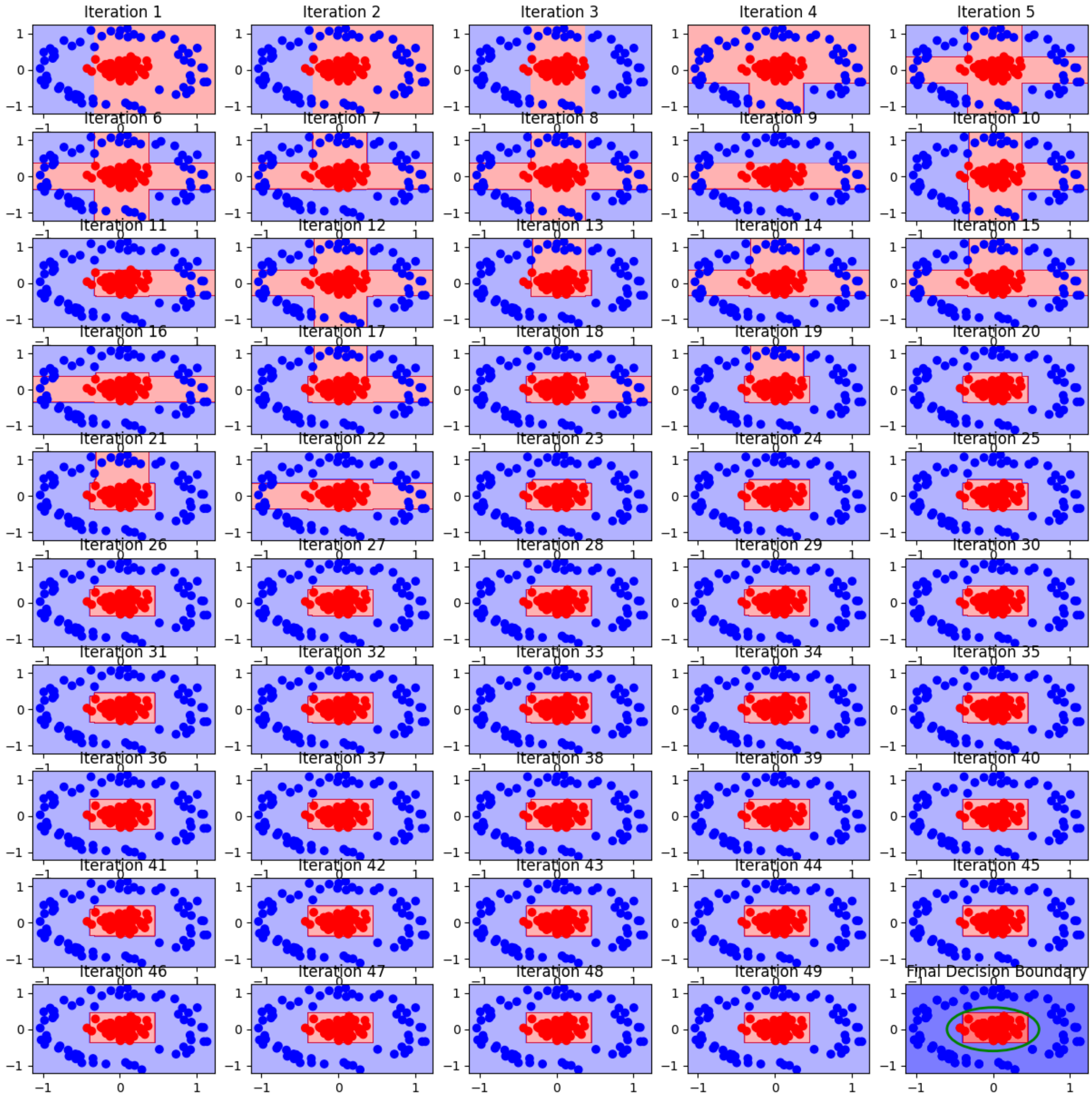
# Task 1

Implement the Adaboost algorithm yourself from scratch.

```
import numpy as np
from sklearn.datasets import make_circles
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
import matplotlib.pyplot as plt
import matplotlib.colors as colors
from sklearn.metrics import accuracy_score

# Step 1: Generate the circles dataset
X, y = make_circles(n_samples=500, noise=0.1, random_state=42,
factor=0.2)
X_train, X_test, y_train, y_test = train_test_split(X, y,
random_state=42)

# Convert labels from {0, 1} to {-1, 1} for Adaboost compatibility
y_train[y_train == 0] = -1
y_test[y_test == 0] = -1

# Step 2: Implement AdaBoost with deeper decision trees to capture
circular patterns
class AdaBoostCustom:
    def __init__(self, weak_classifier=DecisionTreeClassifier,
n_estimators=50, eta=0.5, max_depth=1):
        self.weak_classifier = weak_classifier
        self.n_estimators = n_estimators
        self.eta = eta
        self.max_depth = max_depth
        self.alphas = []
        self.classifiers = []

    def fit(self, X, y):
        n_samples, _ = X.shape
        # Initialize weights
        w = np.ones(n_samples) / n_samples

        for t in range(self.n_estimators):
            # Train weak classifier (now with higher max_depth to
capture non-linearity)
            clf = self.weak_classifier(max_depth=self.max_depth)
            clf.fit(X, y, sample_weight=w)
            y_pred = clf.predict(X)

            # Compute weighted error
```

```
            error = np.dot(w, (y_pred != y))
            if error > 0.5:
                break

            # Compute alpha
            alpha = self.eta * np.log((1 - error) / error)
            self.alphas.append(alpha)
            self.classifiers.append(clf)

            # Update weights
            w *= np.exp(alpha * (y_pred != y))
            w /= np.sum(w)  # Normalize weights

    def predict(self, X):
        # Initialize predictions
        final_pred = np.zeros(X.shape[0])

        for alpha, clf in zip(self.alphas, self.classifiers):
            final_pred += alpha * clf.predict(X)

        return np.sign(final_pred)

# Step 3: Visualize decision boundaries
def plot_decision_boundary(clf, X, y, ax=None, title=""):
    if ax is None:
        ax = plt.gca()
    x_min, x_max = X[:, 0].min() - 0.1, X[:, 0].max() + 0.1
    y_min, y_max = X[:, 1].min() - 0.1, X[:, 1].max() + 0.1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01),
                         np.arange(y_min, y_max, 0.01))
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    ax.contour(xx, yy, Z, alpha=0.3,
cmap=colors.ListedColormap(["blue", "red"]))
    ax.scatter(X[:, 0], X[:, 1], c=y,
cmap=colors.ListedColormap(["blue", "red"]))
    ax.set_title(title)

# Step 4: Circle boundary visualization
def plot_circle_boundary(ax):
    # Add a green circle as boundary
    circle = plt.Circle((0, 0), 0.6, color='green', fill=False,
linewidth=2, label="True Circle Boundary")
    ax.add_artist(circle)

# Instantiate the AdaBoost algorithm with deeper decision trees
ada_boost = AdaBoostCustom(n_estimators=50, eta=0.5, max_depth=1)

# Train AdaBoost
ada_boost.fit(X_train, y_train)
```

```
# Visualize the decision boundary at each iteration and final decision
boundary
fig, axes = plt.subplots(10, 5, figsize=(15, 15))
axes = axes.ravel()

for t in range(ada_boost.n_estimators):
    ada_boost_iter = AdaBoostCustom(n_estimators=t + 1, eta=0.5,
max_depth=1)
    ada_boost_iter.fit(X_train, y_train)
    plot_decision_boundary(ada_boost_iter, X_test, y_test, ax=axes[t],
title=f"Iteration {t+1}")
    #plot_circle_boundary(axes[t])  # Add circle boundary

# Final decision boundary visualization
plot_decision_boundary(ada_boost, X_test, y_test, ax=axes[-1],
title="Final Decision Boundary")
plot_circle_boundary(axes[-1])  # Add circle boundary
plt.show()

# Check final accuracy
print("\n")
y_pred = ada_boost.predict(X_test)
print("Final Accuracy:", accuracy_score(y_test, y_pred))
```




```
Final Accuracy: 0.992
```

# Task 2

Run your Adaboost implementation with several weak classifiers such as LogReg, DecisionStump, DecisionTree(depth=3), Linear SVM, and LDA. Tune the method's hyperparameters (both Adaboost and the underlying weak classifier) for maximizing the classification performance. Based on the data visualization, you can achieve >98% performance fairly easily. Generate the decision boundary visualizations as the above figure pair for each model class.

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import make_circles
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.metrics import accuracy_score

# Generate the circles dataset
X, y = make_circles(n_samples=500, noise=0.1, random_state=42,
factor=0.2)
y = np.where(y == 0, -1, 1)  # Convert labels to {-1, 1}
X_train, X_test, y_train, y_test = train_test_split(X, y,
random_state=42)

# Helper function to calculate weighted error
def weighted_error(y_true, y_pred, weights):
    return np.sum(weights * (y_true != y_pred))

# Adaboost implementation
class AdaBoost:
    def __init__(self, learner_name, weak_learner, T=50, eta=0.5):
        self.weak_learner = weak_learner
        self.learner_name = learner_name
        self.T = T
        self.eta = eta
        self.alphas = []
        self.models = []

    def fit(self, X, y):
        n_samples = X.shape[0]
        weights = np.full(n_samples, 1/n_samples)

        for t in range(self.T):
            model = self.weak_learner()
            if self.learner_name != "LDA":
                model.fit(X, y, sample_weight=weights)  # Always fit
with sample weights
            else:
                model.fit(X, y)  # Always fit without sample weights
            y_pred = model.predict(X)

            error = weighted_error(y, y_pred, weights) /
np.sum(weights)
            alpha_t = self.eta * np.log((1 - error) / (error + 1e-10))
```

```
            self.alphas.append(alpha_t)
            self.models.append(model)

            # Update weights
            weights *= np.exp(-alpha_t * y * y_pred)
            weights /= np.sum(weights)  # Normalize

    def predict(self, X):
        final_pred = np.zeros(X.shape[0])
        for alpha, model in zip(self.alphas, self.models):
            final_pred += alpha * model.predict(X)
        return np.sign(final_pred)

# Function to tune hyperparameters for a specific weak learner
def tune_hyperparameters(learner_name, weak_learner, param_grid):
    best_accuracy = 0
    best_params = None

    for params in param_grid:
        adaboost = AdaBoost(learner_name=learner_name,
weak_learner=lambda: weak_learner(**params), T=50,
eta=params.get('eta', 0.5))
        adaboost.fit(X_train, y_train)
        y_pred = adaboost.predict(X_test)
        accuracy = accuracy_score(y_test, y_pred)

        if accuracy > best_accuracy:
            best_accuracy = accuracy
            best_params = params

    print(f"Best parameters for {learner_name}: {best_params} with
accuracy: {best_accuracy:.4f}")

    return best_params  # Return best parameters

# Function to find the best eta using the best estimator
def tune_eta(learner_name, weak_learner, best_params, eta_values):
    best_accuracy = 0
    best_eta = None
    errors = []

    for eta in eta_values:
        adaboost = AdaBoost(learner_name=learner_name,
weak_learner=lambda: weak_learner(**best_params), T=50, eta=eta)
        adaboost.fit(X_train, y_train)
        y_pred = adaboost.predict(X_test)
        accuracy = accuracy_score(y_test, y_pred)
        error = 1 - accuracy

        errors.append((eta, error))  # Store eta and corresponding
```

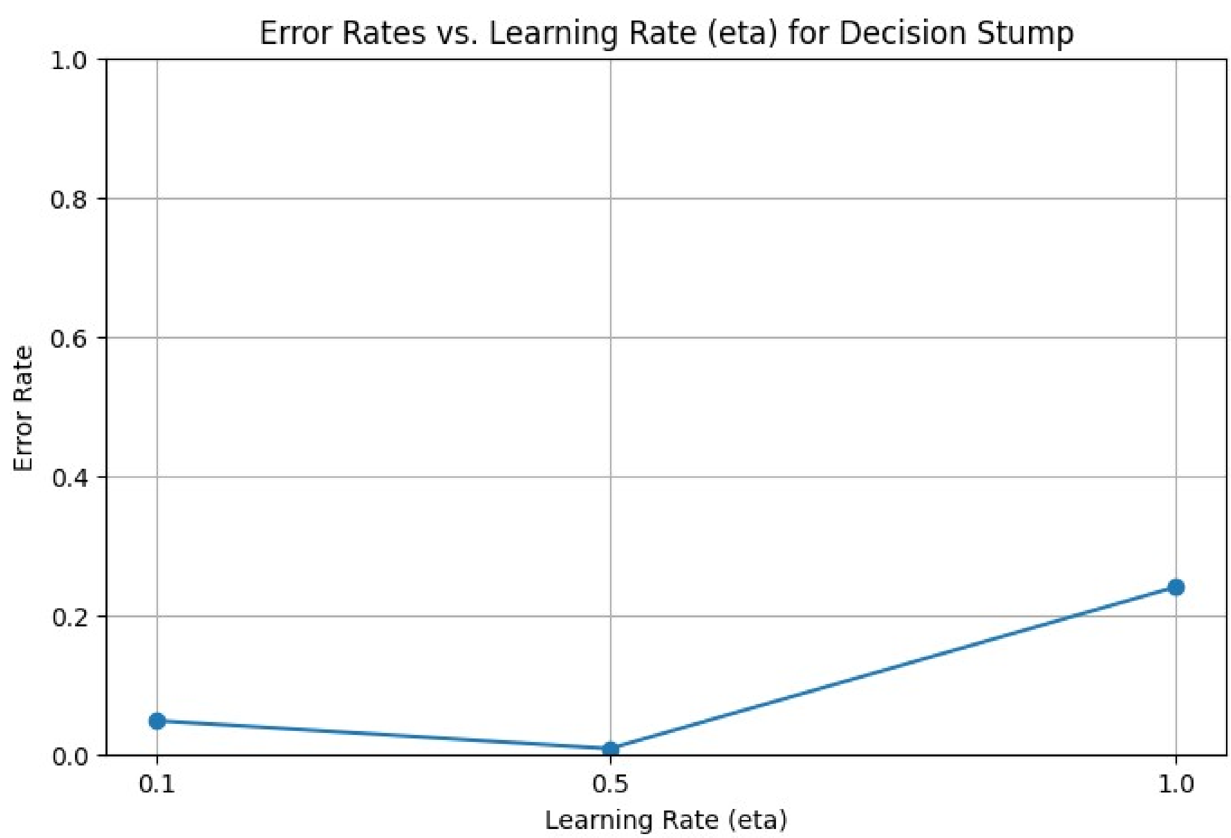
```python
error

        print(f"Parameters: {best_params}, eta: {eta}, Accuracy: 
{accuracy:.4f}, Error: {error:.4f}")

        if accuracy > best_accuracy:
            best_accuracy = accuracy
            best_eta = eta

    print(f"Best eta for {learner_name}: {best_eta} with accuracy: 
{best_accuracy:.4f}")
    print("\n")

    return best_eta, errors  # Return best eta and errors for plotting

# Define weak learners with hyperparameter grids
weak_learners_params = {
    "Logistic Regression": lambda **params: 
LogisticRegression(solver='lbfgs', max_iter=1000, C=params.get('C', 
1.0)),
    "Decision Stump": lambda **params: 
DecisionTreeClassifier(max_depth=1),
    "Decision Tree (depth=3)": lambda **params: 
DecisionTreeClassifier(max_depth=3),
    "Linear SVM": lambda **params: SVC(kernel='rbf', probability=True, 
C=params.get('C', 1)),
    "LDA": lambda **params: LinearDiscriminantAnalysis(),
}

# Hyperparameter grids
param_grids = {
    "Logistic Regression": [{'C': c} for c in [0.1, 1, 10]],
    "Decision Stump": [{}],
    "Decision Tree (depth=3)": [{}],
    "Linear SVM": [{'C': c} for c in [0.1, 1, 10]],
    "LDA": [{}],
}

# Eta values for tuning
eta_values = [0.1, 0.5, 1]

# Dictionary to hold best parameters and errors for plotting
all_best_params = {}
all_errors = {}

# Run tuning for each weak learner to find best hyperparameters and 
then best eta
for learner_name, weak_learner in weak_learners_params.items():
    print(f"Tuning hyperparameters for {learner_name}...")
    best_params = tune_hyperparameters(learner_name, weak_learner, 
```

```
param_grids[learner_name])

    print(f"Tuning eta for {learner_name} with best params:
{best_params}...")
    best_eta, errors = tune_eta(learner_name, weak_learner,
best_params, eta_values)

    all_best_params[learner_name] = (best_params, best_eta)  # Store
best parameters and eta
    all_errors[learner_name] = errors  # Store errors for plotting

# Plotting separate error plots for each algorithm
for learner_name, errors in all_errors.items():
    plt.figure(figsize=(8, 5))
    eta_values = [error[0] for error in errors]
    error_rates = [error[1] for error in errors]

    plt.plot(eta_values, error_rates, marker='o')
    plt.title(f'Error Rates vs. Learning Rate (eta) for
{learner_name}')
    plt.xlabel('Learning Rate (eta)')
    plt.ylabel('Error Rate')
    plt.xticks(np.unique(eta_values))  # Unique eta values
    plt.grid()
    plt.ylim(0, 1)
    plt.show()

for i, (learner_name, (best_params, best_eta)) in
enumerate(all_best_params.items()):
    # Create the model with the best parameters and best eta
    if learner_name == "LDA":
        model = weak_learners_params[learner_name]()
    else:
        model = weak_learners_params[learner_name](**best_params)

    model.fit(X_train, y_train)  # Fit the model to the training data

plt.tight_layout()
plt.show()
```

```
Tuning hyperparameters for Logistic Regression...
Best parameters for Logistic Regression: {'C': 1} with accuracy:
0.9280
Tuning eta for Logistic Regression with best params: {'C': 1}...
Parameters: {'C': 1}, eta: 0.1, Accuracy: 0.4880, Error: 0.5120
Parameters: {'C': 1}, eta: 0.5, Accuracy: 0.9280, Error: 0.0720
Parameters: {'C': 1}, eta: 1, Accuracy: 0.4880, Error: 0.5120
Best eta for Logistic Regression: 0.5 with accuracy: 0.9280
```

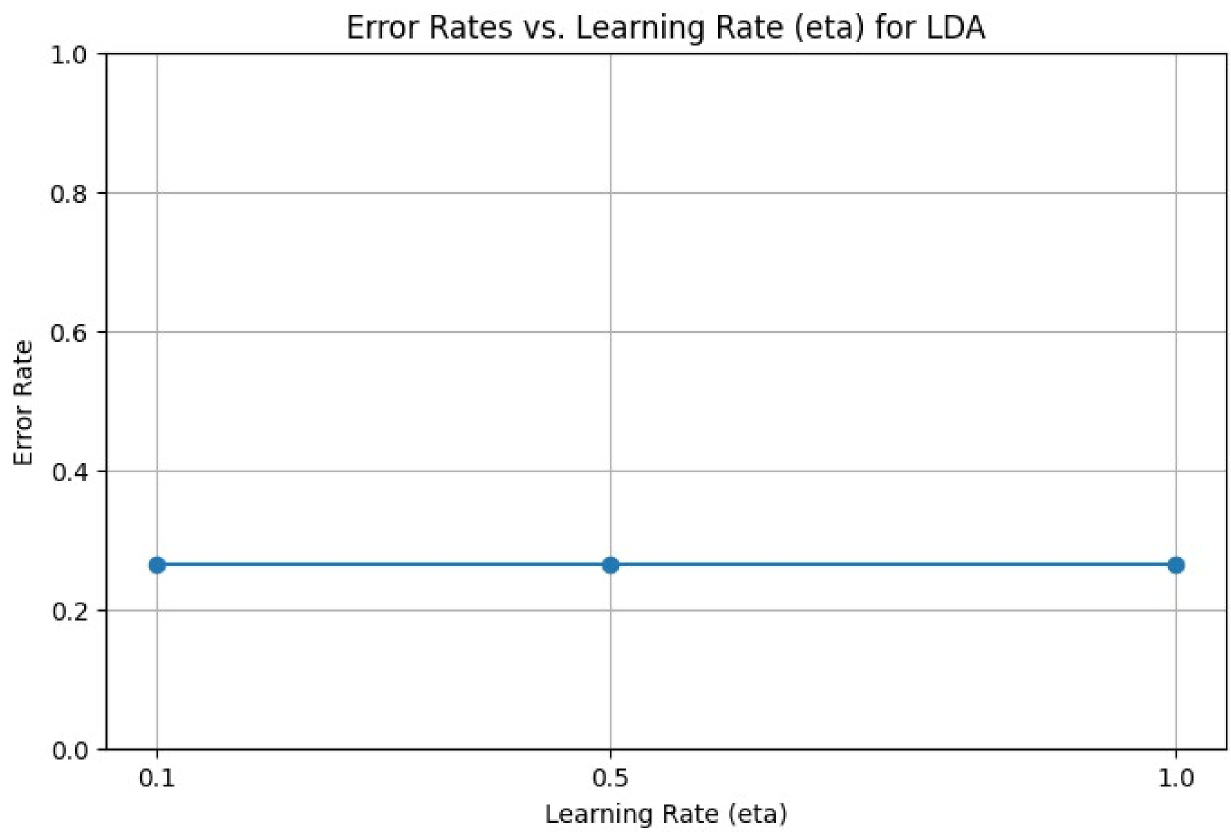
```
Tuning hyperparameters for Decision Stump...
Best parameters for Decision Stump: {} with accuracy: 0.9920
Tuning eta for Decision Stump with best params: {}...
Parameters: {}, eta: 0.1, Accuracy: 0.9520, Error: 0.0480
Parameters: {}, eta: 0.5, Accuracy: 0.9920, Error: 0.0080
Parameters: {}, eta: 1, Accuracy: 0.7600, Error: 0.2400
Best eta for Decision Stump: 0.5 with accuracy: 0.9920


Tuning hyperparameters for Decision Tree (depth=3)...
Best parameters for Decision Tree (depth=3): {} with accuracy: 0.9920
Tuning eta for Decision Tree (depth=3) with best params: {}...
Parameters: {}, eta: 0.1, Accuracy: 0.9920, Error: 0.0080
Parameters: {}, eta: 0.5, Accuracy: 0.9920, Error: 0.0080
Parameters: {}, eta: 1, Accuracy: 1.0000, Error: 0.0000
Best eta for Decision Tree (depth=3): 1 with accuracy: 1.0000


Tuning hyperparameters for Linear SVM...
Best parameters for Linear SVM: {'C': 10} with accuracy: 1.0000
Tuning eta for Linear SVM with best params: {'C': 10}...
Parameters: {'C': 10}, eta: 0.1, Accuracy: 1.0000, Error: 0.0000
Parameters: {'C': 10}, eta: 0.5, Accuracy: 1.0000, Error: 0.0000
Parameters: {'C': 10}, eta: 1, Accuracy: 1.0000, Error: 0.0000
Best eta for Linear SVM: 0.1 with accuracy: 1.0000


Tuning hyperparameters for LDA...
Best parameters for LDA: {} with accuracy: 0.7360
Tuning eta for LDA with best params: {}...
Parameters: {}, eta: 0.1, Accuracy: 0.7360, Error: 0.2640
Parameters: {}, eta: 0.5, Accuracy: 0.7360, Error: 0.2640
Parameters: {}, eta: 1, Accuracy: 0.7360, Error: 0.2640
Best eta for LDA: 0.1 with accuracy: 0.7360
```


Error Rates vs. Learning Rate (eta) for Logistic Regression
1.0
0.8
0.6
0.4
0.2
0.0
Error Rate
0.1
0.5
1.0
Learning Rate (eta)


Error Rates vs. Learning Rate (eta) for Decision Stump
1.0
0.8
0.6
0.4
0.2
0.0
Error Rate
0.1
0.5
1.0
Learning Rate (eta)


Error Rates vs. Learning Rate (eta) for Decision Tree (depth=3)
Error Rate
Learning Rate (eta)
0.0
0.2
0.4
0.6
0.8
1.0
0.1
0.5
1.0


Error Rates vs. Learning Rate (eta) for Linear SVM
Error Rate
Learning Rate (eta)
0.0
0.2
0.4
0.6
0.8
1.0
0.1
0.5
1.0




```
<Figure size 640x480 with 0 Axes>
```

Code for Deicsion boundary and plot for error rate vs eta for different algorithm

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import make_circles
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.metrics import accuracy_score

# Generate the circles dataset
X, y = make_circles(n_samples=500, noise=0.1, random_state=42,
factor=0.2)
y = np.where(y == 0, -1, 1)  # Convert labels to {-1, 1}
X_train, X_test, y_train, y_test = train_test_split(X, y,
random_state=42)

# Helper function to calculate weighted error
def weighted_error(y_true, y_pred, weights):
    return np.sum(weights * (y_true != y_pred))
```

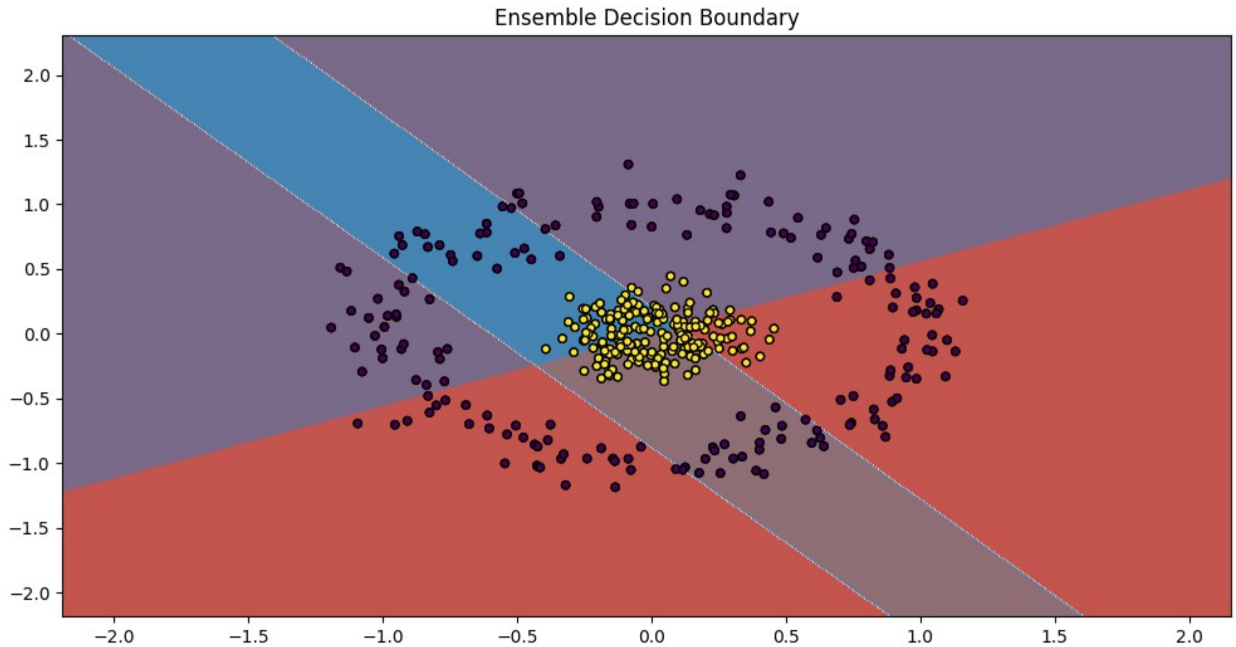
```
# Adaboost implementation
class AdaBoost:
    def __init__(self, learner_name, weak_learner, T=50, eta=0.5):
        self.weak_learner = weak_learner
        self.learner_name = learner_name
        self.T = T
        self.eta = eta
        self.alphas = []
        self.models = []

    def fit(self, X, y):
        n_samples = X.shape[0]
        weights = np.full(n_samples, 1/n_samples)

        plt.figure(figsize=(12, 6))

        for t in range(self.T):
            model = self.weak_learner()
            if self.learner_name != "LDA":
                model.fit(X, y, sample_weight=weights)  # Always fit
with sample weights
            else:
                model.fit(X, y)  # Always fit without sample weights
            y_pred = model.predict(X)
            # Compute the weighted error
            error = weighted_error(y, y_pred, weights) /
np.sum(weights)
            alpha_t = self.eta * np.log((1 - error) / (error + 1e-10))
            self.alphas.append(alpha_t)
            self.models.append(model)

            # Update weights
            weights *= np.exp(-alpha_t * y * y_pred)
            weights /= np.sum(weights)  # Normalize

            # Plot the decision boundary after each iteration
            self.plot_classifier_fit(X, y, model, t + 1)

        self.plot_final_decision_boundary(X, y)

    def predict(self, X):
        final_pred = np.zeros(X.shape[0])
        for alpha, model in zip(self.alphas, self.models):
            final_pred += alpha * model.predict(X)
        return np.sign(final_pred)

    def plot_classifier_fit(self, X, y, model, iteration):
        """Plots classifier fit at every iteration without clearing
previous iterations."""
```

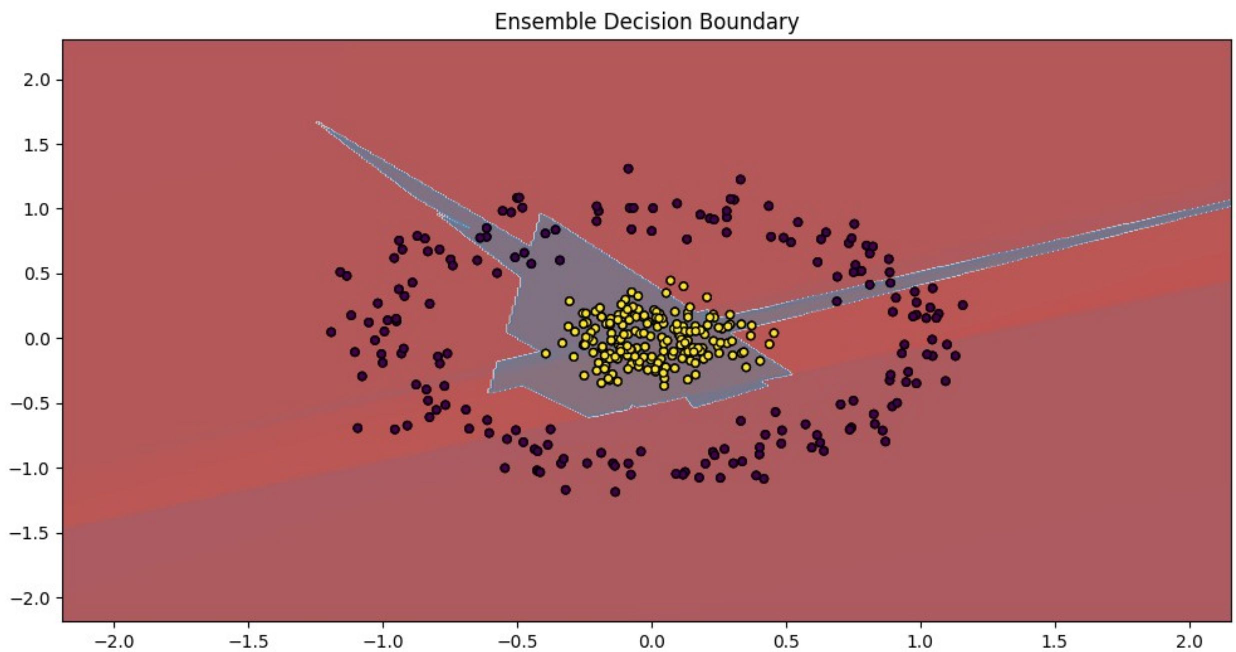
```
        x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
        y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
        xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01),
                             np.arange(y_min, y_max, 0.01))
        Z = model.predict(np.c_[xx.ravel(), yy.ravel()])
        Z = Z.reshape(xx.shape)

        # Plot decision boundary of current iteration
        plt.contourf(xx, yy, Z, alpha=0.3, cmap=plt.cm.RdBu, levels=[-
1, 0, 1])
        plt.scatter(X[:, 0], X[:, 1], c=y, edgecolors='k', marker='o',
s=20)
        plt.title(f'Classifier fit after {iteration} iterations')

    def plot_final_decision_boundary(self, X, y):
        """Plots the final ensembled decision boundary."""
        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.arange(x_min, x_max, 0.01),
                             np.arange(y_min, y_max, 0.01))
        Z = self.predict(np.c_[xx.ravel(), yy.ravel()])
        Z = Z.reshape(xx.shape)

        plt.contourf(xx, yy, Z, alpha=0.4, cmap=plt.cm.RdBu)
        plt.scatter(X[:, 0], X[:, 1], c=y, edgecolors='k', marker='o',
s=20)
        plt.title('Ensemble Decision Boundary')
        plt.show()

# Function to tune hyperparameters for a specific weak learner
def tune_hyperparameters(learner_name, weak_learner, param_grid):
    best_accuracy = 0
    best_params = None

    for params in param_grid:
        adaboost = AdaBoost(learner_name=learner_name,
weak_learner=lambda: weak_learner(**params), T=50,
eta=params.get('eta', 0.5))
        adaboost.fit(X_train, y_train)
        y_pred = adaboost.predict(X_test)
        accuracy = accuracy_score(y_test, y_pred)

        if accuracy > best_accuracy:
            best_accuracy = accuracy
            best_params = params

    print(f"Best parameters for {learner_name}: {best_params} with
accuracy: {best_accuracy:.4f}")

    return best_params  # Return best parameters
```

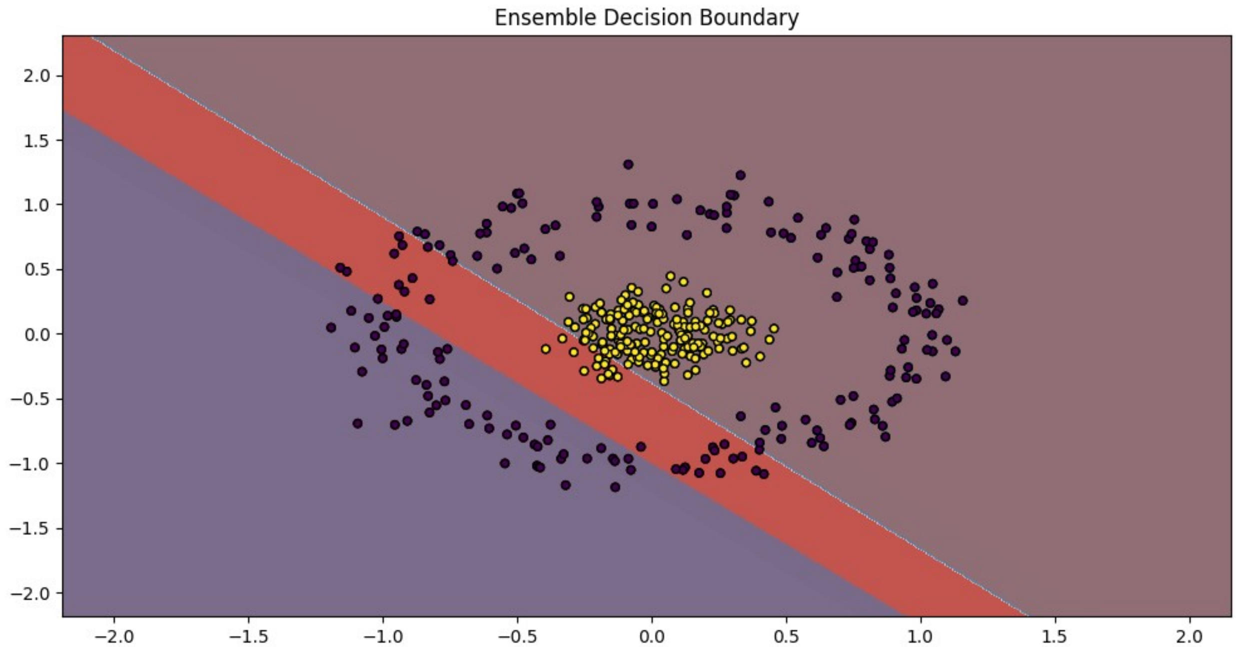
```
# Function to find the best eta using the best estimator
def tune_eta(learner_name, weak_learner, best_params, eta_values):
    best_accuracy = 0
    best_eta = None
    errors = []

    for eta in eta_values:
        adaboost = AdaBoost(learner_name=learner_name,
weak_learner=lambda: weak_learner(**best_params), T=50, eta=eta)
        adaboost.fit(X_train, y_train)
        y_pred = adaboost.predict(X_test)
        accuracy = accuracy_score(y_test, y_pred)
        error = 1 - accuracy

        errors.append((eta, error))  # Store eta and corresponding
error

        print(f"Parameters: {best_params}, eta: {eta}, Accuracy:
{accuracy:.4f}, Error: {error:.4f}")

        if accuracy > best_accuracy:
            best_accuracy = accuracy
            best_eta = eta

    print(f"Best eta for {learner_name}: {best_eta} with accuracy:
{best_accuracy:.4f}")
    print("\n")

    return best_eta, errors  # Return best eta and errors for plotting

# Define weak learners with hyperparameter grids
weak_learners_params = {
    "Logistic Regression": lambda **params:
LogisticRegression(solver='lbfgs', max_iter=1000, C=params.get('C',
1.0)),
    "Decision Stump": lambda **params:
DecisionTreeClassifier(max_depth=1),
    "Decision Tree (depth=3)": lambda **params:
DecisionTreeClassifier(max_depth=3),
    "Linear SVM": lambda **params: SVC(kernel='rbf', probability=True,
C=params.get('C', 1)),
    "LDA": lambda **params: LinearDiscriminantAnalysis(),
}

# Hyperparameter grids
param_grids = {
    "Logistic Regression": [{'C': c} for c in [0.1, 1, 10]],
    "Decision Stump": [{}],
    "Decision Tree (depth=3)": [{}],
```

```
    "Linear SVM": [{'C': c} for c in [0.1, 1, 10]],
    "LDA": [{}],
}

# Eta values for tuning
eta_values = [0.1, 0.5, 1]

# Dictionary to hold best parameters and errors for plotting
all_best_params = {}
all_errors = {}

# Run tuning for each weak learner to find best hyperparameters and
then best eta
for learner_name, weak_learner in weak_learners_params.items():
    print(f"Tuning hyperparameters for {learner_name}...")
    best_params = tune_hyperparameters(learner_name, weak_learner,
param_grids[learner_name])

    print(f"Tuning eta for {learner_name} with best params:
{best_params}...")
    best_eta, errors = tune_eta(learner_name, weak_learner,
best_params, eta_values)

    all_best_params[learner_name] = (best_params, best_eta)  # Store
best parameters and eta
    all_errors[learner_name] = errors  # Store errors for plotting

# Plotting separate error plots for each algorithm
for learner_name, errors in all_errors.items():
    plt.figure(figsize=(8, 5))
    eta_values = [error[0] for error in errors]
    error_rates = [error[1] for error in errors]

    plt.plot(eta_values, error_rates, marker='o')
    plt.title(f'Error Rates vs. Learning Rate (eta) for
{learner_name}')
    plt.xlabel('Learning Rate (eta)')
    plt.ylabel('Error Rate')
    plt.xticks(np.unique(eta_values))  # Unique eta values
    plt.grid()
    plt.ylim(0, 1)
    plt.show()
```

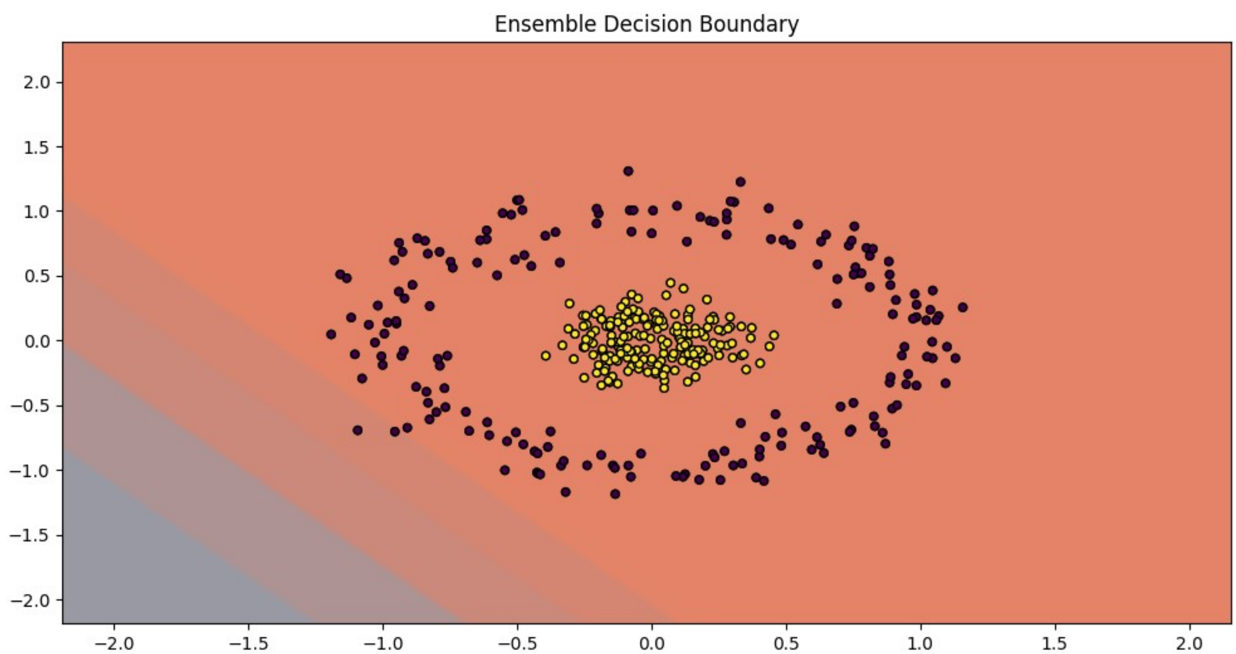
```
Tuning hyperparameters for Logistic Regression...
```


Ensemble Decision Boundary
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0

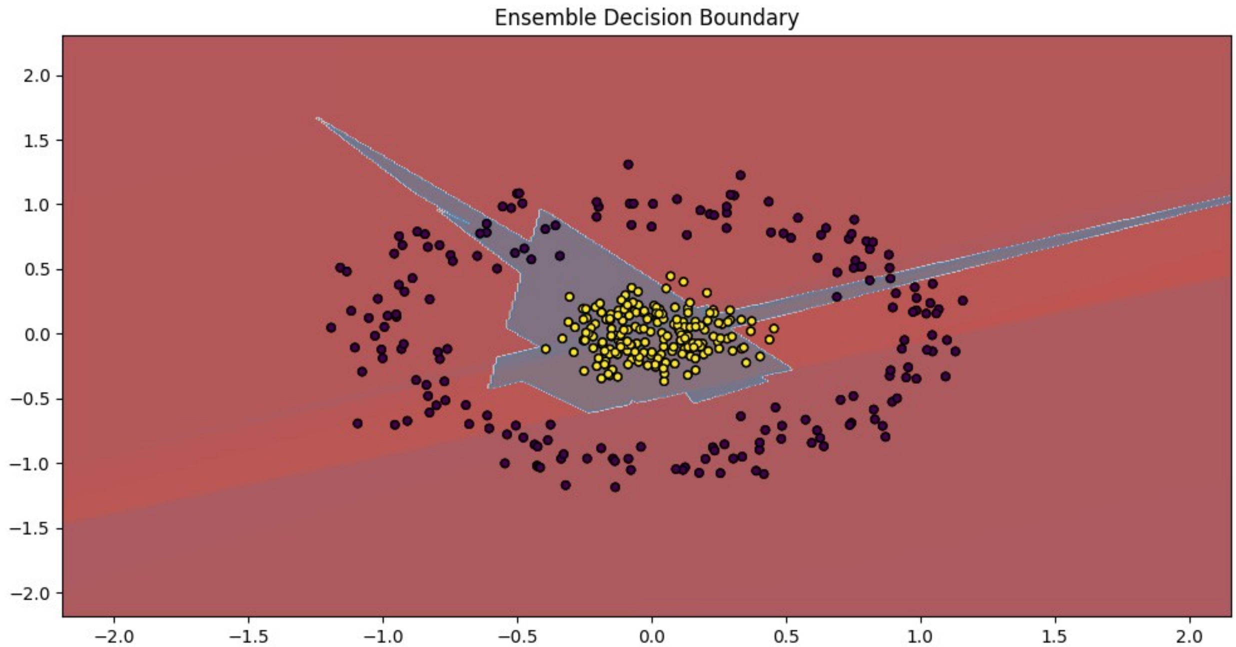

Ensemble Decision Boundary
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0



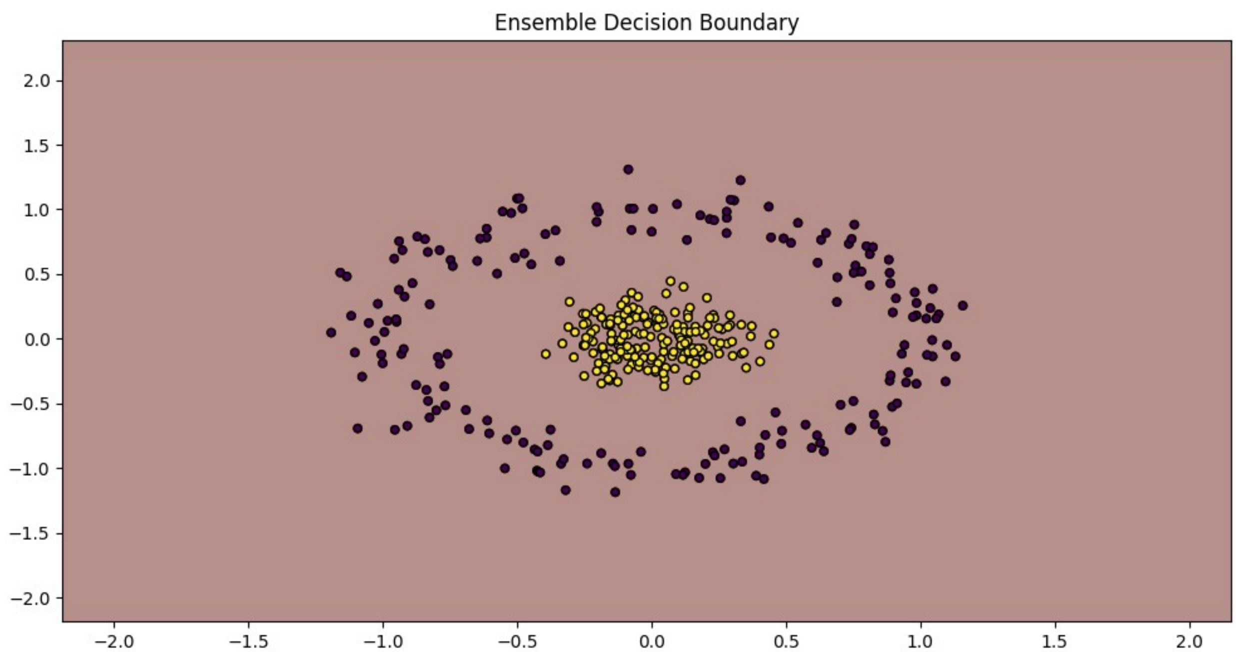

```
Best parameters for Logistic Regression: {'C': 1} with accuracy:
0.9280
Tuning eta for Logistic Regression with best params: {'C': 1}...
```



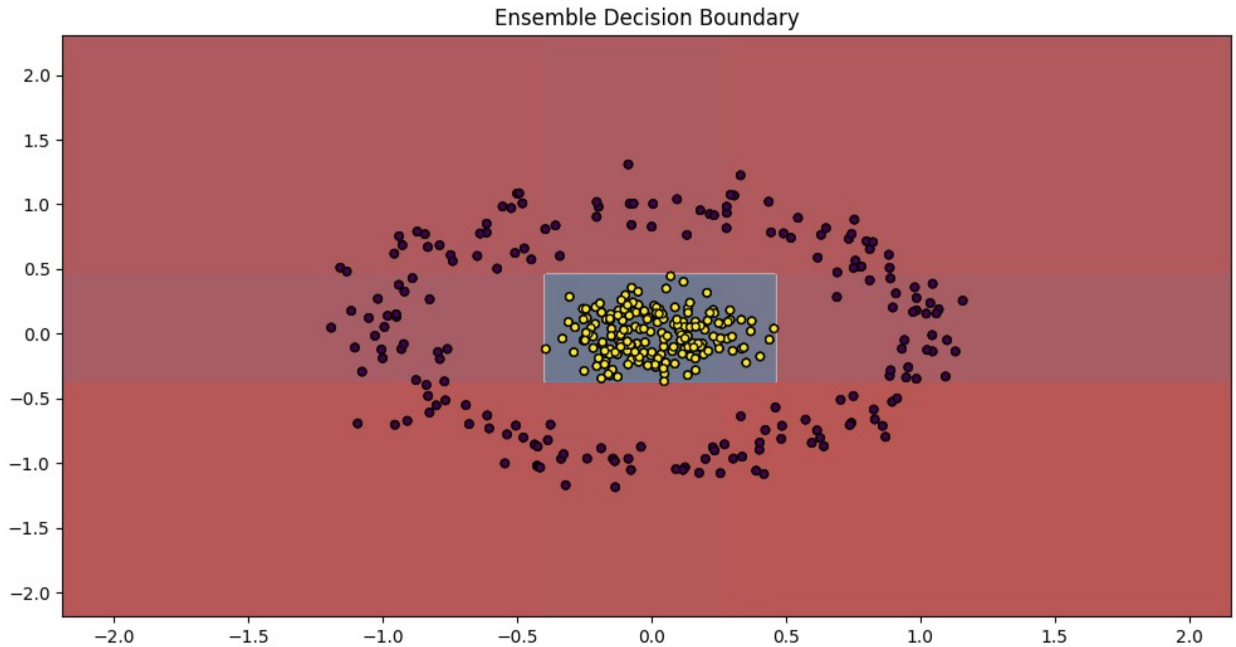

```
Parameters: {'C': 1}, eta: 0.1, Accuracy: 0.4880, Error: 0.5120
```



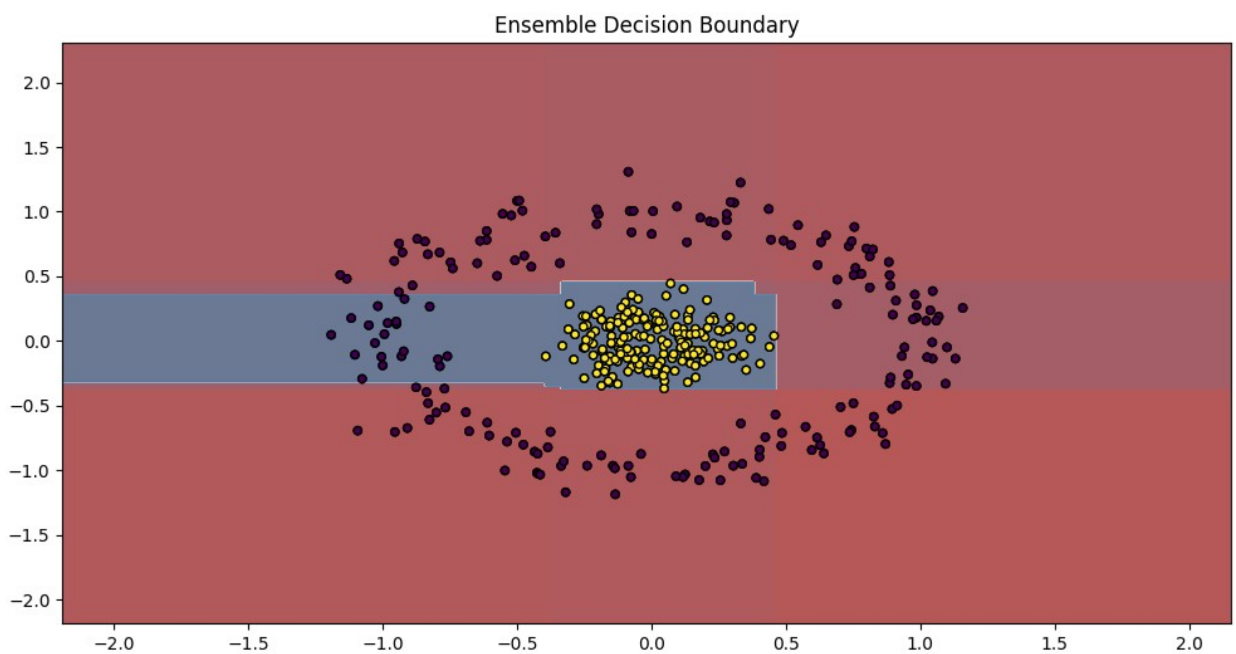

```
Parameters: {'C': 1}, eta: 0.5, Accuracy: 0.9280, Error: 0.0720
```



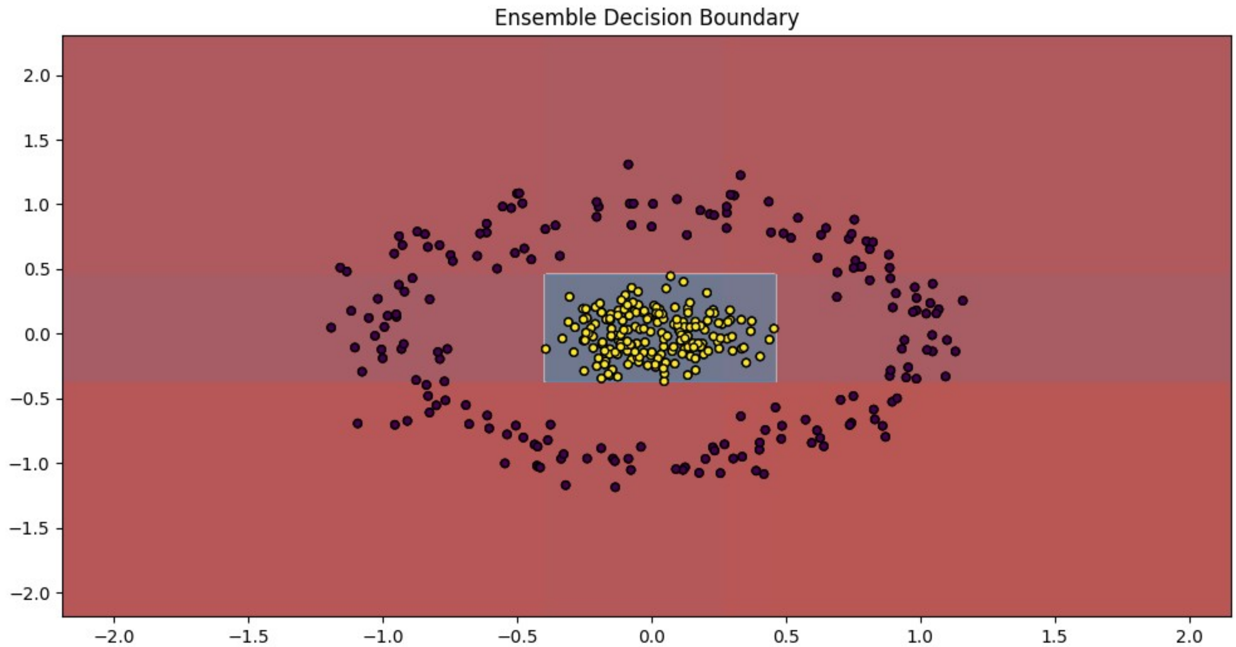

```
Parameters: {'C': 1}, eta: 1, Accuracy: 0.4880, Error: 0.5120
Best eta for Logistic Regression: 0.5 with accuracy: 0.9280


Tuning hyperparameters for Decision Stump...
```



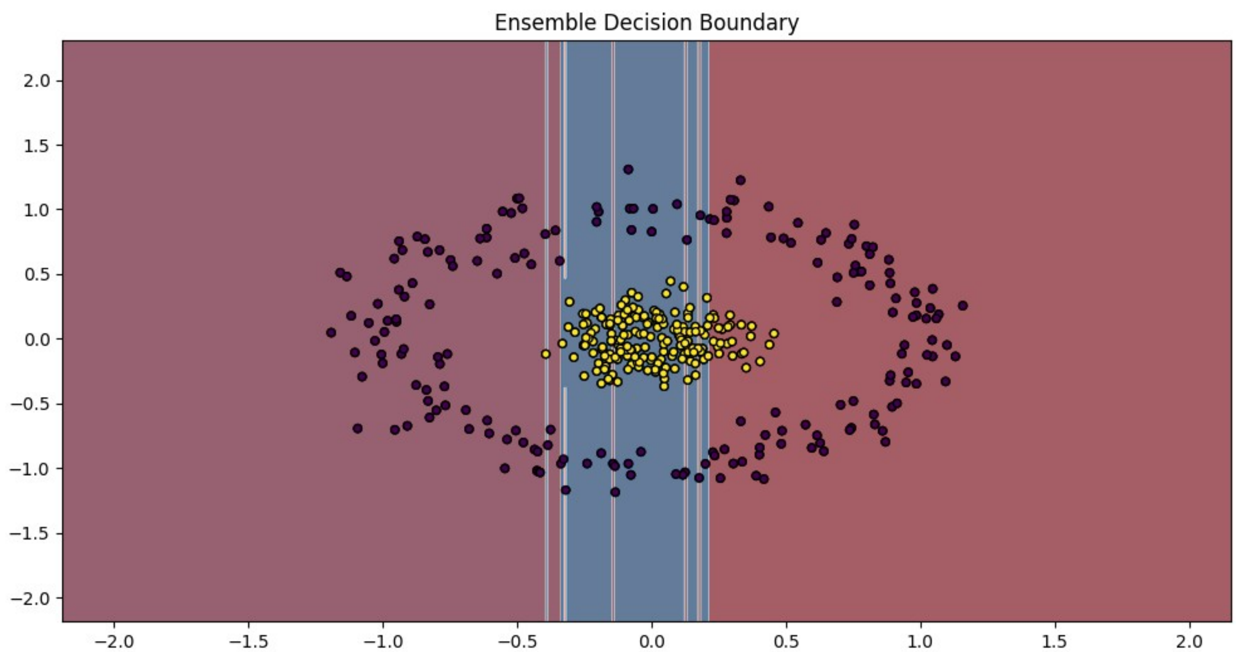

```
Best parameters for Decision Stump: {} with accuracy: 0.9920
Tuning eta for Decision Stump with best params: {}...
```



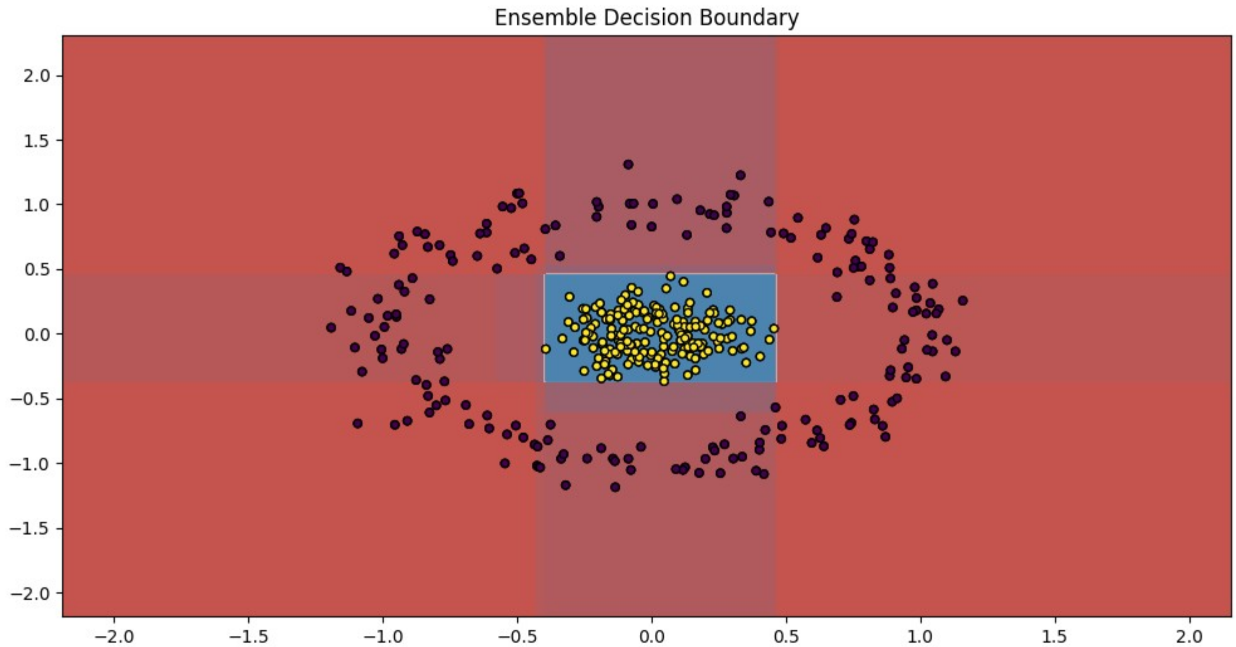

```
Parameters: {}, eta: 0.1, Accuracy: 0.9520, Error: 0.0480
```



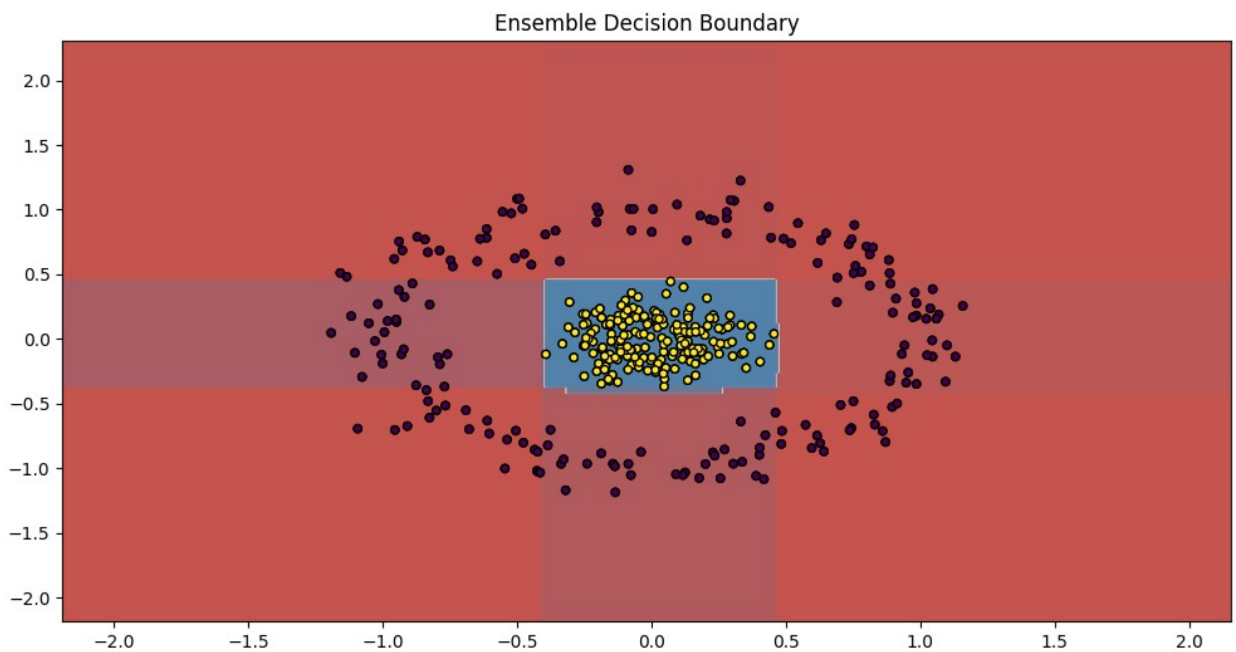

```
Parameters: {}, eta: 0.5, Accuracy: 0.9920, Error: 0.0080
```



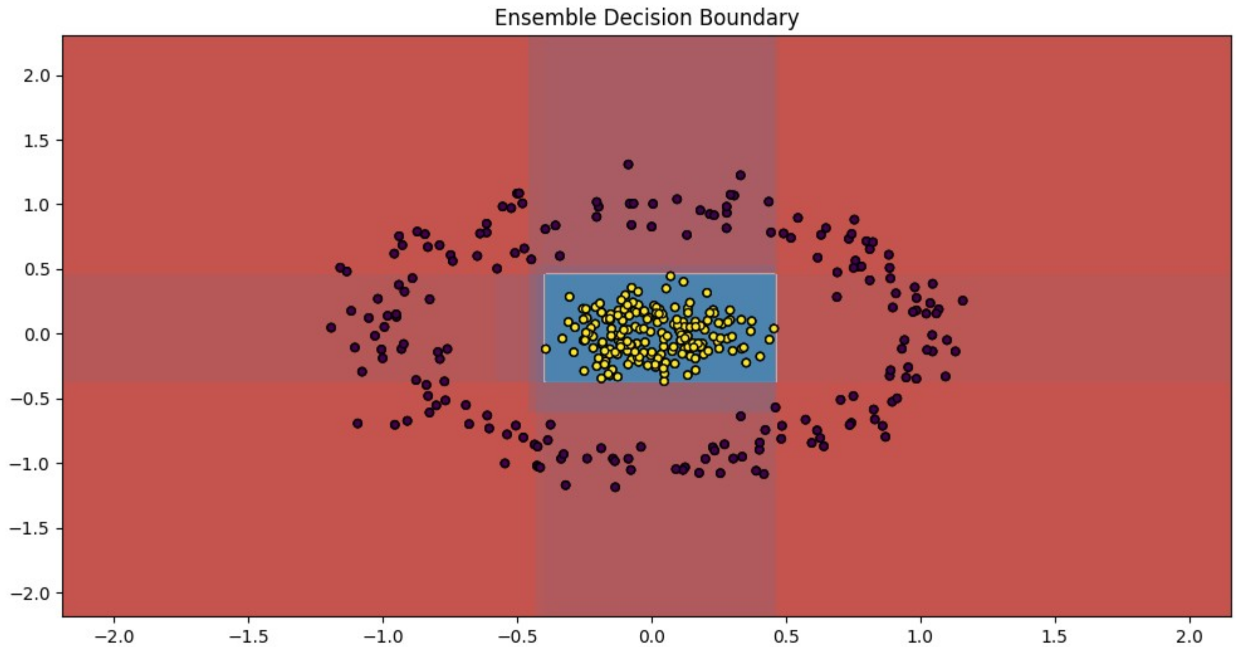

```
Parameters: {}, eta: 1, Accuracy: 0.7600, Error: 0.2400
Best eta for Decision Stump: 0.5 with accuracy: 0.9920


Tuning hyperparameters for Decision Tree (depth=3)...
```



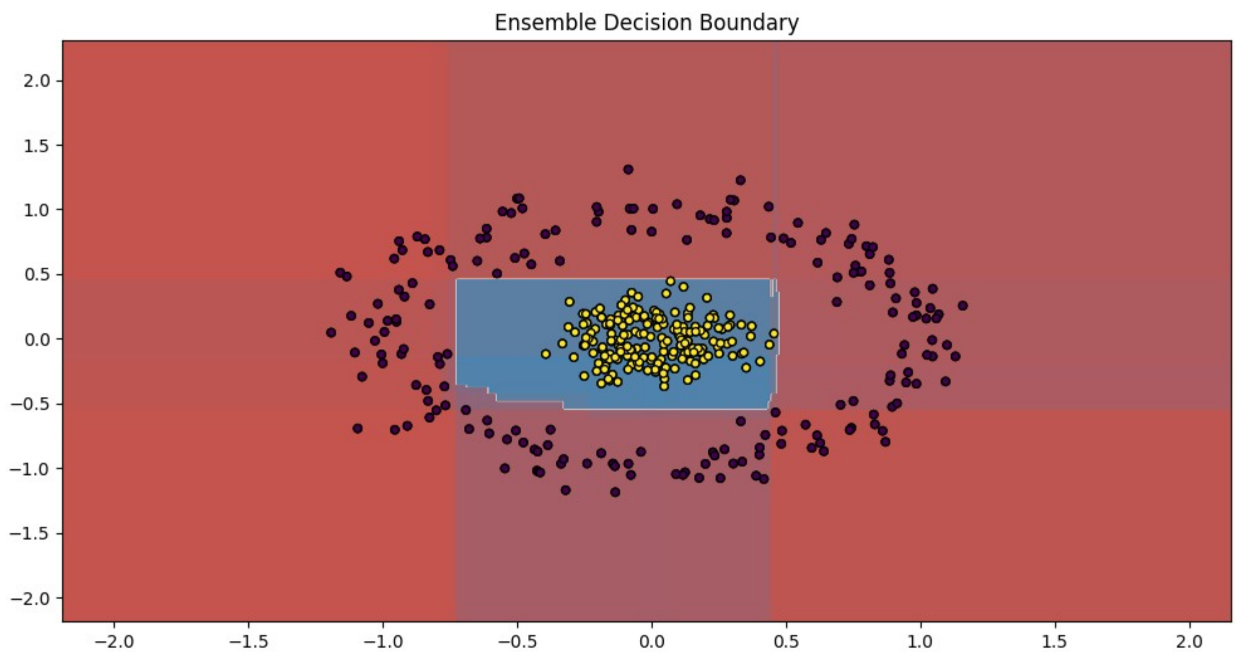

```
Best parameters for Decision Tree (depth=3): {} with accuracy: 0.9920
Tuning eta for Decision Tree (depth=3) with best params: {}...
```



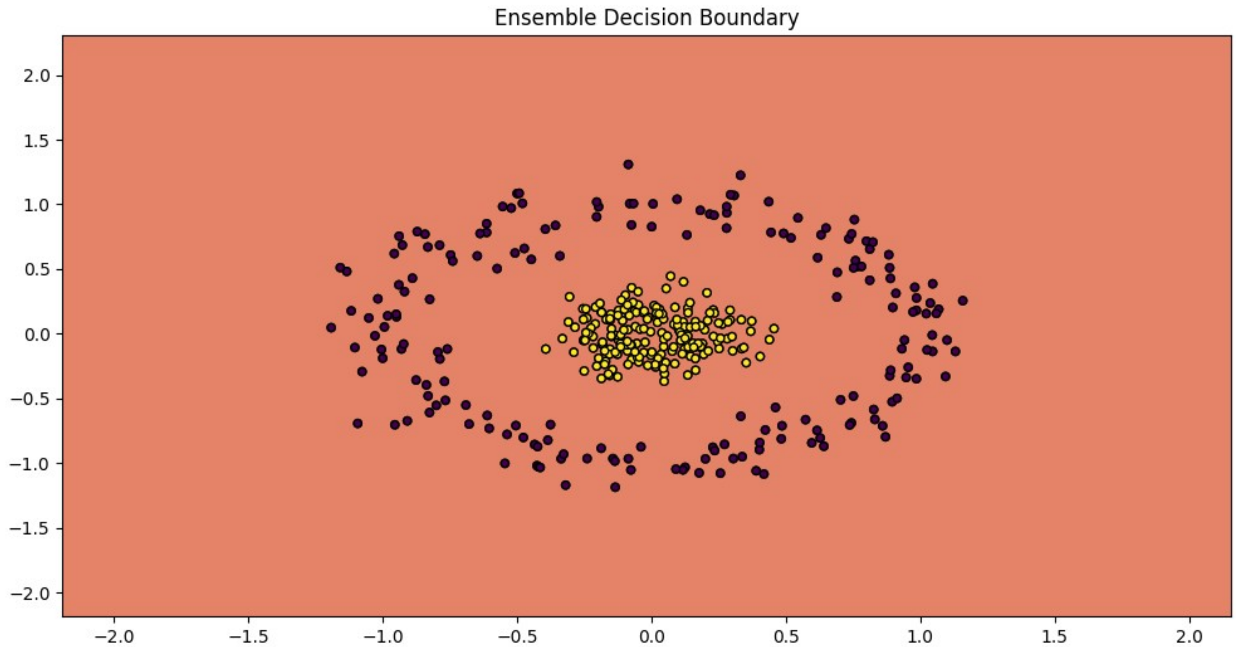

```
Parameters: {}, eta: 0.1, Accuracy: 0.9920, Error: 0.0080
```



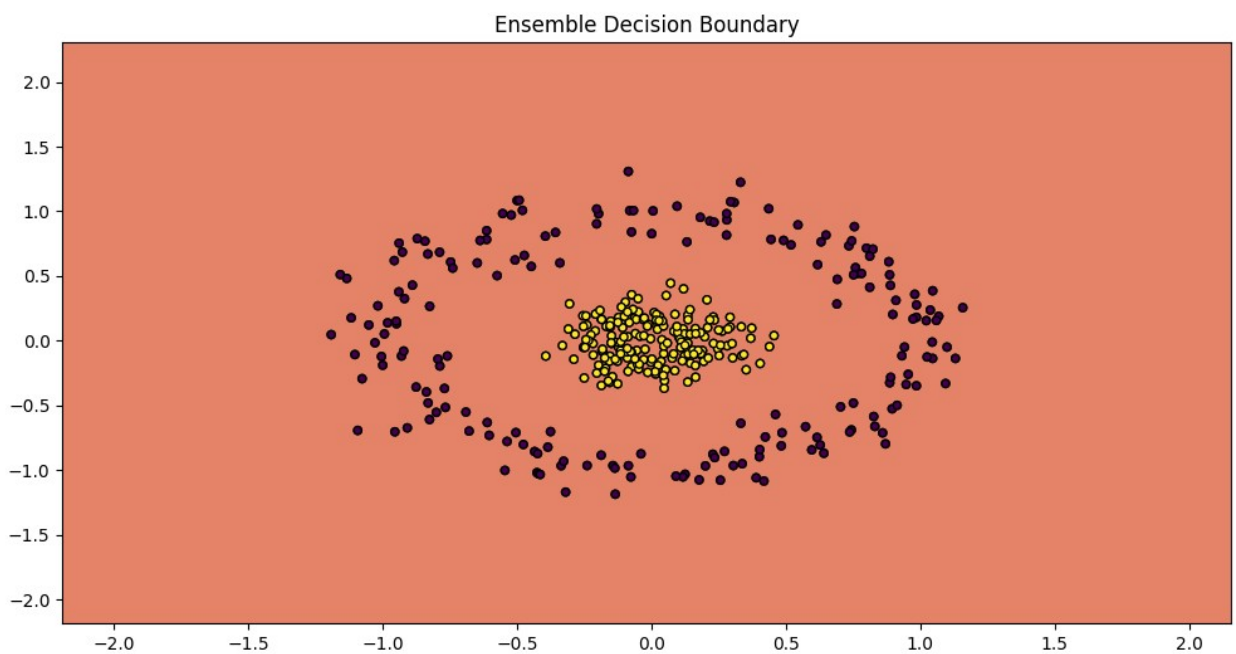

```
Parameters: {}, eta: 0.5, Accuracy: 0.9920, Error: 0.0080
```



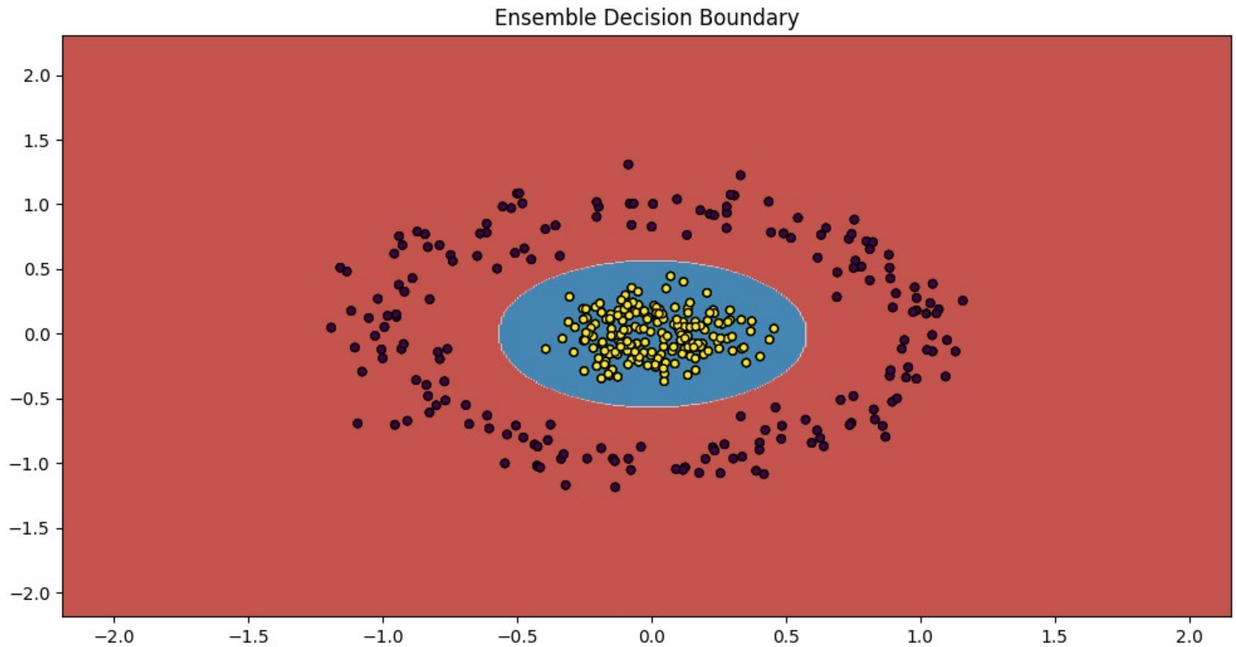

```
Parameters: {}, eta: 1, Accuracy: 1.0000, Error: 0.0000
Best eta for Decision Tree (depth=3): 1 with accuracy: 1.0000


Tuning hyperparameters for Linear SVM...
```



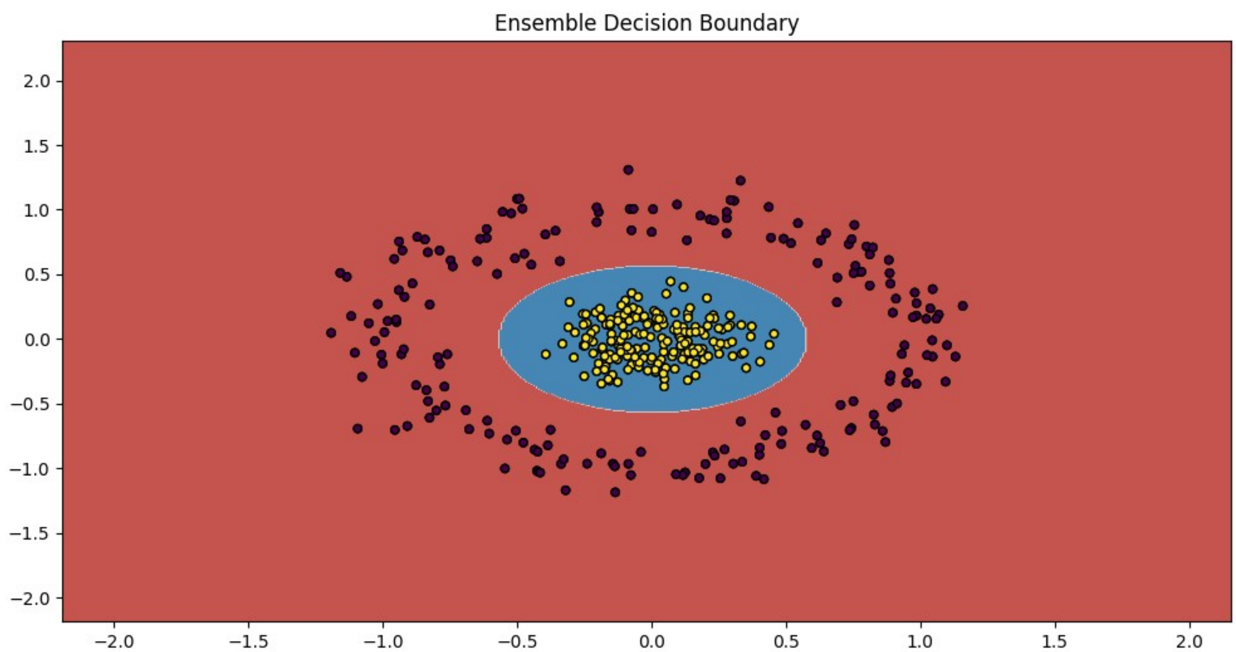
Ensemble Decision Boundary
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0

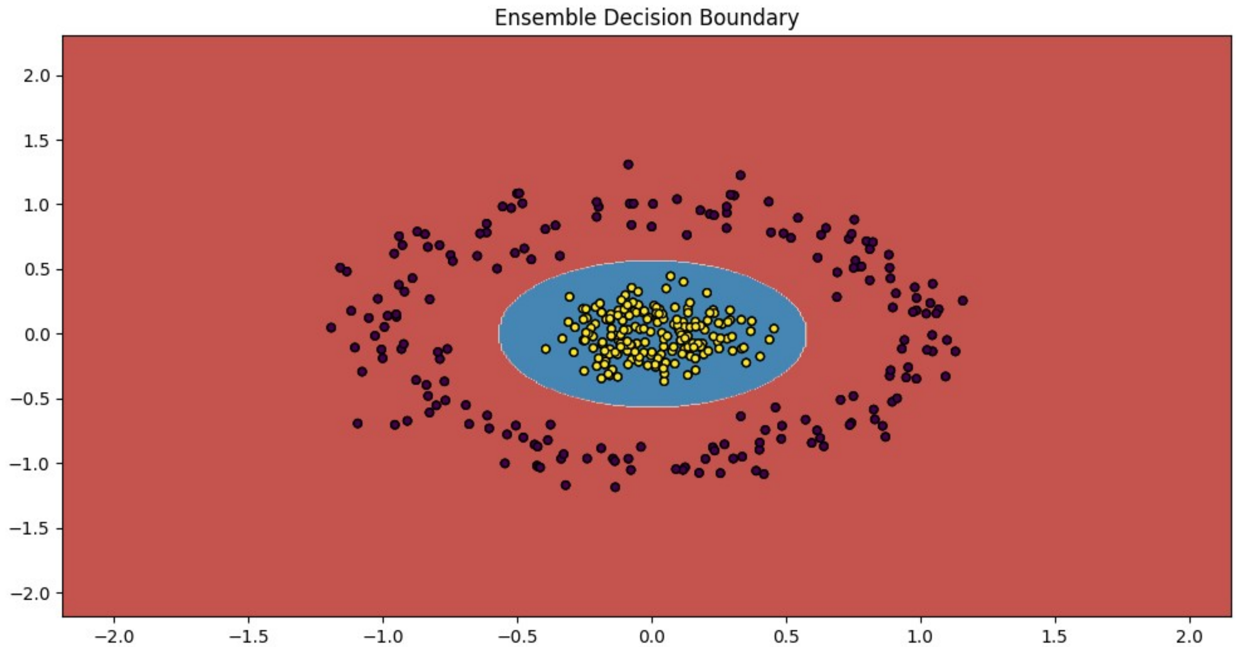
Ensemble Decision Boundary
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0



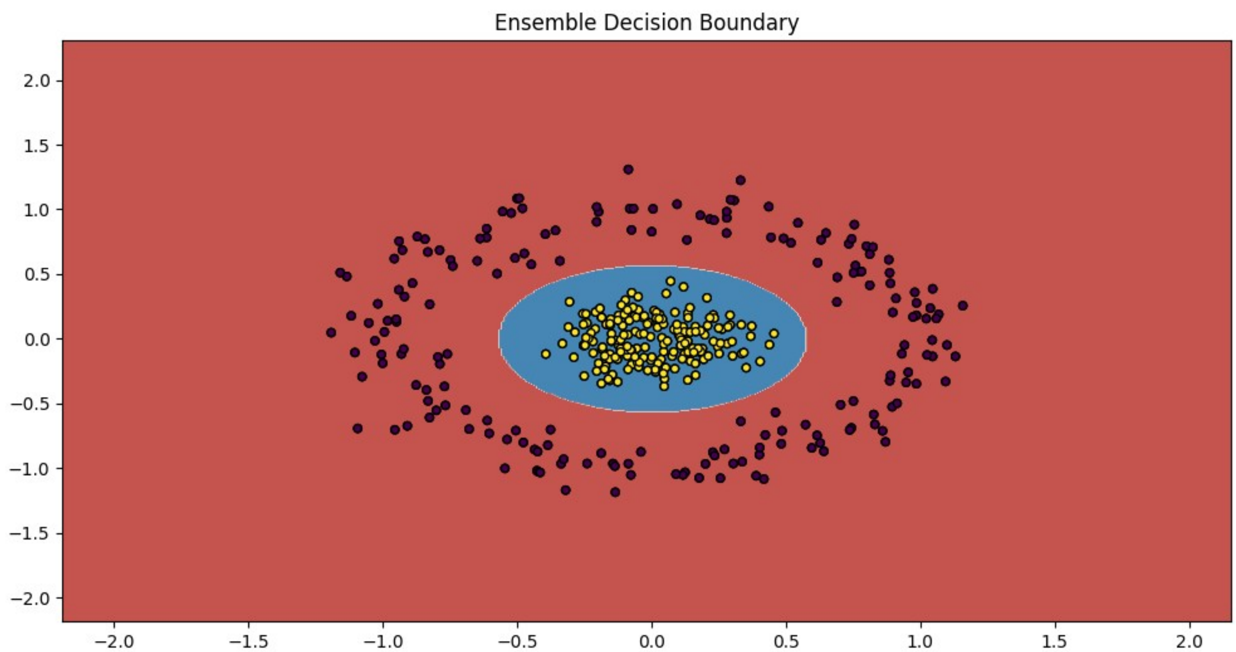

```
Best parameters for Linear SVM: {'C': 10} with accuracy: 1.0000
Tuning eta for Linear SVM with best params: {'C': 10}...
```



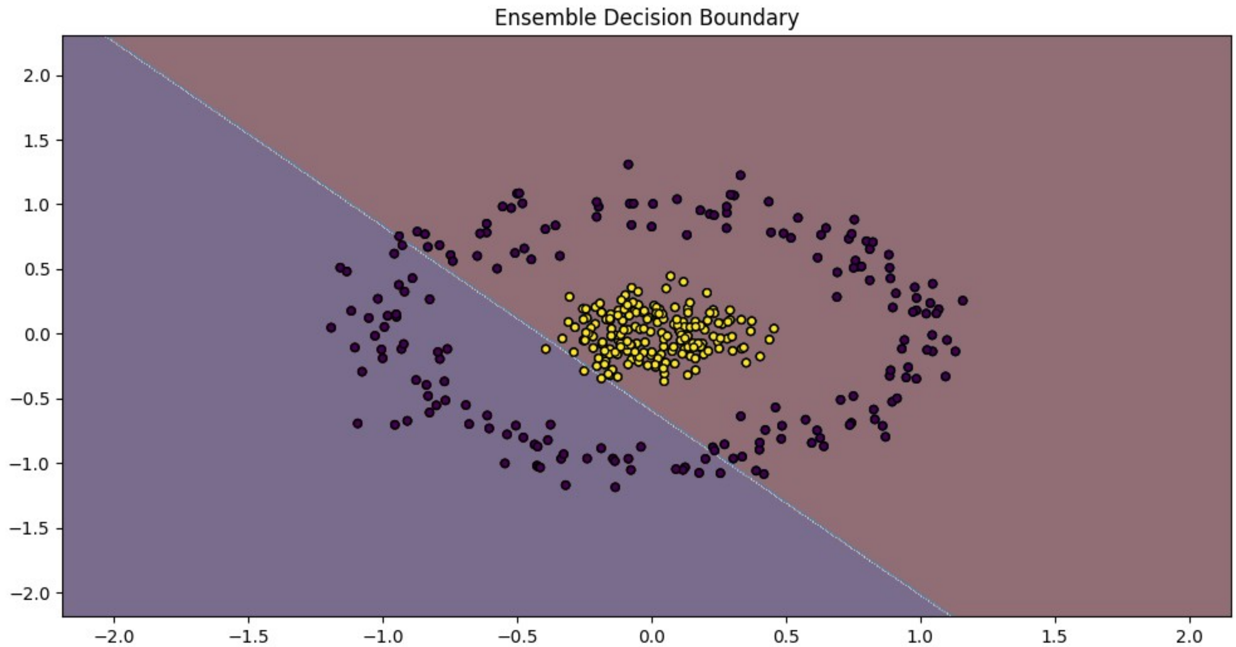

```
Parameters: {'C': 10}, eta: 0.1, Accuracy: 1.0000, Error: 0.0000
```



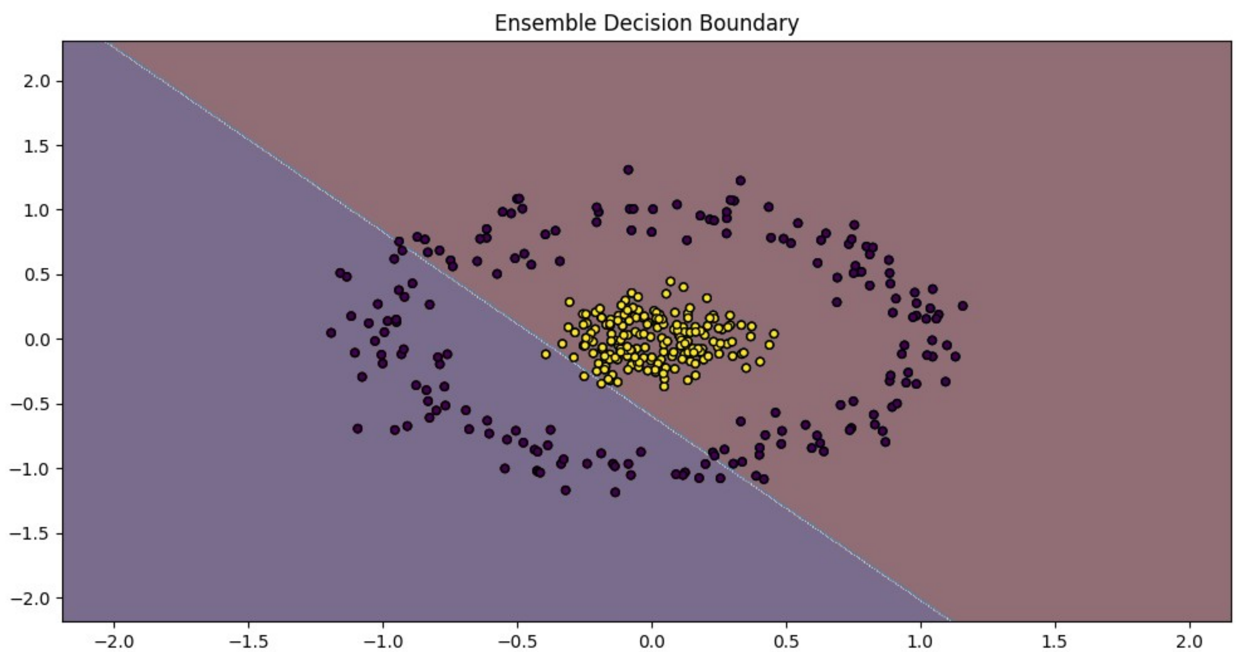

```
Parameters: {'C': 10}, eta: 0.5, Accuracy: 1.0000, Error: 0.0000
```



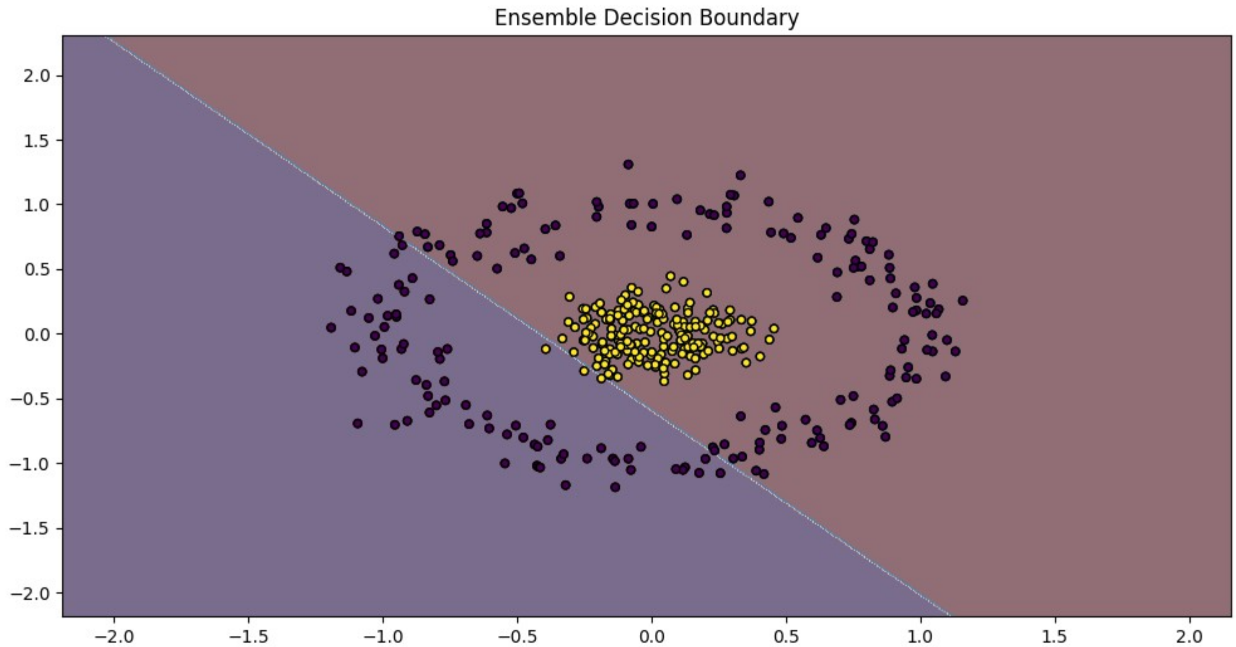

```
Parameters: {'C': 10}, eta: 1, Accuracy: 1.0000, Error: 0.0000
Best eta for Linear SVM: 0.1 with accuracy: 1.0000


Tuning hyperparameters for LDA...
```



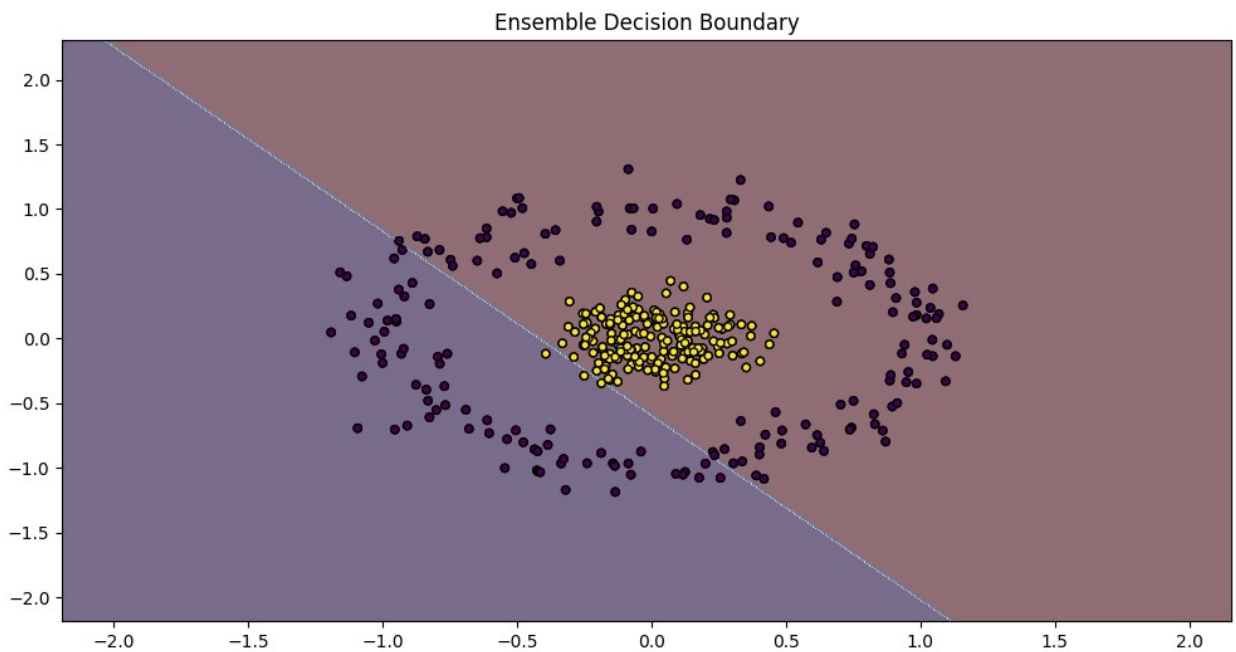

```
Best parameters for LDA: {} with accuracy: 0.7360
Tuning eta for LDA with best params: {}...
```




```
Parameters: {}, eta: 0.1, Accuracy: 0.7360, Error: 0.2640
```

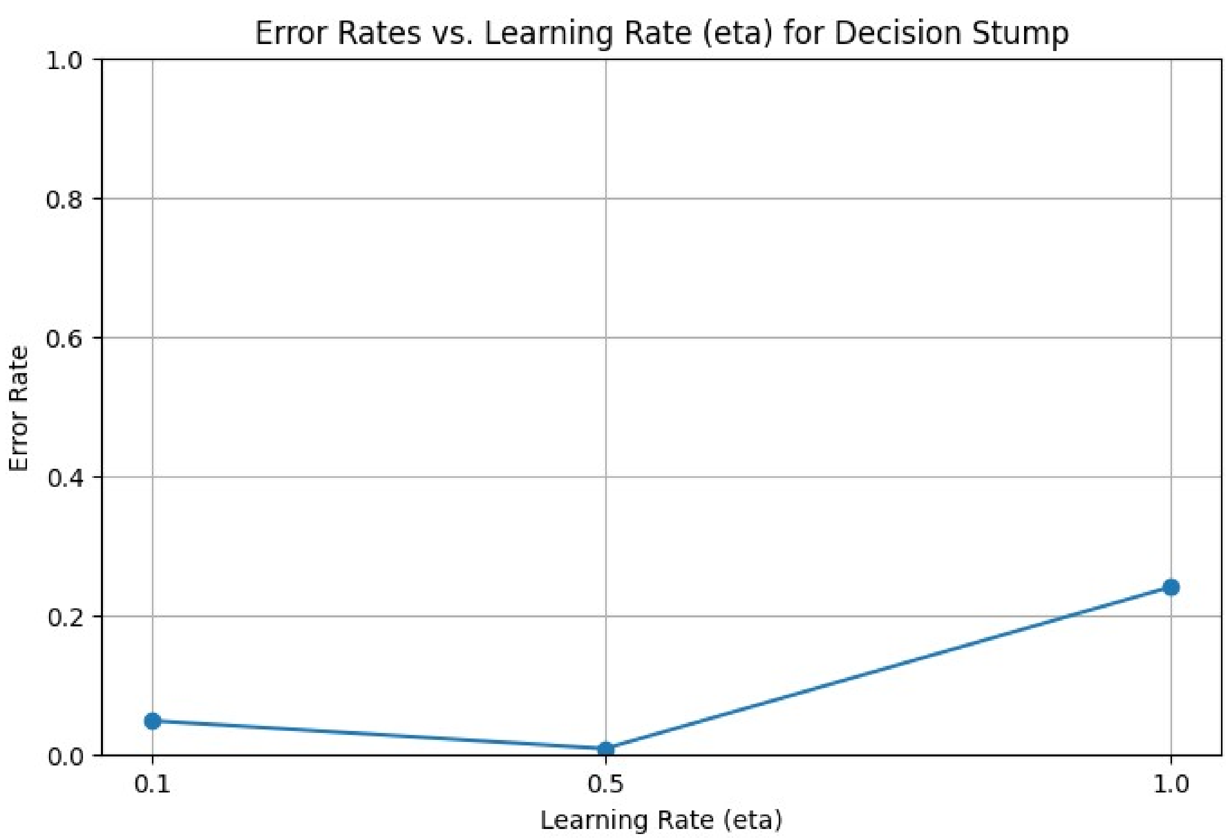



```
Parameters: {}, eta: 0.5, Accuracy: 0.7360, Error: 0.2640
```

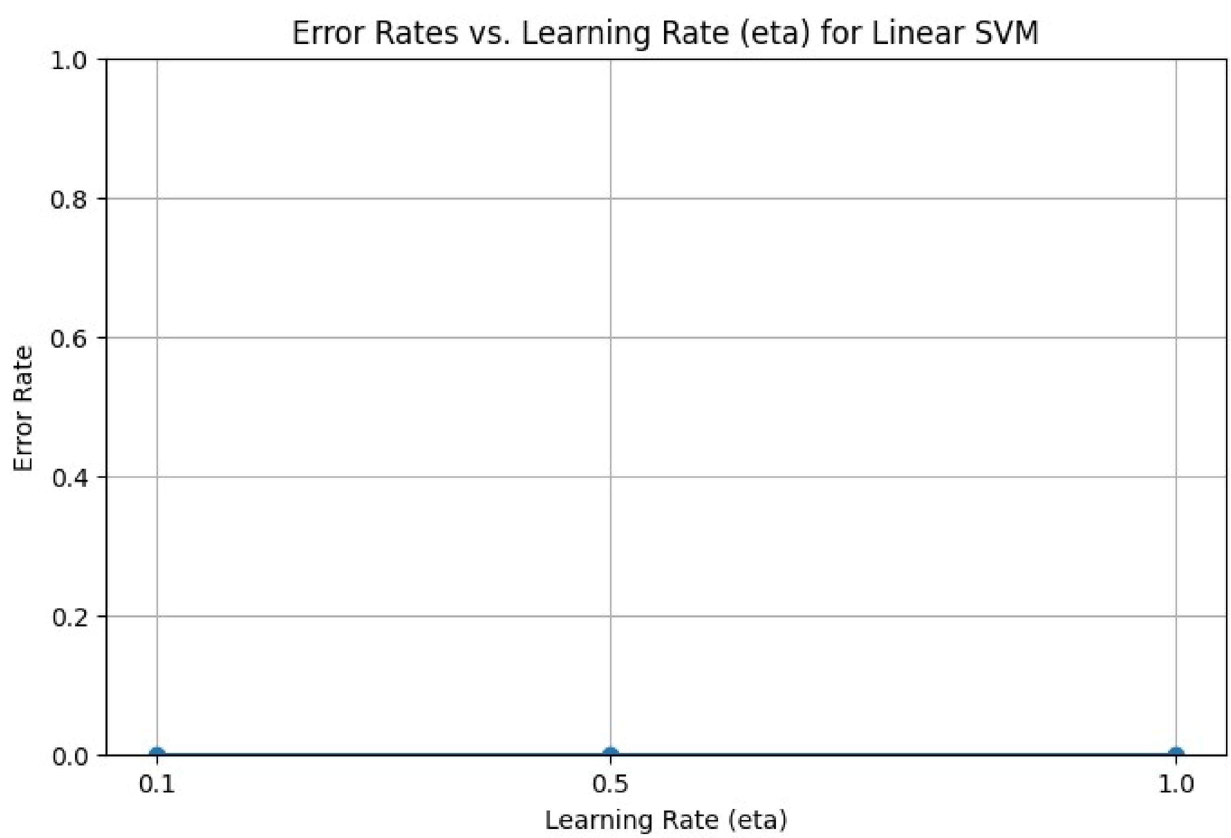


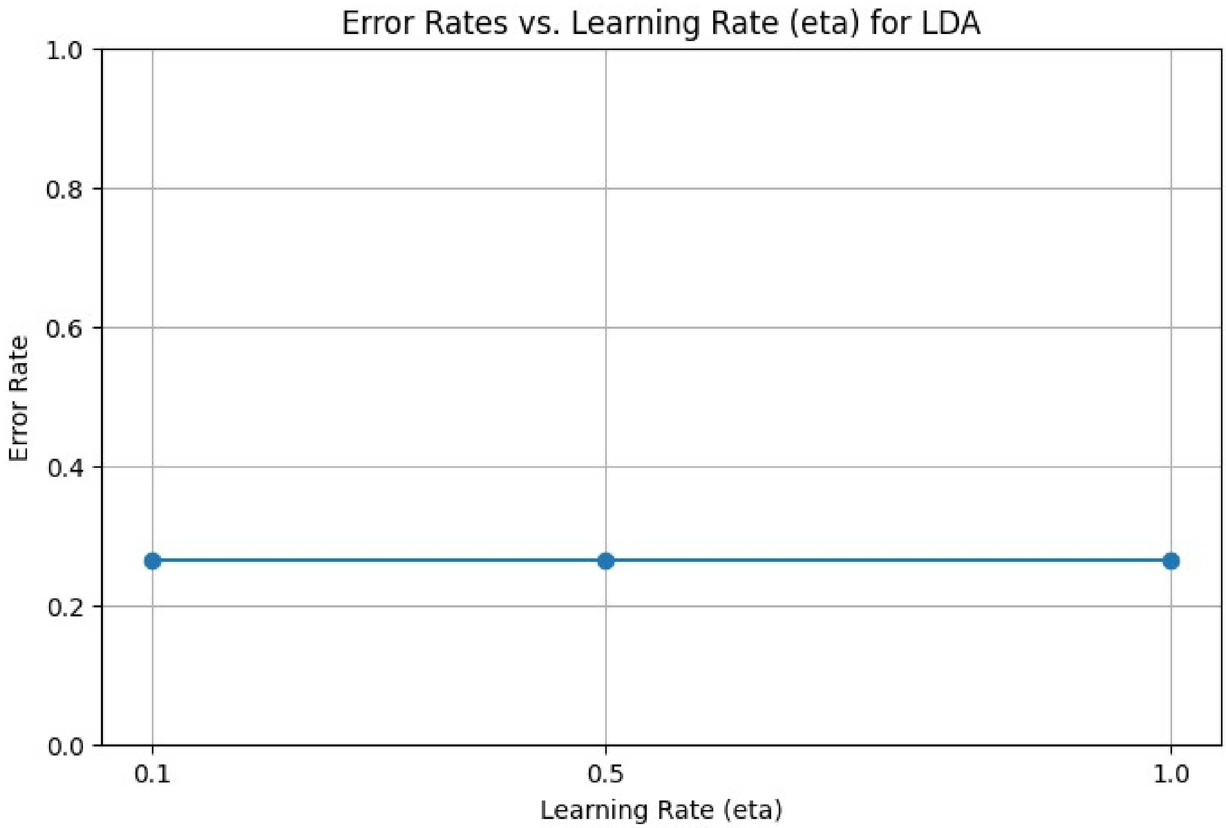

```
Parameters: {}, eta: 1, Accuracy: 0.7360, Error: 0.2640
Best eta for LDA: 0.1 with accuracy: 0.7360
```


Error Rates vs. Learning Rate (eta) for Logistic Regression
Error Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.1
0.5
1.0
Learning Rate (eta)


Error Rates vs. Learning Rate (eta) for Decision Stump
Error Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.1
0.5
1.0
Learning Rate (eta)


Error Rates vs. Learning Rate (eta) for Decision Tree (depth=3)
1.0
0.8
0.6
0.4
0.2
0.0
Error Rate
0.1
0.5
1.0
Learning Rate (eta)


Error Rates vs. Learning Rate (eta) for Linear SVM
1.0
0.8
0.6
0.4
0.2
0.0
Error Rate
0.1
0.5
1.0
Learning Rate (eta)


Error Rates vs. Learning Rate (eta) for LDA
Error Rate
Learning Rate (eta)
1.0
0.8
0.6
0.4
0.2
0.0
0.1
0.5
1.0