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#AICTE OASIS INFOBYTE
#Data Science Projects
#1.Iris Flower Classification Project
#Introduction
This project explores the fascinating world of machine learning through
the lens of the Iris flower dataset, one of the most famous datasets
used for classification tasks. Our objective is to build a predictive
model capable of distinguishing between the three species of Iris flowers
— setosa, versicolor, and virginica — based on the physical dimensions of
their petals and sepals. By applying machine learning techniques, we aim
to uncover the patterns that define the uniqueness of each species.
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#Data Loading and Preprocessing
The dataset is loaded from a CSV file named Iris (1).csv.
The preprocessing steps involve removing the 'Id' column,
as it does not contribute to the model's ability to learn
the classification task. Additionally, the categorical 'Species'
column is encoded into numerical form, enabling the machine learning
algorithms to process the labels.
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In [1]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
```

In [3]:
```
iris_data = pd.read_csv('Iris (1).csv')
```

In [4]:
```
iris_data.drop('Id', axis=1, inplace=True)
```

In [5]:
```
le = LabelEncoder()
iris_data['Species'] = le.fit_transform(iris_data['Species'])
```

In [6]:
```
X = iris_data.drop('Species', axis=1)
y = iris_data['Species']
```

In [7]:
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X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta
```

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#Model Selection and Training
For this classification task, the k-Nearest Neighbors (k-NN) algorithm
was chosen due to its simplicity and efficiency in handling small
datasets like ours. The k-NN algorithm works by finding the 'k' training
samples closest in distance to a new point and predicts the label
from these. The model is trained with n_neighbors=3, a choice made
based on preliminary experiments and literature that suggests a small
k value often works well for simple classification tasks.
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In [8]:
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from sklearn.neighbors import KNeighborsClassifier
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In [9]:
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knn = KNeighborsClassifier(n_neighbors=3)
```

In [10]:
```
knn.fit(X_train, y_train)
```

Out[10]:
```
KNeighborsClassifier(n_neighbors=3)
```

In [11]:
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y_pred = knn.predict(X_test)
```

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#Model Evaluation
To assess the performance of our k-Nearest Neighbors model, we employ several metri

#Accuracy measures the proportion of correct predictions over the total number of i
#The confusion matrix provides insight into the types of errors made by the classif
#The classification report shows key metrics such as precision, recall, and f1-scor
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In [12]:
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from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
```

In [13]:
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accuracy = accuracy_score(y_test, y_pred)
```

In [14]:
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class_report = classification_report(y_test, y_pred, target_names=le.classes_)
```

In [15]:
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conf_matrix = confusion_matrix(y_test, y_pred)
```

In [16]:
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print(f"Accuracy: {accuracy * 100:.2f}%")
print("\nClassification Report:\n", class_report)
print("\nConfusion Matrix:\n", conf_matrix)
```

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Accuracy: 100.00%

Classification Report:
                  precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        19
Iris-versicolor       1.00      1.00      1.00        13
 Iris-virginica       1.00      1.00      1.00        13

       accuracy                           1.00        45
      macro avg       1.00      1.00      1.00        45
   weighted avg       1.00      1.00      1.00        45


Confusion Matrix:
 [[19  0  0]
 [ 0 13  0]
 [ 0  0 13]]
```

In [17]:
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#Cross-Validation
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In [18]:
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from sklearn.model_selection import cross_val_score

# Using the k-NN model as an example
knn_cv = KNeighborsClassifier(n_neighbors=3)

# 10-fold cross-validation
cv_scores = cross_val_score(knn_cv, X, y, cv=10)

print(f"CV Scores: {cv_scores}")
print(f"CV Average Score: {cv_scores.mean():.4f}")
```

```
CV Scores: [1.         0.93333333 1.         0.93333333 0.86666667 1.
 0.93333333 1.         1.         1.        ]
CV Average Score: 0.9667
```

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#Model Comparison
To ensure we have the best model for our Iris flower
classification task, it's essential to compare the performance
of several machine learning algorithms. This comparison includes
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not only our initial k-Nearest Neighbors model but also Decision
Trees, Support Vector Machines (SVM), and Random Forests.
By evaluating each model's accuracy through cross-validation,
we can identify which model is most effective at predicting the
species of Iris flowers.
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In [19]:

```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier

# Initialize the models
models = {
    "k-NN": KNeighborsClassifier(n_neighbors=3),
    "Decision Tree": DecisionTreeClassifier(),
    "SVM": SVC(),
    "Random Forest": RandomForestClassifier()
}

# Compare models using cross-validation
for name, model in models.items():
    cv_scores = cross_val_score(model, X, y, cv=10)
    print(f"{name} Accuracy: {cv_scores.mean():.4f}")
```

```
k-NN Accuracy: 0.9667
Decision Tree Accuracy: 0.9533
SVM Accuracy: 0.9733
Random Forest Accuracy: 0.9667
```

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#Hyperparameter Tuning
After comparing various models, we proceed to fine-tune the hyperparameters
of our best-performing model. Hyperparameter tuning is crucial as it
can significantly enhance a model's ability to make accurate
predictions. For our k-Nearest Neighbors (k-NN) model, we will use
GridSearchCV to search for the optimal number of neighbors (n_neighbors)
that yields the highest cross-validation accuracy.
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In [20]:

```python
import numpy as np
```

In [21]:

```python
from sklearn.model_selection import GridSearchCV

# Grid search for k-NN
param_grid = {'n_neighbors': np.arange(1, 30)}
knn_gs = GridSearchCV(KNeighborsClassifier(), param_grid, cv=10)
knn_gs.fit(X, y)

print(f"Best parameters: {knn_gs.best_params_}")
print(f"Best score: {knn_gs.best_score_:.4f}")
```

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Best parameters: {'n_neighbors': 13}
Best score: 0.9800
```

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#Feature Importance and Insights
Gaining insights into which features most significantly impact our model's predicti
insights into the Iris species classification. For models like Random Forest, we ca
importance, which quantifies how much each feature contributes to the model's decis
can help in understanding the characteristics that differentiate the species from o
```

In [22]:

```python
from matplotlib import pyplot as plt
```

In [23]:

```python
rf = RandomForestClassifier(n_estimators=100)
rf.fit(X_train, y_train)

# Extracting feature importance
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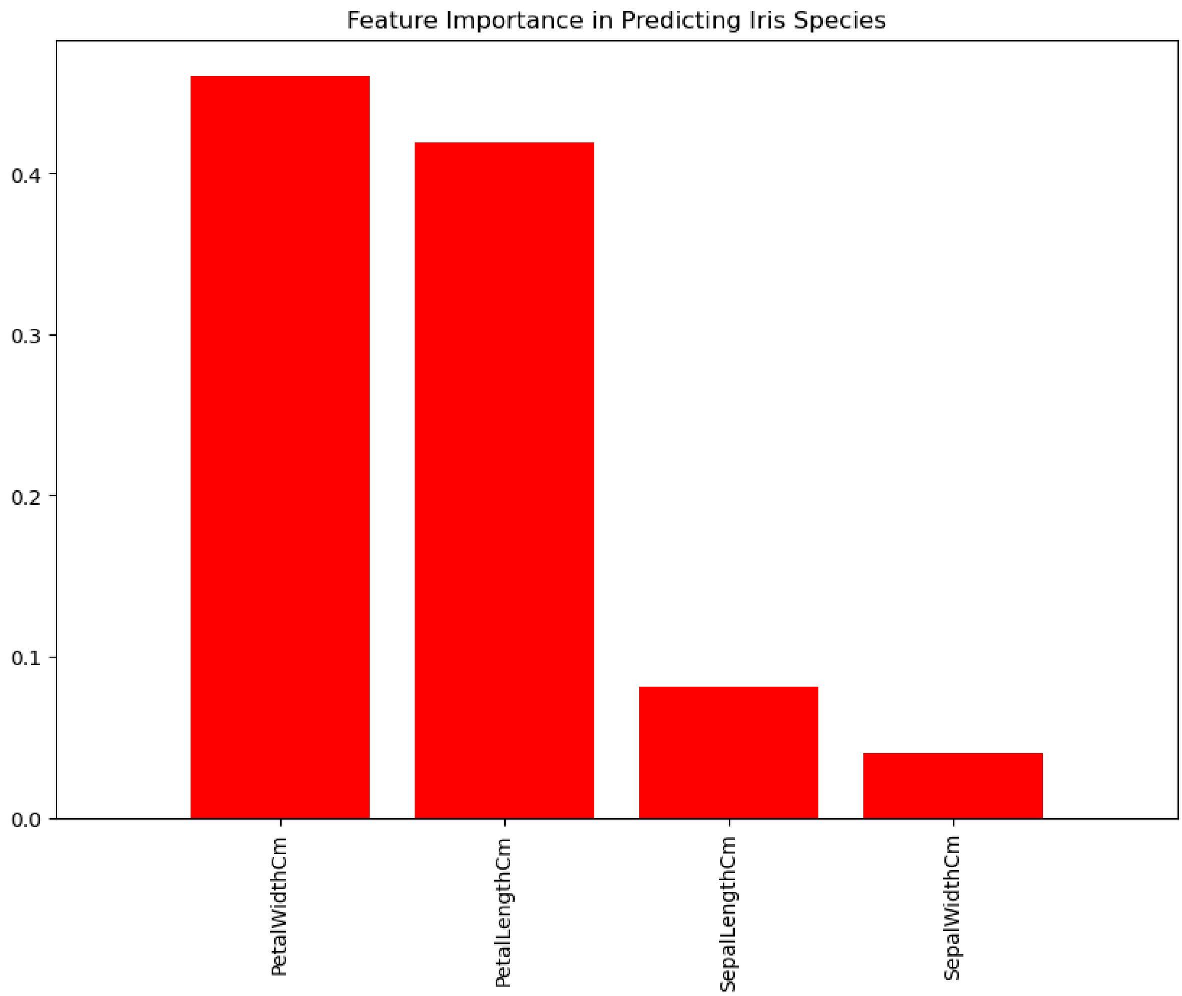
```python
importances = rf.feature_importances_
features = X.columns
indices = np.argsort(importances)[::-1]

# Visualizing the feature importance
plt.figure(figsize=(10, 7))
plt.title('Feature Importance in Predicting Iris Species')
plt.bar(range(X_train.shape[1]), importances[indices], color="r", align="center")
plt.xticks(range(X_train.shape[1]), features[indices], rotation=90)
plt.xlim([-1, X_train.shape[1]])
plt.show()
```



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#Conclusion and Final Thoughts
Through this project, we've navigated the end-to-end process of a
machine learning task—from data preprocessing and model selection
to evaluation and insight extraction. The Iris Flower Classification
project illustrates the power of machine learning in deriving
meaningful predictions and insights from data. As we've seen, different
models and techniques can be applied to enhance our understanding and
performance on the task.

The exploration of feature importance further underscores the practical
implications of our findings, offering a window into the biological
distinctions between Iris species. Such insights are invaluable not
only in the context of this project but also in broader applications
where understanding the influence of specific features is crucial.

Moving forward, there's always room for experimentation, such as
trying out more sophisticated models, feature engineering techniques,
or diving deeper into model interpretability. The field of machine
learning is vast and constantly evolving, offering endless opportunities
for learning and growth.
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In [24]:

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# Identify misclassified examples
errors = y_test != y_pred
misclassified_samples = X_test[errors]
```

In [25]:

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#Interactive Analysis
import plotly.express as px

# Interactive scatter plot of sepal length vs. sepal width
fig = px.scatter(iris_data, x="SepalLengthCm", y="SepalWidthCm", color="Species", t
fig.show()
```

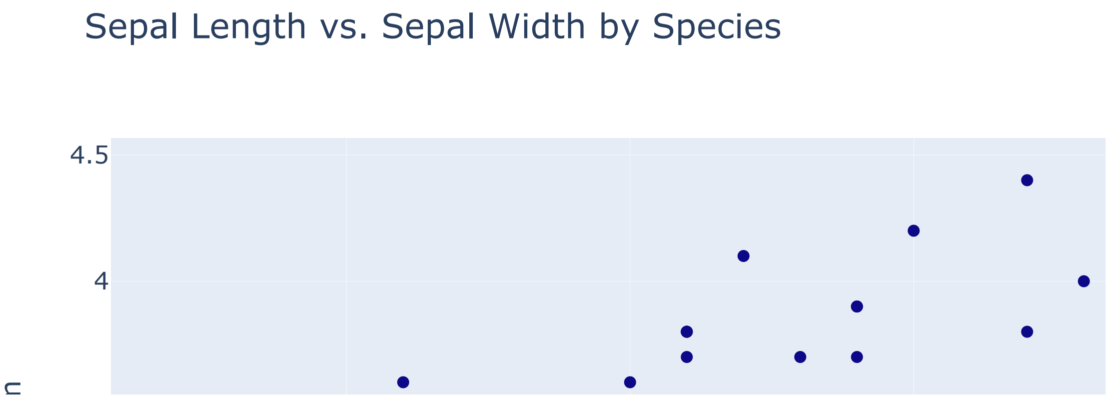

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