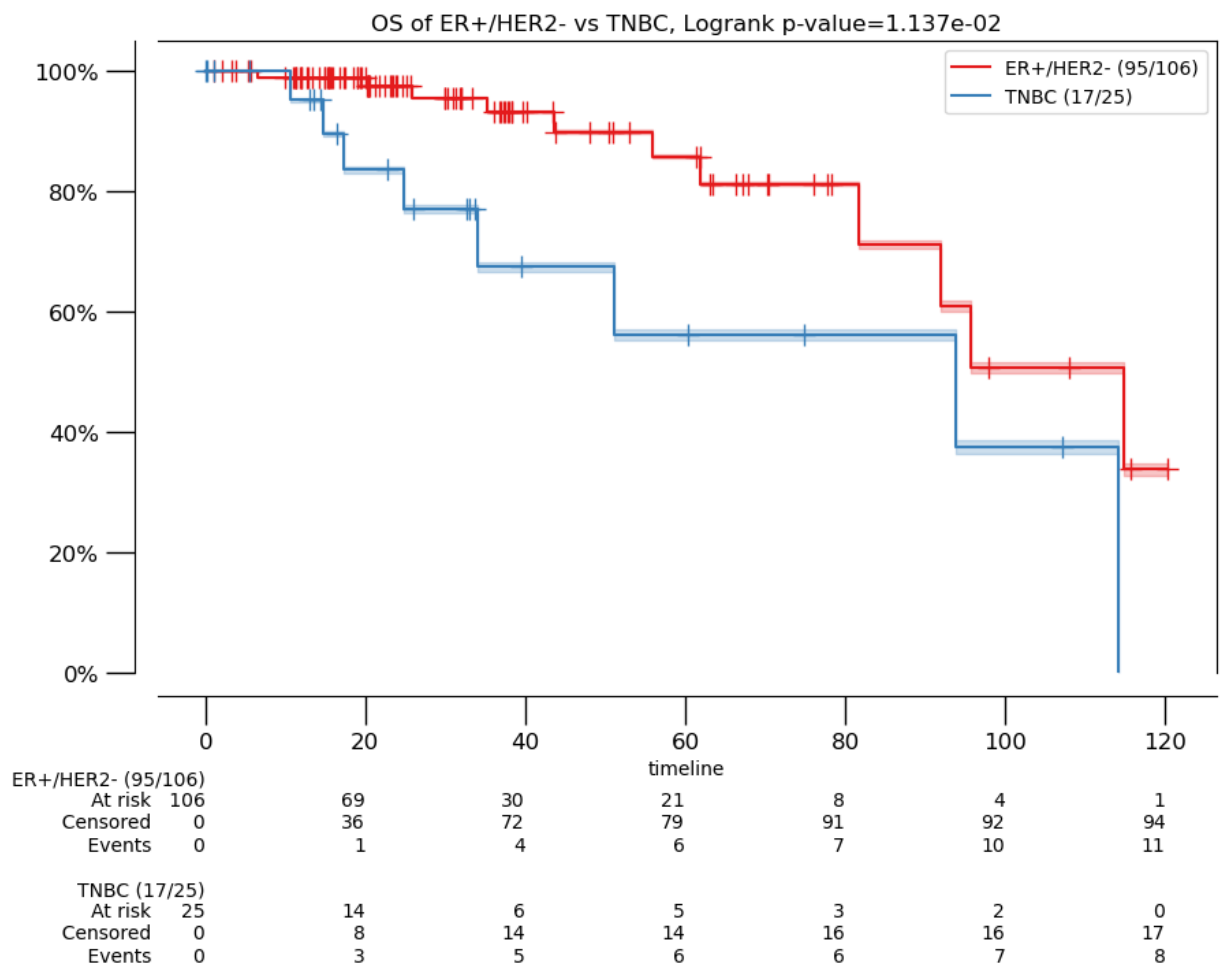
```
cv_test_predicted_df_ihc["Subtype"][(cv_test_predicted_df_ihc["er_status_by_ihc"]=="Positive") & (cv_test_predicted_df_ihc["her2_status_by_ihc"]=="Negative")] = "ER+/HER2-"
```

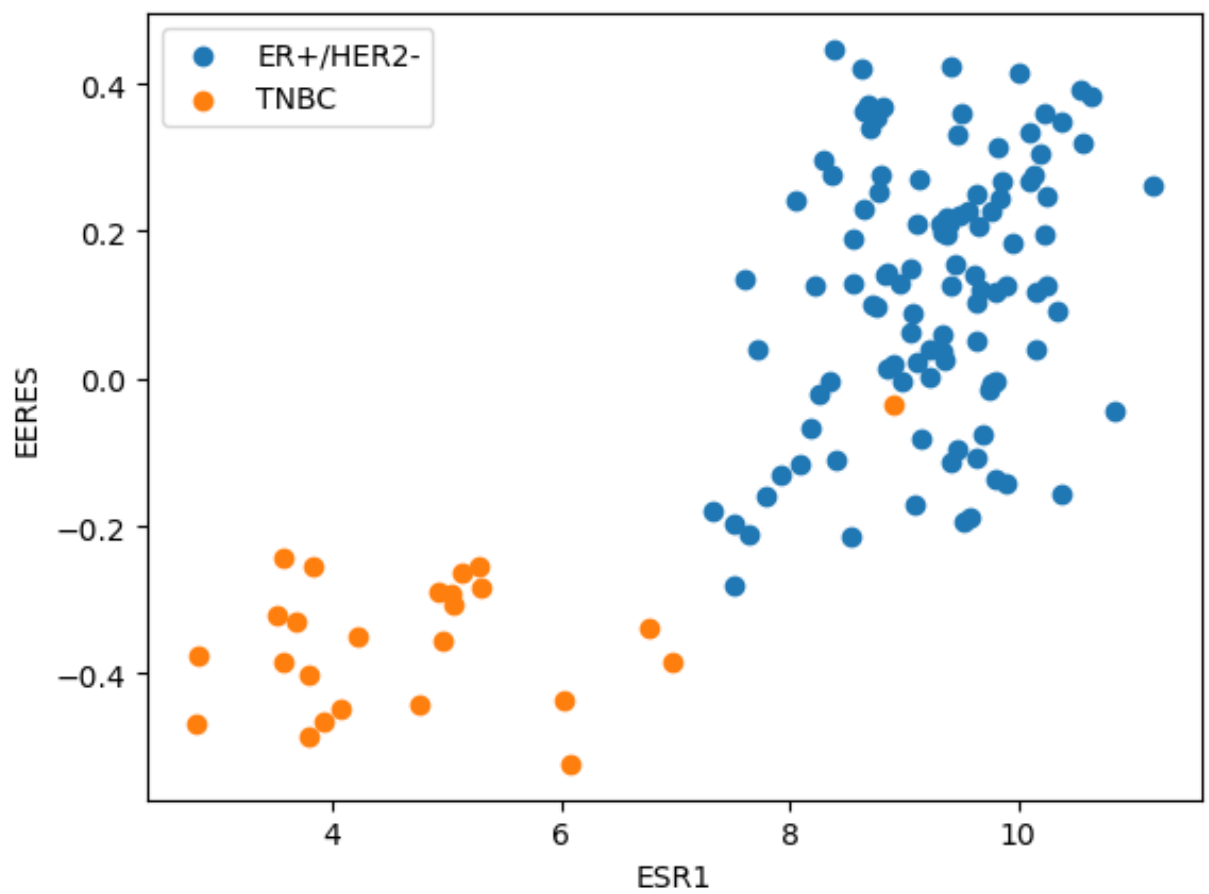
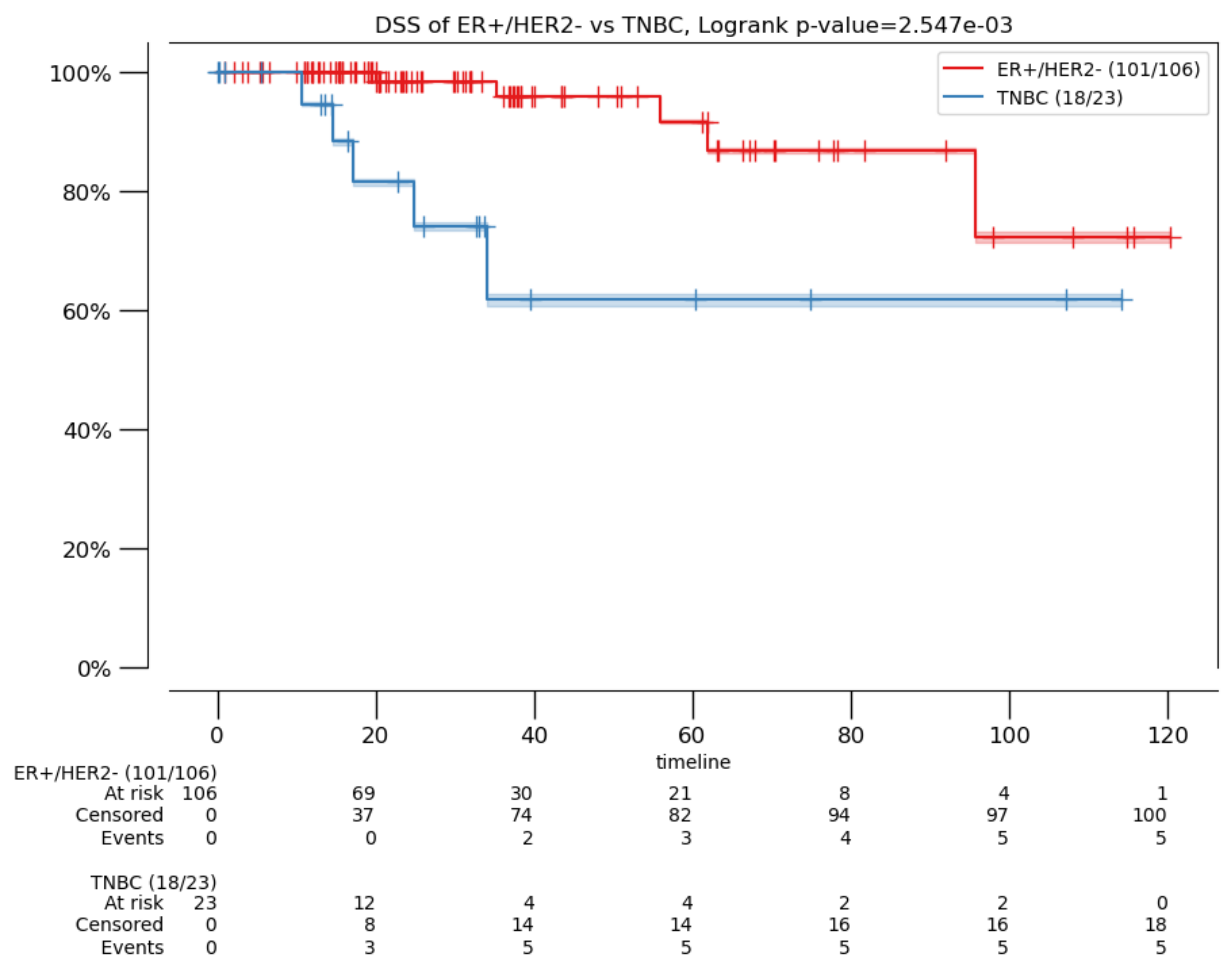
```
/tmp/ipykernel_93586/4221478194.py:5: SettingWithCopyWarning:  
A value is trying to be set on a copy of a slice from a DataFrame
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
cv_test_predicted_df_ihc["Subtype"][(cv_test_predicted_df_ihc["er_status_by_ihc"]=="Negative") & (cv_test_predicted_df_ihc["her2_status_by_ihc"]=="Negative") & (cv_test_predicted_df_ihc["pr_status_by_ihc"]=="Negative")] = "TNBC"
```





