Experiment No. 4

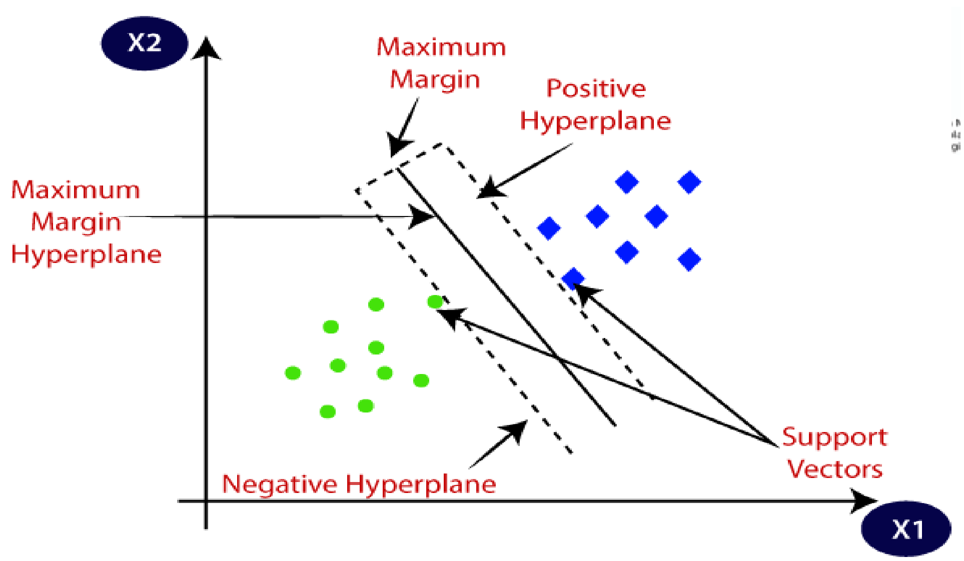
Aim: Implementation of Support Vector Machine Algorithm.

Objective: Ablility to perform various feature engineering tasks, apply Support Vector Machine and create the Confusion Matrix.

Theory:

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:



<u>Hyperplane and Support Vectors in the SVM algorithm:</u>

Hyperplane: There can be multiple lines/decision boundaries to segregate the classes in n-dimensional space, but we need to find out the best decision boundary that helps to classify the data points. This best boundary is known as the hyperplane of SVM.

The dimensions of the hyperplane depend on the features present in the dataset, which means if there are 2 features (as shown in image), then hyperplane will be a straight line. And if there are 3 features, then hyperplane will be a 2-dimension plane.

We always create a hyperplane that has a maximum margin, which means the maximum distance between the data points.

Support Vectors:
The data points or vectors that are the closest to the hyperplane and which affect the position of the hyperplane are termed as Support Vector. Since these vectors support the hyperplane, hence called a Support vector.

Implementation of Support Vector Machine

1. Data Pre-processing step
2. Fitting the SVM classifier to the training set
3. Predicting the test set result
4. Creating the confusion matrix
5. Visualizing the training set result
6. Visualizing the test set result

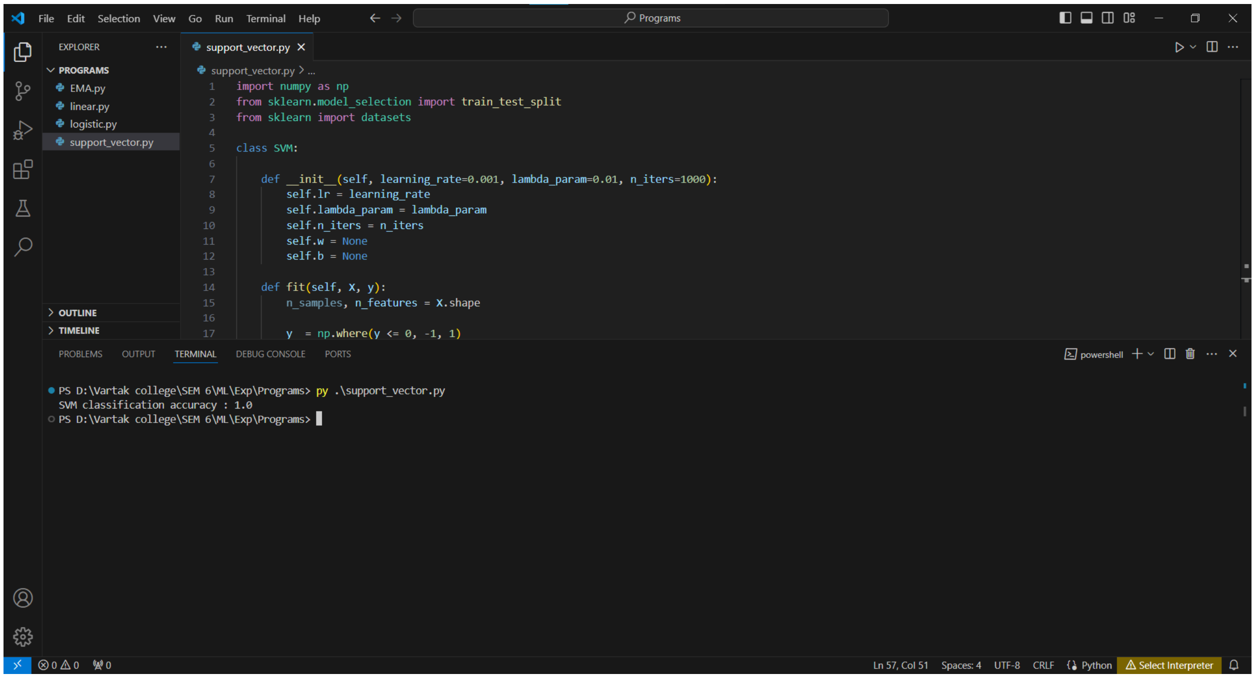
Implementation:

Support Vector Machines:

```
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn import datasets
class SVM:
    def __init__(self, learning_rate=0.001, lambda_param=0.01, n_iters=1000):
        self.lr = learning_rate
        self.lambda_param = lambda_param
        self.n_iters = n_iters
        self.w = None
        self.b = None
    def fit(self, X, y):
        n_samples, n_features = X.shape
        y_ = np.where(y <= 0, -1, 1)
        # Weights Initialization
        self.w = np.zeros(n_features)
```

```
        self.b = 0
        for _ in range(self.n_iters):
            for idx, x_i in enumerate(X):
                condition = y_[idx] * (np.dot(x_i, self.w) - self.b) >= 1
                if condition:
                    self.w -= self.lr * (2 * self.lambda_param * self.w)
                else:
                    self.w -= self.lr * (2 * self.lambda_param * self.w - np.dot(x_i, y_[idx]))
                    self.b -= self.lr * y_[idx]
    def predict(self, X):
        approx = np.dot(X, self.w) - self.b
        return np.sign(approx)
if __name__ == "__main__":
    X, y = datasets.make_blobs(
        n_samples=50, n_features=2, centers=2, cluster_std=1.05, random_state=40
    )
    y = np.where(y == 0, -1, 1)
    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=0.2, random_state=123
    )
    clf = SVM()
    clf.fit(X_train, y_train)
    predictions = clf.predict(X_test)
    def accuracy(y_true, y_pred):
        accuracy = np.sum(y_true == y_pred) / len(y_true)
        return accuracy
    print(f"SVM classification accuracy : {accuracy(y_test, predictions)}")
```

Output:



Conclusion:

Support Vector Machine (SVM) is a powerful algorithm for classification tasks, aiming to create the best decision boundary or hyperplane to segregate data points into classes. By selecting support vectors, SVM maximizes the margin between classes, enhancing robustness and generalization. The implementation of SVM involves preprocessing data, fitting the classifier to the training set, predicting test set results, and creating a confusion matrix to evaluate performance. SVM demonstrates high accuracy in classifying data points, making it a valuable tool in machine learning.