In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import linear_model
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
data = pd.read_csv('column_2C_weka.csv')
print(plt.style.available) # look at available plot styles
plt.style.use('ggplot')
```

```
['Solarize_Light2', '_classic_test_patch', '_mpl-gallery', '_mpl-gallery-nogrid', 'bmh', 'classic', 'dark_backgr
ound', 'fast', 'fivethirtyeight', 'ggplot', 'grayscale', 'seaborn-v0_8', 'seaborn-v0_8-bright', 'seaborn-v0_8-co
lorblind', 'seaborn-v0_8-dark', 'seaborn-v0_8-dark-palette', 'seaborn-v0_8-darkgrid', 'seaborn-v0_8-deep', 'seab
orn-v0_8-muted', 'seaborn-v0_8-notebook', 'seaborn-v0_8-paper', 'seaborn-v0_8-pastel', 'seaborn-v0_8-poster', 's
eaborn-v0_8-talk', 'seaborn-v0_8-ticks', 'seaborn-v0_8-white', 'seaborn-v0_8-whitegrid', 'tableau-colorblind10']
```

In [3]:
```
data.head()
```

Out[3]:

	pelvic_incidence	pelvic_tilt numeric	lumbar_lordosis_angle	sacral_slope	pelvic_radius	degree_spondylolisthesis	class
0	63.027817	22.552586	39.609117	40.475232	98.672917	-0.254400	Abnormal
1	39.056951	10.060991	25.015378	28.995960	114.405425	4.564259	Abnormal
2	68.832021	22.218482	50.092194	46.613539	105.985135	-3.530317	Abnormal
3	69.297008	24.652878	44.311238	44.644130	101.868495	11.211523	Abnormal
4	49.712859	9.652075	28.317406	40.060784	108.168725	7.918501	Abnormal

In [4]:
```
data.info()
```

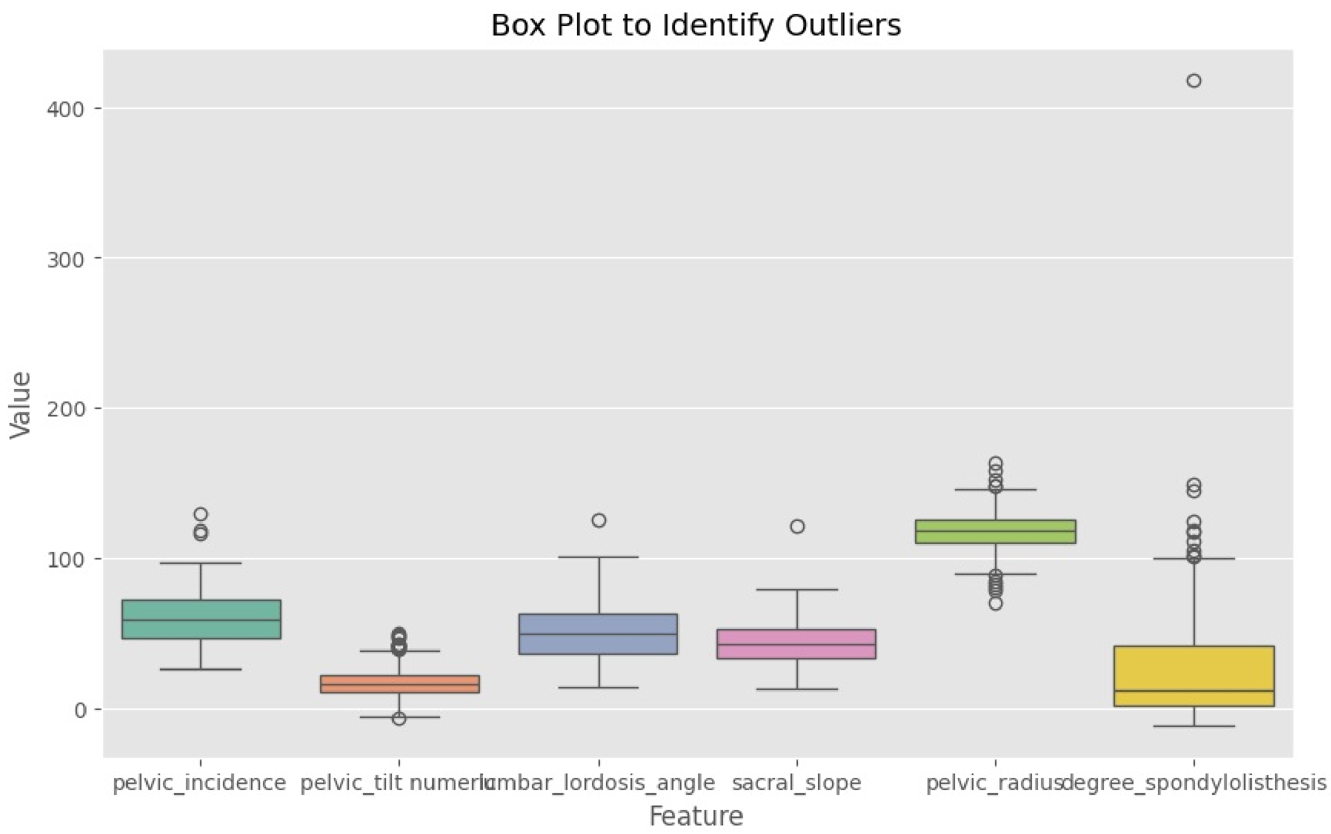
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 310 entries, 0 to 309
Data columns (total 7 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   pelvic_incidence          310 non-null    float64
 1   pelvic_tilt numeric       310 non-null    float64
 2   lumbar_lordosis_angle     310 non-null    float64
 3   sacral_slope              310 non-null    float64
 4   pelvic_radius             310 non-null    float64
 5   degree_spondylolisthesis  310 non-null    float64
 6   class                     310 non-null    object 
dtypes: float64(6), object(1)
memory usage: 17.1+ KB
```

In [5]:
```
data.describe()
```

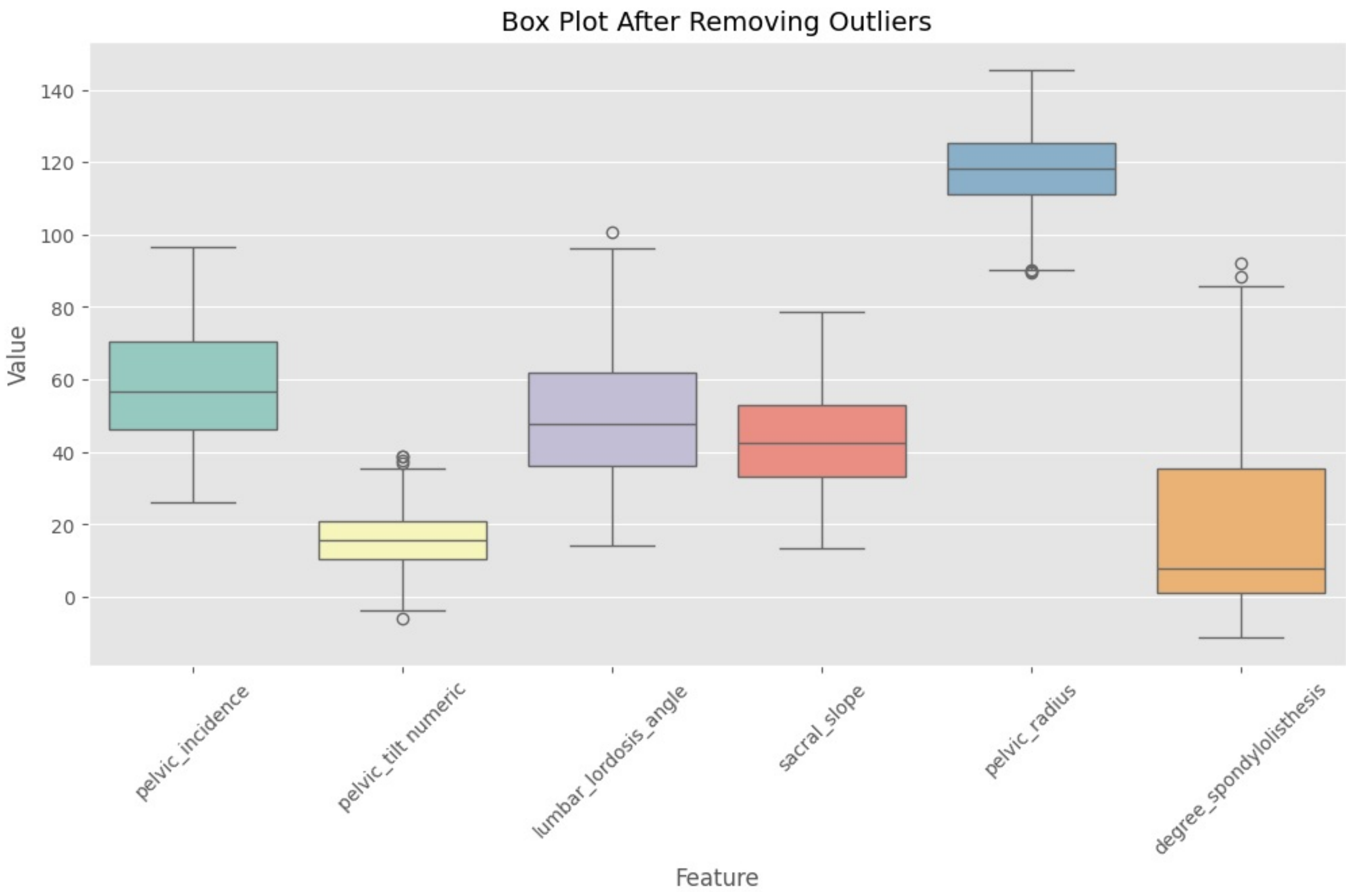
Out[5]:

	pelvic_incidence	pelvic_tilt numeric	lumbar_lordosis_angle	sacral_slope	pelvic_radius	degree_spondylolisthesis
count	310.000000	310.000000	310.000000	310.000000	310.000000	310.000000
mean	60.496653	17.542822	51.930930	42.953831	117.920655	26.296694
std	17.236520	10.008330	18.554064	13.423102	13.317377	37.559027
min	26.147921	-6.554948	14.000000	13.366931	70.082575	-11.058179
25%	46.430294	10.667069	37.000000	33.347122	110.709196	1.603727
50%	58.691038	16.357689	49.562398	42.404912	118.268178	11.767934
75%	72.877696	22.120395	63.000000	52.695888	125.467674	41.287352
max	129.834041	49.431864	125.742385	121.429566	163.071041	418.543082

In [6]:
```
melted_data = data.melt(id_vars="class", var_name="Feature", value_name="Value")

# Create box plots for each feature
plt.figure(figsize=(10, 6))
sns.boxplot(x="Feature", y="Value", data=melted_data, palette="Set2")

# Add a title
plt.title("Box Plot to Identify Outliers", fontsize=14)
plt.show()
```

