PCOS_Diagnosis

July 14, 2025

[12]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
```

[14]:
```
pcos_df=pd.read_csv("pcos_dataset.csv")
pcos_df
```

[14]:

	Age	BMI	Menstrual_Irregularity	Testosterone_Level(ng/dL)	\
0	24	34.7	1	25.2	
1	37	26.4	0	57.1	
2	32	23.6	0	92.7	
3	28	28.8	0	63.1	
4	25	22.1	1	59.8	
..	…	…	…	…	
995	34	18.4	1	95.7	
996	45	28.9	1	28.5	
997	37	28.3	0	32.4	
998	41	27.3	0	95.6	
999	22	21.9	1	78.9	

	Antral_Follicle_Count	PCOS_Diagnosis
0	20	0
1	25	0
2	28	0
3	26	0
4	8	0
..	…	…
995	23	0
996	7	0
997	28	0
998	9	0
999	7	0

```
[1000 rows x 6 columns]
```

[22]:
```
pcos_df.isnull().sum()#check for null values
```

[22]:
```
Age                           0
BMI                           0
Menstrual_Irregularity        0
Testosterone_Level(ng/dL)     0
Antral_Follicle_Count         0
PCOS_Diagnosis                0
dtype: int64
```

[24]:
```
pcos_df.describe()#descriptive statistics
```

[24]:
```
                Age         BMI  Menstrual_Irregularity  \
count  1000.000000  1000.00000             1000.000000
mean     31.771000    26.38700                0.530000
std       8.463462     4.93554                0.499349
min      18.000000    18.10000                0.000000
25%      24.000000    21.90000                0.000000
50%      32.000000    26.40000                1.000000
75%      39.000000    30.50000                1.000000
max      45.000000    35.00000                1.000000

       Testosterone_Level(ng/dL)  Antral_Follicle_Count  PCOS_Diagnosis
count                1000.000000            1000.000000     1000.000000
mean                   60.159500              17.469000        0.199000
std                    23.160204               7.069301        0.399448
min                    20.000000               5.000000        0.000000
25%                    41.700000              12.000000        0.000000
50%                    60.000000              18.000000        0.000000
75%                    80.300000              23.250000        0.000000
max                    99.800000              29.000000        1.000000
```

[28]:
```
pcos_df.corr()#checking for correlation between the variables
```

[28]:
```
                                Age       BMI  Menstrual_Irregularity  \
Age                        1.000000 -0.049455                0.032300
BMI                       -0.049455  1.000000                0.031189
Menstrual_Irregularity     0.032300  0.031189                1.000000
Testosterone_Level(ng/dL) -0.050129  0.003811                0.042694
Antral_Follicle_Count      0.017841  0.030724                0.035851
PCOS_Diagnosis            -0.064675  0.377852                0.469376

                          Testosterone_Level(ng/dL)  Antral_Follicle_Count  \
Age                                       -0.050129               0.017841
BMI                                        0.003811               0.030724
```

```
Menstrual_Irregularity                  0.042694              0.035851
Testosterone_Level(ng/dL)               1.000000              0.011976
Antral_Follicle_Count                   0.011976              1.000000
PCOS_Diagnosis                          0.200817              0.192014

                            PCOS_Diagnosis
Age                              -0.064675
BMI                               0.377852
Menstrual_Irregularity            0.469376
Testosterone_Level(ng/dL)         0.200817
Antral_Follicle_Count             0.192014
PCOS_Diagnosis                    1.000000
```

[32]:
```
pcos_df['PCOS_Diagnosis'].value_counts()#check balance
```

[32]:
```
PCOS_Diagnosis
0    801
1    199
Name: count, dtype: int64
```

[42]:
```
#split dataset into features and labels
X=pcos_df.drop(columns=['Age','PCOS_Diagnosis'],axis=1)
y=pcos_df['PCOS_Diagnosis']
```

[44]:
```
print(X)
```

```
      BMI  Menstrual_Irregularity  Testosterone_Level(ng/dL)  \
0    34.7                       1                       25.2
1    26.4                       0                       57.1
2    23.6                       0                       92.7
3    28.8                       0                       63.1
4    22.1                       1                       59.8
..    …                       …                       …
995  18.4                       1                       95.7
996  28.9                       1                       28.5
997  28.3                       0                       32.4
998  27.3                       0                       95.6
999  21.9                       1                       78.9

     Antral_Follicle_Count
0                       20
1                       25
2                       28
3                       26
4                        8
..                      …
995                     23
996                      7
```

```
997                    28
998                     9
999                     7

[1000 rows x 4 columns]
```

[46]:
```
print(y)
```

```
0      0
1      0
2      0
3      0
4      0
      ..
995    0
996    0
997    0
998    0
999    0
Name: PCOS_Diagnosis, Length: 1000, dtype: int64
```

[326]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,␣
↪random_state=42)#split data
```

[328]:
```
#standardize features
scaler=StandardScaler()
X_train_scaled=scaler.fit_transform(X_train)
X_test_scaled=scaler.transform(X_test)
```

[330]:
```
from imblearn.over_sampling import SMOTE
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train_scaled,␣
↪y_train)
```

[332]:
```
#create and train the model
model=LogisticRegression()
model.fit(X_train_scaled,y_train)
```

[332]:
```
LogisticRegression()
```

[334]:
```
#make predictions
y_pred=model.predict(X_test_scaled)
```

[336]:
```
#evaluate the model
accuracy=accuracy_score(y_test,y_pred)
print("Accuracy:",accuracy)
```

```
Accuracy: 0.9
```

[338]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

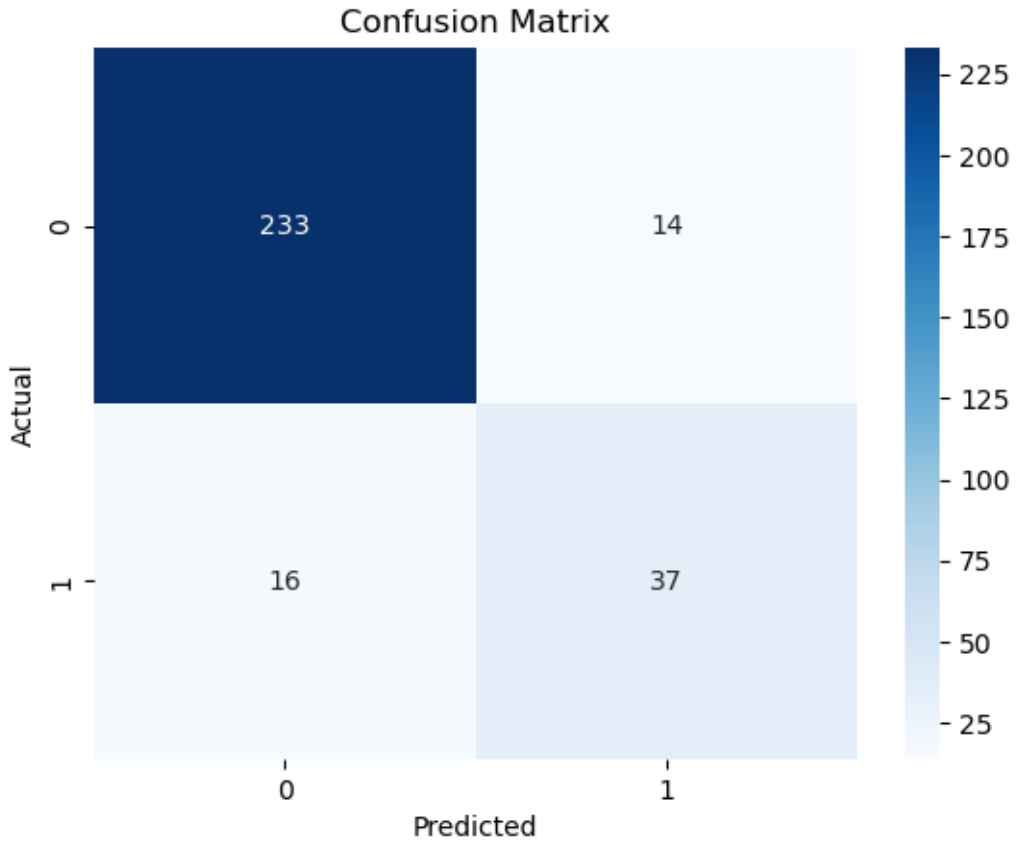
```
              precision    recall  f1-score   support

           0       0.94      0.94      0.94       247
           1       0.73      0.70      0.71        53

    accuracy                           0.90       300
   macro avg       0.83      0.82      0.83       300
weighted avg       0.90      0.90      0.90       300
```

[340]:
```
from sklearn.metrics import confusion_matrix


cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```



[344]:
```
import numpy as np
print("Before SMOTE:", np.bincount(y_train))
print("After SMOTE :", np.bincount(y_train_resampled))
```

```
Before SMOTE: [554 146]
After SMOTE : [554 554]
```

[346]:
```
from xgboost import XGBClassifier

model = XGBClassifier(random_state=42)
```

[348]:
```
model.fit(X_train_scaled,y_train)
```

[348]:
```
XGBClassifier(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=None, feature_types=None,
              feature_weights=None, gamma=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=None, max_bin=None, max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None, n_estimators=None,
              n_jobs=None, num_parallel_tree=None, …)
```

[350]:
```
y_pred=model.predict(X_test_scaled)
```

[352]:
```
#evaluate the model
accuracy=accuracy_score(y_test,y_pred)
print("Accuracy:",accuracy)
```

```
Accuracy: 0.9966666666666667
```

[354]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

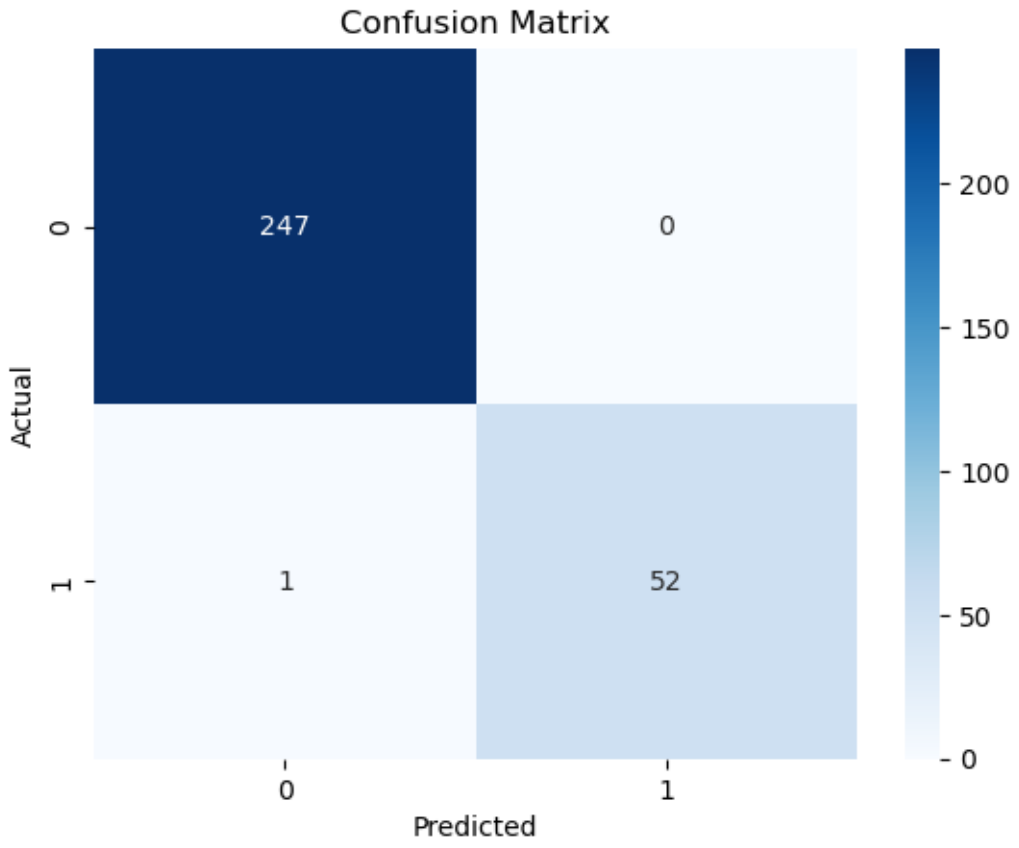
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       247
           1       1.00      0.98      0.99        53

    accuracy                           1.00       300
   macro avg       1.00      0.99      0.99       300
weighted avg       1.00      1.00      1.00       300
```

[356]:
```
from sklearn.metrics import confusion_matrix


cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```



[370]:
```
new_data=np.array([[27.4,1,90.0,21],
                   [24.5,0,50.4,20],
                   [26.8,1,80.6,26],
                   [27.7,0,50.8,23]])
```

[438]:
```
new_data = pd.DataFrame({
    'BMI': [27.4,24.5,26.8,27.7],
    'Menstrual_Irregularity': [1,0,1,0],
    'Testosterone_Level(ng/dL)': [90.0,50.4,80.6,60.6],
    'Antral_Follicle_Count': [21,20,26,23]
```

```
})
```

[440]:
```
new_data
```

[440]:
```
    BMI  Menstrual_Irregularity  Testosterone_Level(ng/dL)  \
0  27.4                        1                       90.0
1  24.5                        0                       50.4
2  26.8                        1                       80.6
3  27.7                        0                       60.6

   Antral_Follicle_Count
0                     21
1                     20
2                     26
3                     23
```

[442]:
```
new_data_scaled=scaler.transform(new_data)
```

[444]:
```
predictions=model.predict(new_data_scaled)
print("Predictions:",predictions)
```

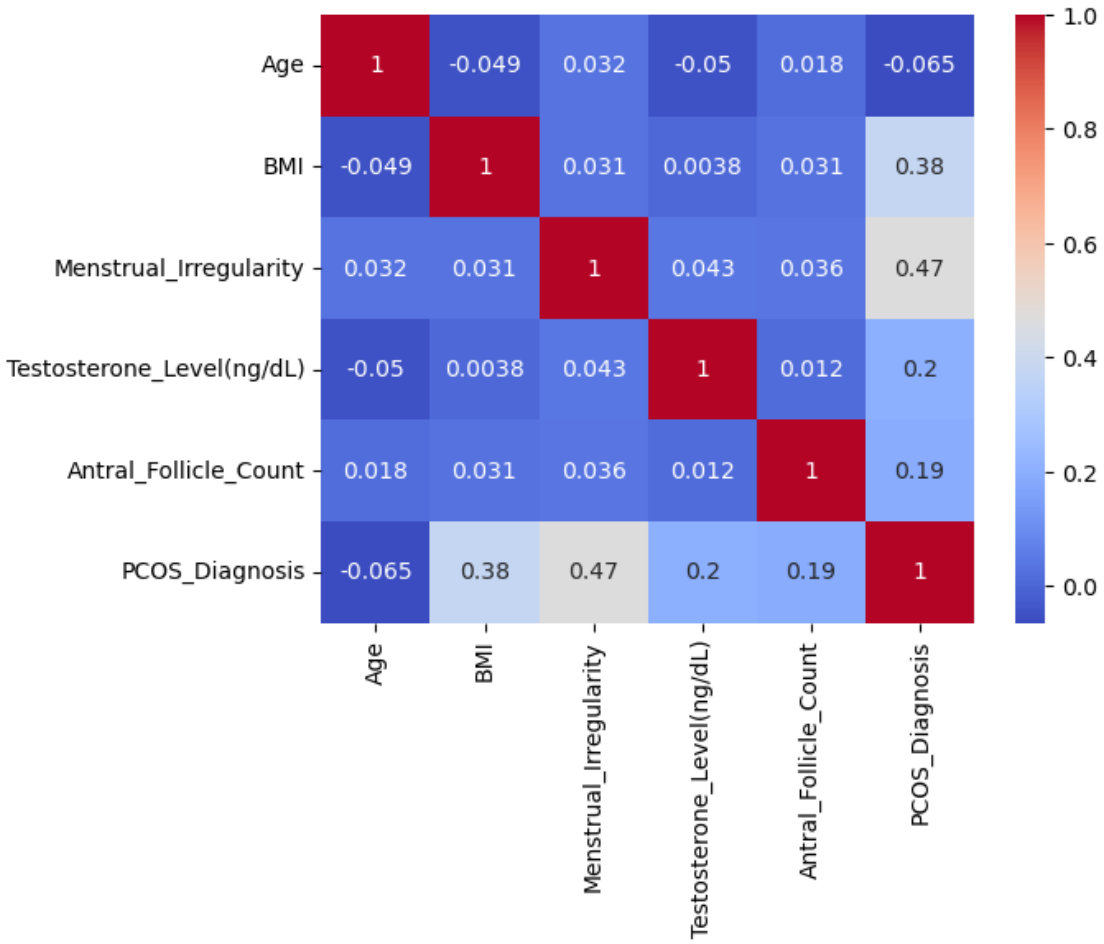
```
Predictions: [1 0 1 0]
```

[446]:
```
#As we can see the prediction outcome depends on the menstrual irregularities␣
 ↪this means that pcos_diagnosis is highly correlated with menstrual␣
 ↪irreguralities as we we wwwn saw earlier
```

[448]:
```
# Lets see how predictions differ by Menstrual_Irregularity
new_data['Prediction'] = predictions
