CSBB 311: MACHINE LEARNING

LAB ASSIGNMENT 9 : Feature Extraction Using PCA

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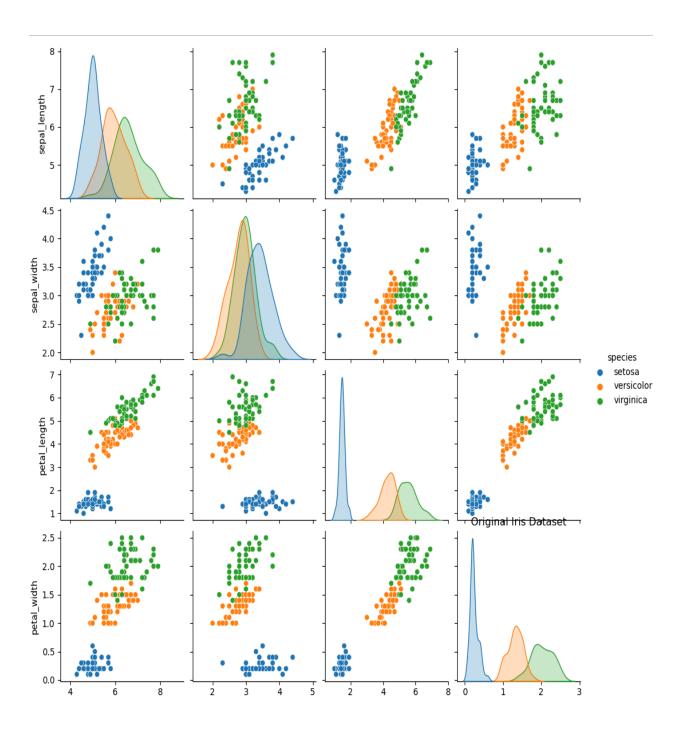
Code -

```
import numpy as np
1
     import pandas as pd
 2
     import matplotlib.pyplot as plt
4
     from sklearn.decomposition import PCA
     from sklearn.model_selection import train_test_split
 5
     from sklearn.neighbors import KNeighborsClassifier
6
     from sklearn.metrics import accuracy_score
7
     import seaborn as sns
8
9
     from mpl_toolkits.mplot3d import Axes3D
10
11
     # Load the Iris dataset from a CSV file
     df = pd.read_csv('iris.csv')
12
13
14
     # Check the first few rows to understand the dataset
15
     print(df.head())
16
     # Separate features and target labels
17
     X = df.drop('species', axis=1) # Features
18
     y = df['species'] # Target labels (species)
19
20
     # Visualize original data using pairplot
21
     sns.pairplot(df, hue='species')
22
23
     plt.title("Original Iris Dataset")
24
     plt.show()
25
26
     # Apply PCA and reduce to 1 component
     pca = PCA(n\_components=1)
27
     X pca 1 = pca.fit transform(X)
28
29
     plt.figure(figsize=(8, 6))
     plt.scatter(X_pca_1, np.zeros_like(X_pca_1), c=y.map({'setosa': 0, 'versicolor': 1,
30
                                                            'virginica': 2}), cmap='viridis')
31
     plt.title("PCA with 1 Component")
32
     plt.xlabel("Principal Component 1")
33
34
     plt.show()
```

```
# Apply PCA and reduce to 2 components
36
37
     pca = PCA(n components=2)
     X pca 2 = pca.fit transform(X)
38
39
     plt.figure(figsize=(8, 6))
40
     plt.scatter(X_pca_2[:, 0], X_pca_2[:, 1], c=y.map({'setosa': 0, 'versicolor': 1,
                                                        'virginica': 2}), cmap='viridis')
41
42
     plt.title("PCA with 2 Components")
43
     plt.xlabel("Principal Component 1")
44
     plt.ylabel("Principal Component 2")
45
     plt.show()
46
47
     # Apply PCA and reduce to 3 components
48
     pca = PCA(n components=3)
49
     X_pca_3 = pca.fit_transform(X)
     fig = plt.figure(figsize=(8, 6))
50
51
     ax = fig.add_subplot(111, projection='3d')
     ax.scatter(X_pca_3[:, 0], X_pca_3[:, 1], X_pca_3[:, 2], c=y.map({\( \big| \) setosa': 0, 'versicolor': 1,
52
                                                                       'virginica': 2}), cmap='viridis')
53
54
     ax.set_title("PCA with 3 Components")
55
     ax.set xlabel("Principal Component 1")
     ax.set ylabel("Principal Component 2")
56
     ax.set zlabel("Principal Component 3")
57
     plt.show()
58
59
60
     # Apply PCA and reduce to all components (4 components)
     pca = PCA(n\_components=4)
61
62
     X pca 4 = pca.fit transform(X)
63
     # Plot the explained variance ratio for each component (how much each component contributes)
64
65
     plt.figure(figsize=(8, 6))
     plt.bar(range(1, 5), pca.explained_variance_ratio_, alpha=0.6, color='g', label='Explained variance ratio')
66
     plt.xlabel('Principal Components')
67
     plt.ylabel('Variance Ratio')
68
     plt.title('Variance Explained by Each Principal Component')
69
70
     plt.show()
```

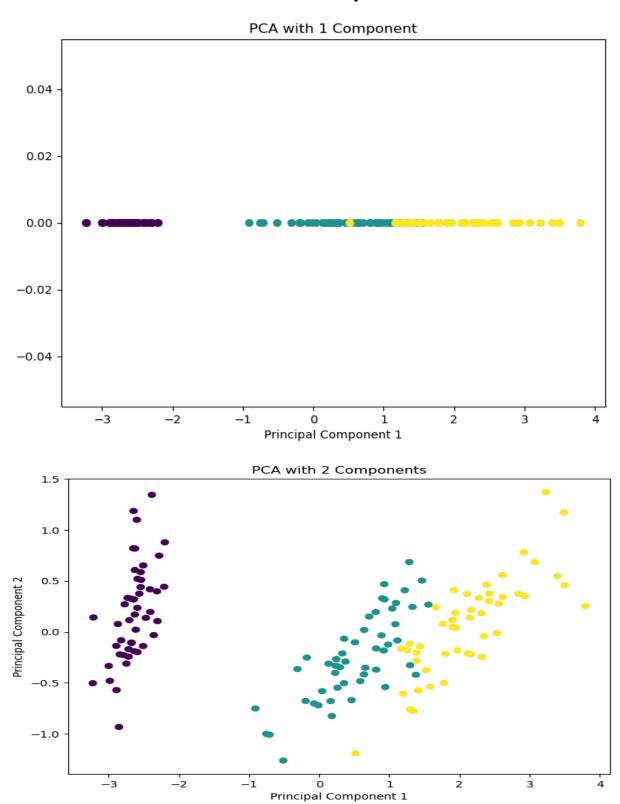
```
72
      # **Find the eigenvalues** (explained variance) for each principal component
 73
      eigenvalues = pca.explained variance
 74
      print("Eigenvalues (Explained Variance) for each component:")
 75
     print(eigenvalues)
 76
 77
      # Plot the eigenvalues (Explained Variance)
     plt.figure(figsize=(8, 6))
 78
     plt.bar(range(1, 5), eigenvalues, alpha=0.6, color='b', label='Eigenvalues')
 79
     plt.xlabel('Principal Components')
 80
 81
     plt.ylabel('Eigenvalue (Explained Variance)')
 82
     plt.title('Eigenvalues (Explained Variance) for Each Principal Component')
     plt.show()
 84
 85
      # Split the dataset into train and test
 86
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
 87
 88
     # List to store accuracy results
 89
     accuracies = []
 90
 91
      # Loop over 1 to 4 principal components
      for n in range(1, 5):
 92
 93
         # Apply PCA
 94
         pca = PCA(n\_components=n)
95
         X_train_pca = pca.fit_transform(X_train)
96
         X_test_pca = pca.transform(X_test)
97
98
         # KNN classifier
         knn = KNeighborsClassifier(n_neighbors=3)
99
         knn.fit(X train pca, y train)
100
101
         # Predict and evaluate accuracy
102
         y pred = knn.predict(X test pca)
103
104
         accuracy = accuracy_score(y_test, y_pred)
105
         accuracies.append(accuracy)
107
        # Plot accuracy vs number of PCA components
108
        plt.figure(figsize=(8, 6))
        plt.plot(range(1, 5), accuracies, marker='o', color='b')
109
        plt.title("KNN Accuracy vs Number of PCA Components")
110
111
        plt.xlabel("Number of PCA Components")
        plt.ylabel("Accuracy")
112
        plt.xticks(range(1, 5))
113
114
        plt.grid(True)
        plt.show()
115
```

Output -

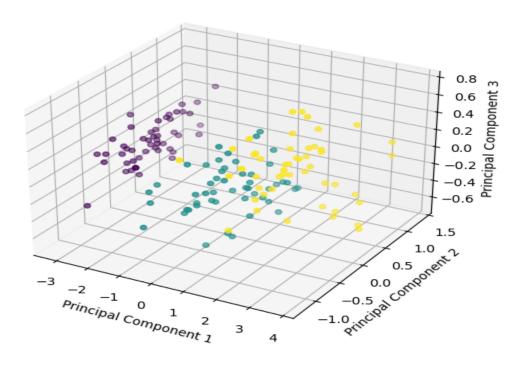


PairPlot

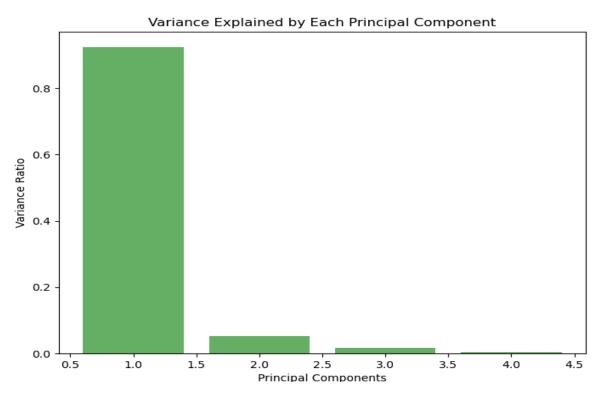
Scatter Plots with Various Components:-



PCA with 3 Components

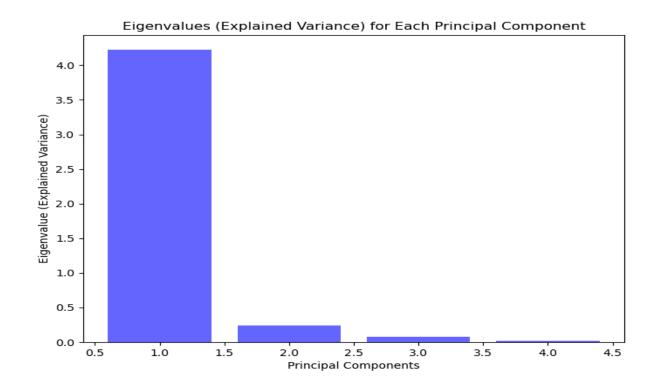


Variance Plot:-



EigenValues For Each Feature :-

Eigenvalues (Explained Variance) for each component: [4.22484077 0.24224357 0.07852391 0.02368303]



Accuracy Graph:-

