Letter Recognition

In [1]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.preprocessing import StandardScaler
```

In [2]:

```python
df = pd.read_csv("letter-recognition.csv")
```

In [3]:

```python
df.head()
```

Out[3]:

	letter	xbox	ybox	width	height	onpix	xbar	ybar	x2bar	y2bar	xybar	x2ybar	xy2bar	xedge	xedgey	yedge	y
0	T	2	8	3	5	1	8	13	0	6	6	10	8	0	8	0	
1	I	5	12	3	7	2	10	5	5	4	13	3	9	2	8	4	
2	D	4	11	6	8	6	10	6	2	6	10	3	7	3	7	3	
3	N	7	11	6	6	3	5	9	4	6	4	4	10	6	10	2	
4	G	2	1	3	1	1	8	6	6	6	6	5	9	1	7	5	

In [4]:

```python
df.describe()
```

Out[4]:

	xbox	ybox	width	height	onpix	xbar	ybar	x2bar
count	20000.000000	20000.000000	20000.000000	20000.00000	20000.000000	20000.000000	20000.000000	20000.000000
mean	4.023550	7.035500	5.121850	5.37245	3.505850	6.897600	7.500450	4.628600
std	1.913212	3.304555	2.014573	2.26139	2.190458	2.026035	2.325354	2.699968
min	0.000000	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000	0.000000
25%	3.000000	5.000000	4.000000	4.00000	2.000000	6.000000	6.000000	3.000000
50%	4.000000	7.000000	5.000000	6.00000	3.000000	7.000000	7.000000	4.000000
75%	5.000000	9.000000	6.000000	7.00000	5.000000	8.000000	9.000000	6.000000
max	15.000000	15.000000	15.000000	15.00000	15.000000	15.000000	15.000000	15.000000

In [5]:

```python
df.shape
```

Out[5]:

```
(20000, 17)
```

In [6]:

```python
df.columns
```

Out[6]:

```
Index(['letter', 'xbox ', 'ybox ', 'width ', 'height', 'onpix ', 'xbar ',
       'ybar ', 'x2bar', 'y2bar ', 'xybar ', 'x2ybar', 'xy2bar', 'xedge ',
       'xedgey', 'yedge ', 'yedgex'],
      dtype='object')
```

In [7]:

```
# Let's 'reindex' the column names
df.columns = ['letter', 'xbox', 'ybox', 'width', 'height', 'onpix', 'xbar',
       'ybar', 'x2bar', 'y2bar', 'xybar', 'x2ybar', 'xy2bar', 'xedge',
       'xedgey', 'yedge', 'yedgex']
df.columns
```

Out[7]:

```
Index(['letter', 'xbox', 'ybox', 'width', 'height', 'onpix', 'xbar', 'ybar',
       'x2bar', 'y2bar', 'xybar', 'x2ybar', 'xy2bar', 'xedge', 'xedgey',
       'yedge', 'yedgex'],
      dtype='object')
```

In [8]:

```
order = list(np.sort(df['letter'].unique()))
print(order)
```

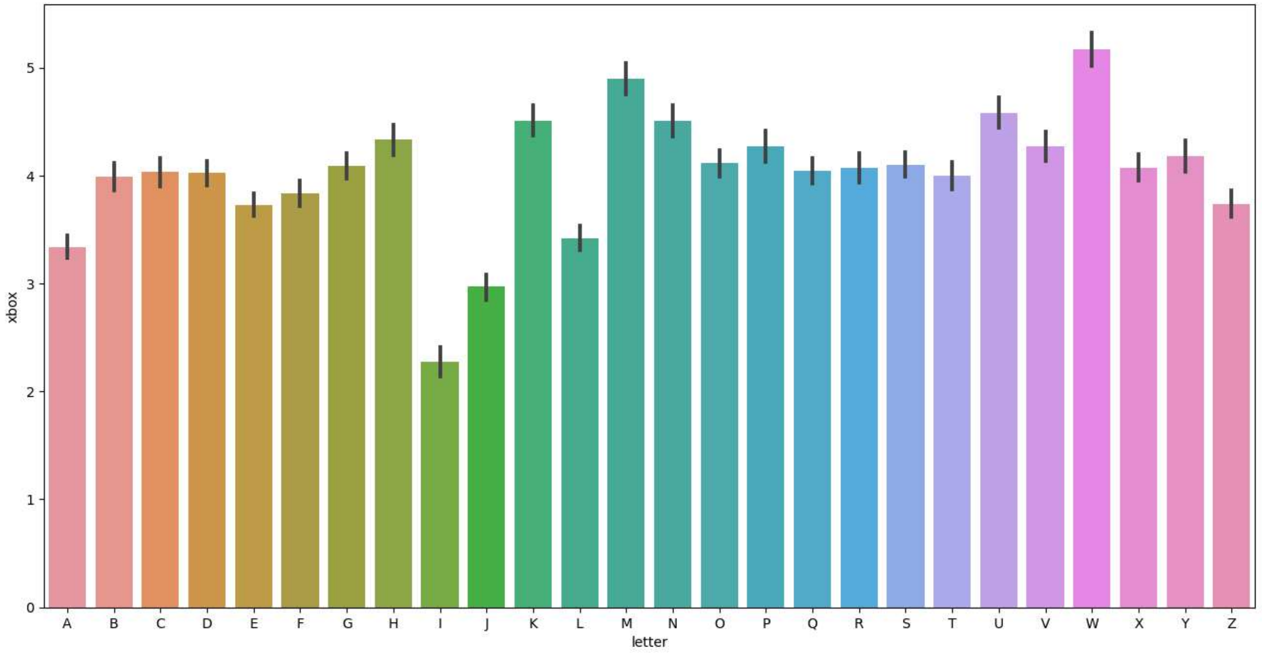
```
['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J', 'K', 'L', 'M', 'N', 'O', 'P', 'Q', 'R', 'S',
'T', 'U', 'V', 'W', 'X', 'Y', 'Z']
```

In [9]:

```
plt.figure(figsize=(16, 8))
sns.barplot(x='letter', y='xbox', data=df, order=order)
```

Out[9]:

```
<Axes: xlabel='letter', ylabel='xbox'>
```



In [10]:

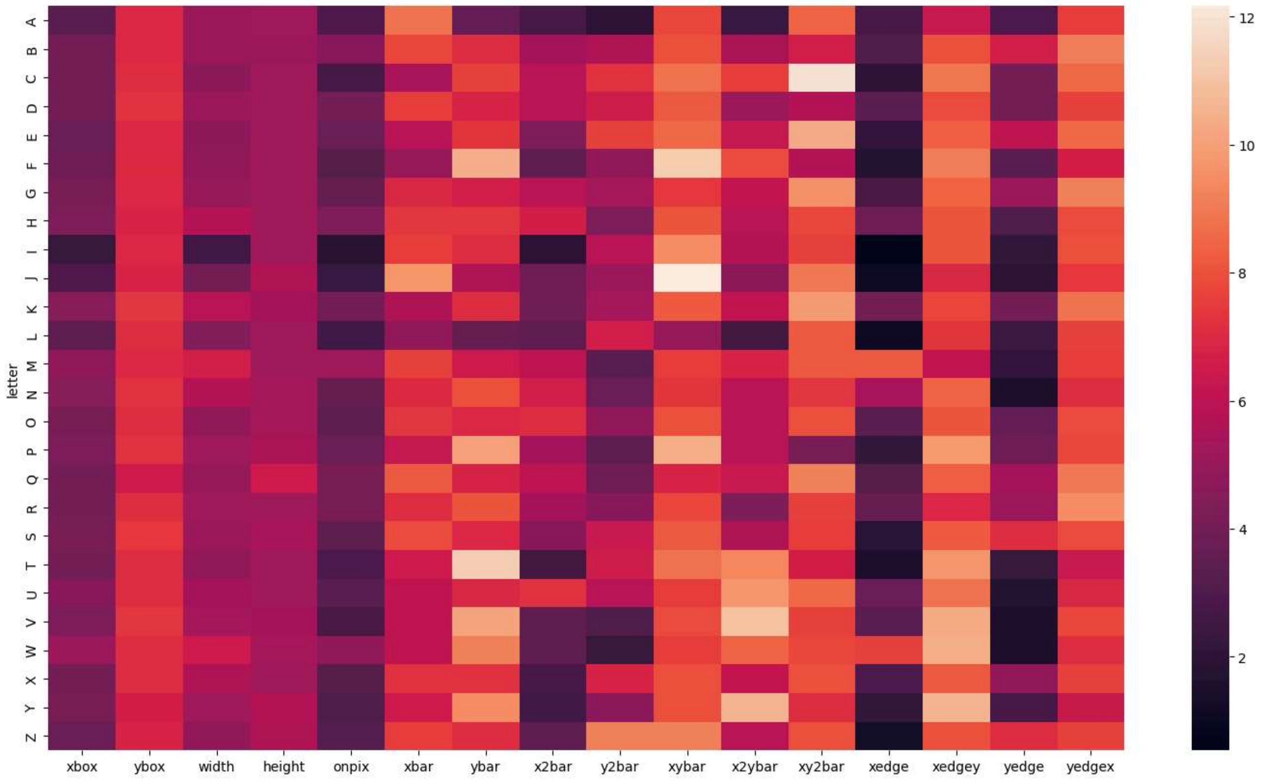
```
df1 = df.groupby('letter').mean()
df1.head()
```

Out[10]:

	xbox	ybox	width	height	onpix	xbar	ybar	x2bar	y2bar	xybar	x2ybar	
letter												
A	3.337136	6.975919	5.128010	5.178707	2.991128	8.851711	3.631179	2.755387	2.043093	7.802281	2.338403	8
B	3.985640	6.962141	5.088773	5.169713	4.596606	7.671018	7.062663	5.366841	5.571802	7.954308	5.506527	6
C	4.031250	7.063859	4.701087	5.296196	2.775815	5.437500	7.627717	5.927989	7.177989	8.773098	7.494565	11
D	4.023602	7.244720	5.170186	5.288199	4.026087	7.539130	6.806211	5.921739	6.508075	8.166460	5.111801	5
E	3.727865	6.944010	4.756510	5.201823	3.679688	5.966146	7.352865	4.223958	7.585938	8.507812	6.242188	10

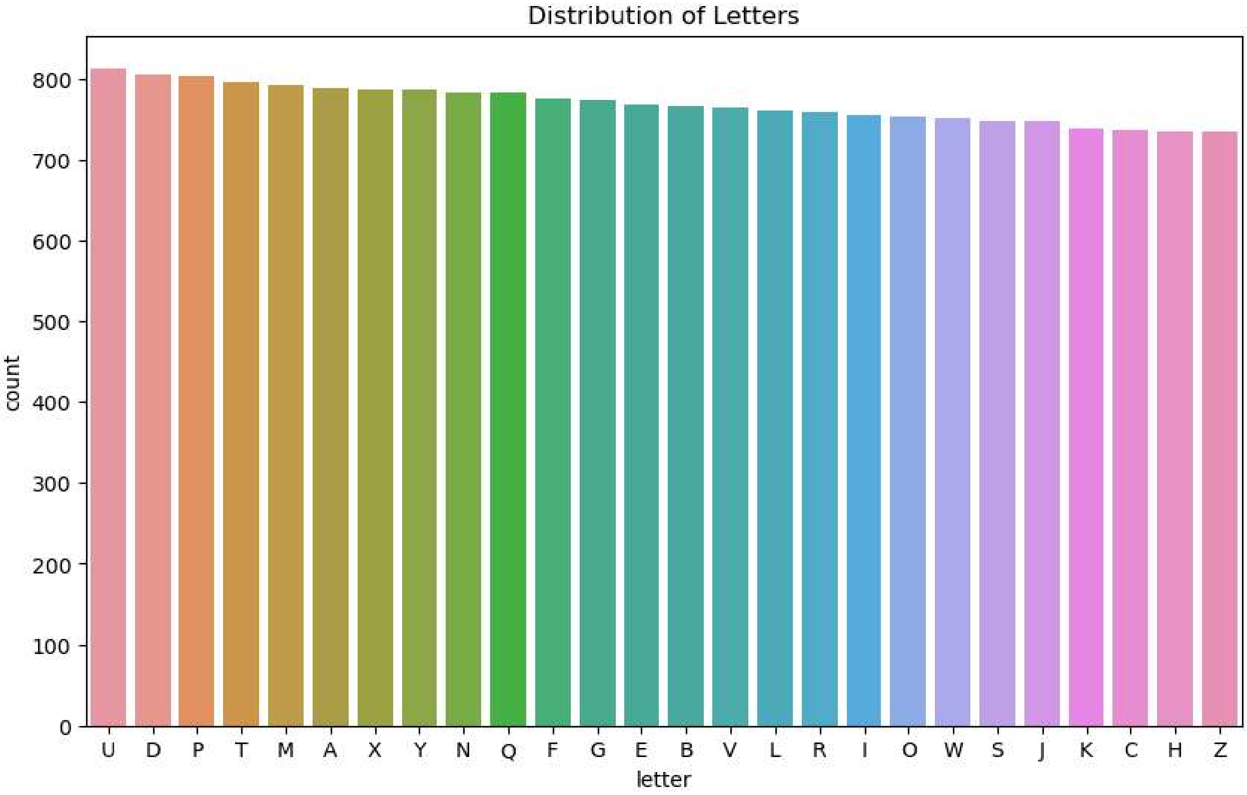
```
In [11]: plt.figure(figsize=(18, 10))
         sns.heatmap(df1)
```

```
Out[11]: <Axes: ylabel='letter'>
```



In [12]:

```
plt.figure(figsize=(10, 6))
sns.countplot(data=df, x='letter', order=df['letter'].value_counts().index)
plt.title("Distribution of Letters")
plt.show()
```



Data Preparation

In [13]:

```
# average feature values
round(df.drop('letter', axis=1).mean(), 2)
```

Out[13]:

```
xbox       4.02
ybox       7.04
width      5.12
height     5.37
onpix      3.51
xbar       6.90
ybar       7.50
x2bar      4.63
y2bar      5.18
xybar      8.28
x2ybar     6.45
xy2bar     7.93
xedge      3.05
xedgey     8.34
yedge      3.69
yedgex     7.80
dtype: float64
```

In [14]:

```
# splitting into X and y
X = df.drop("letter", axis = 1)
y = df['letter']
```

In [15]:

```
# Scale the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Spliting into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
```

Linear SVM

In [16]:

```
# Create and train the Linear SVM model
svm_model = SVC(kernel='linear', C=1)
svm_model.fit(X_train, y_train)

# predict
y_pred = svm_model.predict(X_test)
```

In [17]:

```
# Calculate accuracy and display results
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')
```

```
Accuracy: 0.86
```

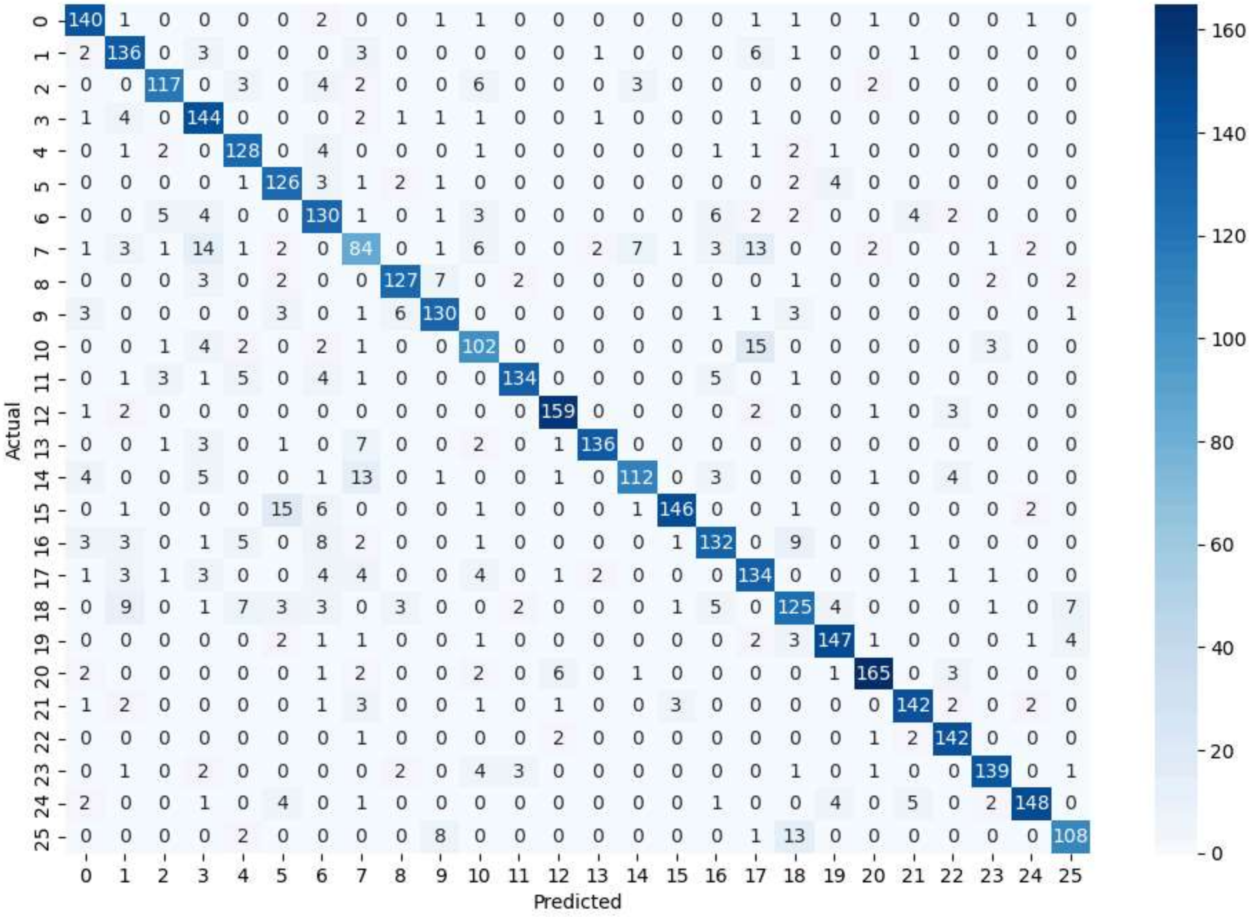
In [18]:

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           A       0.87      0.94      0.90       149
           B       0.81      0.89      0.85       153
           C       0.89      0.85      0.87       137
           D       0.76      0.92      0.83       156
           E       0.83      0.91      0.87       141
           F       0.80      0.90      0.85       140
           G       0.75      0.81      0.78       160
           H       0.65      0.58      0.61       144
           I       0.90      0.87      0.89       146
           J       0.86      0.87      0.87       149
           K       0.75      0.78      0.77       130
           L       0.95      0.86      0.91       155
           M       0.93      0.95      0.94       168
           N       0.96      0.90      0.93       151
           O       0.90      0.77      0.83       145
           P       0.96      0.84      0.90       173
           Q       0.84      0.80      0.82       166
           R       0.75      0.84      0.79       160
           S       0.76      0.73      0.74       171
           T       0.91      0.90      0.91       163
           U       0.94      0.90      0.92       183
           V       0.91      0.90      0.90       158
           W       0.90      0.96      0.93       148
           X       0.93      0.90      0.92       154
           Y       0.95      0.88      0.91       168
           Z       0.88      0.82      0.85       132

    accuracy                           0.86      4000
   macro avg       0.86      0.86      0.86      4000
weighted avg       0.86      0.86      0.86      4000
```

In [19]:

```python
# Create a confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Plot the confusion matrix
plt.figure(figsize=(12, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
0	140	1	0	0	0	0	2	0	0	1	1	0	0	0	0	0	0	1	1	0	1	0	0	0	1	0
1	2	136	0	3	0	0	0	3	0	0	0	0	0	1	0	0	0	6	1	0	0	1	0	0	0	0
2	0	0	117	0	3	0	4	2	0	0	6	0	0	0	3	0	0	0	0	0	2	0	0	0	0	0
3	1	4	0	144	0	0	0	2	1	1	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0
4	0	1	2	0	128	0	4	0	0	0	1	0	0	0	0	0	1	1	2	1	0	0	0	0	0	0
5	0	0	0	0	1	126	3	1	2	1	0	0	0	0	0	0	0	0	2	4	0	0	0	0	0	0
6	0	0	5	4	0	0	130	1	0	1	3	0	0	0	0	0	6	2	2	0	0	4	2	0	0	0
7	1	3	1	14	1	2	0	84	0	1	6	0	0	2	7	1	3	13	0	0	2	0	0	1	2	0
8	0	0	0	3	0	2	0	0	127	7	0	2	0	0	0	0	0	0	1	0	0	0	0	2	0	2
9	3	0	0	0	0	3	0	1	6	130	0	0	0	0	0	0	1	1	3	0	0	0	0	0	0	1
10	0	0	1	4	2	0	2	1	0	0	102	0	0	0	0	0	0	15	0	0	0	0	0	3	0	0
11	0	1	3	1	5	0	4	1	0	0	0	134	0	0	0	0	5	0	1	0	0	0	0	0	0	0
12	1	2	0	0	0	0	0	0	0	0	0	0	159	0	0	0	0	2	0	0	1	0	3	0	0	0
13	0	0	1	3	0	1	0	7	0	0	2	0	1	136	0	0	0	0	0	0	0	0	0	0	0	0
14	4	0	0	5	0	0	1	13	0	1	0	0	1	0	112	0	3	0	0	0	1	0	4	0	0	0
15	0	1	0	0	0	15	6	0	0	0	1	0	0	0	1	146	0	0	1	0	0	0	0	0	2	0
16	3	3	0	1	5	0	8	2	0	0	1	0	0	0	0	1	132	0	9	0	0	1	0	0	0	0
17	1	3	1	3	0	0	4	4	0	0	4	0	1	2	0	0	0	134	0	0	0	1	1	1	0	0
18	0	9	0	1	7	3	3	0	3	0	0	2	0	0	0	1	5	0	125	4	0	0	0	1	0	7
19	0	0	0	0	0	2	1	1	0	0	1	0	0	0	0	0	0	2	3	147	1	0	0	0	1	4
20	2	0	0	0	0	0	1	2	0	0	2	0	6	0	1	0	0	0	0	1	165	0	3	0	0	0
21	1	2	0	0	0	0	1	3	0	0	1	0	1	0	0	3	0	0	0	0	0	142	2	0	2	0
22	0	0	0	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	1	2	142	0	0	0
23	0	1	0	2	0	0	0	0	2	0	4	3	0	0	0	0	0	0	1	0	1	0	0	139	0	1
24	2	0	0	1	0	4	0	1	0	0	0	0	0	0	0	0	1	0	0	4	0	5	0	2	148	0
25	0	0	0	0	2	0	0	0	0	8	0	0	0	0	0	0	0	1	13	0	0	0	0	0	0	108

Non-Linear SVM

In [20]:

```python
# Train a non-linear SVM model (e.g., using a radial basis function kernel)
svm = SVC(kernel='rbf', C=1.0, gamma='scale', random_state=101)
svm.fit(X_train, y_train)
```

Out[20]:

```
▾        SVC          i ?
                      (https://scikit-
                      learn.org/1.4/modules/generated/sklearn.svm.SVC.html)
SVC(random_state=101)
```

In [21]:

```python
# Make predictions on the test set
y_pred = svm.predict(X_test)
```

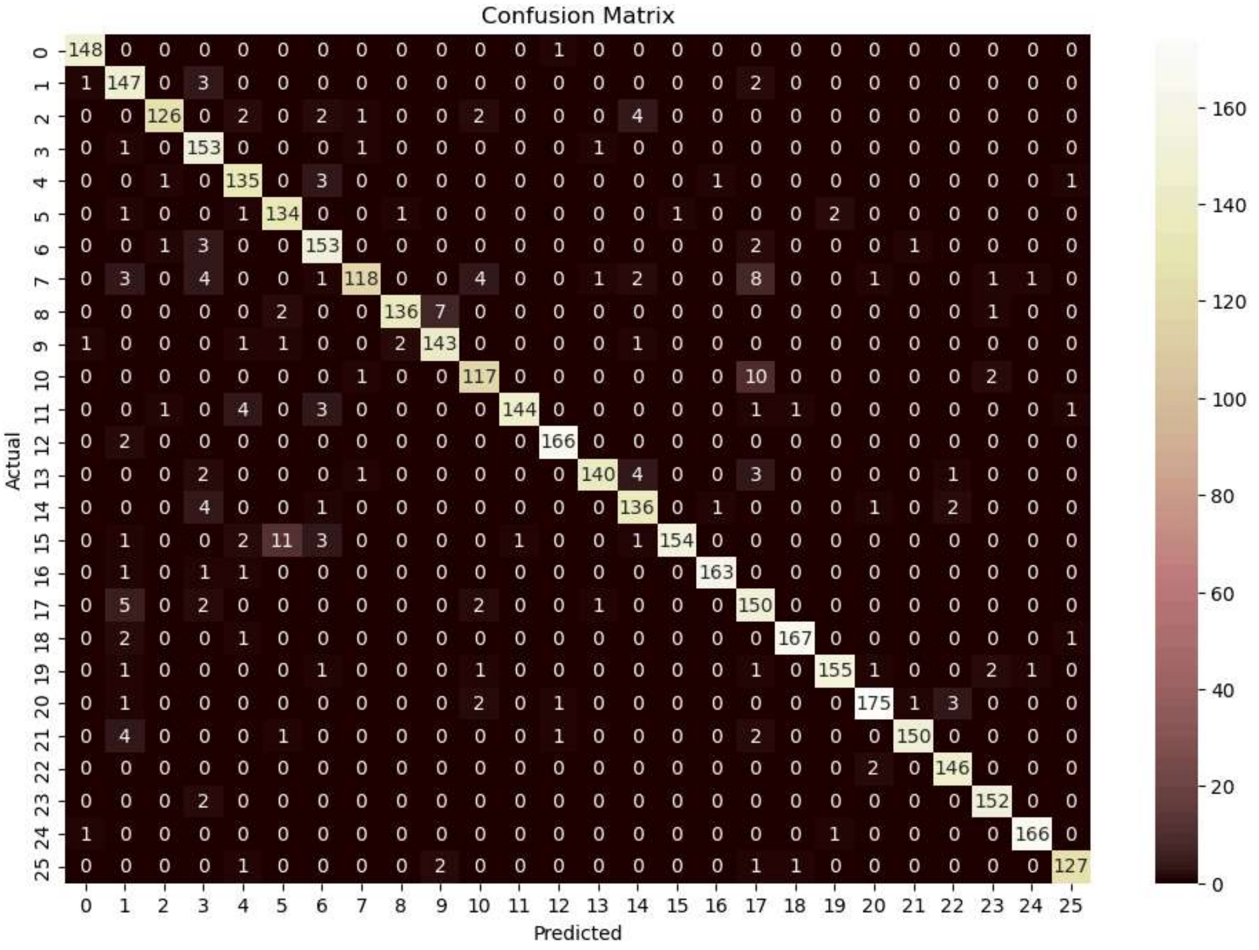
In [22]:

```
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.95

Classification Report:
              precision    recall  f1-score   support

           A       0.98      0.99      0.99       149
           B       0.87      0.96      0.91       153
           C       0.98      0.92      0.95       137
           D       0.88      0.98      0.93       156
           E       0.91      0.96      0.93       141
           F       0.90      0.96      0.93       140
           G       0.92      0.96      0.94       160
           H       0.97      0.82      0.89       144
           I       0.98      0.93      0.95       146
           J       0.94      0.96      0.95       149
           K       0.91      0.90      0.91       130
           L       0.99      0.93      0.96       155
           M       0.98      0.99      0.99       168
           N       0.98      0.93      0.95       151
           O       0.92      0.94      0.93       145
           P       0.99      0.89      0.94       173
           Q       0.99      0.98      0.98       166
           R       0.83      0.94      0.88       160
           S       0.99      0.98      0.98       171
           T       0.98      0.95      0.97       163
           U       0.97      0.96      0.96       183
           V       0.99      0.95      0.97       158
           W       0.96      0.99      0.97       148
           X       0.96      0.99      0.97       154
           Y       0.99      0.99      0.99       168
           Z       0.98      0.96      0.97       132

    accuracy                           0.95      4000
   macro avg       0.95      0.95      0.95      4000
weighted avg       0.95      0.95      0.95      4000
```

In [23]:

```
# Create a confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Visualize the confusion matrix using a heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='pink')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
0	148	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	147	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0
2	0	0	126	0	2	0	2	1	0	0	2	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0
3	0	1	0	153	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	1	0	135	0	3	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
5	0	1	0	0	1	134	0	0	1	0	0	0	0	0	0	1	0	0	0	2	0	0	0	0	0	0
6	0	0	1	3	0	0	153	0	0	0	0	0	0	0	0	0	0	2	0	0	0	1	0	0	0	0
7	0	3	0	4	0	0	1	118	0	0	4	0	0	1	2	0	0	8	0	0	1	0	0	1	1	0
8	0	0	0	0	0	2	0	0	136	7	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
9	1	0	0	0	1	1	0	0	2	143	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	1	0	0	117	0	0	0	0	0	0	10	0	0	0	0	0	2	0	0
11	0	0	1	0	4	0	3	0	0	0	0	144	0	0	0	0	0	1	1	0	0	0	0	0	0	1
12	0	2	0	0	0	0	0	0	0	0	0	0	166	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	2	0	0	0	1	0	0	0	0	0	140	4	0	0	3	0	0	0	0	1	0	0	0
14	0	0	0	4	0	0	1	0	0	0	0	0	0	0	136	0	1	0	0	0	1	0	2	0	0	0
15	0	1	0	0	2	11	3	0	0	0	0	1	0	0	1	154	0	0	0	0	0	0	0	0	0	0
16	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	163	0	0	0	0	0	0	0	0	0
17	0	5	0	2	0	0	0	0	0	0	2	0	0	1	0	0	0	150	0	0	0	0	0	0	0	0
18	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	167	0	0	0	0	0	0	1
19	0	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	1	0	155	1	0	0	2	1	0
20	0	1	0	0	0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0	175	1	3	0	0	0
21	0	4	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	2	0	0	0	150	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	146	0	0	0
23	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	152	0	0
24	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	166	0
25	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	127

Social Network Ads Prediction using SVM

In [24]:

```
df = pd.read_csv('Social_Network_Ads.csv')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   User ID          400 non-null    int64 
 1   Gender           400 non-null    object
 2   Age              400 non-null    int64 
 3   EstimatedSalary  400 non-null    int64 
 4   Purchased        400 non-null    int64 
dtypes: int64(4), object(1)
memory usage: 15.8+ KB
```

In [25]:

```
df.head()
```

Out[25]:

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0

In [26]:

```
# Assuming your DataFrame is named 'df'
df.drop(['User ID', 'Gender'], axis=1, inplace=True)
```

In [27]:

```
df.head()
```

Out[27]:

	Age	EstimatedSalary	Purchased
0	19	19000	0
1	35	20000	0
2	26	43000	0
3	27	57000	0
4	19	76000	0

In [28]:

```
X = df.drop('Purchased', axis=1)
Y = df['Purchased']
```

In [29]:

```
from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test = train_test_split(X, Y, test_size=0.20, random_state=42)
```

In [30]:

```
from sklearn.svm import SVC
```

In [31]:

```
svm_clf = SVC(kernel='rbf', C=1.0)
svm_clf.fit(x_train, y_train)
```

Out[31]:

```
▾  SVC ⓘ ?
        (https://scikit-
        learn.org/1.4/modules/generated/sklearn.svm.SVC.html)
SVC()
```

In [32]:

```
y_pred = svm_clf.predict(x_test)
```

In [33]:

```
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

In [34]:

```
score = accuracy_score(y_test, y_pred)
print(score)
```

```
0.7375
```

In [35]:

```
mat = confusion_matrix(y_test, y_pred)
print(mat)
```

```
[[49  3]
 [18 10]]
```

In [36]:

```
report = classification_report(y_test, y_pred)
print(report)
```

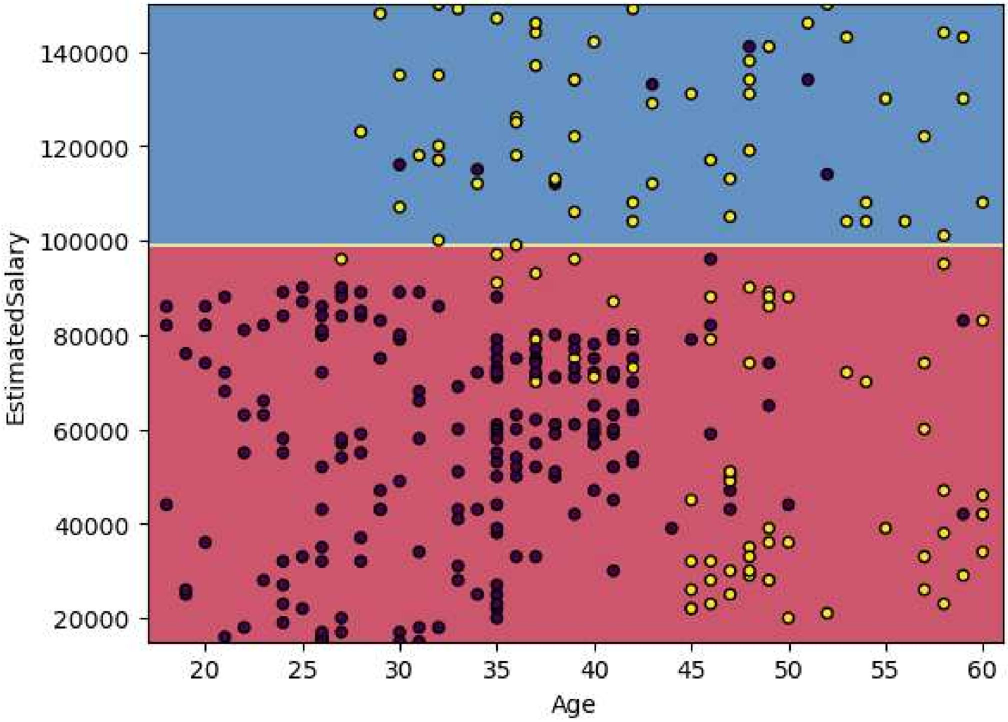
```
              precision    recall  f1-score   support

           0       0.73      0.94      0.82        52
           1       0.77      0.36      0.49        28

    accuracy                           0.74        80
   macro avg       0.75      0.65      0.66        80
weighted avg       0.74      0.74      0.71        80
```

In [37]:

```
from sklearn.inspection import DecisionBoundaryDisplay
```

In [38]:

```
# Plot Decision Boundary
DecisionBoundaryDisplay.from_estimator(
        svm_clf,
        x_train,
        response_method="predict",
        cmap=plt.cm.Spectral,
        alpha=0.8,
        xlabel='Age',
        ylabel='EstimatedSalary',
    )

# Scatter plot
plt.scatter(x_train['Age'], x_train['EstimatedSalary'],
            c=y_train,
            s=20, edgecolors="k")
plt.show()
```



IRIS Flower Prediction using Non-Linear SVM

In [39]:

```
df=pd.read_csv("IRIS.csv")
```

In [40]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
 4   species       150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

In [41]:
```
df.species.unique()
```

Out[41]:
```
array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object)
```

In [42]:
```
df['species'] = df['species'].replace({'Iris-setosa':1, 'Iris-versicolor':2, 'Iris-virginica':3}
```

In [43]:
```
df.head()
```

Out[43]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	1
1	4.9	3.0	1.4	0.2	1
2	4.7	3.2	1.3	0.2	1
3	4.6	3.1	1.5	0.2	1
4	5.0	3.6	1.4	0.2	1

In [44]:
```
# Select X and y without feature_names

X = df[['sepal_length','petal_width']].values  # Select the first two features for visualization
y = df.species
```

In [45]:
```
from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test = train_test_split(X, y, test_size=0.20, random_state=42)
```

In [46]:
```
from sklearn.svm import SVC
```

In [47]:
```
svm_clf = SVC(kernel='poly',degree=5, random_state=42)
svm_clf.fit(x_train, y_train)
```

Out[47]:
```
▾                    SVC                    i ?
SVC(degree=5, kernel='poly', random_state=42)
```
(https://scikit-learn.org/1.4/modules/generated/sklearn.svm.SVC.html)

In [48]:
```
y_pred = svm_clf.predict(x_test)
```

In [49]:
```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

In [50]:
```
score = accuracy_score(y_test, y_pred)
print(score)
```

```
1.0
```

In [51]:
```
report = classification_report(y_test, y_pred)
print(report)
```

```
              precision    recall  f1-score   support

           1       1.00      1.00      1.00        10
           2       1.00      1.00      1.00         9
           3       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

In [52]:
```
mat = confusion_matrix(y_test, y_pred)
print(mat)
```

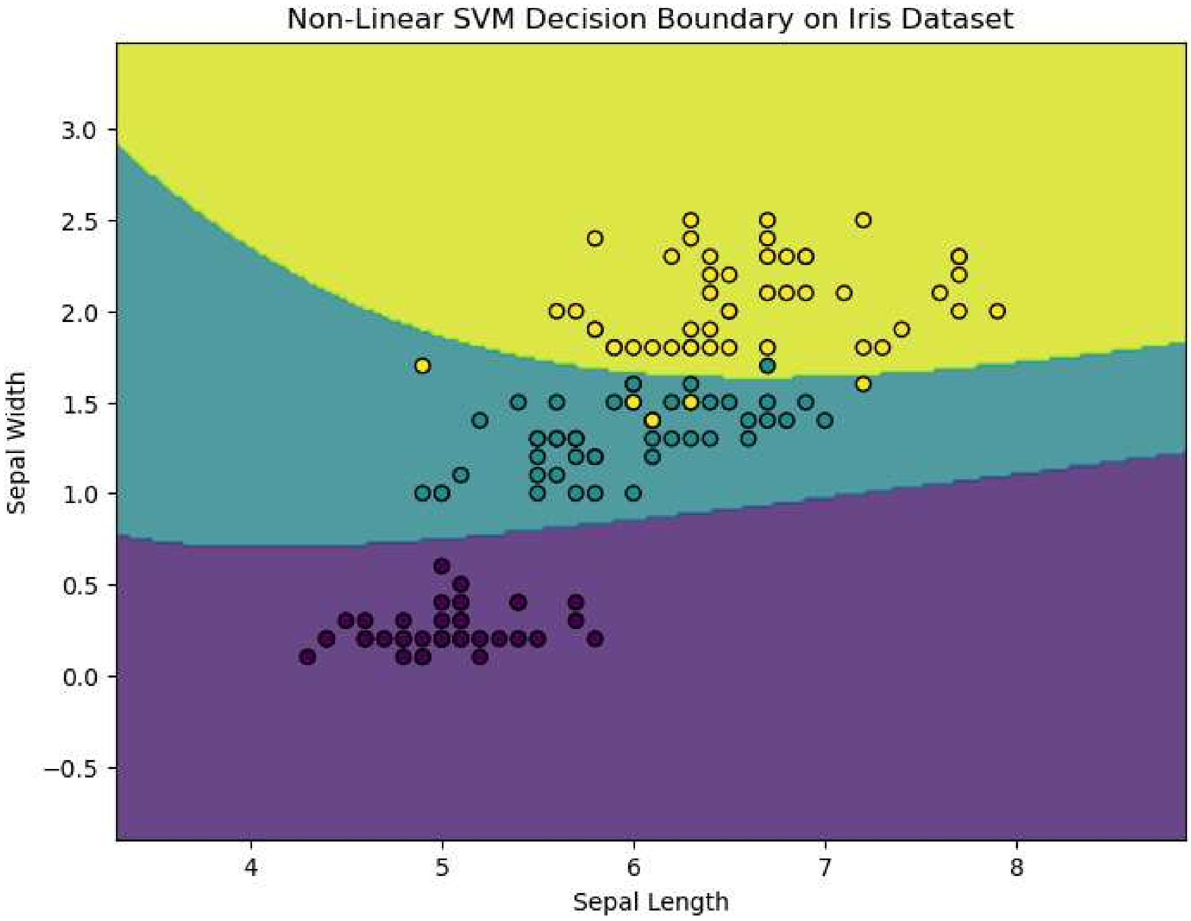
```
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

In [53]:
```
# Define Grid for Visualization

x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.02),
                     np.arange(y_min, y_max, 0.02))
```

In [54]:
```
# Make Predictions on Mesh Grid

Z = svm_clf.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
```

In [55]:

```
# Plot Decision Boundary and Data Points

plt.figure(figsize=(8, 6))
plt.contourf(xx, yy, Z, alpha=0.8)
plt.scatter(X[:, 0], X[:, 1], c=y, edgecolors='k', marker='o')
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.title('Non-Linear SVM Decision Boundary on Iris Dataset')
plt.show()
```



In [ ]: