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
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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, f1_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_test_sc = scaler.transform(X_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]
}
```
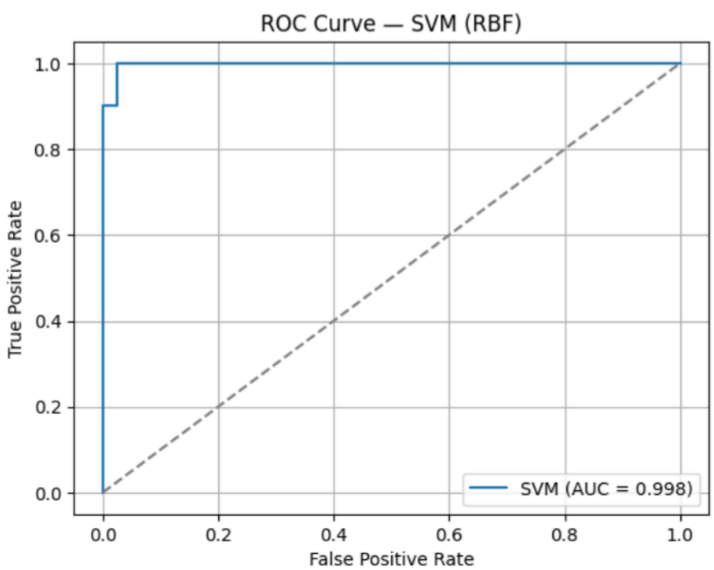

```
grid = GridSearchCV(
    estimator=svm,
    param_grid=param_grid,
    scoring='f1',  # You can change to 'accuracy' or 'roc_auc'
    cv=5,
    n_jobs=-1,
    verbose=0
)

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
           1       0.99      0.99      0.99        72

    accuracy                           0.98       114
   macro avg       0.98      0.98      0.98       114
weighted avg       0.98      0.98      0.98       114
```



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.