Lab-6

Iris Classify

1. Import libraries:

```
In [79]: #import all library
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split,StratifiedKFold,cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
```

2. Loading the dataset.:

Load dataset

```
In [80]: iris_dataset = pd.read_csv('D:\Iris ML\dataset\Iris1.csv')
```

3. Summarizing the dataset:

- Dimensions of the dataset.

dimension

```
In [81]: iris_dataset.shape
Out[81]: (150, 6)
```

- Peek at the data itself.

peek

```
In [82]: iris_dataset.head()
```

Out[82]:

	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

- Statistical summary of all attributes.

Statistical summary

```
In [84]: iris_dataset.describe()
```

Out[84]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	38.250000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.350000	1.300000
75%	112.750000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

- Breakdown of the data by the class variable.

Breakdown by class variable

```
In [85]: iris_dataset['Id'].value_counts()

Out[85]: Id
         1      1
         95     1
         97     1
         98     1
         99     1
               ..
         51     1
         52     1
         53     1
         54     1
         150    1
         Name: count, Length: 150, dtype: int64
```

```
In [86]: iris_dataset['SepalLengthCm'].value_counts()

Out[86]: SepalLengthCm
         5.0    10
         5.1     9
         6.3     9
         5.7     8
         6.7     8
         5.8     7
         5.5     7
         6.4     7
         4.9     6
         5.4     6
         6.1     6
         6.0     6
         5.6     6
         4.8     5
         6.5     5
         6.2     4
         7.7     4
         6.9     4
         4.6     4
         5.2     4
         5.9     3
         4.4     3
         7.2     3
         6.8     3
         6.6     2
         4.7     2
         7.6     1
         7.4     1
         7.3     1
         7.0     1
         7.1     1
         5.3     1
         4.3     1
         4.5     1
         7.9     1
         Name: count, dtype: int64
```

```
In [87]: iris_dataset['SepalWidthCm'].value_counts()

Out[87]: SepalWidthCm
         3.0    26
         2.8    14
         3.2    13
         3.1    12
         3.4    12
         2.9    10
         2.7     9
         2.5     8
         3.5     6
         3.3     6
         3.8     6
         2.6     5
         2.3     4
         3.7     3
         2.4     3
         2.2     3
         3.6     3
         3.9     2
         4.4     1
         4.0     1
         4.1     1
         4.2     1
         2.0     1
         Name: count, dtype: int64
```

```
In [88]: iris_dataset['PetalLengthCm'].value_counts()

Out[88]: PetalLengthCm
         1.5    14
         1.4    12
         5.1     8
         4.5     8
         1.6     7
         1.3     7
         5.6     6
         4.7     5
         4.9     5
         4.0     5
         4.2     4
         5.0     4
         4.4     4
         4.8     4
         1.7     4
         3.9     3
         4.6     3
         5.7     3
         4.1     3
         5.5     3
         6.1     3
         5.8     3
         3.3     2
         5.4     2
         6.7     2
         5.3     2
         5.9     2
         6.0     2
         1.2     2
         4.3     2
         1.9     2
         3.5     2
         5.2     2
         3.0     1
         1.1     1
         3.7     1
         3.8     1
         6.6     1
         6.3     1
         1.0     1
         6.9     1
         3.6     1
         6.4     1
         Name: count, dtype: int64
```

