Upload the ZIP in Colab

```
import zipfile
from google.colab import files
uploaded = files.upload()

with zipfile.ZipFile("archive (4).zip", 'r') as zip_ref:
    zip_ref.extractall("iris_data")
```

Choose Files archive (4).zip

- **archive (4).zip**(application/x-zip-compressed) - 1010 bytes, last modified: 7/1/2025 - 100% done

```
Saving archive (4).zip to archive (4) (1).zip
```

Import Zip File

```
import zipfile

with zipfile.ZipFile("archive (4).zip", 'r') as zip_ref:
    zip_ref.extractall("iris_data")
```

Extract the ZIP

```
import os
print(os.listdir("iris_data"))
```

```
['IRIS.csv']
```

Load the CSV

```
import pandas as pd
df = pd.read_csv("iris_data/IRIS.csv")
print(df.head())
```

```
   sepal_length  sepal_width  petal_length  petal_width      species
0           5.1          3.5           1.4          0.2  Iris-setosa
1           4.9          3.0           1.4          0.2  Iris-setosa
2           4.7          3.2           1.3          0.2  Iris-setosa
3           4.6          3.1           1.5          0.2  Iris-setosa
4           5.0          3.6           1.4          0.2  Iris-setosa
```

Show Details

```
print(df.isnull().sum())
# Check info
print(df.info())
```

```
sepal_length    0
sepal_width     0
petal_length    0
petal_width     0
species         0
dtype: int64
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
 4   species       150 non-null    object
```

```
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
None
```

Check for missing values

```
# Check missing values
print(df.isnull().sum())
```

```
sepal_length    0
sepal_width     0
petal_length    0
petal_width     0
species         0
dtype: int64
```

Inspect columns

```
print(df.columns)
```

```
Index(['sepal_length', 'sepal_width', 'petal_length', 'petal_width',
       'species'],
      dtype='object')
```

Drop unnecessary columns

```
if 'Id' in df.columns:
    df = df.drop('Id', axis=1)
```

Encode the target label

```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
df['species'] = le.fit_transform(df['species'])

print(df['species'].value_counts())
```

```
species
0    50
1    50
2    50
Name: count, dtype: int64
```

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

# Load the Iris dataset
from sklearn.datasets import load_iris
iris = load_iris()
df = pd.DataFrame(data=iris.data, columns=iris.feature_names)

# Create the correlation matrix
corr_matrix = df.corr()

# Plot the heatmap
plt.figure(figsize=(8,6))
sns.heatmap(corr_matrix, annot=True, cmap='Blues', linewidths=0.5)
plt.title("Feature Correlation Heatmap - Iris Dataset")
plt.show()
```

🌳 Random Forest Classifier

🌳 Random Forest Classifier

✔️ Type: Ensemble method (many decision trees working together)

✔️ How it works:

builds many decision trees on random subsets of data/features

averages their predictions (majority vote for classification)

each tree might overfit, but averaging them reduces overfitting

✔️ Advantages:

works well with nonlinear and complex relationships

robust to outliers

handles missing data reasonably

works with minimal feature scaling

✔️ Disadvantages:

more computationally heavy

harder to interpret

can overfit on small datasets without tuning.

Train-test split

```
from sklearn.model_selection import train_test_split
from sklearn.datasets import load_iris

iris = load_iris()
X = pd.DataFrame(data=iris.data, columns=iris.feature_names)
y = pd.Series(data=iris.target, name='species')


X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

Train the Model Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier

# initialize
clf = RandomForestClassifier(random_state=42)

# train
clf.fit(X_train, y_train)
```

```
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

Evaluate the Model

```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# predictions
y_pred = clf.predict(X_test)

# accuracy
print("Accuracy:", accuracy_score(y_test, y_pred))

# detailed report
print("\nClassification Report:\n", classification_report(y_test, y_pred))

# confusion matrix
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
Accuracy: 0.9

Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       0.82      0.90      0.86        10
           2       0.89      0.80      0.84        10

    accuracy                           0.90        30
   macro avg       0.90      0.90      0.90        30
weighted avg       0.90      0.90      0.90        30


Confusion Matrix:
 [[10  0  0]
 [ 0  9  1]
 [ 0  2  8]]
```

➕ Logistic Regression

➕ Logistic Regression

✔ Type: Linear model

✔ How it works:

fits a straight line (in high dimensions: a hyperplane)

predicts probabilities using a logistic/sigmoid function

uses coefficients for each feature

✔ Advantages:

easy to interpret (coefficients = feature impact)

fast to train

performs well if the data is linearly separable

very simple and robust

✔ Disadvantages:

poor performance on strongly nonlinear relationships

needs scaled features if large feature differences

underfits on complex patterns

Train Logistic Regression

```
from sklearn.linear_model import LogisticRegression

# Logistic Regression with multinomial
logreg = LogisticRegression(multi_class='multinomial', solver='lbfgs', max_iter=200, random_state=42)

logreg.fit(X_train, y_train)

y_pred = logreg.predict(X_test)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1
  warnings.warn(
```

Evaluate Logistic Regression

```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

print("Logistic Regression Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
Logistic Regression Accuracy: 0.9666666666666667

Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      0.90      0.95        10
           2       0.91      1.00      0.95        10

    accuracy                           0.97        30
   macro avg       0.97      0.97      0.97        30
weighted avg       0.97      0.97      0.97        30


Confusion Matrix:
 [[10  0  0]
 [ 0  9  1]
 [ 0  0 10]]
```

Both Training and Testing accuracy

```
logreg = LogisticRegression(multi_class='multinomial', solver='lbfgs', max_iter=200, random_state=42)
logreg.fit(X_train, y_train)
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1
  warnings.warn(
LogisticRegression
LogisticRegression(max_iter=200, multi_class='multinomial', random_state=42)
```

```
# predict on training data
y_train_pred = logreg.predict(X_train)
```

```
# accuracy on training set
train_acc = accuracy_score(y_train, y_train_pred)
print("Training Accuracy:", train_acc)

# accuracy on test set
test_acc = accuracy_score(y_test, y_pred)
print("Testing Accuracy:", test_acc)
```

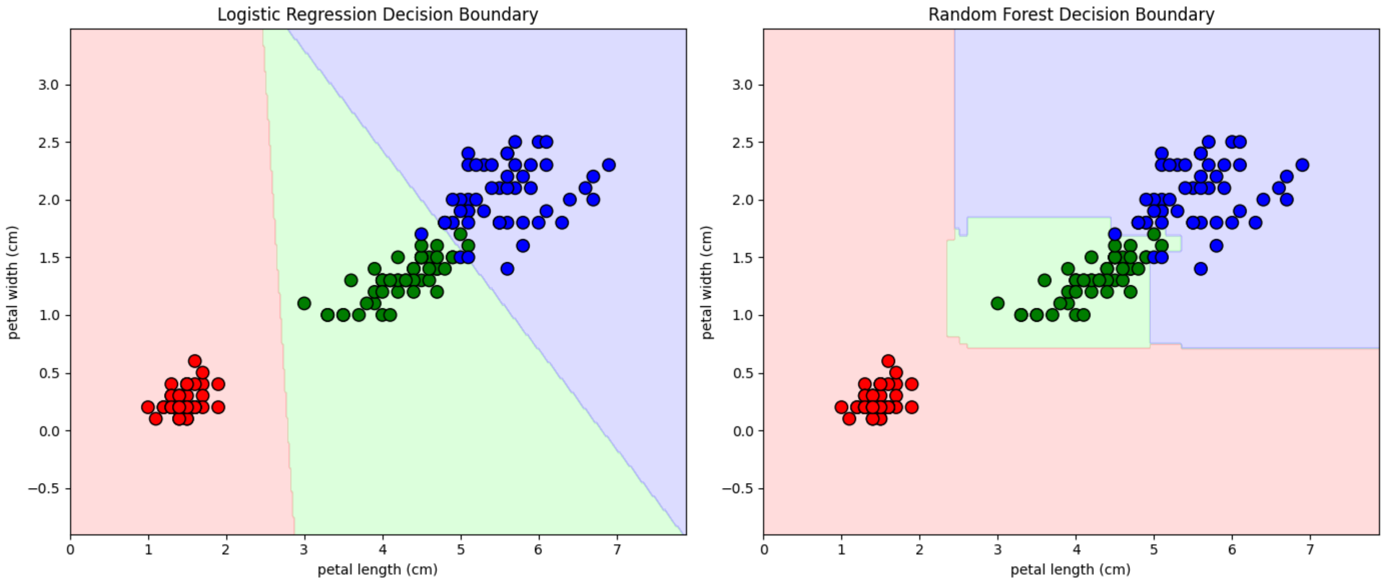
```
Training Accuracy: 0.975
Testing Accuracy: 0.9666666666666667
```

Decision Boundary Visualization for LogisticRegression And RandomForestClassifier

```
import matplotlib.pyplot as plt
import numpy as np
from matplotlib.colors import ListedColormap
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.datasets import load_iris
import pandas as pd

# Load the Iris dataset
iris = load_iris()
X = pd.DataFrame(data=iris.data, columns=iris.feature_names)
y = pd.Series(data=iris.target, name='species')


# choose 2 features
feature_x = 'petal length (cm)'
feature_y = 'petal width (cm)'

X_vis = X[[feature_x, feature_y]].values
y_vis = y

# train logistic regression on 2 features
logreg2d = LogisticRegression(multi_class='multinomial', solver='lbfgs', max_iter=200, random_state=42)
logreg2d.fit(X_vis, np.array(y_vis))

# train random forest on 2 features
rf2d = RandomForestClassifier(random_state=42)
rf2d.fit(X_vis, np.array(y_vis))

# meshgrid for visualization
x_min, x_max = X_vis[:, 0].min() - 1, X_vis[:, 0].max() + 1
y_min, y_max = X_vis[:, 1].min() - 1, X_vis[:, 1].max() + 1
xx, yy = np.meshgrid(
    np.arange(x_min, x_max, 0.02),
    np.arange(y_min, y_max, 0.02)
)

# predictions
Z_logreg = logreg2d.predict(np.c_[xx.ravel(), yy.ravel()]).reshape(xx.shape)
Z_rf = rf2d.predict(np.c_[xx.ravel(), yy.ravel()]).reshape(xx.shape)

# plot
plt.figure(figsize=(14,6))

# Logistic Regression plot
plt.subplot(1,2,1)
cmap_bg = ListedColormap(['#FFAAAA', '#AAFFAA', '#AAAAFF'])
cmap_pts = ListedColormap(['red', 'green', 'blue'])

plt.contourf(xx, yy, Z_logreg, alpha=0.4, cmap=cmap_bg)
plt.scatter(X_vis[:, 0], X_vis[:, 1], c=np.array(y_vis), cmap=cmap_pts, edgecolor='k', s=80)
plt.title("Logistic Regression Decision Boundary")
plt.xlabel(feature_x)
plt.ylabel(feature_y)

# Random Forest plot
plt.subplot(1,2,2)
```

```
plt.contourf(xx, yy, Z_rf, alpha=0.4, cmap=cmap_bg)
plt.scatter(X_vis[:, 0], X_vis[:, 1], c=np.array(y_vis), cmap=cmap_pts, edgecolor='k', s=80)
plt.title("Random Forest Decision Boundary")
plt.xlabel(feature_x)
plt.ylabel(feature_y)

plt.tight_layout()
plt.show()
```

```
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:1247: FutureWarning: 'multi_class' was deprecated in version 1
  warnings.warn(
```



Accuracy Comparison

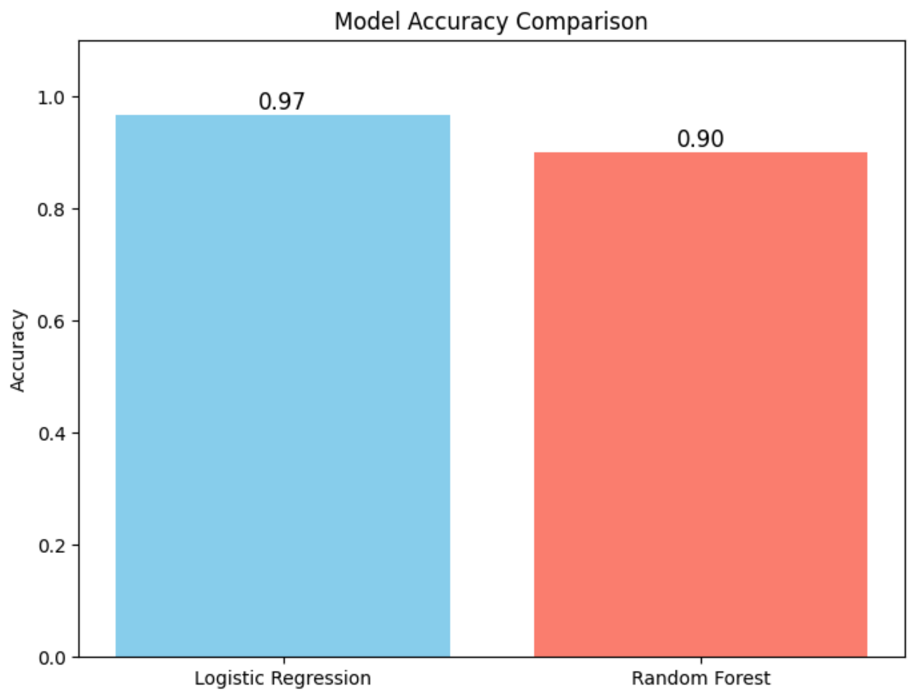
```
# Assuming you already have these
logreg_accuracy = accuracy_score(y_test, logreg.predict(X_test))    # around 97%
rf_accuracy = accuracy_score(y_test, clf.predict(X_test))           # around 90%

# for clarity, print
print(f"Logistic Regression accuracy: {logreg_accuracy:.2f}")
print(f"Random Forest accuracy: {rf_accuracy:.2f}")
```

```
Logistic Regression accuracy: 0.97
Random Forest accuracy: 0.90
```

Plot the bar graph

```
import matplotlib.pyplot as plt

models = ['Logistic Regression', 'Random Forest']
accuracies = [logreg_accuracy, rf_accuracy]

plt.figure(figsize=(8,6))
bars = plt.bar(models, accuracies, color=['skyblue', 'salmon'])

# add data labels
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval + 0.01, f"{yval:.2f}", ha='center', fontsize=12)

plt.ylim(0, 1.1)
plt.ylabel("Accuracy")
plt.title("Model Accuracy Comparison")
```

```
plt.show()
```



✅ Quick Visualization Difference

Random Forest:

builds wiggly, irregular boundaries

great for complicated patterns

Logistic Regression:

draws straight lines

great for simple, clean, linearly separable data