```
import numpy as np
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.preprocessing import LabelEncoder
import seaborn as sns
import matplotlib.pyplot as plt
from mpl_toolkits import mplot3d
df = pd.read_csv("IRIS.csv")
# Define features and target variable
X = df.drop(columns=['species'])
y = df['species']
#Visualizing pairplot of the features of the data
sns.pairplot(df, hue='species')
plt.show()
\overrightarrow{\exists}
        sepal_length
o
         4.5
         4.0
      sepal_width
         3.5
         3.0
         2.5
         2.0
                                                                                                                                               species
                                                                                                                                               Iris-setosa
                                                                                                                                               Iris-versicolor
           6
                                                                                                                                              Iris-virginica
        petal_length
w b g
           2
         2.5 -
         2.0
      petal_width
         0.5
         0.0
                                                                                                       8
                                                                                                           0
```

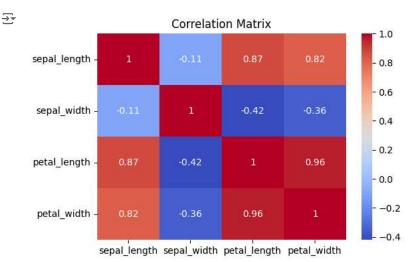
sepal_length

sepal_width

petal_length

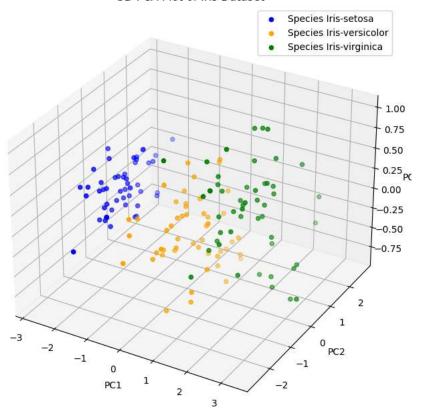
petal_width

```
#Visualizing the correlation of the features
df_numeric = df.drop(columns=['species'])
correlation_matrix = df_numeric.corr()
plt.figure(figsize=(6,4))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title("Correlation Matrix")
plt.show()
```



```
# Standardize the dataset
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
# Apply PCA to reduce to 3 principal components
pca = PCA(n_components=3)
X_pca = pca.fit_transform(X_scaled)
pca_df = pd.DataFrame(data=X_pca, columns=['PC1', 'PC2', 'PC3'])
pca_df['species'] = y
# Plotting
fig = plt.figure(figsize=(10,8))
ax = fig.add_subplot(111, projection='3d')
# Scatter plot
colors = ['blue', 'orange', 'green'] # Colors for each species (setosa, versicolor, virginica)
for species_id, color in zip(pca_df['species'].unique(), colors):
    species_subset = pca_df[pca_df['species'] == species_id]
    ax.scatter (species\_subset['PC1'], \ species\_subset['PC2'], \ species\_subset['PC3'], \ c=color, \ label=f'Species \ \{species\_id\}')
# Set labels and title
ax.set_xlabel('PC1')
ax.set_ylabel('PC2')
ax.set zlabel('PC3')
ax.set_title('3D PCA Plot of Iris Dataset')
# Add legend
ax.legend()
# Show plot
plt.show()
```

3D PCA Plot of Iris Dataset

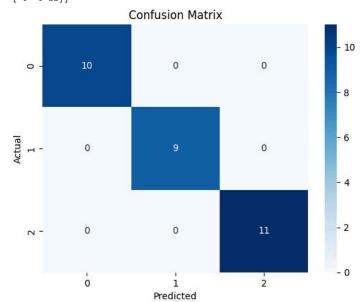


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```
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Train Logistic Regression on the PCA-reduced data
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
# Make predictions
y_pred = logreg.predict(X_test)
# Evaluate the classifier
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}\n")
print("Confusion Matrix:")
print(conf matrix)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
print()
print("Classification Report:")
print(class_report)
```

→ Accuracy: 1.00

Confusion Matrix: [[10 0 0] [0 9 0] [0 0 11]]



Classification Report:

	precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	10
Iris-versicolor	1.00	1.00	1.00	9
Iris-virginica	1.00	1.00	1.00	11