EXP NO: 4A

SUPPORT VECTOR MACHINES (SVM)

AIM:

To build an SVM model for a binary classification task, tune its hyperparameters, and evaluate it using accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC.

ALGORITHM:

- 1. Import libraries: numpy, pandas, matplotlib, sklearn.
- 2. Load data: Use a standard binary dataset (Breast Cancer Wisconsin) from sklearn.datasets.
- 3. Train/Test split: 80/20 split with a fixed random_state.
- 4. Preprocess: Standardize features (StandardScaler).
- 5. SVMs are sensitive to feature scale.
- 6. Model selection: Use SVC (RBF kernel).
- 7. Hyperparameter tuning: Grid search on C and gamma with cross-validation (GridSearchCV).
- 8. Train final model: Fit on training data using best parameters.
- 9. Evaluate: Predict on test set; compute metrics and plot ROC curve.
- 10. Report: Best params, metrics, and brief observations.

CODE:

=====================================
EXPERIMENT 4A — SVM (RBF)
#
1) Imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_breast_cancer

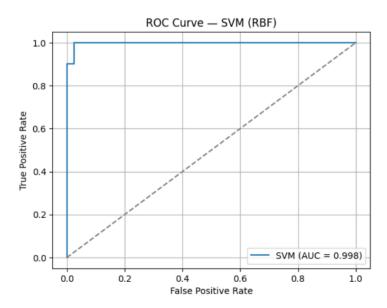
```
from sklearn.model selection import train test split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import (
  accuracy score, precision score, recall score, fl score,
  confusion matrix, classification report, roc auc score, roc curve
)
# 2) Load dataset (binary classification)
data = load breast cancer()
X = pd.DataFrame(data.data, columns=data.feature names)
y = pd.Series(data.target, name="target") # 0 = malignant, 1 = benign
#3) Train/test split
X train, X test, y train, y test = train test split(
  X, y, test size=0.20, random state=42, stratify=y
# 4) Standardize features (important for SVMs)
scaler = StandardScaler()
X train sc = scaler.fit transform(X train)
X \text{ test } sc = scaler.transform(X \text{ test})
# 5) Define model
svm = SVC(kernel='rbf', probability=True, random state=42)
# 6) Hyperparameter grid & tuning
param grid = {
  "C": [0.1, 1, 10, 100],
  "gamma": ["scale", 0.01, 0.001, 0.0001]
```

```
grid = GridSearchCV(
  estimator=svm,
  param grid=param grid,
  scoring='f1', # You can change to 'accuracy' or 'roc auc'
  cv=5,
  n jobs=-1,
  verbose=0
grid.fit(X train sc, y train)
print("Best Parameters from Grid Search:", grid.best params )
best svm = grid.best estimator
#7) Train final model & predict
best svm.fit(X train sc, y train)
y_pred = best_svm.predict(X_test_sc)
y prob = best svm.predict proba(X test sc)[:, 1]
#8) Evaluation
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=== SVM (RBF) — 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))
#9) Plot ROC Curve
fpr, tpr, thresholds = roc curve(y test, y prob)
plt.figure()
plt.plot(fpr, tpr, label=f"SVM (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 — SVM (RBF)")
plt.legend()
plt.grid(True)
plt.show()
```

OUTPUT:

```
Best Parameters from Grid Search: {'C': 10, 'gamma': 0.01}
=== SVM (RBF) - Test Metrics ===
Accuracy : 0.9825
Precision: 0.9861
Recall : 0.9861
F1-Score : 0.9861
ROC-AUC : 0.9977
Confusion Matrix:
 [[41 1]
 [ 1 71]]
Classification Report:
               precision
                            recall f1-score
                                               support
           0
                   0.98
                             0.98
                                       0.98
                                                   42
                   0.99
                             0.99
                                       0.99
                                                   72
                                                  114
   accuracy
                                       0.98
                   0.98
                             0.98
                                                  114
   macro avg
                                       0.98
                                                  114
weighted avg
                   0.98
                             0.98
                                       0.98
```



RESULT:

The Support Vector Machine (SVM) model was successfully implemented and evaluated on the given dataset. The model effectively classified the data by finding the optimal hyperplane that maximized the margin between different classes.

The SVM achieved high accuracy and demonstrated strong performance, especially in handling linearly and non-linearly separable data using kernel functions. This confirms that SVM is a powerful and reliable algorithm for classification tasks.