Team Member


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GitHub Link : https://github.com/Sup3000gt/Machine-Learning-Project (https://github.com/Sup3000gt/Machine-Learning-Project)

Machine Learning Fundamental Project

In [89]:
```
from sklearn import datasets
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Step1. Load and Preprocessing the Data

In [90]:
```
iris = datasets.load_iris()
```

In [91]:
```
# Create a DataFrame
df_iris = pd.DataFrame(data=iris.data, columns=iris.feature_names)

# Add the target variable to the DataFrame
df_iris['species'] = iris.target

# Map the target integers to the actual species names for better readabilit
df_iris['species'] = df_iris['species'].map(dict(enumerate(iris.target_name

# Show the DataFrame
df_iris
```

Out[91]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	virginica
146	6.3	2.5	5.0	1.9	virginica
147	6.5	3.0	5.2	2.0	virginica
148	6.2	3.4	5.4	2.3	virginica
149	5.9	3.0	5.1	1.8	virginica

150 rows × 5 columns

In [92]:
```
# Split our X and Y
X = df_iris.drop('species', axis=1)
Y = df_iris['species']
```

Step 1.1 check if there is any NaN value

In [93]:
```
missing_value = X.isnull().sum()
# show if any missing value
missing_value
```

Out[93]:
```
sepal length (cm)    0
sepal width (cm)     0
petal length (cm)    0
petal width (cm)     0
dtype: int64
```

Step 1.2 Normalize the data to see if any outlier

In [94]:
```
# we will implement Z-score Normalize

def Z_scores(df): # take in a date frame as a parameter
    means = df.mean()
    stds = df.std()
    z_score = (df - means) / stds
    return z_score
```

In [95]:
```
normalized_df = Z_scores(X)
normalized_df
```

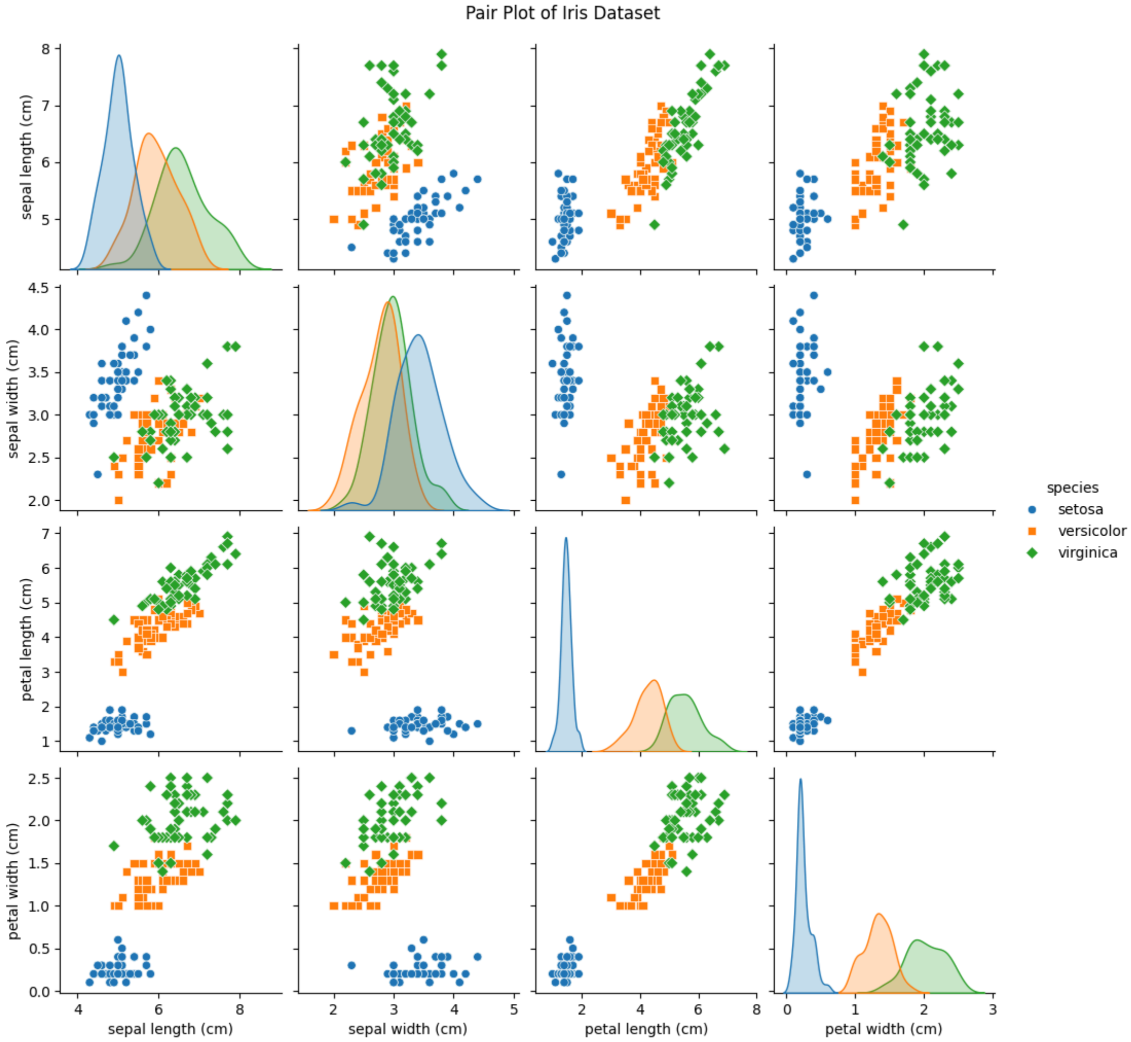
Out[95]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	-0.897674	1.015602	-1.335752	-1.311052
1	-1.139200	-0.131539	-1.335752	-1.311052
2	-1.380727	0.327318	-1.392399	-1.311052
3	-1.501490	0.097889	-1.279104	-1.311052
4	-1.018437	1.245030	-1.335752	-1.311052
...	...	...	...	...
145	1.034539	-0.131539	0.816859	1.443994
146	0.551486	-1.278680	0.703564	0.919223
147	0.793012	-0.131539	0.816859	1.050416
148	0.430722	0.786174	0.930154	1.443994
149	0.068433	-0.131539	0.760211	0.788031

150 rows × 4 columns

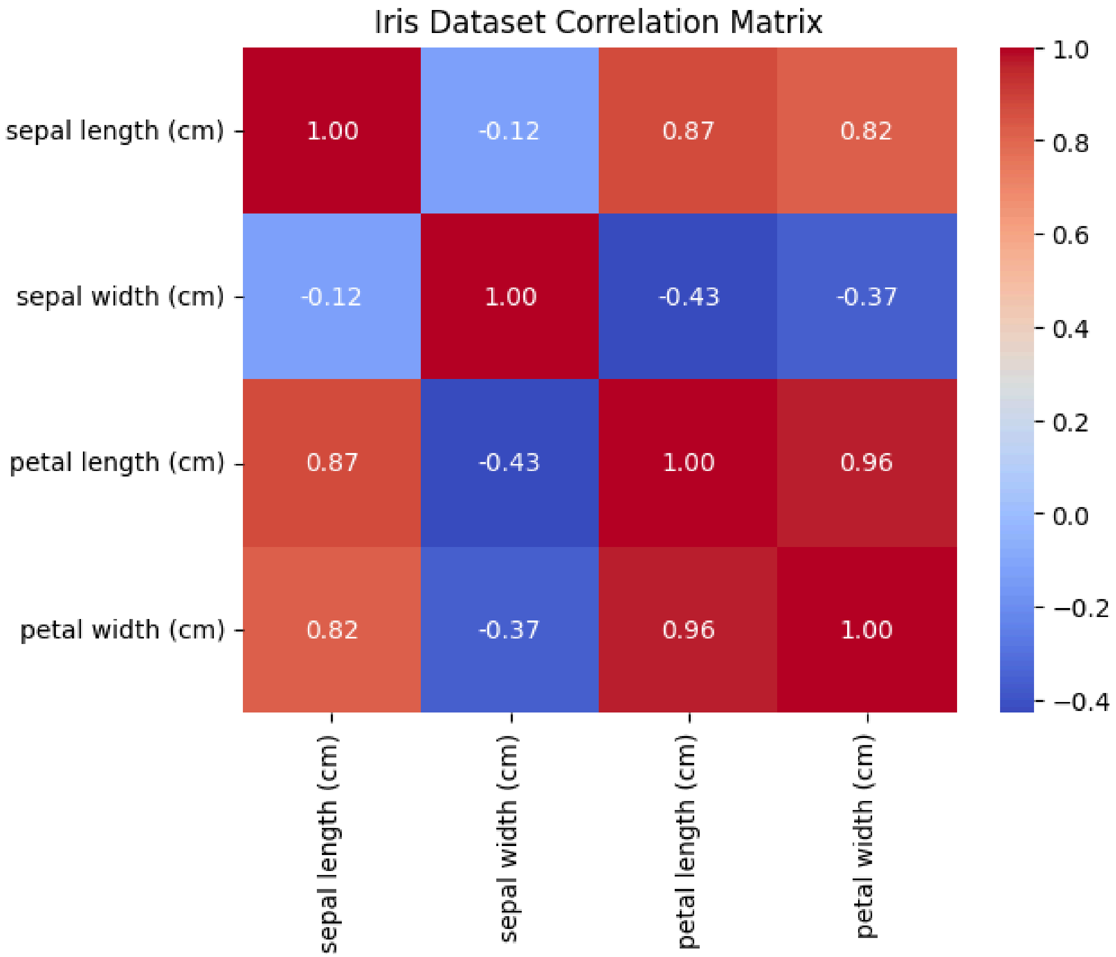
Step 1.3 Scatter Plot Visualizations

In [96]:
```
# Load the Iris dataset
iris = datasets.load_iris()
df = pd.DataFrame(data=iris.data, columns=iris.feature_names)
df['species'] = iris.target_names[iris.target]

# Pair Plot
sns.pairplot(df, hue="species", markers=["o", "s", "D"])
plt.suptitle("Pair Plot of Iris Dataset", y=1.02)

# Show the plot
plt.show()
```



Step 1.Correlation Visualization

In [97]:
```
correlation_matrix = np.corrcoef(iris.data.T)
sns.heatmap(correlation_matrix, annot=True, fmt='.2f', cmap='coolwarm',
            xticklabels=iris.feature_names, yticklabels=iris.feature_names)
plt.title('Iris Dataset Correlation Matrix')
plt.show()
```



Step 1.5 Split the data for training

In [99]:
```
from sklearn.model_selection import train_test_split

# 80/20 split
X_train, X_test, y_train, y_test = train_test_split(normalized_df, Y, test_

# Double the training data
X_train_doubled = np.vstack((X_train, X_train, X_train, X_train))
y_train_doubled = np.append(y_train, y_train)
y_train_doubled = np.append(y_train_doubled, y_train)
y_train_doubled = np.append(y_train_doubled, y_train)

# Add Gaussian noise to the training data
mean = 0
std_dev = 0.05
noise = np.random.normal(mean, std_dev, size=X_train_doubled.shape)
X_train_noisy = X_train_doubled + noise

# check the shape
(X_train_noisy.shape, X_test.shape), (y_train_doubled.shape, y_test.shape)
```

Out[99]:
```
(((480, 4), (30, 4)), ((480,), (30,)))
```

Model building/Cross-Validation/Evaluation

In [100]:
```
from sklearn.svm import SVC
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold, cross_validate
```

K-fold Cross-validation with shuffle and K= 5

In [101]:
```
# set up K-fold Cross-validation with shuffle
kf = KFold(n_splits=5, shuffle=True, random_state=42)
```

List of Kernels we want to try

In [102]:
```
kernels = ['linear', 'rbf', 'poly']
```

Evaluation Metrics

In [103]:
```
# Accuracy, Precision, Recall, F1 scores
metrics = ['accuracy', 'precision_macro', 'recall_macro', 'f1_macro']
```

Functions to evaluate different kernels

In [104]:
```
"""
this function will take in 4 hyper-parameters
- Kernels
- X_train
- y_train
- Cross-Validation we define early
"""
def eval_kernels(kernels, X_train, y_train, cv):
    # dictionary to save the result
    results = {}

    for kernel in kernels:
        # create our support vector classifier
        model = SVC(kernel = kernel, random_state=42)
        cv_results = cross_validate(model, X_train, y_train, cv=cv, scoring
        scores = {
            'Accuracy': round(cv_results['test_accuracy'].mean() * 100, 2),
            'Precision': round(cv_results['test_precision_macro'].mean() *
            'Recall': round(cv_results['test_recall_macro'].mean() * 100, 2
            'F1 Score': round(cv_results['test_f1_macro'].mean() * 100, 2)
        }
        results[kernel.capitalize()] = scores
    return results
```

Call our Functions

In [105]:
```
"""
result are now a form of dictionary with kernel name as key, and value is a
with different evaluation metrics as a key and value is the float represent
"""
results = eval_kernels(kernels, X_train_noisy, y_train_doubled, kf)
```

In [106]:
```
# display our result
for kernel, metrics in results.items():
    print(f"{kernel} Kernel:")
    for metric, value in metrics.items():
        print(f"  {metric}: {value}%")
    print()  # better separation
```

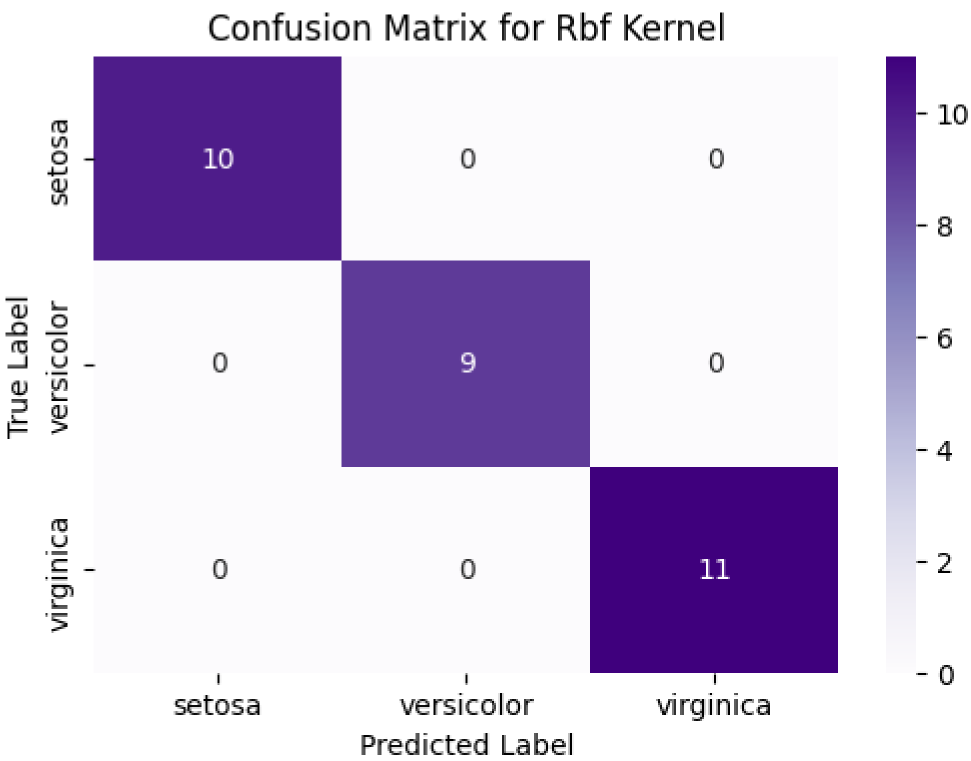
```
Linear Kernel:
  Accuracy: 96.88%
  Precision: 96.92%
  Recall: 96.96%
  F1 Score: 96.82%

Rbf Kernel:
  Accuracy: 97.5%
  Precision: 97.52%
  Recall: 97.6%
  F1 Score: 97.47%

Poly Kernel:
  Accuracy: 95.62%
  Precision: 95.74%
  Recall: 95.66%
  F1 Score: 95.57%
```

Performance Visualizations

In [107]:
```
from sklearn.metrics import *
```

In [108]:
```
# Since Linear Kernel have best accuracy, let's use it

kernel = 'rbf'
model = SVC(kernel=kernel, random_state=42)

# Fit the model
model.fit(X_train_noisy, y_train_doubled)

# Prediction
y_pred = model.predict(X_test)

# Generate the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Plot using matplotlib and seaborn
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt="d", cmap='Purples', xticklabels=iris.targe
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title(f'Confusion Matrix for {kernel.capitalize()} Kernel')
plt.show()
```

```
c:\users\nick_\appdata\local\programs\python\python38\lib\site-packages\sk
learn\base.py:458: UserWarning: X has feature names, but SVC was fitted wi
thout feature names
  warnings.warn(
```



In [ ]: