Diabetes classification

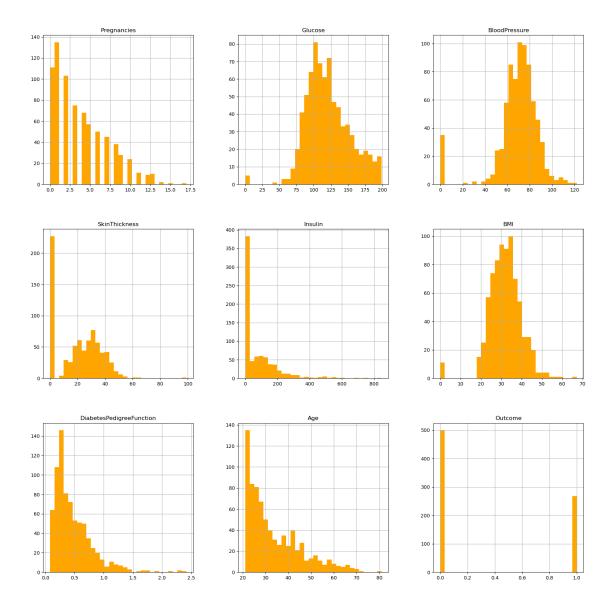
March 26, 2024

```
[11]: import pandas as pd
      import numpy as np
      import seaborn as sns
      import matplotlib.pyplot as plt
[12]: df = pd.read_csv("./Data/diabetes.csv", sep = ",")
      df.head()
[12]:
         Pregnancies
                      Glucose BloodPressure SkinThickness
                                                               Insulin
                                                                          BMI
      0
                   6
                           148
                                           72
                                                           35
                                                                      0
                                                                         33.6
      1
                   1
                           85
                                                           29
                                                                         26.6
                                            66
                                                                      0
      2
                   8
                           183
                                            64
                                                            0
                                                                      0
                                                                         23.3
                                                           23
                   1
                            89
                                            66
                                                                     94
                                                                         28.1
      3
                           137
                                            40
                                                           35
                                                                    168
                                                                        43.1
         DiabetesPedigreeFunction
                                    Age
                                         Outcome
      0
                             0.627
                                     50
                                                1
      1
                             0.351
                                                0
                                     31
      2
                             0.672
                                     32
                                                1
      3
                             0.167
                                                0
                                     21
      4
                             2.288
                                     33
                                                1
[13]: df.tail()
[13]:
           Pregnancies
                        Glucose BloodPressure SkinThickness
                                                                 Insulin
                                                                            BMI
      763
                    10
                             101
                                             76
                                                             48
                                                                      180
                                                                           32.9
      764
                     2
                             122
                                             70
                                                             27
                                                                        0 36.8
      765
                     5
                             121
                                             72
                                                             23
                                                                      112 26.2
      766
                     1
                             126
                                             60
                                                              0
                                                                        0 30.1
      767
                      1
                              93
                                             70
                                                             31
                                                                        0 30.4
           DiabetesPedigreeFunction Age
                                          Outcome
      763
                               0.171
                                       63
      764
                               0.340
                                       27
                                                  0
      765
                               0.245
                                       30
                                                  0
      766
                               0.349
                                                  1
                                       47
```

767 0.315 23 0

$1 \quad EDA$

```
[14]:
     df.describe()
[14]:
             Pregnancies
                              Glucose
                                        BloodPressure
                                                        SkinThickness
                                                                           Insulin
      count
              768.000000
                           768.000000
                                           768.000000
                                                           768.000000
                                                                        768.000000
      mean
                3.845052
                           120.894531
                                            69.105469
                                                            20.536458
                                                                         79.799479
      std
                 3.369578
                            31.972618
                                            19.355807
                                                            15.952218
                                                                        115.244002
      min
                0.000000
                             0.000000
                                             0.000000
                                                             0.000000
                                                                          0.000000
      25%
                 1.000000
                            99.000000
                                                             0.000000
                                                                          0.00000
                                            62.000000
      50%
                3.000000
                           117.000000
                                            72.000000
                                                            23.000000
                                                                         30.500000
      75%
                 6.000000
                           140.250000
                                            80.00000
                                                            32.000000
                                                                        127.250000
      max
               17.000000
                           199.000000
                                           122.000000
                                                            99.000000
                                                                        846.000000
                     BMI
                          DiabetesPedigreeFunction
                                                                      Outcome
                                                             Age
             768.000000
                                         768.000000
                                                      768.000000
                                                                  768.000000
      count
              31.992578
      mean
                                           0.471876
                                                       33.240885
                                                                     0.348958
      std
               7.884160
                                           0.331329
                                                       11.760232
                                                                     0.476951
      min
               0.000000
                                           0.078000
                                                       21.000000
                                                                     0.000000
      25%
                                                       24.000000
              27.300000
                                           0.243750
                                                                     0.000000
      50%
              32.000000
                                           0.372500
                                                       29.000000
                                                                     0.000000
      75%
              36.600000
                                           0.626250
                                                       41.000000
                                                                     1.000000
              67.100000
                                           2.420000
                                                       81.000000
                                                                     1.000000
      max
[15]: df.hist(bins = 30, figsize = (20, 20), color = 'orange')
      plt.show()
```

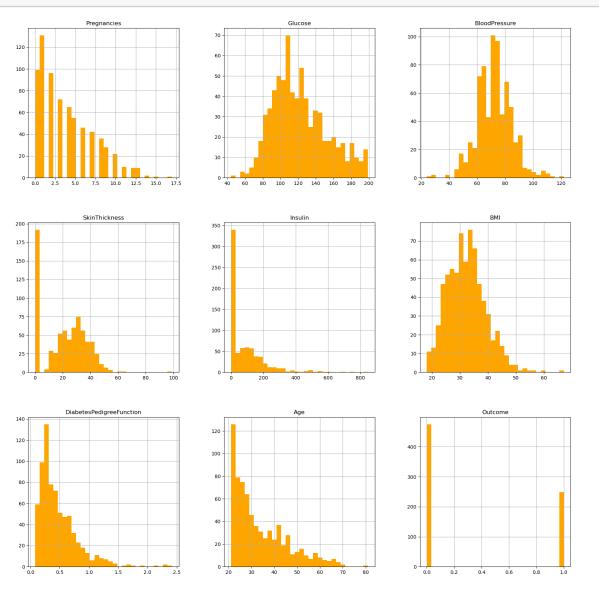


Insights from the histograms:

- There are more young study participants.
- The zero values in the skin thickness field indicate that the collagen level was not measured for all patients.
- Similarly, zero values for glucose, blood presure, and bmi indicate missing measurements. A glucose level of zero would mean the patient is in a coma or worse.
- There are about twice as many patients without diabetes (outcome = 0) than with diabetes (outcome = 1)

```
[16]: df = df[(df["BloodPressure"] > 0) & (df["BMI"] > 0) & (df["Glucose"] > 0)]
df.hist(bins = 30, figsize = (20, 20), color = 'orange')
```

plt.show()



- [17]: # Check the number of records left after cleaning df.shape
- [17]: (724, 9)
- [18]: ## Export the histograms to an image file

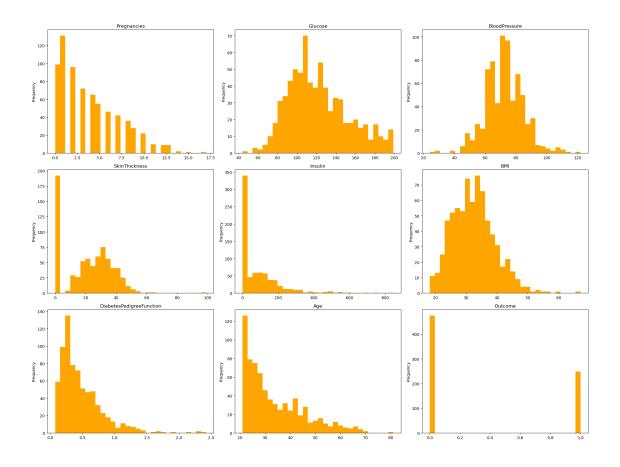
 # Determine the number of rows and columns for subplots

 num_cols = 3

 num_rows = -(-len(df.columns) // num_cols) # Ceiling division to ensure enough_

 +rows

```
# Create a figure and axes
fig, axes = plt.subplots(nrows=num_rows, ncols=num_cols, figsize=(20,__
 45*num_rows))
# Flatten the axes array for easy iteration
axes = axes.flatten()
# Plot histogram for each column
for i, (col, ax) in enumerate(zip(df.columns, axes)):
    df[col].plot(kind='hist', bins=30, ax=ax, color='orange')
    ax.set_title(col)
# Remove any extra empty subplots
for j in range(i + 1, len(axes)):
   fig.delaxes(axes[j])
# Adjust layout
plt.tight_layout()
# Save the figure
plt.savefig('img/histograms_diabetes.png')
# Show the plot
plt.show()
```



```
[19]: # Create a correlation matrix

corr_matrix = df.corr()

corr_matrix
```

[19]:		Pregnancie	s Glucos	se BloodPressure	SkinThickness	\	
	Pregnancies	1.00000	0 0.13491	0.209668	-0.095683		
	Glucose	0.13491	5 1.00000	0.223331	0.074381		
	BloodPressure	0.20966	8 0.22333	1.000000	0.011777		
	SkinThickness	-0.09568	3 0.07438	0.011777	1.000000		
	Insulin	-0.08005	9 0.33789	96 -0.046856	0.420874		
	BMI	0.01234	2 0.22327	76 0.287403	0.401528		
	${\tt DiabetesPedigreeFunction}$	-0.02599	6 0.13663	-0.000075	0.176253		
	Age	0.55706	6 0.26356	0.324897	-0.128908		
	Outcome	0.22441	7 0.48838	0.166703	0.092030		
		Insulin	BMI	DiabetesPedigreeF	unction \		
	Pregnancies	-0.080059	0.012342	-0.025996			
	Glucose	0.337896	37896 0.223276 0.136630				
	BloodPressure	-0.046856	0.287403	-0.000075			

```
SkinThickness
                         0.420874 0.401528
                                                             0.176253
Insulin
                                                             0.182656
                         1.000000 0.191831
BMI
                         0.191831 1.000000
                                                             0.154858
DiabetesPedigreeFunction 0.182656 0.154858
                                                             1.000000
                         -0.049412 0.020835
                                                             0.023098
Outcome
                         0.145488 0.299375
                                                             0.184947
                              Age
                                    Outcome
                         0.557066 0.224417
Pregnancies
Glucose
                         0.263560 0.488384
BloodPressure
                         0.324897 0.166703
SkinThickness
                        -0.128908 0.092030
Insulin
                        -0.049412 0.145488
BMI
                         0.020835 0.299375
DiabetesPedigreeFunction 0.023098 0.184947
                         1.000000 0.245741
Outcome
                         0.245741 1.000000
```

[]:

```
[20]: # Plot the correlation matrix

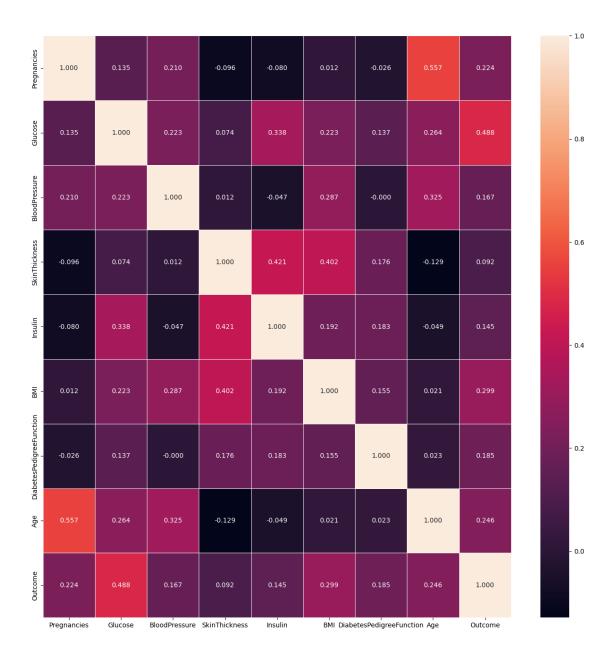
plt.figure(figsize = (16, 16))

_ = sns.heatmap(corr_matrix, annot = True, fmt = ".3f", linewidths = .5)

plt.show()

fig = _.get_figure()

fig.savefig('img/corr_mat_diabetes.png')
```



There are significant correlations between BMI and skin thickness, skin thickness and insulin, glucose and insulin, glucose and outcome, blood presure and age and blood presure and bmi.

2 Split the data into training and test sets

```
[21]: # split the dataframe into target and features

y = df["Outcome"] # target
X = df.drop(columns = ["Outcome"]) # features
```

```
# Verify that the split was performed correctly
      print(X.shape)
      print(y.shape)
     (724, 8)
     (724,)
[22]: from collections import Counter
      counter = Counter(y)
      print(counter)
     Counter({0: 475, 1: 249})
[23]: # estimate scale pos weight value
      estimate = counter[0] / counter[1]
      print('Estimate: %.3f' % estimate)
     Estimate: 1.908
[24]: # split the labels and features into training and testing sets
      from sklearn.model_selection import train_test_split
      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,_u
      →random_state = 21, stratify = y)
      # Verify that the split was performed correctly
      print('Training set')
      print(X_train.shape)
      print(y_train.shape)
      print()
      print('Testing set')
      print(X_test.shape)
      print(y_test.shape)
      print()
     Training set
     (506, 8)
     (506,)
     Testing set
     (218, 8)
     (218,)
```

```
[25]: # Verify that the index has been shuffled
     print(X.index)
     print()
     print(X_train.index)
     Index([ 0,
                            3,
                                 4,
                                      5,
                  1,
                       2,
                                          6,
                                               8, 10, 11,
            758, 759, 760, 761, 762, 763, 764, 765, 766, 767],
           dtype='int64', length=724)
     Index([711, 180, 364, 94, 406, 388, 526, 283, 580, 361,
            119, 146, 334, 165, 39, 510, 727, 742, 482, 724],
           dtype='int64', length=506)
```

3 Train an XGBoost Classifier in scikit-learn

max_depth = 8,
 alpha = 25,
 n_estimators = 100,
 scale_pos_weight=1.908
)

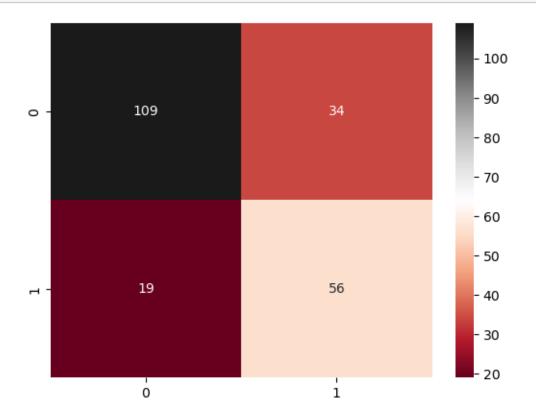
xgb_classifier.fit(X_train, y_train)

[27]: XGBClassifier(alpha=25, base_score=None, booster=None, callbacks=None, colsample_bylevel=None, colsample_bynode=None, colsample_bytree=None, device=None, early_stopping_rounds=None, enable_categorical=False, eval_metric='error', feature_types=None, gamma=None, grow_policy=None, importance_type=None, interaction_constraints=None, learning_rate=0.1, max_bin=None, max_cat_threshold=None, max_cat_to_onehot=None, max_delta_step=None, max_depth=8, max_leaves=None, min_child_weight=None, missing=nan, monotone_constraints=None, multi_strategy=None, n_estimators=100, n_jobs=None, num_parallel_tree=None, ...)

4 Test the model

```
[28]: # predict the performance score of the trained model using the testing dataset
      result = xgb_classifier.score(X_test, y_test)
      print("Accuracy: {}".format(result))
     Accuracy: 0.7568807339449541
[29]: # make predictions on the test data
      y_predict = xgb_classifier.predict(X_test)
      y_predict
[29]: array([0, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0,
             0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1,
             0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0,
             0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1,
             0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1,
             0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1,
             1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0,
             1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1,
             0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0,
             1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0])
[30]: # print the performance report
      from sklearn.metrics import classification_report
      print(classification_report(y_test, y_predict))
                                recall f1-score
                   precision
                                                   support
                                  0.76
                0
                        0.85
                                            0.80
                                                       143
                1
                        0.62
                                  0.75
                                            0.68
                                                        75
                                            0.76
                                                       218
         accuracy
                        0.74
                                  0.75
                                            0.74
                                                       218
        macro avg
                        0.77
                                  0.76
                                            0.76
     weighted avg
                                                       218
[31]: # print the confusion matrix
      from sklearn.metrics import confusion_matrix
      cm = confusion_matrix(y_test, y_predict)
      sns.heatmap(cm, fmt = 'd', annot = True, cmap = 'RdGy')
```

```
plt.savefig('img/conf_mat_diabetes.png')
```



```
[]:
[32]: from sklearn.feature_selection import SelectKBest
    from sklearn.feature_selection import chi2
    from sklearn.metrics import accuracy_score

[33]: X_train = X_train.drop(columns = "DiabetesPedigreeFunction")
    X_test = X_test.drop(columns = "DiabetesPedigreeFunction")

[34]: selected_features = SelectKBest(chi2, k = 6).fit(X_train, y_train)
    print('Score List: ', selected_features.scores_)
    print()
    print('Feature list: ', X_train.columns)

Score List: [ 40.78847338 909.12635978 30.21003989 102.44195607
    2747.73180153
    66.43702699 120.93811566]

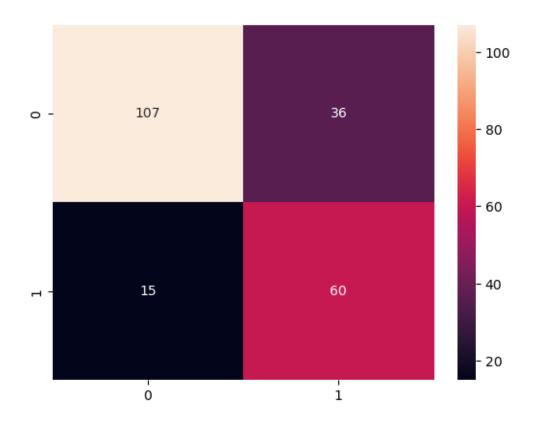
Feature list: Index(['Pregnancies', 'Glucose', 'BloodPressure',
```

```
'SkinThickness', 'Insulin',
            'BMI', 'Age'],
           dtype='object')
[35]: X_train_2 = selected_features.transform(X_train)
      X_test_2 = selected_features.transform(X_test)
      evalset = [(X_train_2, y_train), (X_test_2, y_test)]
      xgb_classifier_2 = XGBClassifier(objective = 'binary:logistic',
                                       eval_metric = 'logloss',
                                       learning_rate = 0.02,
                                       max_depth = 8,
                                       alpha = 17,
                                       n_{estimators} = 230,
                                       min_child_weight = 1,
                                       scale_pos_weight = 1.908,
                                       use_label_encoder = False,
                                       seed = 21).fit(X_train_2, y_train, eval_set =_
      ⇔evalset, verbose = 0)
      result2 = xgb_classifier_2.score(X_test_2, y_test)
      print()
      print("Accuracy: {}".format(result2))
      print()
      print('Accuracy is: ', accuracy_score(y_test, xgb_classifier_2.
       →predict(X_test_2)))
      print()
      cm_2 = confusion_matrix(y_test, xgb_classifier_2.predict(X_test_2))
      sns.heatmap(cm_2, annot = True, fmt = 'd')
```

Accuracy: 0.7660550458715596

Accuracy is: 0.7660550458715596

[35]: <Axes: >



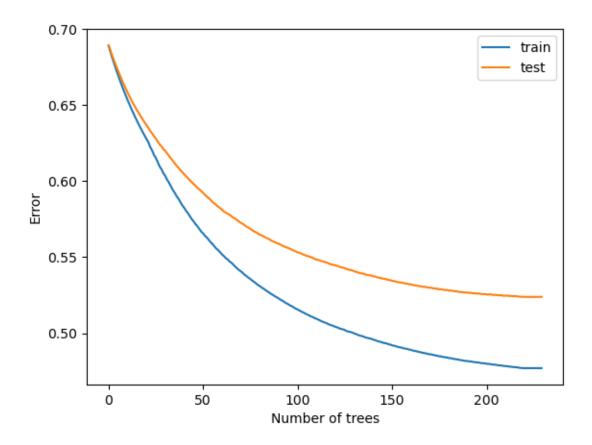
```
[36]: results = xgb_classifier_2.evals_result()

plt.plot(results['validation_0']['logloss'], label = 'train')
plt.plot(results['validation_1']['logloss'], label = 'test')

plt.xlabel('Number of trees')
plt.ylabel('Error')

plt.legend()

plt.show()
```



```
[37]: print(result2)
```

0.7660550458715596

```
[]:
```

```
[48]: from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import cross_val_score

# CV model

kfold = StratifiedKFold(n_splits=10, shuffle=True, random_state = 21)
results = cross_val_score(xgb_classifier_2, X, y, cv=kfold)
print("Accuracy: %.2f%% (%.2f%%)" % (results.mean()*100, results.std()*100))
```

Accuracy: 75.27% (7.22%)

```
[92]: # stratified k-fold cross validation evaluation of xgboost model
from numpy import loadtxt
import xgboost
from sklearn.model_selection import StratifiedKFold
```

```
from sklearn.model_selection import cross_val_score
# load data
df = pd.read_csv('./Data/diabetes.csv')
df = df[(df["BloodPressure"] > 0) & (df["BMI"] > 0) & (df["Glucose"] > 0)]
df = df.drop(columns = ["DiabetesPedigreeFunction", "Pregnancies", __
 ⇔"BloodPressure"])
# split data into X and y
y = df["Outcome"] # target
X = df.drop(columns = ["Outcome"]) # features
# CV model
model = xgboost.XGBClassifier(objective = 'binary:logistic',
                                eval_metric = 'logloss',
                                learning_rate = 0.0045,
                                max depth = 10,
                                alpha = 17,
                                n = 200,
                                min_child_weight = 1,
                                 scale_pos_weight = 1.853,
                                use_label_encoder = False,
                                 seed = 21)
kfold = StratifiedKFold(n_splits=15, shuffle = True, random_state=7)
results = cross_val_score(model, X, y, cv=kfold)
print("Accuracy: %.2f%% (%.2f%%)" % (results.mean()*100, results.std()*100))
```

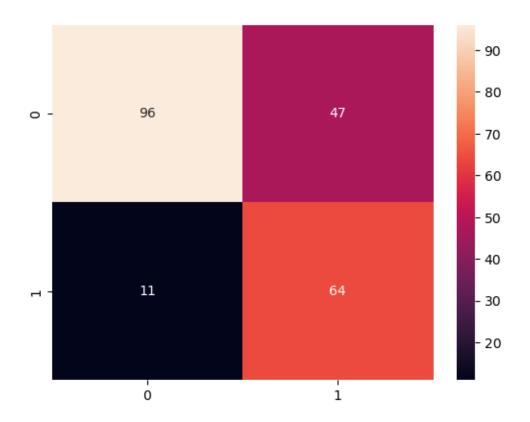
Accuracy: 76.11% (4.85%)

```
learning_rate = 0.0045,
                                 max_depth = 10,
                                 alpha = 17,
                                 n_{estimators} = 200,
                                 min_child_weight = 1,
                                 scale_pos_weight = 1.853,
                                 use_label_encoder = False,
                                 seed = 21
                               )
xgb_classifier_3.fit(X_train, y_train)
# predict the performance score of the trained model using the testing dataset
result3 = xgb_classifier_3.score(X_test, y_test)
print("Accuracy: {}".format(result3))
print(classification_report(y_test, y_predict))
cm_3 = confusion_matrix(y_test, xgb_classifier_3.predict(X_test))
sns.heatmap(cm_3, annot = True, fmt = 'd')
```

Accuracy: 0.7339449541284404

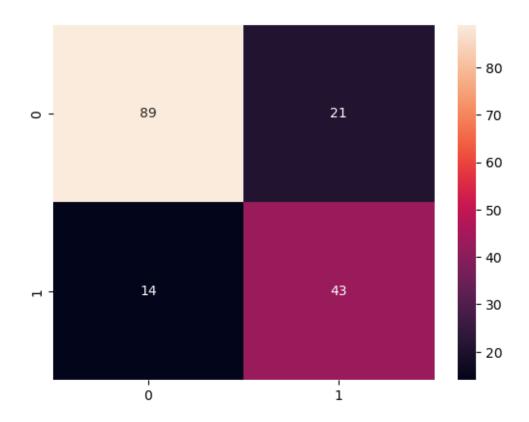
	precision	recall	f1-score	support
	_			
0	0.85	0.76	0.80	143
1	0.62	0.75	0.68	75
accuracy			0.76	218
macro avg	0.74	0.75	0.74	218
weighted avg	0.77	0.76	0.76	218

[95]: <Axes: >



```
X_test_2 = selected_features.transform(X_test)
evalset = [(X_train_2, y_train), (X_test_2, y_test)]
xgb_classifier_2 = XGBClassifier(objective = 'binary:logistic',
                                  eval_metric = 'logloss',
                                 learning_rate = 0.0045,
                                 max_depth = 10,
                                  alpha = 17,
                                 n estimators = 200,
                                 min_child_weight = 1,
                                  scale_pos_weight = 1.853,
                                 use_label_encoder = False,
                                  seed = 21).fit(X_train_2, y_train, eval_set =__
 ⇔evalset, verbose = 0)
result2 = xgb_classifier_2.score(X_test_2, y_test)
print()
print("Accuracy: {}".format(result2))
print()
print(classification_report(y_test, xgb_classifier_2.predict(X_test_2)))
cm_2 = confusion_matrix(y_test, xgb_classifier_2.predict(X_test_2))
sns.heatmap(cm_2, annot = True, fmt = 'd')
Score List: [1018.65928828 115.79423973 2884.35013363 76.14062403
150.1224944 ]
Feature list: Index(['Glucose', 'SkinThickness', 'Insulin', 'BMI', 'Age'],
dtype='object')
Accuracy: 0.7904191616766467
              precision
                          recall f1-score
                                              support
           0
                   0.86
                             0.81
                                       0.84
                                                  110
           1
                   0.67
                             0.75
                                       0.71
                                                   57
                                       0.79
                                                  167
   accuracy
  macro avg
                   0.77
                             0.78
                                       0.77
                                                  167
                             0.79
                                       0.79
weighted avg
                   0.80
                                                  167
```

[115]: <Axes: >



```
[121]: from sklearn.metrics import log_loss, roc_auc_score

# Calculate log loss
print(log_loss(y_test, xgb_classifier_2.predict_proba(X_test_2)))

print()

# Calculate ROC AUC
print(roc_auc_score(y_test, xgb_classifier_2.predict_proba(X_test_2)[:, 1]))
```

0.5954343241184004

0.8209728867623605

[]: