

## #Breast Cancer Classification using SVM

### ##Objective

To build and evaluate a Support Vector Machine (SVM) model to classify breast cancer tumors as Benign or Malignant using the Breast Cancer dataset from Scikit-learn.

### ##Problem Statement

Early detection of breast cancer is critical. This task uses machine learning to classify tumors based on medical features. SVM is chosen because it performs well on high-dimensional data and binary classification problems.

### ##Dataset Details

- Dataset Source: `sklearn.datasets.load_breast_cancer`
- Total Samples: 569
- Features: 30 numerical features
- Target Variable:
  - 0 → Malignant
  - 1 → Benign

### ##Tools & Libraries Used

- Python
- NumPy
- Pandas
- Scikit-learn
- Matplotlib
- Jupyter Notebook

### ##Step-by-Step Procedure

#### 1. Load the Dataset

The breast cancer dataset is loaded using Scikit-learn and split into features (X) and target (y).

#### 2. Data Preprocessing

- Checked dataset shape and target distribution
- Applied StandardScaler to normalize feature values

#### 3. Train-Test Split

The dataset is split into:

- 80% Training data
- 20% Testing data

#### 4. Train SVM (Linear Kernel)

A baseline SVM model with a linear kernel is trained and evaluated.

#### 5. Train SVM (RBF Kernel)

An SVM model with RBF kernel is trained to capture non-linear patterns.

#### 6. Hyperparameter Tuning

GridSearchCV is used to find optimal values for:

- C (Regularization parameter)
- Gamma (Kernel coefficient)

## 7. Model Evaluation

The best model is evaluated using:

- Accuracy Score
- Confusion Matrix
- Classification Report
- ROC Curve and AUC Score

### ##Results

- RBF kernel outperformed linear kernel
- Achieved high accuracy (above 95%)
- ROC-AUC score indicated strong classification performance

### ##Files Included

- SVM\_Breast\_Cancer.ipynb – Implementation Notebook
- README.md – Project Documentation

### ##Conclusion

This task demonstrates the effectiveness of Support Vector Machines in medical diagnosis problems. Proper feature scaling and hyperparameter tuning significantly improve model performance.