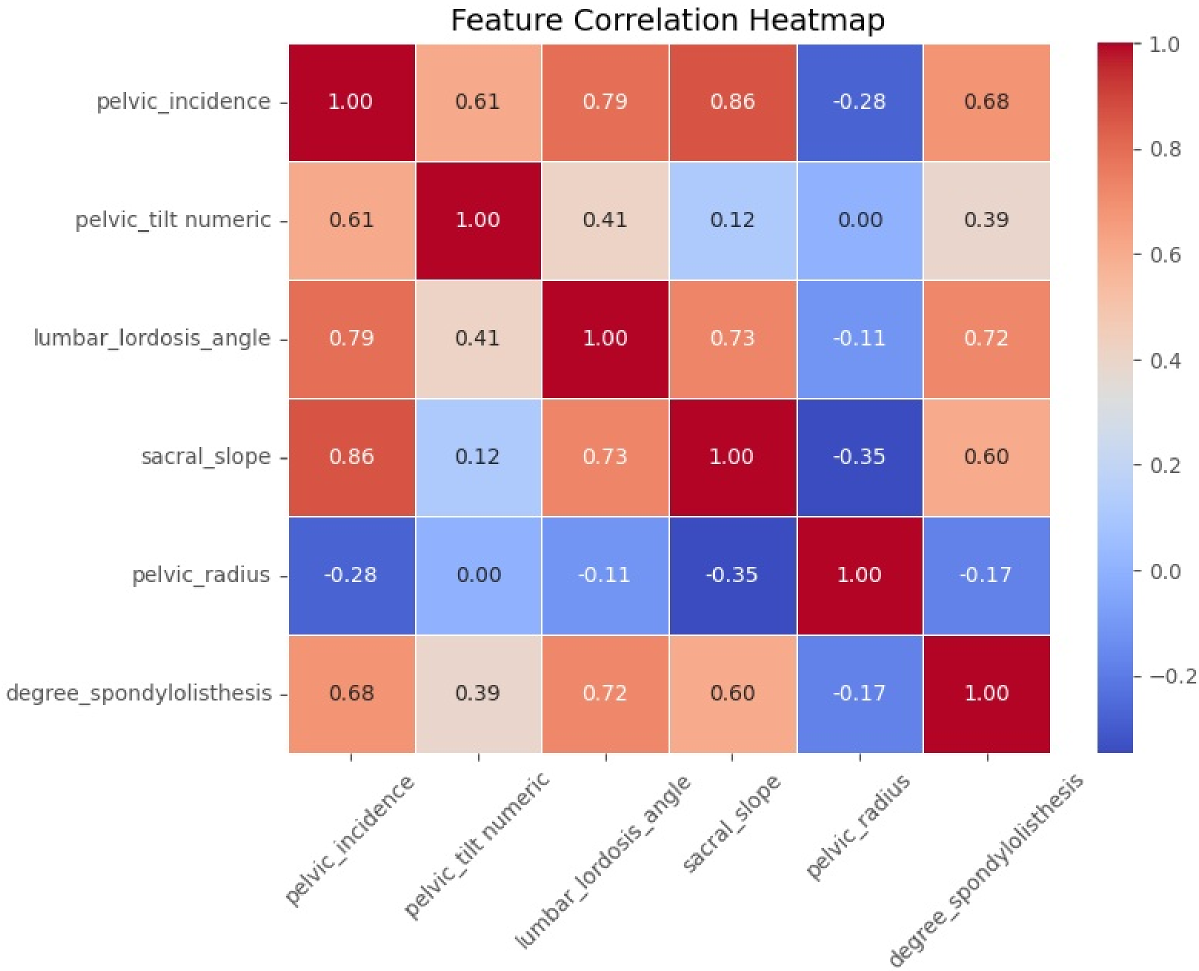


In [7]:
```python
def remove_outliers_iqr(df, columns):
    for column in columns:
        Q1 = df[column].quantile(0.25)  # First quartile
        Q3 = df[column].quantile(0.75)  # Third quartile
        IQR = Q3 - Q1  # Interquartile range
        lower_bound = Q1 - 1.5 * IQR  # Lower bound
        upper_bound = Q3 + 1.5 * IQR  # Upper bound
        df = df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]
    return df

# Only select numeric columns for outlier detection
columns_to_check = [
    'pelvic_incidence', 'pelvic_tilt numeric', 'lumbar_lordosis_angle',
    'sacral_slope', 'pelvic_radius', 'degree_spondylolisthesis'
]

# Remove outliers
cleaned_data = remove_outliers_iqr(data, columns_to_check)

# Visualize the cleaned data with boxplot (excluding 'class')
melted_cleaned_data = cleaned_data.melt(id_vars="class", var_name="Feature", value_name="Value")
plt.figure(figsize=(12, 6))
sns.boxplot(x="Feature", y="Value", data=melted_cleaned_data, palette="Set3")
plt.title("Box Plot After Removing Outliers", fontsize=14)
plt.xticks(rotation=45)
plt.show()
```



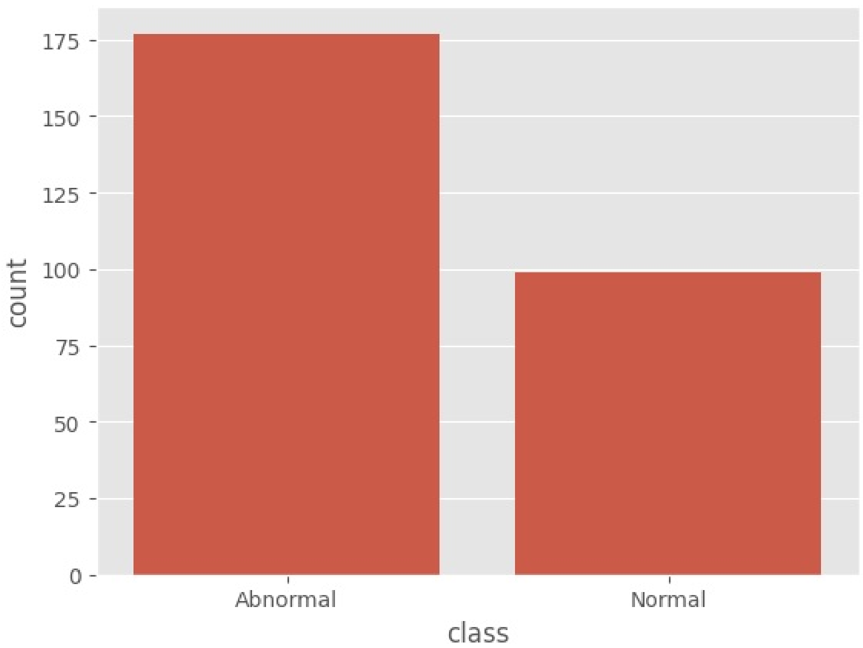
In [8]:

```
correlation_matrix = cleaned_data.drop('class', axis=1).corr()

# Plot heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(
    correlation_matrix,
    annot=True,  # Display correlation coefficients
    cmap="coolwarm",  # Color map for better visualization
    fmt=".2f",  # Format for annotations
    linewidths=0.5
)

# Add a title for clarity
plt.title("Feature Correlation Heatmap", fontsize=14)
plt.xticks(rotation=45)
plt.show()
```



In [9]:
```
sns.countplot(x="class", data=cleaned_data)
data.loc[:,'class'].value_counts()
```

Out[9]:
```
class
Abnormal    210
Normal      100
Name: count, dtype: int64
```



KNeighbor Classifier

In [10]:
```
from sklearn.neighbors import KNeighborsClassifier #Output is Non-Linear
from sklearn.model_selection import train_test_split
x,y = cleaned_data.loc[:,cleaned_data.columns != 'class'], cleaned_data.loc[:,'class']
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.3,random_state = 0)
knn = KNeighborsClassifier()
knn.fit(x_train,y_train)
prediction = knn.predict(x_test)
```

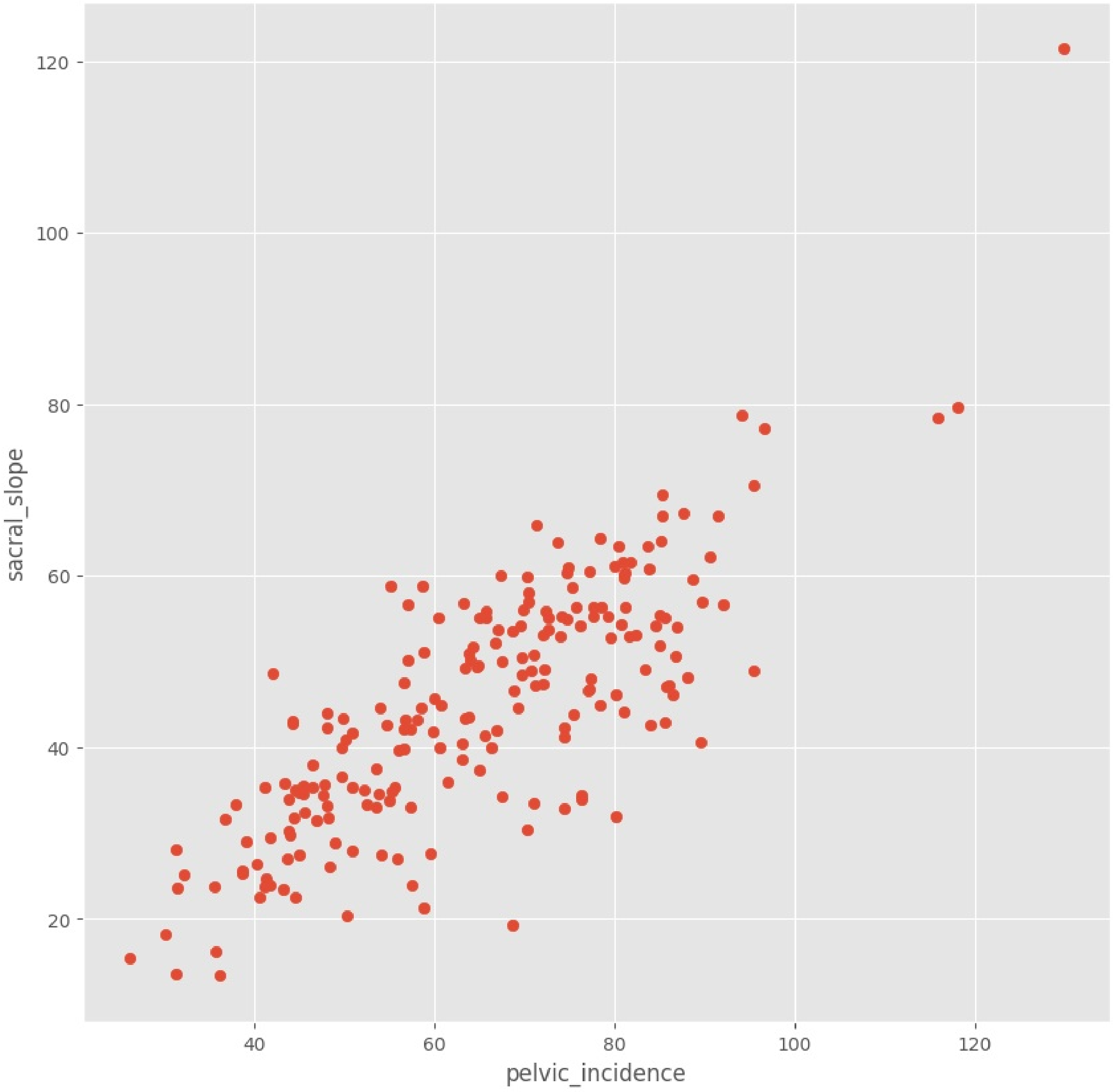
```python
print('With KNN (K=1) accuracy is: ',knn.score(x_test,y_test)) # accuracy
```

```
With KNN (K=1) accuracy is:  0.8674698795180723
```

In [50]:
```python
knn.predict([[63.027817,22.552586,39.609117,40.475232,98.672917,-0.254400]])
```

Out[50]:
```
array(['Abnormal'], dtype=object)
```

In [12]:
```python
# create data1 that includes pelvic_incidence that is feature and sacral_slope that is target variable
data1 = data[data['class'] =='Abnormal']
x = np.array(data1.loc[:,'pelvic_incidence']).reshape(-1,1)
y = np.array(data1.loc[:,'sacral_slope']).reshape(-1,1)
# Scatter
plt.figure(figsize=[10,10])
plt.scatter(x=x,y=y)
plt.xlabel('pelvic_incidence')
plt.ylabel('sacral_slope')
plt.show()
```

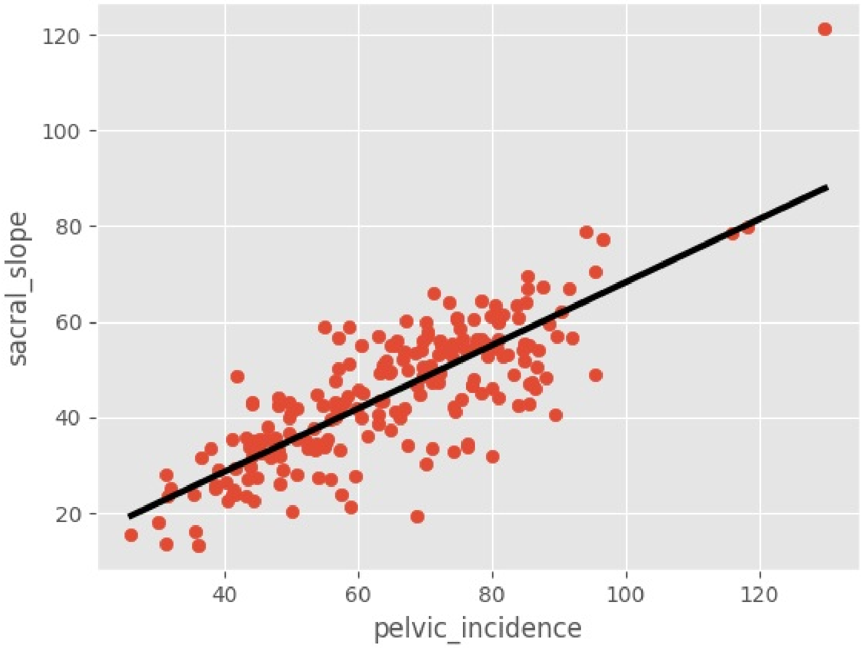


Linear Regression

In [13]:
```python
# LinearRegression
from sklearn.linear_model import LinearRegression
reg = LinearRegression()
# Predict space
predict_space = np.linspace(min(x), max(x)).reshape(-1,1)
# Fit
reg.fit(x,y)
# Predict
predicted = reg.predict(predict_space)
# R^2
print('R^2 score: ',reg.score(x, y))
```

```
# Plot regression line and scatter
plt.plot(predict_space, predicted, color='black', linewidth=3)
plt.scatter(x=x,y=y)
plt.xlabel('pelvic_incidence')
plt.ylabel('sacral_slope')
plt.show()
```

```
R^2 score:  0.6458410481075871
```



Cross Validation

In [14]:

```
# CV
from sklearn.model_selection import cross_val_score
reg = LinearRegression()
k = 5
cv_result = cross_val_score(reg,x,y,cv=k)
print('CV Scores: ',cv_result)
print('CV scores average: ',np.sum(cv_result)/k)
```

```
CV Scores:  [0.32924233 0.61683991 0.53117056 0.1954798  0.29299864]
CV scores average:  0.3931462502884869
```

Lasso

In [15]:

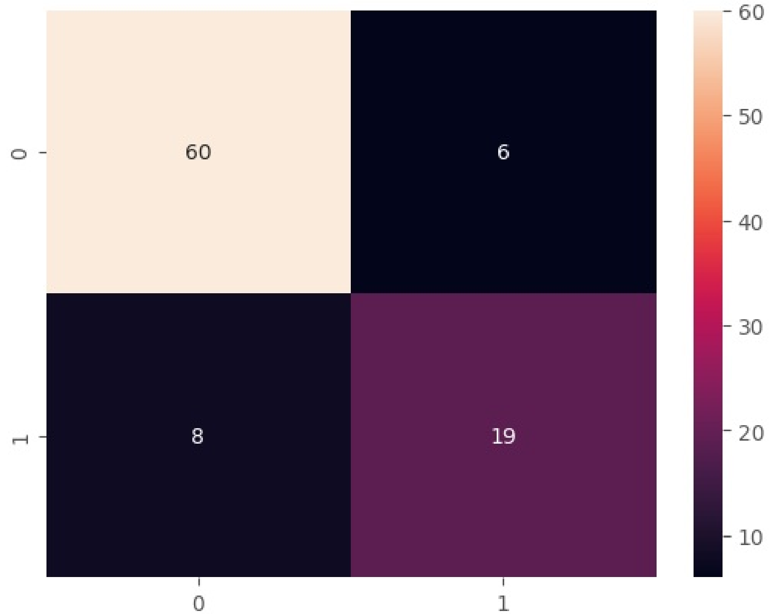
```
from sklearn.linear_model import Lasso
data1 = data[data['class'] =='Abnormal']
x = np.array(data1.loc[:,['pelvic_incidence','pelvic_tilt numeric','lumbar_lordosis_angle','pelvic_radius'] ])
x_train,x_test,y_train,y_test = train_test_split(x,y,random_state = 3, test_size = 0.3)
lasso = Lasso(alpha = 0.1)
lasso.fit(x_train,y_train)
ridge_predict = lasso.predict(x_test)
print('Lasso score: ',lasso.score(x_test,y_test))
```

```
Lasso score:  0.9999985469460118
Lasso coefficients:  [ 9.98901381e-01 -9.98137804e-01  3.13359061e-05 -0.00000000e+00]
```

Random Forest

In [16]:

```
# Confusion matrix with random forest
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.ensemble import RandomForestClassifier
x,y = data.loc[:,data.columns != 'class'], data.loc[:,'class']
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.3,random_state = 1)
rf = RandomForestClassifier(random_state = 4)
rf.fit(x_train,y_train)
rf.score
y_pred = rf.predict(x_test)
cm = confusion_matrix(y_test,y_pred)

# visualize with seaborn library
sns.heatmap(cm,annot=True,fmt="d")
plt.show()
```