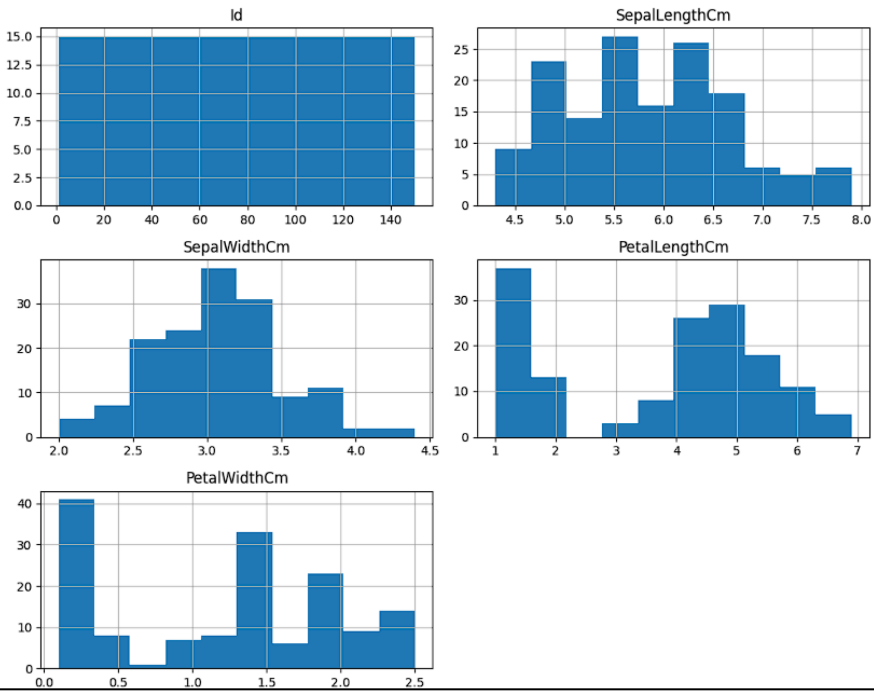
```
In [89]: iris_dataset['PetalWidthCm'].value_counts()

Out[89]: PetalWidthCm
         0.2    28
         1.3    13
         1.8    12
         1.5    12
         1.4     8
         2.3     8
         1.0     7
         0.4     7
         0.3     7
         0.1     6
         2.1     6
         2.0     6
         1.2     5
         1.9     5
         1.6     4
         2.5     3
         2.2     3
         2.4     3
         1.1     3
         1.7     2
         0.6     1
         0.5     1
         Name: count, dtype: int64
```

4. Visualizing the dataset.

- Univariate plots to better understand each attribute.

Univarited Plot

In [90]:
```
iris_dataset.hist(figsize=(10, 8))
plt.tight_layout()
plt.show()
```



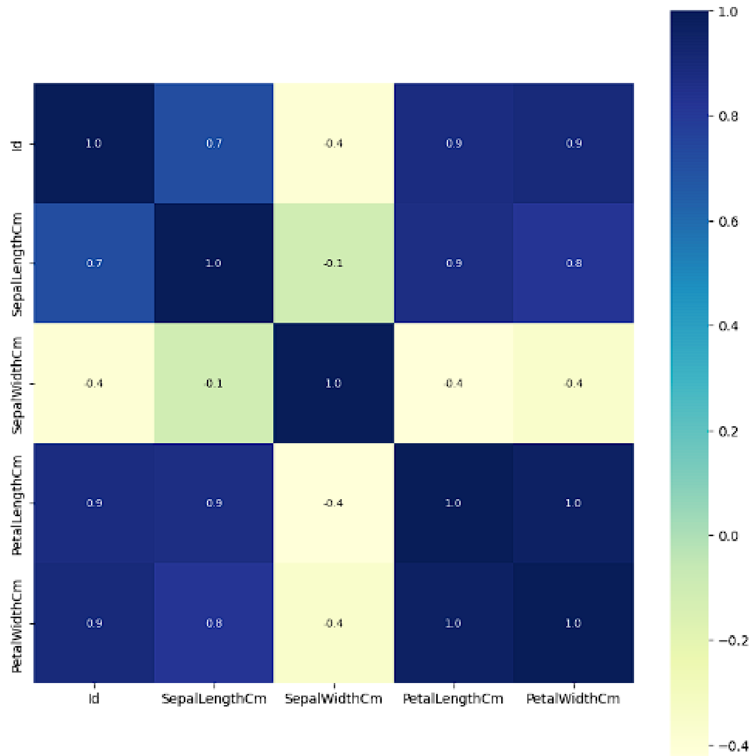
- Multivariate plots to better understand the relationships between attributes.

Multivariate plots

In [92]:
```
corr = X.corr()
```

In [93]:
```
plt.figure(figsize=(10,10))
sns.heatmap(corr,cbar=True,square=True,fmt='.1f',annot=True,annot_kws={'size':8},cmap='YlGnBu')
```

Out[93]: <Axes: >



5. Evaluating some algorithms.

- Separate out a validation dataset.

```
In [94]: y = iris_dataset['Species']

In [95]: print(y)

0        Iris-setosa
1        Iris-setosa
2        Iris-setosa
3        Iris-setosa
4        Iris-setosa
             ...
145    Iris-virginica
146    Iris-virginica
147    Iris-virginica
148    Iris-virginica
149    Iris-virginica
Name: Species, Length: 150, dtype: object
```

Split the data

```
In [96]: X_train, X_validation, y_train, y_validation = train_test_split(X, y, test_size=0.2, random_state=1, stratify=y)

In [97]: print(y)

0        Iris-setosa
1        Iris-setosa
2        Iris-setosa
3        Iris-setosa
4        Iris-setosa
             ...
145    Iris-virginica
146    Iris-virginica
147    Iris-virginica
148    Iris-virginica
149    Iris-virginica
Name: Species, Length: 150, dtype: object

In [98]: print(y.shape,y_train.shape,y_validation.shape)

(150,) (120,) (30,)

In [99]: print(X)

      Id  SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm
0      1            5.1           3.5            1.4           0.2
1      2            4.9           3.0            1.4           0.2
2      3            4.7           3.2            1.3           0.2
3      4            4.6           3.1            1.5           0.2
4      5            5.0           3.6            1.4           0.2
..   ...            ...           ...            ...           ...
145  146            6.7           3.0            5.2           2.3
146  147            6.3           2.5            5.0           1.9
147  148            6.5           3.0            5.2           2.0
148  149            6.2           3.4            5.4           2.3
149  150            5.9           3.0            5.1           1.8

[150 rows x 5 columns]

In [100]: print(X.shape,X_train.shape,X_validation.shape)
```

- Set-up the test harness to use 10-fold cross validation.

Set-up the test harness to use 10-fold cross validation.

```
In [101]: # Set-up 10-fold cross-validation
kfold = StratifiedKFold(n_splits=10, random_state=1, shuffle=True)
```

- Build multiple different models to predict species from flower measurements

1. Logistic Regression (LR)

Logistic Regression (LR)

```
In [102]: # Create a Logistic Regression model
model = LogisticRegression(solver='liblinear', multi_class='ovr')

In [103]: # Perform 10-fold cross-validation and evaluate the model
cv_results = cross_val_score(model, X_train, y_train, cv=kfold, scoring='accuracy'

# Output cross-validation results
print(f"Logistic Regression: {cv_results.mean():.4f} ({cv_results.std():.4f})")

Logistic Regression: 0.9333 (0.0624)
```

```
In [104]:
# Train the Logistic Regression model on the training dataset
model.fit(X_train, y_train)

Out[104]: LogisticRegression(multi_class='ovr', solver='liblinear')
```

```
In [105]: # Make predictions on the validation dataset
predictions = model.predict(X_validation)

# Evaluate accuracy on the validation dataset
print(f"Accuracy on validation set: {accuracy_score(y_validation, predictions):.4f}")

Accuracy on validation set: 0.9000
```

2. Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis

```
In [106]: lda = LinearDiscriminantAnalysis()

In [107]: # Perform 10-fold cross-validation on the training dataset
cv_results = cross_val_score(lda, X_train, y_train, cv=kfold, scoring='accuracy')

In [108]: # Print cross-validation results
print(f"LDA: {cv_results.mean():.4f} ({cv_results.std():.4f})")

LDA: 1.0000 (0.0000)

In [109]: # Train the LDA model on the entire training dataset
lda.fit(X_train, y_train)

Out[109]: LinearDiscriminantAnalysis()
```

```
In [110]: # Make predictions on the validation dataset
predictions = lda.predict(X_validation)

In [111]:
# Evaluate the accuracy on the validation dataset
accuracy = accuracy_score(y_validation, predictions)
print(f"Accuracy on validation set: {accuracy:.4f}")

Accuracy on validation set: 1.0000
```

3. K-Nearest Neighbors (KNN).

```
In [112]: # Initialize the KNN model
knn = KNeighborsClassifier()

In [113]: # Evaluate KNN model using 10-fold cross-validation
cv_results = cross_val_score(knn, X_train, y_train, cv=kfold, scoring='accuracy')

# Print the cross-validation accuracy results
print(f"KNN Cross-Validation Accuracy: {cv_results.mean():.4f} ({cv_results.std():.4f})")

KNN Cross-Validation Accuracy: 1.0000 (0.0000)

In [114]: # Train the KNN model on the full training dataset
knn.fit(X_train, y_train)

Out[114]: KNeighborsClassifier()
```

```
In [115]: # Make predictions on the validation dataset
          predictions = knn.predict(X_validation)

          # Evaluate the model performance on the validation dataset
          accuracy = accuracy_score(y_validation, predictions)
          print(f"Accuracy on Validation Set: {accuracy:.4f}")

          Accuracy on Validation Set: 1.0000
```

4. Classification and Regression Trees (CART).

```
In [120]: # Initialize the CART model
          cart_model = DecisionTreeClassifier()

In [121]: # Display cross-validation results
          print(f"CART - Cross-Validation Accuracy: {cv_results.mean():.4f} ({cv_results.std():.4f})")

          CART - Cross-Validation Accuracy: 1.0000 (0.0000)

In [122]: # Train the CART model on the entire training dataset
          cart_model.fit(X_train, y_train)

Out[122]: DecisionTreeClassifier()
```

```
In [123]: # Make predictions on the validation dataset
          predictions = cart_model.predict(X_validation)

          # Evaluate the performance on the validation dataset
          validation_accuracy = accuracy_score(y_validation, predictions)
          print(f"CART - Accuracy on validation set: {validation_accuracy:.4f}")

          CART - Accuracy on validation set: 1.0000
```

5. Gaussian Naive Bayes (NB).

```
In [124]: # Initialize Gaussian Naive Bayes model
          model = GaussianNB()

In [125]: print(f"Gaussian Naive Bayes cross-validation accuracy: {cv_results.mean():.4f} ({cv_results.std():.4f})")

          Gaussian Naive Bayes cross-validation accuracy: 1.0000 (0.0000)

In [126]: # Fit the model on the training dataset
          model.fit(X_train, y_train)

Out[126]: GaussianNB()
```

```
In [127]: # Make predictions on the validation dataset
          predictions = model.predict(X_validation)

          # Evaluate accuracy on the validation dataset
          accuracy = accuracy_score(y_validation, predictions)
          print(f"Accuracy on validation set: {accuracy:.4f}")

          Accuracy on validation set: 0.9667
```

6. Support Vector Machines (SVM).

Support Vector Machines (SVM).

```
In [116]: # Initialize the SVM model
          model = SVC(gamma='auto')

In [117]: print(f"SVM: {cv_results.mean():.4f} ({cv_results.std():.4f})")

          SVM: 1.0000 (0.0000)

In [118]: # Train the SVM model on the training dataset
          model.fit(X_train, y_train)

Out[118]: SVC(gamma='auto')
```

```
In [119]: # Make predictions on the validation dataset
          predictions = model.predict(X_validation)

          # Evaluate the accuracy on the validation dataset
          print(f"Accuracy on validation set: {accuracy_score(y_validation, predictions):.4f}")

          Accuracy on validation set: 1.0000
```

- Accuracy of the models:

  - Logistic Regression (LR): **0.9000**
  - Linear Discriminant Analysis (LDA):**1.000**
  - K-Nearest Neighbors (KNN).**1.000**
  - Classification and Regression Trees (CART).**: 1.000**
  - Gaussian Naive Bayes (NB).**0.9667**
  - Support Vector Machines (SVM).: **1.000**