data_mining_assignment2

October 29, 2024

1 Assignment 2

1.1 Data Management Class for Edge Histograms

[65]:
```
import os
import warnings
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import (
    accuracy_score,
    classification_report,
    confusion_matrix,
    f1_score,
)
from sklearn.model_selection import StratifiedKFold, cross_val_score,␣
 ↪train_test_split
from sklearn.neural_network import MLPClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.svm import LinearSVC
from sklearn.tree import DecisionTreeClassifier

warnings.filterwarnings("ignore")


class DataLoader:
    def __init__(self, edge_histograms_dir="./EdgeHistograms"):
        self.edge_histograms_dir = edge_histograms_dir
        self.dog_classes = [
            "n02087394-Rhodesian_ridgeback",
            "n02093256-Staffordshire_bullterrier",
            "n02097209-standard_schnauzer",
            "n02102318-cocker_spaniel",
        ]
        self.dog_labels = [
            "Rhodesian Ridgeback",
            "Staffordshire Bullterrier",
```

```
            "Standard Schnauzer",
            "Cocker Spaniel",
        ]
        self.X = []
        self.y = []

    def load_data(self):
        for dog_class in self.dog_classes:
            class_dir = os.path.join(self.edge_histograms_dir, dog_class)
            if not os.path.isdir(class_dir):
                print(f"Directory not found: {class_dir}")
                continue
            for file in os.listdir(class_dir):
                if file.endswith(".npy"):
                    histogram_path = os.path.join(class_dir, file)
                    hist = np.load(histogram_path)
                    self.X.append(hist)
                    self.y.append(dog_class)

        self.X = np.array(self.X)
        self.y = np.array(self.y)

        return self.X, self.y
```

1.2 Data Preprocessing Class

[66]:
```
class DataPreprocessor:
    def __init__(self, test_size=0.2, random_state=42):
        self.test_size = test_size
        self.random_state = random_state
        self.scaler = StandardScaler()

    def split_and_scale(self, X, y):
        X_train, X_test, y_train, y_test = train_test_split(
            X, y, test_size=self.test_size, random_state=self.random_state,␣
↪stratify=y
        )

        X_train_scaled = self.scaler.fit_transform(X_train)
        X_test_scaled = self.scaler.transform(X_test)

        return X_train_scaled, X_test_scaled, y_train, y_test
```

1.3 Model Evaluation Class

[67]:
```python
class ModelEvaluator:
    def __init__(self, dog_classes, dog_labels):
        self.dog_classes = dog_classes
        self.dog_labels = dog_labels

    def perform_cross_validation(self, model, X, y, cv=5):
        skf = StratifiedKFold(n_splits=cv, shuffle=True, random_state=42)
        scores = cross_val_score(model, X, y, cv=skf, scoring="accuracy")
        return scores.mean()

    def plot_confusion_matrix(self, y_true, y_pred, title):
        cm = confusion_matrix(y_true, y_pred, labels=self.dog_classes)
        plt.figure(figsize=(8, 6))
        sns.heatmap(
            cm,
            annot=True,
            fmt="d",
            cmap="Blues",
            xticklabels=self.dog_labels,
            yticklabels=self.dog_labels,
        )
        plt.xlabel("Predicted")
        plt.ylabel("True")
        plt.title(title)
        plt.show()

    def evaluate_model(self, model, X_train, y_train, X_test, y_test,␣
↪model_name):
        # Cross-validation
        cv_score = self.perform_cross_validation(model, X_train, y_train)
        print(f"{model_name} Mean CV Accuracy: {cv_score:.4f}")

        # Fit and predict
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)

        # Plot confusion matrix
        self.plot_confusion_matrix(y_test, y_pred, f"{model_name} Confusion␣
↪Matrix")

        # Calculate metrics
        accuracy = accuracy_score(y_test, y_pred)
        f1 = f1_score(y_test, y_pred, average="weighted")

        print(f"\n{model_name} Test Accuracy: {accuracy:.4f}")
```

```
        print(f"{model_name} Test F1-Score: {f1:.4f}")
        print(f"\n{model_name} Classification Report:")
        print(classification_report(y_test, y_pred, target_names=self.
↪dog_classes))

        return accuracy, f1, cv_score
```

1.4 SVM Model Selection Class

[68]:
```
class SVMModelSelector:
    def __init__(self, C_values=[0.1, 1, 10, 100]):
        self.C_values = C_values

    def perform_cv_analysis(self, X_train, y_train):
        validation_errors_standard = []
        training_errors_standard = []
        validation_errors_stratified = []
        training_errors_stratified = []

        # Standard CV
        for C in self.C_values:
            svm = LinearSVC(C=C, max_iter=1000, random_state=42)

            scores = cross_val_score(svm, X_train, y_train, cv=5,␣
↪scoring="accuracy")
            validation_errors_standard.append(1 - scores.mean())

            svm.fit(X_train, y_train)
            train_pred = svm.predict(X_train)
            training_errors_standard.append(1 - accuracy_score(y_train,␣
↪train_pred))

        # Stratified CV
        skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
        for C in self.C_values:
            svm = LinearSVC(C=C, max_iter=1000, random_state=42)

            scores = cross_val_score(svm, X_train, y_train, cv=skf,␣
↪scoring="accuracy")
            validation_errors_stratified.append(1 - scores.mean())

            svm.fit(X_train, y_train)
            train_pred = svm.predict(X_train)
            training_errors_stratified.append(1 - accuracy_score(y_train,␣
↪train_pred))

        return (
```

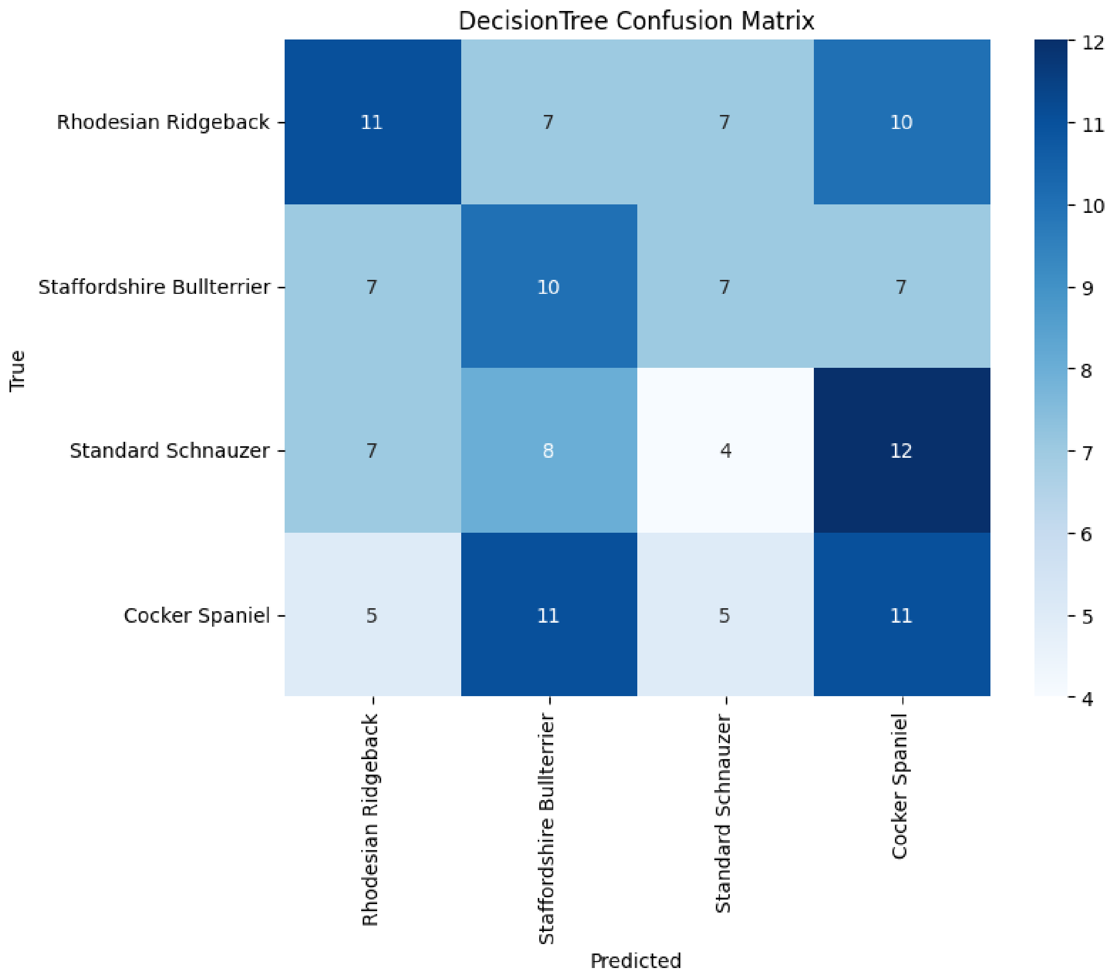
```
            validation_errors_standard,
            training_errors_standard,
            validation_errors_stratified,
            training_errors_stratified,
        )

    def plot_error_curves(self, errors):
        val_std, train_std, val_strat, train_strat = errors
        plt.figure(figsize=(10, 6))
        plt.plot(
            self.C_values,
            np.array(val_std) * 100,
            marker="o",
            label="Validation Error (Standard CV)",
        )
        plt.plot(
            self.C_values,
            np.array(train_std) * 100,
            marker="o",
            label="Training Error (Standard CV)",
        )
        plt.plot(
            self.C_values,
            np.array(val_strat) * 100,
            marker="s",
            label="Validation Error (Stratified CV)",
        )
        plt.plot(
            self.C_values,
            np.array(train_strat) * 100,
            marker="s",
            label="Training Error (Stratified CV)",
        )
        plt.xlabel("C")
        plt.ylabel("Mean Error (%)")
        plt.title("Error Rates vs C for LinearSVC")
        plt.legend()
        plt.grid(True)
        plt.show()
```

1.5 Main Execution

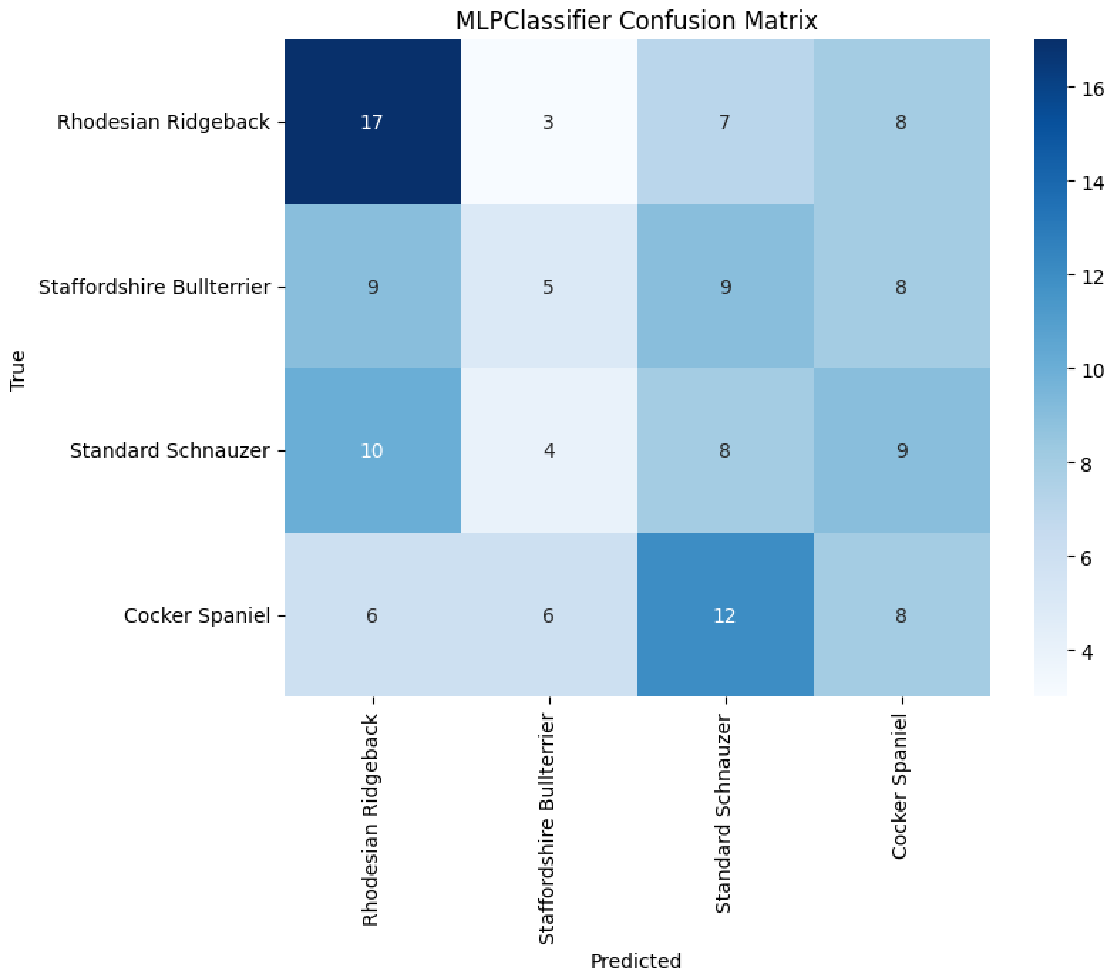
[69]:
```
# Initialize and load data
data_loader = DataLoader()
X, y = data_loader.load_data()
print(f"Total samples: {X.shape[0]}")
print(f"Feature dimension: {X.shape[1]}")
```

```python
print(f"Classes: {np.unique(y)}")

# Preprocess data
preprocessor = DataPreprocessor()
X_train_scaled, X_test_scaled, y_train, y_test = preprocessor.
  ↪split_and_scale(X, y)
print(f"\nTraining samples: {X_train_scaled.shape[0]}")
print(f"Test samples: {X_test_scaled.shape[0]}")

# Initialize models
models = {
    "DecisionTree": DecisionTreeClassifier(max_depth=10, random_state=42),
    "MLPClassifier": MLPClassifier(hidden_layer_sizes=(10, 10, 10),␣
  ↪random_state=42),
    "RandomForest": RandomForestClassifier(random_state=42),
}

# Evaluate models
evaluator = ModelEvaluator(data_loader.dog_classes, data_loader.dog_labels)
results = {}
for name, model in models.items():
    results[name] = evaluator.evaluate_model(
        model, X_train_scaled, y_train, X_test_scaled, y_test, name
    )
```

```
Total samples: 641
Feature dimension: 36
Classes: ['n02087394-Rhodesian_ridgeback' 'n02093256-Staffordshire_bullterrier'
 'n02097209-standard_schnauzer' 'n02102318-cocker_spaniel']

Training samples: 512
Test samples: 129
DecisionTree Mean CV Accuracy: 0.3030
```




```
DecisionTree Test Accuracy: 0.2791
DecisionTree Test F1-Score: 0.2750

DecisionTree Classification Report:
                                      precision    recall  f1-score   support

      n02087394-Rhodesian_ridgeback        0.37      0.31      0.34        35
n02093256-Staffordshire_bullterrier        0.28      0.32      0.30        31
       n02097209-standard_schnauzer        0.17      0.13      0.15        31
           n02102318-cocker_spaniel        0.28      0.34      0.31        32

                           accuracy                            0.28       129
                          macro avg        0.27      0.28      0.27       129
                       weighted avg        0.28      0.28      0.27       129

MLPClassifier Mean CV Accuracy: 0.4023
```

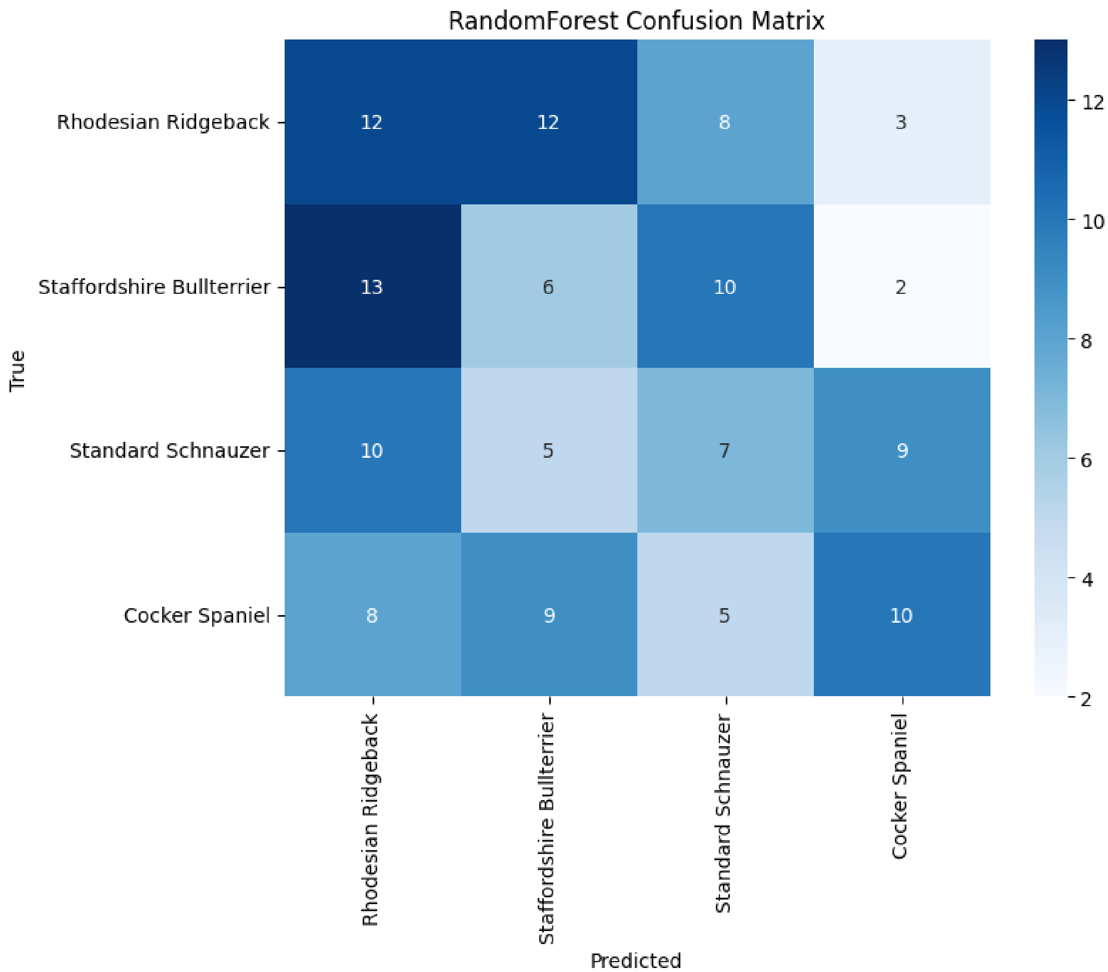


MLPClassifier Test Accuracy: 0.2946
MLPClassifier Test F1-Score: 0.2873

MLPClassifier Classification Report:

	precision	recall	f1-score	support
n02087394-Rhodesian_ridgeback	0.40	0.49	0.44	35
n02093256-Staffordshire_bullterrier	0.28	0.16	0.20	31
n02097209-standard_schnauzer	0.22	0.26	0.24	31
n02102318-cocker_spaniel	0.24	0.25	0.25	32
accuracy			0.29	129
macro avg	0.29	0.29	0.28	129
weighted avg	0.29	0.29	0.29	129

RandomForest Mean CV Accuracy: 0.3615




```
RandomForest Test Accuracy: 0.2730
```

RandomForest Test Accuracy: 0.2713
RandomForest Test F1-Score: 0.2730

RandomForest Classification Report:

	precision	recall	f1-score	support
n02087394-Rhodesian_ridgeback	0.28	0.34	0.31	35
n02093256-Staffordshire_bullterrier	0.19	0.19	0.19	31
n02097209-standard_schnauzer	0.23	0.23	0.23	31
n02102318-cocker_spaniel	0.42	0.31	0.36	32
accuracy			0.27	129
macro avg	0.28	0.27	0.27	129
weighted avg	0.28	0.27	0.27	129

1.6 Visual Comparison of Confusion Matrices

Based on visual inspection of the confusion matrices, the **MLPClassifier** appears to be the best method because:

- It shows darker blue colors along the diagonal, particularly for Rhodesian Ridgeback (17 correct predictions)
- The off-diagonal values (misclassifications) are generally lighter in color
- More consistent diagonal pattern indicating better class-wise predictions
- Better balance in predictions across classes compared to other methods

1.7 Best Method Based on Mean Validation Accuracies

Looking at the 5-fold cross-validation accuracies:

- DecisionTree: 0.3030
- MLPClassifier: 0.4023
- RandomForest: 0.3615

The **MLPClassifier** performs best with a mean validation accuracy of 40.23%.

1.8 Best Method Based on Test Set Accuracies

Test accuracies for each method:

- DecisionTree: 0.2791 (27.91%)
- MLPClassifier: 0.2946 (29.46%)
- RandomForest: 0.2713 (27.13%)

The **MLPClassifier** achieves the highest test accuracy at 29.46%.

1.9 Best Method Based on F-measure

F-measure scores on the test set:

- DecisionTree: 0.2750
- MLPClassifier: 0.2873
- RandomForest: 0.2730

The **MLPClassifier** again performs best with an F-measure of 0.2873.

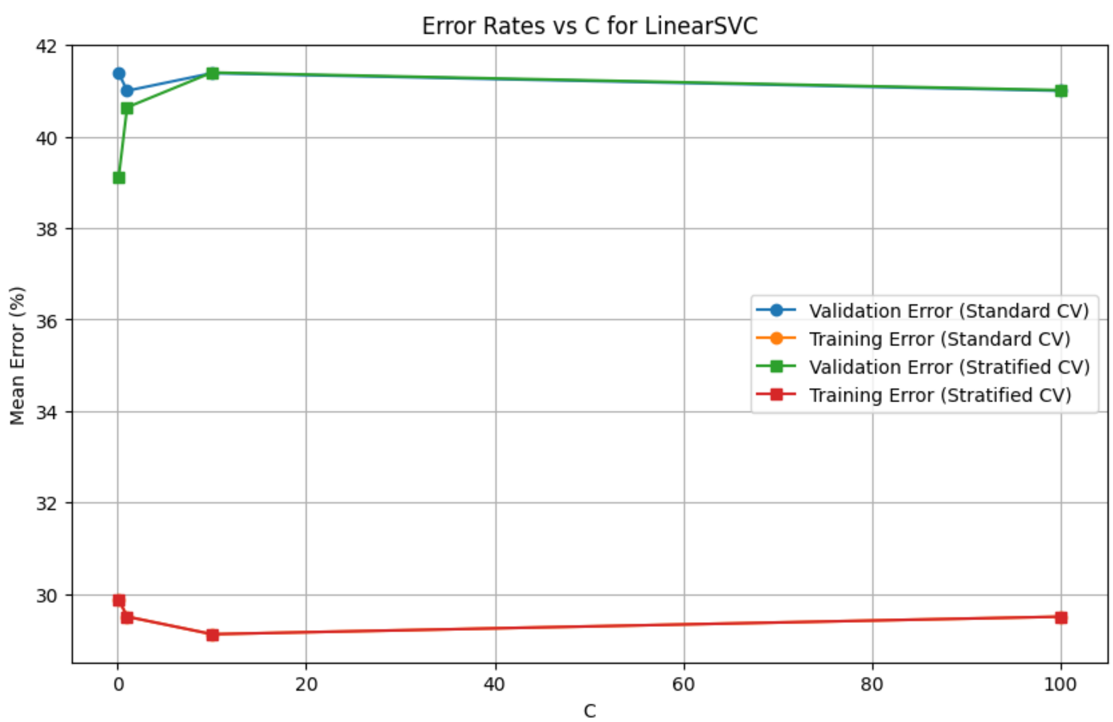
Overall Conclusion: The MLPClassifier consistently performs best across all evaluation metrics (visual confusion matrix analysis, mean validation accuracy, test accuracy, and F-measure), though it's worth noting that all models show relatively low performance overall, suggesting this is a challenging classification task.

1.10 SVM Analysis for Two Classes

[70]:
```
# Select two classes
selected_classes = data_loader.dog_classes[:2]
mask_train = np.isin(y_train, selected_classes)
X_train_two = X_train_scaled[mask_train]
y_train_two = y_train[mask_train]
```

```python
mask_test = np.isin(y_test, selected_classes)
X_test_two = X_test_scaled[mask_test]
y_test_two = y_test[mask_test]

print(f"Selected Classes Training samples: {X_train_two.shape[0]}")
print(f"Selected Classes Test samples: {X_test_two.shape[0]}")

# Perform SVM analysis
svm_selector = SVMModelSelector()
error_curves = svm_selector.perform_cv_analysis(X_train_two, y_train_two)
svm_selector.plot_error_curves(error_curves)

# Find best C value and evaluate final model
best_C_index = np.argmin(error_curves[2])  # Using stratified validation errors
best_C = svm_selector.C_values[best_C_index]
print(f"\nBest C value (lowest stratified validation error): {best_C}")

final_svm = LinearSVC(C=best_C, max_iter=1000, random_state=42)
final_svm.fit(X_train_two, y_train_two)
test_pred = final_svm.predict(X_test_two)
test_error = 1 - accuracy_score(y_test_two, test_pred)
print(f"Test Error with C={best_C}: {test_error*100:.2f}%")
```

```
Selected Classes Training samples: 261
Selected Classes Test samples: 66
```



```
Best C value (lowest stratified validation error): 0.1
Test Error with C=0.1: 34.85%
```

1.11 Analysis of Error Curves and C Values

1.11.1 Lowest Mean Error for Each Curve:

1. **Validation Error (Standard CV)**: Lowest at C = 0.1 (~41%)
2. **Training Error (Standard CV)**: Lowest at C = 0.1 (~29%)
3. **Validation Error (Stratified CV)**: Lowest at C = 0.1 (~39%)
4. **Training Error (Stratified CV)**: Lowest at C = 0.1 (~29%)

1.11.2 Model Complexity and C Parameter:

1. **Relationship between C and Model Complexity**:
   - The C parameter in SVM controls the trade-off between maximizing the margin and minimizing classification errors
   - Lower C values (e.g., 0.1) create larger margins but allow more misclassifications
   - Higher C values (e.g., 100) enforce stricter classification, leading to smaller margins but fewer training errors
   - Therefore, as C increases, the model complexity increases
2. **Overfitting/Underfitting Analysis**:
   - The gap between training and validation errors remains relatively constant across all C values
   - Training errors (~29%) are consistently lower than validation errors (~39-41%)
   - The modest and consistent gap between training and validation errors suggests neither severe overfitting nor underfitting
   - The fact that best performance is achieved at the lowest C value (0.1) suggests the simpler model is more appropriate for this data

1.12 Test Set Performance

Using the best C value (C = 0.1) from stratified cross-validation:

- The test error is 34.85%
- This test error falls between the training (~29%) and validation errors (~39%), indicating good generalization
- The model's performance on unseen data aligns well with what we would expect based on the cross-validation results

The results suggest that a simpler SVM model (lower C) is more appropriate for this classification task, and the model achieves consistent performance across training, validation, and test sets.