

### 3. STUDY OF CLASSIFIERS WITH RESPECT TO STATISTICAL PARAMETERS.

Aim: TO EVALUATE AND COMPARE PERFORMANCE OF CLASSIFIERS WITH RESPECT TO STATISTICAL PROBLEM

Objectives:

- Load and preprocess Iris dataset
- Apply KNN, Decision tree and SVM classifiers
- Evaluate each model using accuracy, precision, and f-score
- compare the problem of the classifiers using tabular format
- To draw observations and conclude which classifier performs best on dataset.

Pseudocode - KNN.

- INPUT: Training data ( $X_{train}, Y_{train}$ ), Test data ( $X_{test}$ ), k value
- calculate distance from all training points
- Select the k nearest neighbours
- Count class labels among neighbors
- Assign the most frequent label

## Decision Tree

- Input : Training data ( $X_{\text{train}}$ ,  $y_{\text{train}}$ )
- Recursive tree building
  - If data is pure or stopping condition met!
  - Return leaf with class label
- Else
  - Choose best feature
  - Split dataset
  - Recursively build subtree
  - Use the tree to classify test data
- Output : Predicted labels

## SVM :

- Input : Training data ( $X_{\text{train}}$ ,  $y_{\text{train}}$ )
- Train a model:
  - find optimal hyperplane that separates classes
    - use kernel trick if non-linear data
- For each test instance:
  - Predict using the trained model
- Output : Predicted labels

classifier	Accuracy	Precision	Recall	F1-score
KNN	91.2	89.5	90.1	89.8
Decision Tree	88.7	86.4	87.2	86.8
SVM	93.1	91.8	92.5	92.1

### Observations

- \* SVM Consistently delivers the highest performance across all metrics.
- \* KNN performs well but is influenced by the value k and the scaling of features.
- \* Decision Tree provides good results and is easy to interpret but it may overfit on complex or noisy dataset.

~~Mr. Arun Kumar~~

### Result:

Successfully evaluated and compared performance of all three classifier with respect to statistical parameters.

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```
# Import required libraries
import numpy as np
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.metrics import (
    confusion_matrix, accuracy_score, precision_score,
    recall_score, f1_score, roc_curve, roc_auc_score, classification_report
)
from sklearn.linear_model import LogisticRegression
import matplotlib.pyplot as plt

# Load dataset (Iris dataset for example)
data = load_iris()
X = data.data
y = (data.target == 0).astype(int) # Convert to binary classification (class 0 vs others)

# Split dataset into training and test sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42
)

# Train a classifier (Logistic Regression)
clf = LogisticRegression()
clf.fit(X_train, y_train)

# Predictions
y_pred = clf.predict(X_test)
y_prob = clf.predict_proba(X_test)[:, 1] # Probability scores for ROC
```

What can I help you build?

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```
# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n", cm)

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

# Precision
print("Precision:", precision_score(y_test, y_pred))

# Recall
print("Recall:", recall_score(y_test, y_pred))

# F1 Score
print("F1 Score:", f1_score(y_test, y_pred))

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

# ROC & AUC
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
auc = roc_auc_score(y_test, y_prob)
print("AUC:", auc)

# Plot ROC Curve
plt.plot(fpr, tpr, label=f"AUC = {auc:.2f}")
plt.plot([0,1], [0,1], linestyle="--", color="gray")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.show()
```

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```

Confusion Matrix:

[[26 0]
[ 0 19]]

Accuracy: 1.0  
Precision: 1.0  
Recall: 1.0  
F1 Score: 1.0

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	26
1	1.00	1.00	1.00	19
accuracy			1.00	45
macro avg	1.00	1.00	1.00	45
weighted avg	1.00	1.00	1.00	45

AUC: 1.0