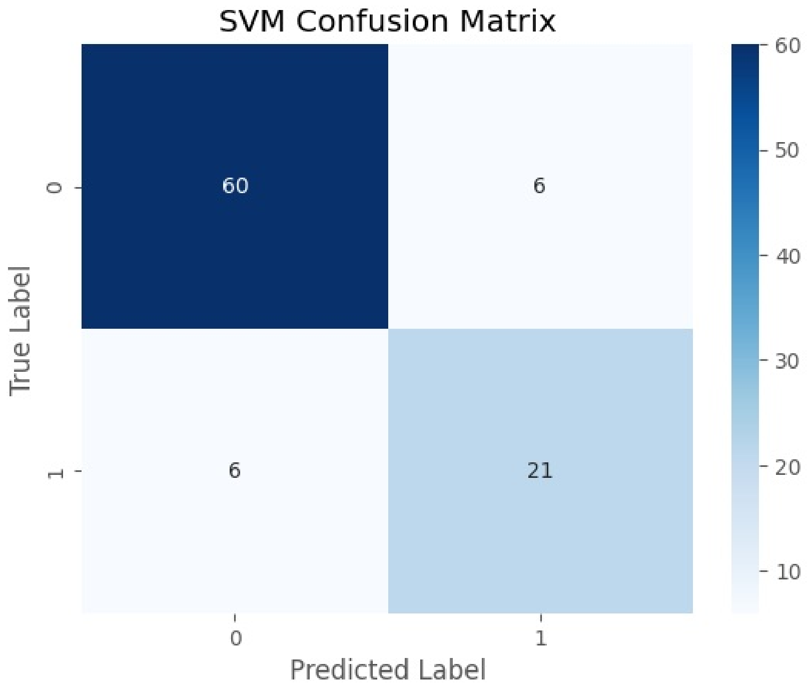


Applying SVM

In [17]:
```
from sklearn.svm import SVC

svm = SVC(kernel='linear', random_state=42)
svm.fit(x_train, y_train)
svm_predictions = svm.predict(x_test)

svm_accuracy = svm.score(x_test, y_test)
print('SVM Accuracy:', svm_accuracy)
```

```
SVM Accuracy: 0.8709677419354839
```

In [18]:
```
svm_cm = confusion_matrix(y_test, svm_predictions)

sns.heatmap(svm_cm, annot=True, fmt="d", cmap="Blues")
plt.title("SVM Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



Voting Method

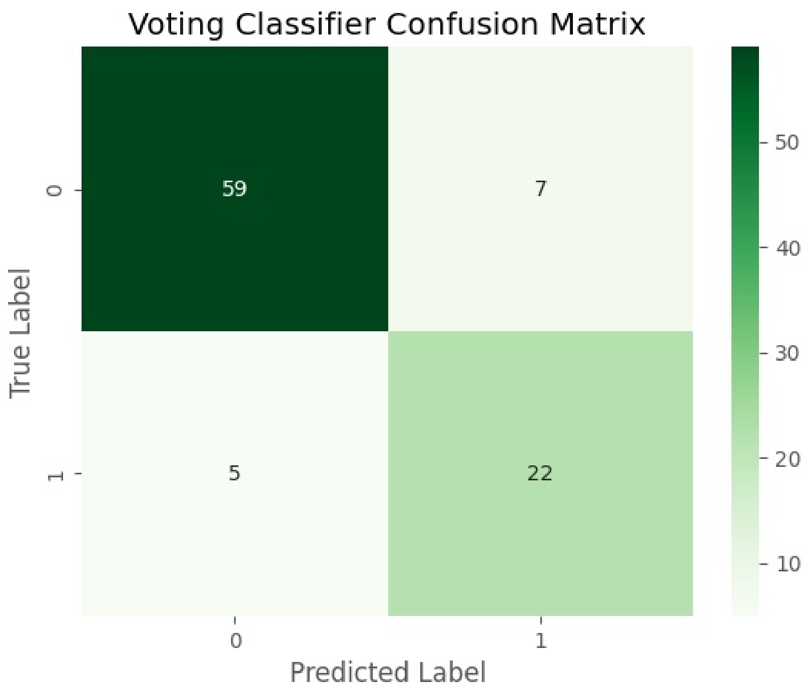
In [19]:
```
from sklearn.ensemble import VotingClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
```

```
log_clf = LogisticRegression(random_state=42)
svc_clf = SVC(kernel='linear', probability=True, random_state=42)  # probability=True for soft voting
knn_clf = KNeighborsClassifier()
```

In [20]:
```
voting_clf = VotingClassifier(
    estimators=[('lr', log_clf), ('svc', svc_clf), ('knn', knn_clf)],
    voting='soft'  # 'hard' for majority voting, 'soft' for weighted probabilities
)

voting_clf.fit(x_train, y_train)

voting_accuracy = voting_clf.score(x_test, y_test)
print('Voting Classifier Accuracy:', voting_accuracy)
```

```
Voting Classifier Accuracy: 0.8709677419354839
```

In [21]:
```
voting_predictions = voting_clf.predict(x_test)
voting_cm = confusion_matrix(y_test, voting_predictions)

sns.heatmap(voting_cm, annot=True, fmt="d", cmap="Greens")
plt.title("Voting Classifier Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

