```python
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report, confusion_matrix


# Defining SVM class
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
        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]

    # Sigmoid function
    def predict(self, X):
        approximation = np.vectorize(lambda x: 1 / (1 + np.exp(-x)))
        return approximation(np.dot(X, self.w) - self.b)

    def predict_class(self, X):
      return np.where(self.predict(X) >= 0.5, 1, -1)


# Generate random sample data
np.random.seed(42)

# Class -1
X_neg = np.random.randn(25, 2) - 2
y_neg = -1 * np.ones(25)

# Class 1
X_pos = np.random.randn(25, 2) + 2
y_pos = np.ones(25)

# Combining the data
X = np.vstack((X_neg, X_pos))
y = np.hstack((y_neg, y_pos))


# Adding noise by flipping the labels of a few points
noise_factor = 0.05  # 10% noise
num_noisy_points = int(noise_factor * len(y))
noisy_indices = np.random.choice(len(y), size=num_noisy_points, replace=False)
y[noisy_indices] = -y[noisy_indices]


# Train the SVM model
svm = SVM()
svm.fit(X, y)


# Making predictions
predictions = svm.predict_class(X)

# Classification report
print("Classification Report:")
print(classification_report(y, predictions))
```

```
Classification Report:
              precision    recall  f1-score   support

        -1.0       0.92      1.00      0.96        23
         1.0       1.00      0.93      0.96        27
```

```
    accuracy                           0.96        50
   macro avg       0.96      0.96      0.96        50
weighted avg       0.96      0.96      0.96        50
```

```
# confusion matrix
print("Confusion Matrix:")
print(confusion_matrix(y, predictions))
```

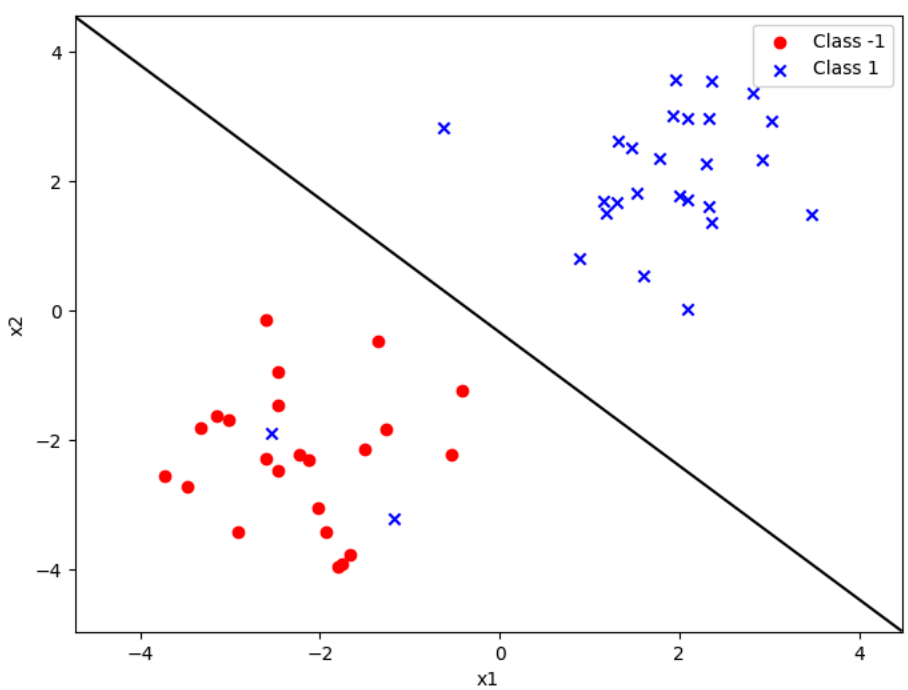
```
Confusion Matrix:
[[23  0]
 [ 2 25]]
```

```
# Extracting data for plotting
x1 = X[:, 0]
x2 = X[:, 1]

# Create a figure and scatter plot the data points
plt.figure(figsize=(8, 6))
plt.scatter(x1[y == -1], x2[y == -1], color='red', marker='o', label='Class -1')
plt.scatter(x1[y == 1], x2[y == 1], color='blue', marker='x', label='Class 1')

# Plot the decision boundary
x1_min, x1_max = X[:, 0].min() - 1, X[:, 0].max() + 1
x2_min, x2_max = X[:, 1].min() - 1, X[:, 1].max() + 1
xx1, xx2 = np.meshgrid(np.arange(x1_min, x1_max, 0.01), np.arange(x2_min, x2_max, 0.01))
Z = svm.predict(np.c_[xx1.ravel(), xx2.ravel()])
Z = Z.reshape(xx1.shape)
plt.contour(xx1, xx2, Z, levels=[0.5], colors='k', linestyles='-')

plt.xlabel('x1')
plt.ylabel('x2')
plt.legend()
plt.show()
```



Report: SVM

Introduction:

This report presents the implementation of a Support Vector Machine (SVM) classifier with a sigmoid decision boundary for a binary classification problem. The SVM is designed to classify a generated dataset into two classes and is evaluated using common performance metrics such as the classification report and confusion matrix. Additionally, the decision boundary is visualized to provide a graphical representation of the classifier's performance.

Dataset:

The dataset consists of 50 data points, 25 from class -1 and 25 from class 1. The data points for class -1 are generated using 'np.random.randn (25, 2) - 2', and the data points for class 1 are generated using 'np.random.randn(25, 2) + 2'. Additionally, 5% of the data points have their labels flipped to introduce noise in the dataset.

SVM Classifier:

The SVM classifier is implemented using the 'SVM' class, which has '__init__', 'fit', 'predict', and 'predict_class' methods. The 'fit' method updates the weights ('self.w') and the bias ('self.b') of the SVM model using the gradient descent optimization.

The 'predict' method uses the sigmoid function to compute the probability of a data point belonging to class 1. The 'predict_class' method classifies the data points based on the sigmoid output, assigning 1 for values greater than or equal to 0.5, and -1 for values less than 0.5.

Results: Classification Report:

class	precision	recall	f1-score	support
-1.0	0.92	1.00	0.96	23
1.0	1.00	0.93	0.96	27
accuracy			0.96	50
macro avg	0.96	0.96	0.96	50
weighted avg	0.96	0.96	0.96	50

Visualization: The code generates a scatter plot of the data points, where the data points from class -1 are plotted in red and the data points from class 1 are plotted in blue. The decision boundary of the SVM classifier is plotted using the ‘contour’ function, showing a non-linear separation between the two classes.

Conclusion:

Overall, the SVM classifier is performing well on the provided dataset, with an accuracy of 96% and good precision, recall, and F1-score for both classes. The confusion matrix shows that the classifier is correctly classifying most of the data points, with only a few misclassifications.