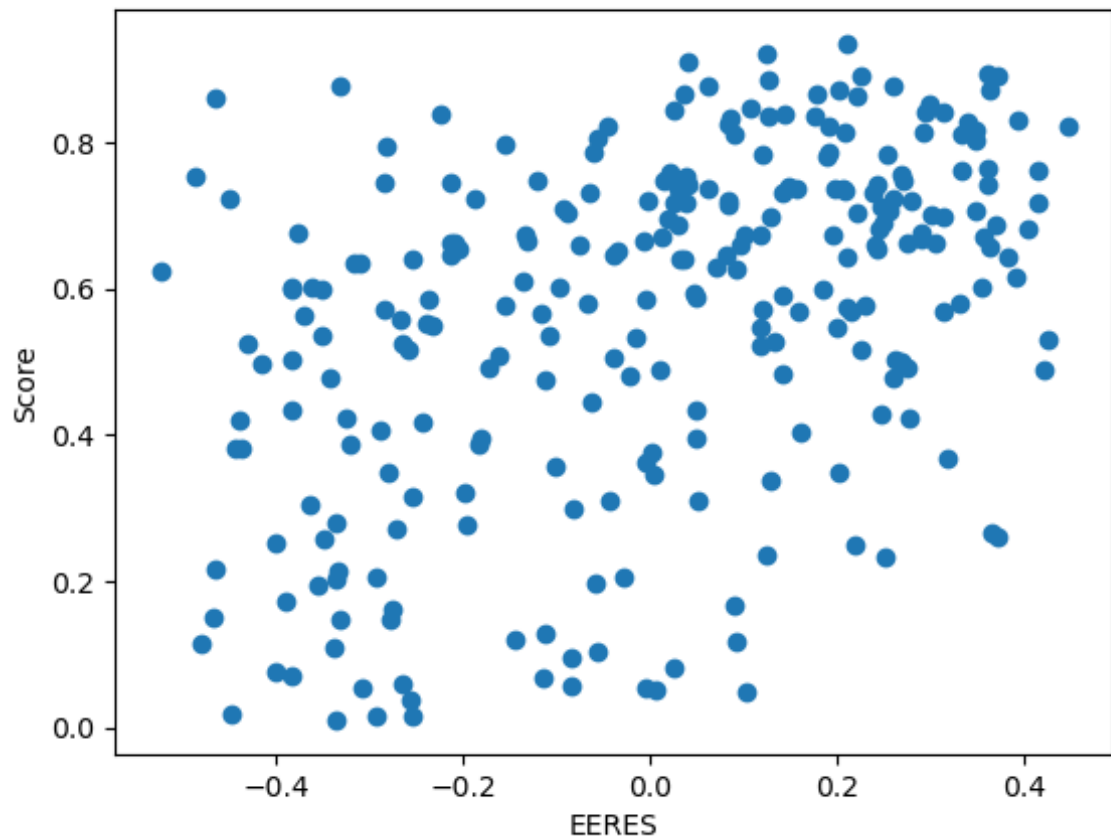


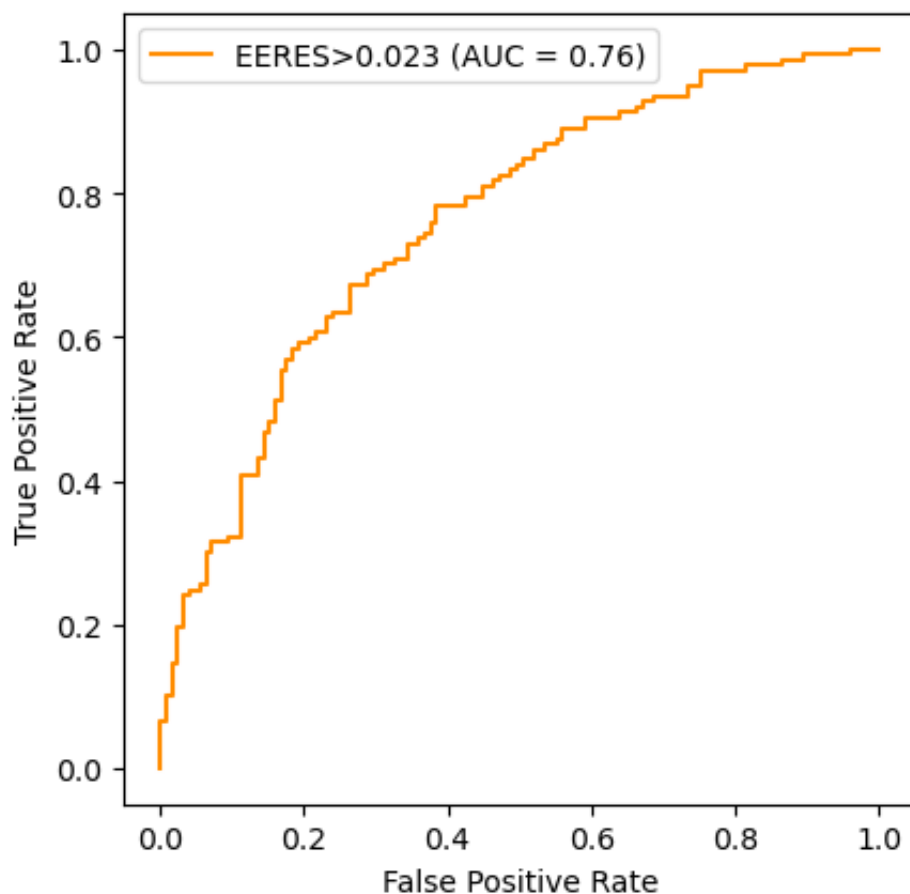
```
In [24]: cv_test_predicted_df_ihc[['score', 'EERES', 'her2_status_by_ihc', 'er_status
```

```
In [33]: plt.scatter(cv_test_predicted_df_ihc["EERES"], cv_test_predicted_df_ihc["Score"])
plt.xlabel("EERES")
plt.ylabel("Score")
r, p = pearsonr(cv_test_predicted_df_ihc["EERES"], cv_test_predicted_df_ihc["Score"])
plt.title(f"Pearson R: {r}, p-value: {p}")

auroc = roc_auc_score(cv_test_predicted_df_ihc["gold"], cv_test_predicted_df_ihc["Score"])
RocCurveDisplay.from_predictions(
    cv_test_predicted_df_ihc["gold"],
    cv_test_predicted_df_ihc["Score"],
    name=f"EERES>{eeres_threshold:.3f}",
    color="darkorange",
)
# plt.plot([0, 1], [0, 1], "k--", label="chance level (AUC = 0.5)")
plt.axis("square")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
# plt.title("Receiver Operating Characteristic")
plt.legend()
plt.show()
```

Pearson R: 0.4458806968945076, p-value: 3.3421079721439386e-14



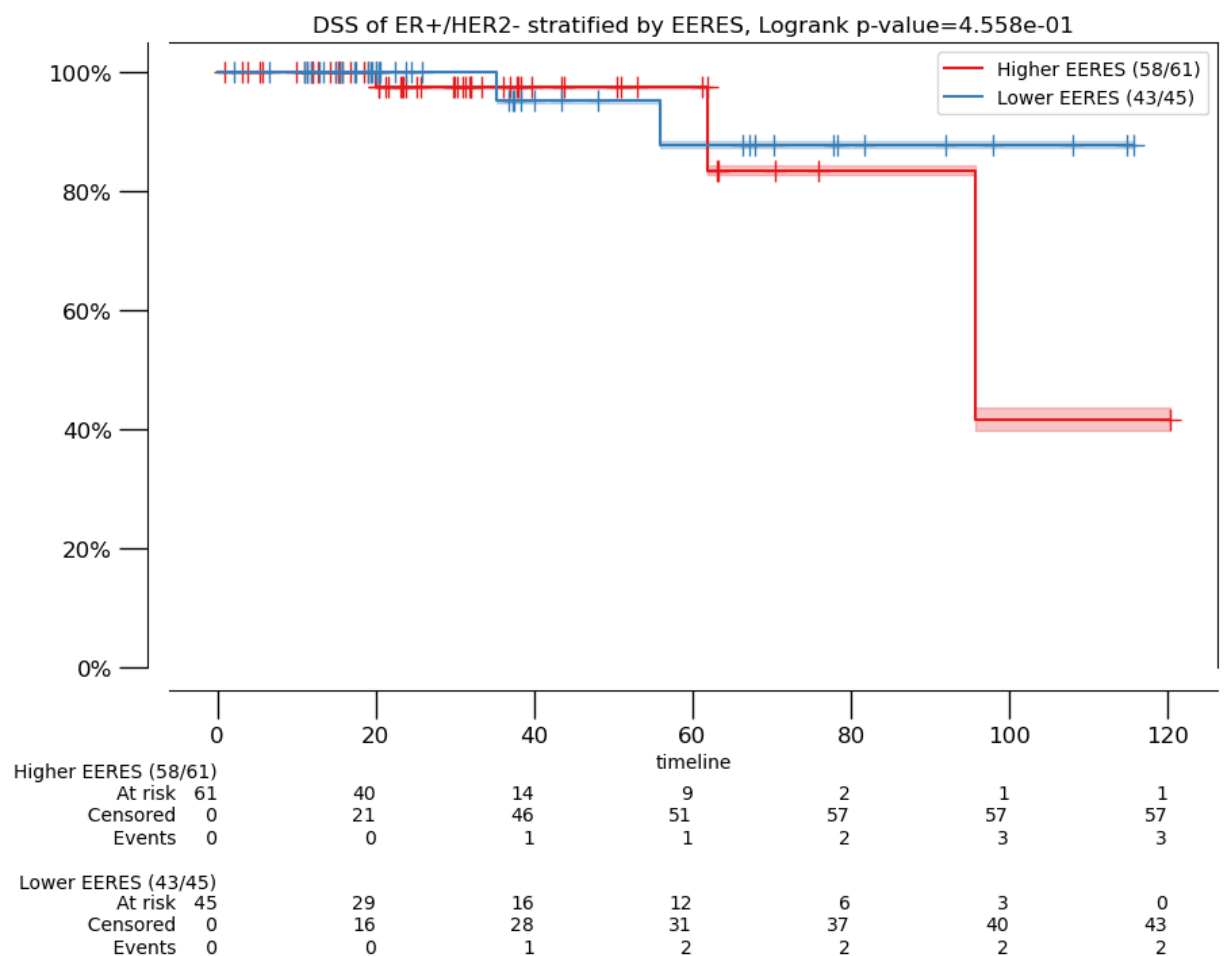
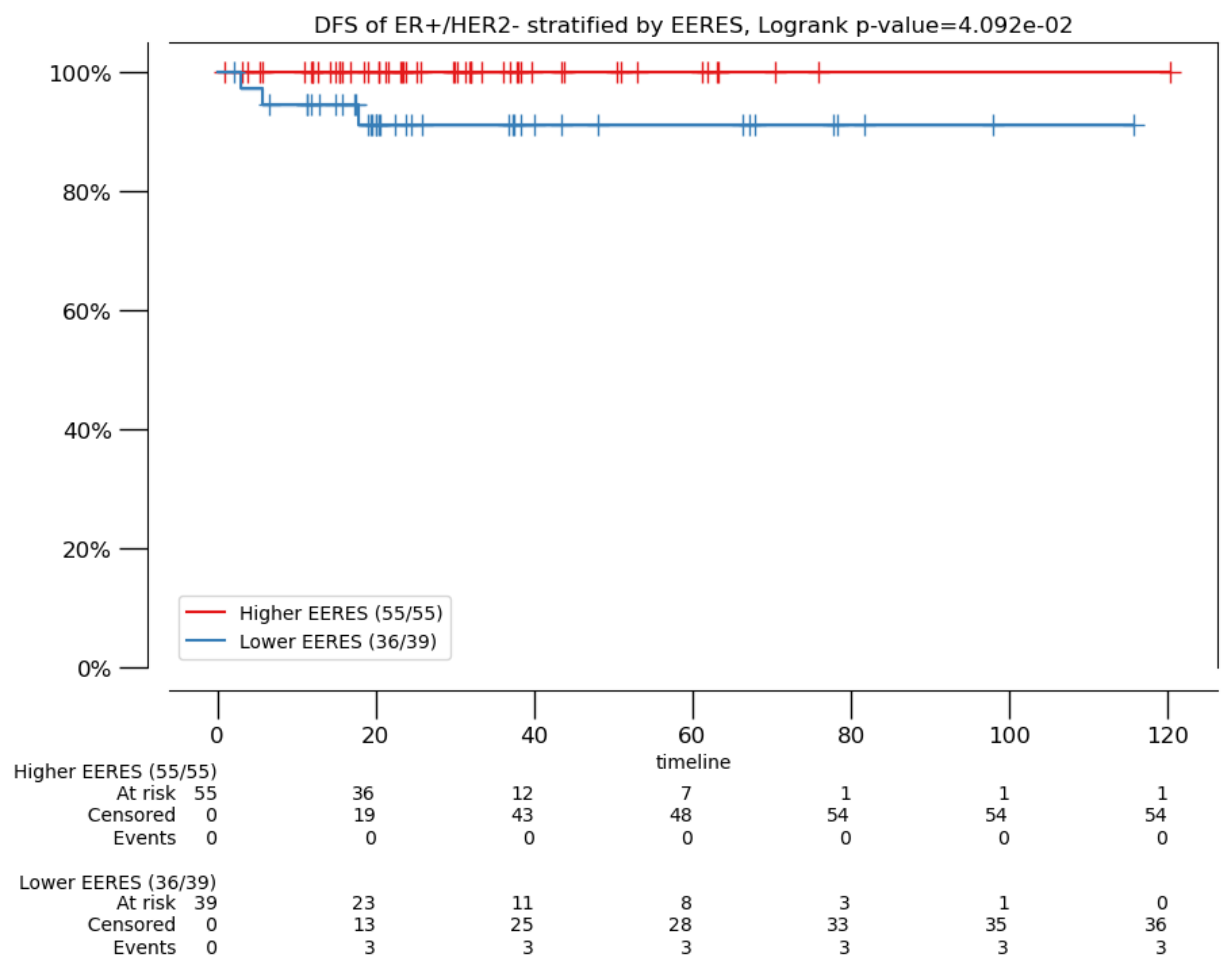


Examine the Survival of the ER+/HER2- testing data (Higher/Lower Predicted Score)

```
In [90]: brca_clinical_testing_erposerb2neg = brca_clinical.join(cv_test_predicte
brca_clinical_testing_erposerb2neg
```

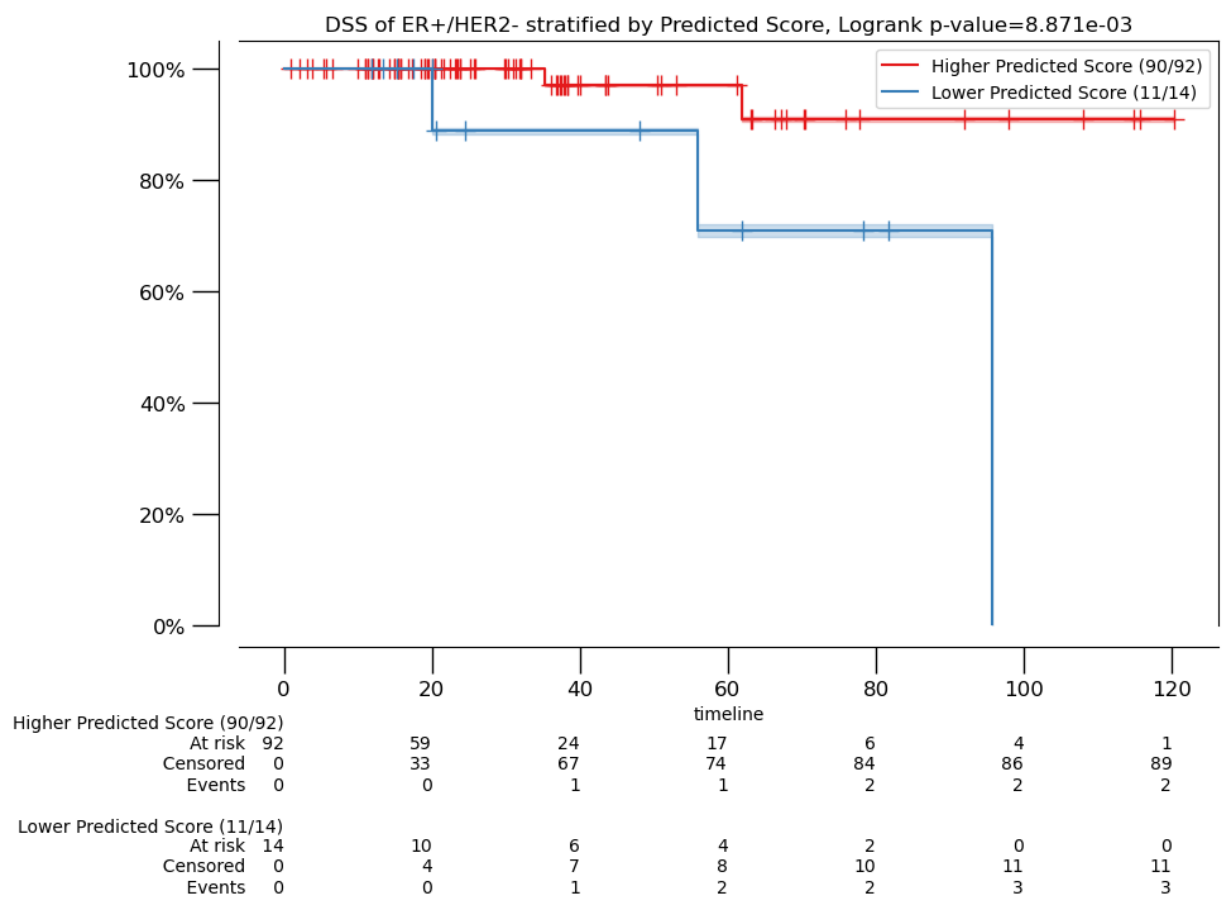
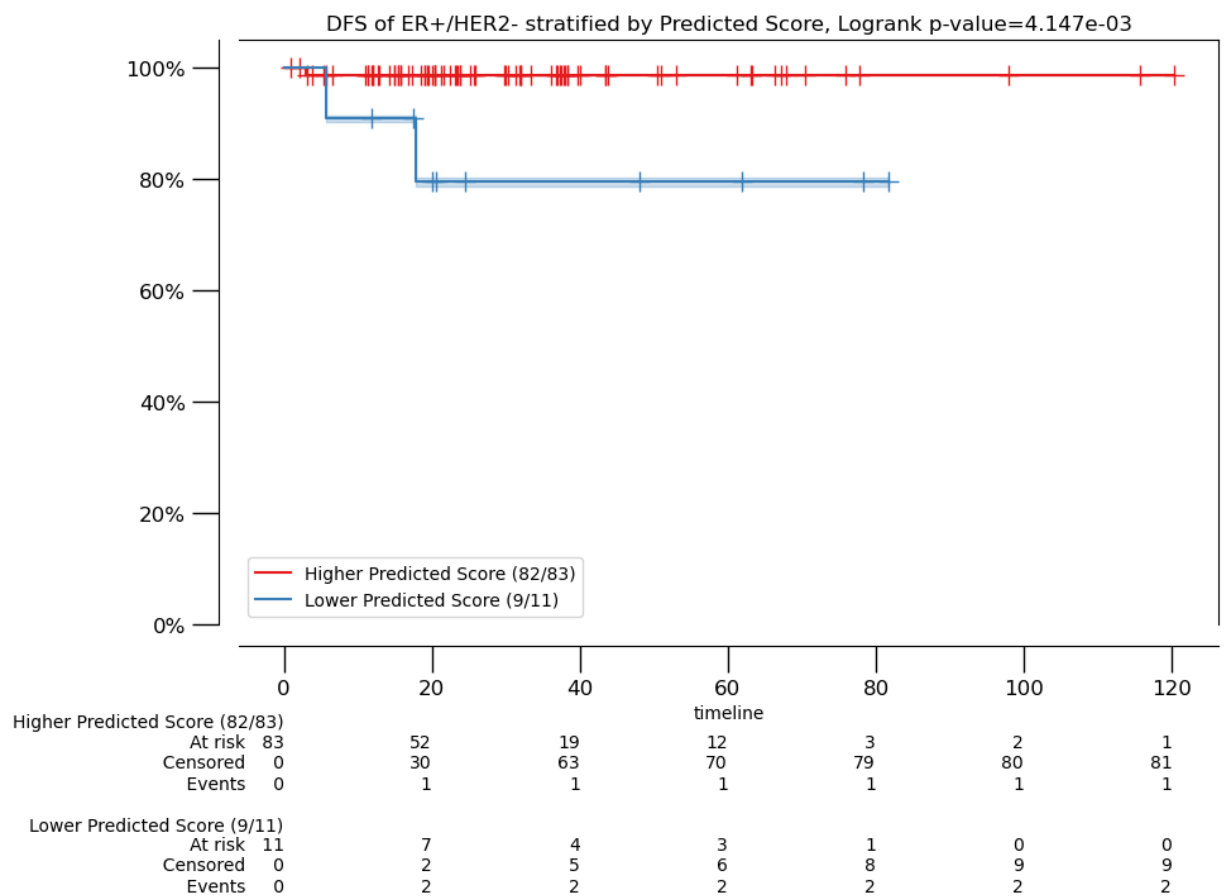
```
brca_clinical_testing_erposerb2neg_dfs = brca_clinical_testing_erposerb2neg
brca_clinical_testing_erposerb2neg_dss = brca_clinical_testing_erposerb2neg
brca_clinical_testing_erposerb2neg_pfs = brca_clinical_testing_erposerb2neg
brca_clinical_testing_erposerb2neg_os = brca_clinical_testing_erposerb2neg
finding_best_threshold_with_FS_SS(brca_clinical_testing_erposerb2neg_dfs
finding_best_threshold_with_FS_SS(brca_clinical_testing_erposerb2neg_pfs
finding_best_threshold_with_FS_SS(brca_clinical_testing_erposerb2neg_dfs
finding_best_threshold_with_FS_SS(brca_clinical_testing_erposerb2neg_pfs
```

