

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# 1. Import the iris dataset
df = pd.read_csv('Iris.csv')
print("Dataset loaded successfully!")
print(f"Dataset shape: {df.shape}")
print(df.head())
```

```
Dataset loaded successfully!
Dataset shape: (150, 6)
   Id SepalLengthCm SepalWidthCm PetalLengthCm PetalWidthCm      Species
0   1           5.1          3.5         1.4         0.2  Iris-setosa
1   2           4.9          3.0         1.4         0.2  Iris-setosa
2   3           4.7          3.2         1.3         0.2  Iris-setosa
3   4           4.6          3.1         1.5         0.2  Iris-setosa
4   5           5.0          3.6         1.4         0.2  Iris-setosa
```

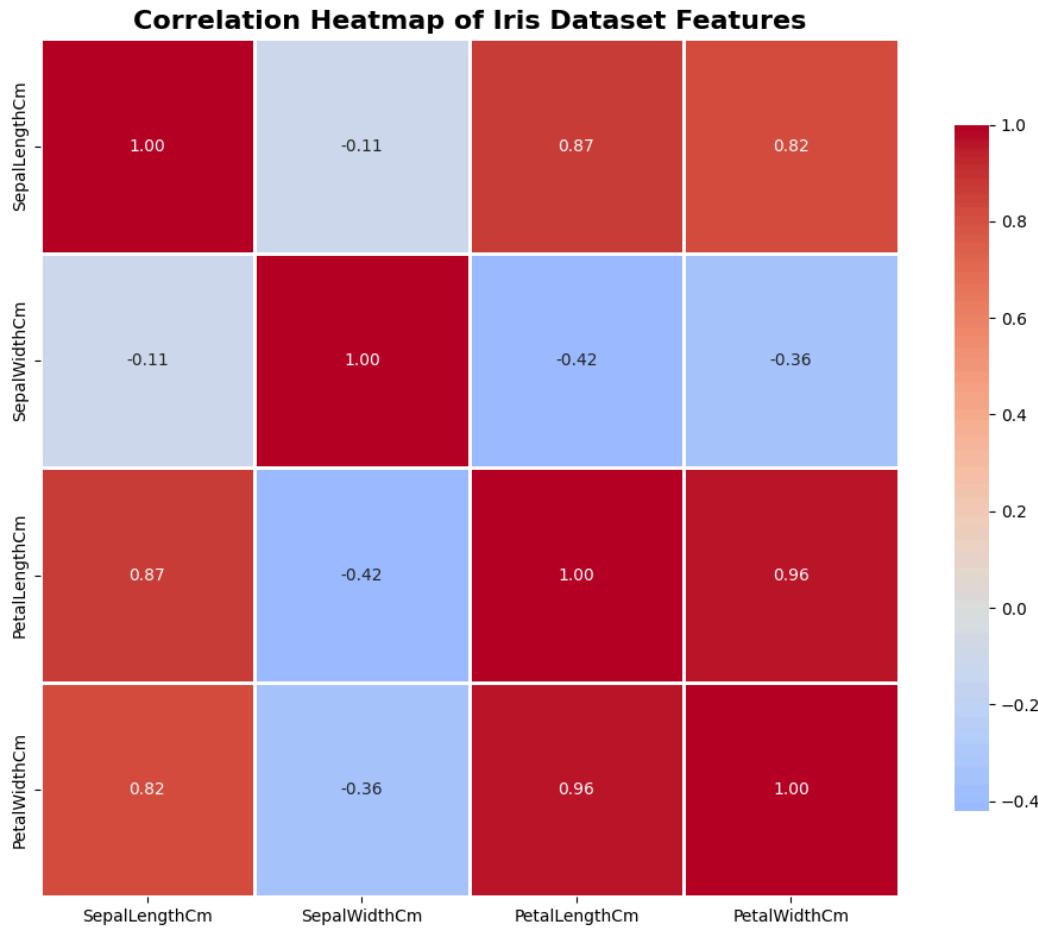
```
# 2. Separate the numeric columns in a dataframe
numeric_cols = ['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm']
df_numeric = df[numeric_cols]
```

```
# 3. Create a correlation matrix
correlation_matrix = df_numeric.corr()
print("Correlation Matrix:")
print(correlation_matrix)
```

```
Correlation Matrix:
   SepalLengthCm SepalWidthCm PetalLengthCm PetalWidthCm
SepalLengthCm    1.000000   -0.109369    0.871754    0.817954
SepalWidthCm     -0.109369    1.000000   -0.420516   -0.356544
PetalLengthCm    0.871754   -0.420516    1.000000    0.962757
PetalWidthCm     0.817954   -0.356544    0.962757    1.000000
```

```
# 4. Plot a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix,
            annot=True, # Show correlation values
            cmap='coolwarm', # Color scheme
            center=0, # Center colormap at 0
            square=True, # Make cells square-shaped
            linewidths=1, # Add gridlines
            cbar_kws={"shrink": 0.8}, # Adjust colorbar size
            fmt='.2f') # Format numbers to 2 decimal places

plt.title('Correlation Heatmap of Iris Dataset Features', fontsize=16, fontweight='bold')
plt.tight_layout()
plt.show()
```



```
# 5. Write inference
print("INFERENCE:")
print("""
1. STRONG POSITIVE CORRELATIONS:
- Petal Length & Petal Width: 0.96 (Very Strong)
  → These features are highly related; longer petals tend to be wider

- Sepal Length & Petal Length: 0.87 (Strong)
  → Flowers with longer sepals tend to have longer petals

- Sepal Length & Petal Width: 0.82 (Strong)
  → Sepal length is a good predictor of petal width

2. WEAK/NEGATIVE CORRELATION:
- Sepal Width & Petal Length: -0.42 (Moderate Negative)
- Sepal Width & Petal Width: -0.37 (Weak Negative)
  → Sepal width behaves differently from petal dimensions
  → This suggests sepal width may help distinguish species

3. KEY INSIGHTS:
- Petal measurements are more strongly correlated with each other
  than sepal measurements

- Sepal width shows the weakest correlations with other features,
  making it potentially valuable for classification

- The strong correlations between petal features suggest they may
  contain redundant information for predictive modeling

4. IMPLICATIONS FOR MODELING:
- Feature reduction techniques (PCA) might be beneficial given
  the high correlations

- Petal length and width could potentially be combined into a
  single feature

- Sepal width's unique behavior suggests it captures different
  information about iris species
""")
```

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Feature reduction techniques (PCA) might be beneficial given