new_data.groupby('Menstrual_Irregularity')['Prediction'].
 ↪value_counts(normalize=True)
```

[448]:
```
Menstrual_Irregularity  Prediction
0                       0             1.0
1                       1             1.0
Name: proportion, dtype: float64
```

[450]:
```
sns.heatmap(pcos_df.corr(), annot=True, cmap='coolwarm')
plt.show()
```

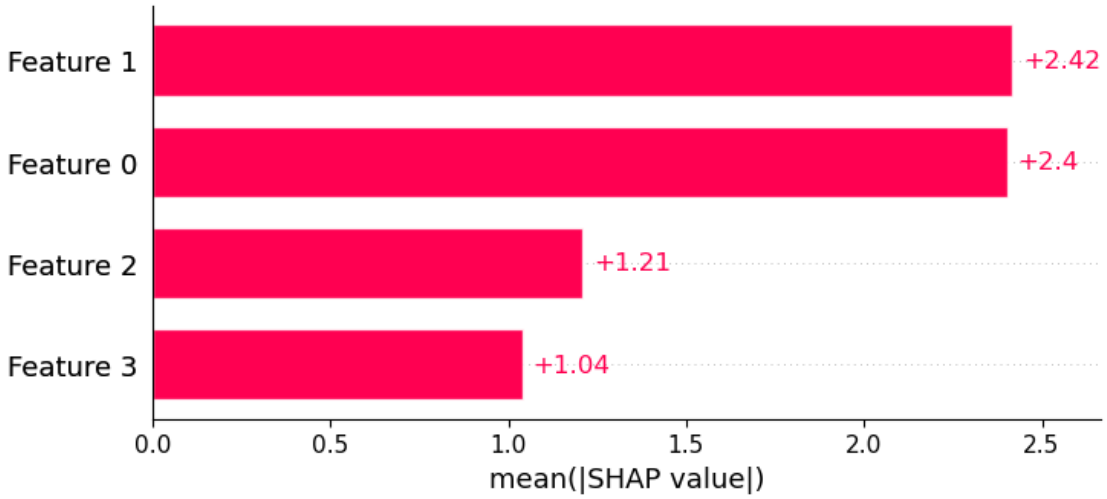


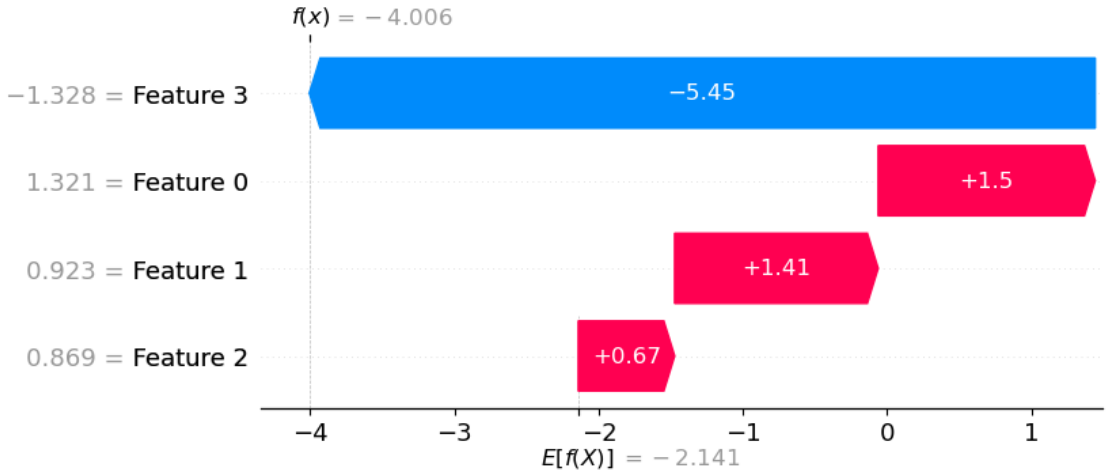
[451]:
```python
#checking for feature importance

import shap

explainer = shap.Explainer(model)
shap_values = explainer(X_test_scaled)

shap.plots.bar(shap_values)  # Global importance
shap.plots.waterfall(shap_values[0])  # One prediction
```





[453]:
```
from sklearn.inspection import permutation_importance

result = permutation_importance(model, X_test_scaled, y_test, n_repeats=10)
importances = result.importances_mean
```

[456]:
```
importances
```

[456]:
```
array([0.15366667, 0.16166667, 0.09933333, 0.077     ])
```

[ ]:
```

```