Final_project

December 10, 2023

[1]:
```
import pandas as pd
import numpy as np
import matplotlib
from matplotlib import pylab as plt
import seaborn as sns
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import recall_score, fbeta_score
from sklearn.metrics import accuracy_score, f1_score
import warnings
warnings.filterwarnings("ignore")
```

[170]:
```
df = pd.read_csv('/Users/suchen/Desktop/Data1030 HW/dermatology_database_1.csv')
```

[53]:
```
print(df.iloc[:,33])
```

```
0      55
1       8
2      26
3      40
4      45
       ..
361    25
362    36
363    28
364    50
365    35
Name: age, Length: 366, dtype: object
```

[52]:
```
df.head()
```

[52]:

	erythema	scaling	definite_borders	itching	koebner_phenomenon	\
0	2	2	0	3	0	
1	3	3	3	2	1	
2	2	1	2	3	1	
3	2	2	2	0	0	

```
4         2        3                 2        2                    2

   polygonal_papules  follicular_papules  oral_mucosal_involvement  \
0                  0                   0                         0
1                  0                   0                         0
2                  3                   0                         3
3                  0                   0                         0
4                  2                   0                         2

   knee_and_elbow_involvement  scalp_involvement  …  \
0                           1                  0  …
1                           1                  1  …
2                           0                  0  …
3                           3                  2  …
4                           0                  0  …

   disappearance_granular_layer  vacuolisation_damage_basal_layer  spongiosis  \
0                             0                                 0           3
1                             0                                 0           0
2                             0                                 2           3
3                             3                                 0           0
4                             2                                 3           2

   saw_tooth_appearance_retes  follicular_horn_plug  \
0                           0                    0
1                           0                    0
2                           2                    0
3                           0                    0
4                           3                    0

   perifollicular_parakeratosis  inflammatory_mononuclear_infiltrate  \
0                             0                                    1
1                             0                                    1
2                             0                                    2
3                             0                                    3
4                             0                                    2

   band_like_infiltrate  age  class
0                     0   55      2
1                     0    8      1
2                     3   26      3
3                     0   40      1
4                     3   45      3

[5 rows x 35 columns]
```

[160]:
```
df1 = df.iloc[:, list(range(0, 11)) + [33]]
df1.info()
```

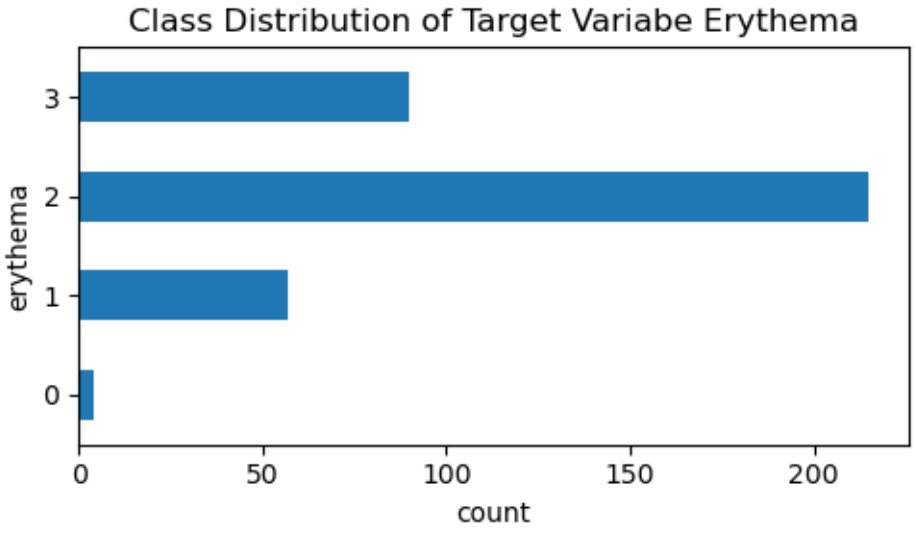
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 366 entries, 0 to 365
Data columns (total 12 columns):
 #   Column                      Non-Null Count  Dtype 
---  ------                      --------------  ----- 
 0   erythema                    366 non-null    int64 
 1   scaling                     366 non-null    int64 
 2   definite_borders            366 non-null    int64 
 3   itching                     366 non-null    int64 
 4   koebner_phenomenon          366 non-null    int64 
 5   polygonal_papules           366 non-null    int64 
 6   follicular_papules          366 non-null    int64 
 7   oral_mucosal_involvement    366 non-null    int64 
 8   knee_and_elbow_involvement  366 non-null    int64 
 9   scalp_involvement           366 non-null    int64 
 10  family_history              366 non-null    int64 
 11  age                         366 non-null    object
dtypes: int64(11), object(1)
memory usage: 34.4+ KB
```

[172]:
```
import pandas as pd

# see the class distribution of the target variable without correct order
class_distribution = df1['erythema'].value_counts()

# see the class distribution of the target variable with correct order
correct_order = [0,1,2,3]

pd.value_counts(df1['erythema']).reindex(correct_order)
```

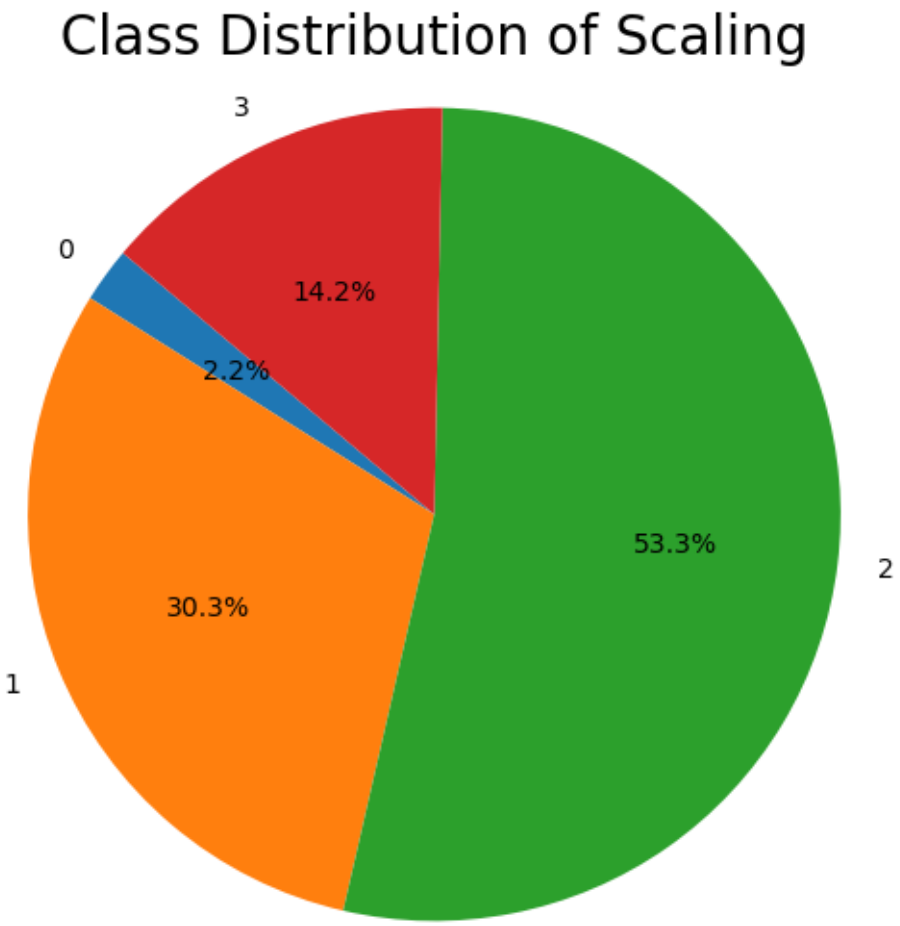
[172]:
```
erythema
0      4
1     57
2    215
3     90
Name: count, dtype: int64
```

[174]:
```
plt.figure(figsize=(5,3))

pd.value_counts(df1['erythema']).reindex(correct_order).plot.barh()
plt.xlabel('count')
plt.ylabel('erythema')
plt.title('Class Distribution of Target Variabe Erythema')
plt.tight_layout()
```

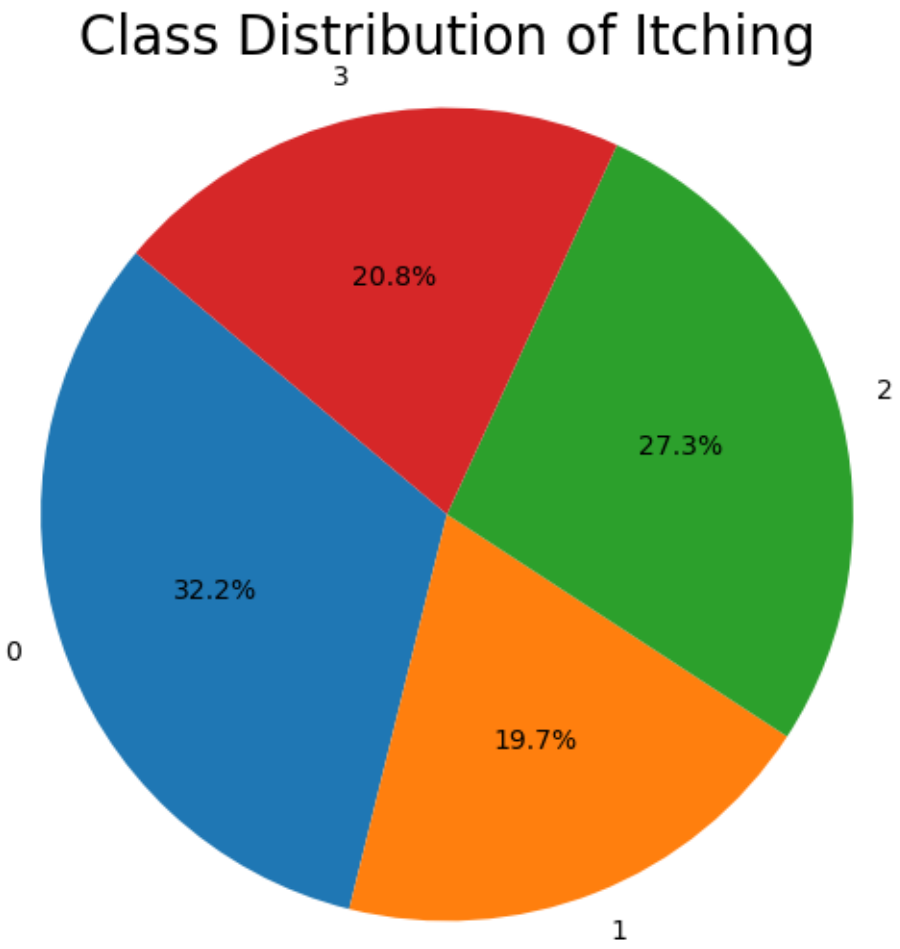
```
# Save the figure
file_path = '/Users/suchen/Desktop/Data1030 HW/final/eda_target.png'
plt.savefig(file_path, dpi=350)


plt.show()
```



[175]:
```
class_counts = pd.value_counts(df1['scaling']).reindex(correct_order)

plt.figure(figsize=(6, 6))
plt.pie(class_counts, labels=correct_order, autopct='%1.1f%%', startangle=140)
plt.title('Class Distribution of Scaling', fontsize = 20)
plt.axis('equal')  # Equal aspect ratio ensures the pie is drawn as a circle.

# Save the figure
file_path = '/Users/suchen/Desktop/Data1030 HW/final/eda_scaling.png'
plt.savefig(file_path, dpi=350)

plt.show()
```



[176]:
```
class_counts01 = pd.value_counts(df1['itching']).reindex(correct_order)

plt.figure(figsize=(6, 6))
plt.pie(class_counts01, labels=correct_order, autopct='%1.1f%%', startangle=140)
plt.title('Class Distribution of Itching', fontsize = 20)
plt.axis('equal')  # Equal aspect ratio ensures the pie is drawn as a circle.

# Save the figure
file_path = '/Users/suchen/Desktop/Data1030 HW/final/eda_itching.png'
plt.savefig(file_path, dpi=350)

plt.show()
s
```

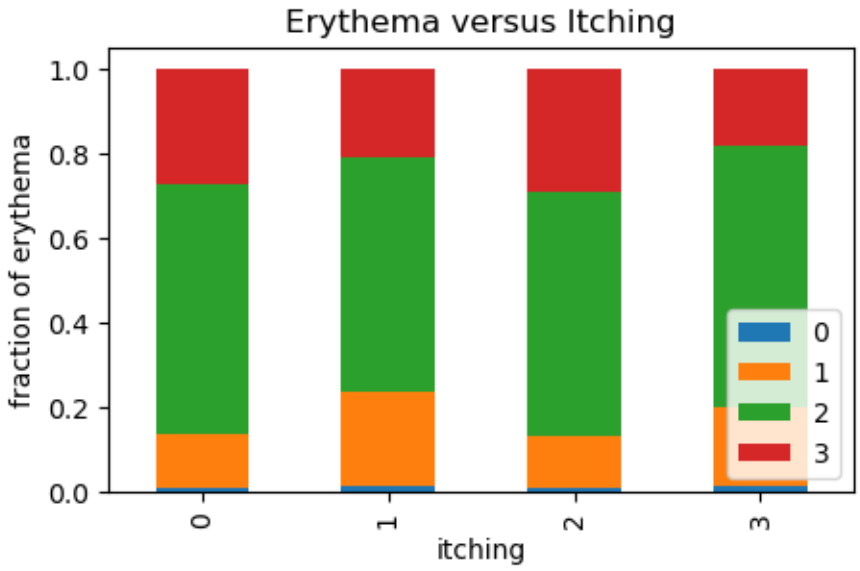


[74]:
```
count_matrix = df1.groupby(['itching', 'erythema']).size().unstack()
print(count_matrix)

count_matrix_norm = count_matrix.div(count_matrix.sum(axis=1),axis=0)
print(count_matrix_norm)
```

```
erythema  0   1   2   3
itching
0         1  15  70  32
1         1  16  40  15
2         1  12  58  29
3         1  14  47  14
erythema         0         1         2         3
itching
0         0.008475  0.127119  0.593220  0.271186
1         0.013889  0.222222  0.555556  0.208333
2         0.010000  0.120000  0.580000  0.290000
```

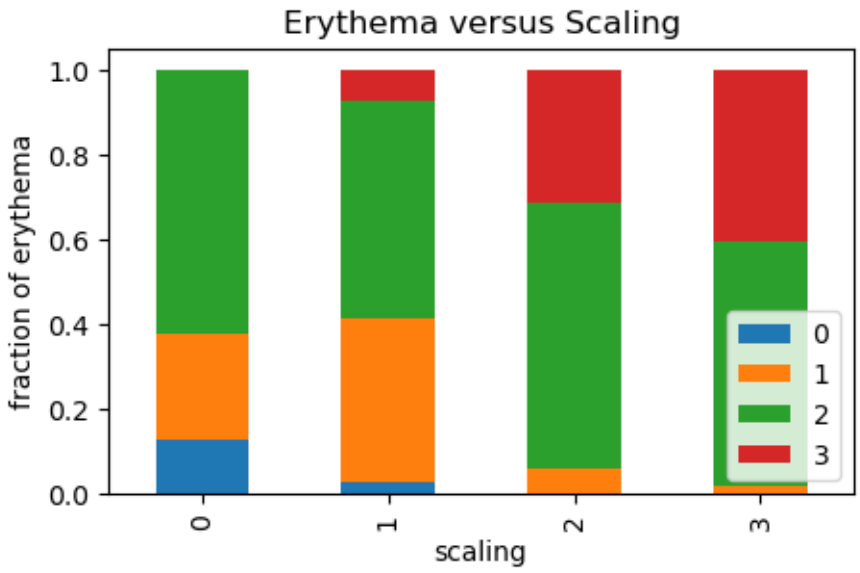
```
3          0.013158   0.184211   0.618421   0.184211
```

[166]:
```
count_matrix_norm.plot(kind='bar', stacked=True,figsize=(5,3))
plt.ylabel('fraction of erythema')
plt.title('Erythema versus Itching')
plt.legend(loc=4)
plt.show()
```



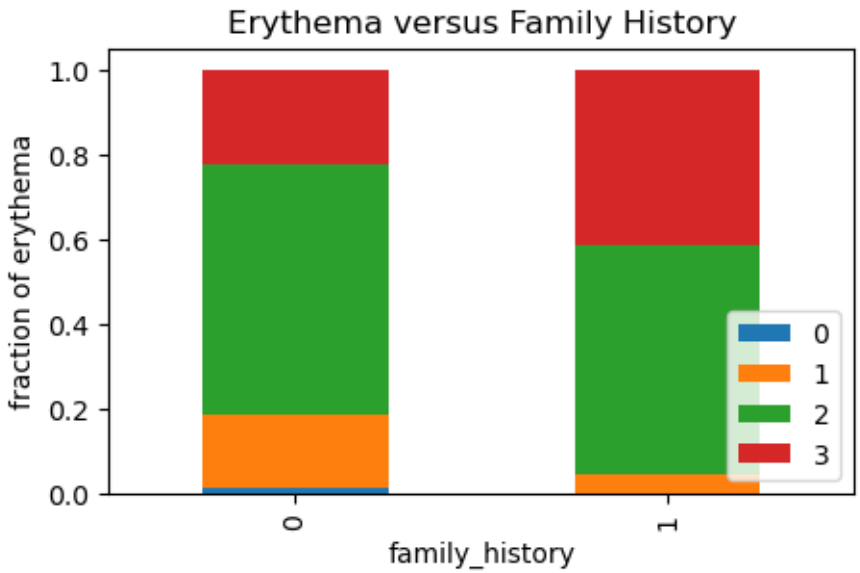
[177]:
```
count_matrix01 = df1.groupby(['scaling', 'erythema']).size().unstack()
#print(count_matrix01)

count_matrix_norm01 = count_matrix01.div(count_matrix01.sum(axis=1),axis=0)
#print(count_matrix_norm)
```

[178]:
```
count_matrix_norm01.plot(kind='bar', stacked=True,figsize=(5,3))
plt.ylabel('fraction of erythema')
plt.title('Erythema versus Scaling')
plt.legend(loc=4)

# Save the figure
file_path = '/Users/suchen/Desktop/Data1030 HW/final/eda_ery_scal.png'
plt.savefig(file_path, dpi=350)

plt.show()
```



[109]:
```
count_matrix02 = df1.groupby(['family_history', 'erythema']).size().unstack()
#print(count_matrix01)

count_matrix_norm02 = count_matrix02.div(count_matrix02.sum(axis=1),axis=0)
#print(count_matrix_norm)
```

[168]:
```
count_matrix_norm02.plot(kind='bar', stacked=True,figsize=(5,3))
plt.ylabel('fraction of erythema')
plt.title('Erythema versus Family History')
plt.legend(loc=4)
plt.show()
```



[87]:
```
pd.set_option('display.max_rows', None)
print(df['age'])
```

```
0      55
1       8
2      26
3      40
4      45
5      41
6      18
7      57
8      22
9      30
10     20
11     21
12     22
13     10
14     65
15     40
16     30
17     38
18     23
19     17
20      8
21     51
22     42
23     44
24     22
```

25	33
26	10
27	17
28	43
29	50
30	50
31	10
32	34
33	?
34	?
35	?
36	?
37	15
38	26
39	46
40	51
41	62
42	15
43	35
44	30
45	48
46	46
47	12
48	52
49	60
50	32
51	35
52	41
53	48
54	51
55	19
56	22
57	29
58	25
59	33
60	8
61	40
62	33
63	42
64	36
65	60
66	36
67	21
68	40
69	21
70	34
71	13
72	52

73	48
74	17
75	25
76	33
77	62
78	52
79	27
80	40
81	31
82	27
83	10
84	55
85	30
86	42
87	48
88	22
89	31
90	50
91	43
92	30
93	42
94	22
95	18
96	35
97	60
98	28
99	13
100	20
101	64
102	43
103	20
104	34
105	39
106	60
107	38
108	44
109	36
110	41
111	18
112	39
113	40
114	47
115	16
116	27
117	52
118	25
119	0
120	33

121	46
122	7
123	30
124	29
125	23
126	8
127	44
128	17
129	16
130	55
131	40
132	34
133	29
134	34
135	25
136	70
137	37
138	41
139	32
140	20
141	19
142	61
143	27
144	36
145	40
146	52
147	27
148	30
149	45
150	34
151	27
152	46
153	52
154	28
155	40
156	55
157	32
158	33
159	47
160	35
161	61
162	22
163	10
164	20
165	55
166	67
167	51
168	20

169	22
170	45
171	55
172	56
173	18
174	40
175	30
176	33
177	40
178	42
179	36
180	27
181	56
182	60
183	20
184	7
185	30
186	19
187	52
188	55
189	23
190	50
191	38
192	25
193	18
194	35
195	22
196	52
197	50
198	33
199	44
200	18
201	25
202	52
203	35
204	40
205	55
206	20
207	60
208	33
209	27
210	50
211	70
212	28
213	30
214	53
215	27
216	50

217	42
218	45
219	35
220	30
221	42
222	18
223	25
224	36
225	40
226	35
227	19
228	50
229	47
230	30
231	42
232	55
233	60
234	65
235	47
236	35
237	52
238	60
239	7
240	8
241	25
242	60
243	50
244	33
245	27
246	55
247	62
248	19
249	50
250	40
251	62
252	36
253	27
254	47
255	50
256	35
257	25
258	60
259	22
260	35
261	36
262	?
263	?
264	?

265	?
266	10
267	12
268	8
269	35
270	62
271	48
272	30
273	57
274	62
275	36
276	18
277	25
278	16
279	50
280	55
281	27
282	55
283	22
284	70
285	22
286	45
287	40
288	28
289	36
290	27
291	42
292	27
293	50
294	34
295	8
296	19
297	36
298	70
299	52
300	25
301	36
302	50
303	34
304	17
305	24
306	22
307	55
308	12
309	43
310	50
311	36
312	26

313	16
314	32
315	51
316	56
317	47
318	51
319	58
320	27
321	32
322	27
323	62
324	53
325	46
326	37
327	49
328	18
329	46
330	33
331	22
332	44
333	36
334	63
335	56
336	60
337	42
338	32
339	51
340	33
341	68
342	50
343	9
344	16
345	35
346	40
347	22
348	10
349	7
350	25
351	9
352	55
353	45
354	56
355	36
356	75
357	45
358	24
359	40
360	25

```
361    25
362    36
363    28
364    50
365    35
Name: age, dtype: object
```

[117]:
```
X = df1.loc[:, df1.columns != 'erythema']
y = df1['erythema']

X.columns
```

[117]:
```
Index(['scaling', 'definite_borders', 'itching', 'koebner_phenomenon',
       'polygonal_papules', 'follicular_papules', 'oral_mucosal_involvement',
       'knee_and_elbow_involvement', 'scalp_involvement', 'family_history',
       'age'],
      dtype='object')
```

[98]:
```
random_state = 42



# stratified train-test split
X_other, X_test, y_other, y_test = train_test_split(X,y,test_size = 0.
  ↪2,stratify=y,random_state=random_state)
print('test balance:',np.unique(y_test,return_counts=True))

# do StratifiedKFold split on other
kf = StratifiedKFold(n_splits=3,shuffle=True,random_state=random_state)
for train_index, val_index in kf.split(X_other,y_other):
    print('new fold')
    X_train = X_other.iloc[train_index]
    y_train = y_other.iloc[train_index]
    X_val = X_other.iloc[val_index]
    y_val = y_other.iloc[val_index]
    print(np.unique(y_train,return_counts=True))
    print(np.unique(y_val,return_counts=True))
```

```
test balance: (array([0, 1, 2, 3]), array([ 1, 12, 43, 18]))
new fold
(array([0, 1, 2, 3]), array([  2,  30, 114,  48]))
(array([0, 1, 2, 3]), array([ 1, 15, 58, 24]))
new fold
(array([0, 1, 2, 3]), array([  2,  30, 115,  48]))
(array([0, 1, 2, 3]), array([ 1, 15, 57, 24]))
new fold
(array([0, 1, 2, 3]), array([  2,  30, 115,  48]))
(array([0, 1, 2, 3]), array([ 1, 15, 57, 24]))
```

[112]:
```
# one hot encoder for family history

# let's collect all categorical features first
onehot_ftrs = ['family_history']
# initialize the encoder
enc = OneHotEncoder(sparse=False,handle_unknown='ignore') # by default,␣
 ↪OneHotEncoder returns a sparse matrix. sparse=False returns a 2D array
# fit the training data
enc.fit(X_train[onehot_ftrs])
print('feature names:',enc.get_feature_names_out(onehot_ftrs))
print(len(enc.get_feature_names_out(onehot_ftrs)))
```

```
feature names: ['family_history_0' 'family_history_1']
2
```

```
/Users/suchen/anaconda3/envs/data1030/lib/python3.11/site-
packages/sklearn/preprocessing/_encoders.py:972: FutureWarning: `sparse` was
renamed to `sparse_output` in version 1.2 and will be removed in 1.4.
`sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
```

[113]:
```
# transform X_train
onehot_train = enc.transform(X_train[onehot_ftrs])
print('transformed train features:')
print(onehot_train)
# transform X_val
onehot_val = enc.transform(X_val[onehot_ftrs])
print('transformed val features:')
print(onehot_val)
# transform X_test
onehot_test = enc.transform(X_test[onehot_ftrs])
print('transformed test features:')
print(onehot_test)
```

```
transformed train features:
[[1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [0. 1.]
 [1. 0.]
 [1. 0.]
```

```
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
```

```
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
```

```
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[1. 0.]
```

```
 [1. 0.]
 [0. 1.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [0. 1.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]]
transformed val features:
[[1. 0.]
 [0. 1.]
 [1. 0.]
 [0. 1.]
 [1. 0.]
 [1. 0.]
 [0. 1.]
 [0. 1.]
 [1. 0.]
 [1. 0.]
```

```
[1. 0.]
[0. 1.]
[1. 0.]
[0. 1.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
```

```
 [1. 0.]
 [0. 1.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [0. 1.]
 [1. 0.]
 [1. 0.]
 [0. 1.]
 [0. 1.]
 [0. 1.]
 [1. 0.]
 [0. 1.]
 [0. 1.]
 [1. 0.]
 [0. 1.]
 [1. 0.]
 [1. 0.]
 [0. 1.]
 [1. 0.]
 [0. 1.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [0. 1.]
 [1. 0.]
 [1. 0.]
 [0. 1.]
 [1. 0.]]
transformed test features:
[[1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
```

```
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[0. 1.]
[0. 1.]
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
```

```
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[0. 1.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]
[1. 0.]]
```

[125]:
```
# ordinal encoder to other attributes

symptoms = [
    "scaling",
    "definite_borders",
    "itching",
    "koebner_phenomenon",
    "polygonal_papules",
    "follicular_papules",
    "oral_mucosal_involvement",
    "knee_and_elbow_involvement",
    "scalp_involvement"
]

degree = [0,1,2,3]
# initialize the encoder
ordinal_ftrs = symptoms # if you have more than one ordinal feature, add the␣
 ↪feature names here
ordinal_cats = [degree, degree, degree, degree, degree, degree, degree, degree,␣
 ↪degree]
# ordinal_cats must contain one list per ordinal feature! each list contains␣
 ↪the ordered list of categories
# of the corresponding feature

enc = OrdinalEncoder(categories = ordinal_cats)   # By default, the categories␣
 ↪are alphabetically ordered
                                                  # which is NOT what you␣
 ↪want usually.
```

```
# fit the training data
enc.fit(X_train[ordinal_ftrs])  # the encoder expects a 2D array, that's why␣
 ↪the column name is in a list

# transform X_train. We could use enc.fit_transform(X_train) to combine fit and␣
 ↪transform
ordinal_train = enc.transform(X_train[ordinal_ftrs])
print('transformed train features:')
print(ordinal_train)
# transform X_val
ordinal_val = enc.transform(X_val[ordinal_ftrs])
print('transformed validation features:')
print(ordinal_val)
# transform X_test
ordinal_test = enc.transform(X_test[ordinal_ftrs])
print('transformed test features:')
print(ordinal_test)
```

```
transformed train features:
[[2. 3. 3. … 2. 0. 0.]
 [2. 2. 2. … 3. 0. 0.]
 [2. 2. 2. … 1. 0. 0.]
 …
 [1. 1. 0. … 0. 0. 0.]
 [2. 2. 0. … 0. 1. 1.]
 [2. 2. 3. … 2. 0. 0.]]
transformed validation features:
[[1. 1. 0. 1. 0. 0. 0. 0. 0.]
 [3. 3. 0. 0. 0. 0. 0. 1. 1.]
 [2. 2. 1. 0. 0. 0. 0. 0. 0.]
 [1. 2. 0. 0. 0. 0. 0. 3. 2.]
 [1. 3. 1. 2. 3. 0. 2. 0. 0.]
 [2. 1. 0. 0. 0. 2. 0. 2. 0.]
 [3. 3. 0. 0. 0. 0. 0. 3. 3.]
 [2. 2. 0. 0. 0. 3. 0. 1. 0.]
 [2. 2. 0. 0. 0. 0. 0. 0. 0.]
 [2. 2. 0. 1. 0. 0. 0. 0. 0.]
 [3. 2. 0. 0. 0. 0. 0. 2. 2.]
 [2. 2. 0. 0. 0. 1. 0. 1. 0.]
 [2. 2. 0. 0. 0. 0. 0. 2. 2.]
 [2. 2. 1. 0. 0. 0. 0. 1. 0.]
 [2. 2. 0. 0. 0. 0. 0. 0. 1.]
 [2. 2. 0. 1. 0. 0. 0. 0. 0.]
 [2. 2. 0. 1. 0. 0. 0. 0. 0.]
 [2. 2. 2. 3. 2. 0. 2. 0. 0.]
 [1. 1. 0. 1. 0. 0. 0. 0. 0.]
```

```
[1. 0. 3. 0. 0. 0. 0. 0. 0.]
[2. 3. 3. 1. 2. 0. 2. 0. 0.]
[2. 1. 1. 0. 0. 0. 0. 0. 0.]
[3. 0. 3. 0. 0. 0. 0. 0. 2.]
[1. 1. 0. 1. 0. 0. 0. 0. 0.]
[1. 1. 2. 0. 0. 0. 0. 0. 0.]
[3. 2. 0. 1. 0. 0. 0. 2. 3.]
[2. 0. 3. 0. 0. 0. 0. 0. 0.]
[1. 1. 3. 0. 3. 0. 1. 0. 0.]
[1. 2. 0. 0. 0. 0. 0. 0. 0.]
[2. 2. 2. 0. 2. 0. 3. 0. 0.]
[1. 3. 3. 0. 0. 0. 0. 0. 0.]
[2. 2. 2. 0. 0. 0. 0. 2. 2.]
[2. 2. 3. 3. 3. 0. 2. 0. 0.]
[1. 0. 2. 0. 0. 0. 0. 0. 0.]
[2. 1. 0. 0. 0. 0. 0. 2. 2.]
[1. 2. 0. 0. 0. 0. 0. 2. 0.]
[1. 0. 3. 0. 0. 0. 0. 0. 0.]
[3. 2. 0. 1. 0. 0. 0. 2. 2.]
[2. 3. 0. 1. 0. 0. 0. 1. 2.]
[2. 2. 0. 0. 0. 0. 0. 3. 2.]
[2. 3. 1. 0. 0. 0. 0. 1. 2.]
[3. 2. 0. 0. 0. 0. 0. 0. 0.]
[3. 3. 0. 1. 0. 0. 0. 2. 0.]
[1. 1. 0. 0. 0. 0. 0. 0. 0.]
[2. 3. 2. 1. 2. 0. 2. 0. 0.]
[2. 2. 2. 2. 0. 0. 0. 3. 0.]
[2. 1. 2. 0. 0. 0. 0. 1. 2.]
[1. 2. 0. 0. 0. 0. 0. 0. 0.]
[1. 1. 1. 1. 0. 1. 0. 2. 3.]
[0. 1. 2. 0. 0. 0. 0. 0. 0.]
[3. 3. 3. 3. 0. 0. 0. 2. 1.]
[3. 2. 1. 0. 0. 0. 0. 2. 2.]
[2. 1. 0. 1. 0. 0. 0. 0. 0.]
[2. 0. 2. 0. 0. 1. 0. 0. 0.]
[2. 1. 1. 0. 0. 2. 0. 0. 0.]
[3. 2. 3. 3. 3. 0. 2. 0. 0.]
[2. 0. 2. 0. 0. 0. 0. 0. 0.]
[1. 2. 1. 1. 0. 1. 0. 2. 3.]
[1. 0. 1. 3. 0. 0. 0. 0. 0.]
[2. 0. 1. 0. 0. 2. 0. 1. 0.]
[2. 1. 0. 2. 0. 0. 0. 0. 0.]
[1. 2. 1. 0. 0. 0. 0. 2. 3.]
[2. 2. 0. 0. 0. 0. 0. 3. 3.]
[2. 3. 2. 2. 2. 0. 2. 0. 0.]
[2. 2. 1. 0. 0. 0. 0. 0. 0.]
[2. 2. 2. 0. 0. 0. 0. 0. 0.]
[2. 2. 3. 2. 2. 0. 2. 0. 0.]
```

```
 [1. 2. 2. 2. 0. 0. 0. 0. 0.]
 [1. 1. 0. 0. 0. 0. 0. 1. 0.]
 [1. 2. 3. 1. 2. 0. 2. 0. 0.]
 [1. 1. 0. 2. 0. 0. 0. 0. 0.]
 [2. 2. 0. 0. 0. 0. 0. 2. 2.]
 [3. 0. 2. 0. 0. 0. 0. 0. 0.]
 [3. 3. 1. 0. 0. 0. 0. 2. 1.]
 [2. 1. 1. 0. 0. 0. 0. 0. 2.]
 [2. 2. 2. 2. 0. 0. 0. 2. 2.]
 [2. 2. 0. 0. 0. 0. 0. 2. 2.]
 [1. 2. 1. 1. 0. 0. 0. 0. 0.]
 [1. 1. 1. 1. 0. 0. 0. 0. 1.]
 [2. 3. 2. 0. 0. 0. 0. 0. 2.]
 [2. 2. 0. 0. 0. 0. 0. 0. 0.]
 [2. 2. 3. 0. 0. 0. 0. 2. 2.]
 [2. 2. 1. 0. 0. 0. 0. 0. 0.]
 [1. 1. 0. 0. 0. 1. 0. 0. 0.]
 [2. 2. 1. 0. 0. 2. 0. 2. 2.]
 [2. 2. 0. 0. 0. 0. 0. 0. 0.]
 [2. 1. 0. 0. 0. 0. 0. 1. 0.]
 [1. 1. 3. 3. 0. 0. 0. 0. 0.]
 [1. 2. 2. 0. 2. 0. 0. 0. 1.]
 [2. 2. 2. 3. 3. 0. 2. 0. 0.]
 [3. 2. 0. 0. 0. 0. 0. 2. 0.]
 [2. 2. 0. 1. 0. 0. 0. 0. 0.]
 [1. 2. 0. 0. 0. 3. 0. 3. 0.]
 [1. 1. 3. 0. 0. 0. 0. 0. 0.]
 [1. 0. 3. 0. 0. 0. 0. 0. 0.]
 [3. 3. 2. 1. 0. 0. 0. 1. 1.]
 [1. 0. 1. 0. 0. 0. 0. 0. 0.]]
transformed test features:
[[2. 2. 1. 1. 0. 0. 0. 0. 0.]
 [2. 2. 2. 0. 3. 0. 2. 0. 0.]
 [2. 2. 0. 2. 0. 0. 0. 3. 2.]
 [2. 1. 1. 0. 0. 0. 0. 0. 1.]
 [2. 2. 2. 2. 0. 0. 0. 0. 2.]
 [1. 2. 2. 1. 0. 0. 0. 0. 0.]
 [3. 3. 0. 0. 0. 0. 0. 2. 3.]
 [1. 3. 0. 1. 0. 0. 0. 0. 2.]
 [2. 2. 3. 2. 0. 0. 0. 0. 2.]
 [1. 1. 0. 0. 0. 0. 0. 0. 0.]
 [2. 2. 2. 0. 0. 0. 0. 0. 1.]
 [1. 3. 3. 3. 3. 0. 0. 2. 0.]
 [3. 3. 3. 0. 3. 0. 3. 0. 0.]
 [2. 2. 1. 0. 0. 2. 0. 0. 0.]
 [2. 0. 0. 0. 0. 2. 0. 1. 1.]
 [2. 1. 1. 0. 0. 2. 0. 2. 0.]
 [1. 1. 2. 0. 0. 3. 0. 1. 2.]
```

```
[1. 2. 3. 1. 3. 0. 3. 0. 0.]
[3. 2. 2. 0. 3. 0. 2. 0. 0.]
[2. 2. 2. 0. 2. 0. 2. 0. 0.]
[1. 0. 1. 0. 0. 2. 0. 0. 0.]
[0. 1. 2. 0. 0. 0. 0. 0. 0.]
[1. 2. 3. 0. 3. 0. 0. 0. 1.]
[3. 2. 2. 0. 0. 0. 0. 2. 0.]
[2. 2. 0. 0. 0. 0. 0. 0. 1.]
[2. 2. 2. 0. 2. 0. 0. 0. 0.]
[2. 2. 3. 2. 0. 0. 0. 2. 3.]
[3. 2. 1. 1. 0. 0. 0. 2. 2.]
[3. 2. 1. 0. 0. 0. 0. 0. 0.]
[2. 1. 2. 0. 0. 0. 0. 0. 0.]
[1. 2. 3. 2. 3. 0. 2. 0. 0.]
[0. 1. 3. 0. 0. 0. 0. 0. 0.]
[2. 2. 1. 0. 0. 0. 0. 0. 0.]
[1. 0. 2. 0. 0. 0. 0. 0. 0.]
[2. 2. 0. 0. 0. 0. 0. 2. 3.]
[0. 0. 0. 0. 0. 0. 3. 0. 0.]
[2. 2. 0. 1. 0. 0. 0. 2. 1.]
[2. 1. 1. 0. 0. 0. 0. 1. 0.]
[1. 2. 0. 0. 0. 3. 0. 3. 0.]
[1. 0. 1. 0. 0. 2. 0. 0. 0.]
[2. 2. 1. 1. 0. 0. 0. 2. 2.]
[2. 1. 0. 0. 0. 0. 0. 0. 0.]
[1. 2. 0. 0. 0. 0. 0. 0. 0.]
[3. 2. 2. 1. 0. 0. 0. 2. 2.]
[1. 2. 2. 0. 0. 0. 0. 1. 0.]
[1. 0. 1. 0. 0. 0. 0. 0. 0.]
[2. 2. 2. 0. 0. 0. 0. 2. 2.]
[2. 1. 1. 0. 0. 1. 0. 1. 1.]
[2. 2. 0. 0. 0. 0. 0. 1. 0.]
[1. 0. 2. 2. 0. 0. 0. 0. 0.]
[2. 3. 0. 0. 0. 0. 0. 3. 0.]
[1. 1. 2. 0. 0. 0. 0. 0. 0.]
[1. 1. 2. 0. 0. 0. 0. 0. 0.]
[1. 1. 0. 1. 0. 0. 0. 0. 0.]
[2. 0. 3. 0. 0. 0. 0. 0. 0.]
[1. 1. 0. 0. 0. 0. 0. 0. 0.]
[2. 2. 3. 2. 0. 0. 0. 1. 1.]
[2. 1. 0. 2. 0. 0. 0. 0. 0.]
[2. 1. 0. 0. 0. 2. 0. 2. 0.]
[2. 2. 0. 0. 0. 0. 0. 2. 2.]
[3. 2. 2. 2. 2. 0. 2. 0. 0.]
[2. 1. 2. 0. 0. 0. 0. 0. 0.]
[2. 0. 2. 0. 0. 0. 0. 0. 2.]
[3. 3. 2. 2. 0. 0. 0. 2. 2.]
[3. 2. 1. 0. 0. 0. 0. 1. 2.]
```

```
 [2. 2. 2. 0. 2. 0. 2. 0. 0.]
 [2. 2. 1. 0. 0. 0. 0. 0. 0.]
 [2. 1. 2. 0. 0. 0. 0. 0. 0.]
 [3. 2. 0. 1. 0. 0. 0. 3. 2.]
 [1. 1. 1. 1. 0. 0. 0. 1. 1.]
 [3. 2. 0. 0. 0. 0. 0. 2. 3.]
 [2. 0. 2. 0. 0. 0. 0. 0. 0.]
 [2. 2. 0. 0. 0. 0. 0. 2. 2.]
 [2. 1. 0. 1. 0. 0. 0. 0. 0.]]
```

[136]:
```
X01 = df1.loc[:, df1.columns != 'erythema']
y01 = df1['erythema']
```

[138]:
```
random_state = 42



# stratified train-test split
X_other1, X_test1, y_other1, y_test1 = train_test_split(X01,y01,test_size = 0.
 ↪2,stratify=y01,random_state=random_state)
print('test balance:',np.unique(y_test,return_counts=True))

# do StratifiedKFold split on other
kf = StratifiedKFold(n_splits=3,shuffle=True,random_state=random_state)
for train_index, val_index in kf.split(X_other1,y_other1):
    print('new fold')
    X_train1 = X_other1.iloc[train_index]
    y_train1 = y_other1.iloc[train_index]
    X_val1 = X_other1.iloc[val_index]
    y_val1 = y_other1.iloc[val_index]
    print(np.unique(y_train1,return_counts=True))
    print(np.unique(y_val1,return_counts=True))
```

```
test balance: (array([0, 1, 2, 3]), array([ 1, 12, 43, 18]))
new fold
(array([0, 1, 2, 3]), array([  2,  30, 114,  48]))
(array([0, 1, 2, 3]), array([ 1, 15, 58, 24]))
new fold
(array([0, 1, 2, 3]), array([  2,  30, 115,  48]))
(array([0, 1, 2, 3]), array([ 1, 15, 57, 24]))
new fold
(array([0, 1, 2, 3]), array([  2,  30, 115,  48]))
(array([0, 1, 2, 3]), array([ 1, 15, 57, 24]))
```

[154]:
```
print(X_train1.shape[0])
print(ordinal_train.shape[0])

print(X_train1.shape[1])
```

```
print(ordinal_train.shape[1])
```

```
195
195
11
9
```

[155]:
```
print(X_test1.shape[0])
print(ordinal_test.shape[0])

print(X_test1.shape[1])
print(ordinal_test.shape[1])
```

```
74
74
11
9
```

[156]:
```
print(X_val1.shape[0])
print(ordinal_val.shape[0])

print(X_val1.shape[1])
print(ordinal_val.shape[1])
```

```
97
97
11
9
```

[161]:
```
df11 = df1

df11.replace('?', np.nan, inplace=True)

# Calculate the fraction of missing values for each column df.isnull().mean()


print(df11['age'].isnull().mean())
```

```
/var/folders/fv/xfwfslxx7hj7m40k0dggq8pm0000gn/T/ipykernel_96876/3936423857.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
  df11.replace('?', np.nan, inplace=True)
```

[161]:
```
0.02185792349726776
```

[163]:
```
missing_fraction_per_column = df11.isnull().mean()

# Calculate the fraction of missing values for the entire dataset
missing_fraction_total = missing_fraction_per_column.mean()

missing_fraction_total
```

[163]:
```
0.0018214936247723133
```

[170]:
```
df['age']
```

[170]:
```
0      55
1       8
2      26
3      40
4      45
5      41
6      18
7      57
8      22
9      30
10     20
11     21
12     22
13     10
14     65
15     40
16     30
17     38
18     23
19     17
20      8
21     51
22     42
23     44
24     22
25     33
26     10
27     17
28     43
29     50
30     50
31     10
32     34
33      ?
34      ?
35      ?
```

36	?
37	15
38	26
39	46
40	51
41	62
42	15
43	35
44	30
45	48
46	46
47	12
48	52
49	60
50	32
51	35
52	41
53	48
54	51
55	19
56	22
57	29
58	25
59	33
60	8
61	40
62	33
63	42
64	36
65	60
66	36
67	21
68	40
69	21
70	34
71	13
72	52
73	48
74	17
75	25
76	33
77	62
78	52
79	27
80	40
81	31
82	27

83	10
84	55
85	30
86	42
87	48
88	22
89	31
90	50
91	43
92	30
93	42
94	22
95	18
96	35
97	60
98	28
99	13
100	20
101	64
102	43
103	20
104	34
105	39
106	60
107	38
108	44
109	36
110	41
111	18
112	39
113	40
114	47
115	16
116	27
117	52
118	25
119	0
120	33
121	46
122	7
123	30
124	29
125	23
126	8
127	44
128	17
129	16

130	55
131	40
132	34
133	29
134	34
135	25
136	70
137	37
138	41
139	32
140	20
141	19
142	61
143	27
144	36
145	40
146	52
147	27
148	30
149	45
150	34
151	27
152	46
153	52
154	28
155	40
156	55
157	32
158	33
159	47
160	35
161	61
162	22
163	10
164	20
165	55
166	67
167	51
168	20
169	22
170	45
171	55
172	56
173	18
174	40
175	30
176	33

177	40
178	42
179	36
180	27
181	56
182	60
183	20
184	7
185	30
186	19
187	52
188	55
189	23
190	50
191	38
192	25
193	18
194	35
195	22
196	52
197	50
198	33
199	44
200	18
201	25
202	52
203	35
204	40
205	55
206	20
207	60
208	33
209	27
210	50
211	70
212	28
213	30
214	53
215	27
216	50
217	42
218	45
219	35
220	30
221	42
222	18
223	25

224	36
225	40
226	35
227	19
228	50
229	47
230	30
231	42
232	55
233	60
234	65
235	47
236	35
237	52
238	60
239	7
240	8
241	25
242	60
243	50
244	33
245	27
246	55
247	62
248	19
249	50
250	40
251	62
252	36
253	27
254	47
255	50
256	35
257	25
258	60
259	22
260	35
261	36
262	?
263	?
264	?
265	?
266	10
267	12
268	8
269	35
270	62

271	48
272	30
273	57
274	62
275	36
276	18
277	25
278	16
279	50
280	55
281	27
282	55
283	22
284	70
285	22
286	45
287	40
288	28
289	36
290	27
291	42
292	27
293	50
294	34
295	8
296	19
297	36
298	70
299	52
300	25
301	36
302	50
303	34
304	17
305	24
306	22
307	55
308	12
309	43
310	50
311	36
312	26
313	16
314	32
315	51
316	56
317	47

318	51
319	58
320	27
321	32
322	27
323	62
324	53
325	46
326	37
327	49
328	18
329	46
330	33
331	22
332	44
333	36
334	63
335	56
336	60
337	42
338	32
339	51
340	33
341	68
342	50
343	9
344	16
345	35
346	40
347	22
348	10
349	7
350	25
351	9
352	55
353	45
354	56
355	36
356	75
357	45
358	24
359	40
360	25
361	25
362	36
363	28
364	50

```
365    35
Name: age, dtype: object
```

[ ]:
```
# final project
# ----------------------
# ------------------------
# ----------------------
```

[ ]:
```
# final project
# start over and split the data again
# so that the codes of final are separated from codes of midterm
```

[81]:
```
df2 = pd.read_csv('/Users/suchen/Desktop/Data1030 HW/dermatology_database_1.
 ↪csv')
# make a subset of the data, removing the "medical terms" features because they␣
 ↪are too academic to understand
df3 = df2.iloc[:, list(range(0, 11)) + [33]]
#df1.info()

# create x and target variable y
X_final = df3.loc[:, df3.columns != 'erythema']
y_final = df3['erythema']
```

[72]:
```
# Assuming you have already loaded your data and created the X_final DataFrame

# Change the integer values in 'erythema' to strings
# Assuming you have already loaded your data and created the X_final DataFrame

# Change the integer values in 'erythema' to strings with a prefix
#y_final = "class " + df3['erythema'].astype(str)

# Now y_final contains the values as strings with the "class" prefix


# Now y_final contains the values as strings
```

[79]:
```
y_final
```

[79]:
```
0      2
1      3
2      2
3      2
4      2
      ..
361    2
362    3
363    3
```

```
364    2
365    3
Name: erythema, Length: 366, dtype: int64
```

[82]:
```
from sklearn.model_selection import train_test_split, StratifiedKFold
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
import numpy as np
import pandas as pd



# Replace '?' with NaN and convert columns to numeric where appropriate
X_final = X_final.replace('?', np.nan).apply(pd.to_numeric, errors='coerce')

# Define random state
random_state = 42

# Stratified train-test split
X_other, X_test, y_other, y_test = train_test_split(
    X_final, y_final, test_size=0.2, stratify=y_final,␣
 ↪random_state=random_state)
print('Test balance:', np.unique(y_test, return_counts=True))

# Stratified K-Fold on X_other
kf = StratifiedKFold(n_splits=3, shuffle=True, random_state=random_state)

for train_index, val_index in kf.split(X_other, y_other):
    print('New fold')

    # Split the data into training and validation sets
    X_train, X_val = X_other.iloc[train_index], X_other.iloc[val_index]
    y_train, y_val = y_other.iloc[train_index], y_other.iloc[val_index]

    # Instantiate the imputer
    iterative_imputer = IterativeImputer(random_state=random_state)

    # Fit the imputer on X_train and transform X_train
    X_train_imputed = iterative_imputer.fit_transform(X_train)

    # Transform X_val using the already fitted imputer
    X_val_imputed = iterative_imputer.transform(X_val)

    # Convert the imputed data back into pandas DataFrames
    X_train = pd.DataFrame(X_train_imputed, columns=X_final.columns)
    X_val = pd.DataFrame(X_val_imputed, columns=X_final.columns)
```

```
    print(np.unique(y_train, return_counts=True))
    print(np.unique(y_val, return_counts=True))

# Transform X_test using the imputer fitted on the last fold of X_other
X_test_imputed = iterative_imputer.transform(X_test)
X_test = pd.DataFrame(X_test_imputed, columns=X_final.columns)
```

```
Test balance: (array([0, 1, 2, 3]), array([ 1, 12, 43, 18]))
New fold
(array([0, 1, 2, 3]), array([  2,  30, 114,  48]))
(array([0, 1, 2, 3]), array([ 1, 15, 58, 24]))
New fold
(array([0, 1, 2, 3]), array([  2,  30, 115,  48]))
(array([0, 1, 2, 3]), array([ 1, 15, 57, 24]))
New fold
(array([0, 1, 2, 3]), array([  2,  30, 115,  48]))
(array([0, 1, 2, 3]), array([ 1, 15, 57, 24]))
```

[83]:
```
# Calculate the fraction of missing values in each column of X_train
missing_fraction = X_train.isna().sum() / len(X_train)

# Optionally, convert to percentage
missing_percentage = missing_fraction * 100

# Display the result
print(missing_fraction)  # or print(missing_percentage) for percentage
```

```
scaling                     0.0
definite_borders            0.0
itching                     0.0
koebner_phenomenon          0.0
polygonal_papules           0.0
follicular_papules          0.0
oral_mucosal_involvement    0.0
knee_and_elbow_involvement  0.0
scalp_involvement           0.0
family_history              0.0
age                         0.0
dtype: float64
```

[55]:
```
```

[84]:
```
import numpy as np
from sklearn.model_selection import KFold, GridSearchCV
from sklearn.metrics import mean_squared_error
from sklearn.pipeline import Pipeline

def MLpipe_KFold_RMSE(X_train, X_test, y_train, y_test,
```

```
                    preprocessor, algorithm, param_grid,
                    algorithm_random_state=None):
    """
    This function applies KFold with 4 folds to the training data and uses␣
↪GridSearchCV for hyperparameter tuning.
    The RMSE is minimized in cross-validation.

