In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.utils.class_weight import compute_class_weight
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split, GridSearchCV, cr
from sklearn.metrics import accuracy_score, recall_score, precision_sc
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.metrics import classification_report
from sklearn.pipeline import Pipeline
from imblearn.pipeline import Pipeline as ImbPipeline
from sklearn.decomposition import PCA
from imblearn.over_sampling import SMOTE, BorderlineSMOTE
from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving pivoted_df.csv to pivoted_df.csv
```

Load the dataframe in, inspect the data.

In [3]:

```
pivoted_df = pd.read_csv('pivoted_df.csv', index_col=0)
```

In [4]:

```
pivoted_df.head()
```

Out[4]:

	season	Age	Throws	Surgery	AB_release_speed_weighted_avg	CH_release_speed_weig
0	2008	37.0	1	0.0	0.0	ε
1	2009	38.0	1	0.0	0.0	ε
2	2010	39.0	1	0.0	0.0	ε
3	2011	40.0	1	0.0	0.0	ε
4	2012	41.0	1	0.0	0.0	ε

5 rows × 130 columns

In [5]:

```
pivoted_df.shape
```

Out[5]:

```
(3688, 130)
```

In [6]:
```
pivoted_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3688 entries, 0 to 3687
Columns: 130 entries, season to SV_vz0_weighted_avg
dtypes: float64(128), int64(2)
memory usage: 3.7 MB
```

In [7]:
```
pivoted_df['Surgery'].value_counts()
```

Out[7]:
```
0.0    2772
1.0     916
Name: Surgery, dtype: int64
```

Time to start modeling! Split target and features and make a baseline model.

In [8]:
```
y = pivoted_df['Surgery']
X = pivoted_df.drop('Surgery', axis=1)
```

In [9]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
```

In [10]:

```python
#Make a pipeline to simplify process
logreg_pipeline = Pipeline([
    ('scale', StandardScaler()),
    ('logreg', LogisticRegression(solver='liblinear'))
])

# Define parameter grid to search
param_grid = {
    'logreg__C': [0.001, 0.01, 0.1, 1, 10, 100],  # Regularization str
    'logreg__penalty': ['l1', 'l2']  # Norm used in the penalization
}

# Initialize GridSearchCV with pipeline, parameter grid, and scoring m
grid_search = GridSearchCV(logreg_pipeline, param_grid, cv=5, scoring=

# Assuming X_train and y_train are already defined
grid_search.fit(X_train, y_train)

# Best parameters found
print("Best parameters: ", grid_search.best_params_)

# Best cross-validation score
print("Best cross-validation score: {:.2f}".format(grid_search.best_sc

# Test set score using the best parameters
print("Test set score: {:.2f}".format(grid_search.score(X_test, y_test
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/svm/_base.py:1244: Conver
genceWarning: Liblinear failed to converge, increase the number of iterat
ions.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/svm/_base.py:1244: Conver
genceWarning: Liblinear failed to converge, increase the number of iterat
ions.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/svm/_base.py:1244: Conver
genceWarning: Liblinear failed to converge, increase the number of iterat
ions.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/svm/_base.py:1244: Conver
genceWarning: Liblinear failed to converge, increase the number of iterat
ions.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/svm/_base.py:1244: Conver
genceWarning: Liblinear failed to converge, increase the number of iterat
ions.
  warnings.warn(

Best parameters:  {'logreg__C': 10, 'logreg__penalty': 'l1'}
Best cross-validation score: 0.76
Test set score: 0.77
```

In [11]:
```
logreg_pipeline = Pipeline([
    ('scale', StandardScaler()),
    ('logreg', LogisticRegression(penalty='l1', C=10.0, solver='liblin
])
```

In [12]:
```
logreg_pipeline.fit(X_train, y_train)
```

Out[12]:
```
Pipeline(steps=[('scale', StandardScaler()),
                ('logreg',
                 LogisticRegression(C=10.0, penalty='l1', solver='libline
ar'))])
```

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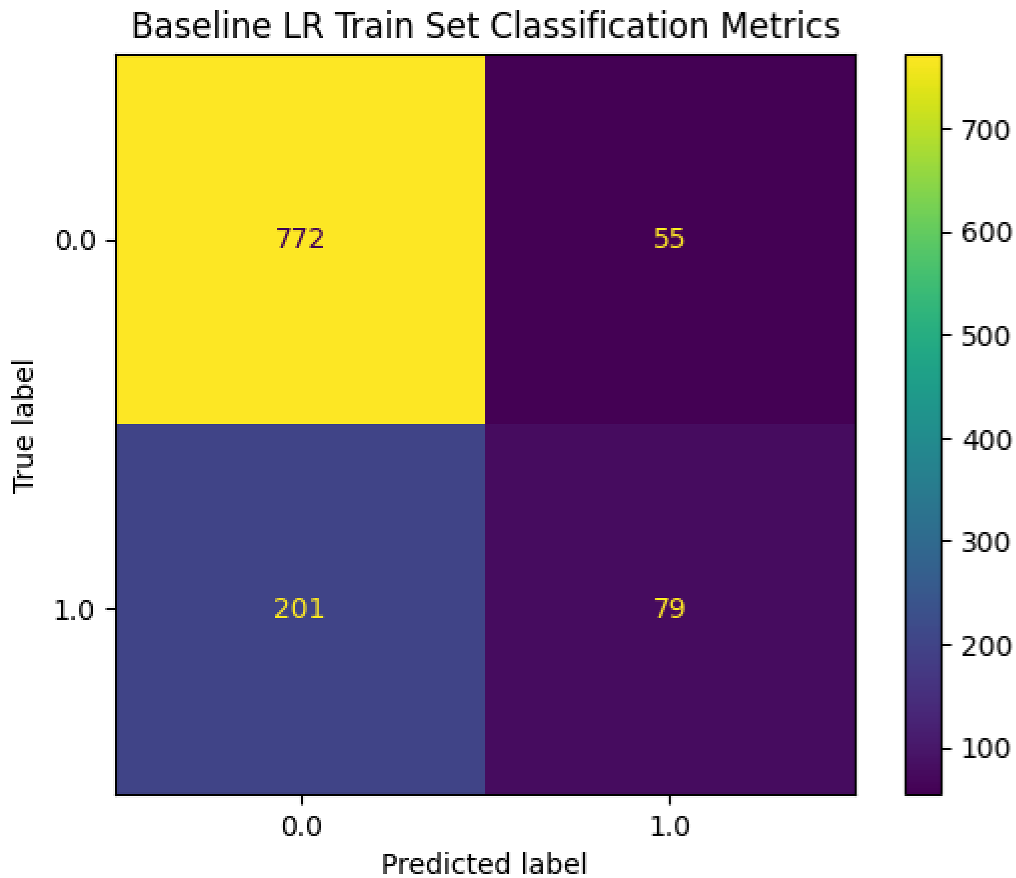
In [13]:
```
logreg_pipeline.score(X_test, y_test)
```

Out[13]:
```
0.7687443541102078
```

In [14]:
```
y_pred = logreg_pipeline.predict(X_test)
```

In [15]:

```
ConfusionMatrixDisplay.from_predictions(y_test, y_pred)
plt.title('Baseline LR Train Set Classification Metrics')
plt.show()
print(classification_report(y_test, y_pred))
```




```
              precision    recall  f1-score   support

         0.0       0.79      0.93      0.86       827
         1.0       0.59      0.28      0.38       280

    accuracy                           0.77      1107
   macro avg       0.69      0.61      0.62      1107
weighted avg       0.74      0.77      0.74      1107
```

Dataset is imbalanced, need to adjust. Should also focus on Recall score since this is a medical issue (better to have False Positive than True Negative!)

In [16]:

```
y = pivoted_df['Surgery']
X = pivoted_df.drop('Surgery', axis=1)
```

In [17]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
```

In [18]:

```
# Set up pipeline
weight_logreg_pipeline = Pipeline([
    ('scale', StandardScaler()),
    ('logreg', LogisticRegression(solver='liblinear'))
])

# Define the parameter grid to search over, including class weights
param_grid = {
    'logreg__C': [0.01, 0.1, 1, 10],
    'logreg__penalty': ['l1', 'l2'],
    'logreg__class_weight': [None, 'balanced', {0: 1, 1: 2}, {0: 1, 1:
    'logreg__max_iter': [5000],
    'logreg__tol': [0.01]
}

# Create a scoring function that focuses on recall for the positive cl
recall_scorer = make_scorer(recall_score, pos_label=1)

# Initialize GridSearch with pipeline, param grid, and recall
grid_search = GridSearchCV(weight_logreg_pipeline, param_grid, cv=5, s

# Fit the grid search to the data
grid_search.fit(X_train, y_train)

# Print the best parameters found and the best recall score
print("Best parameters: ", grid_search.best_params_)
print("Best cross-validation recall score: {:.2f}".format(grid_search.

# Evaluate the best model on the test set
best_model = grid_search.best_estimator_
y_pred = best_model.predict(X_test)
print("Test set recall score: {:.2f}".format(recall_score(y_test, y_pr
```

```
Best parameters:  {'logreg__C': 0.01, 'logreg__class_weight': {0: 1, 1:
5}, 'logreg__max_iter': 5000, 'logreg__penalty': 'l1', 'logreg__tol': 0.0
1}
Best cross-validation recall score: 0.87
Test set recall score: 0.85
```

In [19]:

```
best_model.fit(X_train, y_train)
```

Out[19]:

```
Pipeline(steps=[('scale', StandardScaler()),
                ('logreg',
                 LogisticRegression(C=0.01, class_weight={0: 1, 1: 5},
                                    max_iter=5000, penalty='l1',
                                    solver='liblinear', tol=0.01))])
```

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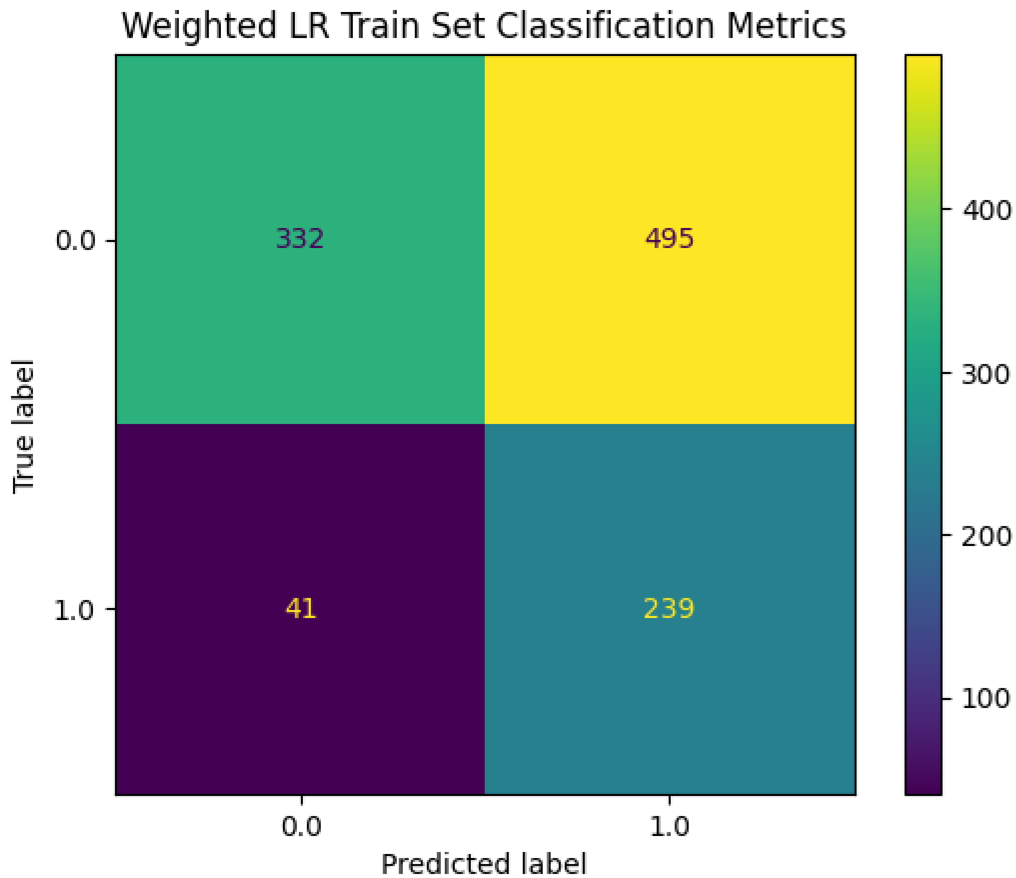
In [20]:
```
best_model.score(X_test, y_test)
```
Out[20]:
```
0.5158084914182475
```

In [21]:
```
y_pred = best_model.predict(X_test)
```

In [22]:
```
ConfusionMatrixDisplay.from_predictions(y_test, y_pred)
plt.title('Weighted LR Train Set Classification Metrics')
plt.show()
print(classification_report(y_test, y_pred))
```




```
              precision    recall  f1-score   support

         0.0       0.89      0.40      0.55       827
         1.0       0.33      0.85      0.47       280

    accuracy                           0.52      1107
   macro avg       0.61      0.63      0.51      1107
weighted avg       0.75      0.52      0.53      1107
```

Much better model. False Negatives is low, other classes much higher.

In [69]:

```
coef = best_model['logreg'].coef_
```

In [70]:

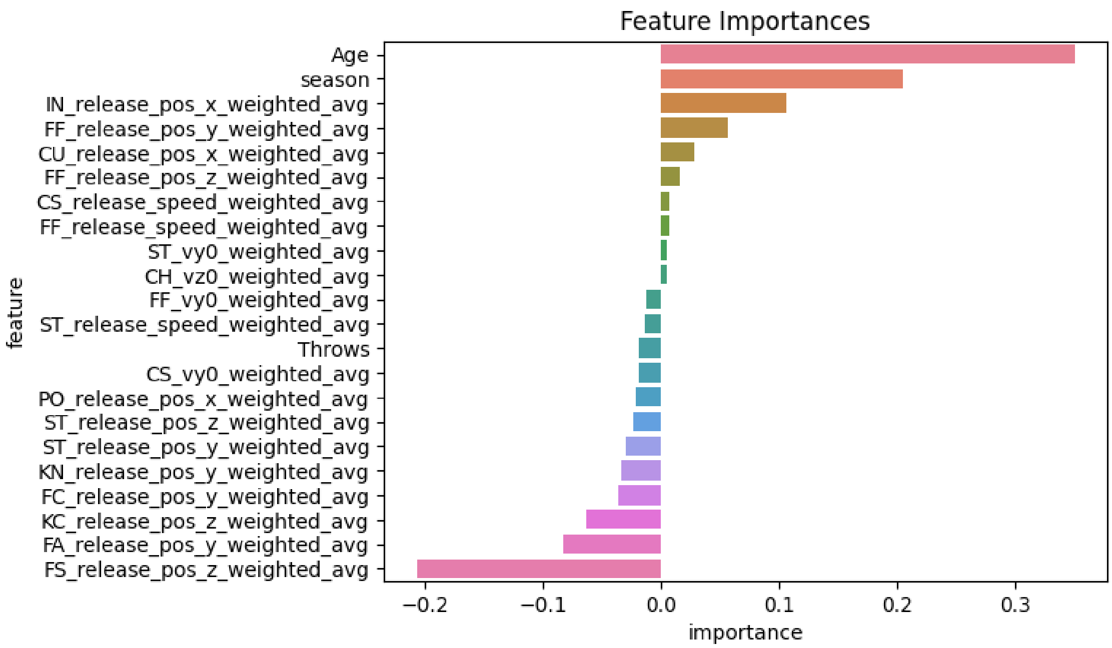
```
features = pivoted_df.columns

zipped = zip(features, coef[0])
sorted_pairs = sorted(zipped, key=lambda x: x[1], reverse=True)
sorted_pairs

feature_importances = pd.DataFrame(sorted_pairs, columns=['feature', '
feature_importances = feature_importances[abs(feature_importances['imp
```

In [71]:

```
sns.barplot(x='importance', y='feature', data=feature_importances, hue
plt.title('Feature Importances')
plt.show()
```



Need to update feature names so they can be understood more easily.

In [72]:

```
feature_importances
```

Out[72]:

	feature	importance
0	Age	0.350397
1	season	0.204704
2	IN_release_pos_x_weighted_avg	0.106614
3	FF_release_pos_y_weighted_avg	0.056850
4	CU_release_pos_x_weighted_avg	0.028929
5	FF_release_pos_z_weighted_avg	0.015752
6	CS_release_speed_weighted_avg	0.007832
7	FF_release_speed_weighted_avg	0.006973
8	ST_vy0_weighted_avg	0.005001
9	CH_vz0_weighted_avg	0.004601
117	FF_vy0_weighted_avg	-0.012434
118	ST_release_speed_weighted_avg	-0.013466
119	Throws	-0.018221
120	CS_vy0_weighted_avg	-0.018479
121	PO_release_pos_x_weighted_avg	-0.020661
122	ST_release_pos_z_weighted_avg	-0.024097
123	ST_release_pos_y_weighted_avg	-0.029266
124	KN_release_pos_y_weighted_avg	-0.033056
125	FC_release_pos_y_weighted_avg	-0.036304
126	KC_release_pos_z_weighted_avg	-0.063441
127	FA_release_pos_y_weighted_avg	-0.082745
128	FS_release_pos_z_weighted_avg	-0.206523

In [73]:

```
# This will rename the index if 'feature' is actually set as the index
feature_importances = feature_importances.set_index('feature')  # Make
feature_importances = feature_importances.rename(index={
    'season': 'Season',
    'IN_release_pos_x_weighted_avg': 'Intentional Walk Release Positio
    'FF_release_pos_y_weighted_avg': 'Fastball Release Position Y-dime
    'CU_release_pos_x_weighted_avg': 'Curveball Release Position X-dim
    'FF_release_pos_z_weighted_avg': 'Fastball Release Position Z-dime
    'CU_release_pos_z_weighted_avg': 'Curveball Release Position Z-dim
    'CS_release_speed_weighted_avg': 'Slow Curve Release Speed avg.',
    'FF_release_speed_weighted_avg': 'Fastball Release Speed avg.',
    'CU_release_speed_weighted_avg': 'Curveball Release Speed avg.',
    'ST_vy0_weighted_avg': 'Sweeper Velocity Y-dimension avg.',
    'CH_vz0_weighted_avg': 'Changeup Velocity Z-dimension avg.',
    'FF_vy0_weighted_avg': 'Fastball Velocity Y-dimension avg.',
    'ST_release_speed_weighted_avg': 'Sweeper Release Speed avg.',
    'CS_vy0_weighted_avg': 'Slow Curve Velocity Y-dimension avg.',
    'PO_release_pos_x_weighted_avg': 'Pick-off Release Position X-dime
    'ST_release_pos_z_weighted_avg': 'Sweeper Release Position Z-dimer
    'ST_release_pos_y_weighted_avg': 'Sweeper Release Position Y-dimer
    'KN_release_pos_y_weighted_avg': 'Knuckleball Release Position Y-c
    'FC_release_pos_y_weighted_avg': 'Cutter Release Position Y-dimens
    'KC_release_pos_z_weighted_avg': 'Knucklecurve Release Position Z-
    'FA_release_pos_y_weighted_avg': '4-seam Fastball Release Positior
    'FS_release_pos_z_weighted_avg': 'Split-finger Release Position Z-

})
```

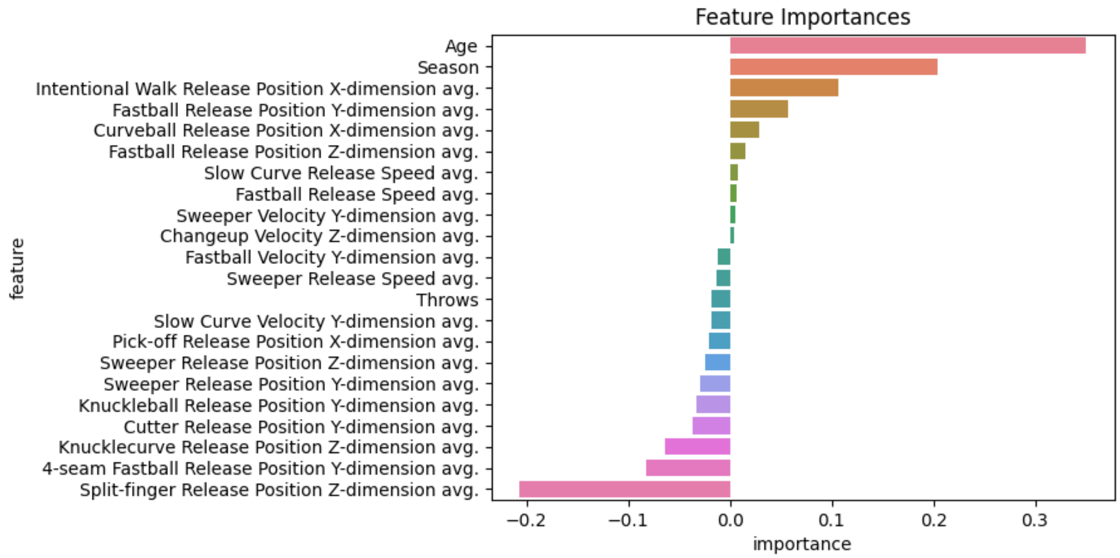
In [74]:

```
feature_importances
```

Out[74]:

feature	importance
Age	0.350397
Season	0.204704
Intentional Walk Release Position X-dimension avg.	0.106614
Fastball Release Position Y-dimension avg.	0.056850
Curveball Release Position X-dimension avg.	0.028929
Fastball Release Position Z-dimension avg.	0.015752
Slow Curve Release Speed avg.	0.007832
Fastball Release Speed avg.	0.006973
Sweeper Velocity Y-dimension avg.	0.005001
Changeup Velocity Z-dimension avg.	0.004601
Fastball Velocity Y-dimension avg.	-0.012434
Sweeper Release Speed avg.	-0.013466
Throws	-0.018221
Slow Curve Velocity Y-dimension avg.	-0.018479
Pick-off Release Position X-dimension avg.	-0.020661
Sweeper Release Position Z-dimension avg.	-0.024097
Sweeper Release Position Y-dimension avg.	-0.029266
Knuckleball Release Position Y-dimension avg.	-0.033056
Cutter Release Position Y-dimension avg.	-0.036304
Knucklecurve Release Position Z-dimension avg.	-0.063441
4-seam Fastball Release Position Y-dimension avg.	-0.082745
Split-finger Release Position Z-dimension avg.	-0.206523

In [75]:
```
sns.barplot(x='importance', y='feature', data=feature_importances, hue
plt.title('Feature Importances')
plt.show()
```



This shows the features that have the most impact in predicting 1.0 surgery (positive and negative)

Decision Tree Classifier, baseline model.

In [ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
```

In [ ]:
```
tree_clf = DecisionTreeClassifier(criterion='gini', max_depth=5)
tree_clf.fit(X_train, y_train)
```

Out[31]:
```
DecisionTreeClassifier(max_depth=5)
```

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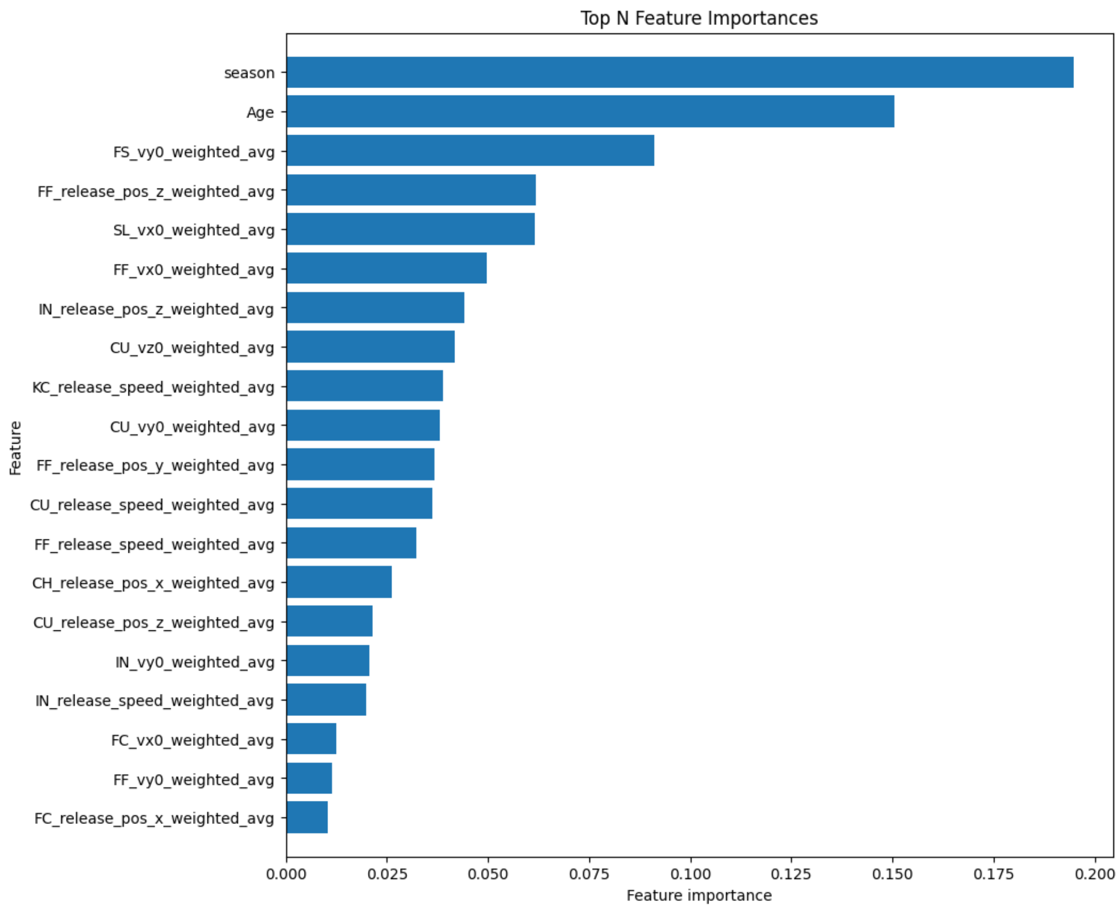
In [ ]:

```
def plot_feature_importances(model, n_top_features=20):
    importances = model.feature_importances_
    indices = np.argsort(importances)[-n_top_features:]
    plt.figure(figsize=(10,10))
    plt.title('Top N Feature Importances')
    plt.barh(range(n_top_features), importances[indices], align='cente
    plt.yticks(range(n_top_features), [X_train.columns[i] for i in inc
    plt.xlabel('Feature importance')
    plt.ylabel('Feature')
    plt.ylim(-1, n_top_features)

plot_feature_importances(tree_clf, n_top_features=20)
plt.show()
```



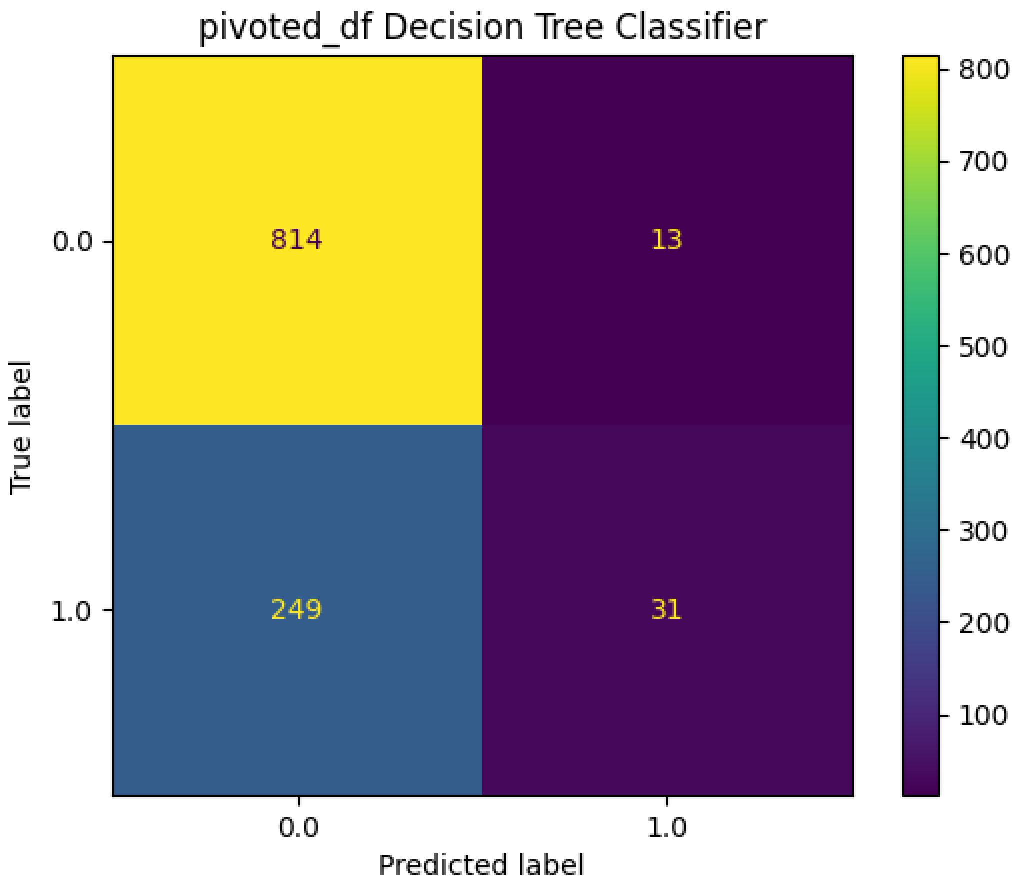
In [ ]:

```
pred = tree_clf.predict(X_test)
```

In [ ]:

```
pred = tree_clf.predict(X_test)

ConfusionMatrixDisplay.from_predictions(y_test, pred)
plt.title('pivoted_df Decision Tree Classifier')
plt.show()
print(classification_report(y_test, pred))
```




```
              precision    recall  f1-score   support

         0.0       0.77      0.98      0.86       827
         1.0       0.70      0.11      0.19       280

    accuracy                           0.76      1107
   macro avg       0.74      0.55      0.53      1107
weighted avg       0.75      0.76      0.69      1107
```

Terrible for TP and FP. Need to adjust. Features are interesting. Mostly fastball, curveball, some slider and split-finger.

In [ ]:

```
y = pivoted_df['Surgery']
X = pivoted_df.drop('Surgery', axis=1)
```

In [ ]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
```

In [ ]:

```
param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [5, 10, 15, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'class_weight': ['balanced', {0:1, 1:2}, {0:1, 1:3}]
}

tree_clf = DecisionTreeClassifier()
scorer = make_scorer(recall_score)
grid_search = GridSearchCV(estimator=tree_clf, param_grid=param_grid,
grid_search.fit(X_train, y_train)

print("Best parameters:", grid_search.best_params_)
print("Best score:", grid_search.best_score_)

best_tree = grid_search.best_estimator_
y_pred = best_tree.predict(X_test)
print("Test recall score:", recall_score(y_test, y_pred))
```

```
Best parameters: {'class_weight': 'balanced', 'criterion': 'gini', 'max_d
epth': 5, 'min_samples_leaf': 2, 'min_samples_split': 10}
Best score: 0.6524852362204725
Test recall score: 0.7607142857142857
```

In [ ]:

```
best_tree.fit(X_train, y_train)
```

Out[38]:

```
DecisionTreeClassifier(class_weight='balanced', max_depth=5, min_samples_
leaf=2,
                       min_samples_split=10)
```

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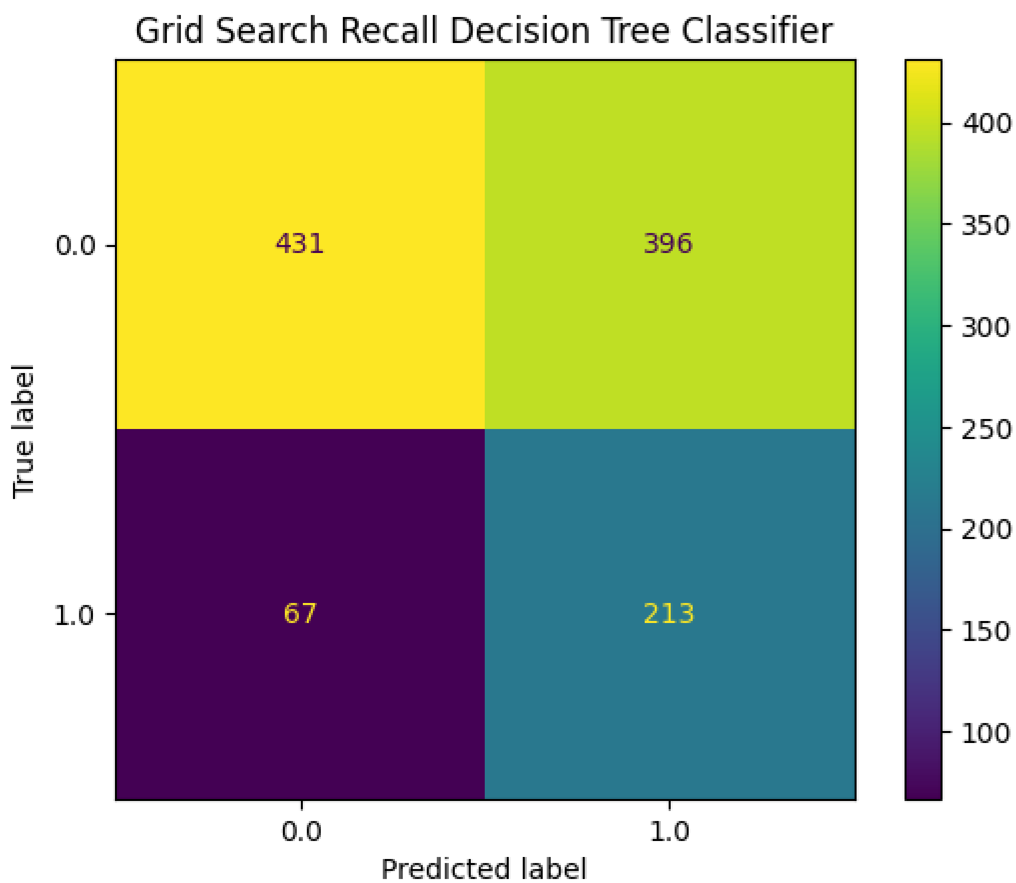
In [ ]:

```
pred = best_tree.predict(X_test)
```

In [ ]:

```
ConfusionMatrixDisplay.from_predictions(y_test, pred)
plt.title('Grid Search Recall Decision Tree Classifier')
plt.show()
print(classification_report(y_test, pred))
```




```
              precision    recall  f1-score   support

         0.0       0.87      0.52      0.65       827
         1.0       0.35      0.76      0.48       280

    accuracy                           0.58      1107
   macro avg       0.61      0.64      0.56      1107
weighted avg       0.74      0.58      0.61      1107
```

The Logistic Regression model with adjusted class weights performed the best.

In [ ]:

```

```