In [1]:
```
import pybaseball as pyb
from pybaseball import statcast, pitching_stats, playerid_lookup, statcast_pitcher, statcast_pitcher_pitch_arsena
import numpy as np
import math
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import glob
import os
import re
import unicodedata
from datetime import datetime
from itertools import groupby
from operator import itemgetter
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_score
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.metrics import classification_report
from sklearn.pipeline import Pipeline
#from imblearn.over_sampling import SMOTE
from catboost import CatBoostClassifier
```

```
C:\Users\johns\anaconda3\Lib\site-packages\pandas\core\arrays\masked.py:60: UserWarning: Pandas requires version '1.
3.6' or newer of 'bottleneck' (version '1.3.5' currently installed).
  from pandas.core import (
```

In [30]:
```
pip install catboost
```

```
Collecting catboost
  Obtaining dependency information for catboost from https://files.pythonhosted.org/packages/e8/37/3afd3c02798734e
fcd7840bfa872d3efc06f5d5c92f9613fea3ff5b4311f/catboost-1.2.3-cp311-cp311-win_amd64.whl.metadata (https://files.pyt
honhosted.org/packages/e8/37/3afd3c02798734efcd7840bfa872d3efc06f5d5c92f9613fea3ff5b4311f/catboost-1.2.3-cp311-cp3
11-win_amd64.whl.metadata)
  Downloading catboost-1.2.3-cp311-cp311-win_amd64.whl.metadata (1.2 kB)
Collecting graphviz (from catboost)
  Obtaining dependency information for graphviz from https://files.pythonhosted.org/packages/de/5e/fcbb22c68208d39
edff467809d06c9d81d7d27426460ebc598e55130c1aa/graphviz-0.20.1-py3-none-any.whl.metadata (https://files.pythonhoste
d.org/packages/de/5e/fcbb22c68208d39edff467809d06c9d81d7d27426460ebc598e55130c1aa/graphviz-0.20.1-py3-none-any.wh
l.metadata)
  Downloading graphviz-0.20.1-py3-none-any.whl.metadata (12 kB)
Requirement already satisfied: matplotlib in c:\users\johns\anaconda3\lib\site-packages (from catboost) (3.7.2)
Requirement already satisfied: numpy>=1.16.0 in c:\users\johns\anaconda3\lib\site-packages (from catboost) (1.24.
3)
Requirement already satisfied: pandas>=0.24 in c:\users\johns\anaconda3\lib\site-packages (from catboost) (2.2.0)
Requirement already satisfied: scipy in c:\users\johns\anaconda3\lib\site-packages (from catboost) (1.11.1)
Requirement already satisfied: plotly in c:\users\johns\anaconda3\lib\site-packages (from catboost) (5.9.0)
Requirement already satisfied: six in c:\users\johns\anaconda3\lib\site-packages (from catboost) (1.16.0)
```

In [2]:
```
complete_100_df = pd.read_csv('complete_100_df.csv', index_col=0)
```

In [24]:
```
complete_100_df
```

	wainwright								
4	adam wainwright	41.0	425794	2023	FF	176	85.715341	-1.22943	
...	...	...	...	...	...	...	...	...	
21386	jeff samardzija	23.0	502188	2008	FS	99	86.302020	-2.33323	
21387	jeff samardzija	23.0	502188	2008	IN	6	68.650000	-2.86833	
21388	jeff samardzija	23.0	502188	2008	PO	1	84.900000	-3.12000	
21389	jeff samardzija	23.0	502188	2008	SI	83	95.686747	-2.49554	
21390	jeff samardzija	23.0	502188	2008	SL	45	83.173333	-2.40533	

21391 rows × 16 columns

In [26]:
```
1 complete_100_df['Surgery'].value_counts()
```

Out[26]:
```
Surgery
0.0    16389
1.0     5002
Name: count, dtype: int64
```

In [23]:
```
1 wainwright_df = complete_100_df[complete_100_df['Name'] == 'adam wainwright']
2 wainwright_df
```

Out[23]:

	Name	Age	pitcher	season	pitch_type	season_total_count_by_pitch_type	release_speed_weighted_avg	release_pos_x_weighted_avg
0	adam wainwright	41.0	425794	2023	CH	91	81.504396	-1.330769
1	adam wainwright	41.0	425794	2023	CS	3	65.733333	-1.520000
2	adam wainwright	41.0	425794	2023	CU	545	71.502569	-1.242385
3	adam wainwright	41.0	425794	2023	FC	403	82.861290	-1.215806
4	adam wainwright	41.0	425794	2023	FF	176	85.715341	-1.229432
...	...	...	...	...	...	...	...	...
20627	adam wainwright	26.0	425794	2008	FC	395	85.016456	-1.160532
20628	adam wainwright	26.0	425794	2008	FF	101	90.300990	-0.982178
20629	adam wainwright	26.0	425794	2008	IN	4	72.800000	-2.007500
20630	adam wainwright	26.0	425794	2008	PO	2	79.800000	-1.285000
20631	adam wainwright	26.0	425794	2008	SI	879	91.307281	-1.113902

95 rows × 16 columns

In [13]:
```
# Correcting the approach to ensure 'Surgery' is 1.0 from the surgery year onwards, including the surgery year its
complete_100_df['Surgery'] = complete_100_df.apply(lambda row: 1.0 if row['season'] >= row['TJ Surgery Year'] else

complete_100_df
```

Out[13]:

avg	release_pos_y_weighted_avg	release_pos_z_weighted_avg	vx0_weighted_avg	vy0_weighted_avg	vz0_weighted_avg	Throws	Surgery	TJ Surgery Year
1769	53.993407	6.145385	4.245696	-118.558747	-4.409017	1	1.0	2011.0
1000	54.506667	6.410000	-0.628298	-95.480064	4.033457	1	1.0	2011.0
1385	54.176661	6.286018	0.256395	-103.981304	0.991996	1	1.0	2011.0
1806	54.015236	6.287072	3.112750	-120.682959	-3.743577	1	1.0	2011.0
1432	53.974261	6.250625	2.547035	-124.786559	-4.628487	1	1.0	2011.0
...	...	...	...	...	...	...	...	...
1232	54.500000	6.583636	6.802709	-126.226226	-5.324773	1	0.0	NaN
1333	54.500000	6.941667	-1.886758	-100.577489	0.512961	1	0.0	NaN
1000	54.500000	6.670000	-2.171512	-124.318167	7.649149	1	0.0	NaN
1542	54.500000	6.357831	9.600795	-139.918356	-4.335994	1	0.0	NaN
1333	54.500000	6.608444	5.891971	-121.694904	-2.673257	1	0.0	NaN

This ensures that we are only counting for 'Surgery' for the year of surgery, and all years going forward.

In [17]:
```
filtered_rows = complete_100_df[(complete_100_df['Surgery'] == 1.0) & (complete_100_df['TJ Surgery Year'].isna())
filtered_rows
```

Out[17]:

Name	Age	pitcher	season	pitch_type	season_total_count_by_pitch_type	release_speed_weighted_avg	release_pos_x_weighted_avg	release_p

In [19]:
```
pd.set_option('display.max_rows', None)
```

In [22]:
```
pd.reset_option('display.max_rows')
```

In [27]:
```
complete_100_df['TJ Surgery Year'].fillna(0.0, inplace=True)
```

```
C:\Users\johns\AppData\Local\Temp\ipykernel_8568\550959113.py:1: FutureWarning: A value is trying to be set on a cop
y of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which
we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or
df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  complete_100_df['TJ Surgery Year'].fillna(0.0, inplace=True)
```

In [7]:
```
"""
# Fill NaN in 'TJ Surgery Year' with 0.0
complete_100_df['TJ Surgery Year'].fillna(0.0, inplace=True)

# Update 'Surgery' based on 'season' and 'TJ Surgery Year'
complete_100_df['Surgery'] = complete_100_df.apply(
    lambda row: 1.0 if row['season'] >= row['TJ Surgery Year'] and row['TJ Surgery Year'] != 0 else 0.0, axis=1
)

# Verify the changes
print(complete_100_df[['Name', 'season', 'TJ Surgery Year', 'Surgery']].head())

# Check the value counts again
print(complete_100_df['Surgery'].value_counts())
"""
```

```
C:\Users\johns\AppData\Local\Temp\ipykernel_32520\2928425957.py:2: FutureWarning: A value is trying to be set on a c
opy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which
we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or
df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  complete_100_df['TJ Surgery Year'].fillna(0.0, inplace=True)

             Name  season  TJ Surgery Year  Surgery
0  adam wainwright    2023           2011.0      1.0
1  adam wainwright    2023           2011.0      1.0
2  adam wainwright    2023           2011.0      1.0
3  adam wainwright    2023           2011.0      1.0
4  adam wainwright    2023           2011.0      1.0
Surgery
0.0    16389
1.0     5002
Name: count, dtype: int64
```

In [28]:
```
complete_100_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 21391 entries, 0 to 21390
Data columns (total 16 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   Name                              21391 non-null  object
 1   Age                               21391 non-null  float64
 2   pitcher                           21391 non-null  int64
 3   season                            21391 non-null  int64
 4   pitch_type                        21391 non-null  object
 5   season_total_count_by_pitch_type  21391 non-null  int64
 6   release_speed_weighted_avg        21391 non-null  float64
 7   release_pos_x_weighted_avg        21391 non-null  float64
 8   release_pos_y_weighted_avg        21391 non-null  float64
 9   release_pos_z_weighted_avg        21391 non-null  float64
 10  vx0_weighted_avg                  21391 non-null  float64
 11  vy0_weighted_avg                  21391 non-null  float64
 12  vz0_weighted_avg                  21391 non-null  float64
 13  Throws                            21391 non-null  int64
 14  Surgery                           21391 non-null  float64
 15  TJ Surgery Year                   21391 non-null  float64
dtypes: float64(10), int64(4), object(2)
memory usage: 2.8+ MB
```

Can probably drop 'Name' and 'TJ Surgery Year' columns

In [66]:
```
funky_df = complete_100_df.drop(columns=['Name', 'TJ Surgery Year'])
```

In [67]:
```
1 funky_df
```

Out[67]:

	Age	pitcher	season	pitch_type	season_total_count_by_pitch_type	release_speed_weighted_avg	release_pos_x_weighted_avg	release_pos
0	41.0	425794	2023	CH	91	81.504396	-1.330769	
1	41.0	425794	2023	CS	3	65.733333	-1.520000	
2	41.0	425794	2023	CU	545	71.502569	-1.242385	
3	41.0	425794	2023	FC	403	82.861290	-1.215806	
4	41.0	425794	2023	FF	176	85.715341	-1.229432	
...	...	...	...	...	...	...	...	...
21386	23.0	502188	2008	FS	99	86.302020	-2.333232	
21387	23.0	502188	2008	IN	6	68.650000	-2.868333	
21388	23.0	502188	2008	PO	1	84.900000	-3.120000	
21389	23.0	502188	2008	SI	83	95.686747	-2.495542	
21390	23.0	502188	2008	SL	45	83.173333	-2.405333	

21391 rows × 14 columns

In [68]:
```
1 funky_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 21391 entries, 0 to 21390
Data columns (total 14 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   Age                               21391 non-null  float64
 1   pitcher                           21391 non-null  int64
 2   season                            21391 non-null  int64
 3   pitch_type                        21391 non-null  object
 4   season_total_count_by_pitch_type  21391 non-null  int64
 5   release_speed_weighted_avg        21391 non-null  float64
 6   release_pos_x_weighted_avg        21391 non-null  float64
 7   release_pos_y_weighted_avg        21391 non-null  float64
 8   release_pos_z_weighted_avg        21391 non-null  float64
 9   vx0_weighted_avg                  21391 non-null  float64
 10  vy0_weighted_avg                  21391 non-null  float64
 11  vz0_weighted_avg                  21391 non-null  float64
 12  Throws                            21391 non-null  int64
 13  Surgery                           21391 non-null  float64
dtypes: float64(9), int64(4), object(1)
memory usage: 2.4+ MB
```

In [69]:
```
1 funky_df['pitch_type'].value_counts()
```

Out[69]:
```
pitch_type
FF    3641
CH    3356
SI    3286
SL    2775
CU    2670
FC    1625
IN    1605
PO    1045
KC     525
FS     390
ST     129
FA     124
EP      90
CS      52
SV      29
KN      25
AB      14
SC      10
Name: count, dtype: int64
```

In [70]:
```
1 funky_df['release_pos_y_weighted_avg'].value_counts()
```

Out[70]:
```
release_pos_y_weighted_avg
54.500000    14019
54.580000        7
54.780000        6
54.360000        6
54.160000        6
             ...
54.247143        1
54.289964        1
54.083586        1
54.099168        1
55.031195        1
Name: count, Length: 6936, dtype: int64
```

In [58]:
```
1 fa_rows = funky_df[funky_df['pitch_type'] == 'FA']
```

In [59]:
```
1 fa_rows
```

Out[59]:

	Age	pitcher	season	pitch_type	season_total_count_by_pitch_type	release_speed_weighted_avg	release_pos_x_weighted_avg	release_pos
67	35.0	477132	2023	FA	1	64.700000	2.520000	
168	33.0	543101	2023	FA	1	77.500000	-1.810000	
196	32.0	543475	2023	FA	1	54.800000	-2.500000	
1869	37.0	425844	2021	FA	9	80.777778	-1.248889	
2892	36.0	425844	2020	FA	57	78.835088	-1.174035	
...	...	...	...	...	...	...	...	
20964	23.0	444836	2008	FA	2	86.550000	2.985000	
21019	27.0	446454	2008	FA	7	89.100000	-2.560000	
21211	25.0	456043	2008	FA	20	89.060000	2.436500	
21219	22.0	456501	2008	FA	1	91.600000	-2.200000	
21228	26.0	456589	2008	FA	6	90.483333	-1.515000	

124 rows × 14 columns

Try condensing pitch_type before the pivot and compare.

In [60]:
```
1 condensed_pitch_type_df = funky_df
```

In [61]:
```
1 pitch_type_mapping = {
2     'FF': 'FB', 'SI': 'FB', 'FC': 'FB', 'FA': 'FB',
3     'CH': 'OS', 'FS': 'OS', 'FO': 'OS', 'SC': 'OS', 'PO': 'OS',
4     'CU': 'BB', 'KC': 'BB', 'CS': 'BB',
5     'SL': 'SB', 'ST': 'SB', 'SV': 'SB', 'KN': 'SB',
6     'EP': 'OT', 'AB': 'OT', 'IN': 'OT'
7 }
8
9 condensed_pitch_type_df['pitch_type_group'] = condensed_pitch_type_df['pitch_type'].map(pitch_type_mapping)
```

In [63]:
```
1  grouped_df = condensed_pitch_type_df.groupby(['Age', 'pitcher', 'season', 'pitch_type_group']).agg(
2      season_total_count_by_pitch_type=('season_total_count_by_pitch_type', 'sum'),
3      release_speed_weighted_avg=('release_speed_weighted_avg', 'mean'),
4      release_pos_x_weighted_avg=('release_pos_x_weighted_avg', 'mean'),
5      release_pos_y_weighted_avg=('release_pos_y_weighted_avg', 'mean'),
6      release_pos_z_weighted_avg=('release_pos_z_weighted_avg', 'mean'),
7      vx0_weighted_avg=('vx0_weighted_avg', 'mean'),
8      vy0_weighted_avg=('vy0_weighted_avg', 'mean'),
9      vz0_weighted_avg=('vz0_weighted_avg', 'mean'),
10     Throws=('Throws', 'first'),  # Assuming Throws doesn't change within groups
11     Surgery=('Surgery', 'first')  # Assuming Surgery doesn't change within groups
12 ).reset_index()
13
```

In [64]:
```
1 grouped_df
```

Out[64]:

	Age	pitcher	season	pitch_type_group	season_total_count_by_pitch_type	release_speed_weighted_avg	release_pos_x_weighted_avg	relea
0	19.0	518516	2009	BB	42	78.269048	3.856905	
1	19.0	518516	2009	FB	98	90.704035	3.717070	
2	19.0	518516	2009	OS	12	83.358333	3.658333	
3	19.0	518516	2009	OT	4	78.175000	3.642500	
4	19.0	605164	2012	BB	1	75.000000	-1.690000	
...	...	...	...	...	...	...	...	...
14707	47.0	119469	2010	OS	306	74.809477	3.145327	
14708	49.0	119469	2012	BB	90	69.217778	2.931333	
14709	49.0	119469	2012	FB	628	78.273372	3.087675	
14710	49.0	119469	2012	OS	301	72.568771	3.122791	
14711	49.0	119469	2012	OT	8	67.700000	3.633750	

14712 rows × 14 columns

In [65]:
```
1 grouped_df['release_pos_y_weighted_avg'].value_counts()
```

Out[65]:
```
release_pos_y_weighted_avg
54.500000    9540
54.160000       3
53.970000       3
53.980000       3
54.110000       3
               ...
54.281383       1
54.396867       1
53.962602       1
54.059634       1
55.724512       1
Name: count, Length: 5138, dtype: int64
```

In [72]:

```
def pivot_metrics(df, index_cols, pivot_col, value_cols):
    """
    Pivot the DataFrame for the specified pivot column.
    :param df: DataFrame to pivot.
    :param index_cols: List of columns to use as the index.
    :param pivot_col: Column to pivot on.
    :param value_cols: Columns whose values are to be spread across pivoted columns.
    :return: Pivoted DataFrame.
    """
    pivoted_dfs = []
    for value_col in value_cols:
        # Pivot each metric column separately and rename to include the pitch_type
        pivoted_df = df.pivot_table(index=index_cols, columns=pivot_col, values=value_col, aggfunc='first').reset_
        pivoted_df.columns = [f"{col}_{value_col}" if col not in index_cols else col for col in pivoted_df.column
        pivoted_dfs.append(pivoted_df)

    # Merge all the pivoted metric DataFrames on the index columns
    from functools import reduce
    final_df = reduce(lambda left, right: pd.merge(left, right, on=index_cols, how='outer'), pivoted_dfs)
    return final_df

# Define the base columns and the metrics you want to pivot
index_cols = ['pitcher', 'season', 'Age', 'Throws', 'Surgery']
pivot_col = 'pitch_type_group'
value_cols = ['release_speed_weighted_avg', 'release_pos_x_weighted_avg', 'release_pos_y_weighted_avg', 'release_

# Pivot the DataFrame
cond_pivoted_df = pivot_metrics(grouped_df, index_cols, pivot_col, value_cols)

cond_pivoted_df.head()
```

Out[72]:

	pitcher	season	Age	Throws	Surgery	BB_release_speed_weighted_avg	FB_release_speed_weighted_avg	OS_release_speed_weighted_avg	OT
0	110683	2008	37.0	1	0.0	75.425843	91.689850	81.458265	
1	110683	2009	38.0	1	0.0	78.181818	93.479869	85.012195	
2	110683	2010	39.0	1	0.0	74.666667	93.001617	84.025000	
3	110683	2011	40.0	1	0.0	76.885714	91.678506	83.846875	
4	110683	2012	41.0	1	0.0	76.427273	91.965592	83.001563	

5 rows × 40 columns

In [73]:
```
1 cond_pivoted_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3688 entries, 0 to 3687
Data columns (total 40 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   pitcher                         3688 non-null   int64
 1   season                          3688 non-null   int64
 2   Age                             3688 non-null   float64
 3   Throws                          3688 non-null   int64
 4   Surgery                         3688 non-null   float64
 5   BB_release_speed_weighted_avg   3059 non-null   float64
 6   FB_release_speed_weighted_avg   3688 non-null   float64
 7   OS_release_speed_weighted_avg   3562 non-null   float64
 8   OT_release_speed_weighted_avg   1610 non-null   float64
 9   SB_release_speed_weighted_avg   2793 non-null   float64
 10  BB_release_pos_x_weighted_avg   3059 non-null   float64
 11  FB_release_pos_x_weighted_avg   3688 non-null   float64
 12  OS_release_pos_x_weighted_avg   3562 non-null   float64
 13  OT_release_pos_x_weighted_avg   1610 non-null   float64
 14  SB_release_pos_x_weighted_avg   2793 non-null   float64
 15  BB_release_pos_y_weighted_avg   3059 non-null   float64
 16  FB_release_pos_y_weighted_avg   3688 non-null   float64
 17  OS_release_pos_y_weighted_avg   3562 non-null   float64
 18  OT_release_pos_y_weighted_avg   1610 non-null   float64
 19  SB_release_pos_y_weighted_avg   2793 non-null   float64
 20  BB_release_pos_z_weighted_avg   3059 non-null   float64
 21  FB_release_pos_z_weighted_avg   3688 non-null   float64
 22  OS_release_pos_z_weighted_avg   3562 non-null   float64
 23  OT_release_pos_z_weighted_avg   1610 non-null   float64
 24  SB_release_pos_z_weighted_avg   2793 non-null   float64
 25  BB_vx0_weighted_avg             3059 non-null   float64
 26  FB_vx0_weighted_avg             3688 non-null   float64
 27  OS_vx0_weighted_avg             3562 non-null   float64
 28  OT_vx0_weighted_avg             1610 non-null   float64
 29  SB_vx0_weighted_avg             2793 non-null   float64
 30  BB_vy0_weighted_avg             3059 non-null   float64
 31  FB_vy0_weighted_avg             3688 non-null   float64
 32  OS_vy0_weighted_avg             3562 non-null   float64
 33  OT_vy0_weighted_avg             1610 non-null   float64
 34  SB_vy0_weighted_avg             2793 non-null   float64
 35  BB_vz0_weighted_avg             3059 non-null   float64
 36  FB_vz0_weighted_avg             3688 non-null   float64
 37  OS_vz0_weighted_avg             3562 non-null   float64
 38  OT_vz0_weighted_avg             1610 non-null   float64
 39  SB_vz0_weighted_avg             2793 non-null   float64
dtypes: float64(37), int64(3)
memory usage: 1.1 MB
```

This condensed DF has 40 columns compared to before where I had 130 columns.

In [74]:
```
1 cond_pivoted_df.fillna(0.0, inplace=True)
```

In [75]:
```
1 cond_pivoted_df.to_csv('cond_pivoted_df.csv')
```

In [76]:
```
1 cond_groovy_df = cond_pivoted_df
```

In [77]:
```
1 cond_groovy_df.drop(columns=['pitcher'], inplace=True)
```

In [78]:
```
1 y = cond_groovy_df['Surgery']
2 X = cond_groovy_df.drop('Surgery', axis=1)
```

In [79]:
```
1 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

In [80]:

```
logreg_pipeline = Pipeline([
    ('scale', StandardScaler()),
    ('logreg', LogisticRegression(solver='liblinear'))
])

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

# Initialize GridSearchCV with the pipeline, parameter grid, and desired scoring metric
grid_search = GridSearchCV(logreg_pipeline, param_grid, cv=5, scoring='accuracy')

# 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_score_))

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

```
C:\Users\johns\anaconda3\Lib\site-packages\sklearn\svm\_base.py:1237: ConvergenceWarning: Liblinear failed to conver
ge, increase the number of iterations.
  warnings.warn(
C:\Users\johns\anaconda3\Lib\site-packages\sklearn\svm\_base.py:1237: ConvergenceWarning: Liblinear failed to conver
ge, increase the number of iterations.
  warnings.warn(
C:\Users\johns\anaconda3\Lib\site-packages\sklearn\svm\_base.py:1237: ConvergenceWarning: Liblinear failed to conver
ge, increase the number of iterations.
  warnings.warn(
C:\Users\johns\anaconda3\Lib\site-packages\sklearn\svm\_base.py:1237: ConvergenceWarning: Liblinear failed to conver
ge, increase the number of iterations.
  warnings.warn(
C:\Users\johns\anaconda3\Lib\site-packages\sklearn\svm\_base.py:1237: ConvergenceWarning: Liblinear failed to conver
ge, increase the number of iterations.
  warnings.warn(

Best parameters:  {'logreg__C': 1, 'logreg__penalty': 'l1'}
Best cross-validation score: 0.75
Test set score: 0.75
```

In [81]:

```
logreg_pipeline = Pipeline([
    ('scale', StandardScaler()),
    ('logreg', LogisticRegression(penalty='l1', C=1.0, solver='liblinear'))
])
```

In [82]:

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

Out[82]:

```
▸ Pipeline (https://scikit-learn.org/1.4/modules/generated/sklearn.pipeline.Pipeline.html)
  ▸ StandardScaler (https://scikit-learn.org/1.4/modules/generated/sklearn.preprocessing.StandardScaler.html)
  ▸ LogisticRegression (https://scikit-learn.org/1.4/modules/generated/sklearn.linear_model.LogisticRegression.html)
```

In [83]:

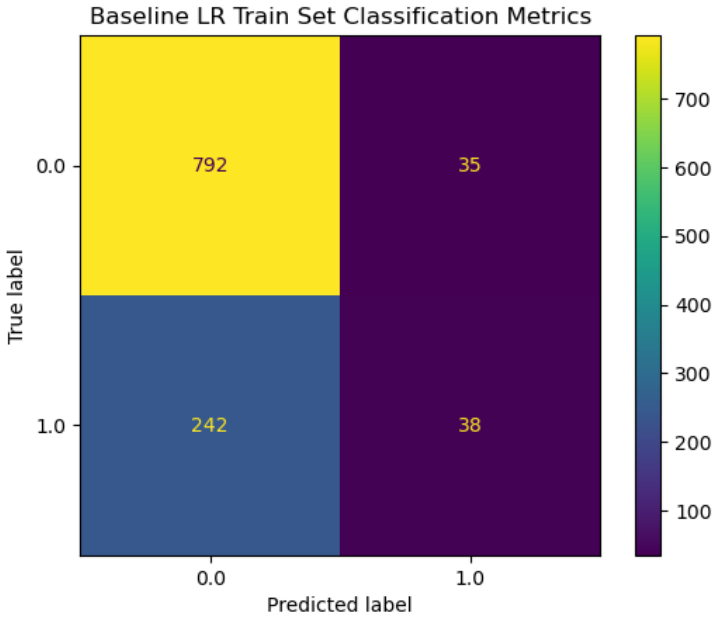
```
logreg_pipeline.score(X_test, y_test)
```

Out[83]: 0.7497741644083108

In [84]:

```
y_pred = logreg_pipeline.predict(X_test)
```

In [85]:
```
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       0.77      0.96      0.85       827
         1.0       0.52      0.14      0.22       280

    accuracy                           0.75      1107
   macro avg       0.64      0.55      0.53      1107
weighted avg       0.70      0.75      0.69      1107
```

recall score was even worse for this. Will try with SMOTE on google colab

In [ ]:
```

```

In [ ]:
```

```

In [31]:
```
def pivot_metrics(df, index_cols, pivot_col, value_cols):
    """
    Pivot the DataFrame for the specified pivot column.
    :param df: DataFrame to pivot.
    :param index_cols: List of columns to use as the index.
    :param pivot_col: Column to pivot on.
    :param value_cols: Columns whose values are to be spread across pivoted columns.
    :return: Pivoted DataFrame.
    """
    pivoted_dfs = []
    for value_col in value_cols:
        # Pivot each metric column separately and rename to include the pitch_type
        pivoted_df = df.pivot_table(index=index_cols, columns=pivot_col, values=value_col, aggfunc='first').reset_
        pivoted_df.columns = [f"{col}_{value_col}" if col not in index_cols else col for col in pivoted_df.column
        pivoted_dfs.append(pivoted_df)

    # Merge all the pivoted metric DataFrames on the index columns
    from functools import reduce
    final_df = reduce(lambda left, right: pd.merge(left, right, on=index_cols, how='outer'), pivoted_dfs)
    return final_df

# Define the base columns and the metrics you want to pivot
index_cols = ['pitcher', 'season', 'Age', 'Throws', 'Surgery']
pivot_col = 'pitch_type'
value_cols = ['release_speed_weighted_avg', 'release_pos_x_weighted_avg', 'release_pos_y_weighted_avg', 'release_

# Pivot the DataFrame
pivoted_df = pivot_metrics(funky_df, index_cols, pivot_col, value_cols)

pivoted_df.head()
```

Out[31]:

	pitcher	season	Age	Throws	Surgery	AB_release_speed_weighted_avg	CH_release_speed_weighted_avg	CS_release_speed_weighted_avg	CU
0	110683	2008	37.0	1	0.0	NaN	82.641530	NaN	
1	110683	2009	38.0	1	0.0	NaN	85.012195	NaN	
2	110683	2010	39.0	1	0.0	NaN	84.150000	NaN	
3	110683	2011	40.0	1	0.0	NaN	83.093750	NaN	
4	110683	2012	41.0	1	0.0	NaN	83.001563	NaN	

5 rows × 131 columns

In [36]:
```
pivoted_df
```

Out[36]:

	pitcher	season	Age	Throws	Surgery	AB_release_speed_weighted_avg	CH_release_speed_weighted_avg	CS_release_speed_weighted_avg
0	110683	2008	37.0	1	0.0	0.0	82.641530	0.0
1	110683	2009	38.0	1	0.0	0.0	85.012195	0.0
2	110683	2010	39.0	1	0.0	0.0	84.150000	0.0
3	110683	2011	40.0	1	0.0	0.0	83.093750	0.0
4	110683	2012	41.0	1	0.0	0.0	83.001563	0.0
...	...	...	...	...	...	...	...	...
3683	672578	2022	25.0	1	0.0	0.0	0.000000	0.0
3684	672578	2023	26.0	1	0.0	0.0	0.000000	0.0
3685	680686	2021	23.0	1	0.0	0.0	89.195000	0.0
3686	680686	2022	24.0	1	0.0	0.0	88.143056	0.0
3687	680686	2023	25.0	1	0.0	0.0	88.580000	0.0

3688 rows × 131 columns

In [35]:
```
pivoted_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3688 entries, 0 to 3687
Columns: 131 entries, pitcher to SV_vz0_weighted_avg
dtypes: float64(128), int64(3)
memory usage: 3.7 MB
```

In [34]:
```
pivoted_df.fillna(0.0, inplace=True)
```

In [54]:
```
pivoted_df.to_csv('pivoted_df.csv')
```

In [37]:
```
pivoted_df.columns
```

Out[37]:
```
Index(['pitcher', 'season', 'Age', 'Throws', 'Surgery',
       'AB_release_speed_weighted_avg', 'CH_release_speed_weighted_avg',
       'CS_release_speed_weighted_avg', 'CU_release_speed_weighted_avg',
       'EP_release_speed_weighted_avg',
       ...
       'FS_vz0_weighted_avg', 'IN_vz0_weighted_avg', 'KC_vz0_weighted_avg',
       'KN_vz0_weighted_avg', 'PO_vz0_weighted_avg', 'SC_vz0_weighted_avg',
       'SI_vz0_weighted_avg', 'SL_vz0_weighted_avg', 'ST_vz0_weighted_avg',
       'SV_vz0_weighted_avg'],
      dtype='object', length=131)
```

In [82]:
```
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

In [91]:
```
pd.reset_option('display.max_columns')
pd.reset_option('display.max_rows')
```

In [38]:
```
groovy_df = pivoted_df
```

Drop 'pitcher' column for groovy_df. Only used as ID, should not be necessary.

In [40]:
```
groovy_df.drop(columns=['pitcher'], inplace=True)
```

In [41]:
```
groovy_df
```

Out[41]:

	season	Age	Throws	Surgery	AB_release_speed_weighted_avg	CH_release_speed_weighted_avg	CS_release_speed_weighted_avg	CU_rele
0	2008	37.0	1	0.0	0.0	82.641530	0.0	
1	2009	38.0	1	0.0	0.0	85.012195	0.0	
2	2010	39.0	1	0.0	0.0	84.150000	0.0	
3	2011	40.0	1	0.0	0.0	83.093750	0.0	
4	2012	41.0	1	0.0	0.0	83.001563	0.0	
...	...	...	...	...	...	...	...	
3683	2022	25.0	1	0.0	0.0	0.000000	0.0	
3684	2023	26.0	1	0.0	0.0	0.000000	0.0	
3685	2021	23.0	1	0.0	0.0	89.195000	0.0	
3686	2022	24.0	1	0.0	0.0	88.143056	0.0	
3687	2023	25.0	1	0.0	0.0	88.580000	0.0	

3688 rows × 130 columns

In [42]:
```
groovy_df['Surgery'].value_counts()
```

Out[42]:
```
Surgery
0.0    2772
1.0     916
Name: count, dtype: int64
```

In [43]:
```
groovy_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 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 [94]:
```
#sns.pairplot(groovy_df, hue='Surgery')
```

In [14]:
```
#ohe = OneHotEncoder(sparse_output=False)
```

In [101]:
```
"""
# Reshape your data as a 2D array of 'pitch_type' column values
pitch_type_array = groovy_df['pitch_type'].values.reshape(-1, 1)

# Fit and transform the 'pitch_type' column to one-hot encoded format
pitch_type_ohe = ohe.fit_transform(pitch_type_array)

# Convert the one-hot encoded result back to a DataFrame
pitch_type_df = pd.DataFrame(pitch_type_ohe, columns=ohe.get_feature_names_out(['pitch_type']))

# Concatenate the new one-hot encoded DataFrame with the original DataFrame (excluding the original 'pitch_type' c
fancy_df = pd.concat([fancy_df.drop('pitch_type', axis=1).reset_index(drop=True), pitch_type_df], axis=1)

fancy_df.head()
"""
```

Out[101]:
```
"\n# Reshape your data as a 2D array of 'pitch_type' column values\npitch_type_array = groovy_df['pitch_type'].value
s.reshape(-1, 1)\n\n# Fit and transform the 'pitch_type' column to one-hot encoded format\npitch_type_ohe = ohe.fit_
transform(pitch_type_array)\n\n# Convert the one-hot encoded result back to a DataFrame\npitch_type_df = pd.DataFram
e(pitch_type_ohe, columns=ohe.get_feature_names_out(['pitch_type']))\n\n# Concatenate the new one-hot encoded DataFr
ame with the original DataFrame (excluding the original 'pitch_type' column)\nfancy_df = pd.concat([fancy_df.drop('p
itch_type', axis=1).reset_index(drop=True), pitch_type_df], axis=1)\n\nfancy_df.head()\n"
```

In [44]:
```
y = groovy_df['Surgery']
X = groovy_df.drop('Surgery', axis=1)
```

In [45]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

In [55]:
```
logreg_pipeline = Pipeline([
    ('scale', StandardScaler()),
    ('logreg', LogisticRegression(solver='liblinear', max_iter=10000))
])

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

# Initialize GridSearchCV with the pipeline, parameter grid, and desired scoring metric
grid_search = GridSearchCV(logreg_pipeline, param_grid, cv=5, scoring='accuracy')

# 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_score_))

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

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

In [48]:
```
logreg_pipeline = Pipeline([
    ('scale', StandardScaler()),
    ('logreg', LogisticRegression(penalty='l1', C=10.0, solver='liblinear'))
])
```

In [49]:
```
logreg_pipeline.fit(X_train, y_train)
```

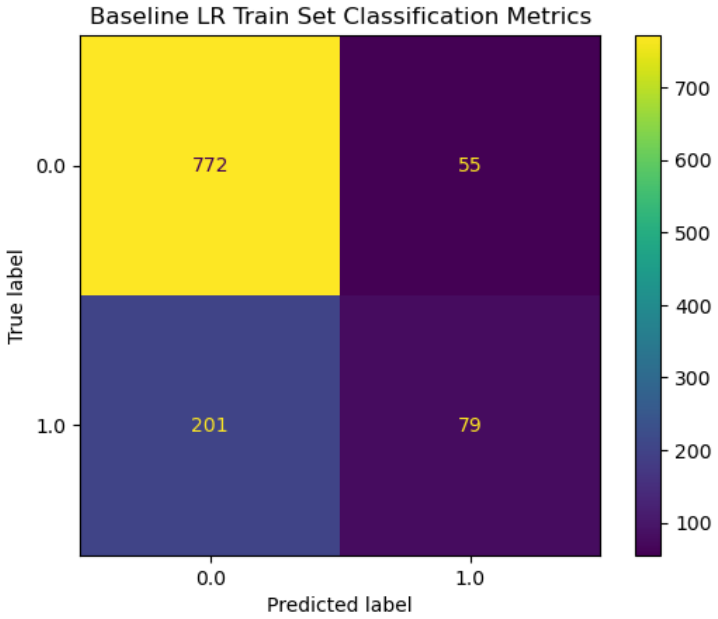
Out[49]:

In [50]:
```
logreg_pipeline.score(X_test, y_test)
```

Out[50]:
```
0.7687443541102078
```

In [51]:
```
y_pred = logreg_pipeline.predict(X_test)
```

In [52]:
```
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
```

Want more false positives (think needs TJ but doesn't need TJ) than false negatives...

Condense features (from 15 pitch types to 4)??

SMOTE? SMOTE Alternatives?

FIX SMOTE ISSUE

In [2]:
```
pip install --user scikit-learn imbalanced-learn
```

```
Requirement already satisfied: scikit-learn in c:\users\johns\anaconda3\lib\site-packages (1.4.1.post1)Note: you may
need to restart the kernel to use updated packages.

Requirement already satisfied: imbalanced-learn in c:\users\johns\anaconda3\lib\site-packages (0.10.1)
Requirement already satisfied: numpy<2.0,>=1.19.5 in c:\users\johns\anaconda3\lib\site-packages (from scikit-learn)
(1.24.3)
Requirement already satisfied: scipy>=1.6.0 in c:\users\johns\anaconda3\lib\site-packages (from scikit-learn) (1.11.
1)
Requirement already satisfied: joblib>=1.2.0 in c:\users\johns\anaconda3\lib\site-packages (from scikit-learn) (1.2.
0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\johns\anaconda3\lib\site-packages (from scikit-lear
n) (2.2.0)
```

In [ ]:
```

```