Could not connect to the reCAPTCHA service. Please check your internet connection and reload to get a reCAPTCHA challenge.

```
import os
os.environ["OPENBLAS_NUM_THREADS"] = "1"
import warnings
warnings.filterwarnings('ignore')

# Core imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import shap
import joblib

# Scikit-learn
from sklearn.model_selection import train_test_split, GridSearchCV, StratifiedKFold
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.feature_selection import SelectKBest, f_classif
from sklearn.metrics import (
    classification_report, confusion_matrix,
    roc_curve, auc, precision_recall_curve, average_precision_score
)
from sklearn.ensemble import RandomForestClassifier, StackingClassifier
from sklearn.svm import SVC

# XGBoost
from xgboost import XGBClassifier, plot_importance

# Imbalanced data
from imblearn.over_sampling import SMOTENC

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures

# Colab file uploader
from google.colab import files

# 1) Load the data
```

```
uploaded = files.upload()
file_path = list(uploaded.keys())[0]
df = pd.read_csv(file_path)

# 2) Create survival targets
df["0.5yr_survival"] = (df["Overall survival [OS] (days)"] >= 180).astype(int)
df["1yr_survival"]  = (df["Overall survival [OS] (days)"] >= 365).astype(int)
df["1.5yr_survival"] = (df["Overall survival [OS] (days)"] >= 545).astype(int)
df["2yr_survival"]  = (df["Overall survival [OS] (days)"] >= 730).astype(int)

# 3) Quick plots of class balance
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
sns.countplot(data=df, x="1yr_survival", palette="Set2")
plt.xticks([0,1], ['<1yr','≥1yr']); plt.title("1yr Survival")
plt.subplot(1, 2, 2)
sns.countplot(data=df, x="2yr_survival", palette="Set1")
plt.xticks([0,1], ['<2yr','≥2yr']); plt.title("2yr Survival")
plt.tight_layout(); plt.show()

# 4) Feature & target lists
features = [
    'Age', 'Sex', 'Preoperative KPS', 'Previous treatment',
    'Histopathological subtype', 'WHO grade', 'IDH status',
    'Operative adjuncts', 'Preoperative contrast enhancing tumor volume (cm3)',
    'Extent of resection [EOR] %', 'EOR Category',
    'Adjuvant therapy', 'Radiotherapy treatment details',
    'Postoperative KPS', 'Postoperative Neurological Deficit'
]
targets = ["0.5yr_survival","1yr_survival","1.5yr_survival","2yr_survival"]

# To store results
base_auc_dict = {}
stacking_auc_dict = {}
best_params_dict = {}

def train_evaluate_model(target):
    print(f"\n=== Training & Evaluating: {target} ===")
    X = df[features]
    y = df[target]
```

```
    # 1) Train/test split
    X_train_raw, X_test_raw, y_train, y_test = train_test_split(
        X, y, test_size=0.2, stratify=y, random_state=42
    )

    # 2) Preprocessing: one-hot categorical, scale numeric
    cat_cols = X_train_raw.select_dtypes(include='object').columns.tolist()
    num_cols = X_train_raw.select_dtypes(include=np.number).columns.tolist()
    preprocessor = ColumnTransformer([
        ('cat', OneHotEncoder(handle_unknown='ignore', sparse_output=False), cat_cols),
        ('num', StandardScaler(), num_cols)
    ])

    X_train_enc = preprocessor.fit_transform(X_train_raw)
    X_test_enc  = preprocessor.transform(X_test_raw)

    # 3) Balance via SMOTENC (only on train)
    n_cat_feats = preprocessor.named_transformers_['cat'].get_feature_names_out().shape[0]
    smote = SMOTENC(categorical_features=list(range(n_cat_feats)), random_state=42)
    X_res, y_res = smote.fit_resample(X_train_enc, y_train)

    # 4) Feature selection: top 15 by ANOVA F-value
    selector = SelectKBest(f_classif, k=min(15, X_res.shape[1]))
    X_res_sel  = selector.fit_transform(X_res, y_res)
    X_test_sel = selector.transform(X_test_enc)

    # 5) Define model grid
    models = {
        'XGB': (XGBClassifier(eval_metric='logloss', use_label_encoder=False, random_state=42), {
            'n_estimators': [100, 200],
            'max_depth':    [3, 4, 5],
            'learning_rate':[0.01, 0.05, 0.1],
            'subsample':    [0.8, 1.0]
        }),
        'RF': (RandomForestClassifier(random_state=42), {
            'n_estimators': [100, 200],
            'max_depth':    [4, 5]
        }),
    'SVM': (Pipeline([
            ('poly', PolynomialFeatures(degree=2, interaction_only=True, include_bias=False)),
```

```
            ('svc', SVC(probability=True, class_weight='balanced', random_state=42))
        ]), {
            'svc__C': [0.1, 1, 10],
            'svc__kernel': ['rbf', 'poly']
        })
    }

    best_estimators = {}
    base_roc = {}
    base_auc = {}
    cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

    for name, (mdl, param_grid) in models.items():
        grid = GridSearchCV(mdl, param_grid, scoring='roc_auc', cv=cv, n_jobs=-1, verbose=1)
        grid.fit(X_res_sel, y_res)
        best = grid.best_estimator_
        best_estimators[name] = best
        best_params_dict[f"{target}_{name}"] = grid.best_params_
        proba = best.predict_proba(X_test_sel)[:,1]
        fpr_i, tpr_i, _ = roc_curve(y_test, proba)
        auc_i = auc(fpr_i, tpr_i)
        base_roc[name] = (fpr_i, tpr_i)
        base_auc[name] = auc_i
        print(f"  → {name}: best_params={grid.best_params_}, AUC={auc_i:.3f}")

    # 6) Stacking ensemble
    stack = StackingClassifier(
        estimators    = list(best_estimators.items()),
        final_estimator = RandomForestClassifier(n_estimators=100, random_state=42),
        cv = cv, n_jobs = -1
    )
    stack.fit(X_res_sel, y_res)
    # compute stacking AUC
    proba_s = stack.predict_proba(X_test_sel)[:,1]
    fpr_s, tpr_s, _ = roc_curve(y_test, proba_s)
    auc_s = auc(fpr_s, tpr_s)
    print(f"  → Stacking AUC = {auc_s:.3f}")

    # store results
    base_auc_dict[target] = base_auc
    stacking_auc_dict[target] = auc_s
```

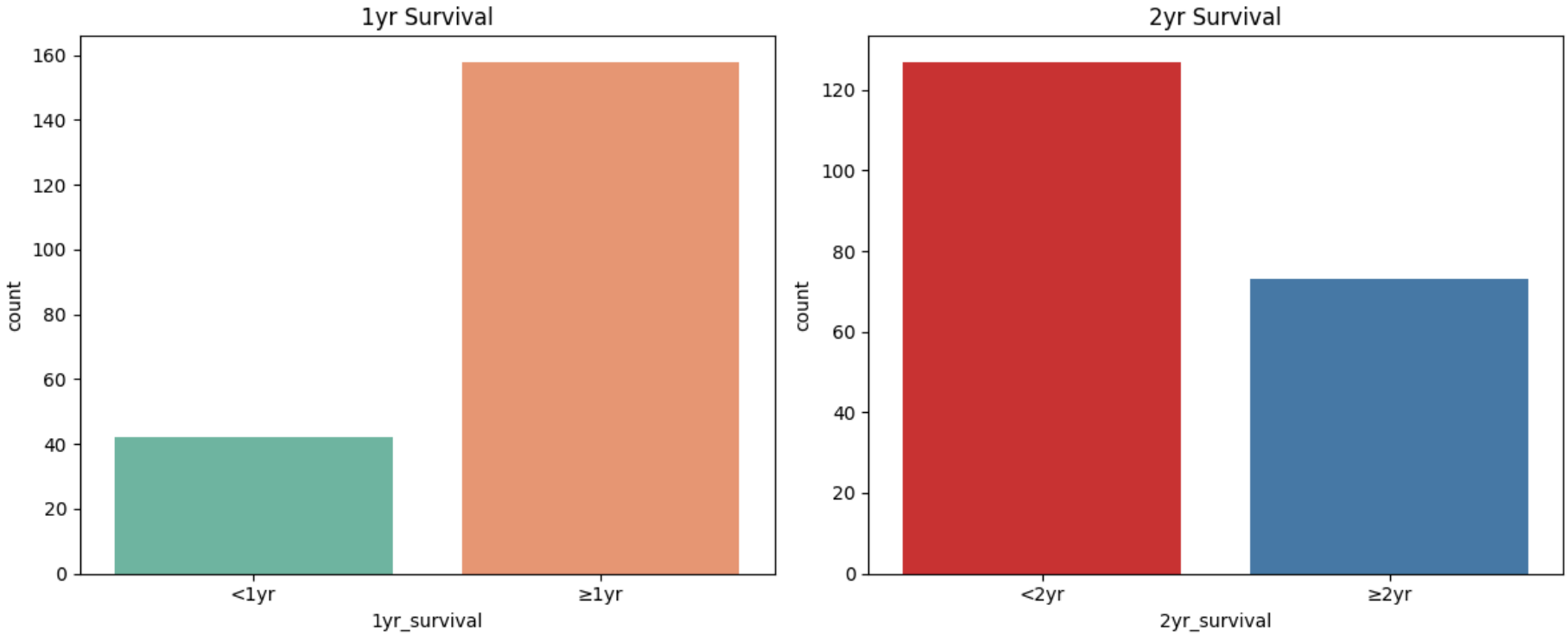
```
    stacking_auc_dict[target] = auc_s

    # 7) Plot all ROC curves
    plt.figure(figsize=(6,5))
    for name, (fpr_i, tpr_i) in base_roc.items():
        plt.plot(fpr_i, tpr_i, label=f"{name} (AUC={base_auc[name]:.3f})")
    plt.plot(fpr_s, tpr_s, label=f"Stacking (AUC={auc_s:.3f})", linewidth=2, linestyle='--')
    plt.plot([0,1],[0,1],'k--')
    plt.title(f'ROC Curves — {target}')
    plt.xlabel('FPR'); plt.ylabel('TPR')
    plt.legend(); plt.grid(True); plt.tight_layout(); plt.show()

    # 8) Classification report & confusion at 0.5
    y_pred = (proba_s >= 0.5).astype(int)
    print(classification_report(y_test, y_pred))
    cm = confusion_matrix(y_test, y_pred)
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=['Neg','Pos'], yticklabels=['Neg','Pos'])
    plt.title('Confusion Matrix (Stacking)'); plt.xlabel('Pred'); plt.ylabel('Actual')
    plt.tight_layout(); plt.show()

    # 9) Precision-Recall (stacking)
    pr_auc = average_precision_score(y_test, proba_s)
    precisions, recalls, _ = precision_recall_curve(y_test, proba_s)
    plt.figure(figsize=(6,5))
    plt.plot(recalls, precisions, label=f'PR AUC = {pr_auc:.3f}')
    plt.title(f'Precision-Recall — {target}')
    plt.xlabel('Recall'); plt.ylabel('Precision')
    plt.legend(); plt.grid(True); plt.tight_layout(); plt.show()

    # 10) SHAP on best XGB
    explainer = shap.Explainer(best_estimators['XGB'])
    shap_vals = explainer(X_test_sel)
    feat_names = selector.get_feature_names_out(preprocessor.get_feature_names_out())
    X_test_df = pd.DataFrame(X_test_sel, columns=feat_names)

    plt.figure(figsize=(8,6))
    shap.summary_plot(shap_vals, X_test_df, plot_type='bar', show=False)
    plt.title('SHAP Feature Importance (XGB)'); plt.tight_layout(); plt.show()

    plt.figure(figsize=(8,6))
```

```
    shap.summary_plot(shap_vals, X_test_df, show=False)
    plt.title('SHAP Beeswarm (XGB)'); plt.tight_layout(); plt.show()

    # 11) Save models
    joblib.dump(best_estimators['XGB'], f"best_xgb_{target}.pkl")
    joblib.dump(stack,          f"stack_model_{target}.pkl")

# Run for each target
for t in targets:
    train_evaluate_model(t)

# Summary of AUCs
print("\n=== Base Model AUCs by Target ===")
for t, aucs in base_auc_dict.items():
    print(f"{t}: " + ", ".join([f"{name}={auc:.3f}" for name, auc in aucs.items()]))
print("\n=== Stacking AUCs ===")
for t, auc in stacking_auc_dict.items():
    print(f"{t}: {auc:.3f}")

# Optional: overall AUC comparison for stacking
plt.figure(figsize=(6,4))
sns.barplot(x=list(stacking_auc_dict.keys()), y=list(stacking_auc_dict.values()))
plt.ylim(0,1); plt.title("Stacking AUC by Target"); plt.ylabel("AUC")
plt.tight_layout(); plt.show()

# Kaplan–Meier analysis (optional)

from lifelines import KaplanMeierFitter

plt.figure(figsize=(8,6))
kmf = KaplanMeierFitter()
for grade, grp in df.groupby('WHO grade'):
    kmf.fit(grp["Overall survival [OS] (days)"]/365,
            grp["1yr_survival"], label=f"WHO Grade {grade}")
    kmf.plot_survival_function()
plt.title("Kaplan–Meier: 1yr Survival by WHO Grade")
plt.xlabel("Years"); plt.ylabel("Survival Probability")
plt.tight_layout(); plt.show()
```

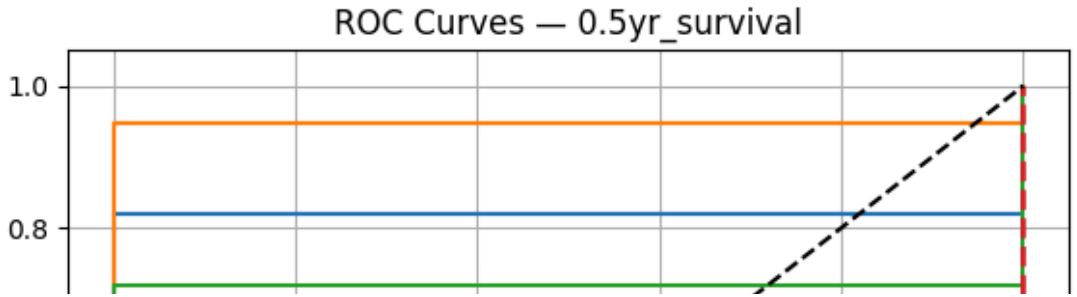
Choose Files patient_datamain.csv

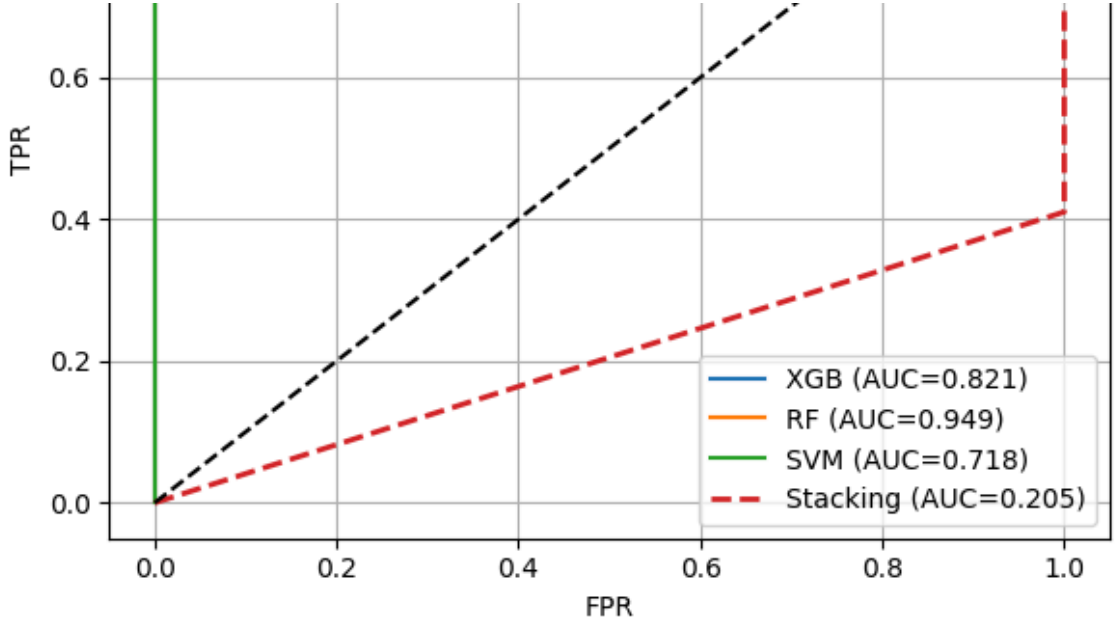
- **patient_datamain.csv**(text/csv) - 29974 bytes, last modified: 4/16/2025 - 100% done

```
Saving patient_datamain.csv to patient_datamain (3).csv
```

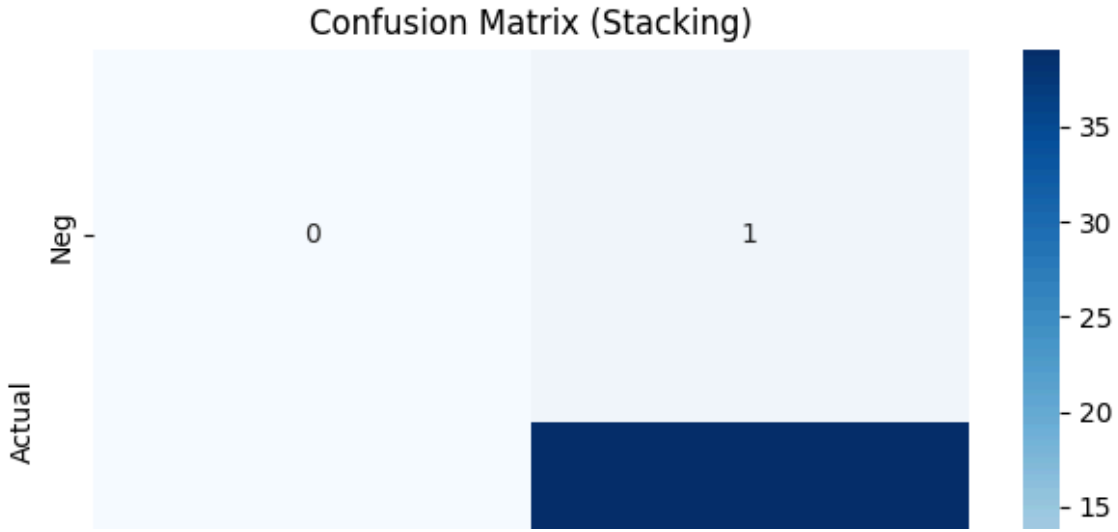


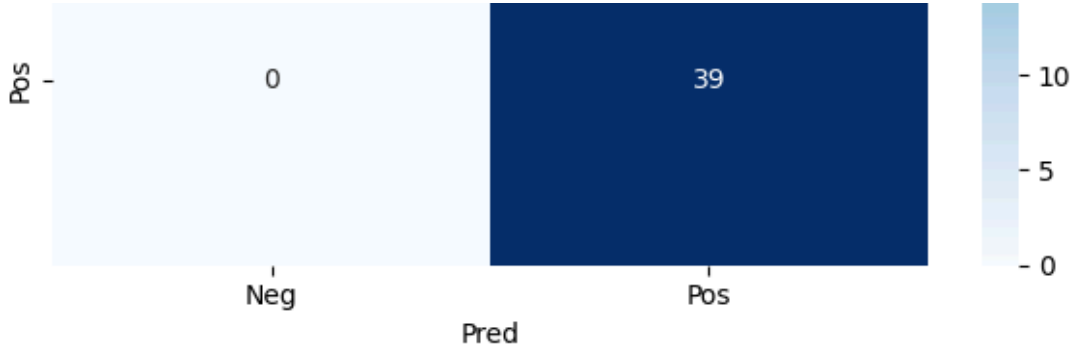

```
=== Training & Evaluating: 0.5yr_survival ===
Fitting 5 folds for each of 36 candidates, totalling 180 fits
  → XGB: best_params={'learning_rate': 0.05, 'max_depth': 3, 'n_estimators': 100, 'subsample': 0.8}, AUC=0.821
Fitting 5 folds for each of 4 candidates, totalling 20 fits
  → RF: best_params={'max_depth': 4, 'n_estimators': 200}, AUC=0.949
Fitting 5 folds for each of 6 candidates, totalling 30 fits
  → SVM: best_params={'svc__C': 0.1, 'svc__kernel': 'poly'}, AUC=0.718
  → Stacking AUC = 0.205
```

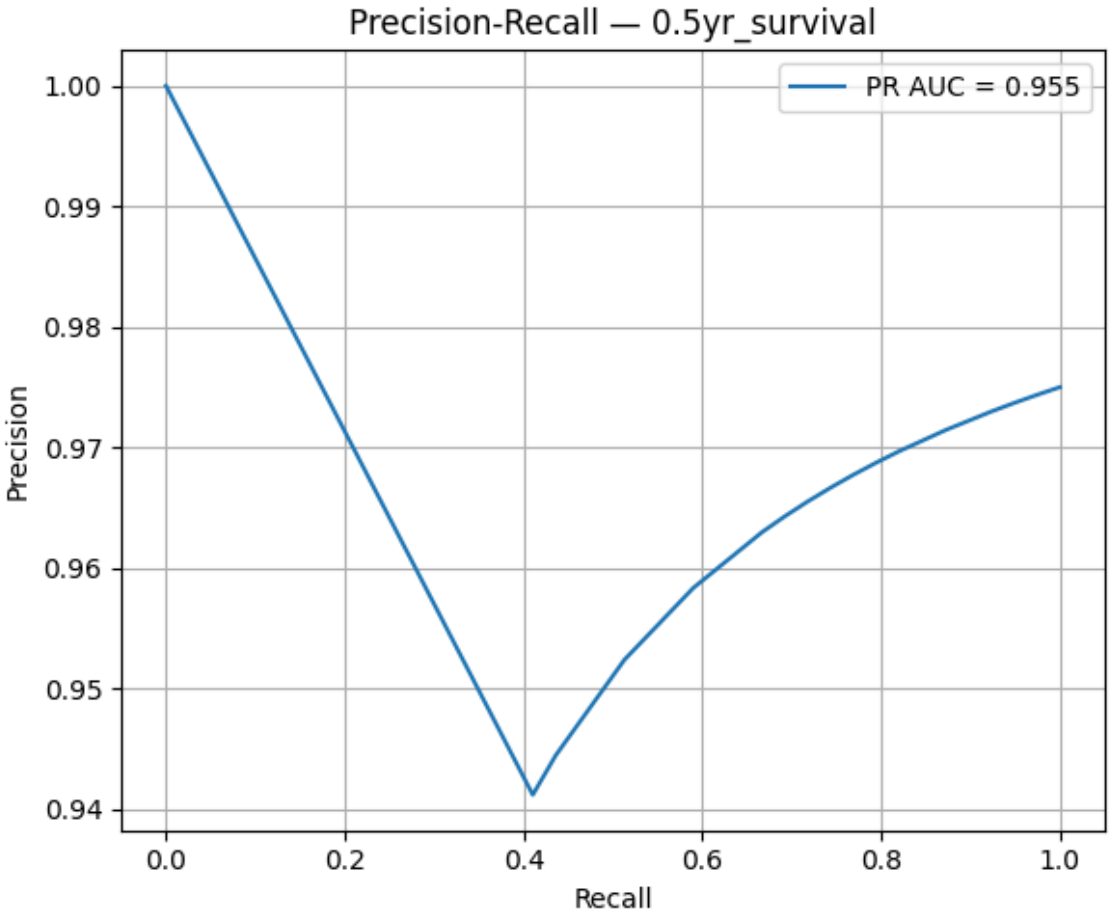


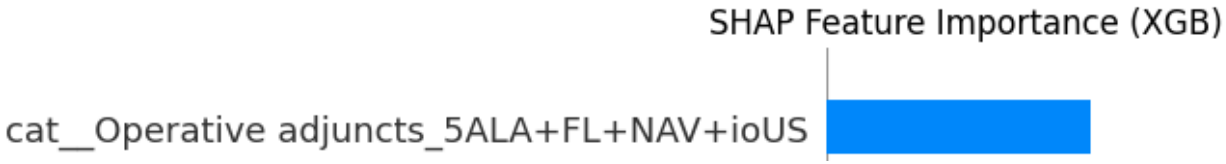


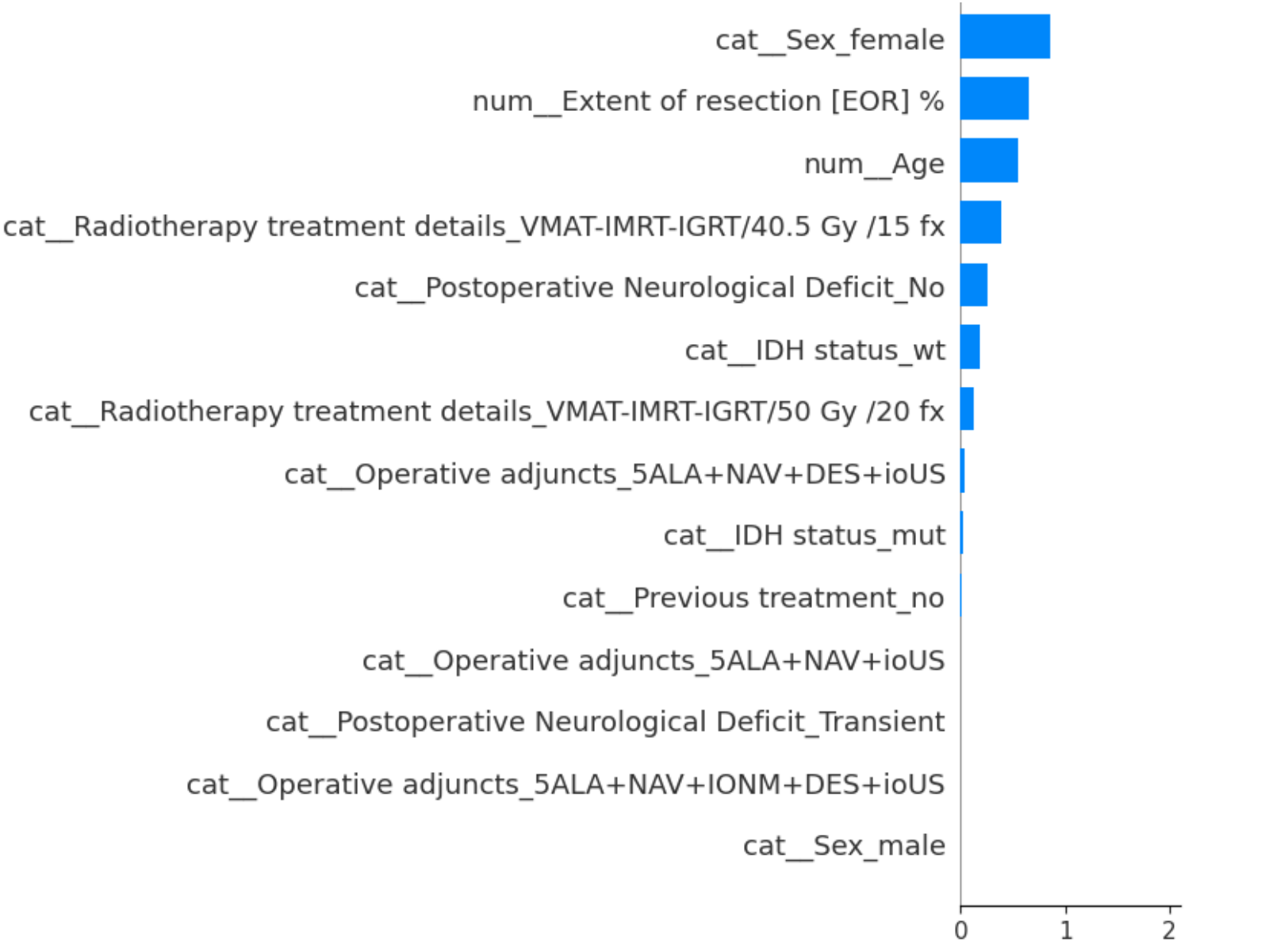
	precision	recall	f1-score	support
0	0.00	0.00	0.00	1
1	0.97	1.00	0.99	39
accuracy			0.97	40
macro avg	0.49	0.50	0.49	40
weighted avg	0.95	0.97	0.96	40

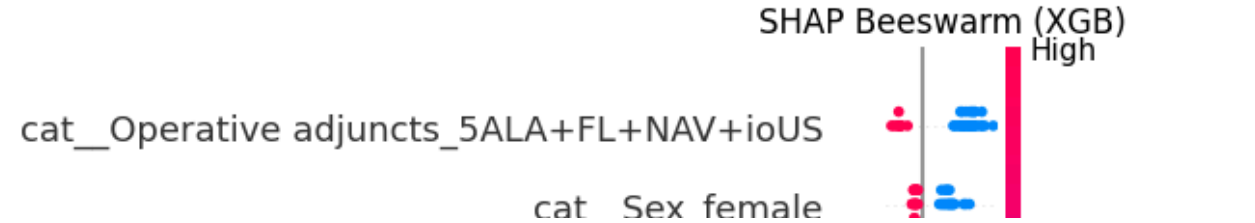


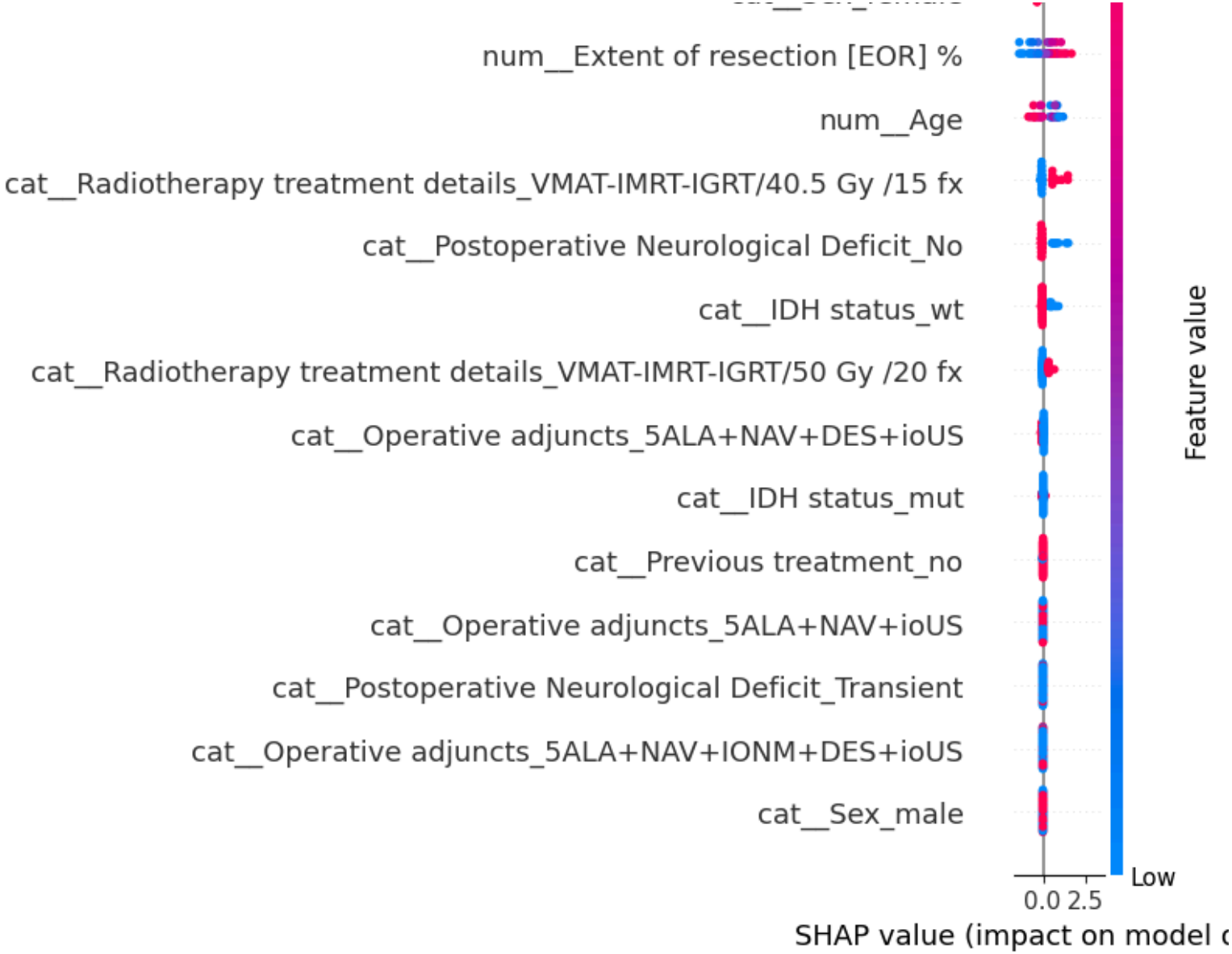

Pos
0
39
10
5
0
Neg
Pos
Pred


Precision-Recall — 0.5yr_survival
PR AUC = 0.955
1.00
0.99
0.98
0.97
0.96
0.95
0.94
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Recall

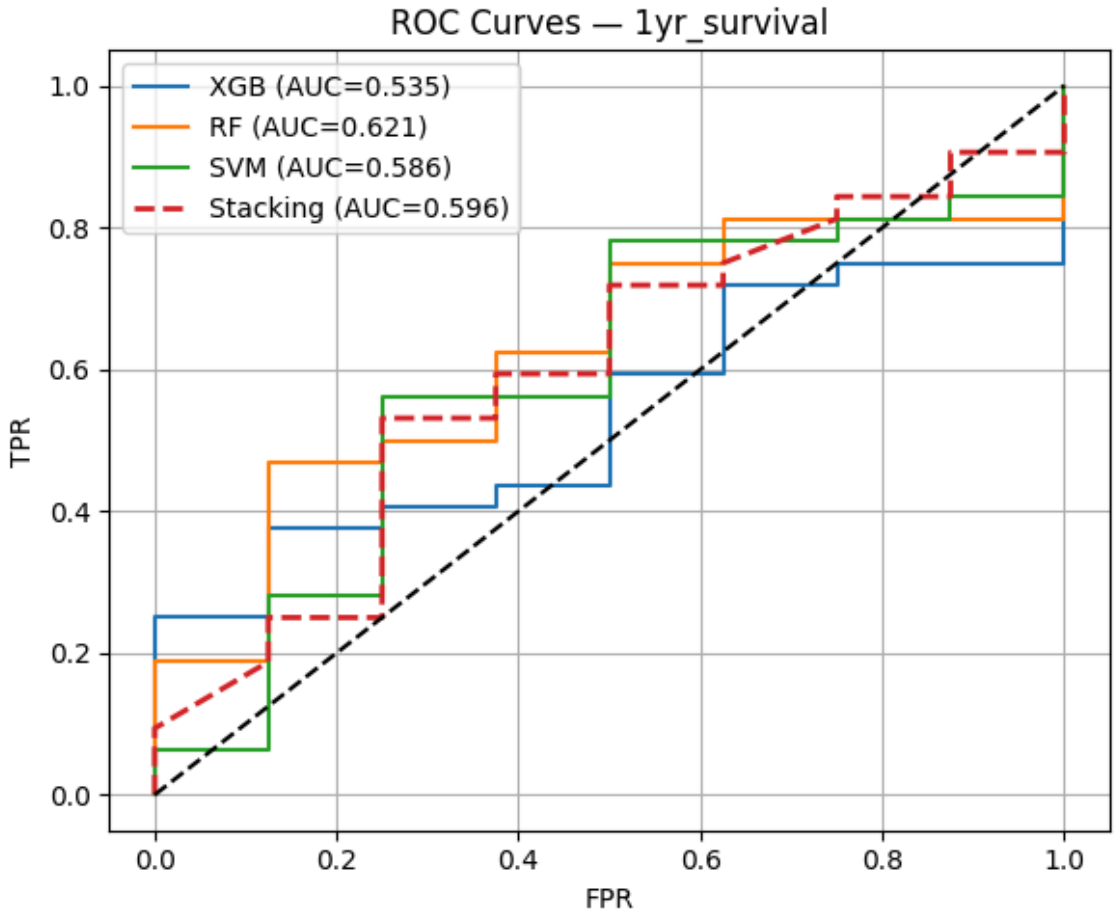

SHAP Feature Importance (XGB)
cat__Operative adjuncts_5ALA+FL+NAV+ioUS


cat__Sex_female
num__Extent of resection [EOR] %
num__Age
cat__Radiotherapy treatment details_VMAT-IMRT-IGRT/40.5 Gy /15 fx
cat__Postoperative Neurological Deficit_No
cat__IDH status_wt
cat__Radiotherapy treatment details_VMAT-IMRT-IGRT/50 Gy /20 fx
cat__Operative adjuncts_5ALA+NAV+DES+ioUS
cat__IDH status_mut
cat__Previous treatment_no
cat__Operative adjuncts_5ALA+NAV+ioUS
cat__Postoperative Neurological Deficit_Transient
cat__Operative adjuncts_5ALA+NAV+IONM+DES+ioUS
cat__Sex_male
0
1
2
mean(|SHAP value|) (average impact on model o

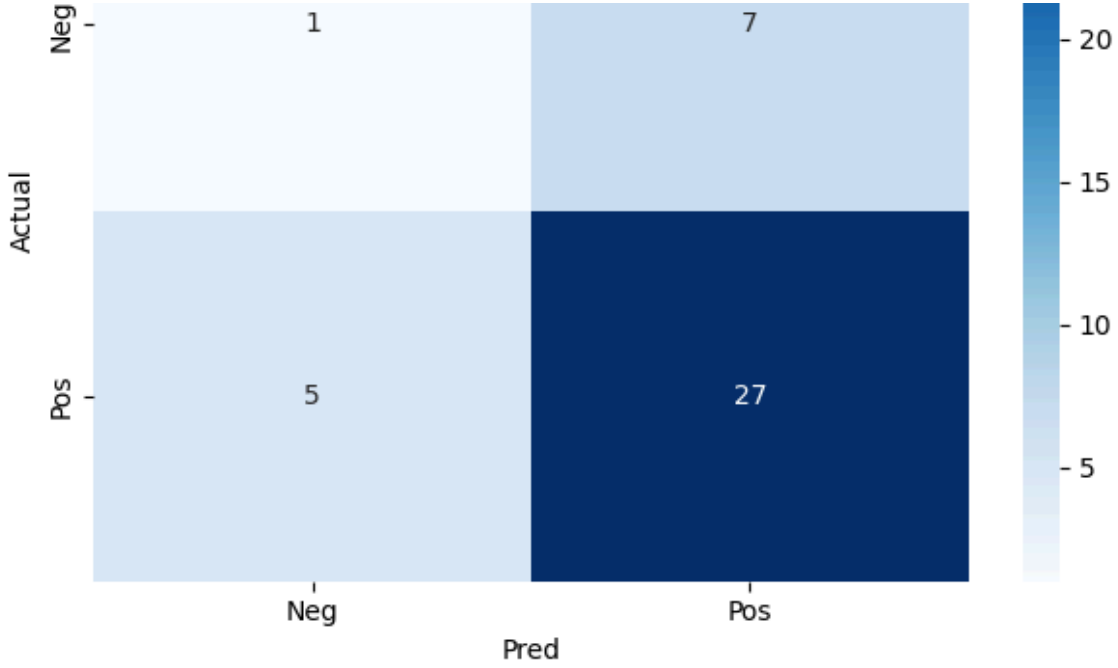

SHAP Beeswarm (XGB)
High
cat__Operative adjuncts_5ALA+FL+NAV+ioUS
cat__Sex_female

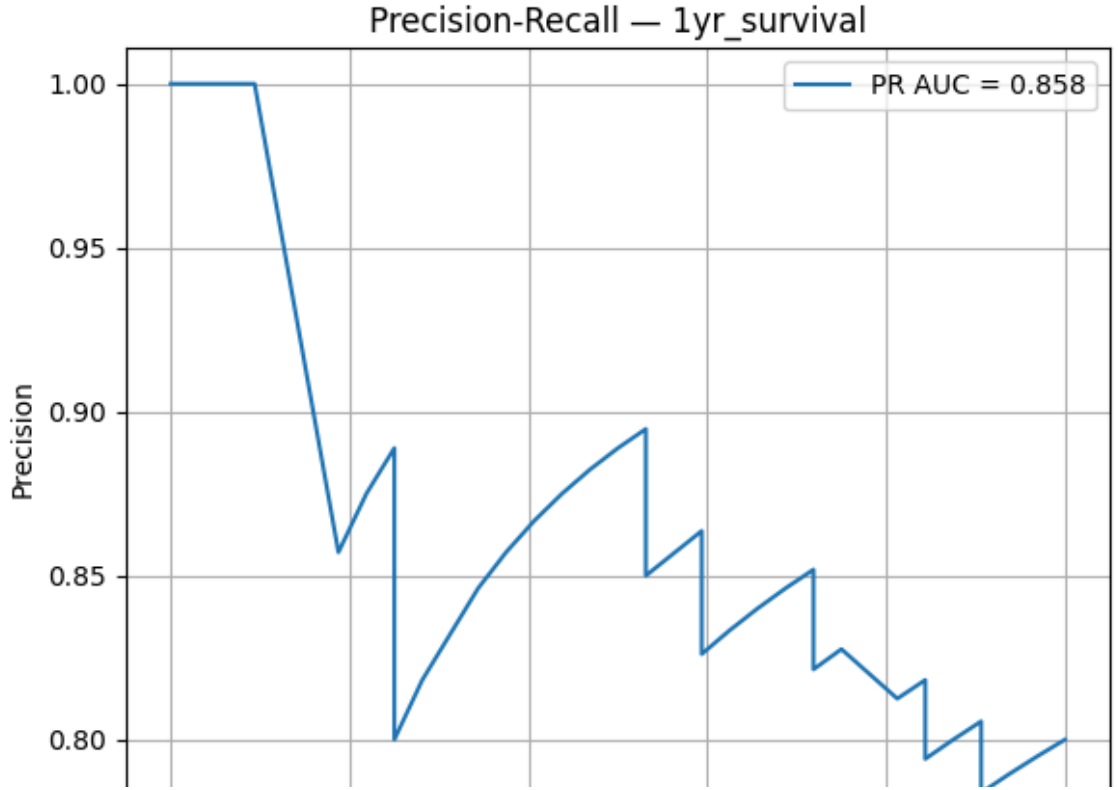


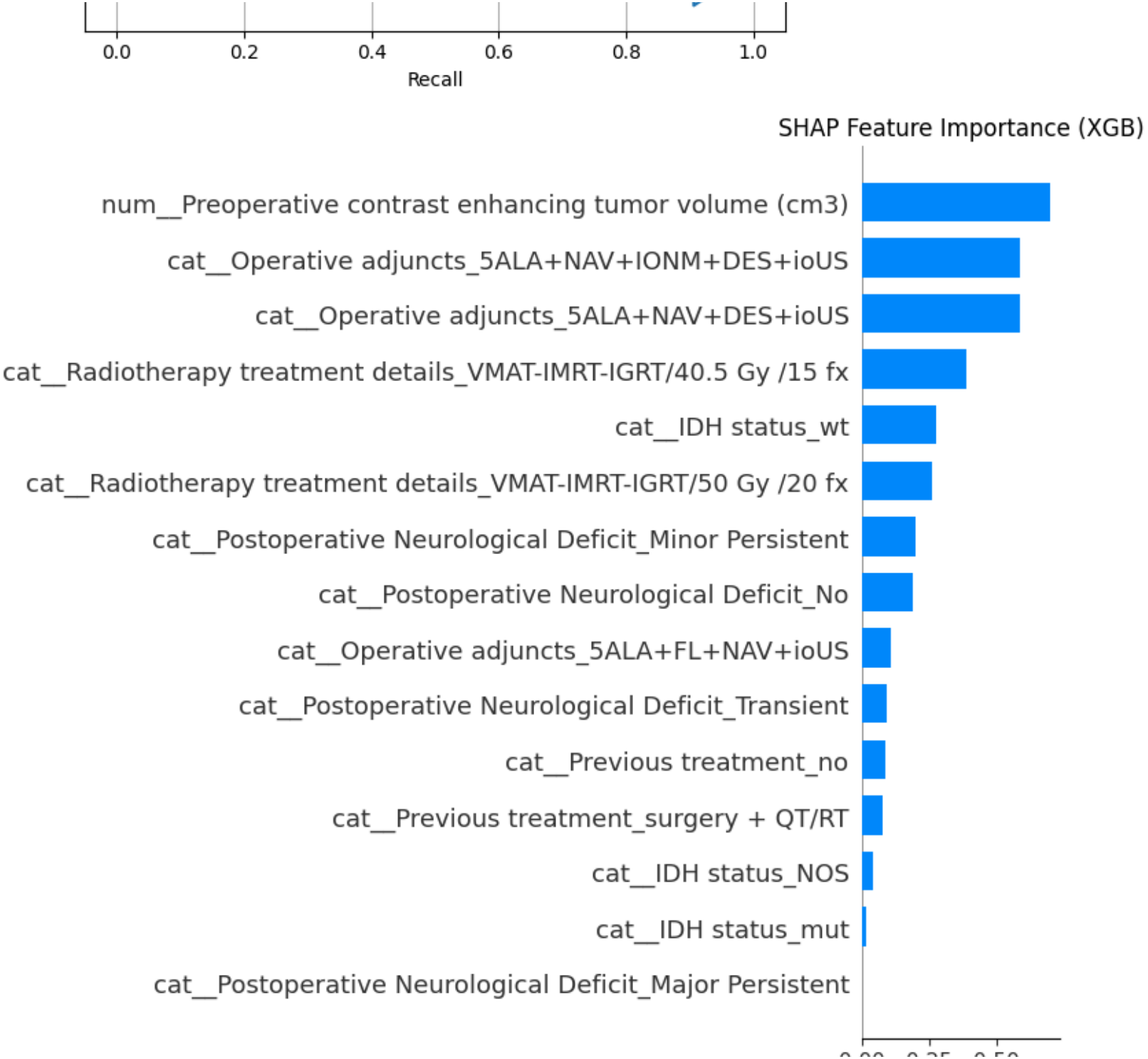

```
=== Training & Evaluating: 1yr_survival ===
Fitting 5 folds for each of 36 candidates, totalling 180 fits
  → XGB: best_params={'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 100, 'subsample': 1.0}, AUC=0.535
Fitting 5 folds for each of 4 candidates, totalling 20 fits
  → RF: best_params={'max_depth': 5, 'n_estimators': 200}, AUC=0.621
Fitting 5 folds for each of 6 candidates, totalling 30 fits
  → SVM: best_params={'svc__C': 1, 'svc__kernel': 'rbf'}, AUC=0.586
  → Stacking AUC = 0.596
```

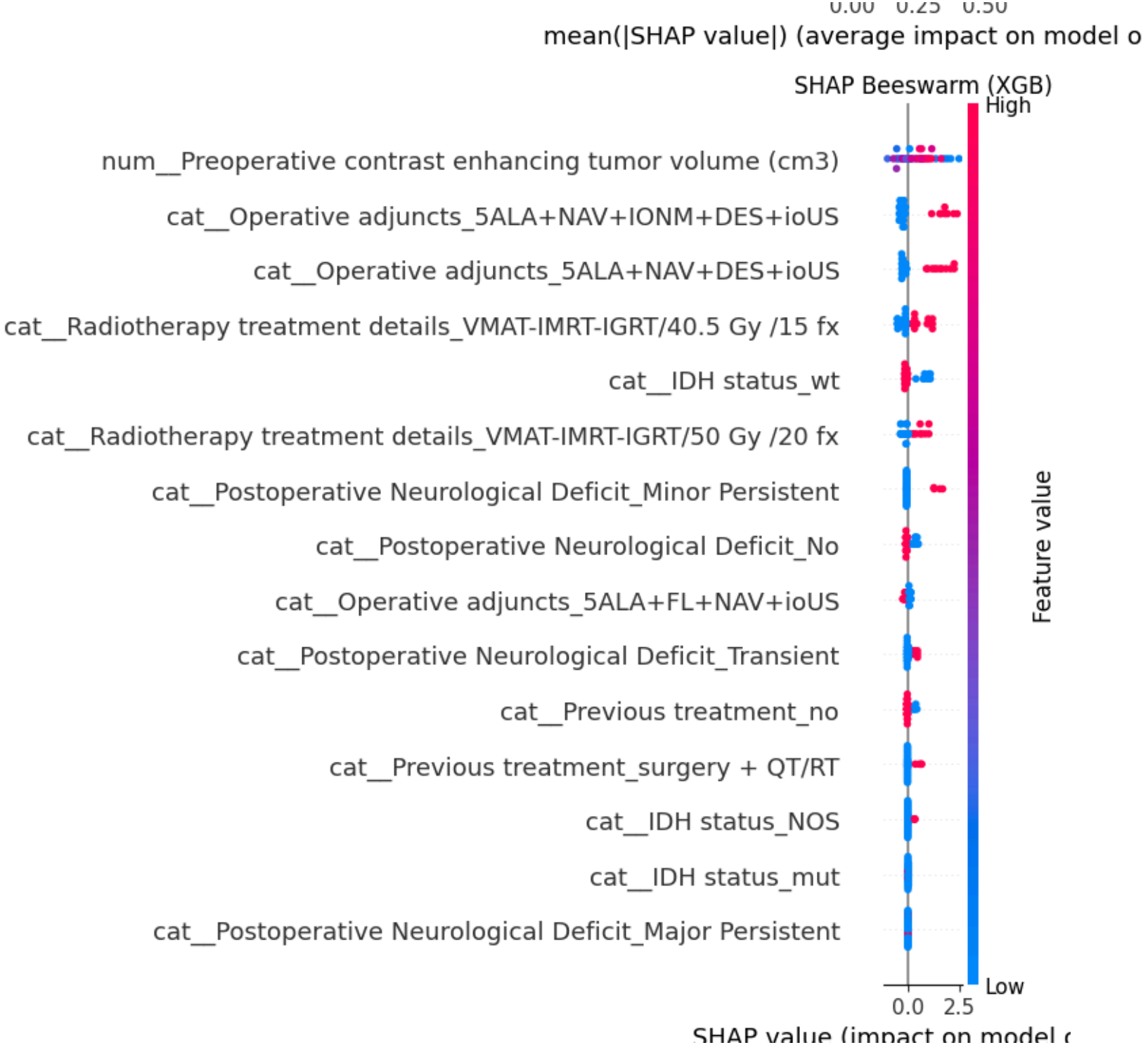


	precision	recall	f1-score	support
0	0.17	0.12	0.14	8
1	0.79	0.84	0.82	32
accuracy			0.70	40
macro avg	0.48	0.48	0.48	40
weighted avg	0.67	0.70	0.68	40

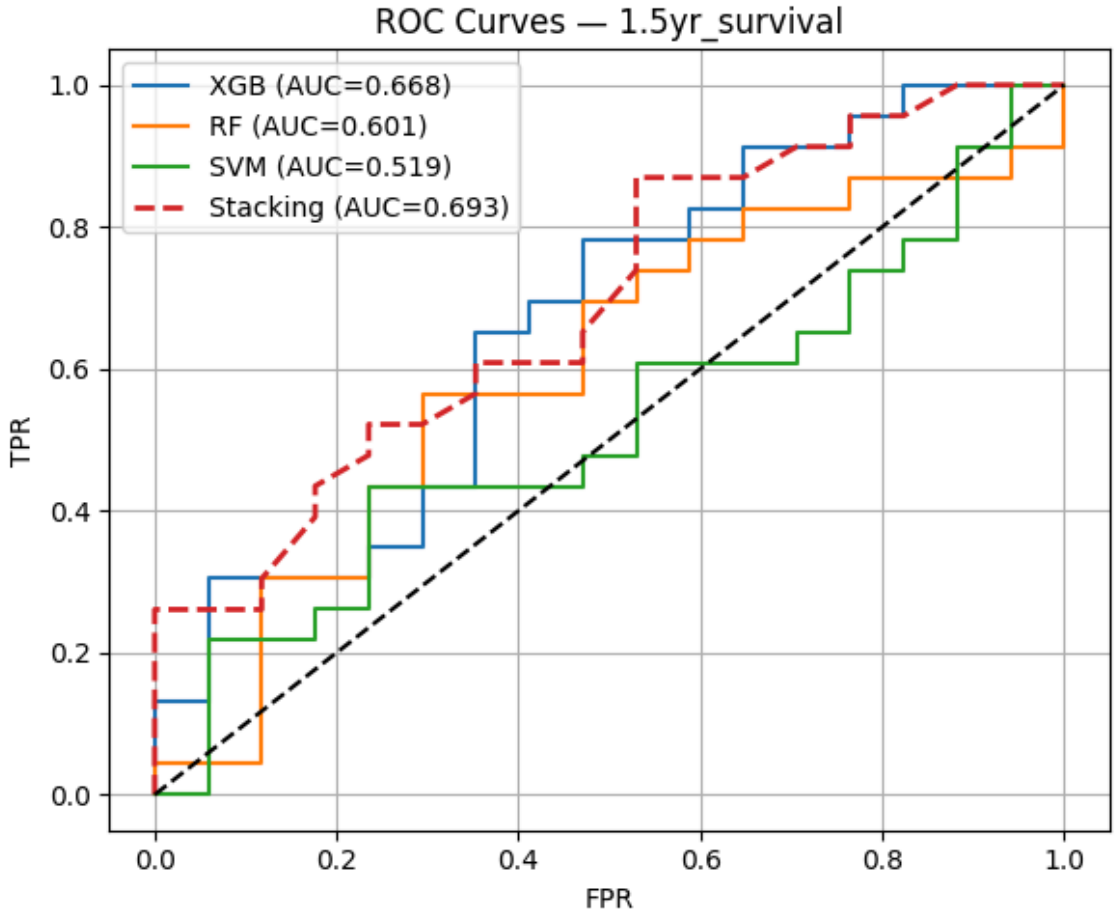

Neg
Pos
Actual
1
7
5
27
Neg
Pos
Pred
20
15
10
5


Precision-Recall — 1yr_survival
PR AUC = 0.858
Precision
1.00
0.95
0.90
0.85
0.80


0.0
0.2
0.4
0.6
0.8
1.0
Recall
SHAP Feature Importance (XGB)
num__Preoperative contrast enhancing tumor volume (cm3)
cat__Operative adjuncts_5ALA+NAV+IONM+DES+ioUS
cat__Operative adjuncts_5ALA+NAV+DES+ioUS
cat__Radiotherapy treatment details_VMAT-IMRT-IGRT/40.5 Gy /15 fx
cat__IDH status_wt
cat__Radiotherapy treatment details_VMAT-IMRT-IGRT/50 Gy /20 fx
cat__Postoperative Neurological Deficit_Minor Persistent
cat__Postoperative Neurological Deficit_No
cat__Operative adjuncts_5ALA+FL+NAV+ioUS
cat__Postoperative Neurological Deficit_Transient
cat__Previous treatment_no
cat__Previous treatment_surgery + QT/RT
cat__IDH status_NOS
cat__IDH status_mut
cat__Postoperative Neurological Deficit_Major Persistent

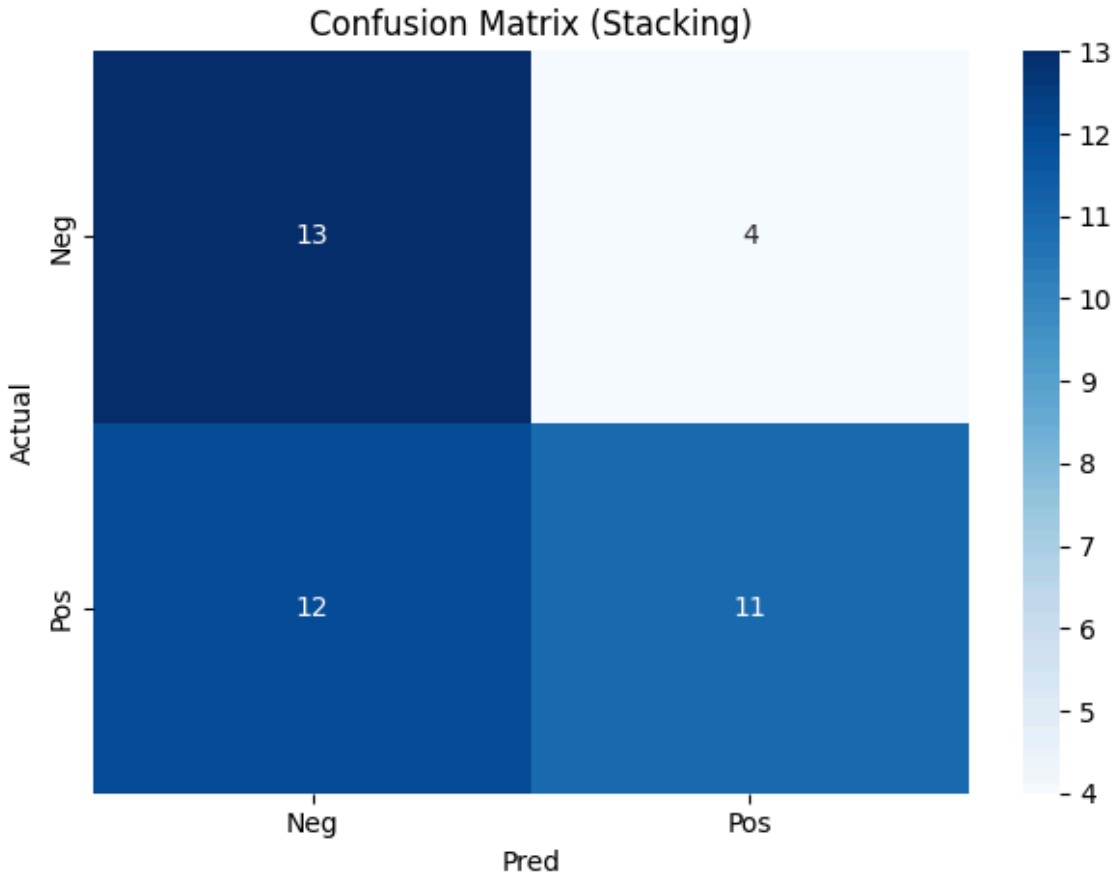

0.00 0.25 0.50
mean(|SHAP value|) (average impact on model o
SHAP Beeswarm (XGB)
num__Preoperative contrast enhancing tumor volume (cm3)
cat__Operative adjuncts_5ALA+NAV+IONM+DES+ioUS
cat__Operative adjuncts_5ALA+NAV+DES+ioUS
cat__Radiotherapy treatment details_VMAT-IMRT-IGRT/40.5 Gy /15 fx
cat__IDH status_wt
cat__Radiotherapy treatment details_VMAT-IMRT-IGRT/50 Gy /20 fx
cat__Postoperative Neurological Deficit_Minor Persistent
cat__Postoperative Neurological Deficit_No
cat__Operative adjuncts_5ALA+FL+NAV+ioUS
cat__Postoperative Neurological Deficit_Transient
cat__Previous treatment_no
cat__Previous treatment_surgery + QT/RT
cat__IDH status_NOS
cat__IDH status_mut
cat__Postoperative Neurological Deficit_Major Persistent
High
Feature value
Low
0.0 2.5
SHAP value (impact on model

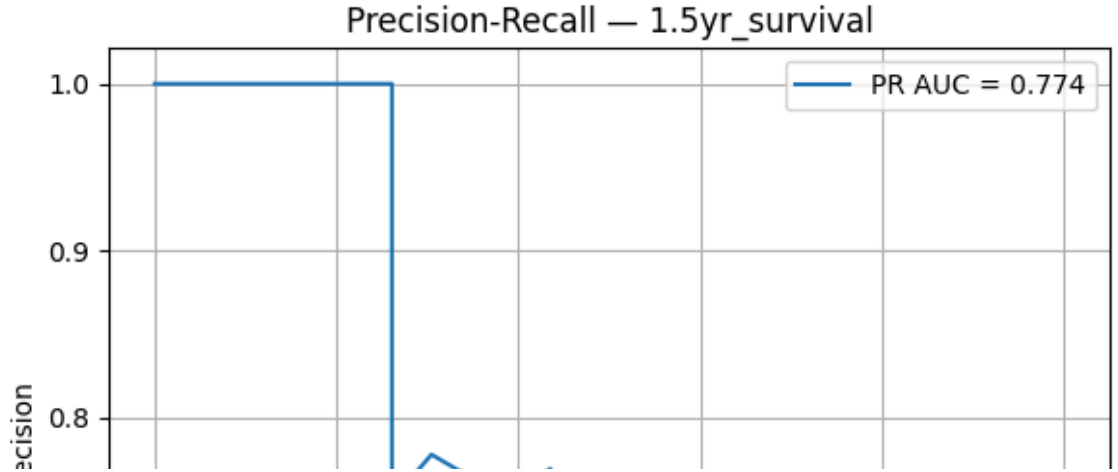
```
=== Training & Evaluating: 1.5yr_survival ===
Fitting 5 folds for each of 36 candidates, totalling 180 fits
  → XGB: best_params={'learning_rate': 0.1, 'max_depth': 5, 'n_estimators': 200, 'subsample': 1.0}, AUC=0.668
Fitting 5 folds for each of 4 candidates, totalling 20 fits
  → RF: best_params={'max_depth': 4, 'n_estimators': 200}, AUC=0.601
Fitting 5 folds for each of 6 candidates, totalling 30 fits
  → SVM: best_params={'svc__C': 10, 'svc__kernel': 'rbf'}, AUC=0.519
  → Stacking AUC = 0.693
```

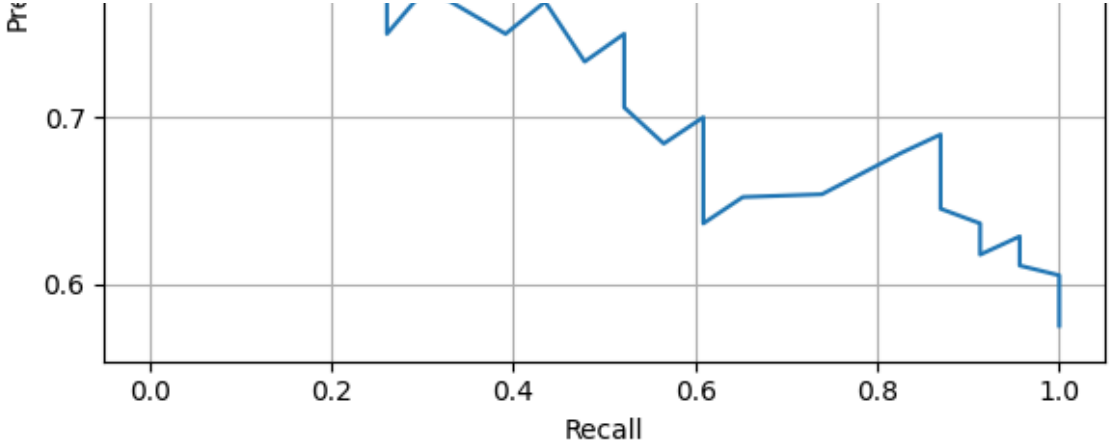


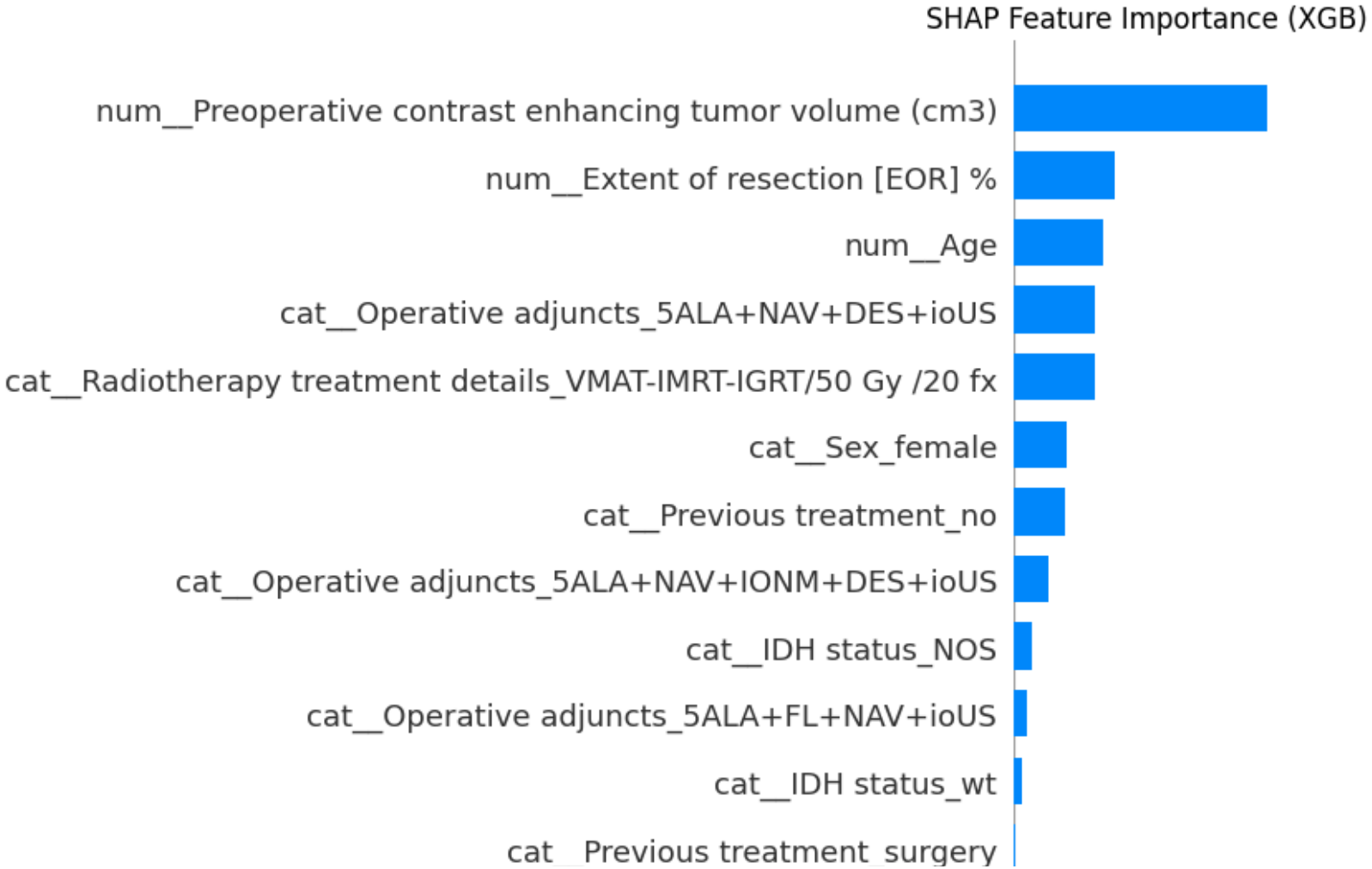
	precision	recall	f1-score	support
0	0.52	0.76	0.62	17
1	0.73	0.48	0.58	23
accuracy			0.60	40

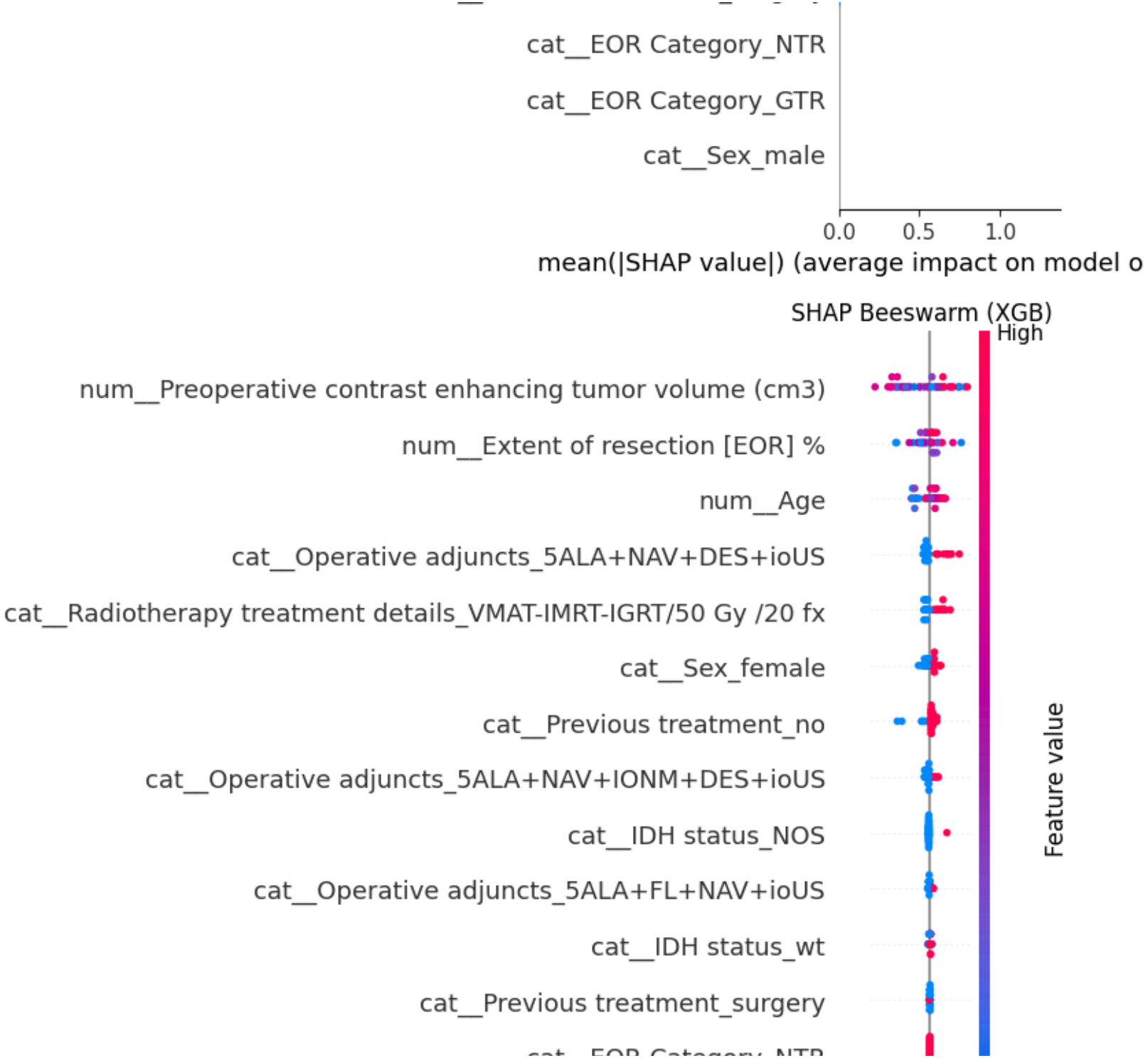
macro avg	0.63	0.62	0.60	40
weighted avg	0.64	0.60	0.60	40

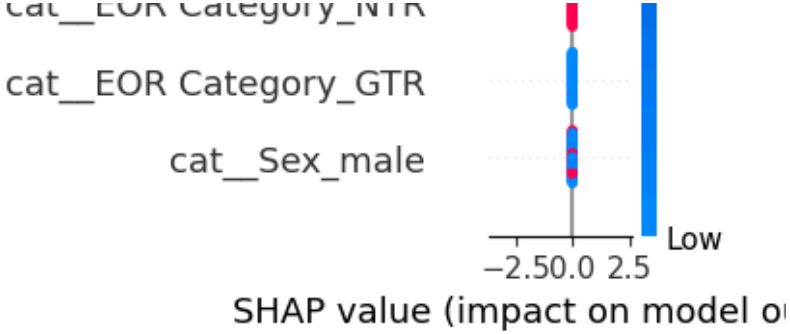




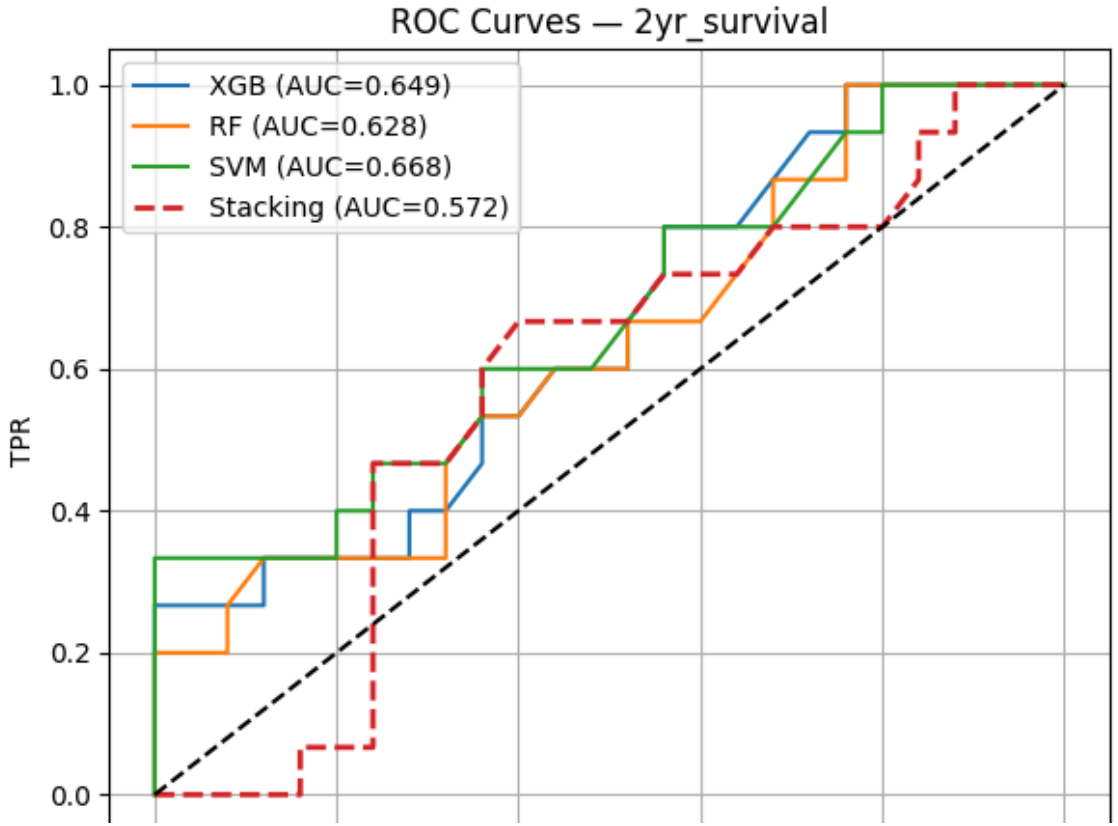

0.7
0.6
0.0
0.2
0.4
0.6
0.8
1.0
Recall


SHAP Feature Importance (XGB)
num__Preoperative contrast enhancing tumor volume (cm3)
num__Extent of resection [EOR] %
num__Age
cat__Operative adjuncts_5ALA+NAV+DES+ioUS
cat__Radiotherapy treatment details_VMAT-IMRT-IGRT/50 Gy /20 fx
cat__Sex_female
cat__Previous treatment_no
cat__Operative adjuncts_5ALA+NAV+IONM+DES+ioUS
cat__IDH status_NOS
cat__Operative adjuncts_5ALA+FL+NAV+ioUS
cat__IDH status_wt
cat__Previous treatment_surgery

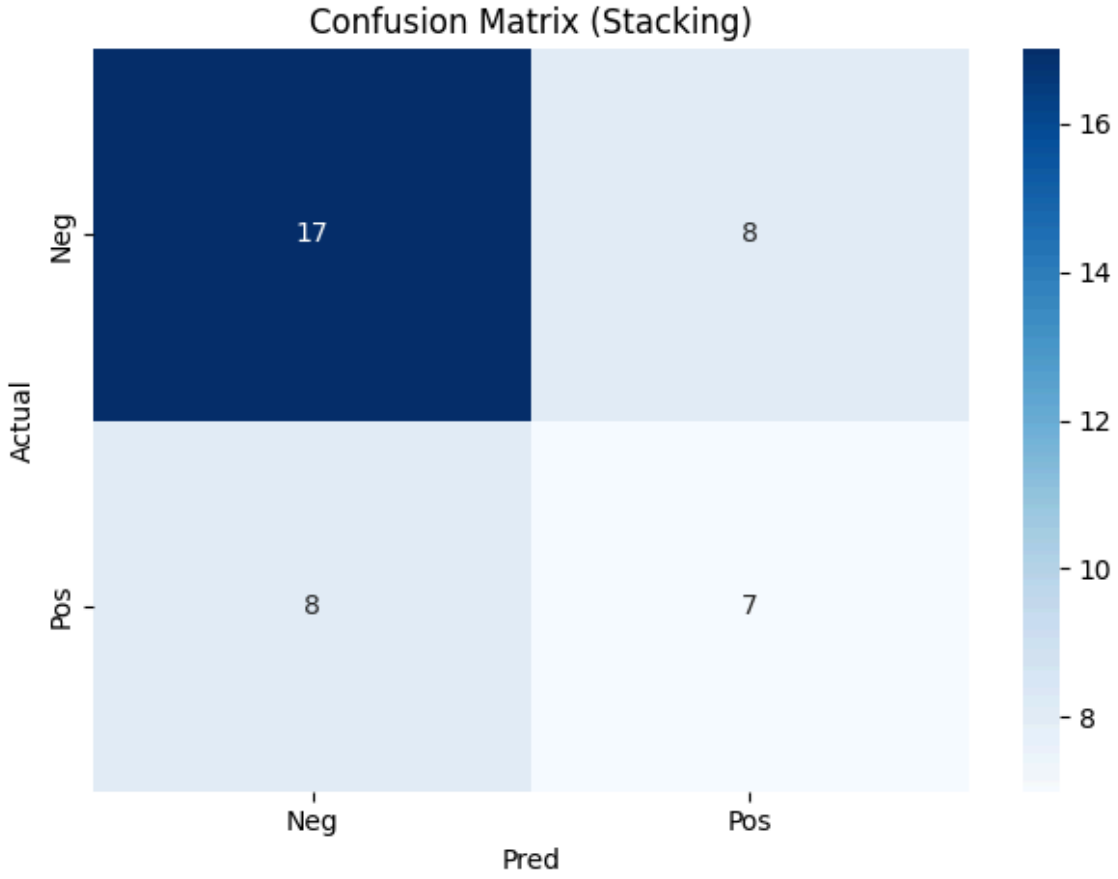

cat__EOR Category_NTR
cat__EOR Category_GTR
cat__Sex_male
0.0
0.5
1.0
mean(|SHAP value|) (average impact on model o
SHAP Beeswarm (XGB)
num__Preoperative contrast enhancing tumor volume (cm3)
num__Extent of resection [EOR] %
num__Age
cat__Operative adjuncts_5ALA+NAV+DES+ioUS
cat__Radiotherapy treatment details_VMAT-IMRT-IGRT/50 Gy /20 fx
cat__Sex_female
cat__Previous treatment_no
cat__Operative adjuncts_5ALA+NAV+IONM+DES+ioUS
cat__IDH status_NOS
cat__Operative adjuncts_5ALA+FL+NAV+ioUS
cat__IDH status_wt
cat__Previous treatment_surgery
High
Feature value

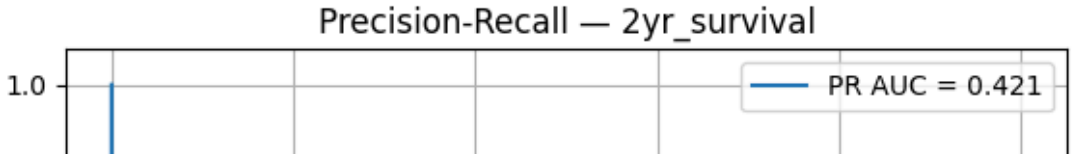


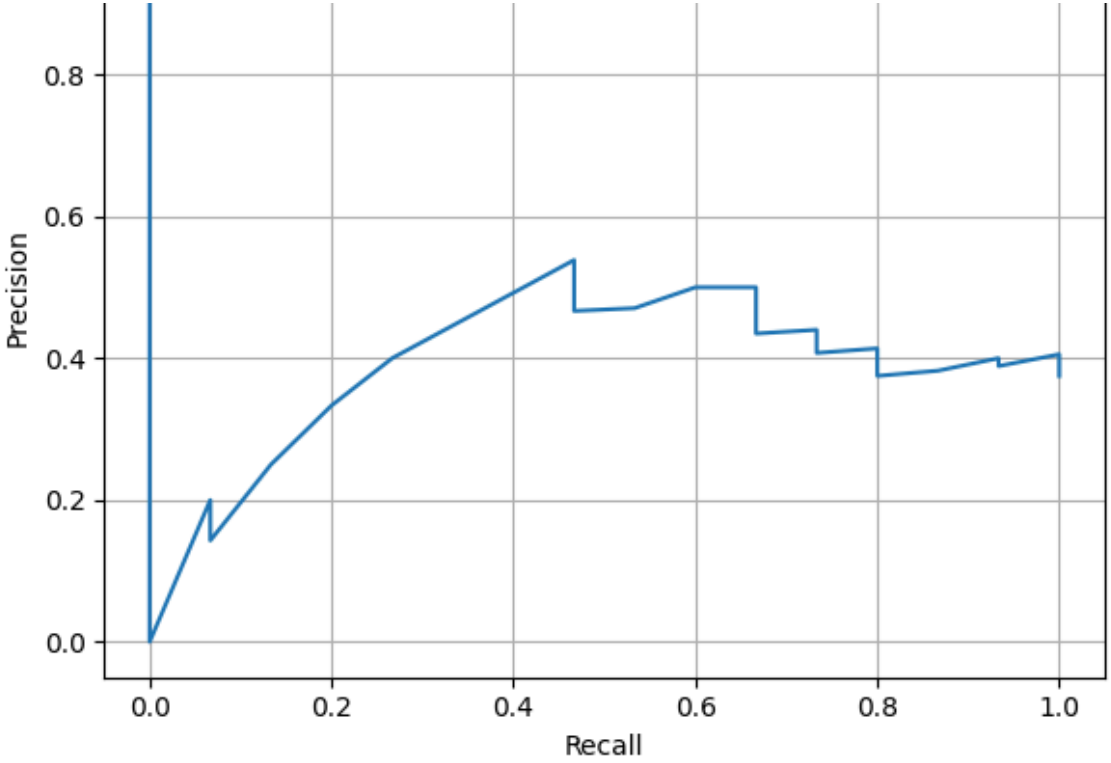

```
=== Training & Evaluating: 2yr_survival ===
Fitting 5 folds for each of 36 candidates, totalling 180 fits
  → XGB: best_params={'learning_rate': 0.05, 'max_depth': 4, 'n_estimators': 200, 'subsample': 0.8}, AUC=0.649
Fitting 5 folds for each of 4 candidates, totalling 20 fits
  → RF: best_params={'max_depth': 5, 'n_estimators': 100}, AUC=0.628
Fitting 5 folds for each of 6 candidates, totalling 30 fits
  → SVM: best_params={'svc__C': 10, 'svc__kernel': 'rbf'}, AUC=0.668
  → Stacking AUC = 0.572
```

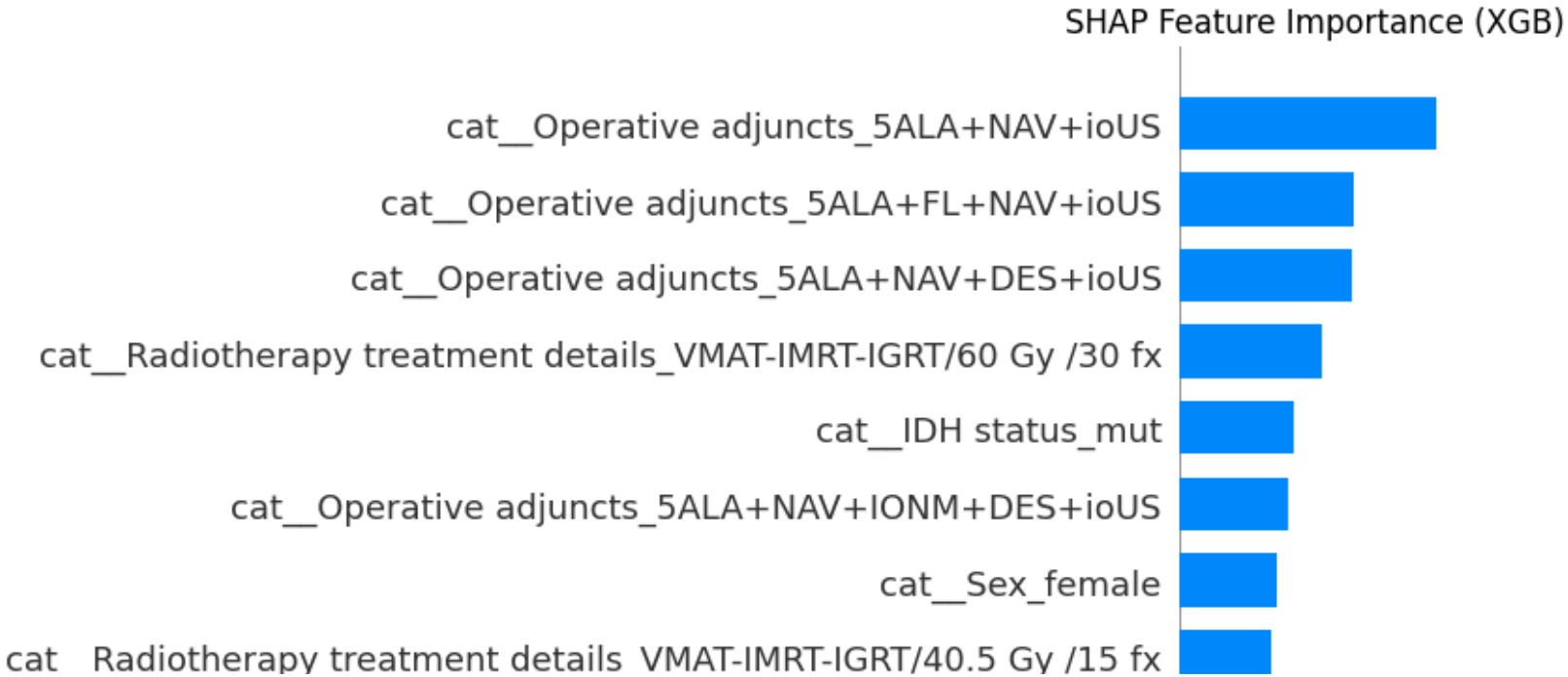


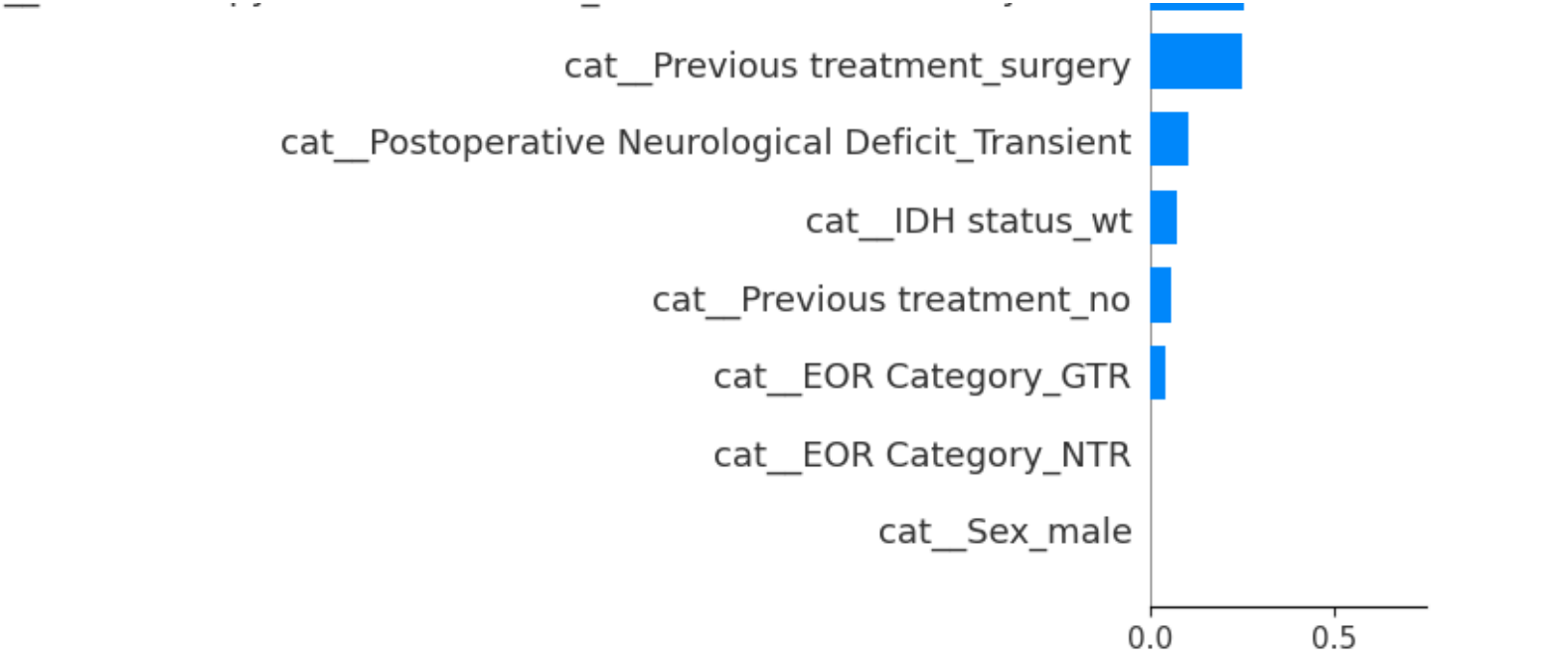
	precision	recall	f1-score	support
0	0.68	0.68	0.68	25
1	0.47	0.47	0.47	15
accuracy			0.60	40
macro avg	0.57	0.57	0.57	40
weighted avg	0.60	0.60	0.60	40

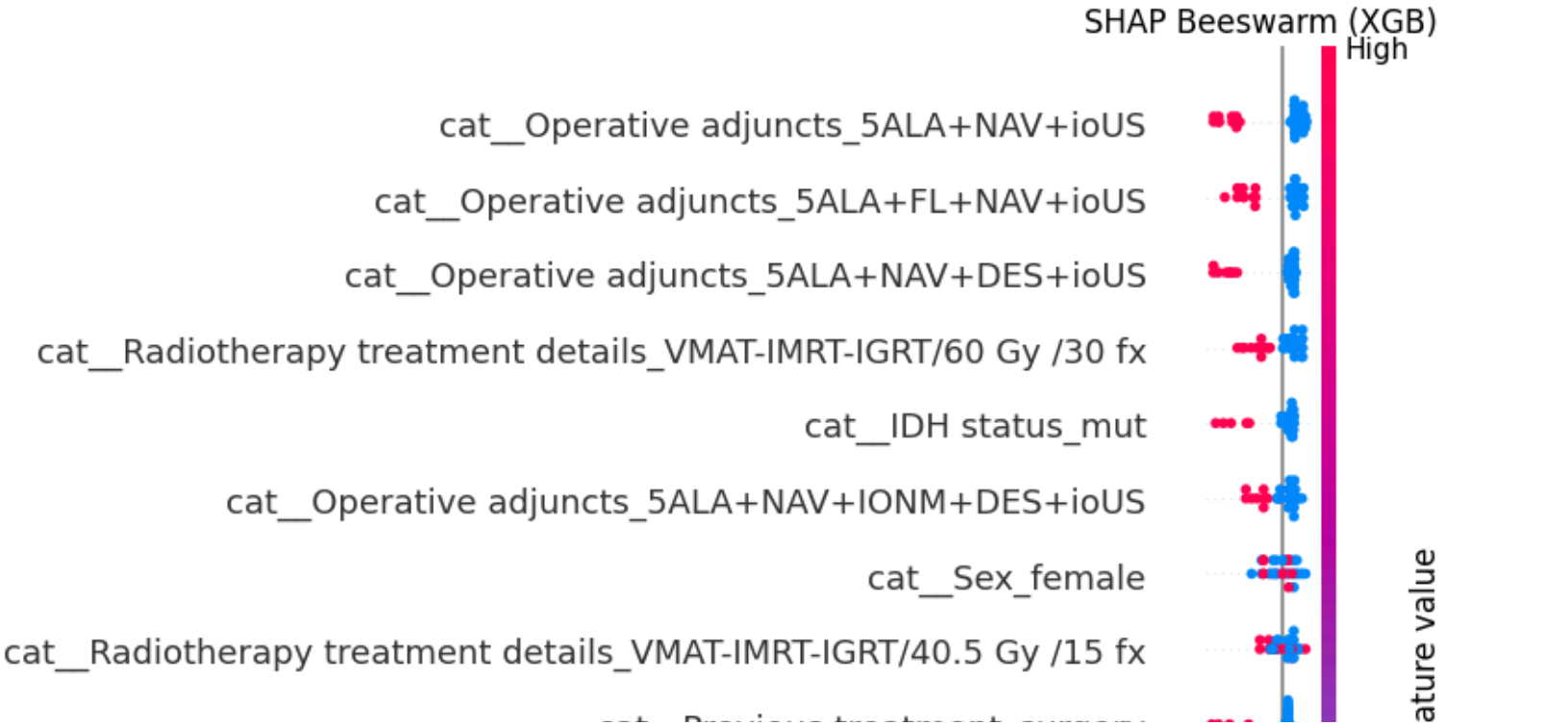


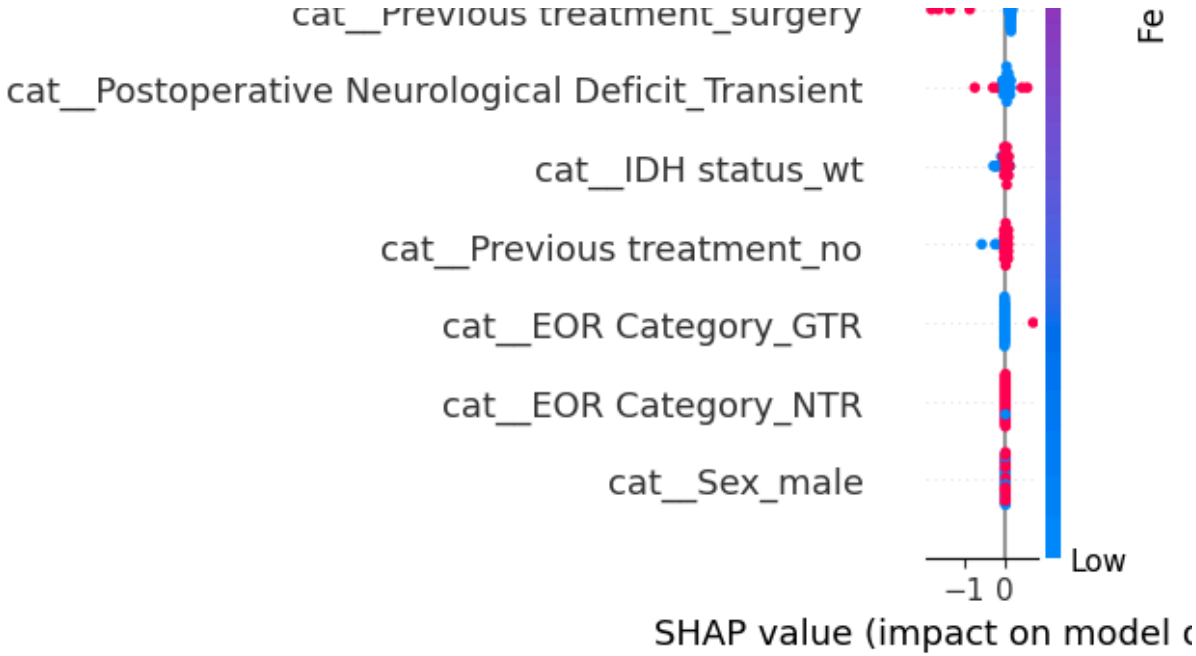



Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

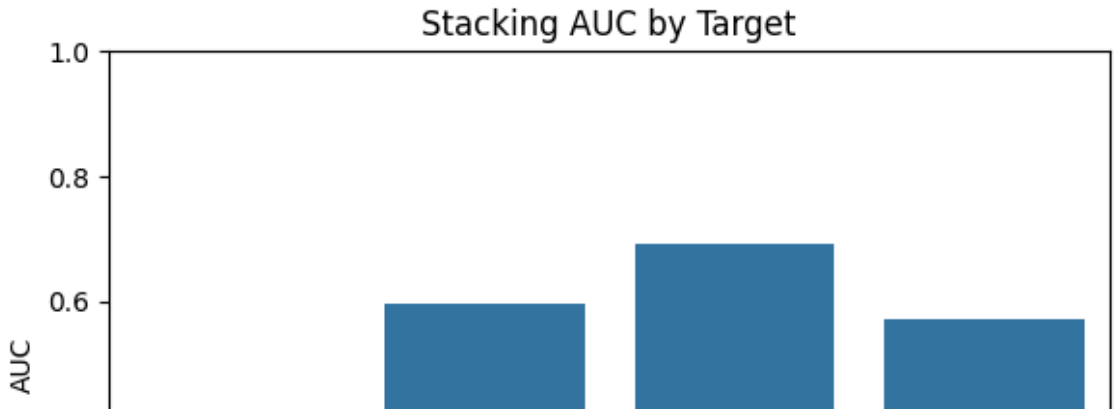

SHAP Feature Importance (XGB)
cat__Operative adjuncts_5ALA+NAV+ioUS
cat__Operative adjuncts_5ALA+FL+NAV+ioUS
cat__Operative adjuncts_5ALA+NAV+DES+ioUS
cat__Radiotherapy treatment details_VMAT-IMRT-IGRT/60 Gy /30 fx
cat__IDH status_mut
cat__Operative adjuncts_5ALA+NAV+IONM+DES+ioUS
cat__Sex_female
cat__Radiotherapy treatment details_VMAT-IMRT-IGRT/40.5 Gy /15 fx

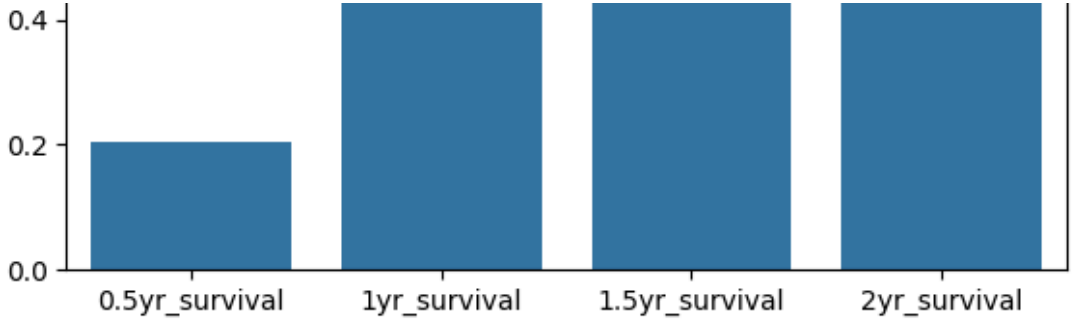

cat__Previous treatment_surgery
cat__Postoperative Neurological Deficit_Transient
cat__IDH status_wt
cat__Previous treatment_no
cat__EOR Category_GTR
cat__EOR Category_NTR
cat__Sex_male
0.0
0.5
mean(|SHAP value|) (average impact on model o

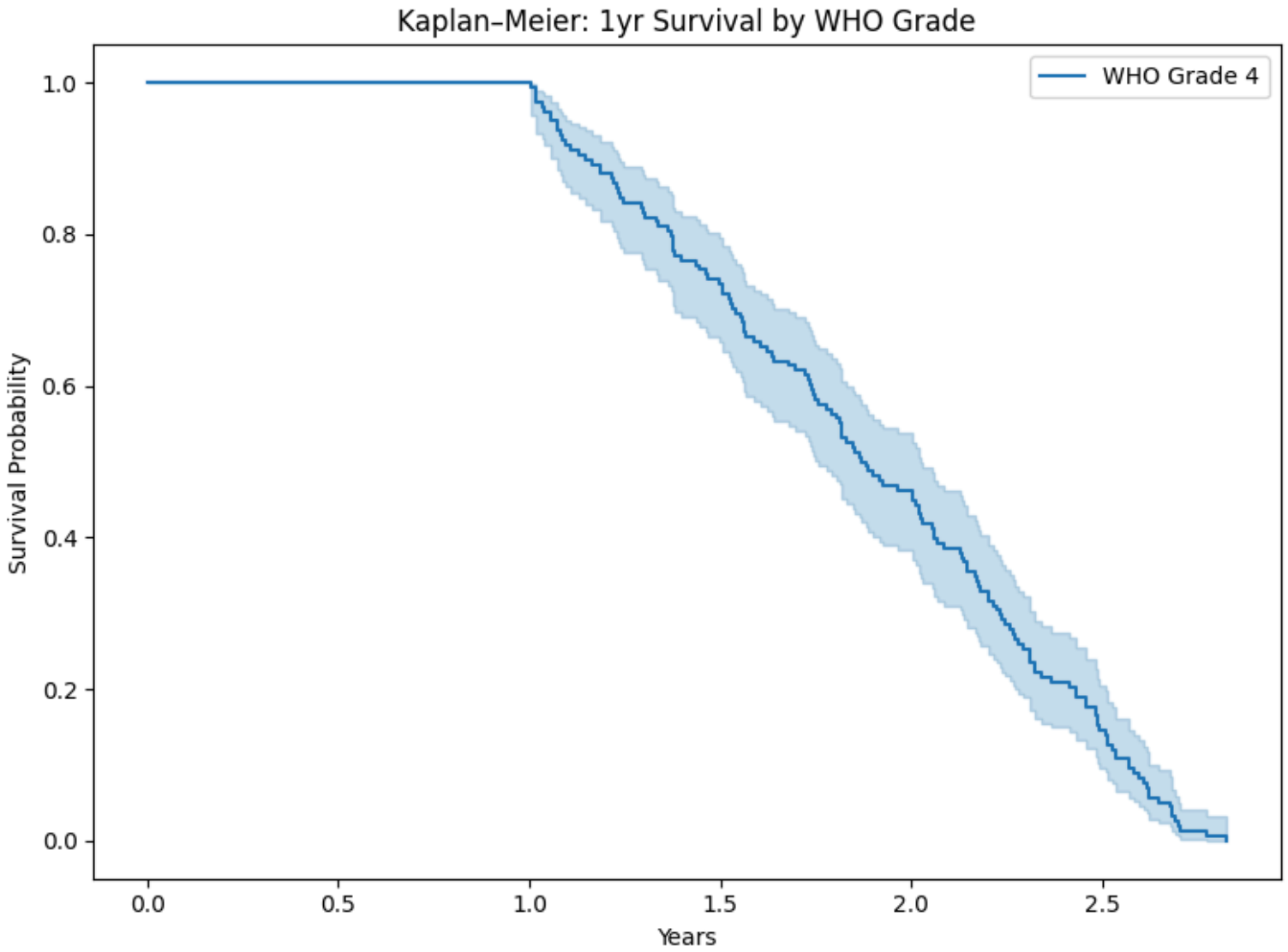

SHAP Beeswarm (XGB)
High
cat__Operative adjuncts_5ALA+NAV+ioUS
cat__Operative adjuncts_5ALA+FL+NAV+ioUS
cat__Operative adjuncts_5ALA+NAV+DES+ioUS
cat__Radiotherapy treatment details_VMAT-IMRT-IGRT/60 Gy /30 fx
cat__IDH status_mut
cat__Operative adjuncts_5ALA+NAV+IONM+DES+ioUS
cat__Sex_female
cat__Radiotherapy treatment details_VMAT-IMRT-IGRT/40.5 Gy /15 fx
ature value




```
=== Base Model AUCs by Target ===
0.5yr_survival: XGB=0.821, RF=0.949, SVM=0.718
1yr_survival: XGB=0.535, RF=0.621, SVM=0.586
1.5yr_survival: XGB=0.668, RF=0.601, SVM=0.519
2yr_survival: XGB=0.649, RF=0.628, SVM=0.668

=== Stacking AUCs ===
0.5yr_survival: 0.205
1yr_survival: 0.596
1.5yr_survival: 0.693
2yr_survival: 0.572
```




0.4
0.2
0.0
0.5yr_survival
1yr_survival
1.5yr_survival
2yr_survival


Kaplan–Meier: 1yr Survival by WHO Grade
WHO Grade 4
Survival Probability
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.5
1.0
1.5
2.0
2.5
Years

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