Best EERES threshold: 0.1109585485096507

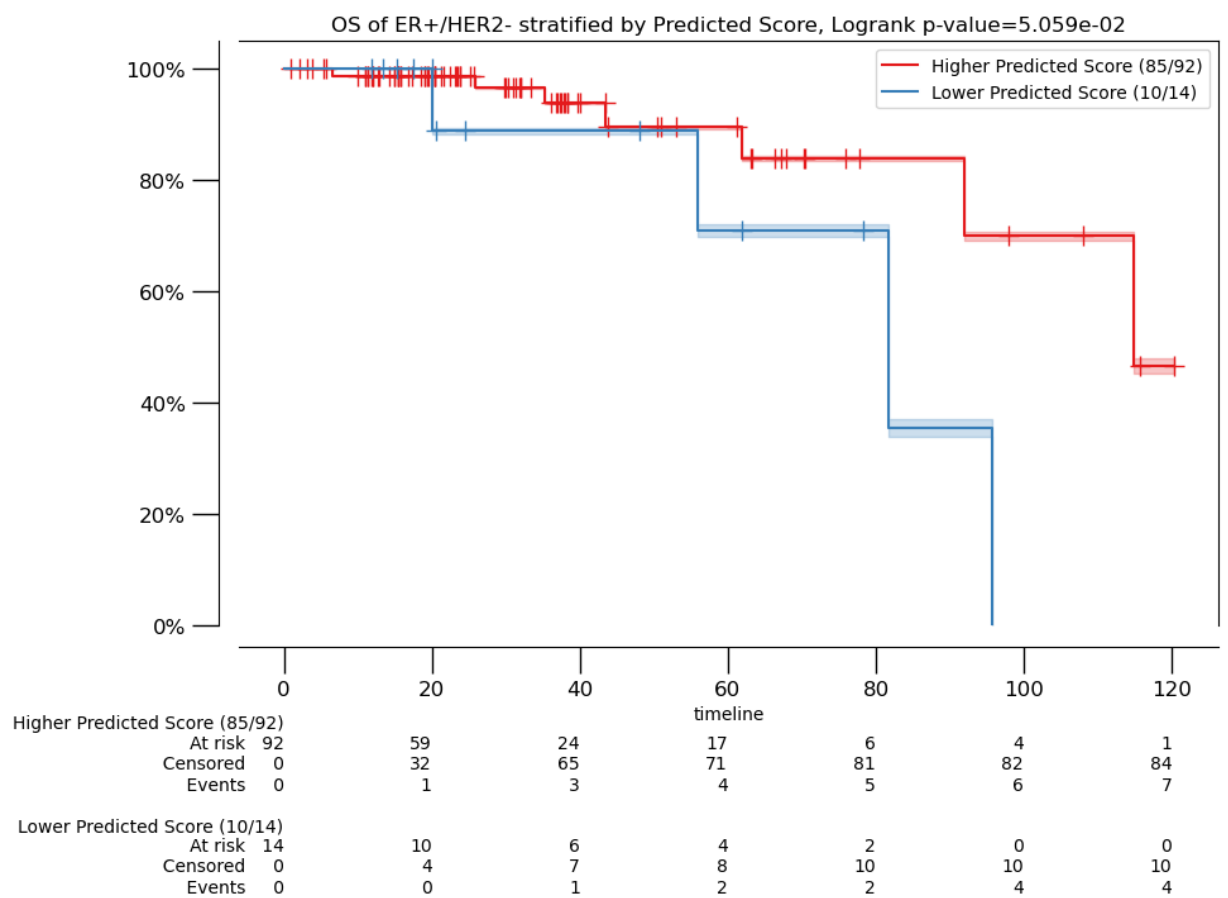
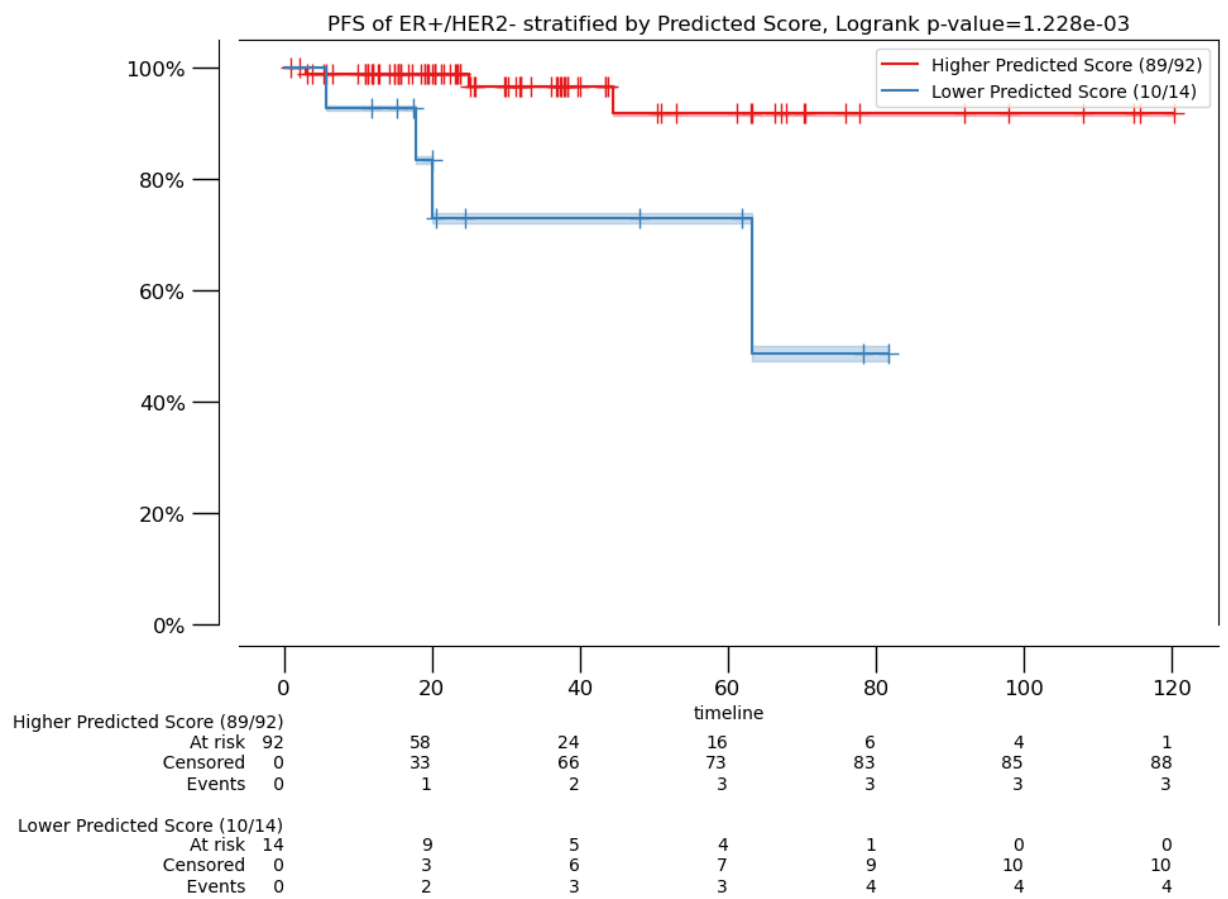


not significant

Best score threshold: 0.3645404119975865



Best score threshold: 0.3645404119975865



```
In [47]: brca_clinical_tnbc = brca_clinical.join(cv_test_predicted_df_ihc[cv_test_

brca_clinical_tnbc_dfs = brca_clinical_tnbc[["DFS_MONTHS", "DFS_STATUS",
brca_clinical_tnbc_dss = brca_clinical_tnbc[["DSS_MONTHS", "DSS_STATUS",
brca_clinical_tnbc_pfs = brca_clinical_tnbc[["PFS_MONTHS", "PFS_STATUS",
brca_clinical_tnbc_os = brca_clinical_tnbc[["OS_MONTHS", "OS_STATUS", "sc

finding_best_threshold_with_FS_SS(brca_clinical_tnbc_dfs, brca_clinical_t
finding_best_threshold_with_FS_SS(brca_clinical_tnbc_dfs, brca_clinical_t

not significant
not significant
```

