

A_1.py\n=====

1. Read CSV file

CSV file not found, skipping...

2. Read Excel file

Excel file not found, skipping...

3. Read JSON file

JSON file not found, skipping...

4. Read CSV from URL

	Month	"1958"	"1959"	"1960"
0	JAN	340	360	417
1	FEB	318	342	391
2	MAR	362	406	419
3	APR	348	396	461
4	MAY	363	420	472

5. Built-in dataset from sklearn

	sepal length (cm)	sepal width (cm)	...	petal width (cm)	target
0	5.1	3.5	...	0.2	0
1	4.9	3.0	...	0.2	0
2	4.7	3.2	...	0.2	0
3	4.6	3.1	...	0.2	0
4	5.0	3.6	...	0.2	0

[5 rows x 5 columns]

6. Built-in dataset from seaborn

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

7. Display dataset info and description

--- Iris Dataset 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 (cm)	150 non-null	float64

```
1  sepal width (cm)    150 non-null    float64
2  petal length (cm)   150 non-null    float64
3  petal width (cm)    150 non-null    float64
4  target              150 non-null    int64
```

dtypes: float64(4), int64(1)

memory usage: 6.0 KB

None

--- Iris Dataset Description ---

	sepal length (cm)	sepal width (cm)	...	petal width (cm)
target				
count	150.000000	150.000000	...	150.000000
150.000000				
mean	5.843333	3.057333	...	1.199333
1.000000				
std	0.828066	0.435866	...	0.762238
0.819232				
min	4.300000	2.000000	...	0.100000
0.000000				
25%	5.100000	2.800000	...	0.300000
0.000000				
50%	5.800000	3.000000	...	1.300000
1.000000				
75%	6.400000	3.300000	...	1.800000
2.000000				
max	7.900000	4.400000	...	2.500000
2.000000				

[8 rows x 5 columns]

A_2.py\n=====

```
Dataset Head
  sepal length (cm)  sepal width (cm)  petal length (cm)  petal width
(cm)
0          5.1          3.5          1.4
0.2
1          4.9          3.0          1.4
0.2
2          4.7          3.2          1.3
0.2
3          4.6          3.1          1.5
0.2
4          5.0          3.6          1.4
0.2
```

Filter Method: Variance Threshold

Selected features based on variance: ['sepal length (cm)', 'petal length

```
(cm)']
```

Filter Method: Correlation

Correlation Matrix:

	sepal length (cm)	...	petal width (cm)
sepal length (cm)	1.000000	...	0.817941
sepal width (cm)	-0.117570	...	-0.366126
petal length (cm)	0.871754	...	0.962865
petal width (cm)	0.817941	...	1.000000

[4 rows x 4 columns]

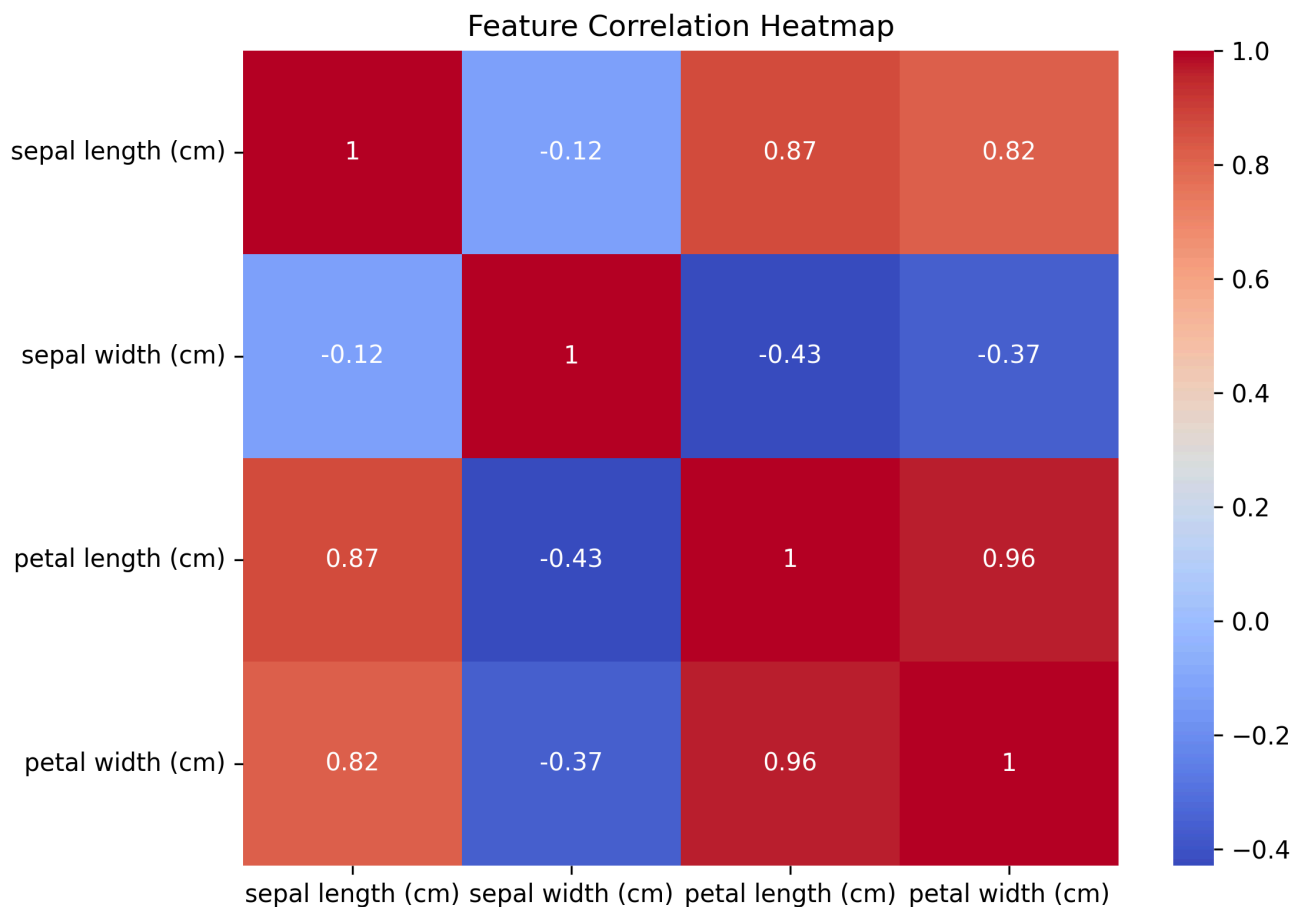
Features after removing highly correlated: ['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)']

Wrapper Method: RFE

Selected features by RFE: ['petal length (cm)', 'petal width (cm)']

Embedded Method: Lasso

Selected features by Lasso: ['petal length (cm)']



A_3.py\n=====

Original Dataset

	MedInc	HouseAge	AveRooms	...	Latitude	Longitude	MedHouseVal
0	8.3252	41.0	6.984127	...	37.88	-122.23	4.526

```

1  8.3014      21.0  6.238137  ...    37.86   -122.22    3.585
2  7.2574      52.0  8.288136  ...    37.85   -122.24    3.521
3  5.6431      52.0  5.817352  ...    37.85   -122.25    3.413
4  3.8462      52.0  6.281853  ...    37.85   -122.25    3.422

```

[5 rows x 9 columns]

Dataset **with** Missing Values

```

      MedInc  HouseAge  AveRooms  ...  Latitude  Longitude  MedHouseVal
0  8.3252      41.0      NaN  ...    37.88    -122.23      4.526
1  8.3014      21.0  6.238137  ...    37.86    -122.22      3.585
2  7.2574      52.0  8.288136  ...    37.85    -122.24      3.521
3  5.6431      52.0  5.817352  ...    37.85    -122.25      3.413
4  3.8462      52.0  6.281853  ...    37.85    -122.25      3.422
5  4.0368      NaN  4.761658  ...    37.85    -122.25      2.697

```

[6 rows x 9 columns]

After Handling Missing Values

```

      MedInc  HouseAge  AveRooms  ...  Latitude  Longitude  MedHouseVal
0  8.3252  41.000000  5.428924  ...    37.88    -122.23      4.526
1  8.3014  21.000000  6.238137  ...    37.86    -122.22      3.585
2  7.2574  52.000000  8.288136  ...    37.85    -122.24      3.521
3  5.6431  52.000000  5.817352  ...    37.85    -122.25      3.413
4  3.8462  52.000000  6.281853  ...    37.85    -122.25      3.422
5  4.0368  28.638355  4.761658  ...    37.85    -122.25      2.697

```

[6 rows x 9 columns]

Standardized Features (first 5 rows)

```

[[ 2.34  0.98  0.   -0.15 -0.97 -0.05  1.05 -1.33]
 [ 2.33 -0.61  0.33 -0.26  0.86 -0.09  1.04 -1.32]
 [ 1.78  1.86  1.16 -0.05 -0.82 -0.03  1.04 -1.33]
 [ 0.93  1.86  0.16 -0.05 -0.77 -0.05  1.04 -1.34]
 [-0.01  1.86  0.34 -0.03 -0.76 -0.09  1.04 -1.34]]

```

Min-Max Scaled Features (first 5 rows)

```

[[0.54 0.78 0.03 0.02 0.01 0.   0.57 0.21]
 [0.54 0.39 0.04 0.02 0.07 0.   0.57 0.21]
 [0.47 1.   0.05 0.02 0.01 0.   0.56 0.21]
 [0.35 1.   0.04 0.02 0.02 0.   0.56 0.21]
 [0.23 1.   0.04 0.02 0.02 0.   0.56 0.21]]

```

Train **and** Test Split

```

X_train shape: (14448, 8)
X_test shape: (6192, 8)
y_train shape: (14448,)
y_test shape: (6192,)

```

A_4.py\n=====

Dataset Head

	mean radius	mean texture	...	worst fractal dimension	target
0	17.99	10.38	...	0.11890	0
1	20.57	17.77	...	0.08902	0
2	19.69	21.25	...	0.08758	0
3	11.42	20.38	...	0.17300	0
4	20.29	14.34	...	0.07678	0

[5 rows x 31 columns]

Train-Test Split

X_train shape: (398, 30)

X_test shape: (171, 30)

Evaluation Metrics

Accuracy: 0.9825

Precision: 0.9907

Recall: 0.9815

Classification Report:

	precision	recall	f1-score	support
0	0.97	0.98	0.98	63
1	0.99	0.98	0.99	108
accuracy			0.98	171
macro avg	0.98	0.98	0.98	171
weighted avg	0.98	0.98	0.98	171

A_5.py\n=====

Dataset Head

	mean radius	mean texture	...	worst symmetry	worst fractal dimension
0	17.99	10.38	...	0.4601	0.11890
1	20.57	17.77	...	0.2750	0.08902
2	19.69	21.25	...	0.3613	0.08758
3	11.42	20.38	...	0.6638	0.17300
4	20.29	14.34	...	0.2364	0.07678

[5 rows x 30 columns]

SVM Evaluation with Different Kernels

Kernel: linear

Accuracy: 0.9766

Precision: 0.9815
Recall: 0.9815

Kernel: poly
Accuracy: 0.8947
Precision: 0.8571
Recall: 1.0000

Kernel: rbf
Accuracy: 0.9766
Precision: 0.9815
Recall: 0.9815

A_6.py\n=====

Comparison of ML Techniques

Logistic Regression:

Accuracy: 0.9825
Precision: 0.9907
Recall: 0.9815

Decision Tree:

Accuracy: 0.9415
Precision: 0.9712
Recall: 0.9352

Random Forest:

Accuracy: 0.9708
Precision: 0.9640
Recall: 0.9907

SVM:

Accuracy: 0.9766
Precision: 0.9815
Recall: 0.9815

KNN:

Accuracy: 0.9591
Precision: 0.9633
Recall: 0.9722

A_7.py\n=====

```

Dataset Head
  sepal length (cm)  sepal width (cm)  petal length (cm)  petal width
(cm)
0          5.1          3.5          1.4
0.2
1          4.9          3.0          1.4
0.2
2          4.7          3.2          1.3
0.2
3          4.6          3.1          1.5
0.2
4          5.0          3.6          1.4
0.2

```

```

Clustering Results
Cluster Labels for first 10 samples: [1 2 2 2 1 1 1 1 2 2]
Centroids of clusters:
[[ 0.57100359 -0.37176778  0.69111943  0.66315198]
 [-0.81623084  1.31895771 -1.28683379 -1.2197118 ]
 [-1.32765367 -0.373138   -1.13723572 -1.11486192]]
Silhouette Score: 0.4799

```

```

Original vs Cluster (first 10 rows):
  Original  Cluster
0         0         1
1         0         2
2         0         2
3         0         2
4         0         1
5         0         1
6         0         1
7         0         1
8         0         2
9         0         2

```

A_8.py\n=====

```

Clustering Results
  Algorithm  Silhouette Score  Adjusted Rand Index
0      KMeans          0.552819          0.730238
1 Agglomerative          0.554324          0.731199

Agglomerative Clustering forms better separated clusters.
Agglomerative clustering is closer to the true Iris classes.

```

B_1.py\n=====

Decision Tree Rules (ID3 style):

```
|--- petal length (cm) <= 2.45
|   |--- class: 0
|--- petal length (cm) > 2.45
|   |--- petal length (cm) <= 4.75
|   |   |--- petal width (cm) <= 1.60
|   |   |   |--- class: 1
|   |   |--- petal width (cm) > 1.60
|   |   |   |--- class: 2
|   |--- petal length (cm) > 4.75
|   |   |--- petal length (cm) <= 5.15
|   |   |   |--- class: 2
|   |   |--- petal length (cm) > 5.15
|   |   |   |--- class: 2
```

Model Accuracy on Test Set: 0.9777777777777777

New Sample: [[5.1, 3.5, 1.4, 0.2]]

Predicted Class: setosa

B_2.py\n=====

Epoch 0, Loss: 0.2616
Epoch 200, Loss: 0.0164
Epoch 400, Loss: 0.0117
Epoch 600, Loss: 0.0093
Epoch 800, Loss: 0.0073

Final Accuracy on Test Data: 0.9824561403508771

B_3.py\n=====

Dataset saved to wine_dataset.csv

First 5 rows of dataset:

	alcohol	malic_acid	ash	...	od280/od315_of_diluted_wines	proline
target						
0	14.23	1.71	2.43	...	3.92	1065.0
0						
1	13.20	1.78	2.14	...	3.40	1050.0
0						
2	13.16	2.36	2.67	...	3.17	1185.0
0						
3	14.37	1.95	2.50	...	3.45	1480.0


```
0
4    13.24          2.59  2.87  ...          2.93    735.0
0
```

[5 rows x 14 columns]

Accuracy: 1.0

Classification Report:

	precision	recall	f1-score	support
class_0	1.00	1.00	1.00	19
class_1	1.00	1.00	1.00	21
class_2	1.00	1.00	1.00	14
accuracy			1.00	54
macro avg	1.00	1.00	1.00	54
weighted avg	1.00	1.00	1.00	54

B_4.py\n=====

Training finished!

Average reward over 2000 episodes: 0.36

Testing trained agent:

Test finished with reward: 0.0

B_5.py\n=====

Epoch 1/5

938/938 ————— 24s 24ms/step - accuracy: 0.9443 - loss: 0.1830 - val_accuracy: 0.9824 - val_loss: 0.0542

Epoch 2/5

938/938 ————— 23s 24ms/step - accuracy: 0.9844 - loss: 0.0504 - val_accuracy: 0.9896 - val_loss: 0.0342

Epoch 3/5

938/938 ————— 22s 24ms/step - accuracy: 0.9887 - loss: 0.0352 - val_accuracy: 0.9866 - val_loss: 0.0393

Epoch 4/5

938/938 ————— 22s 24ms/step - accuracy: 0.9918 - loss: 0.0263 - val_accuracy: 0.9907 - val_loss: 0.0289

Epoch 5/5

938/938 ————— 22s 24ms/step - accuracy: 0.9932 - loss: 0.0223 - val_accuracy: 0.9892 - val_loss: 0.0342

313/313 - 2s - 5ms/step - accuracy: 0.9892 - loss: 0.0342

Test Accuracy: 0.9891999959945679