    Parameters:
    - X_train, X_test: Pre-split feature matrices
    - y_train, y_test: Pre-split target variables
    - preprocessor: Combined preprocessor for one-hot encoding, ordinal␣
↪encoding, and standard scaling
    - algorithm: Initialized ML algorithm (e.g., Lasso regression)
    - param_grid: Parameter grid for GridSearchCV
    - algorithm_random_state: Optional list of random states for the algorithm

    Returns:
    - best_models: List of best models from each random state
    - test_scores: List of corresponding test scores
    """
    # If algorithm_random_state is None, use a range of random states
    if algorithm_random_state is None:
        random_states = np.arange(10)  # 10 different random states
    else:
        random_states = algorithm_random_state

    best_models = []
    test_scores = []
    all_predictions = []

    # Check if the algorithm has a 'random_state' parameter
    algorithm_has_random_state = 'random_state' in algorithm.get_params()

    for random_state in random_states:
        print(f"Random State: {random_state}")

        # KFold with 4 folds
        kf = KFold(n_splits=4, shuffle=True, random_state=random_state)

        # Initialize pipeline with the combined preprocessor and algorithm
        pipeline = Pipeline([
            ('preprocessor', preprocessor),
            ('algorithm', algorithm)
        ])

        # Set algorithm's random state if applicable
        if algorithm_has_random_state and random_state is not None:
```

```
            algorithm.set_params(**{'random_state': random_state})

        # GridSearchCV
        grid_search = GridSearchCV(pipeline, param_grid=param_grid, cv=kf,␣
↪scoring='neg_mean_squared_error', n_jobs=-1)
        grid_search.fit(X_train, y_train)

        # Print GridSearchCV results
        print(f"Best parameters: {grid_search.best_params_}")

        # Predict on the test set
        y_pred = grid_search.predict(X_test)
        all_predictions.append(y_pred)

        # Calculate RMSE
        rmse = np.sqrt(mean_squared_error(y_test, y_pred))
        test_scores.append(rmse)
        print(f"Test RMSE: {rmse}\n")

        # Save the best model
        best_models.append(grid_search.best_estimator_)

    # Print mean and standard deviation of test scores
    print(f"Mean Test RMSE: {np.mean(test_scores)}")
    print(f"Standard Deviation of Test RMSE: {np.std(test_scores)}")
    #print(y_pred)

    return best_models, test_scores, all_predictions
```

[85]:
```
# Create an empty DataFrame with the desired columns
results_df = pd.DataFrame(columns=['Model Name', 'Mean of RMSE', 'SD of RMSE'])
```

[86]:
```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder, StandardScaler
from sklearn.linear_model import Lasso
from sklearn.impute import SimpleImputer
from sklearn.ensemble import RandomForestRegressor

# One-Hot Encoding Preprocessor
onehot_ftrs = ['family_history']
one_hot_preprocessor = ColumnTransformer(
    transformers=[
        ('onehot', OneHotEncoder(), onehot_ftrs)
    ])


# Symptoms and their degree categories
```

```
symptoms = [
    "scaling",
    "definite_borders",
    "itching",
    "koebner_phenomenon",
    "polygonal_papules",
    "follicular_papules",
    "oral_mucosal_involvement",
    "knee_and_elbow_involvement",
    "scalp_involvement"
]

degree = [0, 1, 2, 3]

# Each symptom has the same set of categories
ordinal_cats = [degree] * len(symptoms)

# Initialize the Ordinal Encoder with specified categories
enc = OrdinalEncoder(categories=ordinal_cats)

# Using ColumnTransformer with column names
ordinal_preprocessor = ColumnTransformer(
    transformers=[
        ('ordinal', enc, symptoms)
    ])

# Standard Scaler
standard_scaler = ColumnTransformer(
    transformers=[
        ('scaler', StandardScaler(), ['age'])
    ])


combined_preprocessor = ColumnTransformer(
    transformers=[
        ('onehot', OneHotEncoder(), onehot_ftrs),  # One-Hot Encoding
        ('ordinal', enc, symptoms),                # Ordinal Encoding
        ('scaler', StandardScaler(), ['age'])      # Standard Scaling
    ])

print('random forest')
print()

# Random Forest Algorithm
random_forest = RandomForestRegressor()  # Initialize RandomForestRegressor

param_grid_rf = {
```

```
    'algorithm__n_estimators': [100, 300, 400],    # Example hyperparameters
    'algorithm__max_depth': [None, 20, 40],        # Example hyperparameters␣
 ↪10 20
    'algorithm__min_samples_split': [10, 30, 60]    # Example hyperparameters␣
 ↪2 5 10
}

best_models, test_scores, all_predictions = MLpipe_KFold_RMSE(
    X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test,
    preprocessor=combined_preprocessor, algorithm=random_forest,␣
 ↪param_grid=param_grid_rf
)
```

```
random forest

Random State: 0
Best parameters: {'algorithm__max_depth': None, 'algorithm__min_samples_split':
10, 'algorithm__n_estimators': 400}
Test RMSE: 0.6414714745793272

Random State: 1
Best parameters: {'algorithm__max_depth': None, 'algorithm__min_samples_split':
10, 'algorithm__n_estimators': 100}
Test RMSE: 0.6512050500402599

Random State: 2
Best parameters: {'algorithm__max_depth': None, 'algorithm__min_samples_split':
30, 'algorithm__n_estimators': 400}
Test RMSE: 0.615276081384775

Random State: 3
Best parameters: {'algorithm__max_depth': None, 'algorithm__min_samples_split':
60, 'algorithm__n_estimators': 300}
Test RMSE: 0.6123720148359012

Random State: 4
Best parameters: {'algorithm__max_depth': None, 'algorithm__min_samples_split':
60, 'algorithm__n_estimators': 400}
Test RMSE: 0.6113659997799069

Random State: 5
Best parameters: {'algorithm__max_depth': None, 'algorithm__min_samples_split':
60, 'algorithm__n_estimators': 400}
Test RMSE: 0.6116375837968588

Random State: 6
Best parameters: {'algorithm__max_depth': None, 'algorithm__min_samples_split':
```

```
10, 'algorithm__n_estimators': 400}
Test RMSE: 0.650971386012876

Random State: 7
Best parameters: {'algorithm__max_depth': None, 'algorithm__min_samples_split':
60, 'algorithm__n_estimators': 400}
Test RMSE: 0.6123210413985772

Random State: 8
Best parameters: {'algorithm__max_depth': None, 'algorithm__min_samples_split':
60, 'algorithm__n_estimators': 100}
Test RMSE: 0.6107808005961228

Random State: 9
Best parameters: {'algorithm__max_depth': None, 'algorithm__min_samples_split':
60, 'algorithm__n_estimators': 400}
Test RMSE: 0.6122380523542572

Mean Test RMSE: 0.6229639484778863
Standard Deviation of Test RMSE: 0.01653886821338424
```

[87]:
```python
# Assuming you have calculated the mean and SD of RMSE
mean_rmse = np.mean(test_scores)
std_rmse = np.std(test_scores)

# Define the model name
model_name = 'random forest'
md
# Check if the model name already exists in the DataFrame
if model_name in results_df['Model Name'].values:
    # Update the existing row
    results_df.loc[results_df['Model Name'] == model_name, 'Mean of RMSE'] =␣
 ↪mean_rmse
    results_df.loc[results_df['Model Name'] == model_name, 'SD of RMSE'] =␣
 ↪std_rmse
else:
    # Create a new DataFrame for the row to be added
    new_row = pd.DataFrame({'Model Name': [model_name],
                            'Mean of RMSE': [mean_rmse],
                            'SD of RMSE': [std_rmse]})

    # Append the new row
    results_df = pd.concat([results_df, new_row], ignore_index=True)
```

[88]:
```python
from sklearn.linear_model import Lasso

print('Lasso Regression')
```

```
print()

# Lasso Regression Algorithm
lasso = Lasso()  # Initialize Lasso

param_grid_lasso = {
    'algorithm__alpha': [0.001, 0.01, 0.1, 1, 10, 20]   # Example␣
 ↪hyperparameters
}

best_models, test_scores, all_predictions = MLpipe_KFold_RMSE(
    X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test,
    preprocessor=combined_preprocessor, algorithm=lasso,␣
 ↪param_grid=param_grid_lasso
)

# Assuming you have calculated the mean and SD of RMSE
mean_rmse = np.mean(test_scores)
std_rmse = np.std(test_scores)

# Define the model name
model_name = 'Lasso'

# Check if the model name already exists in the DataFrame
if model_name in results_df['Model Name'].values:
    # Update the existing row
    results_df.loc[results_df['Model Name'] == model_name, 'Mean of RMSE'] =␣
 ↪mean_rmse
    results_df.loc[results_df['Model Name'] == model_name, 'SD of RMSE'] =␣
 ↪std_rmse
else:
    # Create a new DataFrame for the row to be added
    new_row = pd.DataFrame({'Model Name': [model_name],
                            'Mean of RMSE': [mean_rmse],
                            'SD of RMSE': [std_rmse]})

    # Append the new row
    results_df = pd.concat([results_df, new_row], ignore_index=True)
```

```
Lasso Regression

Random State: 0
Best parameters: {'algorithm__alpha': 0.001}
Test RMSE: 0.643099967121582

Random State: 1
Best parameters: {'algorithm__alpha': 0.001}
```

```
Test RMSE: 0.643099967121582

Random State: 2
Best parameters: {'algorithm__alpha': 0.001}
Test RMSE: 0.643099967121582

Random State: 3
Best parameters: {'algorithm__alpha': 0.01}
Test RMSE: 0.6160239002901914

Random State: 4
Best parameters: {'algorithm__alpha': 0.01}
Test RMSE: 0.6160239002901914

Random State: 5
Best parameters: {'algorithm__alpha': 0.01}
Test RMSE: 0.6160239002901914

Random State: 6
Best parameters: {'algorithm__alpha': 0.001}
Test RMSE: 0.643099967121582

Random State: 7
Best parameters: {'algorithm__alpha': 0.001}
Test RMSE: 0.643099967121582

Random State: 8
Best parameters: {'algorithm__alpha': 0.1}
Test RMSE: 0.6189957261133908

Random State: 9
Best parameters: {'algorithm__alpha': 0.001}
Test RMSE: 0.643099967121582

Mean Test RMSE: 0.6325667229713458
Standard Deviation of Test RMSE: 0.012926183877966025
```

[109]:
```
results_df
```

[109]:

	Model Name	Mean of RMSE	SD of RMSE
0	random forest	0.647258	0.003724
1	Lasso	0.632567	0.012926

[89]:
```
from sklearn.linear_model import Ridge

print('Ridge Regression')
print()
```

```
# Ridge Regression Algorithm
ridge = Ridge()  # Initialize Ridge

param_grid_ridge = {
    'algorithm__alpha': [0.001, 0.01, 0.1, 5, 20, 30]    # Example␣
 ↪hyperparameters
}

best_models, test_scores, all_predictions = MLpipe_KFold_RMSE(
    X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test,
    preprocessor=combined_preprocessor, algorithm=ridge,␣
 ↪param_grid=param_grid_ridge
)

# Assuming you have calculated the mean and SD of RMSE
mean_rmse = np.mean(test_scores)
std_rmse = np.std(test_scores)

# Define the model name
model_name = 'Ridge'

# Check if the model name already exists in the DataFrame
if model_name in results_df['Model Name'].values:
    # Update the existing row
    results_df.loc[results_df['Model Name'] == model_name, 'Mean of RMSE'] =␣
 ↪mean_rmse
    results_df.loc[results_df['Model Name'] == model_name, 'SD of RMSE'] =␣
 ↪std_rmse
else:
    # Create a new DataFrame for the row to be added
    new_row = pd.DataFrame({'Model Name': [model_name],
                            'Mean of RMSE': [mean_rmse],
                            'SD of RMSE': [std_rmse]})

    # Append the new row
    results_df = pd.concat([results_df, new_row], ignore_index=True)
```

```
Ridge Regression

Random State: 0
Best parameters: {'algorithm__alpha': 20}
Test RMSE: 0.6165012335916666

Random State: 1
Best parameters: {'algorithm__alpha': 5}
Test RMSE: 0.6329959915342647
```

```
Random State: 2
Best parameters: {'algorithm__alpha': 5}
Test RMSE: 0.6329959915342647

Random State: 3
Best parameters: {'algorithm__alpha': 20}
Test RMSE: 0.6165012335916666

Random State: 4
Best parameters: {'algorithm__alpha': 20}
Test RMSE: 0.6165012335916666

Random State: 5
Best parameters: {'algorithm__alpha': 20}
Test RMSE: 0.6165012335916666

Random State: 6
Best parameters: {'algorithm__alpha': 5}
Test RMSE: 0.6329959915342647

Random State: 7
Best parameters: {'algorithm__alpha': 5}
Test RMSE: 0.6329959915342647

Random State: 8
Best parameters: {'algorithm__alpha': 20}
Test RMSE: 0.6165012335916666

Random State: 9
Best parameters: {'algorithm__alpha': 5}
Test RMSE: 0.6329959915342647

Mean Test RMSE: 0.6247486125629657
Standard Deviation of Test RMSE: 0.008247378971299013
```

[167]:
```python
from sklearn.linear_model import ElasticNet

print('Elastic Net Regression')
print()

# Elastic Net Regression Algorithm
elastic_net = ElasticNet()  # Initialize Elastic Net

param_grid_elastic_net = {
    'algorithm__alpha': [0.005, 0.01, 0.015, 0.02, 10, 100],   # Example␣
 ↪hyperparameters
```

```
    'algorithm__l1_ratio': [0.3, 0.5, 0.9]                # Example␣
 ↪hyperparameters
}

best_models, test_scores, all_predictions = MLpipe_KFold_RMSE(
    X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test,
    preprocessor=combined_preprocessor, algorithm=elastic_net,␣
 ↪param_grid=param_grid_elastic_net
)

# Assuming you have calculated the mean and SD of RMSE
mean_rmse = np.mean(test_scores)
std_rmse = np.std(test_scores)

# Define the model name
model_name = 'Elastic Net'

# Check if the model name already exists in the DataFrame
if model_name in results_df['Model Name'].values:
    # Update the existing row
    results_df.loc[results_df['Model Name'] == model_name, 'Mean of RMSE'] =␣
 ↪mean_rmse
    results_df.loc[results_df['Model Name'] == model_name, 'SD of RMSE'] =␣
 ↪std_rmse
else:
    # Create a new DataFrame for the row to be added
    new_row = pd.DataFrame({'Model Name': [model_name],
                            'Mean of RMSE': [mean_rmse],
                            'SD of RMSE': [std_rmse]})

    # Append the new row
    results_df = pd.concat([results_df, new_row], ignore_index=True)
```

```
Elastic Net Regression

Random State: 0
Best parameters: {'algorithm__alpha': 0.01, 'algorithm__l1_ratio': 0.3}
Test RMSE: 0.6332536488698115

Random State: 1
Best parameters: {'algorithm__alpha': 0.015, 'algorithm__l1_ratio': 0.3}
Test RMSE: 0.6274284756293566

Random State: 2
Best parameters: {'algorithm__alpha': 0.01, 'algorithm__l1_ratio': 0.3}
Test RMSE: 0.6332536488698115
```

```
Random State: 3
Best parameters: {'algorithm__alpha': 0.02, 'algorithm__l1_ratio': 0.3}
Test RMSE: 0.622371052257872

Random State: 4
Best parameters: {'algorithm__alpha': 0.02, 'algorithm__l1_ratio': 0.3}
Test RMSE: 0.622371052257872

Random State: 5
Best parameters: {'algorithm__alpha': 0.02, 'algorithm__l1_ratio': 0.5}
Test RMSE: 0.6141118033950913

Random State: 6
Best parameters: {'algorithm__alpha': 0.015, 'algorithm__l1_ratio': 0.3}
Test RMSE: 0.6274284756293566

Random State: 7
Best parameters: {'algorithm__alpha': 0.015, 'algorithm__l1_ratio': 0.3}
Test RMSE: 0.6274284756293566

Random State: 8
Best parameters: {'algorithm__alpha': 0.02, 'algorithm__l1_ratio': 0.9}
Test RMSE: 0.6041535720330047

Random State: 9
Best parameters: {'algorithm__alpha': 0.01, 'algorithm__l1_ratio': 0.3}
Test RMSE: 0.6332536488698115

Mean Test RMSE: 0.6245053853441342
Standard Deviation of Test RMSE: 0.008868840515081649
```

[90]:
```python
from sklearn.svm import SVR

print('Support Vector Regression (SVR)')
print()

# SVR Algorithm
svr = SVR()  # Initialize SVR

param_grid_svr = {
    'algorithm__C': [0.001, 0.01, 0.1, 0.15, 10, 100],      # Example␣
 ↪hyperparameters
    'algorithm__kernel': ['linear', 'rbf', 'poly'],       # Example␣
 ↪hyperparameters
    'algorithm__degree': [2, 4, 5],                      # Example␣
 ↪hyperparameters
    'algorithm__epsilon': [0.01, 0.1, 3]               # Example hyperparameters
```

```
}

best_models, test_scores, all_predictions = MLpipe_KFold_RMSE(
    X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test,
    preprocessor=combined_preprocessor, algorithm=svr, param_grid=param_grid_svr
)

# Assuming you have calculated the mean and SD of RMSE
mean_rmse = np.mean(test_scores)
std_rmse = np.std(test_scores)

# Define the model name
model_name = 'SVR'

# Check if the model name already exists in the DataFrame
if model_name in results_df['Model Name'].values:
    # Update the existing row
    results_df.loc[results_df['Model Name'] == model_name, 'Mean of RMSE'] =␣
 ↪mean_rmse
    results_df.loc[results_df['Model Name'] == model_name, 'SD of RMSE'] =␣
 ↪std_rmse
else:
    # Create a new DataFrame for the row to be added
    new_row = pd.DataFrame({'Model Name': [model_name],
                            'Mean of RMSE': [mean_rmse],
                            'SD of RMSE': [std_rmse]})

    # Append the new row
    results_df = pd.concat([results_df, new_row], ignore_index=True)
```

```
Support Vector Regression (SVR)

Random State: 0
Best parameters: {'algorithm__C': 10, 'algorithm__degree': 2,
'algorithm__epsilon': 0.1, 'algorithm__kernel': 'linear'}
Test RMSE: 0.6587936761253084

Random State: 1
Best parameters: {'algorithm__C': 10, 'algorithm__degree': 2,
'algorithm__epsilon': 0.1, 'algorithm__kernel': 'linear'}
Test RMSE: 0.6587936761253084

Random State: 2
Best parameters: {'algorithm__C': 0.15, 'algorithm__degree': 2,
'algorithm__epsilon': 0.1, 'algorithm__kernel': 'linear'}
Test RMSE: 0.6408512271325166
```

```
Random State: 3
Best parameters: {'algorithm__C': 0.15, 'algorithm__degree': 2,
'algorithm__epsilon': 0.1, 'algorithm__kernel': 'linear'}
Test RMSE: 0.6408512271325166

Random State: 4
Best parameters: {'algorithm__C': 0.15, 'algorithm__degree': 2,
'algorithm__epsilon': 0.1, 'algorithm__kernel': 'linear'}
Test RMSE: 0.6408512271325166

Random State: 5
Best parameters: {'algorithm__C': 0.01, 'algorithm__degree': 2,
'algorithm__epsilon': 0.1, 'algorithm__kernel': 'linear'}
Test RMSE: 0.6324036641064412

Random State: 6
Best parameters: {'algorithm__C': 0.15, 'algorithm__degree': 2,
'algorithm__epsilon': 0.1, 'algorithm__kernel': 'linear'}
Test RMSE: 0.6408512271325166

Random State: 7
Best parameters: {'algorithm__C': 0.15, 'algorithm__degree': 2,
'algorithm__epsilon': 0.1, 'algorithm__kernel': 'linear'}
Test RMSE: 0.6408512271325166

Random State: 8
Best parameters: {'algorithm__C': 0.15, 'algorithm__degree': 2,
'algorithm__epsilon': 0.1, 'algorithm__kernel': 'rbf'}
Test RMSE: 0.6355163210615447

Random State: 9
Best parameters: {'algorithm__C': 0.1, 'algorithm__degree': 2,
'algorithm__epsilon': 0.1, 'algorithm__kernel': 'linear'}
Test RMSE: 0.6364607039072628

Mean Test RMSE: 0.6426224176988449
Standard Deviation of Test RMSE: 0.008553309473837997
```

[113]:
```python
from sklearn.neighbors import KNeighborsRegressor

print('k-Nearest Neighbors (KNN) Regression')
print()

# KNN Regression Algorithm
knn = KNeighborsRegressor()  # Initialize KNN Regressor

param_grid_knn = {
```

```
    'algorithm__n_neighbors': [3, 5, 7, 9],           # Example hyperparameters
    'algorithm__weights': ['uniform', 'distance'],    # Example hyperparameters
    'algorithm__p': [1, 2]                            # Example hyperparameters
}

best_models, test_scores, all_predictions = MLpipe_KFold_RMSE(
    X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test,
    preprocessor=combined_preprocessor, algorithm=knn, param_grid=param_grid_knn
)


# Assuming you have calculated the mean and SD of RMSE
mean_rmse = np.mean(test_scores)
std_rmse = np.std(test_scores)

# Define the model name
model_name = 'KNN'

# Check if the model name already exists in the DataFrame
if model_name in results_df['Model Name'].values:
    # Update the existing row
    results_df.loc[results_df['Model Name'] == model_name, 'Mean of RMSE'] =␣
 ↪mean_rmse
    results_df.loc[results_df['Model Name'] == model_name, 'SD of RMSE'] =␣
 ↪std_rmse
else:
    # Create a new DataFrame for the row to be added
    new_row = pd.DataFrame({'Model Name': [model_name],
                            'Mean of RMSE': [mean_rmse],
                            'SD of RMSE': [std_rmse]})

    # Append the new row
    results_df = pd.concat([results_df, new_row], ignore_index=True)
```

```
k-Nearest Neighbors (KNN) Regression

Random State: 0
Best parameters: {'algorithm__n_neighbors': 9, 'algorithm__p': 2,
'algorithm__weights': 'distance'}
Test RMSE: 0.649899341938019

Random State: 1
Best parameters: {'algorithm__n_neighbors': 9, 'algorithm__p': 1,
'algorithm__weights': 'uniform'}
Test RMSE: 0.6736372320869647

Random State: 2
```

```
Best parameters: {'algorithm__n_neighbors': 7, 'algorithm__p': 2,
'algorithm__weights': 'distance'}
Test RMSE: 0.6576913935483626

Random State: 3
Best parameters: {'algorithm__n_neighbors': 9, 'algorithm__p': 1,
'algorithm__weights': 'uniform'}
Test RMSE: 0.6736372320869647

Random State: 4
Best parameters: {'algorithm__n_neighbors': 5, 'algorithm__p': 2,
'algorithm__weights': 'distance'}
Test RMSE: 0.6657990055665614

Random State: 5
Best parameters: {'algorithm__n_neighbors': 9, 'algorithm__p': 2,
'algorithm__weights': 'distance'}
Test RMSE: 0.649899341938019

Random State: 6
Best parameters: {'algorithm__n_neighbors': 9, 'algorithm__p': 2,
'algorithm__weights': 'uniform'}
Test RMSE: 0.6666666666666667

Random State: 7
Best parameters: {'algorithm__n_neighbors': 9, 'algorithm__p': 2,
'algorithm__weights': 'uniform'}
Test RMSE: 0.6666666666666667

Random State: 8
Best parameters: {'algorithm__n_neighbors': 9, 'algorithm__p': 2,
'algorithm__weights': 'uniform'}
Test RMSE: 0.6666666666666667

Random State: 9
Best parameters: {'algorithm__n_neighbors': 9, 'algorithm__p': 2,
'algorithm__weights': 'uniform'}
Test RMSE: 0.6666666666666667

Mean Test RMSE: 0.663723021383156
Standard Deviation of Test RMSE: 0.008087779729014503
```

[91]:
```python
import xgboost as xgb

print('XGBoost Regression')
print()
```

```
# XGBoost Regression Algorithm
xgb_regressor = xgb.XGBRegressor()  # Initialize XGBoost Regressor

param_grid_xgb = {
    'algorithm__n_estimators': [20, 30, 50],  # Example hyperparameters
    'algorithm__learning_rate': [0.1, 0.12, 0.15],  # Example hyperparameters
    'algorithm__max_depth': [1, 2, 3],  # Example hyperparameters
}

best_models, test_scores, all_predictions = MLpipe_KFold_RMSE(
    X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test,
    preprocessor=combined_preprocessor, algorithm=xgb_regressor,␣
 ↪param_grid=param_grid_xgb
)

# Assuming you have calculated the mean and SD of RMSE
mean_rmse = np.mean(test_scores)
std_rmse = np.std(test_scores)

# Define the model name
model_name = 'XGBoost'

# Check if the model name already exists in the DataFrame
if model_name in results_df['Model Name'].values:
    # Update the existing row
    results_df.loc[results_df['Model Name'] == model_name, 'Mean of RMSE'] =␣
 ↪mean_rmse
    results_df.loc[results_df['Model Name'] == model_name, 'SD of RMSE'] =␣
 ↪std_rmse
else:
    # Create a new DataFrame for the row to be added
    new_row = pd.DataFrame({'Model Name': [model_name],
                            'Mean of RMSE': [mean_rmse],
                            'SD of RMSE': [std_rmse]})

    # Append the new row
    results_df = pd.concat([results_df, new_row], ignore_index=True)
```

```
XGBoost Regression

Random State: 0
Best parameters: {'algorithm__learning_rate': 0.1, 'algorithm__max_depth': 2,
'algorithm__n_estimators': 50}
Test RMSE: 0.6219785674651628

Random State: 1
Best parameters: {'algorithm__learning_rate': 0.15, 'algorithm__max_depth': 2,
```

```
'algorithm__n_estimators': 30}
Test RMSE: 0.6191239689261039

Random State: 2
Best parameters: {'algorithm__learning_rate': 0.12, 'algorithm__max_depth': 3,
'algorithm__n_estimators': 30}
Test RMSE: 0.6303590568420018

Random State: 3
Best parameters: {'algorithm__learning_rate': 0.15, 'algorithm__max_depth': 2,
'algorithm__n_estimators': 30}
Test RMSE: 0.6191239689261039

Random State: 4
Best parameters: {'algorithm__learning_rate': 0.12, 'algorithm__max_depth': 2,
'algorithm__n_estimators': 30}
Test RMSE: 0.6059589763581087

Random State: 5
Best parameters: {'algorithm__learning_rate': 0.15, 'algorithm__max_depth': 2,
'algorithm__n_estimators': 30}
Test RMSE: 0.6191239689261039

Random State: 6
Best parameters: {'algorithm__learning_rate': 0.12, 'algorithm__max_depth': 2,
'algorithm__n_estimators': 30}
Test RMSE: 0.6059589763581087

Random State: 7
Best parameters: {'algorithm__learning_rate': 0.12, 'algorithm__max_depth': 1,
'algorithm__n_estimators': 30}
Test RMSE: 0.6117689924024035

Random State: 8
Best parameters: {'algorithm__learning_rate': 0.1, 'algorithm__max_depth': 2,
'algorithm__n_estimators': 30}
Test RMSE: 0.6046380567827411

Random State: 9
Best parameters: {'algorithm__learning_rate': 0.12, 'algorithm__max_depth': 1,
'algorithm__n_estimators': 30}
Test RMSE: 0.6117689924024035

Mean Test RMSE: 0.6149803525389241
Standard Deviation of Test RMSE: 0.007920526713801555
```

[182]:
```
from sklearn.metrics import mean_squared_error

# Step 1: Concatenate all y_test arrays (assuming they are of the same length)
all_y_test = np.concatenate([y_test] * len(all_predictions))  # Replicate␣
 ↪y_test for each set of predictions

# Step 2: Calculate the mean of the combined y_test array
mean_y_test = all_y_test.mean()

# Step 3: Compute the RMSE for each individual y_test array
rmse_list = []
for y_pred in all_predictions:
    mean_predictions = np.full(shape=y_pred.shape, fill_value=mean_y_test)  #␣
 ↪Create mean predictions
    rmse = np.sqrt(mean_squared_error(y_pred, mean_predictions))  # Calculate␣
 ↪RMSE
    rmse_list.append(rmse)

# Step 4: Average these RMSEs
baseline_rmse = np.mean(rmse_list)

print(f"Baseline RMSE across all iterations: {baseline_rmse}")




# Calculate the standard deviation of the RMSE values in rmse_list
baseline_rmse_sd = np.std(rmse_list)

print(f"Standard Deviation of Baseline RMSE: {baseline_rmse_sd}")
```

```
Baseline RMSE across all iterations: 0.38570301899846604
Standard Deviation of Baseline RMSE: 0.025143493147237114
```

[92]:
```
# Find the index of the model with the lowest RMSE
min_rmse_index = test_scores.index(min(test_scores))

# Retrieve the best model's test RMSE and predictions
best_rmse = test_scores[min_rmse_index]
best_predictions = all_predictions[min_rmse_index]

print(f"Lowest Test RMSE: {best_rmse}")
print(f"Predictions of the Best Model: {best_predictions}")


print()
```

```python
# Convert the list of predictions to a NumPy array
all_predictions_array = np.array(all_predictions)

# Calculate the element-wise mean of the predictions
average_predictions = np.mean(all_predictions_array, axis=0)

print("Average Predictions from All Iterations:", average_predictions)

print()
new_predict = best_models[min_rmse_index].predict(X_test)
print(new_predict)
```

```
Lowest Test RMSE: 0.6046380567827411
Predictions of the Best Model: [2.1006901 2.2233882 2.0130107 2.2969584
2.1581006 1.6922238 2.4707396
 1.7224228 1.9878582 1.7155268 2.1574965 1.7267067 2.2748163 2.1021945
 2.4044316 2.2472372 1.7195994 1.7267067 2.3069696 2.2233882 1.3975533
 1.4892049 1.5480663 2.3069696 2.4479048 2.2233882 2.568398  2.4087882
 2.3069696 2.19901   1.8760502 1.4159615 2.2233882 1.5187471 2.4537265
 1.3767357 2.1581006 2.19901   1.6526048 1.4214658 2.0933802 2.19901
 1.7159928 1.9899911 1.6857938 1.5426595 2.4479048 2.4044316 2.2233882
 1.5426595 2.2016006 1.6853278 1.6853278 1.8005775 2.1520698 1.5194039
 2.1111603 2.0937943 2.2472372 2.1574965 2.1842713 2.19901   2.2969584
 2.241682  2.5314863 2.2233882 2.3084388 2.19901   2.3870006 1.7019534
 2.4707396 2.19901   2.280799  2.0937943]

Average Predictions from All Iterations: [2.1604505 2.2698581 2.023004  2.328669
2.2168834 1.7024231 2.5941148
 1.7727709 2.0419657 1.7619365 2.2114985 1.7450182 2.3088367 2.1302354
 2.4896817 2.3084273 1.7494694 1.7364576 2.363523  2.2763467 1.4162166
 1.5175667 1.5848763 2.3577878 2.488439  2.2763467 2.7488441 2.5023084
 2.3577878 2.2437918 1.9465678 1.4222866 2.2763467 1.5436019 2.539364
 1.4176433 2.2118323 2.2437918 1.6697851 1.4711144 2.1627724 2.2437918
 1.759902  2.098999  1.7189032 1.6024892 2.5407195 2.496309  2.2672365
 1.5956639 2.210498  1.7138504 1.7209377 1.8884369 2.148242  1.5419734
 2.1542225 2.1461537 2.3084273 2.1949422 2.2418911 2.2437918 2.328669
 2.313622  2.6056786 2.2763467 2.3979425 2.2437918 2.429503  1.7349313
 2.5941148 2.2066934 2.322369  2.1461537]

[2.1006901 2.2233882 2.0130107 2.2969584 2.1581006 1.6922238 2.4707396
 1.7224228 1.9878582 1.7155268 2.1574965 1.7267067 2.2748163 2.1021945
 2.4044316 2.2472372 1.7195994 1.7267067 2.3069696 2.2233882 1.3975533
 1.4892049 1.5480663 2.3069696 2.4479048 2.2233882 2.568398  2.4087882
 2.3069696 2.19901   1.8760502 1.4159615 2.2233882 1.5187471 2.4537265
 1.3767357 2.1581006 2.19901   1.6526048 1.4214658 2.0933802 2.19901
 1.7159928 1.9899911 1.6857938 1.5426595 2.4479048 2.4044316 2.2233882
 1.5426595 2.2016006 1.6853278 1.6853278 1.8005775 2.1520698 1.5194039
```

```
2.1111603 2.0937943 2.2472372 2.1574965 2.1842713 2.19901   2.2969584
2.241682  2.5314863 2.2233882 2.3084388 2.19901   2.3870006 1.7019534
2.4707396 2.19901   2.280799  2.0937943]
```

[93]:
```
results_df
```

[93]:

	Model Name	Mean of RMSE	SD of RMSE
0	random forest	0.622964	0.016539
1	Lasso	0.632567	0.012926
2	Ridge	0.624749	0.008247
3	SVR	0.642622	0.008553
4	XGBoost	0.614980	0.007921

[168]:
```
# Create a figure and axis
fig, ax = plt.subplots()

# Create a table and remove the axes
table = ax.table(cellText=results_df.values, colLabels=results_df.columns,␣
 ↪loc='center')
ax.axis('off')

# Center align the columns
for cell in table._cells.values():
    cell.set_text_props(horizontalalignment='center')

# Save the figure
file_path = '/Users/suchen/Desktop/Data1030 HW/final/models_and_rmse.png'
plt.savefig(file_path, dpi=350)



# Show the plot
plt.show()
# Save the figure
#plt.savefig('dataframe_image.png', dpi=300)

# Show the plot
plt.show()
```

Model Name	Mean of RMSE	SD of RMSE
random forest	0.6229639484778863	0.01653886821338424
Lasso	0.6325667229713458	0.012926183877966025
Ridge	0.6247486125629657	0.008247378971299013
SVR	0.6426224176988449	0.008553309473837997
XGBoost	0.6149803525389241	0.007920526713801555
Elastic Net	0.6245053853441342	0.008868840515081649

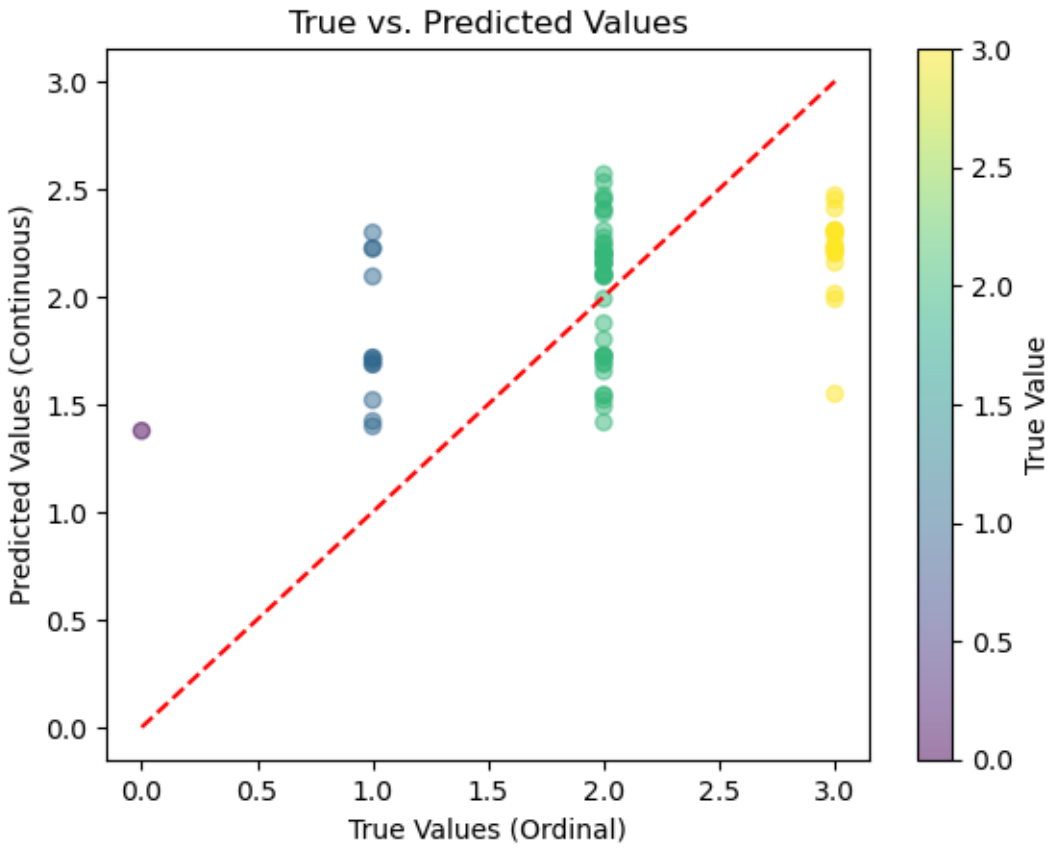
[148]:
```
import pandas as pd

data = {
    'Model Name': ['Random Forest', 'Lasso', 'Ridge', 'Elastic Net', 'SVR',␣
 ↪'XGBoost'],
    'Hyperparameter': [
        'n_estimators, max_depth, min_sample_split',
        'alpha',
        'alpha',
        'alpha, l1_ratio]',
        'C, kernel, degree, epsilon',
        'n_estimators, learning_rate, max_depth'
    ],
}

hyper = pd.DataFrame(data)

# Create a figure and axis
fig, ax = plt.subplots()

# Create a table and remove the axes
table = ax.table(cellText=hyper.values, colLabels=hyper.columns, loc='center')
ax.axis('off')
```

```
# Center align the columns
for cell in table._cells.values():
    cell.set_text_props(horizontalalignment='center')

# Save the figure
file_path = '/Users/suchen/Desktop/Data1030 HW/final/models_and_hyper.png'
plt.savefig(file_path, dpi=350)



# Show the plot
plt.show()
# Save the figure
#plt.savefig('dataframe_image.png', dpi=300)

# Show the plot
plt.show()
```

Model Name	Hyperparameter
Random Forest	n_estimators, max_depth, min_sample_split
Lasso	alpha
Ridge	alpha
Elastic Net	alpha, l1_ratio]
SVR	C, kernel, degree, epsilon
XGBoost	n_estimators, learning_rate, max_depth

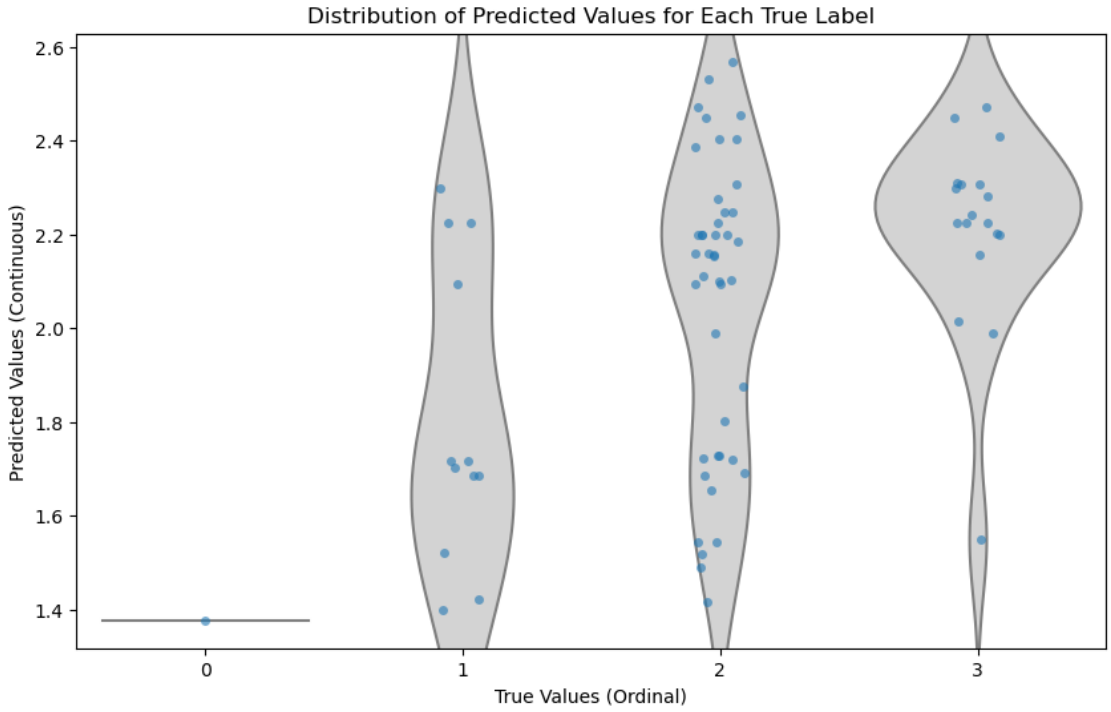
[147]:
```
import matplotlib.pyplot as plt

# Assuming y_test and average_predictions are defined
# y_test = [...]
```

```
# average_predictions = [...]

# Create a scatter plot
plt.scatter(y_test, new_predict, alpha=0.5, c=y_test, cmap='viridis')

# Plot a line for perfect predictions
plt.plot([0, 3], [0, 3], color='red', linestyle='--')

# Label the axes
plt.xlabel('True Values (Ordinal)')
plt.ylabel('Predicted Values (Continuous)')
plt.title('True vs. Predicted Values')

# Adding a color bar to explain color coding
plt.colorbar(label='True Value')

# Save the figure
file_path = '/Users/suchen/Desktop/Data1030 HW/final/true_pred01.png'
plt.savefig(file_path, dpi=350)


# Show the plot
plt.show()
```



[146]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming you have already found the best model and predicted using X_test
# y_pred = best_model.predict(X_test)  # Uncomment if not already done

# Create a dataframe for plotting (if not already in dataframe format)
import pandas as pd
data = pd.DataFrame({
    'True Label': y_test,
    'Predicted Value': new_predict
})

# Set up the figure
plt.figure(figsize=(10, 6))

# Create a violin plot to show the distribution of predicted values for each␣
 ↪true label
sns.violinplot(x='True Label', y='Predicted Value', data=data, inner=None,␣
 ↪color='lightgray')
```

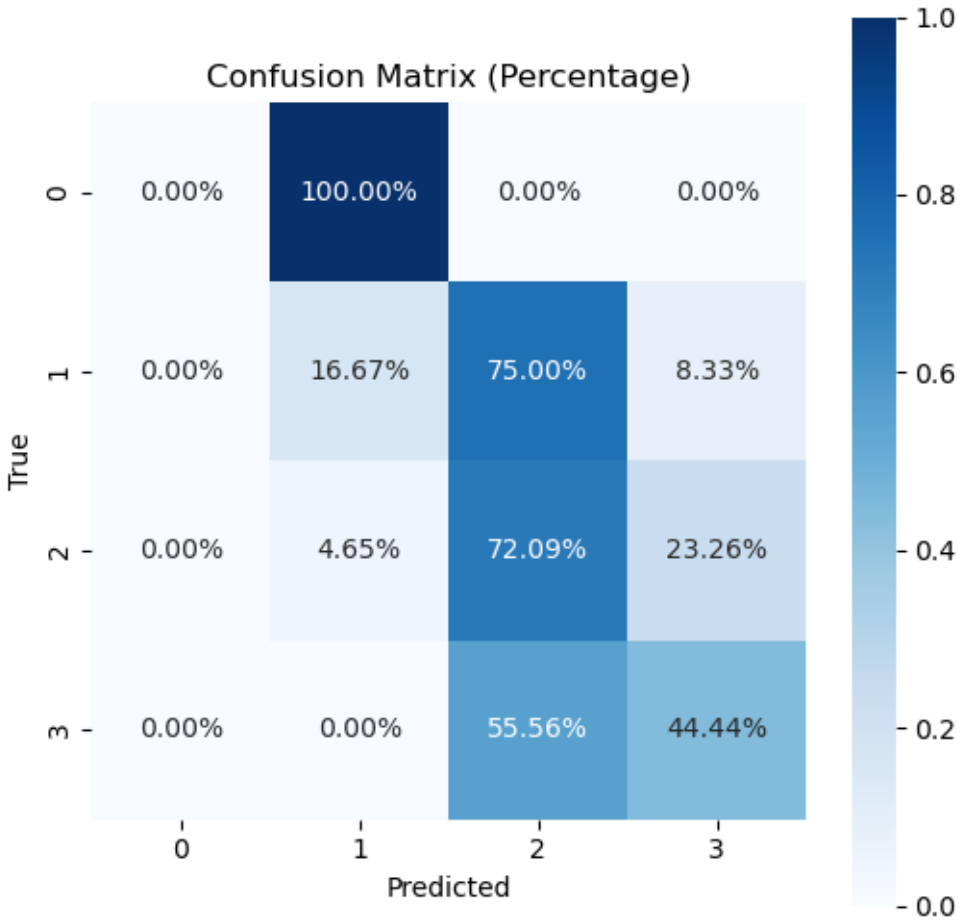
```
# Overlay a scatter plot to show individual predictions
sns.stripplot(x='True Label', y='Predicted Value', data=data, jitter=True,␣
 ↪alpha=0.6)

# Adding titles and labels
plt.title('Distribution of Predicted Values for Each True Label')
plt.xlabel('True Values (Ordinal)')
plt.ylabel('Predicted Values (Continuous)')

# Save the figure
file_path = '/Users/suchen/Desktop/Data1030 HW/final/true_pred02.png'
plt.savefig(file_path, dpi=350)

# Show the plot
plt.show()
```



[145]:
```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import confusion_matrix
import seaborn as sns
```

```
filtered_predictions = []

for prediction in new_predict:
    if 0 <= prediction < 0.75:
        filtered_predictions.append(0)
    elif 0.75 <= prediction < 1.5:
        filtered_predictions.append(1)
    elif 1.5 <= prediction < 2.25:
        filtered_predictions.append(2)
    elif 2.25 <= prediction <= 3:
        filtered_predictions.append(3)

print(filtered_predictions)



# Calculate the confusion matrix
conf_matrix = confusion_matrix(y_test, filtered_predictions)

# Normalize the confusion matrix by row
conf_matrix_normalized = conf_matrix.astype('float') / conf_matrix.sum(axis=1)[:
 ↪, np.newaxis]

# Create a heatmap for the normalized confusion matrix
plt.figure(figsize=(6, 6))
sns.heatmap(conf_matrix_normalized, annot=True, fmt=".2%", cmap="Blues",␣
 ↪square=True,
            xticklabels=np.unique(y_test), yticklabels=np.unique(y_test))
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix (Percentage)')
# Save the figure
file_path = '/Users/suchen/Desktop/Data1030 HW/final/confusion_matrix.png'
plt.savefig(file_path, dpi=350)
plt.show()
```

```
[2, 2, 2, 3, 2, 2, 3, 2, 2, 2, 2, 2, 3, 2, 3, 2, 2, 2, 3, 2, 1, 1, 2, 3, 3, 2,
3, 3, 3, 2, 2, 1, 2, 2, 3, 1, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 3, 3, 2, 2, 2, 2, 2,
2, 2, 2, 2, 2, 2, 2, 2, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2]
```



[166]:
```
# Calculate the mean or median of the target variable
mean_erythema = y_test.mean()
# median_erythema = y_final.median() # Use this if you prefer median

# Predict this mean/median value for all observations
y_pred_baseline = [mean_erythema] * len(y_test)

# Calculate the RMSE
mse_baseline = mean_squared_error(y_test, y_pred_baseline)
rmse_baseline = np.sqrt(mse_baseline)

print(rmse_baseline)
results_df
```

```
0.6756756756756757
```

[166]:

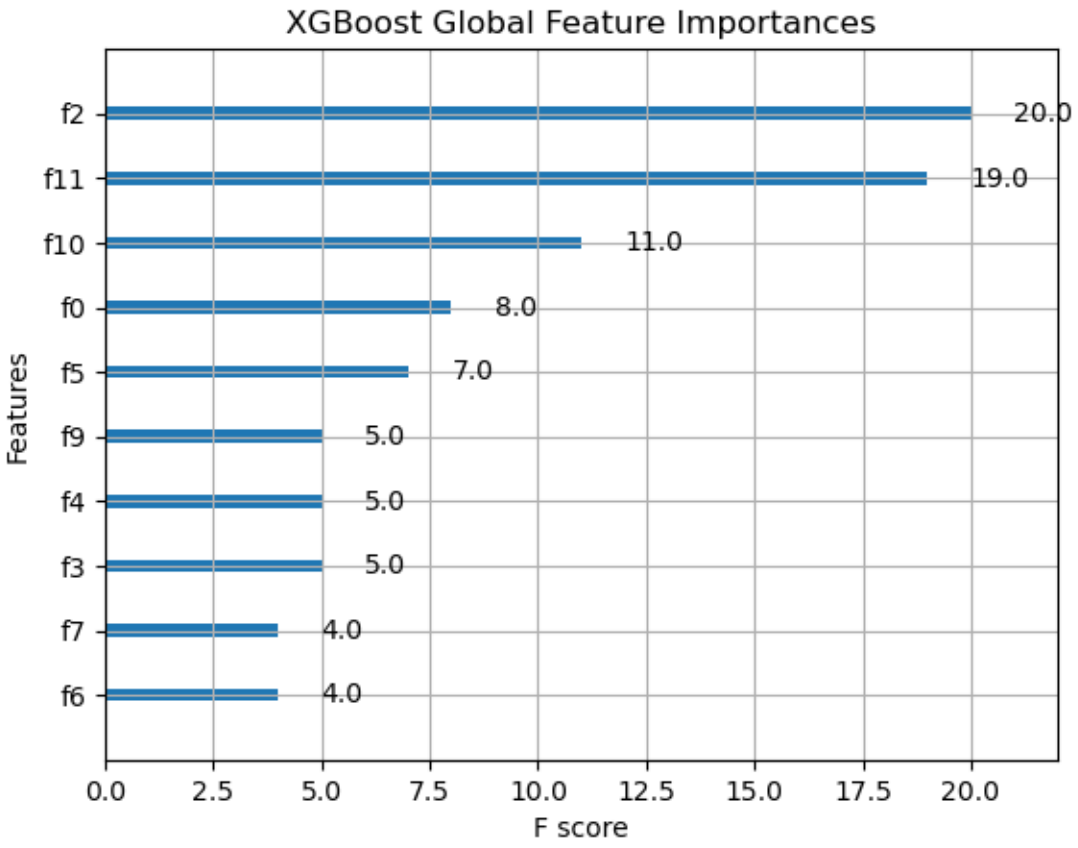
	Model Name	Mean of RMSE	SD of RMSE
0	random forest	0.622964	0.016539

```
1           Lasso      0.632567    0.012926
2           Ridge      0.624749    0.008247
3             SVR      0.642622    0.008553
4         XGBoost      0.614980    0.007921
```

[184]:
```
#filtered_df = results_df[results_df['Model Name'] != 'Ridge']

# Print the remaining rows
#filtered_df
```

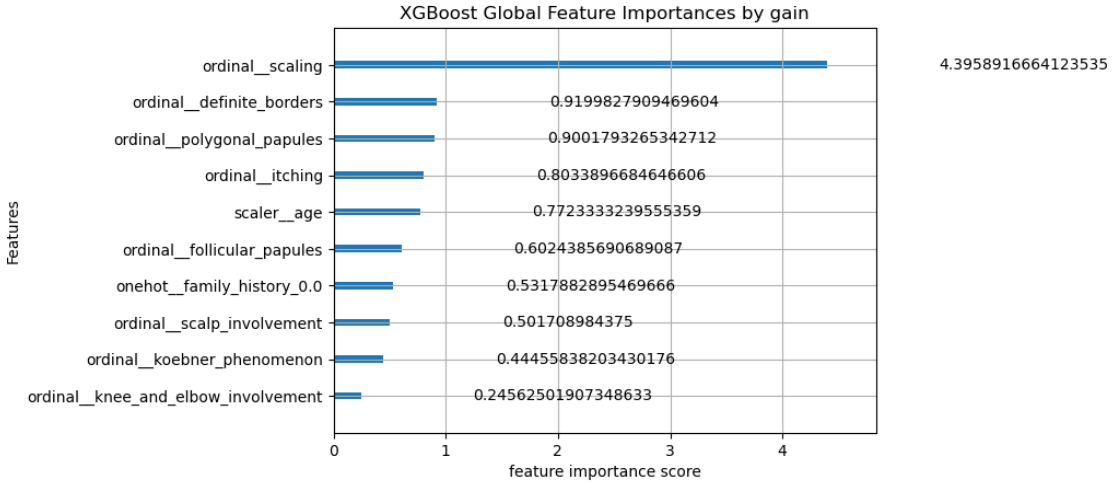
[184]:
```
       Model Name  Mean of RMSE  SD of RMSE
0   random forest      0.647258    0.003724
1           Lasso      0.632567    0.012926
3     Elastic Net      0.628257    0.013568
4             SVR      0.646501    0.006843
5             KNN      0.663723    0.008088
6         XGBoost      0.627934    0.017606
```

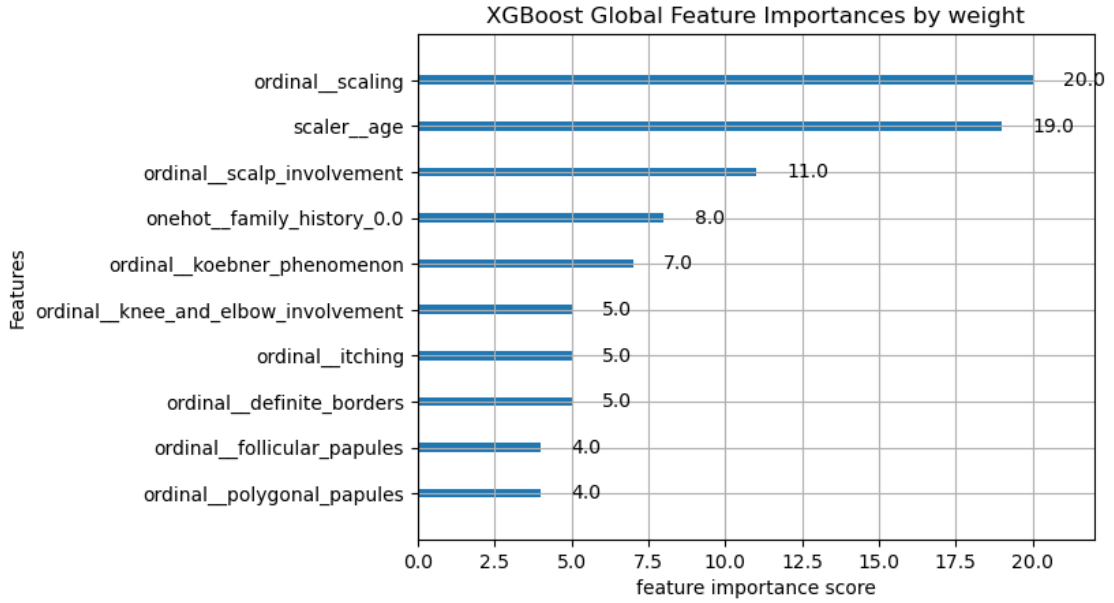
[32]:
```
import xgboost as xgb
import matplotlib.pyplot as plt

# Assuming xgb_regressor is your trained XGBoost model
# xgb_regressor = ...

# Retrieve the best model
best_model = best_models[min_rmse_index]

# The XGBoost regressor is the second step in your pipeline
trained_xgb_model = best_model.named_steps['algorithm']

xgb_regressor = trained_xgb_model

# Plot global feature importances
xgb.plot_importance(xgb_regressor)
plt.title("XGBoost Global Feature Importances")
plt.show()
```

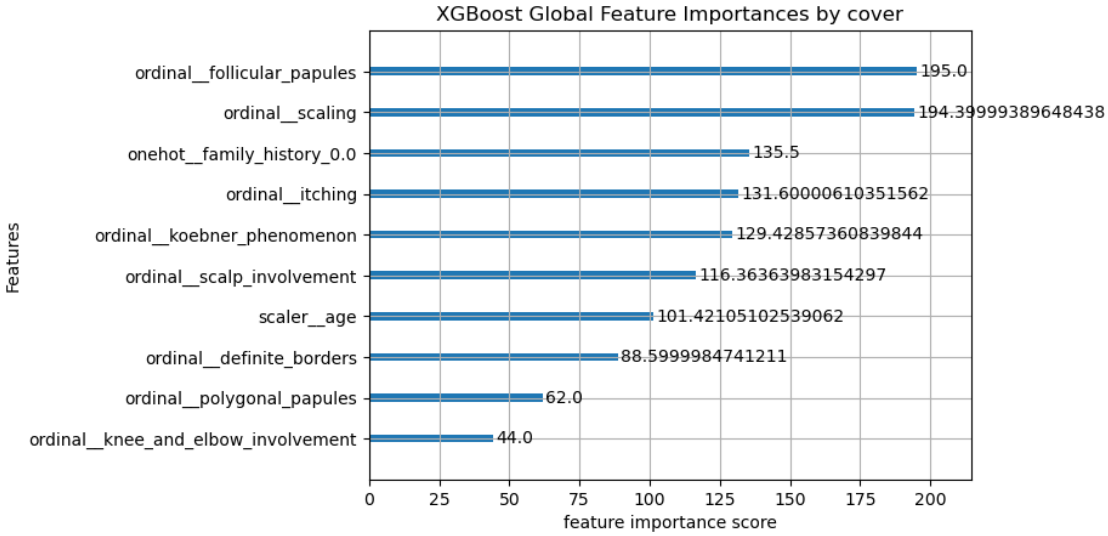


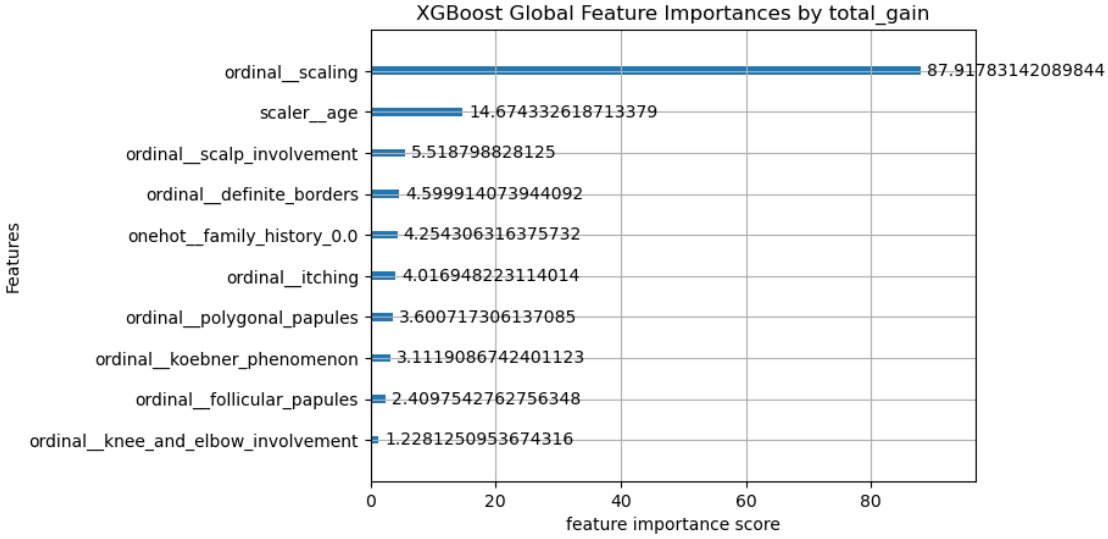
[104]:
```
# Print out the names of the steps in the pipeline
#print(best_model.named_steps.keys())

# Replace 'correct_preprocessor_name' with the actual name you found
fitted_preprocessor = best_model.named_steps['preprocessor']


# Get feature names after preprocessing and convert them to a list
feature_names = list(fitted_preprocessor.get_feature_names_out())

# Extract the trained XGBoost model
xgb_regressor = best_model.named_steps['algorithm']

# Assign feature names to the XGBoost model
xgb_regressor.get_booster().feature_names = feature_names

# Plot global feature importances
# Plot global feature importances
feature_importance_criteria = ["gain", "weight", "cover", "total_gain",␣
 ↪"total_cover"]
```

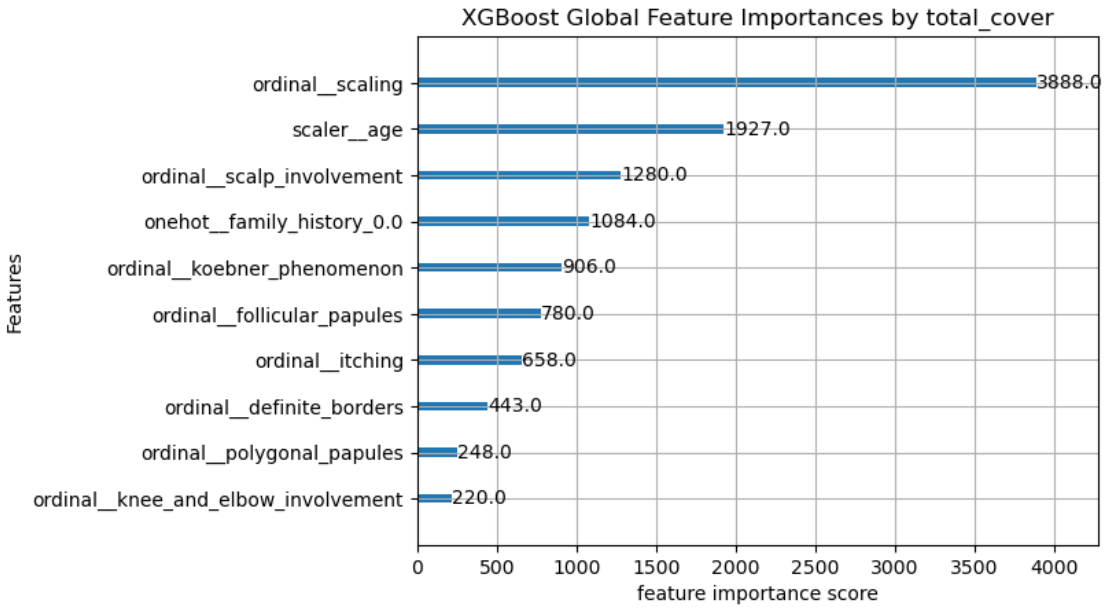
```
for feature in feature_importance_criteria:
    xgb.plot_importance(xgb_regressor, importance_type=feature)
    plt.title("XGBoost Global Feature Importances by {}".format(feature))
    plt.xlabel('feature importance score')
    plt.show()
```





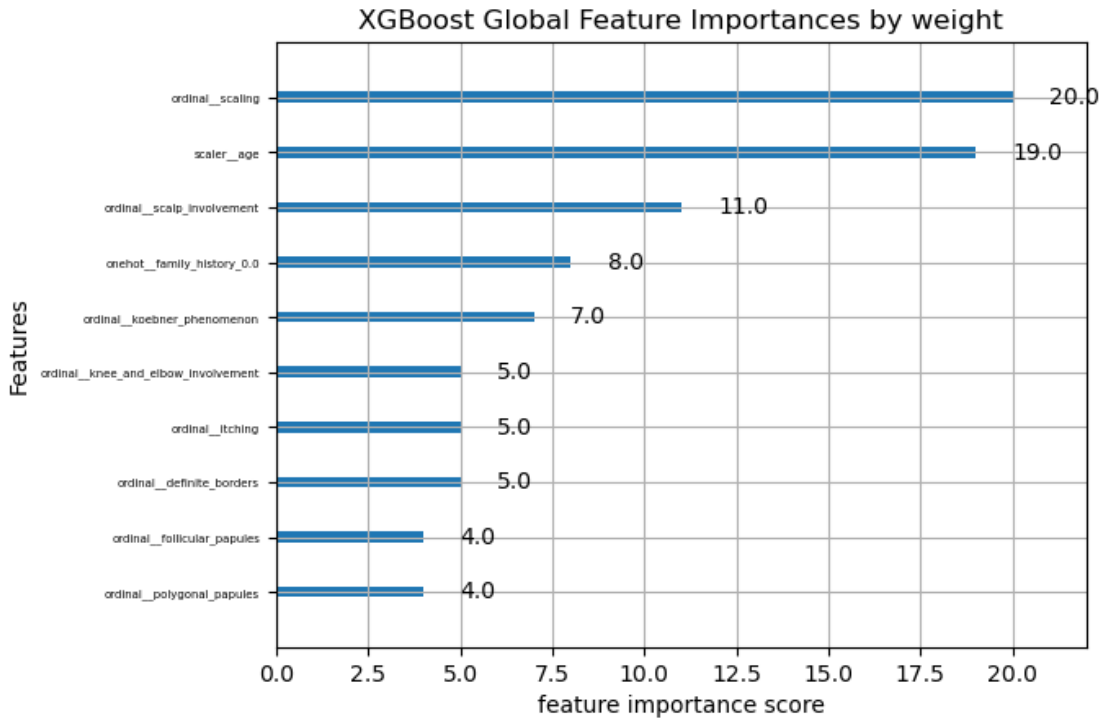

XGBoost Global Feature Importances by cover
ordinal__follicular_papules
ordinal__scaling
onehot__family_history_0.0
ordinal__itching
ordinal__koebner_phenomenon
ordinal__scalp_involvement
scaler__age
ordinal__definite_borders
ordinal__polygonal_papules
ordinal__knee_and_elbow_involvement
195.0
194.39999389648438
135.5
131.60000610351562
129.42857360839844
116.36363983154297
101.42105102539062
88.5999984741211
62.0
44.0
Features
0
25
50
75
100
125
150
175
200
feature importance score


XGBoost Global Feature Importances by total_gain
ordinal__scaling
scaler__age
ordinal__scalp_involvement
ordinal__definite_borders
onehot__family_history_0.0
ordinal__itching
ordinal__polygonal_papules
ordinal__koebner_phenomenon
ordinal__follicular_papules
ordinal__knee_and_elbow_involvement
87.91783142089844
14.674332618713379
5.518798828125
4.599914073944092
4.254306316375732
4.016948223114014
3.600717306137085
3.1119086742401123
2.4097542762756348
1.2281250953674316
Features
0
20
40
60
80
feature importance score

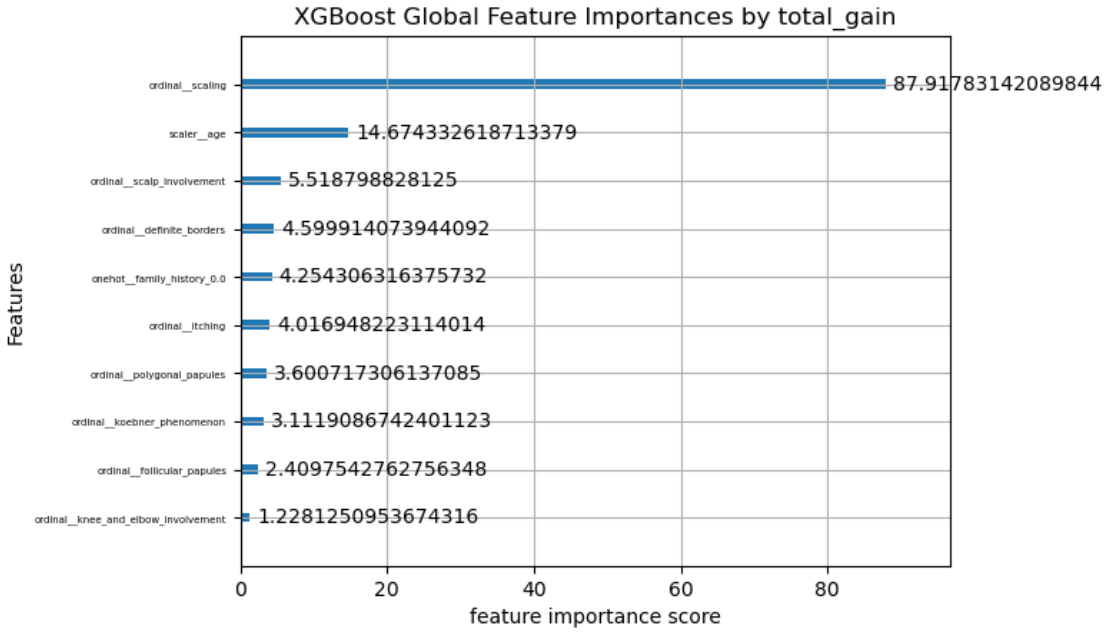


[185]:
```
# Plot global feature importances
# Plot global feature importances

# Increase the figure size to accommodate the labels
plt.figure(figsize=(10, 6))  # Adjust the width and height as needed


xgb.plot_importance(xgb_regressor, importance_type='weight')
plt.title("XGBoost Global Feature Importances by weight")
plt.xlabel('feature importance score')

# Make y-axis labels smaller
plt.tick_params(axis='y', labelsize=5)

# Save the figure
file_path = '/Users/suchen/Desktop/Data1030 HW/final/global01.png'
plt.savefig(file_path, dpi=350)

plt.show()
```

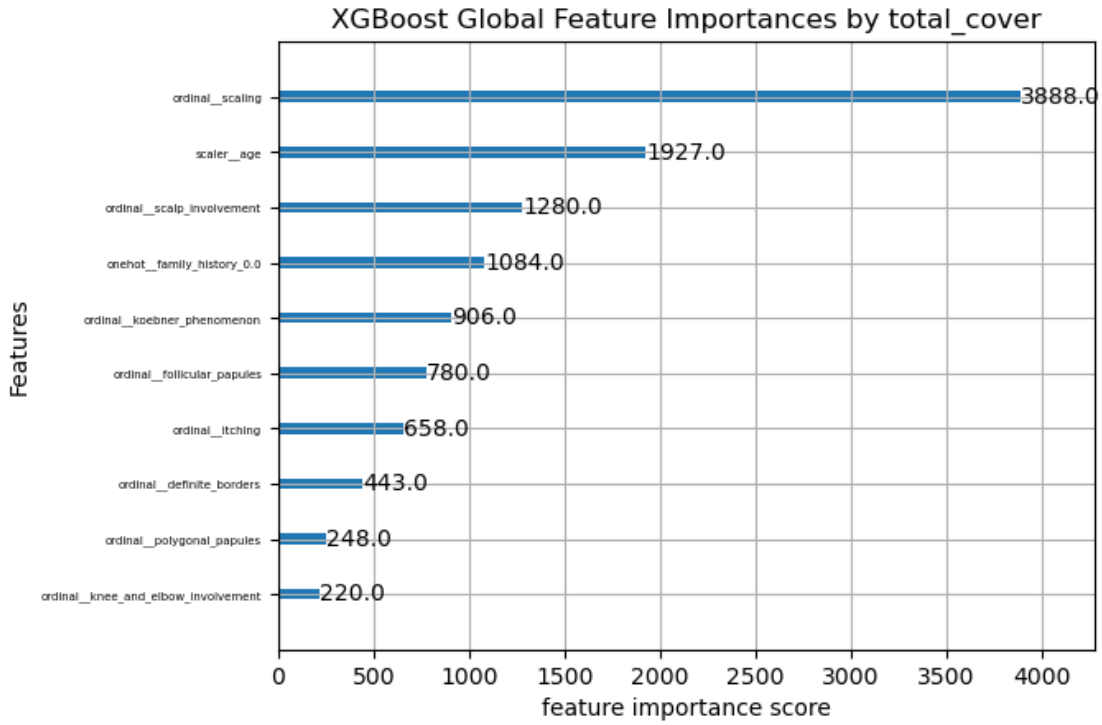
```
<Figure size 1000x600 with 0 Axes>
```



[157]:
```
# Plot global feature importances
# Plot global feature importances


xgb.plot_importance(xgb_regressor, importance_type='total_gain')
plt.title("XGBoost Global Feature Importances by total_gain")
plt.xlabel('feature importance score')

# Make y-axis labels smaller
plt.tick_params(axis='y', labelsize=5)


# Save the figure
file_path = '/Users/suchen/Desktop/Data1030 HW/final/global02.png'
plt.savefig(file_path, dpi=350)

plt.show()
```



[158]:
```
# Plot global feature importances
# Plot global feature importances


xgb.plot_importance(xgb_regressor, importance_type='total_cover')
plt.title("XGBoost Global Feature Importances by total_cover")
plt.xlabel('feature importance score')

# Make y-axis labels smaller
plt.tick_params(axis='y', labelsize=5)


# Save the figure
file_path = '/Users/suchen/Desktop/Data1030 HW/final/global03.png'
plt.savefig(file_path, dpi=350)

plt.show()
```



[60]:
```
dff = pd.read_csv('/Users/suchen/Desktop/Data1030 HW/dermatology_database_1.
 ↪csv')
# make a subset of the data, removing the "medical terms" features because they␣
 ↪are too academic to understand
dff = dff.iloc[:, list(range(0, 11)) + [33]]
#df1.info()

# create x and target variable y
X_local = dff.loc[:, dff.columns != 'erythema']
y_local = dff['erythema']


from sklearn.model_selection import train_test_split, StratifiedKFold
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
import numpy as np
import pandas as pd



# Replace '?' with NaN and convert columns to numeric where appropriate
X_local = X_local.replace('?', np.nan).apply(pd.to_numeric, errors='coerce')
```

```
# Define random state
random_state = 42

# Stratified train-test split
X_other0, X_test0, y_other0, y_test0 = train_test_split(
    X_local, y_local, test_size=0.2, stratify=y_local,␣
 ↪random_state=random_state)
print('Test balance:', np.unique(y_test0, return_counts=True))



# Transform X_test using the imputer fitted on the last fold of X_other
X_test_imputed0 = iterative_imputer.transform(X_test0)
X_test0 = pd.DataFrame(X_test_imputed, columns=X_local.columns)
```

```
Test balance: (array([0, 1, 2, 3]), array([ 1, 12, 43, 18]))
```

[181]:
```
import shap

# Assuming 'best_model' is the best model from your GridSearchCV results
best_model = best_models[test_scores.index(min(test_scores))]

# Extract the trained XGBoost model from the pipeline
xgb_model = best_model.named_steps['algorithm']

# Create a background dataset from the preprocessed training data
# Use the combined_preprocessor to transform a sample of X_train
background_data = combined_preprocessor.fit_transform(X_train.sample(100,␣
 ↪random_state=0))

# Create a SHAP explainer using the XGBoost model
explainer = shap.KernelExplainer(model=xgb_model.predict, data=background_data)

# Compute SHAP values for a single prediction or a set of predictions
# Preprocess the instance from X_test before passing it to shap_values
# Use combined_preprocessor to transform the test instance
single_instance = combined_preprocessor.transform(X_test.iloc[0:1, :])
shap_values = explainer.shap_values(single_instance)

# Plot SHAP values for the first prediction
shap.initjs()
shap.force_plot(explainer.expected_value, shap_values, single_instance)
```

```
  0%|          | 0/1 [00:00<?, ?it/s]
```

```
<IPython.core.display.HTML object>
```

[181]:
```
<shap.plots._force.AdditiveForceVisualizer at 0x16395b410>
```

[46]:
```
# Fit and transform a sample of X_train to get feature names
background_data = combined_preprocessor.fit_transform(X_train.sample(100,␣
↪random_state=0))

# Get feature names from the preprocessor
feature_names = combined_preprocessor.get_feature_names_out()
```

[48]:
```
# Preprocess the test instance
single_instance = combined_preprocessor.transform(X_test.iloc[0:1, :])

# Convert single instance to DataFrame with feature names
single_instance_df = pd.DataFrame(single_instance, columns=feature_names)
```

[109]:
```
import pandas as pd
import shap

# Convert background data and single instance to DataFrame with feature names
background_data_df = pd.DataFrame(background_data, columns=feature_names)
single_instance_df = pd.DataFrame(single_instance, columns=feature_names)

# Assuming 'best_model' is the best model from your GridSearchCV results
best_model = best_models[test_scores.index(min(test_scores))]

# Extract the trained XGBoost model from the pipeline
xgb_model = best_model.named_steps['algorithm']


# Create a SHAP TreeExplainer using the XGBoost model
explainer = shap.TreeExplainer(xgb_model)

# Compute SHAP values for the single instance
shap_values = explainer.shap_values(single_instance_df)

# Plot SHAP values for the first prediction
shap.initjs()
shap.force_plot(explainer.expected_value, shap_values[0], single_instance_df.
↪iloc[0,:])
```

```
<IPython.core.display.HTML object>
```

[109]:
```
<shap.plots._force.AdditiveForceVisualizer at 0x152b42810>
```

[139]:
```
import pandas as pd
import shap

# Fit the preprocessor with the training data
combined_preprocessor.fit(X_train)
```

```
# Preprocess X_test using the same preprocessor as used for training
X_test_preprocessed = combined_preprocessor.transform(X_test)

# Assuming 'best_model' is the best model from your GridSearchCV results
best_model = best_models[test_scores.index(min(test_scores))]

# Extract the trained XGBoost model from the pipeline
xgb_model = best_model.named_steps['algorithm']


# Create a SHAP TreeExplainer using the XGBoost model
explainer = shap.TreeExplainer(xgb_model)



# Compute SHAP values for the preprocessed test data
shap_values = explainer.shap_values(X_test_preprocessed)

shap_sum = np.abs(shap_values).mean(axis=0)

# Get feature names from the preprocessor
feature_names = list(fitted_preprocessor.get_feature_names_out())

# If X_test_preprocessed is a numpy array, create a DataFrame for plotting␣
 ↪purposes
X_test_preprocessed_df = pd.DataFrame(X_test_preprocessed,␣
 ↪columns=feature_names)


top_indices = np.argsort(shap_sum)[-10:]
top_features = np.array(feature_names)[top_indices]
shap_values_top = shap_values[:, top_indices]


# Plot SHAP values for the first prediction in the test set
shap.initjs()
shap.plots.force(explainer.expected_value, shap_values[10],␣
 ↪X_test_preprocessed_df.iloc[0], show = False)

# Save the figure
# Save the figure
```

```
<IPython.core.display.HTML object>
```

[139]:
```
<shap.plots._force.AdditiveForceVisualizer at 0x150496a50>
```

[65]:
```
shap_values
```

[65]:
```
array([[-1.06895622e-02,  0.00000000e+00,  1.42631426e-01,
         1.06353210e-02,  1.18157975e-02, -5.95146641e-02,
        -5.24820667e-03,  7.05089141e-03,  0.00000000e+00,
         1.62689912e-03, -1.91816688e-02,  2.11309381e-02],
       [-1.06895622e-02,  0.00000000e+00,  1.46033704e-01,
         1.45352604e-02,  1.18157975e-02,  4.25568819e-02,
         1.18775228e-02,  7.05089141e-03,  0.00000000e+00,
         1.62689912e-03, -1.91816688e-02,  1.73294619e-02],
       [-7.07209390e-03,  0.00000000e+00,  1.66764066e-01,
         1.59222633e-03,  1.66166574e-02, -5.95146641e-02,
        -5.24820667e-03,  2.88439868e-03,  0.00000000e+00,
        -2.03965716e-02,  4.25474830e-02, -1.25595659e-01],
       [-1.06895622e-02,  0.00000000e+00,  1.99663371e-01,
         7.94092566e-03,  1.18157975e-02,  3.78625095e-02,
        -5.24820667e-03,  3.98021098e-03,  0.00000000e+00,
         1.62689912e-03,  5.96212149e-02, -1.00476071e-02],
       [-1.06895622e-02,  0.00000000e+00,  1.82936803e-01,
         1.59222633e-03,  1.18157975e-02, -5.95146641e-02,
        -5.24820667e-03,  3.98021098e-03,  0.00000000e+00,
         1.62689912e-03,  4.12160233e-02, -1.00476071e-02],
       [-9.51647386e-03,  0.00000000e+00, -3.35346192e-01,
         3.13452333e-02,  1.24679711e-02, -2.78708916e-02,
        -2.17546634e-02,  9.12568625e-03,  0.00000000e+00,
         1.62689912e-03, -1.09801339e-02,  1.27744511e-01],
       [-1.06895622e-02,  0.00000000e+00,  2.08905101e-01,
         5.49216475e-03,  1.47030586e-02,  4.25568819e-02,
        -5.24820667e-03,  2.88439868e-03,  0.00000000e+00,
         3.83148678e-02,  1.41985849e-01,  3.14020514e-02],
       [-9.51647386e-03,  0.00000000e+00, -3.44626069e-01,
         2.23021396e-02,  3.23683098e-02, -2.78708916e-02,
        -2.17546634e-02,  3.98021098e-03,  0.00000000e+00,
         1.62689912e-03,  2.07121838e-02,  4.47685570e-02],
       [-8.14387389e-03,  0.00000000e+00,  1.74798563e-01,
         1.59222633e-03, -3.72863747e-02, -5.95146641e-02,
        -5.24820667e-03,  3.98021098e-03,  0.00000000e+00,
         1.62689912e-03,  4.12160233e-02, -1.25595659e-01],
       [-9.51647386e-03,  0.00000000e+00, -3.60928774e-01,
         1.74249280e-02,  3.23683098e-02,  1.68984905e-02,
        -2.17546634e-02,  7.05089141e-03,  0.00000000e+00,
         1.62689912e-03, -1.28439497e-02,  4.47685570e-02],
       [-7.07209390e-03,  0.00000000e+00,  1.88291490e-01,
         5.49216475e-03,  1.18157975e-02,  4.25568819e-02,
        -5.24820667e-03,  3.98021098e-03,  0.00000000e+00,
         1.62689912e-03,  4.12160233e-02, -1.25595659e-01],
       [-1.05882538e-02,  0.00000000e+00, -3.08526635e-01,
```

```
  3.13452333e-02, -4.97857518e-02, -2.78708916e-02,
  4.92342487e-02,  5.95507957e-03,  0.00000000e+00,
  2.72271177e-03, -1.09801339e-02,  4.47685570e-02],
[-1.17613422e-02,  0.00000000e+00,  2.30994865e-01,
  1.45352604e-02, -3.18065248e-02,  4.25568819e-02,
  1.18775228e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.82917770e-02,  2.76005790e-02],
[-8.93023424e-03,  0.00000000e+00,  1.90536514e-01,
  1.45352604e-02,  1.18157975e-02,  4.25568819e-02,
 -5.24820667e-03, -9.87124816e-02,  0.00000000e+00,
 -5.95949357e-03, -2.98109427e-02, -9.02161002e-03],
[ 1.17358051e-01,  0.00000000e+00,  1.90498441e-01,
 -1.47396661e-02,  1.24649815e-02,  3.78625095e-02,
 -5.24820667e-03, -1.09674357e-01,  0.00000000e+00,
 -5.95949357e-03,  9.50521380e-02,  8.63843486e-02],
[ 1.17358051e-01,  0.00000000e+00,  1.63491890e-01,
 -3.28498427e-03,  7.66412076e-03,  3.78625095e-02,
 -5.24820667e-03, -1.37322515e-01,  0.00000000e+00,
  1.15735047e-02, -3.16747613e-02,  8.63843486e-02],
[-1.99124161e-02,  0.00000000e+00, -3.90805900e-01,
  2.86508370e-02,  1.24679711e-02,  1.68984905e-02,
 -2.17546634e-02, -8.47700909e-02,  0.00000000e+00,
 -5.95949357e-03,  7.45482892e-02, -5.85233886e-03],
[-1.05882538e-02,  0.00000000e+00, -3.08526635e-01,
  3.13452333e-02, -4.97857518e-02, -2.78708916e-02,
  4.92342487e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.09801339e-02,  4.47685570e-02],
[-1.06895622e-02,  0.00000000e+00,  2.16566309e-01,
  1.45352604e-02,  9.90219880e-03,  4.25568819e-02,
  1.18775228e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.82917770e-02,  3.14020514e-02],
[-1.06895622e-02,  0.00000000e+00,  1.42232239e-01,
  1.45352604e-02,  1.18157975e-02,  4.25568819e-02,
  1.18775228e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.91816688e-02,  2.11309381e-02],
[-7.75714591e-03,  0.00000000e+00, -4.19880897e-01,
 -7.65897781e-02,  1.24679711e-02,  1.68984905e-02,
 -2.17546634e-02, -9.87124816e-02,  0.00000000e+00,
 -5.95949357e-03, -2.34732255e-02,  4.57945578e-02],
[-9.51647386e-03,  0.00000000e+00, -4.38110411e-01,
  1.74249280e-02,  1.24679711e-02,  1.68984905e-02,
 -2.17546634e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.28439497e-02, -8.44715312e-02],
[-1.05882538e-02,  0.00000000e+00, -4.30869371e-01,
  2.62020770e-02, -4.97857518e-02,  2.15928610e-02,
  4.92342487e-02,  3.98021098e-03,  0.00000000e+00,
  1.62689912e-03,  2.07121838e-02, -8.44715312e-02],
```

```
[-1.06895622e-02,  0.00000000e+00,  2.64870614e-01,
  1.45352604e-02,  9.90219880e-03,  4.25568819e-02,
 -5.24820667e-03,  5.95507957e-03,  0.00000000e+00,
  2.72271177e-03, -1.82917770e-02,  2.23511772e-04],
[ 1.42281860e-01,  0.00000000e+00,  1.98996410e-01,
  5.49216475e-03,  1.24649815e-02,  4.25568819e-02,
 -5.24820667e-03,  5.75908693e-03,  0.00000000e+00,
  1.62689912e-03,  4.12160233e-02,  2.32578628e-03],
[-1.06895622e-02,  0.00000000e+00,  1.42232239e-01,
  1.45352604e-02,  1.18157975e-02,  4.25568819e-02,
  1.18775228e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.91816688e-02,  2.11309381e-02],
[ 1.57286793e-01,  0.00000000e+00,  1.63296983e-01,
  1.59222633e-03, -2.53613442e-02, -5.95146641e-02,
 -5.24820667e-03,  6.73807040e-03,  0.00000000e+00,
  3.83148678e-02,  1.74380124e-01,  1.16480283e-01],
[ 1.42281860e-01,  0.00000000e+00,  2.34027699e-01,
  1.59222633e-03,  5.75052248e-03, -5.95146641e-02,
 -5.24820667e-03,  4.66327509e-03,  0.00000000e+00,
  2.72271177e-03,  4.21059206e-02,  3.99739668e-02],
[-1.06895622e-02,  0.00000000e+00,  2.64870614e-01,
  1.45352604e-02,  9.90219880e-03,  4.25568819e-02,
 -5.24820667e-03,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.82917770e-02,  2.23511772e-04],
[-1.06895622e-02,  0.00000000e+00,  1.59357995e-01,
 -3.28498427e-03,  1.18157975e-02,  3.78625095e-02,
 -5.24820667e-03,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -2.10454855e-02,  2.11309381e-02],
[ 1.45458147e-01,  0.00000000e+00, -3.25549275e-01,
  3.13452333e-02, -3.78607213e-02, -2.78708916e-02,
  4.92342487e-02,  8.82976782e-03,  0.00000000e+00,
  1.62689912e-03, -1.09801339e-02,  4.13842201e-02],
[-6.97078556e-03,  0.00000000e+00, -3.97749007e-01,
  1.74249280e-02, -4.97857518e-02,  1.68984905e-02,
 -2.17546634e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.28439497e-02, -1.38368368e-01],
[-1.06895622e-02,  0.00000000e+00,  1.59357995e-01,
  1.45352604e-02,  1.18157975e-02,  4.25568819e-02,
 -5.24820667e-03,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.91816688e-02,  2.11309381e-02],
[-9.51647386e-03,  0.00000000e+00, -4.28035676e-01,
 -7.65897781e-02,  1.24679711e-02,  1.68984905e-02,
 -2.17546634e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.28439497e-02,  2.90108323e-02],
[-1.06895622e-02,  0.00000000e+00,  1.99033692e-01,
  5.49216475e-03,  1.66166574e-02,  4.25568819e-02,
 -5.24820667e-03,  2.88439868e-03,  0.00000000e+00,
```

```
  3.83148678e-02,  1.74380124e-01, -1.00476071e-02],
[-9.51647386e-03,  0.00000000e+00, -4.76465315e-01,
 -7.65897781e-02,  3.23683098e-02,  1.68984905e-02,
 -2.17546634e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.28439497e-02, -8.44715312e-02],
[-1.06895622e-02,  0.00000000e+00,  1.46957412e-01,
  1.59222633e-03,  1.66166574e-02, -5.95146641e-02,
 -5.24820667e-03,  2.88439868e-03,  0.00000000e+00,
  2.72271177e-03,  4.12160233e-02,  2.11309381e-02],
[-1.06895622e-02,  0.00000000e+00,  1.59357995e-01,
 -3.28498427e-03,  1.18157975e-02,  3.78625095e-02,
 -5.24820667e-03,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -2.10454855e-02,  2.11309381e-02],
[-7.75714591e-03,  0.00000000e+00, -3.60928774e-01,
  3.52451727e-02,  3.23683098e-02,  2.15928610e-02,
 -2.17546634e-02, -1.12418249e-01,  0.00000000e+00,
 -1.15457801e-02, -2.02779509e-02,  9.76485834e-02],
[-7.75714591e-03,  0.00000000e+00, -4.19880897e-01,
 -7.65897781e-02,  1.24679711e-02,  1.68984905e-02,
 -2.17546634e-02, -9.87124816e-02,  0.00000000e+00,
 -5.95949357e-03, -2.34732255e-02,  4.57945578e-02],
[ 9.16373059e-02,  0.00000000e+00,  1.75698817e-01,
  1.59222633e-03,  7.66412076e-03, -5.95146641e-02,
 -5.24820667e-03,  4.66327509e-03,  0.00000000e+00,
  2.72271177e-03,  4.12160233e-02, -1.67484283e-01],
[-1.06895622e-02,  0.00000000e+00,  1.54557139e-01,
 -3.28498427e-03,  1.66166574e-02,  3.78625095e-02,
 -5.24820667e-03,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -2.10454855e-02,  2.11309381e-02],
[-9.51647386e-03,  0.00000000e+00, -3.69083554e-01,
  3.52451727e-02,  3.23683098e-02,  2.15928610e-02,
 -2.17546634e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.09801339e-02,  2.90108323e-02],
[-7.07209390e-03,  0.00000000e+00,  1.81704521e-01,
  1.59222633e-03,  9.90219880e-03, -5.95146641e-02,
 -5.24820667e-03,  2.88439868e-03,  0.00000000e+00,
  2.72271177e-03,  4.21059206e-02, -1.79519027e-01],
[-9.51647386e-03,  0.00000000e+00, -3.79382163e-01,
  3.52451727e-02,  1.24679711e-02,  2.15928610e-02,
 -2.17546634e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.09801339e-02,  2.90108323e-02],
[-9.51647386e-03,  0.00000000e+00, -4.19880897e-01,
 -7.65897781e-02,  1.24679711e-02,  1.68984905e-02,
 -2.17546634e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.28439497e-02,  4.47685570e-02],
[ 1.42281860e-01,  0.00000000e+00,  2.03797266e-01,
  5.49216475e-03,  7.66412076e-03,  4.25568819e-02,
```

```
 -5.24820667e-03,  4.66327509e-03,  0.00000000e+00,
  2.72271177e-03,  4.12160233e-02,  2.32578628e-03],
[ 1.19692698e-01,  0.00000000e+00,  1.72618732e-01,
  7.94092566e-03,  7.66412076e-03,  3.78625095e-02,
 -5.24820667e-03, -1.09674357e-01,  0.00000000e+00,
 -5.95949357e-03,  9.50521380e-02, -2.62665842e-03],
[-1.06895622e-02,  0.00000000e+00,  1.85735658e-01,
  1.45352604e-02,  1.66166574e-02,  4.25568819e-02,
 -5.24820667e-03,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.91816688e-02, -1.00476071e-02],
[-9.51647386e-03,  0.00000000e+00, -3.83999735e-01,
 -7.17484728e-02,  1.24679711e-02, -2.38240194e-02,
 -2.17546634e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.28439497e-02,  4.47685570e-02],
[-1.06895622e-02,  0.00000000e+00,  1.85735658e-01,
  1.45352604e-02,  1.66166574e-02,  4.25568819e-02,
 -5.24820667e-03,  5.95507957e-03,  0.00000000e+00,
 -2.03965716e-02, -1.78502090e-02, -1.00476071e-02],
[-9.51647386e-03,  0.00000000e+00, -3.71227384e-01,
  1.74249280e-02,  1.24679711e-02,  1.68984905e-02,
 -2.17546634e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.28439497e-02,  4.47685570e-02],
[-9.51647386e-03,  0.00000000e+00, -3.71227384e-01,
  1.74249280e-02,  1.24679711e-02,  1.68984905e-02,
 -2.17546634e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.28439497e-02,  4.47685570e-02],
[-9.51647386e-03,  0.00000000e+00, -3.25047553e-01,
  2.22662315e-02,  3.23683098e-02, -2.38240194e-02,
 -2.17546634e-02,  9.12568625e-03,  0.00000000e+00,
  1.62689912e-03, -1.28439497e-02,  1.27744511e-01],
[-1.17613422e-02,  0.00000000e+00,  1.89073682e-01,
 -2.59655751e-02, -3.72863747e-02,  3.78625095e-02,
 -5.24820667e-03,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -2.10454855e-02,  1.73294619e-02],
[-5.89900510e-03,  0.00000000e+00, -3.77532512e-01,
  1.74249280e-02,  3.23683098e-02,  1.68984905e-02,
 -2.17546634e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.28439497e-02, -1.38368368e-01],
[-1.17613422e-02,  0.00000000e+00,  1.58793375e-01,
  1.59222633e-03, -3.72863747e-02, -5.95146641e-02,
 -5.24820667e-03,  3.98021098e-03,  0.00000000e+00,
  1.62689912e-03,  4.12160233e-02,  1.73294619e-02],
[-1.06895622e-02,  0.00000000e+00,  1.37830570e-01,
  1.55631965e-03,  1.66166574e-02, -5.54677919e-02,
 -5.24820667e-03,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -2.10454855e-02,  2.11309381e-02],
[ 1.17358051e-01,  0.00000000e+00,  1.58691034e-01,
```

```
 -3.28498427e-03,  1.24649815e-02,  3.78625095e-02,
 -5.24820667e-03, -1.37322515e-01,  0.00000000e+00,
  1.15735047e-02, -3.16747613e-02,  8.63843486e-02],
[-7.07209390e-03,  0.00000000e+00,  1.75260574e-01,
  5.49216475e-03,  1.66166574e-02,  4.25568819e-02,
 -5.24820667e-03,  2.88439868e-03,  0.00000000e+00,
  2.72271177e-03,  4.12160233e-02, -1.17365584e-01],
[-1.06895622e-02,  0.00000000e+00,  2.31018305e-01,
  1.06353210e-02,  9.90219880e-03, -5.95146641e-02,
  1.18775228e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.82917770e-02,  2.23511772e-04],
[-1.06895622e-02,  0.00000000e+00,  1.59357995e-01,
 -3.28498427e-03,  1.18157975e-02,  3.78625095e-02,
 -5.24820667e-03,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -2.10454855e-02,  2.11309381e-02],
[-1.06895622e-02,  0.00000000e+00,  2.22343966e-01,
 -1.47396661e-02,  1.18157975e-02,  3.78625095e-02,
 -5.24820667e-03,  3.98021098e-03,  0.00000000e+00,
  1.62689912e-03,  5.96212149e-02, -1.00476071e-02],
[-1.06895622e-02,  0.00000000e+00,  2.29893818e-01,
  1.59222633e-03,  9.90219880e-03, -5.95146641e-02,
 -5.24820667e-03,  2.88439868e-03,  0.00000000e+00,
  2.72271177e-03,  4.21059206e-02,  2.76005790e-02],
[ 1.42281860e-01,  0.00000000e+00,  2.46952817e-01,
  5.49216475e-03,  5.75052248e-03,  4.25568819e-02,
 -5.24820667e-03,  5.75908693e-03,  0.00000000e+00,
  1.62689912e-03,  4.21059206e-02,  4.37754393e-02],
[-1.06895622e-02,  0.00000000e+00,  1.46033704e-01,
  1.45352604e-02,  1.18157975e-02,  4.25568819e-02,
  1.18775228e-02,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -1.91816688e-02,  1.73294619e-02],
[-1.06895622e-02,  0.00000000e+00,  1.59357995e-01,
  1.45352604e-02,  1.18157975e-02,  4.25568819e-02,
 -5.24820667e-03,  9.12568625e-03,  0.00000000e+00,
  1.62689912e-03, -1.91816688e-02,  1.04106888e-01],
[-1.06895622e-02,  0.00000000e+00,  1.59357995e-01,
 -3.28498427e-03,  1.18157975e-02,  3.78625095e-02,
 -5.24820667e-03,  7.05089141e-03,  0.00000000e+00,
  1.62689912e-03, -2.10454855e-02,  2.11309381e-02],
[ 1.42281860e-01,  0.00000000e+00,  2.25425377e-01,
  1.59222633e-03,  1.05513828e-02, -5.95146641e-02,
 -5.24820667e-03,  4.66327509e-03,  0.00000000e+00,
 -2.03965716e-02,  4.34373766e-02,  4.37754393e-02],
[-9.51647386e-03,  0.00000000e+00, -3.63079488e-01,
  3.34921405e-02,  1.24679711e-02, -2.38240194e-02,
 -2.17546634e-02,  3.98021098e-03,  0.00000000e+00,
  1.62689912e-03,  3.91173735e-02,  2.90108323e-02],
```

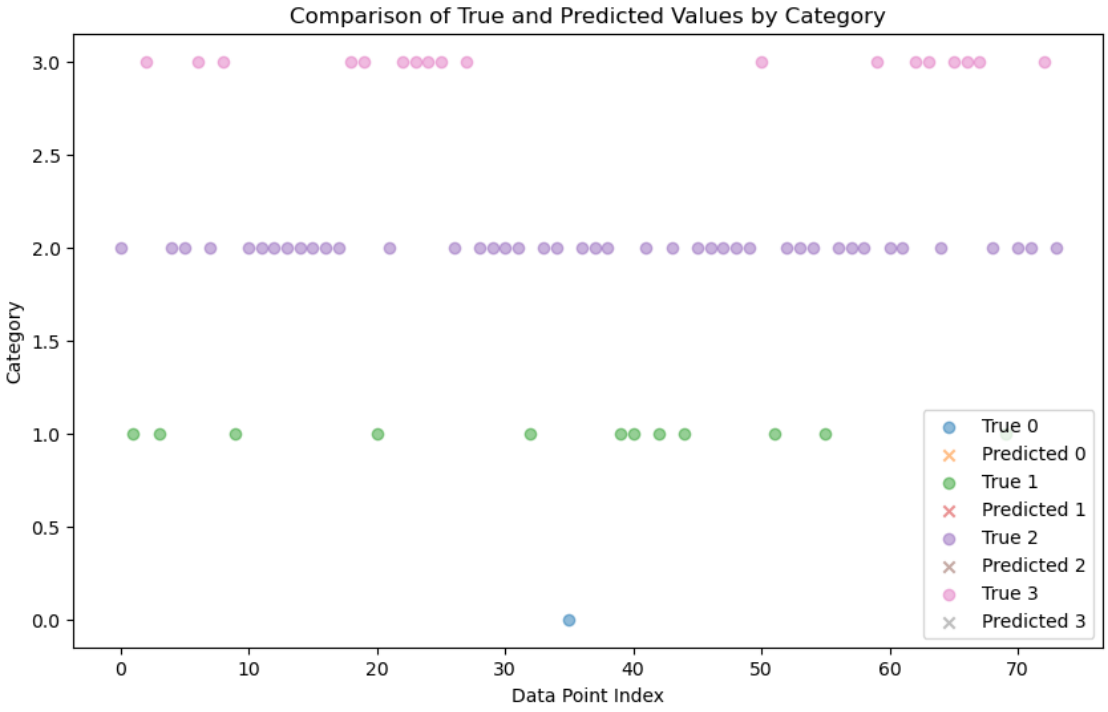
```
       [-1.06895622e-02,  0.00000000e+00,  2.08905101e-01,
         5.49216475e-03,  1.47030586e-02,  4.25568819e-02,
        -5.24820667e-03,  2.88439868e-03,  0.00000000e+00,
         3.83148678e-02,  1.41985849e-01,  3.14020514e-02],
       [-1.06895622e-02,  0.00000000e+00,  2.13217109e-01,
        -2.59655751e-02,  1.18157975e-02,  3.78625095e-02,
        -5.24820667e-03,  7.05089141e-03,  0.00000000e+00,
         1.62689912e-03, -2.10454855e-02, -1.00476071e-02],
       [-1.06895622e-02,  0.00000000e+00,  1.94862515e-01,
         5.49216475e-03,  1.66166574e-02,  4.25568819e-02,
        -5.24820667e-03,  2.88439868e-03,  0.00000000e+00,
         2.72271177e-03,  4.12160233e-02, -1.00476071e-02],
       [-1.06895622e-02,  0.00000000e+00,  1.37830570e-01,
         1.55631965e-03,  1.66166574e-02, -5.54677919e-02,
        -5.24820667e-03,  7.05089141e-03,  0.00000000e+00,
         1.62689912e-03, -2.10454855e-02,  2.11309381e-02]], dtype=float32)
```

[179]:
```
X_train.info()

X_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 195 entries, 0 to 194
Data columns (total 11 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   scaling                     195 non-null    float64
 1   definite_borders            195 non-null    float64
 2   itching                     195 non-null    float64
 3   koebner_phenomenon          195 non-null    float64
 4   polygonal_papules           195 non-null    float64
 5   follicular_papules          195 non-null    float64
 6   oral_mucosal_involvement    195 non-null    float64
 7   knee_and_elbow_involvement  195 non-null    float64
 8   scalp_involvement           195 non-null    float64
 9   family_history              195 non-null    float64
 10  age                         195 non-null    float64
dtypes: float64(11)
memory usage: 16.9 KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 74 entries, 0 to 73
Data columns (total 11 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   scaling                     74 non-null     float64
 1   definite_borders            74 non-null     float64
 2   itching                     74 non-null     float64
 3   koebner_phenomenon          74 non-null     float64
```

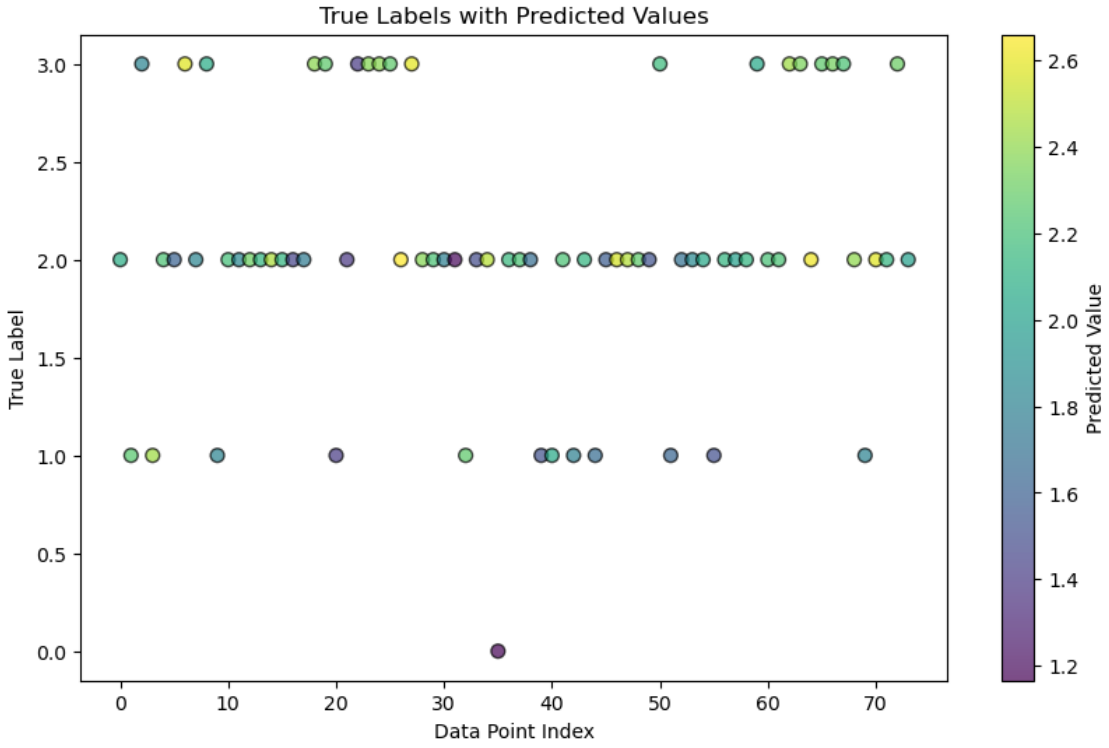
```
 4   polygonal_papules           74 non-null     float64
 5   follicular_papules          74 non-null     float64
 6   oral_mucosal_involvement    74 non-null     float64
 7   knee_and_elbow_involvement  74 non-null     float64
 8   scalp_involvement           74 non-null     float64
 9   family_history              74 non-null     float64
 10  age                         74 non-null     float64
dtypes: float64(11)
memory usage: 6.5 KB
```

[146]:
```
import matplotlib.pyplot as plt
import numpy as np

# Assuming you have already found the best model and predicted using X_test
# y_pred = best_model.predict(X_test)  # Uncomment if not already done

# Set up the figure
plt.figure(figsize=(10, 6))

# Unique categories in the target variable
categories = [0, 1, 2, 3]

# Plot for each category
for category in categories:
    # Boolean arrays for true and predicted values of this category
    is_true_category = (y_test == category)
    is_pred_category = (y_pred == category)

    # Indices for plotting
    indices = np.arange(len(y_test))

    # Scatter plot for true values of this category
    plt.scatter(indices[is_true_category], y_test[is_true_category], alpha=0.5,␣
 ↪label=f'True {category}', marker='o')

    # Scatter plot for predicted values of this category
    plt.scatter(indices[is_pred_category], y_pred[is_pred_category], alpha=0.5,␣
 ↪label=f'Predicted {category}', marker='x')

# Adding titles, labels, and legend
plt.title('Comparison of True and Predicted Values by Category')
plt.xlabel('Data Point Index')
plt.ylabel('Category')
plt.legend()

# Show the plot
plt.show()
```



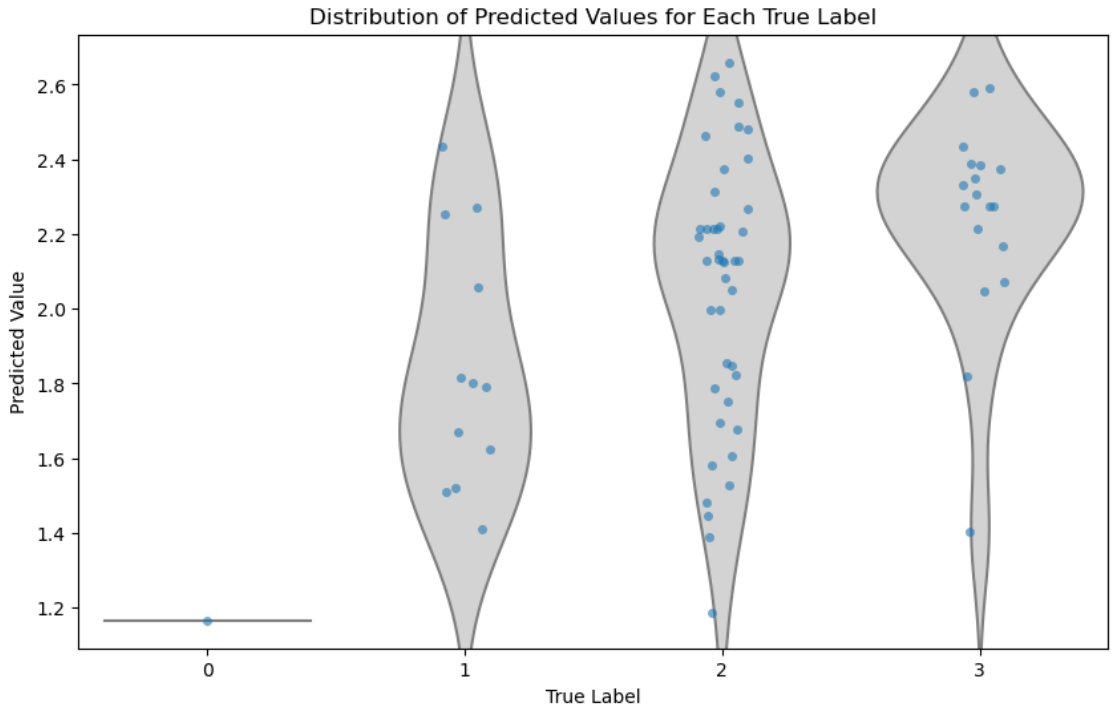
[147]:
```
import matplotlib.pyplot as plt
import numpy as np

# Assuming you have already found the best model and predicted using X_test
# y_pred = best_model.predict(X_test)  # Uncomment if not already done

# Set up the figure
plt.figure(figsize=(10, 6))

# Indices for plotting
indices = np.arange(len(y_test))

# Scatter plot
scatter = plt.scatter(indices, y_test, alpha=0.7, c=y_pred, cmap='viridis',␣
 ↪edgecolor='k', s=50)

# Color bar indicating predicted values
cbar = plt.colorbar(scatter)
cbar.set_label('Predicted Value')

# Adding titles and labels
plt.title('True Labels with Predicted Values')
plt.xlabel('Data Point Index')
plt.ylabel('True Label')
```

```
# Show the plot
plt.show()
```



[148]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming you have already found the best model and predicted using X_test
# y_pred = best_model.predict(X_test)  # Uncomment if not already done

# Create a dataframe for plotting (if not already in dataframe format)
import pandas as pd
data = pd.DataFrame({
    'True Label': y_test,
    'Predicted Value': y_pred
})

# Set up the figure
plt.figure(figsize=(10, 6))

# Create a violin plot to show the distribution of predicted values for each␣
 ↪true label
```

```
sns.violinplot(x='True Label', y='Predicted Value', data=data, inner=None,␣
 ↪color='lightgray')

# Overlay a scatter plot to show individual predictions
sns.stripplot(x='True Label', y='Predicted Value', data=data, jitter=True,␣
 ↪alpha=0.6)

# Adding titles and labels
plt.title('Distribution of Predicted Values for Each True Label')
plt.xlabel('True Label')
plt.ylabel('Predicted Value')

# Show the plot
plt.show()
```



[137]:
```
results_df
```

[137]:

	Model Name	Mean of RMSE	SD of RMSE
0	random forest	0.647258	0.003724
1	Lasso	0.632567	0.012926
2	Ridge	0.625203	0.000000
3	Elastic Net	0.628257	0.013568
4	SVR	0.646501	0.006843
5	KNN	0.663723	0.008088

```
6        XGBoost      0.627934    0.017606
```

[138]:
```
# Calculate the mean or median of the target variable
mean_erythema = y_final.mean()
# median_erythema = y_final.median() # Use this if you prefer median

# Predict this mean/median value for all observations
y_pred_baseline = [mean_erythema] * len(y_final)

# Calculate the RMSE
mse_baseline = mean_squared_error(y_final, y_pred_baseline)
rmse_baseline = np.sqrt(mse_baseline)

print(f"Baseline RMSE: {rmse_baseline}")
```

```
Baseline RMSE: 0.6638444698329595
```

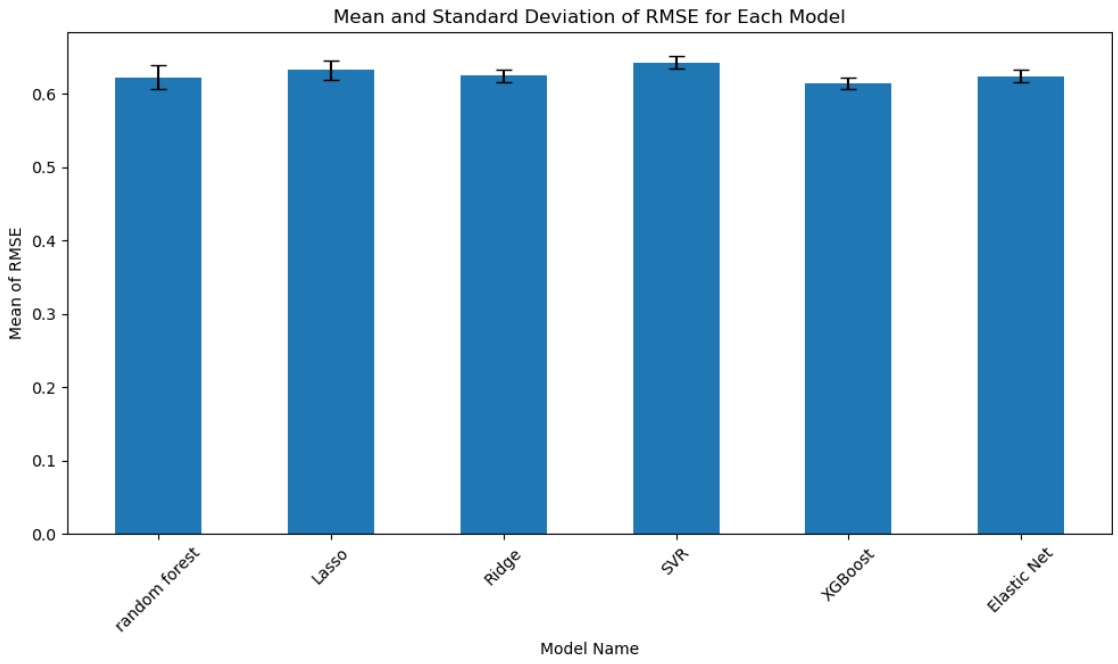
[68]:
```
results_df
```

[68]:

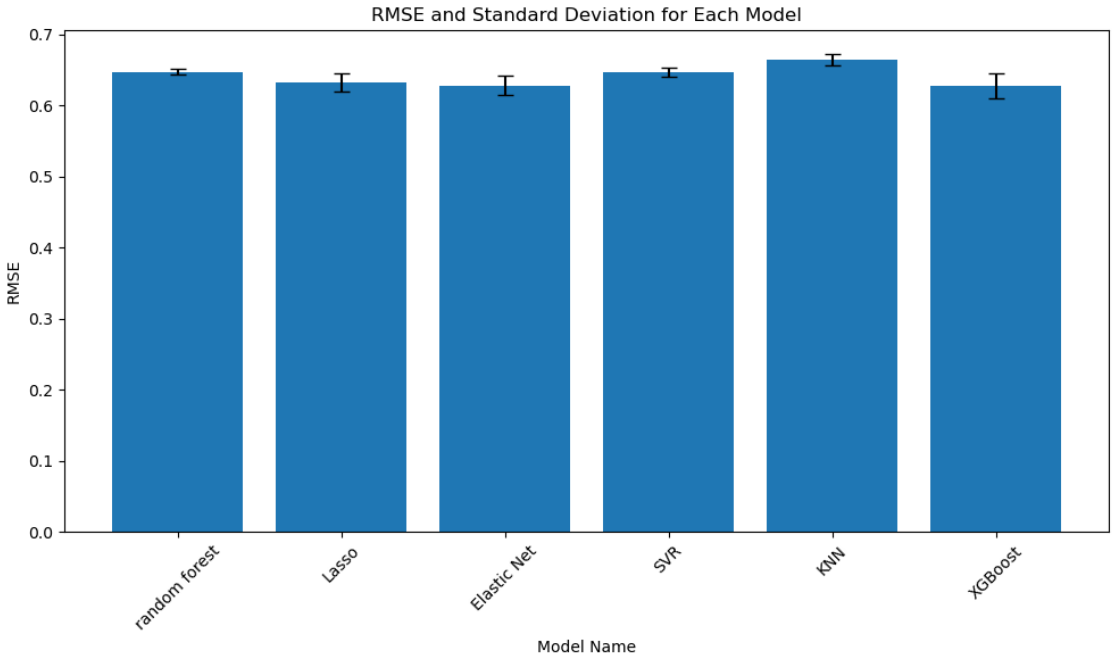
	Model Name	Mean of RMSE	SD of RMSE
0	random forest	0.622964	0.016539
1	Lasso	0.632567	0.012926
2	Ridge	0.624749	0.008247
3	Elastic Net	0.624505	0.008869
4	SVR	0.642622	0.008553
5	XGBoost	0.614980	0.007921

[169]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Assuming results_df is your DataFrame and it's already defined
# Example structure of results_df:
# results_df = pd.DataFrame({
#     'model name': ['Model A', 'Model B', 'Model C'],
#     'mean of rmse': [1.2, 1.5, 1.3],
#     'sd of rmse': [0.1, 0.2, 0.15]
# })

# Create a bar plot
plt.figure(figsize=(10, 6))
plt.bar(results_df['Model Name'], results_df['Mean of RMSE'],␣
 ↪yerr=results_df['SD of RMSE'], capsize=5, width = 0.5)
plt.xlabel('Model Name')
plt.ylabel('Mean of RMSE')
plt.title('Mean and Standard Deviation of RMSE for Each Model')
plt.xticks(rotation=45) # Rotates the model names for better visibility
plt.tight_layout()
```

```
# Save the figure
file_path = '/Users/suchen/Desktop/Data1030 HW/final/model_performance.png'
plt.savefig(file_path, dpi=350)


# Show the plot
plt.show()
```



[185]:
```
# Create a bar plot
plt.figure(figsize=(10, 6))
plt.bar(filtered_df['Model Name'], filtered_df['Mean of RMSE'],␣
 ↪yerr=filtered_df['SD of RMSE'], capsize=5)
plt.xlabel('Model Name')
plt.ylabel('RMSE')
plt.title('RMSE and Standard Deviation for Each Model')
plt.xticks(rotation=45) # Rotates the model names for better visibility
plt.tight_layout()

# Show the plot
plt.show()
```



[ ]:
```
# use it as a classification problem
# one more time
# -------------------
# --------------------
# --------------------
```

[ ]:
```
df2 = pd.read_csv('/Users/suchen/Desktop/Data1030 HW/dermatology_database_1.
 ↪csv')
# make a subset of the data, removing the "medical terms" features because they␣
 ↪are too academic to understand
df3 = df2.iloc[:, list(range(0, 11)) + [33]]
#df1.info()

# create x and target variable y
X_final = df3.loc[:, df3.columns != 'erythema']
y_final = df3['erythema']
```

[74]:
```
from sklearn.model_selection import train_test_split, StratifiedKFold
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
import numpy as np
import pandas as pd
```

```python
# Replace '?' with NaN and convert columns to numeric where appropriate
X_final = X_final.replace('?', np.nan).apply(pd.to_numeric, errors='coerce')

# Define random state
random_state = 42

# Stratified train-test split
X_other, X_test, y_other, y_test = train_test_split(
    X_final, y_final, test_size=0.2, stratify=y_final,␣
 ↪random_state=random_state)
print('Test balance:', np.unique(y_test, return_counts=True))

# Stratified K-Fold on X_other
kf = StratifiedKFold(n_splits=3, shuffle=True, random_state=random_state)

for train_index, val_index in kf.split(X_other, y_other):
    print('New fold')

    # Split the data into training and validation sets
    X_train, X_val = X_other.iloc[train_index], X_other.iloc[val_index]
    y_train, y_val = y_other.iloc[train_index], y_other.iloc[val_index]

    # Instantiate the imputer
    iterative_imputer = IterativeImputer(random_state=random_state)

    # Fit the imputer on X_train and transform X_train
    X_train_imputed = iterative_imputer.fit_transform(X_train)

    # Transform X_val using the already fitted imputer
    X_val_imputed = iterative_imputer.transform(X_val)

    # Convert the imputed data back into pandas DataFrames
    X_train = pd.DataFrame(X_train_imputed, columns=X_final.columns)
    X_val = pd.DataFrame(X_val_imputed, columns=X_final.columns)

    print(np.unique(y_train, return_counts=True))
    print(np.unique(y_val, return_counts=True))

# Transform X_test using the imputer fitted on the last fold of X_other
X_test_imputed = iterative_imputer.transform(X_test)
X_test = pd.DataFrame(X_test_imputed, columns=X_final.columns)
```

```
Test balance: (array([0, 1, 2, 3]), array([ 1, 12, 43, 18]))
New fold
(array([0, 1, 2, 3]), array([  2,  30, 114,  48]))
(array([0, 1, 2, 3]), array([ 1, 15, 58, 24]))
New fold
(array([0, 1, 2, 3]), array([  2,  30, 115,  48]))
```

```
(array([0, 1, 2, 3]), array([ 1, 15, 57, 24]))
New fold
(array([0, 1, 2, 3]), array([  2,  30, 115,  48]))
(array([0, 1, 2, 3]), array([ 1, 15, 57, 24]))
```

[77]:
```python
import numpy as np
from sklearn.model_selection import KFold, GridSearchCV
from sklearn.metrics import accuracy_score
from sklearn.pipeline import Pipeline

def MLpipe_KFold_Classification(X_train, X_test, y_train, y_test,
                                preprocessor, algorithm, param_grid,
                                algorithm_random_state=None):
    """
    This function applies KFold with 4 folds to the training data and uses GridSearchCV for hyperparameter tuning.
    The accuracy is maximized in cross-validation.

    Parameters remain the same as your original function.
    """
    if algorithm_random_state is None:
        random_states = np.arange(10)  # 10 different random states
    else:
        random_states = algorithm_random_state

    best_models = []
    test_scores = []

    algorithm_has_random_state = 'random_state' in algorithm.get_params()

    for random_state in random_states:
        print(f"Random State: {random_state}")

        kf = KFold(n_splits=4, shuffle=True, random_state=random_state)

        pipeline = Pipeline([
            ('preprocessor', preprocessor),
            ('algorithm', algorithm)
        ])

        if algorithm_has_random_state and random_state is not None:
            algorithm.set_params(**{'random_state': random_state})

        # Change here: Using 'accuracy' as scoring metric
        grid_search = GridSearchCV(pipeline, param_grid=param_grid, cv=kf, scoring='accuracy', n_jobs=-1)
        grid_search.fit(X_train, y_train)
```

```
        print(f"Best parameters: {grid_search.best_params_}")

        y_pred = grid_search.predict(X_test)

        # Change here: Using accuracy for evaluation
        accuracy = accuracy_score(y_test, y_pred)
        test_scores.append(accuracy)
        print(f"Test Accuracy: {accuracy}\n")

        best_models.append(grid_search.best_estimator_)

    print(f"Mean Test Accuracy: {np.mean(test_scores)}")
    print(f"Standard Deviation of Test Accuracy: {np.std(test_scores)}")
    print(y_pred)

    return best_models, test_scores
```

[78]:
```
from sklearn.ensemble import RandomForestClassifier

# Random Forest Algorithm for Classification
random_forest_classifier = RandomForestClassifier()  # Initialize␣
 ↪RandomForestClassifier

param_grid_rf = {
    'algorithm__n_estimators': [100, 200, 300],    # Example hyperparameters
    'algorithm__max_depth': [None, 10, 20],        # Example hyperparameters
    'algorithm__min_samples_split': [2, 5, 10]     # Example hyperparameters
}

best_models, test_scores = MLpipe_KFold_Classification(
    X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test,
    preprocessor=combined_preprocessor, algorithm=random_forest_classifier,␣
 ↪param_grid=param_grid_rf
)
```

```
Random State: 0
Best parameters: {'algorithm__max_depth': 10, 'algorithm__min_samples_split': 5,
'algorithm__n_estimators': 100}
Test Accuracy: 0.5

Random State: 1
Best parameters: {'algorithm__max_depth': 10, 'algorithm__min_samples_split': 5,
'algorithm__n_estimators': 100}
Test Accuracy: 0.527027027027027

Random State: 2
Best parameters: {'algorithm__max_depth': None, 'algorithm__min_samples_split':
```

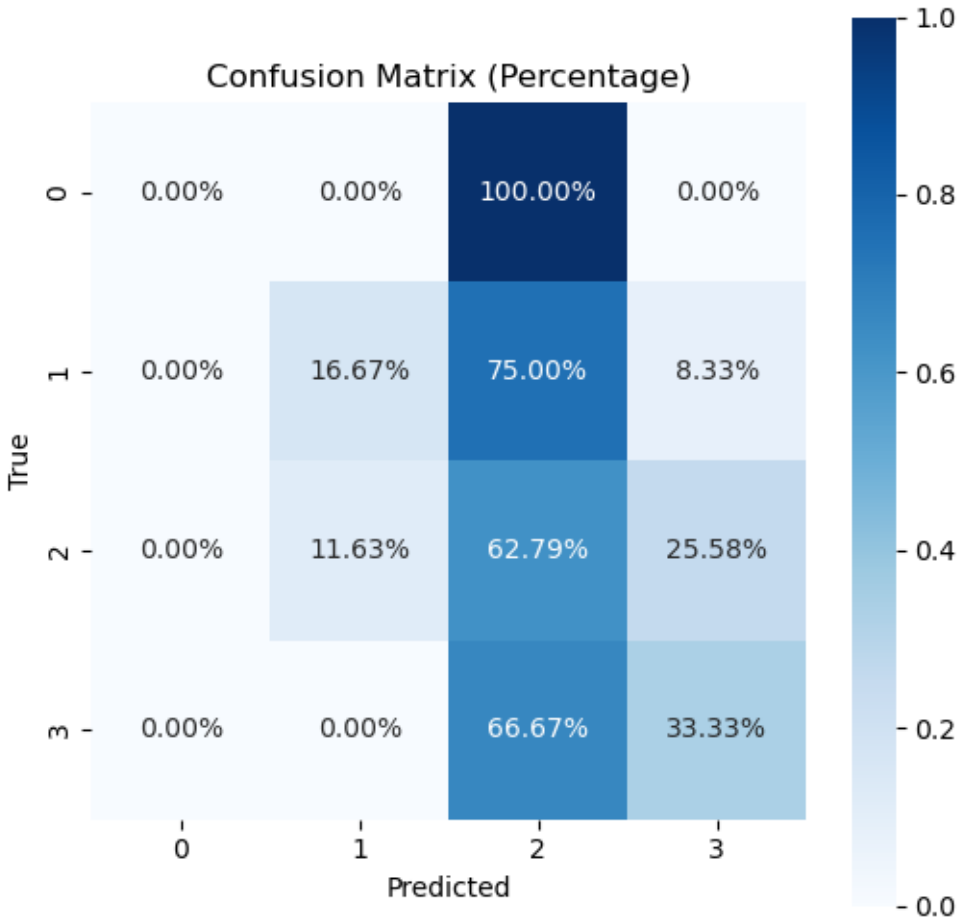
```
10, 'algorithm__n_estimators': 200}
Test Accuracy: 0.4864864864864865

Random State: 3
Best parameters: {'algorithm__max_depth': None, 'algorithm__min_samples_split':
10, 'algorithm__n_estimators': 200}
Test Accuracy: 0.47297297297297297

Random State: 4
Best parameters: {'algorithm__max_depth': 10, 'algorithm__min_samples_split': 2,
'algorithm__n_estimators': 200}
Test Accuracy: 0.5135135135135135

Random State: 5
Best parameters: {'algorithm__max_depth': 10, 'algorithm__min_samples_split':
10, 'algorithm__n_estimators': 200}
Test Accuracy: 0.4864864864864865

Random State: 6
Best parameters: {'algorithm__max_depth': 10, 'algorithm__min_samples_split':
10, 'algorithm__n_estimators': 300}
Test Accuracy: 0.4864864864864865

Random State: 7
Best parameters: {'algorithm__max_depth': 10, 'algorithm__min_samples_split': 5,
'algorithm__n_estimators': 300}
Test Accuracy: 0.5405405405405406

Random State: 8
Best parameters: {'algorithm__max_depth': None, 'algorithm__min_samples_split':
2, 'algorithm__n_estimators': 100}
Test Accuracy: 0.4864864864864865

Random State: 9
Best parameters: {'algorithm__max_depth': None, 'algorithm__min_samples_split':
10, 'algorithm__n_estimators': 300}
Test Accuracy: 0.5

Mean Test Accuracy: 0.5000000000000001
Standard Deviation of Test Accuracy: 0.020043779694853135
[2 2 2 3 2 2 3 2 2 2 3 2 2 2 3 2 1 2 2 2 1 1 2 3 3 2 3 3 3 2 2 1 2 2 3 2 2
 2 2 1 2 2 2 2 2 1 3 3 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 3 2 3 2 2 2 3 2 2 2]
```

[79]:
```
# Find the index of the model with the lowest RMSE
min_rmse_index = test_scores.index(min(test_scores))
```

```
print()
new_predict01 = best_models[min_rmse_index].predict(X_test)
print(new_predict01)
```

```
[2 2 2 3 2 2 3 2 2 2 3 2 2 2 3 2 1 2 2 2 1 1 2 3 3 2 3 3 3 2 2 1 2 1 3 2 2
 2 2 1 2 2 2 2 2 1 3 3 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 3 2 3 2 3 2 3 2 2 2]
```

[80]:
```
# Calculate the confusion matrix
conf_matrix = confusion_matrix(y_test, new_predict01)

# Normalize the confusion matrix by row
conf_matrix_normalized = conf_matrix.astype('float') / conf_matrix.sum(axis=1)[:
 ↪, np.newaxis]

# Create a heatmap for the normalized confusion matrix
plt.figure(figsize=(6, 6))
sns.heatmap(conf_matrix_normalized, annot=True, fmt=".2%", cmap="Blues",␣
 ↪square=True,
            xticklabels=np.unique(y_test), yticklabels=np.unique(y_test))
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix (Percentage)')
plt.show()
```



[76]:
```
# Create an empty DataFrame with the desired columns
results_class = pd.DataFrame(columns=['Model Name', 'Mean of RMSE', 'SD of␣
 ↪RMSE'])

# Assuming you have calculated the mean and SD of RMSE
mean_rmse = np.mean(test_scores)
std_rmse = np.std(test_scores)

# Define the model name
model_name = 'random forest'

# Check if the model name already exists in the DataFrame
if model_name in results_class['Model Name'].values:
    # Update the existing row
    results_class.loc[results_class['Model Name'] == model_name, 'Mean of␣
 ↪RMSE'] = mean_rmse
```

```
    results_class.loc[results_class['Model Name'] == model_name, 'SD of RMSE']␣
 ↪= std_rmse
else:
    # Create a new DataFrame for the row to be added
    new_row = pd.DataFrame({'Model Name': [model_name],
                            'Mean of RMSE': [mean_rmse],
                            'SD of RMSE': [std_rmse]})

    # Append the new row
    results_class = pd.concat([results_class, new_row], ignore_index=True)
```

[128]:
```
from sklearn.linear_model import LogisticRegression

# Logistic Regression with increased max_iter and different solver
logistic_regression = LogisticRegression(multi_class='multinomial',␣
 ↪max_iter=1000, solver='lbfgs')

param_grid_lr = {
    'algorithm__C': [0.01, 0.1, 1, 10, 100],  # Example regularization parameter
    # Removed 'sag' and 'saga' from solvers to focus on 'lbfgs' and 'newton-cg'
    'algorithm__solver': ['newton-cg', 'lbfgs']
}

best_models, test_scores = MLpipe_KFold_Classification(
    X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test,
    preprocessor=combined_preprocessor, algorithm=logistic_regression,␣
 ↪param_grid=param_grid_lr
)


# Assuming you have calculated the mean and SD of RMSE
mean_rmse = np.mean(test_scores)
std_rmse = np.std(test_scores)

# Define the model name
model_name = 'logistic'

# Check if the model name already exists in the DataFrame
if model_name in results_class['Model Name'].values:
    # Update the existing row
    results_class.loc[results_class['Model Name'] == model_name, 'Mean of␣
 ↪RMSE'] = mean_rmse
    results_class.loc[results_class['Model Name'] == model_name, 'SD of RMSE']␣
 ↪= std_rmse
else:
    # Create a new DataFrame for the row to be added
    new_row = pd.DataFrame({'Model Name': [model_name],
```

```
                            'Mean of RMSE': [mean_rmse],
                            'SD of RMSE': [std_rmse]})

    # Append the new row
    results_class = pd.concat([results_class, new_row], ignore_index=True)
```

```
Random State: 0
Best parameters: {'algorithm__C': 0.01, 'algorithm__solver': 'newton-cg'}
Test Accuracy: 0.581081081081081

Random State: 1
Best parameters: {'algorithm__C': 0.1, 'algorithm__solver': 'newton-cg'}
Test Accuracy: 0.5675675675675675

Random State: 2
Best parameters: {'algorithm__C': 1, 'algorithm__solver': 'newton-cg'}
Test Accuracy: 0.5135135135135135

Random State: 3
Best parameters: {'algorithm__C': 1, 'algorithm__solver': 'newton-cg'}
Test Accuracy: 0.5135135135135135

Random State: 4
Best parameters: {'algorithm__C': 0.01, 'algorithm__solver': 'newton-cg'}
Test Accuracy: 0.581081081081081

Random State: 5
Best parameters: {'algorithm__C': 0.01, 'algorithm__solver': 'newton-cg'}
Test Accuracy: 0.581081081081081

Random State: 6
Best parameters: {'algorithm__C': 1, 'algorithm__solver': 'newton-cg'}
Test Accuracy: 0.5135135135135135

Random State: 7
Best parameters: {'algorithm__C': 0.1, 'algorithm__solver': 'newton-cg'}
Test Accuracy: 0.5675675675675675

Random State: 8
Best parameters: {'algorithm__C': 0.01, 'algorithm__solver': 'newton-cg'}
Test Accuracy: 0.581081081081081

Random State: 9
Best parameters: {'algorithm__C': 0.01, 'algorithm__solver': 'newton-cg'}
Test Accuracy: 0.581081081081081

Mean Test Accuracy: 0.558108108108108
Standard Deviation of Test Accuracy: 0.02963744891819095
```

```
[2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2]
```

[129]:
```
from sklearn.svm import SVC

# SVM Classifier for Multi-class Classification
svm_classifier = SVC()  # Initialize SVM Classifier

# Define the parameter grid for SVM
param_grid_svm = {
    'algorithm__C': [0.1, 1, 10, 100],   # Regularization parameter
    'algorithm__kernel': ['linear', 'poly', 'rbf', 'sigmoid'],  # Type of kernel
    'algorithm__gamma': ['scale', 'auto']  # Kernel coefficient
}

best_models, test_scores = MLpipe_KFold_Classification(
    X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test,
    preprocessor=combined_preprocessor, algorithm=svm_classifier,␣
 ↪param_grid=param_grid_svm
)

# Assuming you have calculated the mean and SD of RMSE
mean_rmse = np.mean(test_scores)
std_rmse = np.std(test_scores)

# Define the model name
model_name = 'SVM'

# Check if the model name already exists in the DataFrame
if model_name in results_class['Model Name'].values:
    # Update the existing row
    results_class.loc[results_class['Model Name'] == model_name, 'Mean of␣
 ↪RMSE'] = mean_rmse
    results_class.loc[results_class['Model Name'] == model_name, 'SD of RMSE']␣
 ↪= std_rmse
else:
    # Create a new DataFrame for the row to be added
    new_row = pd.DataFrame({'Model Name': [model_name],
                            'Mean of RMSE': [mean_rmse],
                            'SD of RMSE': [std_rmse]})

    # Append the new row
    results_class = pd.concat([results_class, new_row], ignore_index=True)
```

```
Random State: 0
Best parameters: {'algorithm__C': 0.1, 'algorithm__gamma': 'scale',
'algorithm__kernel': 'poly'}
Test Accuracy: 0.5675675675675675
```

```
Random State: 1
Best parameters: {'algorithm__C': 0.1, 'algorithm__gamma': 'scale',
'algorithm__kernel': 'linear'}
Test Accuracy: 0.581081081081081

Random State: 2
Best parameters: {'algorithm__C': 0.1, 'algorithm__gamma': 'scale',
'algorithm__kernel': 'poly'}
Test Accuracy: 0.5675675675675675

Random State: 3
Best parameters: {'algorithm__C': 1, 'algorithm__gamma': 'scale',
'algorithm__kernel': 'poly'}
Test Accuracy: 0.44594594594594594

Random State: 4
Best parameters: {'algorithm__C': 0.1, 'algorithm__gamma': 'scale',
'algorithm__kernel': 'linear'}
Test Accuracy: 0.581081081081081

Random State: 5
Best parameters: {'algorithm__C': 1, 'algorithm__gamma': 'scale',
'algorithm__kernel': 'sigmoid'}
Test Accuracy: 0.6351351351351351

Random State: 6
Best parameters: {'algorithm__C': 1, 'algorithm__gamma': 'scale',
'algorithm__kernel': 'sigmoid'}
Test Accuracy: 0.6351351351351351

Random State: 7
Best parameters: {'algorithm__C': 0.1, 'algorithm__gamma': 'scale',
'algorithm__kernel': 'linear'}
Test Accuracy: 0.581081081081081

Random State: 8
Best parameters: {'algorithm__C': 0.1, 'algorithm__gamma': 'scale',
'algorithm__kernel': 'rbf'}
Test Accuracy: 0.581081081081081

Random State: 9
Best parameters: {'algorithm__C': 1, 'algorithm__gamma': 'auto',
'algorithm__kernel': 'sigmoid'}
Test Accuracy: 0.6351351351351351

Mean Test Accuracy: 0.581081081081081
Standard Deviation of Test Accuracy: 0.052337612786586704
```

```
[2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 3 2 2 2 2 2 2 2 2 3 2 2
 2 2 1 2 2 2 2 2 1 2 2 2 2 3 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 3 2]
```

[130]:
```
from sklearn.neighbors import KNeighborsClassifier

# KNN Classifier for Multi-class Classification
knn_classifier = KNeighborsClassifier()  # Initialize KNN Classifier

# Define the parameter grid for KNN
param_grid_knn = {
    'algorithm__n_neighbors': [3, 5, 10, 15],  # Number of neighbors
    'algorithm__weights': ['uniform', 'distance'],  # Weight function used in␣
 ↪prediction
    'algorithm__metric': ['euclidean', 'manhattan', 'minkowski']  # Distance␣
 ↪metric
}

best_models, test_scores = MLpipe_KFold_Classification(
    X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test,
    preprocessor=combined_preprocessor, algorithm=knn_classifier,␣
 ↪param_grid=param_grid_knn
)

# Assuming you have calculated the mean and SD of RMSE
mean_rmse = np.mean(test_scores)
std_rmse = np.std(test_scores)

# Define the model name
model_name = 'KNN'

# Check if the model name already exists in the DataFrame
if model_name in results_class['Model Name'].values:
    # Update the existing row
    results_class.loc[results_class['Model Name'] == model_name, 'Mean of␣
 ↪RMSE'] = mean_rmse
    results_class.loc[results_class['Model Name'] == model_name, 'SD of RMSE']␣
 ↪= std_rmse
else:
    # Create a new DataFrame for the row to be added
    new_row = pd.DataFrame({'Model Name': [model_name],
                            'Mean of RMSE': [mean_rmse],
                            'SD of RMSE': [std_rmse]})

    # Append the new row
    results_class = pd.concat([results_class, new_row], ignore_index=True)
```

```
Random State: 0
Best parameters: {'algorithm__metric': 'euclidean', 'algorithm__n_neighbors':
```

```
15, 'algorithm__weights': 'distance'}
Test Accuracy: 0.4864864864864865

Random State: 1
Best parameters: {'algorithm__metric': 'euclidean', 'algorithm__n_neighbors':
10, 'algorithm__weights': 'distance'}
Test Accuracy: 0.5135135135135135

Random State: 2
Best parameters: {'algorithm__metric': 'euclidean', 'algorithm__n_neighbors':
10, 'algorithm__weights': 'uniform'}
Test Accuracy: 0.527027027027027

Random State: 3
Best parameters: {'algorithm__metric': 'manhattan', 'algorithm__n_neighbors':
10, 'algorithm__weights': 'uniform'}
Test Accuracy: 0.47297297297297297

Random State: 4
Best parameters: {'algorithm__metric': 'manhattan', 'algorithm__n_neighbors':
15, 'algorithm__weights': 'distance'}
Test Accuracy: 0.5405405405405406

Random State: 5
Best parameters: {'algorithm__metric': 'euclidean', 'algorithm__n_neighbors':
15, 'algorithm__weights': 'uniform'}
Test Accuracy: 0.527027027027027

Random State: 6
Best parameters: {'algorithm__metric': 'euclidean', 'algorithm__n_neighbors':
10, 'algorithm__weights': 'distance'}
Test Accuracy: 0.5135135135135135

Random State: 7
Best parameters: {'algorithm__metric': 'euclidean', 'algorithm__n_neighbors':
15, 'algorithm__weights': 'uniform'}
Test Accuracy: 0.527027027027027

Random State: 8
Best parameters: {'algorithm__metric': 'manhattan', 'algorithm__n_neighbors':
15, 'algorithm__weights': 'uniform'}
Test Accuracy: 0.527027027027027

Random State: 9
Best parameters: {'algorithm__metric': 'euclidean', 'algorithm__n_neighbors':
10, 'algorithm__weights': 'uniform'}
Test Accuracy: 0.527027027027027
```

```
Mean Test Accuracy: 0.5162162162162163
Standard Deviation of Test Accuracy: 0.019860727644187916
[2 2 2 2 3 2 2 2 3 2 2 2 2 3 2 2 2 2 2 2 1 1 2 3 3 2 2 2 3 2 2 1 3 2 2 2 2
 2 2 2 2 3 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2]
```

[135]:
```
from xgboost import XGBClassifier

# XGBoost Classifier for Multi-class Classification
xgboost_classifier = XGBClassifier()  # Initialize XGBClassifier

# Define the parameter grid for XGBoost
param_grid_xgb = {
    'algorithm__n_estimators': [100, 200, 300],  # Number of trees
    'algorithm__max_depth': [3, 6, 9],           # Depth of each tree
    'algorithm__learning_rate': [0.01, 0.1, 0.2], # Step size shrinkage
    'algorithm__subsample': [0.7, 0.8, 1],       # Subsample ratio of the␣
 ↪training instances
    'algorithm__colsample_bytree': [0.7, 0.8, 1] # Subsample ratio of columns␣
 ↪for each split
}

best_models, test_scores = MLpipe_KFold_Classification(
    X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test,
    preprocessor=combined_preprocessor, algorithm=xgboost_classifier,␣
 ↪param_grid=param_grid_xgb
)

# Assuming you have calculated the mean and SD of RMSE
mean_rmse = np.mean(test_scores)
std_rmse = np.std(test_scores)

# Define the model name
model_name = 'XGBoost'

# Check if the model name already exists in the DataFrame
if model_name in results_class['Model Name'].values:
    # Update the existing row
    results_class.loc[results_class['Model Name'] == model_name, 'Mean of␣
 ↪RMSE'] = mean_rmse
    results_class.loc[results_class['Model Name'] == model_name, 'SD of RMSE']␣
 ↪= std_rmse
else:
    # Create a new DataFrame for the row to be added
    new_row = pd.DataFrame({'Model Name': [model_name],
                            'Mean of RMSE': [mean_rmse],
                            'SD of RMSE': [std_rmse]})
```

```
    # Append the new row
    results_class = pd.concat([results_class, new_row], ignore_index=True)
```

```
Random State: 0
Best parameters: {'algorithm__colsample_bytree': 0.8,
'algorithm__learning_rate': 0.01, 'algorithm__max_depth': 3,
'algorithm__n_estimators': 300, 'algorithm__subsample': 1}
Test Accuracy: 0.5540540540540541

Random State: 1
Best parameters: {'algorithm__colsample_bytree': 0.7,
'algorithm__learning_rate': 0.01, 'algorithm__max_depth': 3,
'algorithm__n_estimators': 100, 'algorithm__subsample': 0.7}
Test Accuracy: 0.47297297297297297

Random State: 2
Best parameters: {'algorithm__colsample_bytree': 1, 'algorithm__learning_rate':
0.01, 'algorithm__max_depth': 3, 'algorithm__n_estimators': 200,
'algorithm__subsample': 0.7}
Test Accuracy: 0.47297297297297297

Random State: 3
Best parameters: {'algorithm__colsample_bytree': 0.7,
'algorithm__learning_rate': 0.01, 'algorithm__max_depth': 3,
'algorithm__n_estimators': 100, 'algorithm__subsample': 0.8}
Test Accuracy: 0.5135135135135135

Random State: 4
Best parameters: {'algorithm__colsample_bytree': 0.7,
'algorithm__learning_rate': 0.01, 'algorithm__max_depth': 3,
'algorithm__n_estimators': 100, 'algorithm__subsample': 0.7}
Test Accuracy: 0.5135135135135135

Random State: 5
Best parameters: {'algorithm__colsample_bytree': 0.7,
'algorithm__learning_rate': 0.01, 'algorithm__max_depth': 3,
'algorithm__n_estimators': 100, 'algorithm__subsample': 0.7}
Test Accuracy: 0.5

Random State: 6
Best parameters: {'algorithm__colsample_bytree': 0.7,
'algorithm__learning_rate': 0.01, 'algorithm__max_depth': 3,
'algorithm__n_estimators': 100, 'algorithm__subsample': 0.7}
Test Accuracy: 0.5135135135135135

Random State: 7
Best parameters: {'algorithm__colsample_bytree': 0.7,
'algorithm__learning_rate': 0.01, 'algorithm__max_depth': 3,
```

```
'algorithm__n_estimators': 200, 'algorithm__subsample': 1}
Test Accuracy: 0.5405405405405406

Random State: 8
Best parameters: {'algorithm__colsample_bytree': 1, 'algorithm__learning_rate':
0.1, 'algorithm__max_depth': 3, 'algorithm__n_estimators': 200,
'algorithm__subsample': 0.8}
Test Accuracy: 0.5675675675675675

Random State: 9
Best parameters: {'algorithm__colsample_bytree': 0.7,
'algorithm__learning_rate': 0.01, 'algorithm__max_depth': 3,
'algorithm__n_estimators': 100, 'algorithm__subsample': 0.7}
Test Accuracy: 0.5405405405405406

Mean Test Accuracy: 0.5189189189189188
Standard Deviation of Test Accuracy: 0.030337762595464394
[2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 2 2 2 2 3 3 2 2 2 1 2 2 2 2 2
 2 2 2 2 2 2 2 2 1 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 3 2 2 2]
```

[136]:
```
results_class
```

[136]:

	Model Name	Mean of RMSE	SD of RMSE
0	random forest	0.500000	0.020044
1	logistic	0.558108	0.029637
2	SVM	0.581081	0.052338
3	KNN	0.516216	0.019861
4	XGBoost	0.518919	0.030338

[ ]:
```

```