Higher/Lower Predicted Score vs TNBC Survival

```

In [105... erposerbb2neg_highscore_tnbc_df = pd.concat([cv_test_predicted_df_ihc[cv_t
cv_test_predicted_df_ihc[(cv_test_predicted_df_ihc['Subtype']=="ER+/HER2-
erposerbb2neg_highscore_tnbc_df.loc[erposerbb2neg_highscore_tnbc_df["Subt
brca_clinical_erposerbb2neg_highscore_tnbc = brca_clinical.join(erposerbb2

erposerbb2neg_lowscore_tnbc_df = pd.concat([cv_test_predicted_df_ihc[cv_t
cv_test_predicted_df_ihc[(cv_test_predicted_df_ihc['Subtype']=="ER+/HER2-
erposerbb2neg_lowscore_tnbc_df.loc[erposerbb2neg_lowscore_tnbc_df["Subtyp
brca_clinical_erposerbb2neg_lowscore_tnbc = brca_clinical.join(erposerbb2

erposerbb2neg_highscore_tnbc_df_pfs = brca_clinical_erposerbb2neg_highsco
result = km.fit(erposerbb2neg_highscore_tnbc_df_pfs[f'PFS_MONTHS'], erpos
km.plot(result, title=f"PFS of ER+/HER2- with higher predicted score VS T
plt.show()

erposerbb2neg_highscore_tnbc_df_os = brca_clinical_erposerbb2neg_highsco
result = km.fit(erposerbb2neg_highscore_tnbc_df_os[f'OS_MONTHS'], erposer
km.plot(result, title=f"OS of ER+/HER2- with higher predicted score VS TN
plt.show()

erposerbb2neg_highscore_tnbc_df_dfs = brca_clinical_erposerbb2neg_highsco
result = km.fit(erposerbb2neg_highscore_tnbc_df_dfs[f'DFS_MONTHS'], erpos
km.plot(result, title=f"DFS of ER+/HER2- with higher predicted score VS T
plt.show()

erposerbb2neg_highscore_tnbc_df_dss = brca_clinical_erposerbb2neg_highsco
result = km.fit(erposerbb2neg_highscore_tnbc_df_dss[f'DSS_MONTHS'], erpos
km.plot(result, title=f"DSS of ER+/HER2- with higher predicted score VS T
plt.show()

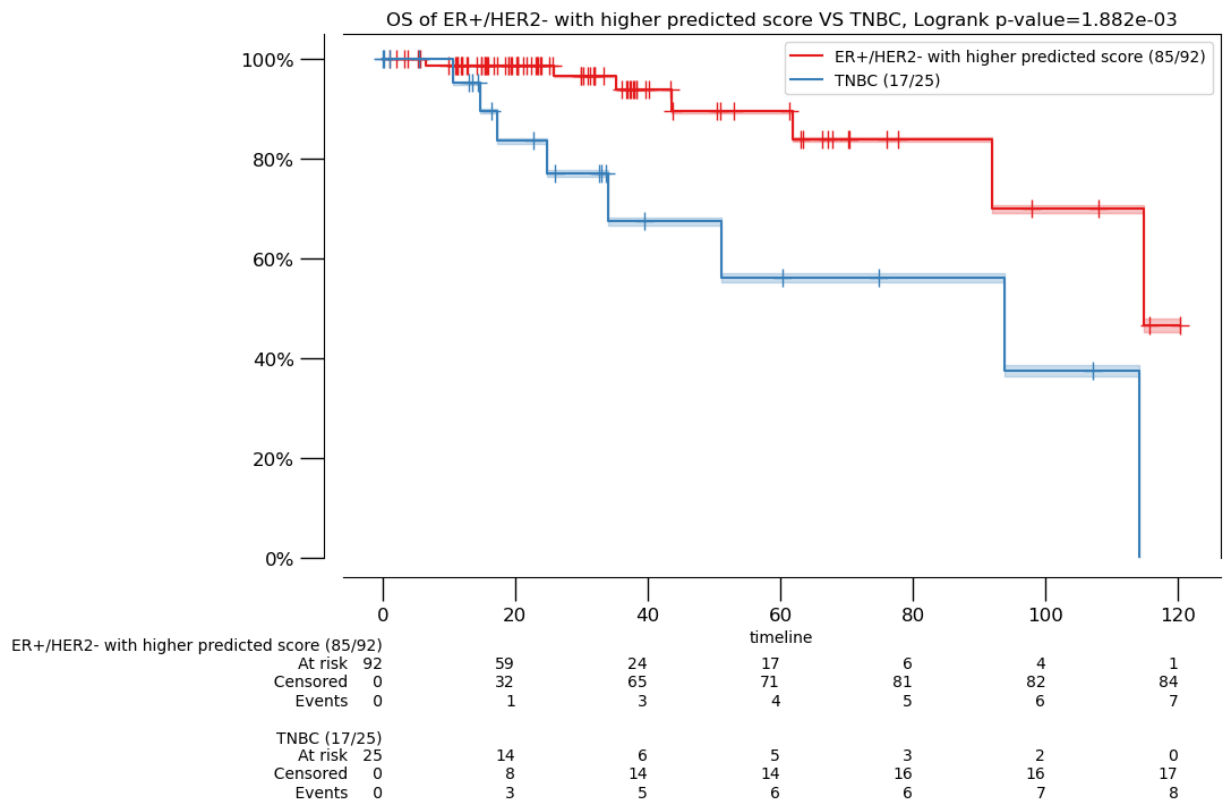
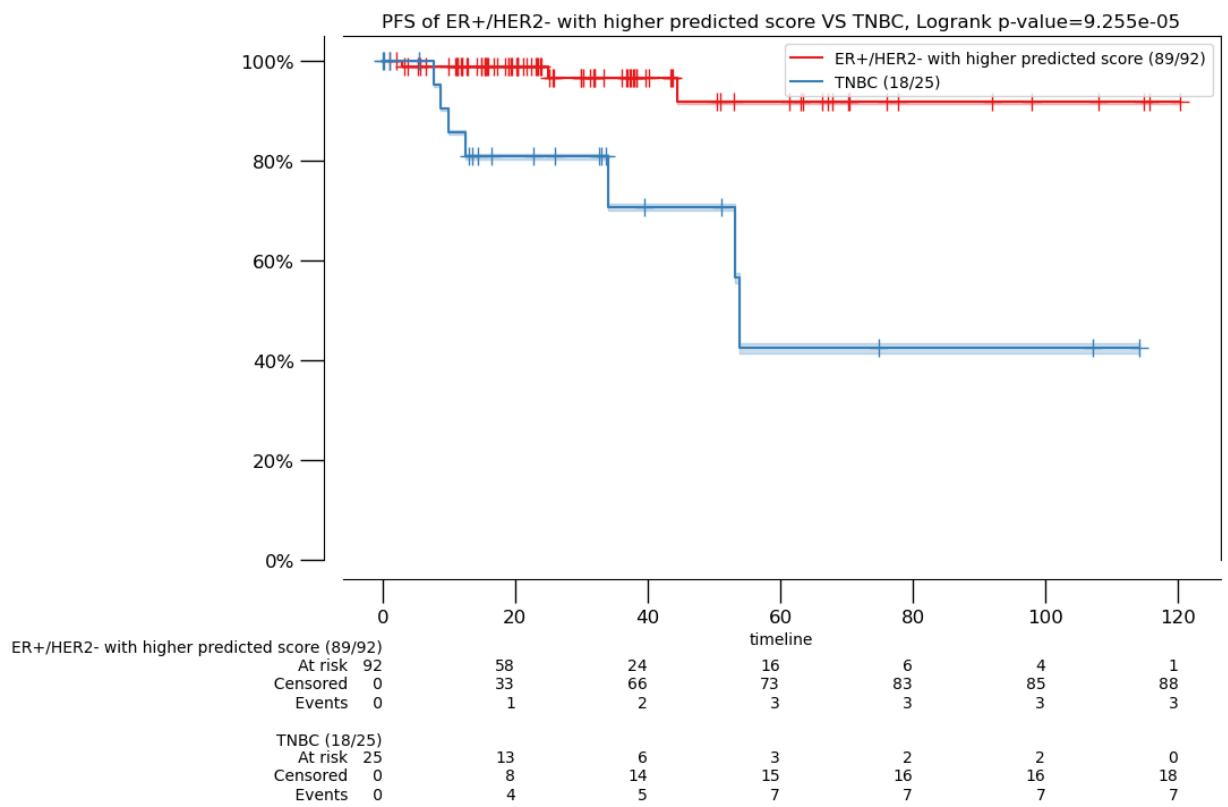
erposerbb2neg_lowscore_tnbc_df_pfs = brca_clinical_erposerbb2neg_lowscore
result = km.fit(erposerbb2neg_lowscore_tnbc_df_pfs[f'PFS_MONTHS'], erpose
km.plot(result, title=f"PFS of ER+/HER2- with lower predicted score VS TN
plt.show()

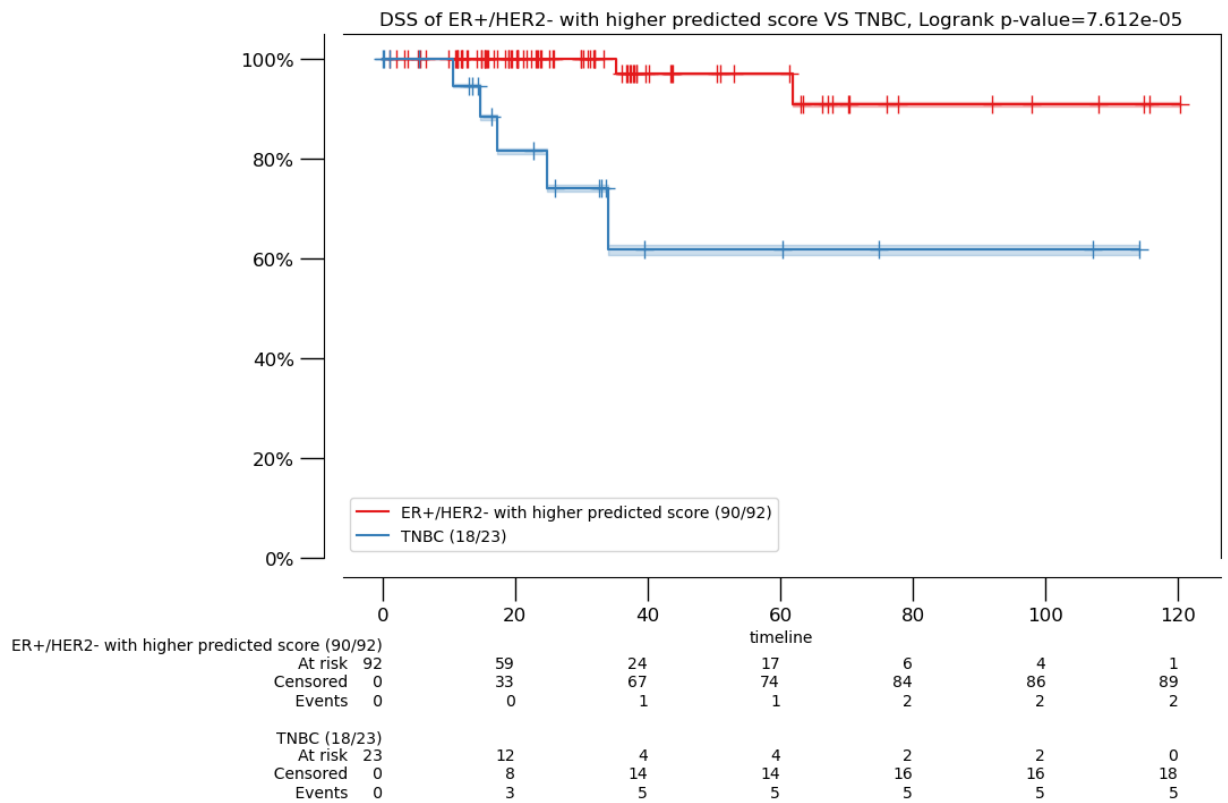
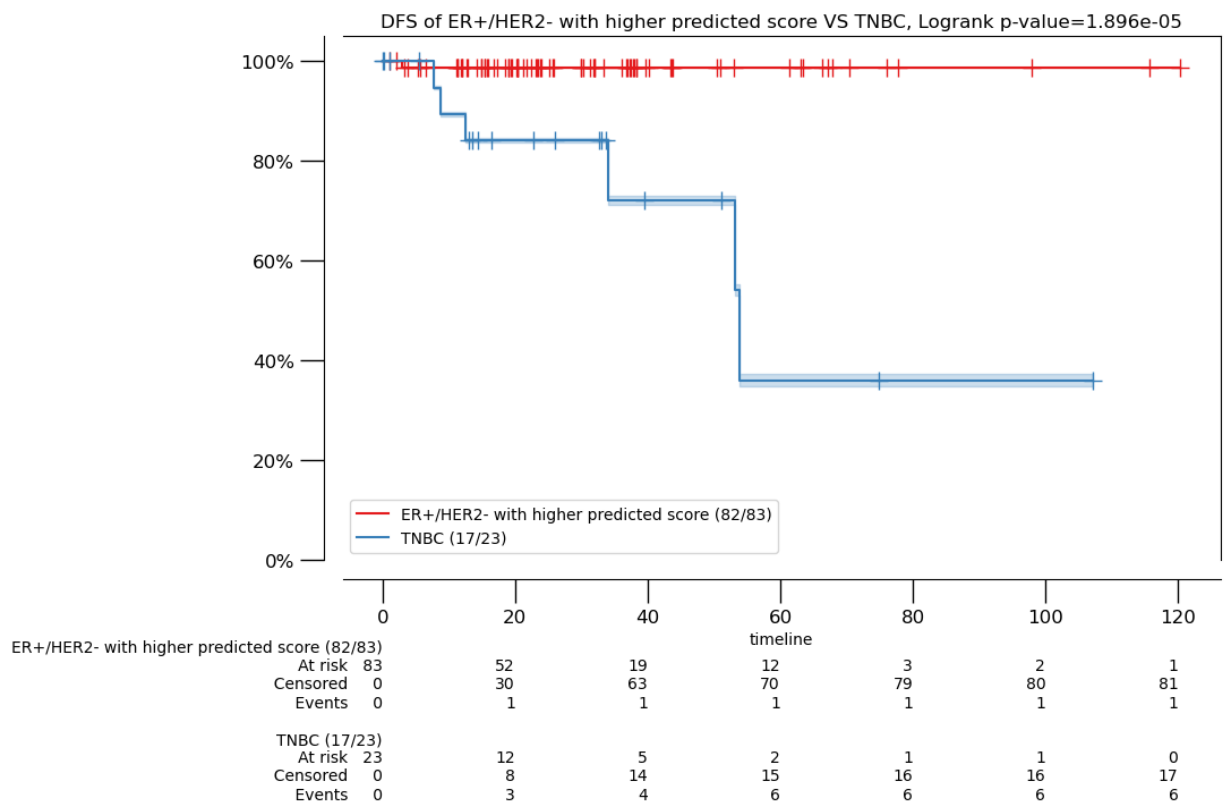
erposerbb2neg_lowscore_tnbc_df_os = brca_clinical_erposerbb2neg_lowscore_
result = km.fit(erposerbb2neg_lowscore_tnbc_df_os[f'OS_MONTHS'], erposerb
km.plot(result, title=f"OS of ER+/HER2- with lower predicted score VS TNB
plt.show()

erposerbb2neg_lowscore_tnbc_df_dfs = brca_clinical_erposerbb2neg_lowscore
result = km.fit(erposerbb2neg_lowscore_tnbc_df_dfs[f'DFS_MONTHS'], erpose
km.plot(result, title=f"DFS of ER+/HER2- with lower predicted score VS TN
plt.show()

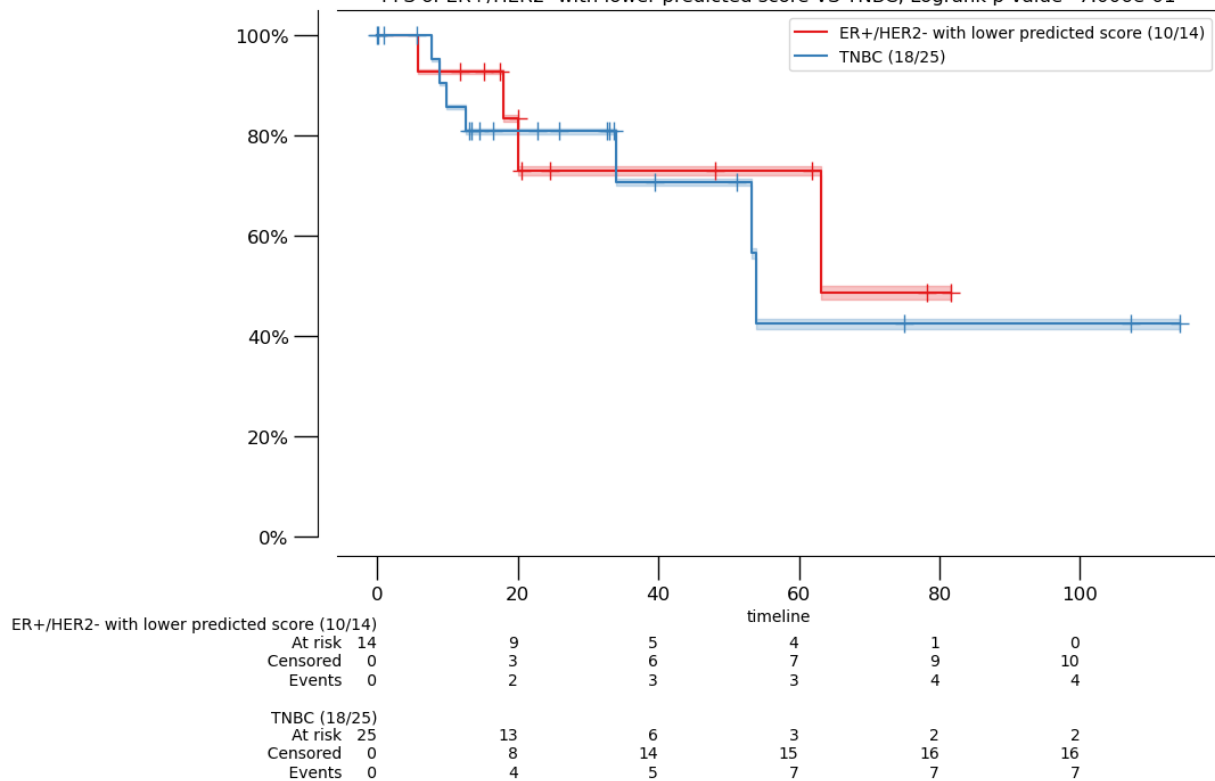
erposerbb2neg_lowscore_tnbc_df_dss = brca_clinical_erposerbb2neg_lowscore
result = km.fit(erposerbb2neg_lowscore_tnbc_df_dss[f'DSS_MONTHS'], erpose
km.plot(result, title=f"DSS of ER+/HER2- with lower predicted score VS TN
plt.show()

```

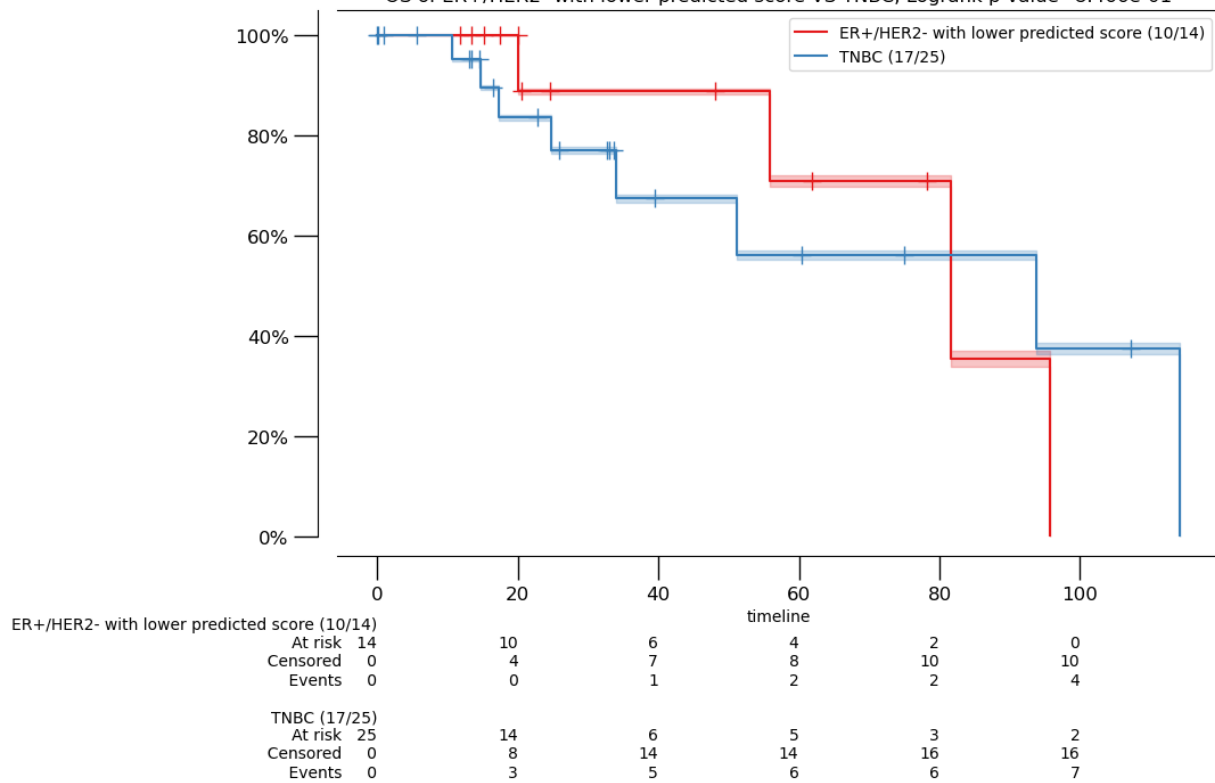


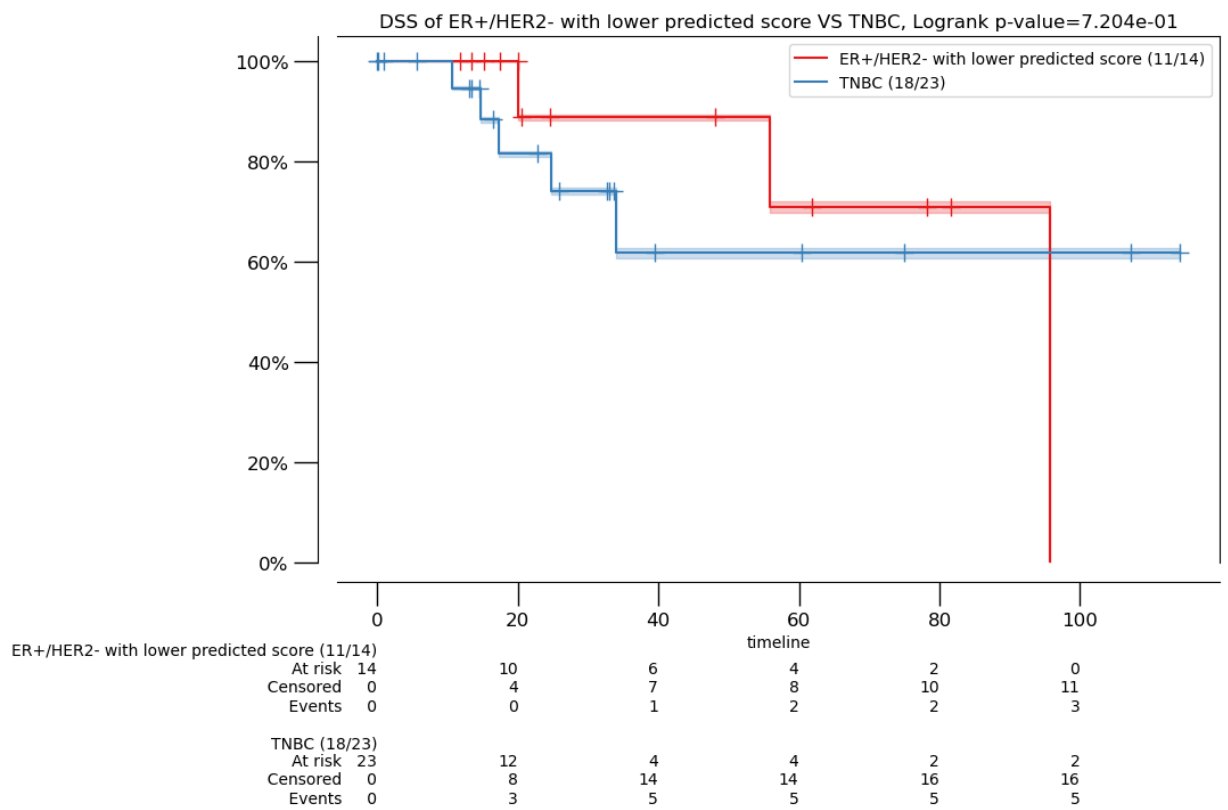
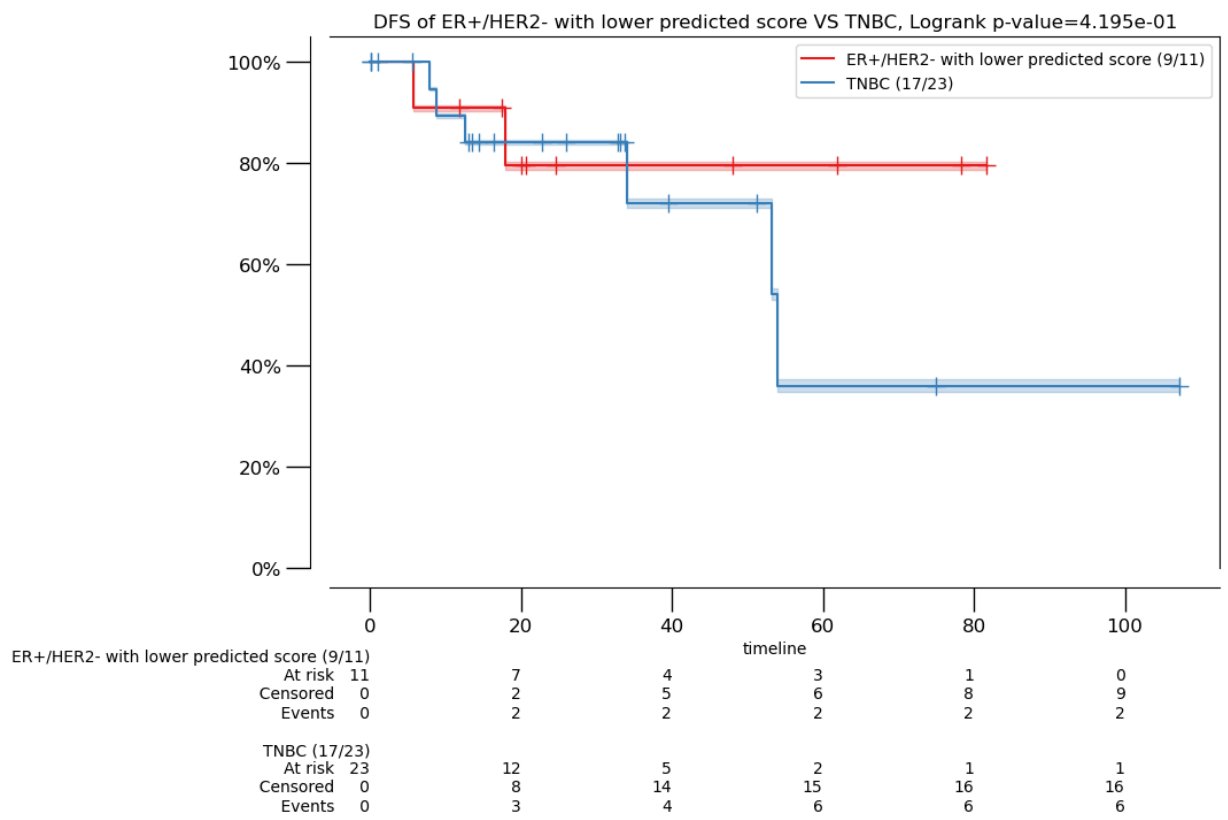


PFS of ER+/HER2- with lower predicted score VS TNBC, Logrank p-value=7.006e-01



OS of ER+/HER2- with lower predicted score VS TNBC, Logrank p-value=8.466e-01





Evaluation with training data

```

In [37]: cv_train_index = y_train.index
cv_train_predicted_df_dict = {}
import torch.nn.functional as F
for fold in range(5):
    cv_train_predicted_df = pd.DataFrame(np.zeros((len(cv_train_index),2)
    file = np.sort(os.listdir(f"{folder}/{str(fold)}"))[-1] # Get the las
    print(f"Fold {fold} model:", file)
    model_path = f"{folder}/{str(fold)}/{file}"
    checkpoint = torch.load(model_path, map_location=torch.device('cpu'))
    model_ft = models.resnet50().to(device)
    model_test = nn.Sequential(model_ft, net_add).to(device)
    model_test.load_state_dict(checkpoint['model_state_dict'])
    model_test.cuda()
    criterion = nn.CrossEntropyLoss()
    epoch_test = checkpoint['epoch']
    loss_test = checkpoint['loss']
    model_test.eval()

    loss_epoch_test=[]
    y_proba = []
    y_gold = []
    y_pred = []
    with torch.no_grad():
        for b, (X, y) in enumerate(train_dataloader):
            outputs = model_test(X.cuda())
            _, preds = torch.max(outputs, 1)
            y_proba += torch.flatten(outputs[:,1]).cpu().tolist()
            y_gold += y.data.cpu().tolist()
            y_pred += preds.cpu().tolist()
        # loss = criterion(outputs.float(), torch.tensor([[1,0] if la
        # loss_epoch_test.append(loss.item())

        auc=roc_auc_score(y_gold,y_proba)
        print(f"Fold {fold} AUROC: {auc}")
    cv_train_predicted_df.loc[cv_train_index,'score'] = y_proba
    cv_train_predicted_df.loc[cv_train_index,'gold'] = y_gold
    cv_train_predicted_df_dict[fold] = cv_train_predicted_df

# Average the scores of the 5 folds
cv_train_predicted_df["score"] = (cv_train_predicted_df_dict[0]["score"]+
                                cv_train_predicted_df_dict[1]["score"]+\
                                cv_train_predicted_df_dict[2]["score"]+\
                                cv_train_predicted_df_dict[3]["score"]+\
                                cv_train_predicted_df_dict[4]["score"])/5

Fold 0 model: epoch_21_loss_0.617512_auroc_0.729207.pt
Fold 0 AUROC: 0.6942643229166666
Fold 1 model: epoch_9_loss_0.674120_auroc_0.596405.pt
Fold 1 AUROC: 0.6580078125
Fold 2 model: epoch_6_loss_0.676420_auroc_0.628654.pt
Fold 2 AUROC: 0.6107552083333334
Fold 3 model: epoch_9_loss_0.650217_auroc_0.667819.pt
Fold 3 AUROC: 0.671875
Fold 4 model: epoch_8_loss_0.667883_auroc_0.647039.pt
Fold 4 AUROC: 0.6402083333333334

```

Evaluation of the survival of the training data

```
In [30]: cv_train_predicted_df_ihc = cv_train_predicted_df.join(meta_erihc, how='i
cv_train_predicted_df_ihc["Subtype"] = None
cv_train_predicted_df_ihc["Subtype"][(cv_train_predicted_df_ihc["er_statu
# cv_predicted_df_ihc["Subtype"]][cv_predicted_df_ihc["her2_status_by_ihc"
cv_train_predicted_df_ihc["Subtype"][(cv_train_predicted_df_ihc["er_statu
cv_train_predicted_df_ihc["EERES"] = brca_earlyes_es.loc[cv_train_predict
cv_train_predicted_df_ihc["ESR1"] = brca_lv3.loc[cv_train_predicted_df_ih

brca_clinical_training = brca_clinical.join(cv_train_predicted_df_ihc, ho
brca_clinical_training_dfs = brca_clinical_training[["DFS_MONTHS", "DFS_S
brca_clinical_training_dss = brca_clinical_training[["DSS_MONTHS", "DSS_S
brca_clinical_training_pfs = brca_clinical_training[["PFS_MONTHS", "PFS_S
brca_clinical_training_os = brca_clinical_training[["OS_MONTHS", "OS_STAT

result = km.fit(brca_clinical_training_pfs['PFS_MONTHS'], brca_clinical_t
km.plot(result, title=f"PFS of ER+/HER2- vs TNBC, Logrank p-value={result
plt.show()
result = km.fit(brca_clinical_training_os['OS_MONTHS'], brca_clinical_tra
km.plot(result, title=f"OS of ER+/HER2- vs TNBC, Logrank p-value={result[
plt.show()
result = km.fit(brca_clinical_training_dfs['DFS_MONTHS'], brca_clinical_t
km.plot(result, title=f"DFS of ER+/HER2- vs TNBC, Logrank p-value={result
plt.show()
result = km.fit(brca_clinical_training_dss['DSS_MONTHS'], brca_clinical_t
km.plot(result, title=f"DSS of ER+/HER2- vs TNBC, Logrank p-value={result
plt.show()

plt.scatter(cv_train_predicted_df_ihc[cv_train_predicted_df_ihc["Subtype"
# plt.scatter(cv_predicted_df_ihc[cv_predicted_df_ihc["Subtype"]=="ERBB2+
plt.scatter(cv_train_predicted_df_ihc[cv_train_predicted_df_ihc["Subtype"
plt.legend(["ER+/HER2-", "TNBC"])
plt.xlabel("ESR1")
plt.ylabel("EERES")
plt.show()
```

/tmp/ipykernel_93586/1740958595.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