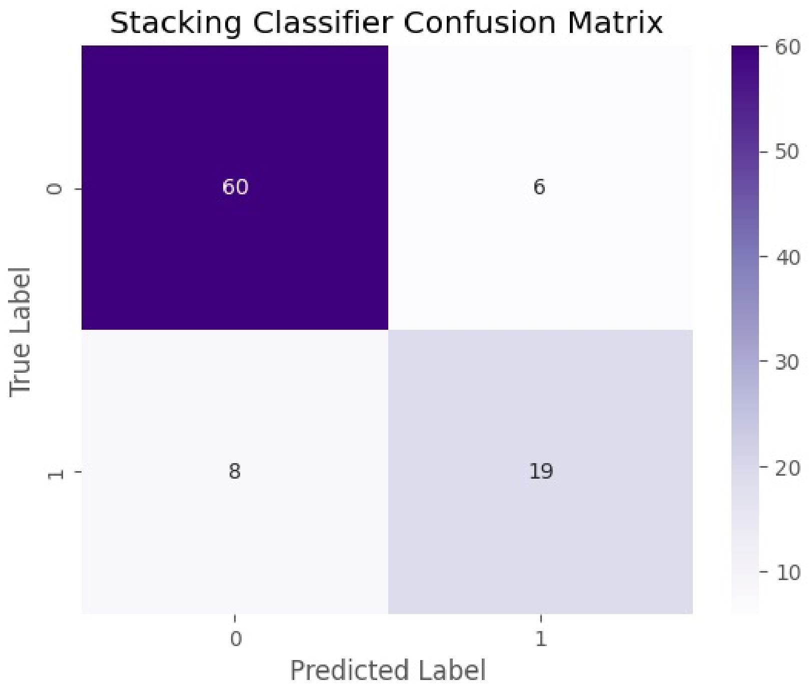


Stacking

In [22]:
```
from sklearn.ensemble import StackingClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier

base_learners = [
    ('svc', SVC(kernel='linear', probability=True, random_state=42)),
    ('knn', KNeighborsClassifier()),
    ('dt', DecisionTreeClassifier(random_state=42))
]

meta_learner = LogisticRegression(random_state=42)

stacking_clf = StackingClassifier(
    estimators=base_learners,
    final_estimator=meta_learner,
    cv=5  # 5-fold cross-validation
)

stacking_clf.fit(x_train, y_train)

stacking_accuracy = stacking_clf.score(x_test, y_test)
print('Stacking Classifier Accuracy:', stacking_accuracy)
```

```
Stacking Classifier Accuracy: 0.8494623655913979
```

In [23]:
```python
# Predictions and Confusion Matrix
stacking_predictions = stacking_clf.predict(x_test)
stacking_cm = confusion_matrix(y_test, stacking_predictions)

# Visualize the Confusion Matrix
sns.heatmap(stacking_cm, annot=True, fmt="d", cmap="Purples")
plt.title("Stacking Classifier Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

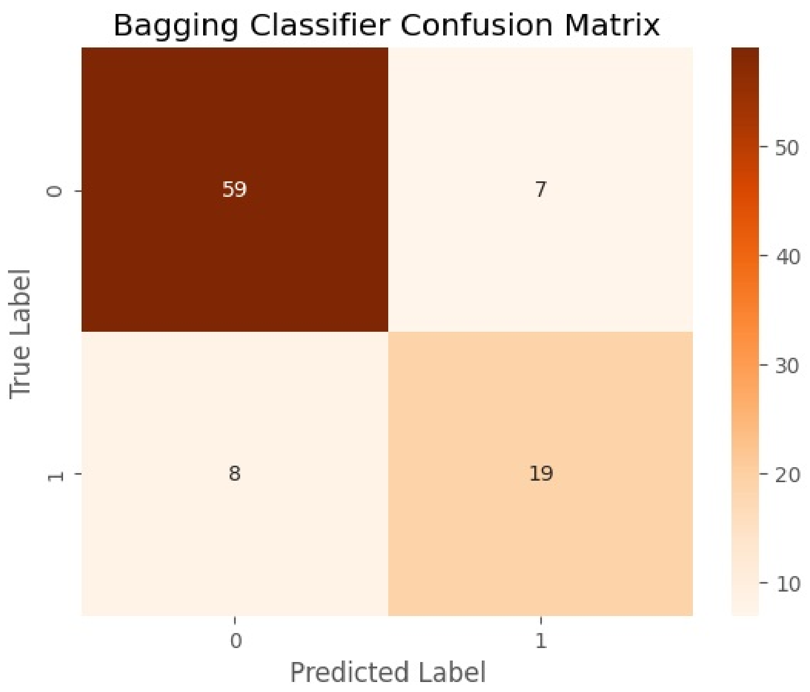


Bagging

In [24]:
```python
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier

base_estimator = DecisionTreeClassifier(random_state=42)

bagging_clf = BaggingClassifier(
    n_estimators=50,        # Number of trees in the ensemble
    max_samples=0.8,        # Fraction of the training data to sample
    max_features=0.8,       # Fraction of features to sample
    oob_score=True,
    bootstrap=True,         # Use bootstrap sampling
    random_state=42
)

bagging_clf.fit(x_train, y_train)

bagging_accuracy = bagging_clf.score(x_test, y_test)
print('Bagging Classifier Accuracy:', bagging_accuracy)
```

```
Bagging Classifier Accuracy: 0.8387096774193549
```

In [25]:
```python
# Predictions and Confusion Matrix
bagging_predictions = bagging_clf.predict(x_test)
bagging_cm = confusion_matrix(y_test, bagging_predictions)

# Visualize the Confusion Matrix
sns.heatmap(bagging_cm, annot=True, fmt="d", cmap="Oranges")
plt.title("Bagging Classifier Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



Boosting

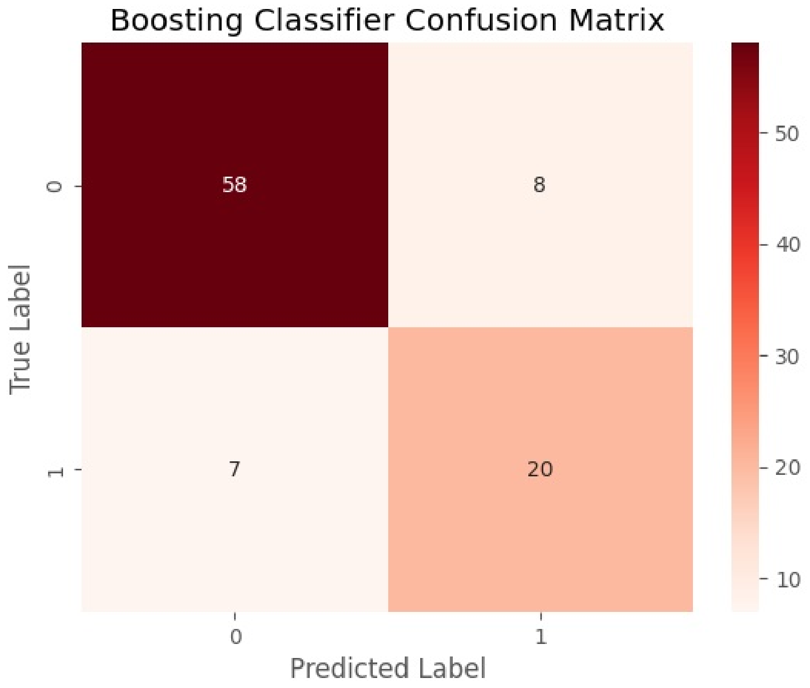
In [26]:

```
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier

base_estimator = DecisionTreeClassifier(max_depth=1, random_state=42)  # Weak learner

boosting_clf = AdaBoostClassifier(
    n_estimators=50,  # Number of weak learners
    learning_rate=1.0,  # Step size for weight updates
    random_state=42
)

boosting_clf.fit(x_train, y_train)

boosting_accuracy = boosting_clf.score(x_test, y_test)
print('Boosting Classifier Accuracy:', boosting_accuracy)
```

```
Boosting Classifier Accuracy: 0.8387096774193549
```

In [27]:

```
boosting_predictions = boosting_clf.predict(x_test)
boosting_cm = confusion_matrix(y_test, boosting_predictions)

sns.heatmap(boosting_cm, annot=True, fmt="d", cmap="Reds")
plt.title("Boosting Classifier Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



CNN

In [28]:
```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Conv1D, Flatten, Dropout
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
import numpy as np

# Prepare the data
x = cleaned_data.loc[:, cleaned_data.columns != 'class'].values
y = cleaned_data['class'].values

# Encode the labels
label_encoder = LabelEncoder()
y = label_encoder.fit_transform(y)

# Standardize the data
scaler = StandardScaler()
x = scaler.fit_transform(x)

# Reshape the input for CNN
x = x.reshape(x.shape[0], x.shape[1], 1)  # Adding a channel dimension

# Train-test split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=0)
```

In [29]:
```
# Build the CNN model
model = Sequential([
    Conv1D(filters=32, kernel_size=2, activation='relu', input_shape=(x_train.shape[1], 1)),
    Dropout(0.2),
    Conv1D(filters=64, kernel_size=2, activation='relu'),
    Dropout(0.2),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(1, activation='sigmoid')  # Use 'softmax' for multi-class classification
])

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Train the model
history = model.fit(x_train, y_train, epochs=10, batch_size=32, validation_data=(x_test, y_test))

# Evaluate the model
test_loss, test_accuracy = model.evaluate(x_test, y_test)
print(f"Test Accuracy: {test_accuracy:.2f}")
```

```
Epoch 1/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 3s 64ms/step - accuracy: 0.3699 - loss: 0.7172 - val_accuracy: 0.5663 - val_loss: 0.632
1
Epoch 2/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.6550 - loss: 0.5881 - val_accuracy: 0.5663 - val_loss: 0.611
3
Epoch 3/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - accuracy: 0.6802 - loss: 0.5331 - val_accuracy: 0.5663 - val_loss: 0.592
3
Epoch 4/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 0.6722 - loss: 0.5533 - val_accuracy: 0.6024 - val_loss: 0.539
2
Epoch 5/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - accuracy: 0.7265 - loss: 0.4644 - val_accuracy: 0.7108 - val_loss: 0.508
5
Epoch 6/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.7372 - loss: 0.5144 - val_accuracy: 0.7952 - val_loss: 0.469
8
Epoch 7/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 0.7932 - loss: 0.4588 - val_accuracy: 0.8193 - val_loss: 0.434
5
Epoch 8/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - accuracy: 0.8140 - loss: 0.4628 - val_accuracy: 0.8193 - val_loss: 0.397
1
Epoch 9/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - accuracy: 0.8351 - loss: 0.4305 - val_accuracy: 0.8193 - val_loss: 0.376
9
Epoch 10/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.8433 - loss: 0.4139 - val_accuracy: 0.8193 - val_loss: 0.372
0
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy: 0.8159 - loss: 0.3735
Test Accuracy: 0.82
```

ANN

In [32]:
```
y_data = data1["class"].values
x_data = data1.drop(["class"],axis = 1)
```

In [33]:
```
x_train, x_test, y_train, y_test = train_test_split(x_data,y_data,test_size = 0.2, random_state = 42)
```

In [ ]:
```
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import cross_val_score
from keras.models import Sequential # initialize neural network library
from keras.layers import Dense # build our layers library

def build_classifier():
    model = Sequential()
    model.add(Dense(units = 96, kernel_initializer = "uniform",activation = "relu", input_dim = x_train.shape[1
    model.add(Dense(units = 48, kernel_initializer = "uniform", activation = "linear"))
    model.add(Dense(units = 1, kernel_initializer = "uniform", activation = "sigmoid"))

    model.compile(optimizer = "adam", loss = "binary_crossentropy", metrics = ["accuracy"])

    return model

classifier = KerasClassifier(build_fn = build_classifier, epochs = 100)
accuracies = cross_val_score(estimator = classifier, X = x_train, y = y_train, cv = 3)
mean = accuracies.mean()
variance = accuracies.std()

print("Accuracy Mean:"+ str(mean))
print("Accuracy Variance:"+ str(variance))
```

In [ ]: