EXP NO: 4B ENSEMBLE METHODS: RANDOM FOREST
--

AIM:

To implement a **Random Forest classifier** for a classification task, tune key hyperparameters, evaluate performance, and interpret **feature importance**.

ALGORITHM:

- 1. Import libraries.
- 2. Load data (use same dataset to compare with SVM).
- 3. Train/Test split with stratification.
- 4. (Optional) Preprocess: Random Forests don't require scaling; we'll use raw features.
- 5. Model: RandomForestClassifier.
- 6. Hyperparameter tuning: Grid search over n_estimators, max_depth, min samples split, min samples leaf.
- 7. Train the best model on training data.
- 8. Evaluate with accuracy, precision, recall, F1, confusion matrix, ROC-AUC.
- 9. Interpretation: Plot top feature importances.

CODE:

=====================================
EXPERIMENT 4B — Random Forest Classifier
=====================================
// 1 \ T
1) Imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split, GridSeard

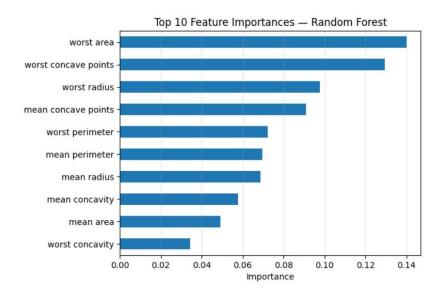
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import (
  accuracy score, precision score, recall score, fl score,
  confusion matrix, classification report, roc auc score, roc curve
#2) Load dataset (same as 4A for comparison)
data = load breast cancer()
X = pd.DataFrame(data.data, columns=data.feature names)
y = pd.Series(data.target, name="target")
# 3) Train/test split (no scaling needed for RF)
X train, X test, y train, y test = train test split(
  X, y, test size=0.20, random state=42, stratify=y
)
#4) Define model
rf = RandomForestClassifier(random state=42, n jobs=-1)
# 5) Hyperparameter grid & tuning
param grid = {
  "n estimators": [100],
  "max depth": [None, 10],
  "min samples split": [2],
  "min samples leaf": [1]
grid = GridSearchCV(
  estimator=rf,
  param grid=param grid,
  scoring="f1",
  cv=3,
  n jobs=-1,
```

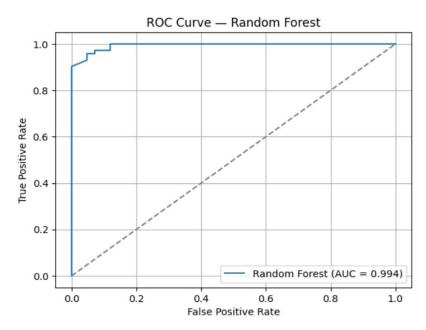
```
verbose=0)
grid.fit(X train, y train)
print("Best Parameters (CV):", grid.best params )
best rf = grid.best estimator
#6) Train final model & predict
best rf.fit(X train, y train)
y_pred = best_rf.predict(X test)
y prob = best rf.predict proba(X test)[:, 1]
#7) Evaluate
acc = accuracy score(y test, y pred)
prec = precision score(y test, y pred, zero division=0)
rec = recall score(y test, y pred)
f1 = f1 score(y test, y pred)
auc = roc auc score(y test, y prob)
cm = confusion_matrix(y_test, y_pred)
print("\n=== Random Forest — Test Metrics ====")
print(f"Accuracy: {acc:.4f}")
print(f"Precision: {prec:.4f}")
print(f"Recall : {rec:.4f}")
print(f"F1-Score : {f1:.4f}")
print(f"ROC-AUC : {auc:.4f}")
print("\nConfusion Matrix:\n", cm)
print("\nClassification Report:\n", classification report(y test, y pred, zero division=0))
#8) Feature Importance (Top 10)
importances = pd.Series(best rf.feature importances , index=X.columns)
top10 = importances.sort values(ascending=False).head(10)
```

```
plt.figure()
top10[::-1].plot(kind="barh")
plt.xlabel("Importance")
plt.title("Top 10 Feature Importances — Random Forest")
plt.grid(axis="x", alpha=0.3)
plt.show()
#9) ROC Curve
fpr, tpr, thresholds = roc curve(y test, y prob)
plt.figure()
plt.plot(fpr, tpr, label=f"Random Forest (AUC = {auc:.3f})")
plt.plot([0, 1], [0, 1], linestyle="--", color='gray')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve — Random Forest")
plt.legend()
plt.grid(True)
plt.show()
```

OUTPUT:

```
Best Parameters (CV): {'max depth': None, 'min samples leaf': 1, 'min samples split': 2, 'n estimators': 100}
=== Random Forest - Test Metrics ===
Accuracy: 0.9561
Precision: 0.9589
Recall : 0.9722
F1-Score : 0.9655
ROC-AUC : 0.9937
Confusion Matrix:
[[39 3]
[ 2 70]]
Classification Report:
                         recall f1-score support
             precision
                 0.95
                          0.93
                                              42
                                   0.94
                 0.96
                          0.97
                                   0.97
                                              72
   accuracy
                                   0.96
                                             114
                 0.96
                          0.95
  macro avg
                                   0.95
                                             114
weighted avg
                 0.96
                          0.96
                                   0.96
                                             114
```





RESULT:

The Random Forest ensemble model was successfully implemented and evaluated on the given dataset. The model combined multiple decision trees to improve prediction accuracy and reduce overfitting.

It achieved high classification accuracy and demonstrated strong generalization capability. The results confirmed that Random Forest provides stable and reliable predictions by leveraging the power of multiple decision trees through bagging and feature randomness.