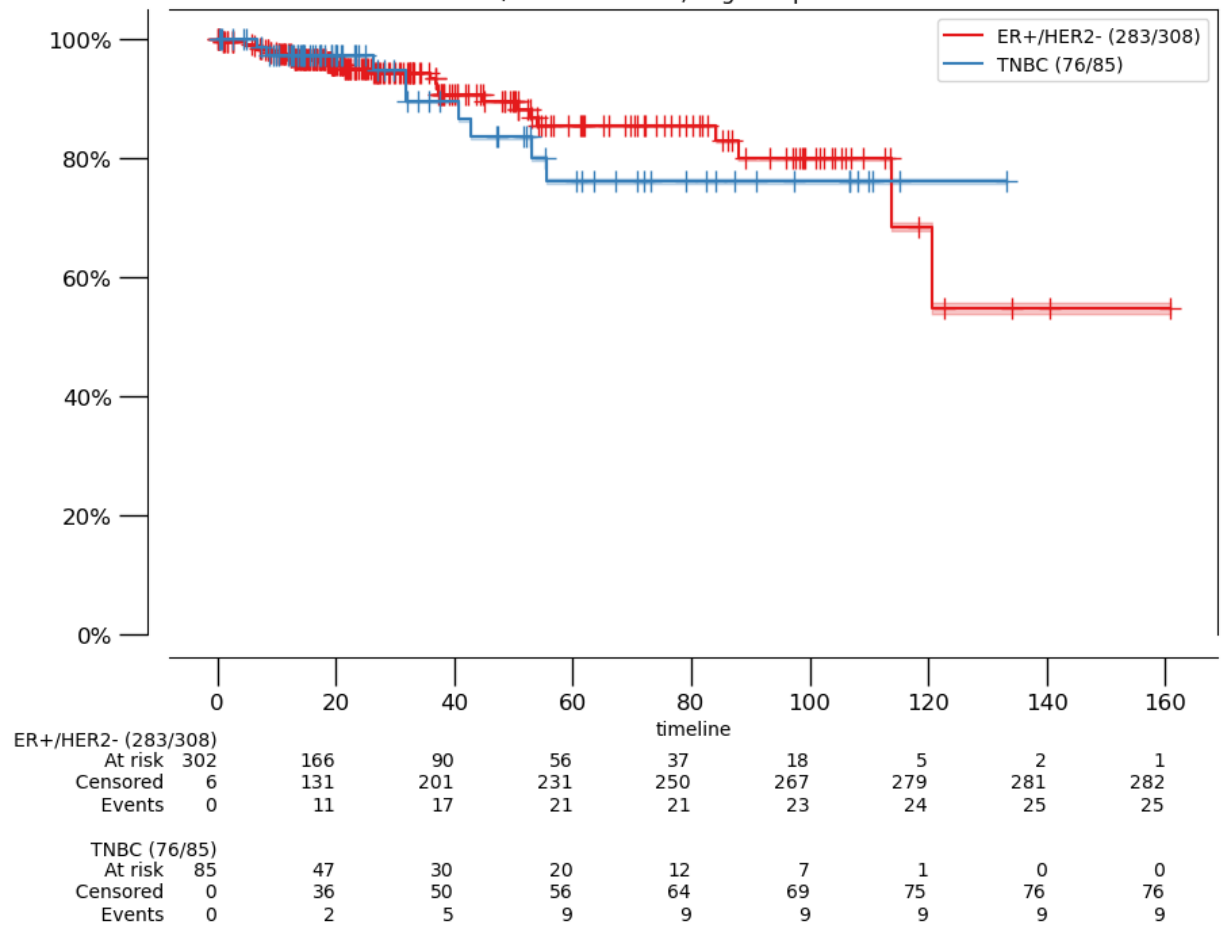
```
cv_train_predicted_df_ihc["Subtype"][(cv_train_predicted_df_ihc["er_statu
atus_by_ihc"]=='Positive') & (cv_train_predicted_df_ihc["her2_status_by_
ihc"]=='Negative')] = "ER+/HER2-"
```

/tmp/ipykernel_93586/1740958595.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

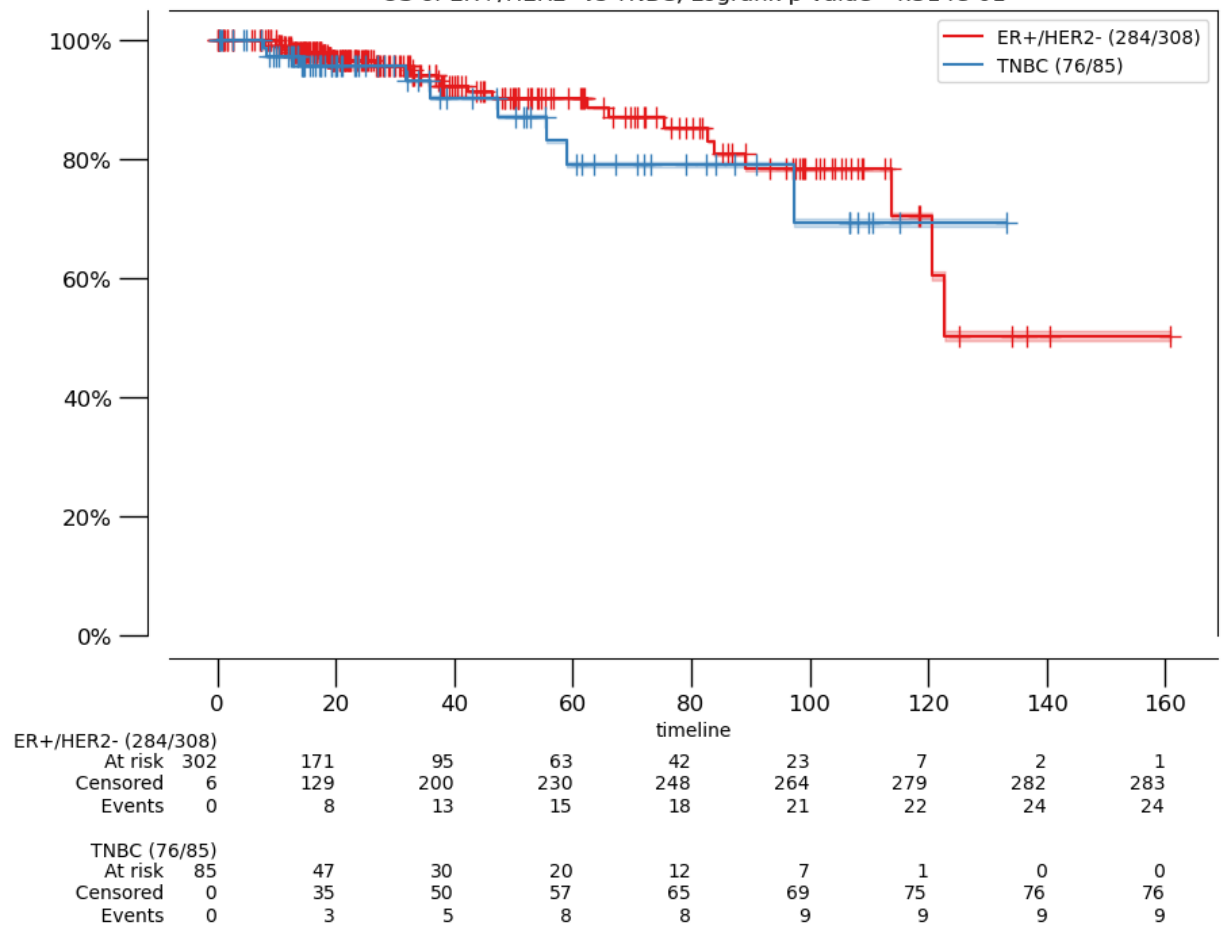
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

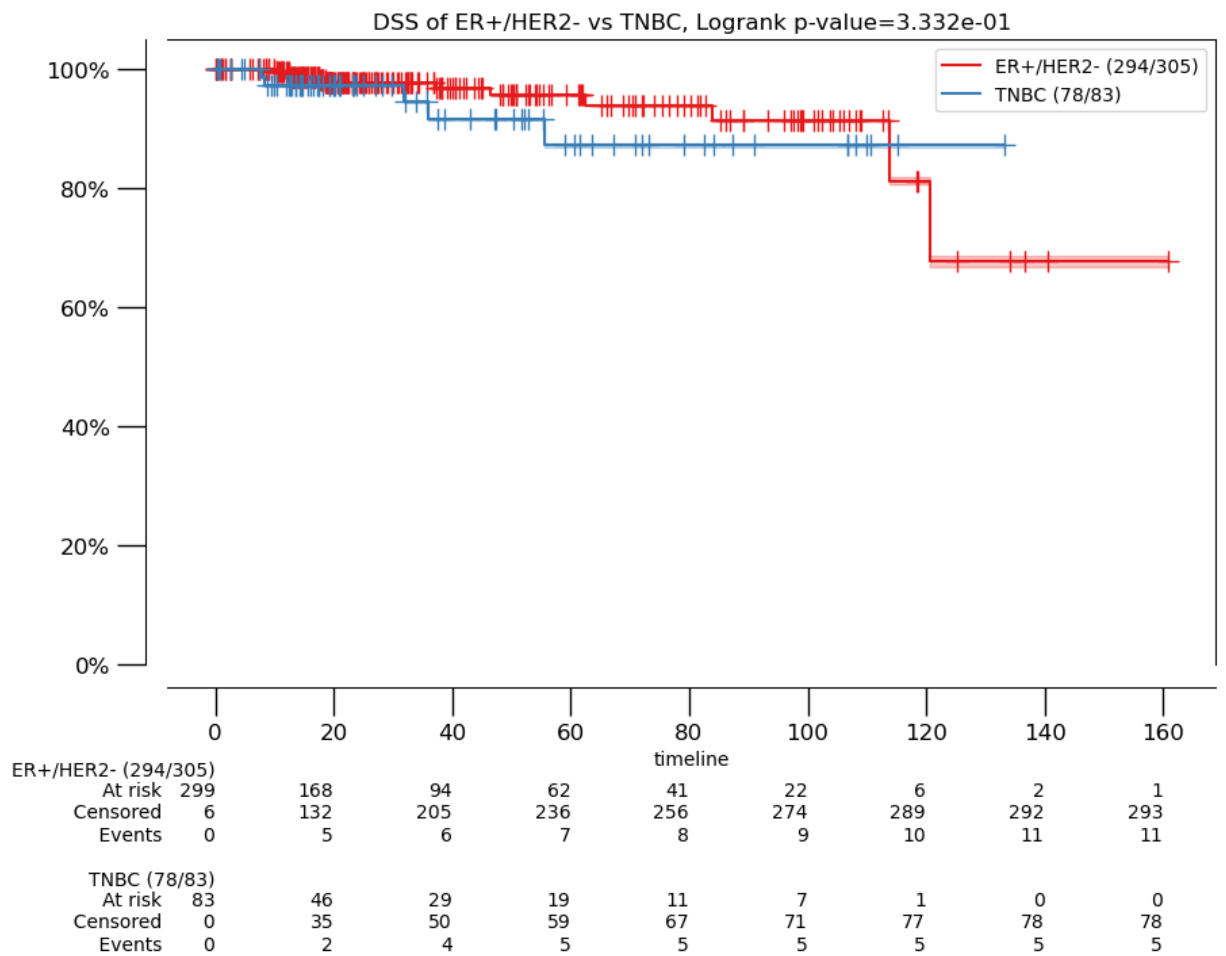
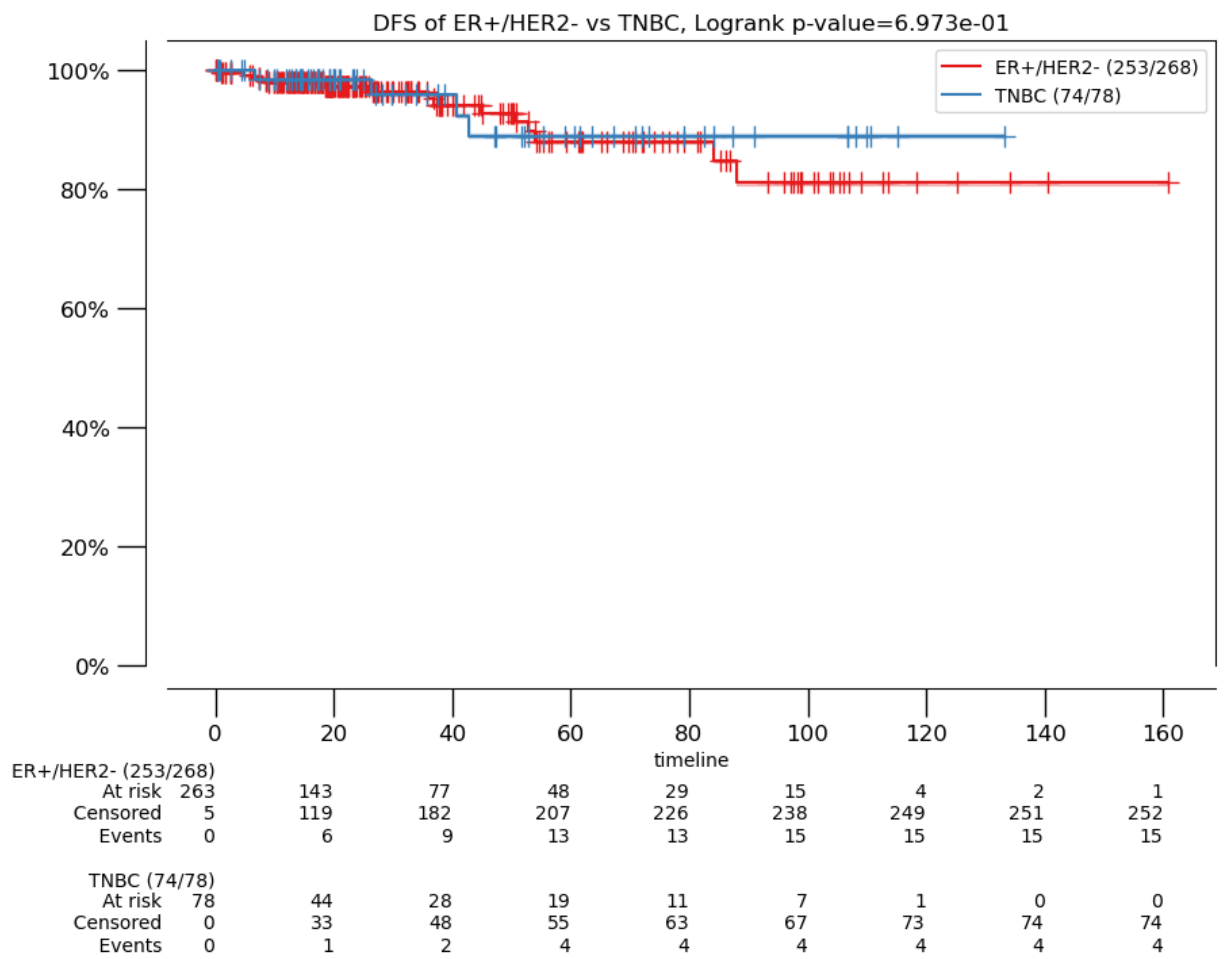
```
cv_train_predicted_df_ihc["Subtype"][(cv_train_predicted_df_ihc["er_statu
atus_by_ihc"]=='Negative') & (cv_train_predicted_df_ihc["her2_status_by_
ihc"]=='Negative') & (cv_train_predicted_df_ihc["pr_status_by_ihc"]=='Ne
gative')] = "TNBC"
```

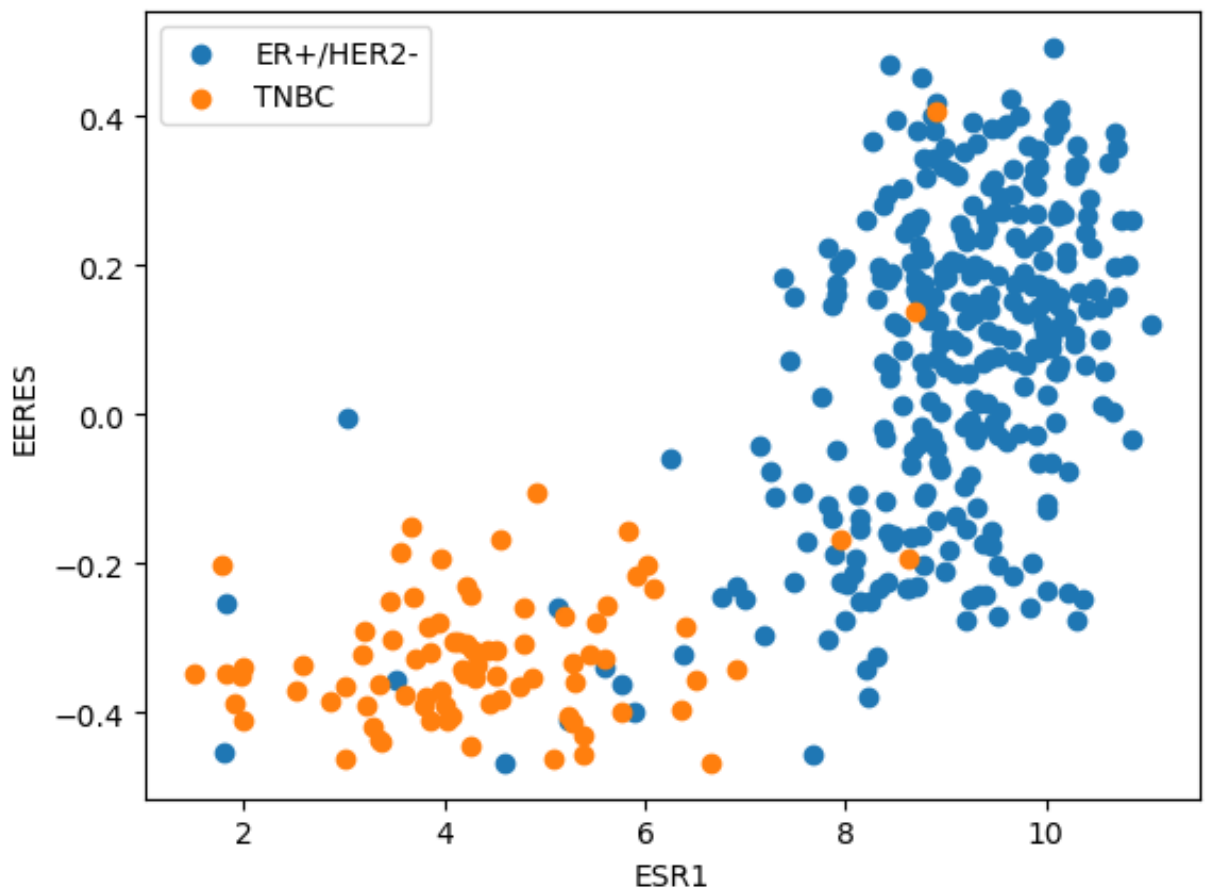
PFS of ER+/HER2- vs TNBC, Logrank p-value=6.297e-01



OS of ER+/HER2- vs TNBC, Logrank p-value=4.514e-01



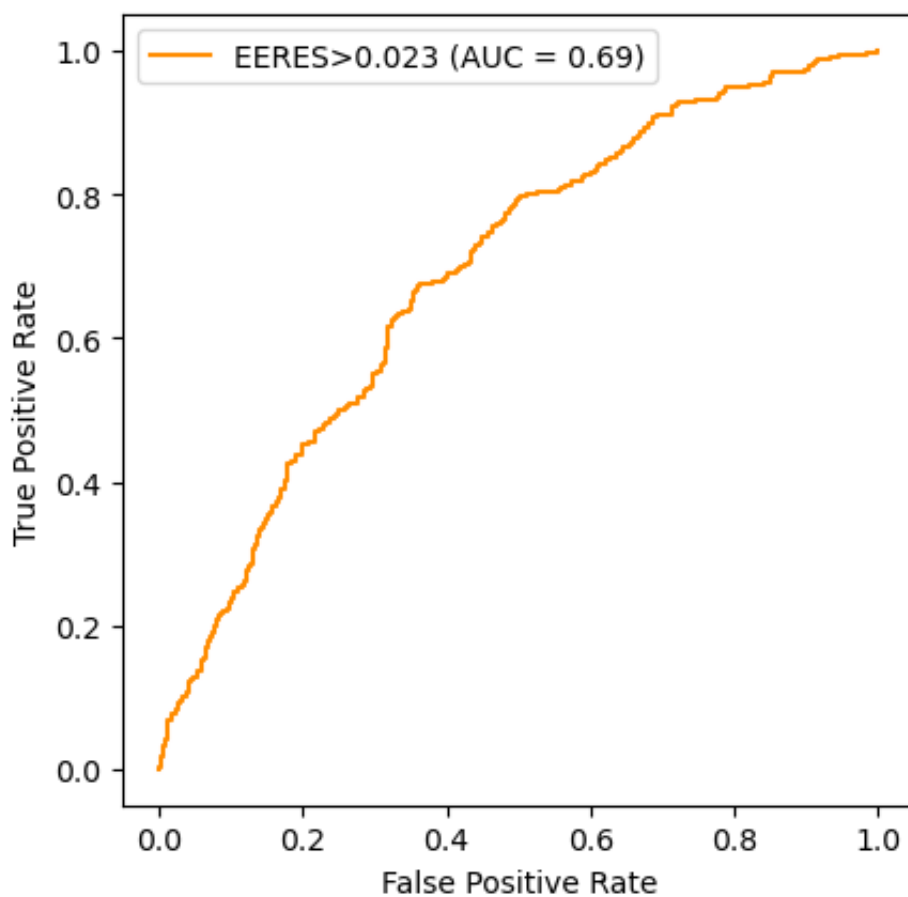
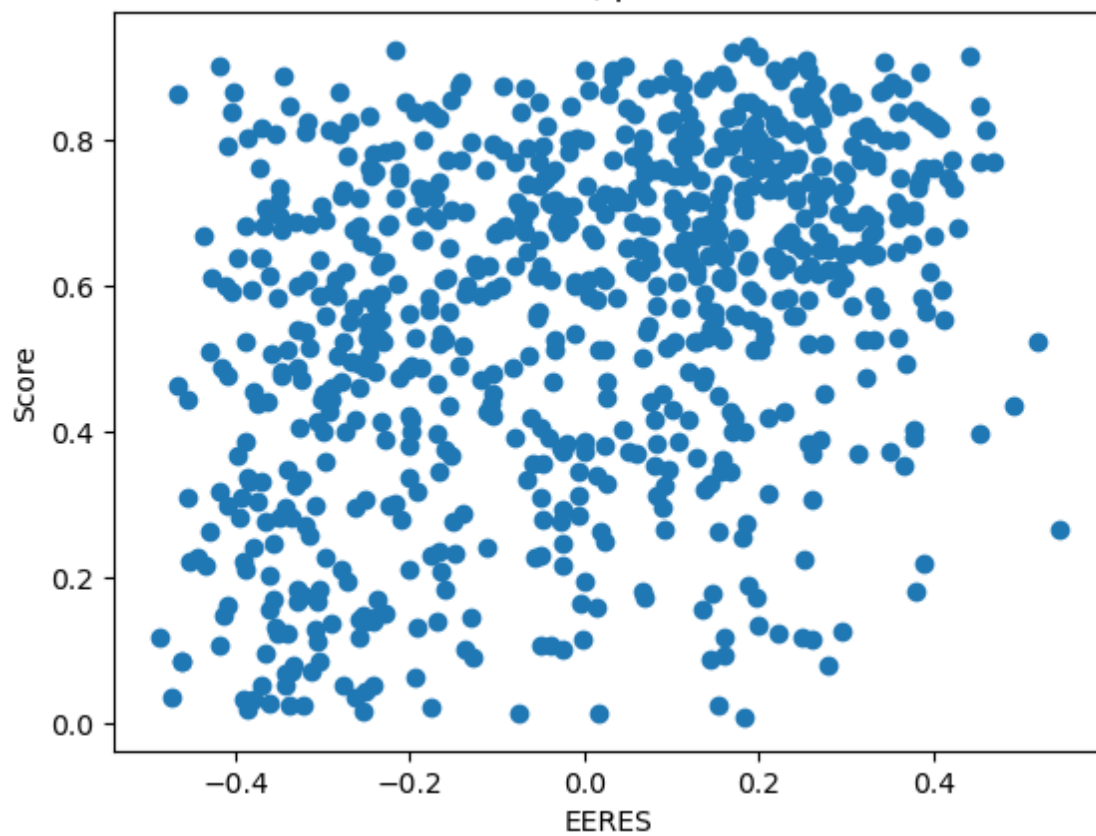




```
In [32]: plt.scatter(cv_train_predicted_df_ihc["EERES"], cv_train_predicted_df_ihc["gold"])
plt.xlabel("EERES")
plt.ylabel("Score")
r, p = pearsonr(cv_train_predicted_df_ihc["EERES"], cv_train_predicted_df_ihc["gold"])
plt.title(f"Pearson R: {r}, p-value: {p}")

auroc = roc_auc_score(cv_train_predicted_df_ihc["gold"], cv_train_predicted_df_ihc["score"])
RocCurveDisplay.from_predictions(
    cv_train_predicted_df_ihc["gold"],
    cv_train_predicted_df_ihc["score"],
    name=f"EERES>{eeres_threshold:.3f}",
    color="darkorange",
)
# plt.plot([0, 1], [0, 1], "k--", label="chance level (AUC = 0.5)")
plt.axis("square")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
# plt.title("Receiver Operating Characteristic")
plt.legend()
plt.show()
```

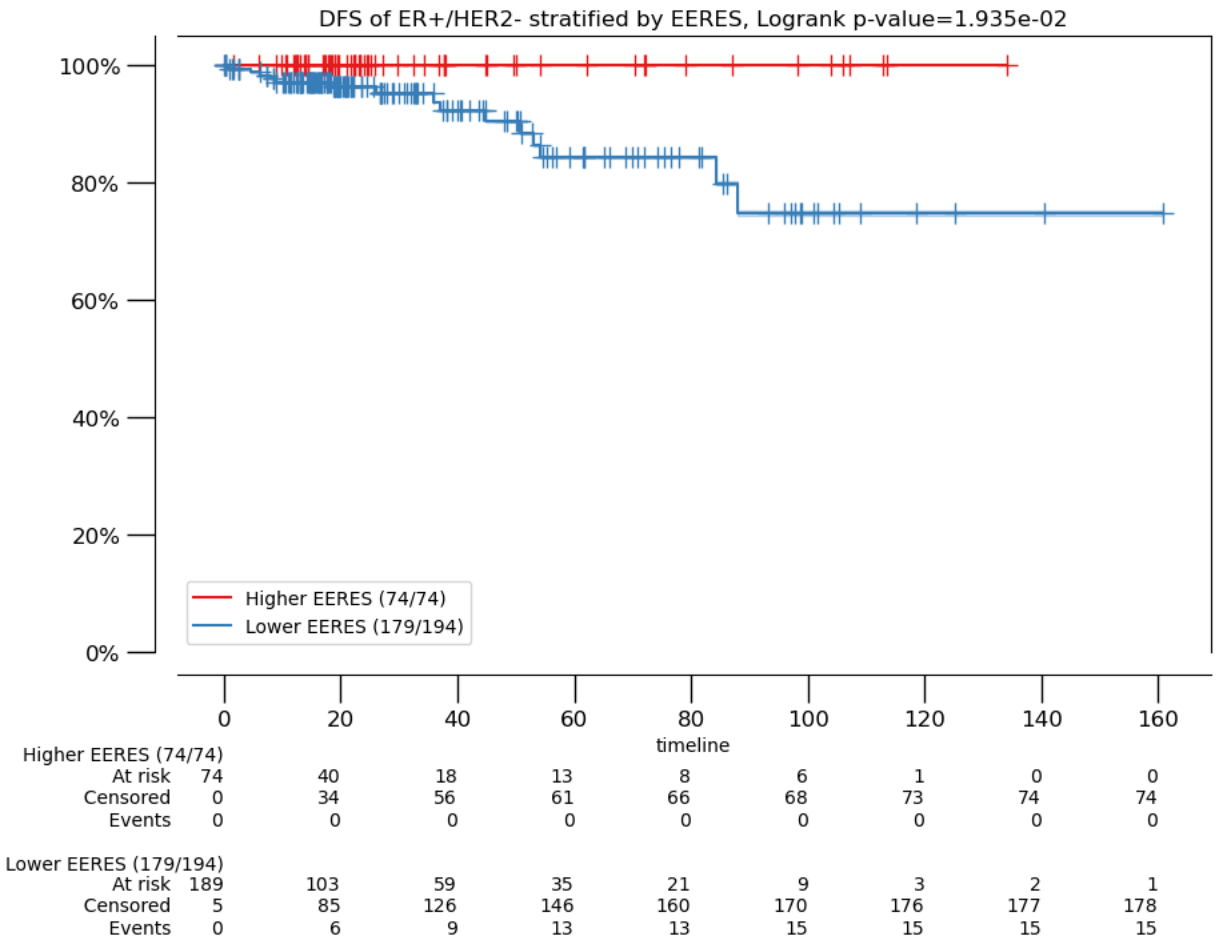
Pearson R: 0.36641120844482955, p-value: 2.5514554355708225e-26

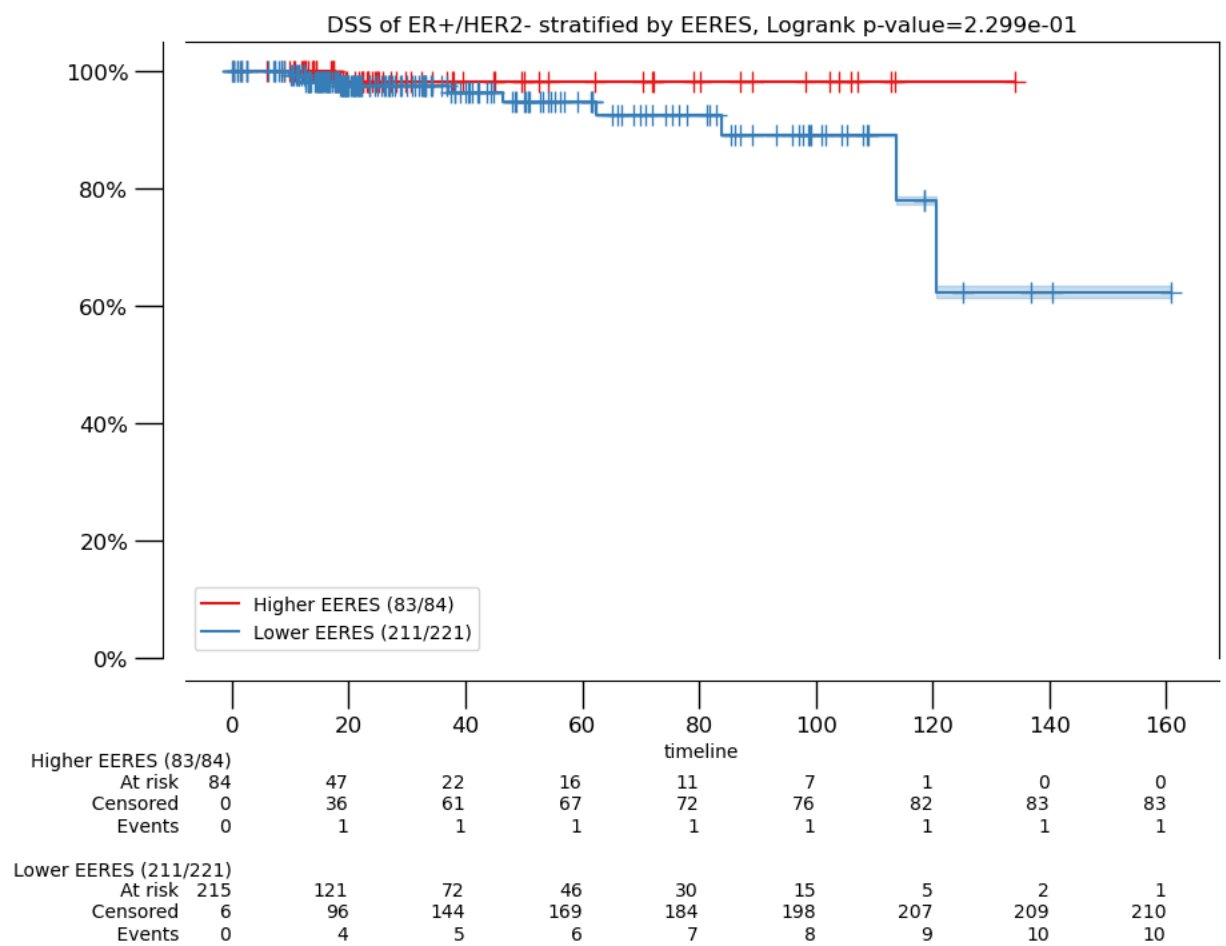


```
In [36]: brca_clinical_training_erposerb2neg = brca_clinical.join(cv_train_predic
brca_clinical_training_erposerb2neg
```

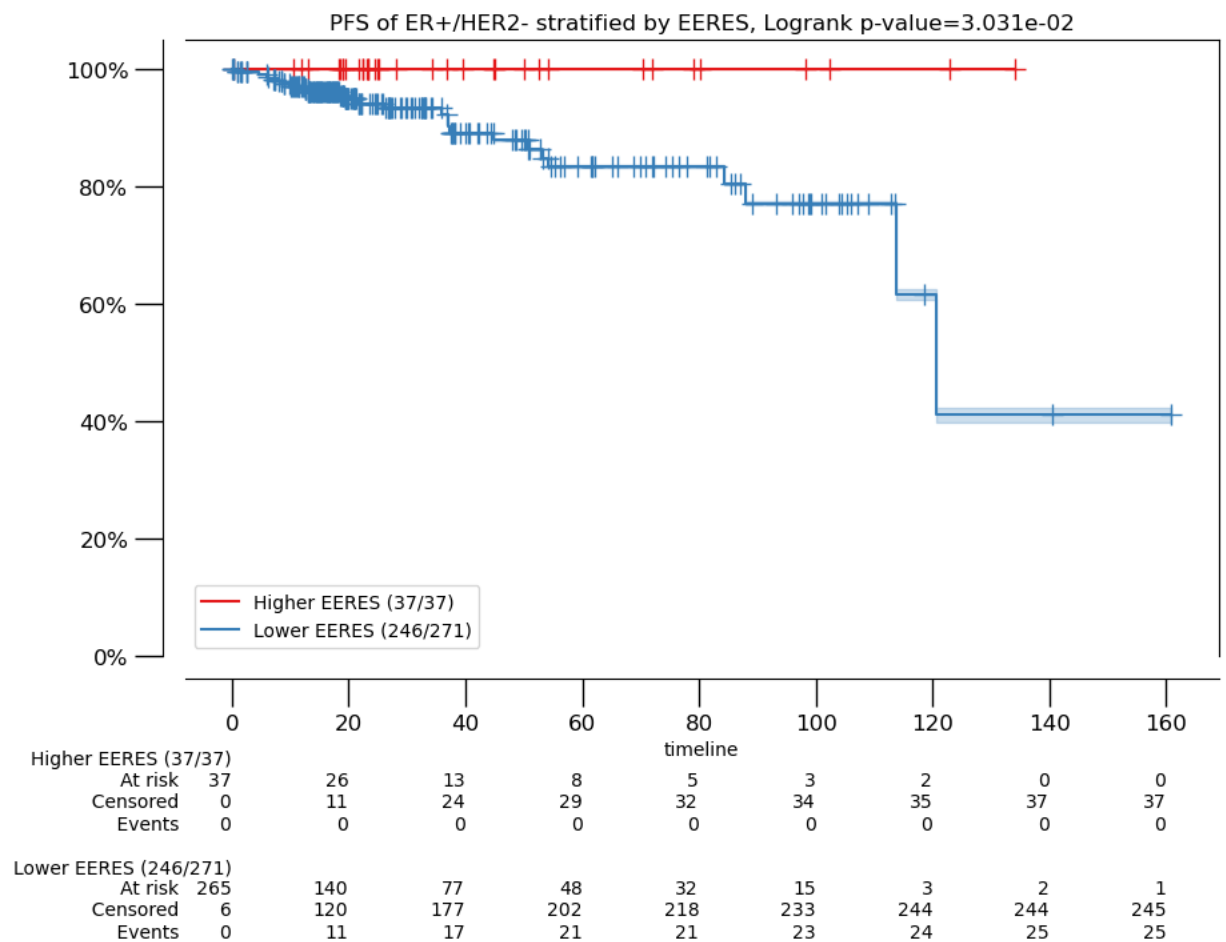
```
brca_clinical_training_erposerb2neg_dfs = brca_clinical_training_erposerb
brca_clinical_training_erposerb2neg_dss = brca_clinical_training_erposerb
brca_clinical_training_erposerb2neg_pfs = brca_clinical_training_erposerb
brca_clinical_training_erposerb2neg_os = brca_clinical_training_erposerb
finding_best_threshold_with_FS_SS(brca_clinical_training_erposerb2neg_df
finding_best_threshold_with_FS_SS(brca_clinical_training_erposerb2neg_pf
finding_best_threshold_with_FS_SS(brca_clinical_training_erposerb2neg_df
finding_best_threshold_with_FS_SS(brca_clinical_training_erposerb2neg_pf
```

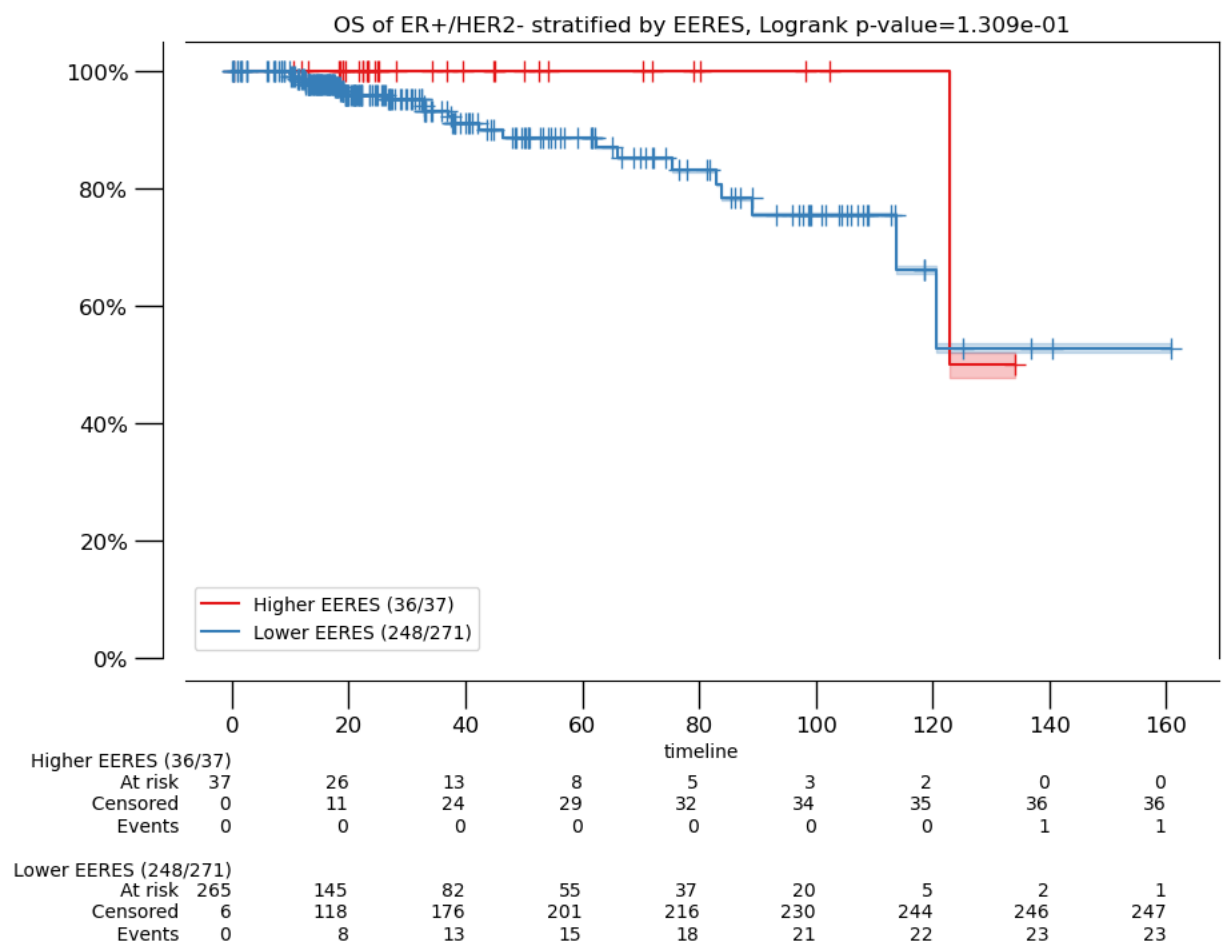
Best EERES threshold: 0.20434858171014614



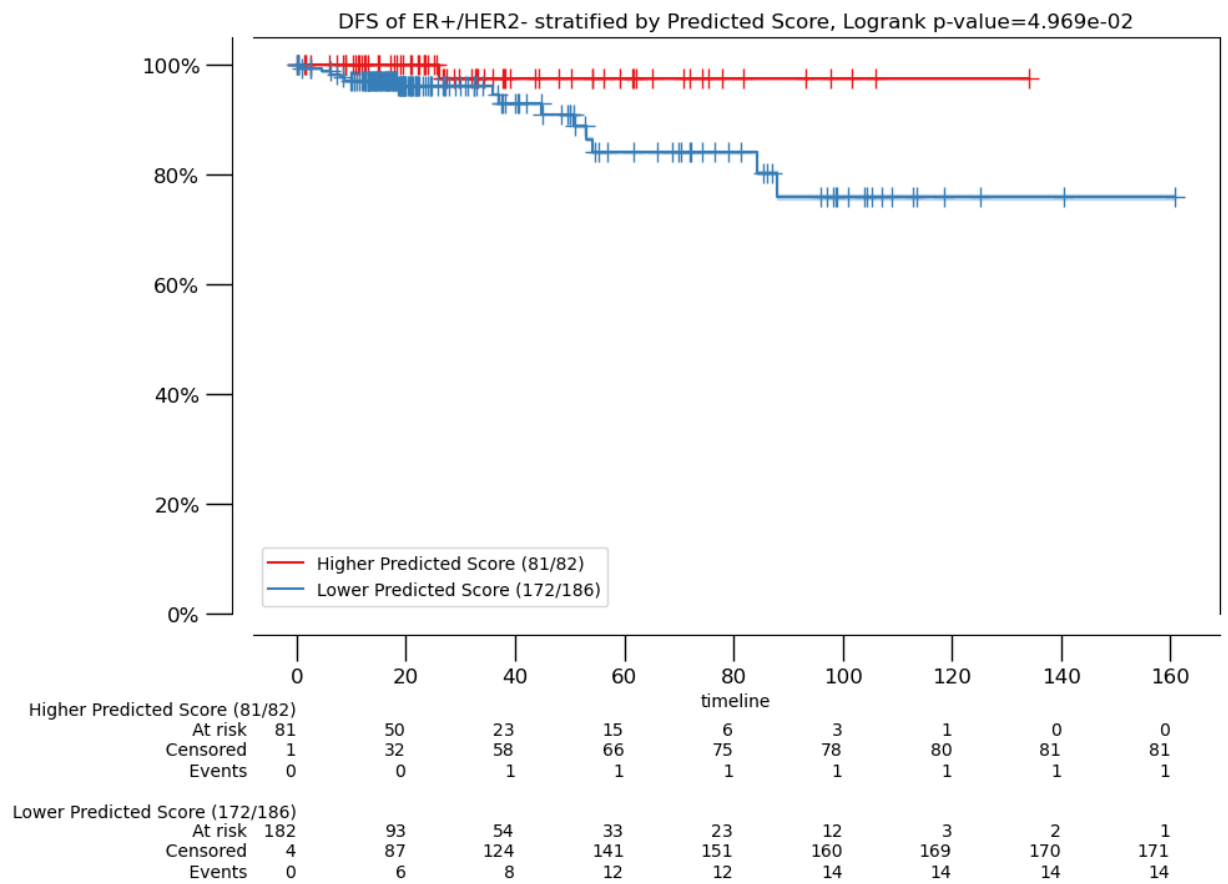


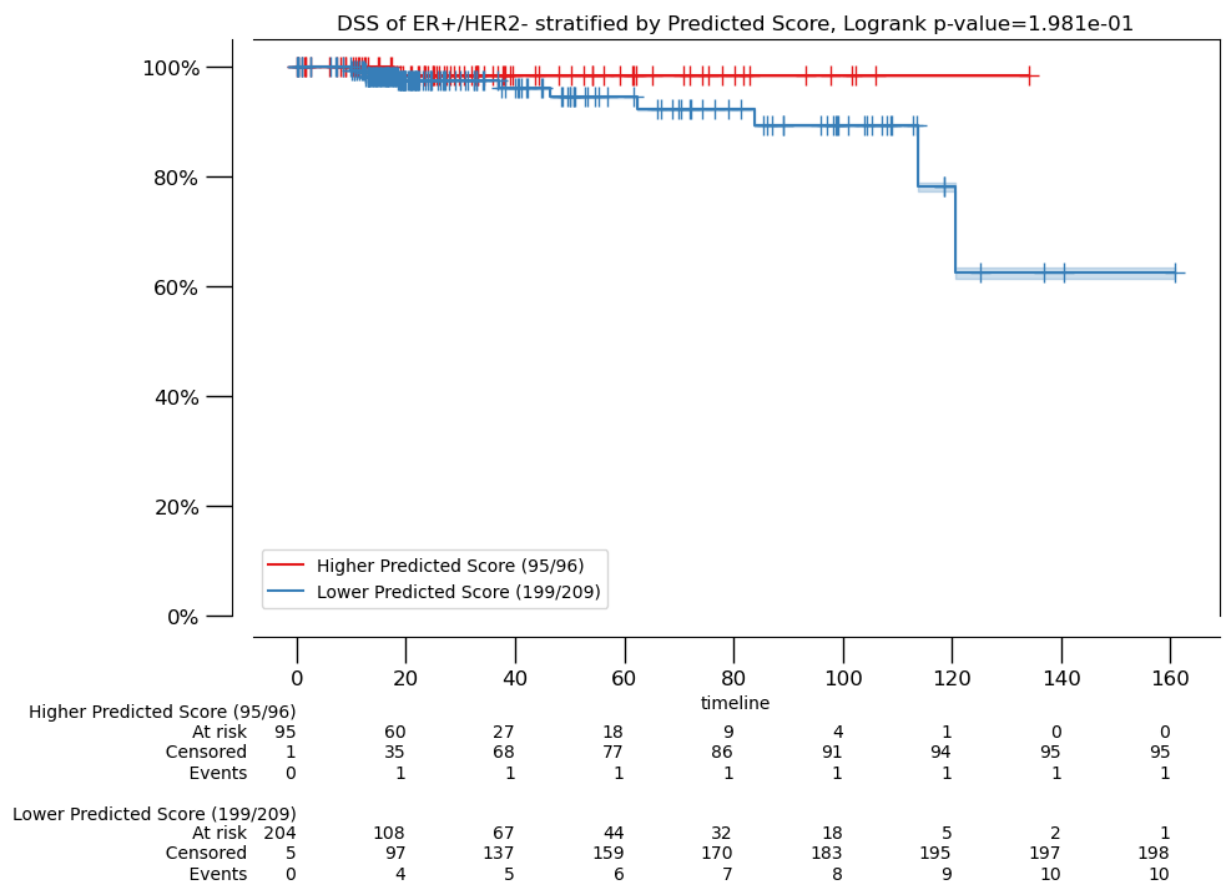
Best EERES threshold: 0.32551106034849975





Best score threshold: 0.7400792701914911





not significant