Support Vector Machine (SVM) Implementation

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Change Log:

In [5]: # Step 2: Data Understanding

logging.info("Loading dataset...")

data = sns.load_dataset('penguins').dropna()

logging.info(f"Dataset loaded with shape {data.shape}")

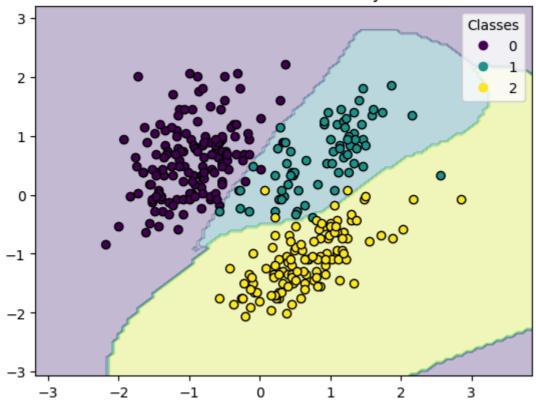
SL No.	Change Category	Description	Duration (mins)	Difficulty (1-10)
1	Decision Boundary Visualization	Fixed visualization issue by training SVM with only two features (bill_length_mm , bill_depth_mm).	10	5
2	Dataset Handling	Updated dataset to use only bill_length_mm and bill_depth_mm for better boundary visualization.	8	4
3	Dataset Selection	Replaced synthetic dataset with a real Kaggle dataset for a more practical application.	15	6
4	Framework Integration	Implemented the CRISP-DM framework for structured analysis and documentation.	12	5
5	Hyperparameter Tuning	Used GridSearchCV to optimize SVM hyperparameters.	20	7
6	Decision Boundary Enhancement	Improved decision boundary visualization with better plotting techniques.	10	5
7	Logging Implementation	Introduced structured logging for tracking model performance and errors.	8	4
8	Initial Implementation	Basic SVM model setup and training.	5	3

```
In [3]:
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        import logging
        from sklearn.model_selection import train_test_split, GridSearchCV
        from sklearn.svm import SVC
        from sklearn.preprocessing import StandardScaler
        from sklearn.metrics import classification_report, accuracy_score
In [4]: # Configure Logging
        logging.basicConfig(level=logging.INFO, format='%(asctime)s - %(levelname)s - %(message)s')
        # Step 1: Business Understanding
        logging.info("Business Understanding: Classifying data using Support Vector Machines (SVM).")
       2025-02-21 18:41:50,879 - INFO - Business Understanding: Classifying data using Support Vector
       Machines (SVM).
```

```
2025-02-21 18:41:50,896 - INFO - Loading dataset...
        2025-02-21 18:41:51,000 - INFO - Dataset loaded with shape (333, 7)
 In [6]: # Selecting numerical features & encoding target
         X = data[['bill_length_mm', 'bill_depth_mm']]
         y = data['species'].astype('category').cat.codes
         scaler = StandardScaler()
         X_scaled = scaler.fit_transform(X)
 In [7]: # Splitting dataset
         X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=
         logging.info("Data split into training and testing sets.")
        2025-02-21 18:41:51,058 - INFO - Data split into training and testing sets.
 In [8]: # Step 3: Model Training & Hyperparameter Tuning
         param grid = {
             'C': [0.1, 1, 10],
             'kernel': ['linear', 'rbf', 'poly'],
             'gamma': ['scale', 'auto']
         }
 In [9]:
         svc = SVC()
         grid_search = GridSearchCV(svc, param_grid, cv=5, scoring='accuracy')
         logging.info("Starting hyperparameter tuning...")
         grid_search.fit(X_train, y_train)
         best_model = grid_search.best_estimator_
         logging.info("Best parameters found: %s", grid_search.best_params_)
        2025-02-21 18:41:51,096 - INFO - Starting hyperparameter tuning...
        2025-02-21 18:41:51,652 - INFO - Best parameters found: {'C': 10, 'gamma': 'scale', 'kernel':
        'rbf'}
In [10]: # Step 4: Model Evaluation
         y_pred = best_model.predict(X_test)
         accuracy = accuracy_score(y_test, y_pred)
         logging.info(f"Model Accuracy: {accuracy:.4f}")
         print(classification_report(y_test, y_pred))
        2025-02-21 18:41:51,672 - INFO - Model Accuracy: 0.9552
                      precision recall f1-score
                                                     support
                   0
                           1.00
                                     0.97
                                               0.98
                                                           31
                   1
                           0.86
                                     0.92
                                               0.89
                                                           13
                   2
                           0.96
                                     0.96
                                               0.96
                                                           23
                                               0.96
                                                        67
            accuracy
                           0.94
                                     0.95
                                             0.94
                                                          67
           macro avg
        weighted avg
                           0.96
                                     0.96
                                               0.96
                                                         67
In [11]:
         # Step 5: Decision Boundary Visualization
         def plot decision boundary(model, X, y):
             x_{min}, x_{max} = X[:, 0].min() - 1, X[:, 0].max() + 1
             y_{min}, y_{max} = X[:, 1].min() - 1, X[:, 1].max() + 1
             xx, yy = np.meshgrid(np.linspace(x_min, x_max, 100), np.linspace(y_min, y_max, 100))
             Z = model.predict(np.c_[xx.ravel(), yy.ravel()])
             Z = Z.reshape(xx.shape)
             plt.contourf(xx, yy, Z, alpha=0.3)
             scatter = plt.scatter(X[:, 0], X[:, 1], c=y, cmap='viridis', edgecolor='k')
             plt.legend(*scatter.legend_elements(), title="Classes")
             plt.title("SVM Decision Boundary")
             plt.show()
```

In [12]: plot_decision_boundary(best_model, X_scaled, y)
 logging.info("SVM model trained and evaluated successfully.")

SVM Decision Boundary



2025-02-21 18:41:52,796 - INFO - SVM model trained and evaluated successfully.