By Kamilla

A2: Classification with SVM, BP and MLR

Github link: https://github.com/kamillok505/A1.git

Support Vector Machines (SVMs): The journey into the world of SVMs begins with an appreciation of its elegance and robustness. SVMs, a quintessential example of supervised learning, are celebrated for their precision in classification, regression, and outlier detection. The beauty of SVMs lies in their ability to thrive in high-dimensional spaces, a characteristic indispensable in handling the intricate datasets of the modern age. This algorithm is akin to a skilled artist, deftly carving out the decision boundary in a multidimensional feature space, separating data points with a finesse that is both mathematically profound and practically invaluable.

Multiple Linear Regression (MLR): MLR, an extension of the simple linear regression, emerges as a versatile tool in statistical modeling. It allows us to weave multiple independent variables into a cohesive predictive model for a single dependent variable. The introduction to MLR in the notebook is like a prelude to a symphony, setting the stage for a harmonious blend of theory and practice. Utilizing Python's Scikit-learn library, this section promises a journey through the nuances of MLR, from the initial steps of data preprocessing to the final act of model evaluation. MLR stands as a testament to the power of statistical methods in uncovering the relationships hidden within data, offering a multi-faceted perspective in predictive analysis.

Bayesian Probability (BP): The world of Bayesian Probability is one of probabilistic intrigue and logical reasoning. BP, steeped in the principles of probability and inference, offers a dynamic approach to understanding uncertainty in data. It is a realm where prior knowledge is harmoniously blended with new evidence to arrive at posterior conclusions. This algorithm is like a seasoned detective, piecing together clues (data) and prior experiences (prior probabilities) to form a coherent picture of the world (posterior probability). The introduction to BP in the notebook is an invitation to delve into the depths of probabilistic thinking, unraveling complex data scenarios with a methodology that is as intellectually satisfying as it is practically effective.

Together, these three algorithms – SVMs, MLR, and BP – form a triad of machine learning prowess. Each brings its unique strengths and perspectives to the table, offering a comprehensive toolkit for tackling the diverse challenges of data analysis and prediction. Their introductions in the respective notebooks are not just openings to individual chapters of machine learning; they are gateways to worlds of analytical possibilities, each waiting to be explored and mastered.

The purpose and applications of the three algorithms – Support Vector Machines (SVMs), Multiple Linear Regression (MLR), and Bayesian Probability (BP) – highlight their diverse capabilities and the wide range of problems they can solve in the field of machine learning and data analysis.

Support Vector Machines (SVMs):

- **Purpose:** SVMs are designed to find the optimal separating hyperplane in a high-dimensional space, which can classify data points into different categories. They are also used for regression and outlier detection. The key purpose of an SVM is to maximize the margin between data points and the decision boundary, ensuring robust classification even in complex datasets.

- **Applications:**
    - **Classification Tasks:** SVMs are extensively used in image recognition, text categorization, and bioinformatics for classifying complex datasets with high accuracy.
    - **Regression Analysis:** In cases where predictive modeling involves continuous data, SVMs can be adapted for regression tasks.
    - **Outlier Detection:** SVMs are effective in identifying anomalies in datasets, such as fraudulent activities in finance or defective items in manufacturing processes.

Multiple Linear Regression (MLR):

- **Purpose:** MLR aims to model the relationship between two or more independent variables and a dependent variable by fitting a linear equation to observed data. The purpose is to understand how changes in the independent variables impact the dependent variable.
- **Applications:**
    - **Economic Forecasting:** MLR is used to predict economic indicators such as GDP growth based on various factors like interest rates, employment levels, and consumer spending.
    - **Business Analysis:** Companies use MLR for predicting sales, understanding customer behavior, and optimizing marketing strategies.
    - **Healthcare Research:** MLR assists in analyzing the impact of multiple factors like diet, lifestyle, and genetics on health outcomes.

Bayesian Probability (BP):

- **Purpose:** BP is used for statistical inference and decision making under uncertainty. It combines prior knowledge with new evidence to update beliefs or predictions. The purpose is to provide a probabilistic framework that can adapt as new data becomes available.
- **Applications:**
    - **Risk Analysis:** In finance and insurance, BP is used to assess and manage risks by updating probabilities as new information becomes available.
    - **Machine Learning:** BP methods underpin many modern machine learning techniques, especially in algorithms that require a probabilistic approach, like Bayesian networks and spam filtering.
    - **Medical Diagnostics:** BP aids in diagnostic decision-making by updating the likelihood of diseases as new symptoms or test results are observed.

Each of these algorithms serves distinct purposes and finds applications in various domains, showcasing the versatility and breadth of machine learning techniques. From predictive modeling in MLR to decision-making under uncertainty in BP, and the robust classification capabilities of SVMs, these algorithms provide powerful tools for analyzing and making sense of the complex world of data.

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The implementation of Support Vector Machines (SVMs), Multiple Linear Regression (MLR), and Bayesian Probability (BP) in Python leverages a range of specialized libraries, each offering tools and functions essential for effective algorithm deployment. Here's an overview of the key libraries used for each of these algorithms:

Support Vector Machines (SVMs):

- **Scikit-learn (sklearn):** This is the primary library used for implementing SVMs in Python. Scikit-learn provides a comprehensive set of tools for machine learning, including support for various SVM models through classes like **SVC** (Support Vector Classification) and **SVR** (Support Vector Regression). It also offers utilities for data splitting, feature scaling, and model evaluation.
- **NumPy (numpy):** Often used alongside Scikit-learn, NumPy is crucial for handling numerical operations and data structures, especially arrays, which are extensively used in data processing for SVMs.
- **Pandas (pandas):** This library is used for data manipulation and analysis, particularly useful for reading and preprocessing datasets before feeding them into an SVM model.

Multiple Linear Regression (MLR):

- **Scikit-learn (sklearn):** It provides the **LinearRegression** class, which is used to create and train MLR models. Scikit-learn also includes functionalities for preprocessing data, splitting datasets into training and testing sets, and evaluating model performance.
- **Pandas (pandas):** Essential for data handling, Pandas allows for easy manipulation and preparation of data for MLR, including handling missing values, converting categorical variables, and more.
- **Statsmodels (statsmodels):** This library is particularly useful for more detailed statistical analysis in MLR, offering extensive summary reports and diagnostics of the regression model.

Bayesian Probability (BP):

- **PyMC3 (pymc3):** A library for probabilistic programming, PyMC3 is ideal for Bayesian statistical modeling and fitting complex models using advanced Markov chain Monte Carlo (MCMC) methods.
- **Scikit-learn (sklearn):** While primarily known for classical machine learning algorithms, Scikit-learn also supports Bayesian methods, particularly in the context of classification and regression.
- **NumPy (numpy) and Pandas (pandas):** These libraries provide the foundational data structures and data manipulation capabilities required for preparing and handling data in Bayesian analysis.

Each of these libraries plays a crucial role in the implementation and application of the respective algorithms. They not only offer the necessary statistical and machine learning tools but also provide a user-friendly interface for data manipulation, model training, and evaluation, making them indispensable in the Python data science ecosystem.

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The significance of the mentioned libraries in the context of Support Vector Machines (SVMs), Multiple Linear Regression (MLR), and Bayesian Probability (BP) reflects their essential roles in enabling effective implementation and analysis within the Python ecosystem. Each library contributes uniquely to the data science workflow, ensuring that these complex algorithms can be applied successfully to real-world problems.

Support Vector Machines (SVMs):

- **Scikit-learn (sklearn):** This library is central to implementing SVMs due to its efficient and straightforward functions for creating and training SVM models. Its comprehensive tools for preprocessing, model selection, and evaluation streamline the process of building robust SVM classifiers and regressors.
- **NumPy (numpy):** NumPy's significance lies in its array data structures and mathematical functions, which are crucial for handling the computations involved in SVMs. Its efficiency in handling large datasets and complex mathematical operations makes it indispensable.
- **Pandas (pandas):** Pandas is significant for its ability to handle and preprocess data, particularly in cleaning, transforming, and organizing datasets into a format suitable for training SVM models.

Multiple Linear Regression (MLR):

- **Scikit-learn (sklearn):** For MLR, Scikit-learn provides not just the implementation of the regression model but also crucial preprocessing and cross-validation tools, helping to ensure the robustness and accuracy of the regression analysis.
- **Pandas (pandas):** The significance of Pandas in MLR lies in its comprehensive data manipulation capabilities, allowing for the efficient handling of datasets, which is a prerequisite for any regression analysis.
- **Statsmodels (statsmodels):** Its importance comes from its detailed statistical modeling capabilities, offering in-depth diagnostic tools and reports that are essential for a thorough understanding and interpretation of MLR models.

Bayesian Probability (BP):

- **PyMC3 (pymc3):** PyMC3 is a critical library for Bayesian analysis, offering advanced functionalities for building Bayesian models and performing statistical inference using MCMC. Its significance is in its ability to handle complex Bayesian models that are often impractical to solve analytically.
- **Scikit-learn (sklearn):** In the context of BP, Scikit-learn is important for preprocessing data and for implementing simpler Bayesian models, providing a bridge between traditional machine learning techniques and probabilistic modeling.
- **NumPy (numpy) and Pandas (pandas):** These libraries are significant for their foundational role in numerical computations and data handling. They facilitate the manipulation and preparation of data, which is a critical step in Bayesian statistical modeling.

Together, these libraries form a comprehensive toolkit, each contributing to different aspects of SVMs, MLR, and BP. Their functionalities range from data handling and preprocessing to model building, training, and evaluation, highlighting their indispensable roles in the field of machine learning and data science.

Data handling is a critical component in the effective implementation of Support Vector Machines (SVMs), Multiple Linear Regression (MLR), and Bayesian Probability (BP). The way data is managed, processed, and prepared directly impacts the performance and accuracy of these algorithms. Here's an overview of the data handling aspects for each of these algorithms:

Support Vector Machines (SVMs):

- **Data Preprocessing:** SVMs require carefully preprocessed data. This includes normalization or standardization to ensure that all features contribute equally to the model, especially important in high-dimensional spaces.
- **Handling Non-Linear Data:** For non-linearly separable data, SVMs use kernel functions to transform data into a higher-dimensional space where it can be linearly separated. This requires careful selection and tuning of kernel parameters.
- **Feature Selection:** Due to SVMs' effectiveness in high-dimensional spaces, feature selection becomes crucial to eliminate redundant or irrelevant features that might lead to overfitting.

Multiple Linear Regression (MLR):

- **Assumption Checks:** MLR requires the data to adhere to specific assumptions like linearity, homoscedasticity, and multicollinearity checks. Ensuring these assumptions are met is a crucial part of data preparation.
- **Categorical Variable Handling:** MLR cannot directly handle categorical variables. These variables need to be converted into numerical form, often through one-hot encoding or label encoding.
- **Outlier Detection and Removal:** Outliers can significantly skew the results of an MLR model. Therefore, identifying and handling outliers is a critical step in the data preparation process.

Bayesian Probability (BP):

- **Data Transformation:** BP methods often require data to be transformed into a format suitable for probabilistic modeling. This includes converting data into likelihoods or probabilities.
- **Incorporating Prior Information:** One of the unique aspects of BP is the incorporation of prior knowledge. Data handling in BP includes the integration of this prior information into the model, which could be in the form of previously observed data or expert knowledge.
- **Handling Missing Data:** Bayesian methods are well-suited to handle missing data by treating them as additional parameters to be estimated, or by using data imputation techniques that are consistent with the Bayesian framework.

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In all three algorithms, the way data is handled can significantly influence the model's performance. This includes how data is cleaned, transformed, and structured, as well as how specific characteristics of the data are addressed, such as non-linearity, categorical variables, and outliers. Effective data handling is thus a critical skill in the arsenal of a data scientist working with SVMs, MLR, or BP.

T essential steps of loading data, splitting it into training and testing sets, training an SVM model, making predictions, and evaluating the model's performance. The visualization part is a bonus, especially useful for understanding how the SVM algorithm classifies data in lower-dimensional spaces. Remember, for more complex datasets, especially those with more than two features, visualization of the decision boundary becomes more challenging and might require dimensionality reduction techniques like PCA.

The notebook includes the use of t-Distributed Stochastic Neighbor Embedding (t-SNE) for dimensionality reduction. This technique is particularly useful for visualizing high-dimensional data in two dimensions.

After training a Bayesian model (presumably a neural network with Bayesian layers), the predictions are visualized in the t-SNE reduced space.

The approach, combining neural networks with Bayesian methods, is indicative of a more modern take on Bayesian analysis, often referred to as Bayesian Deep Learning. It leverages the power of neural networks to handle complex patterns in data while incorporating Bayesian principles to manage uncertainty and provide probabilistic interpretations of the model outputs.

Data Visualization with t-SNE: The notebook uses t-Distributed Stochastic Neighbor Embedding (t-SNE) for dimensionality reduction, which is particularly useful for visualizing high-dimensional data in two dimensions.
Implementing Multiple Linear Regression:

The notebook demonstrates the implementation of MLR using Scikit-lean’s LinearRegression class. This is accompanied by the use of cross-validation to assess the model's performance.

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```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score
import numpy as np

mlr_model = LinearRegression()

# Performing cross-validation
n_splits = 5
scores = cross_val_score(mlr_model, X, y, cv=n_splits, scoring='neg_mean_squared_error')

# Calculating average Mean Squared Error
average_mse = np.mean(-scores)
print("Average Mean Squared Error:", average_mse)
```

In this notebook, MLR is used to model the relationship between multiple independent variables and a dependent variable. The t-SNE visualization aids in understanding the dataset's structure before applying MLR. The implementation of MLR with cross-validation provides a robust way to estimate the model's performance, specifically using Mean Squared Error (MSE) as a metric. This approach reflects a standard procedure in machine learning for regression tasks, emphasizing model evaluation and validation.

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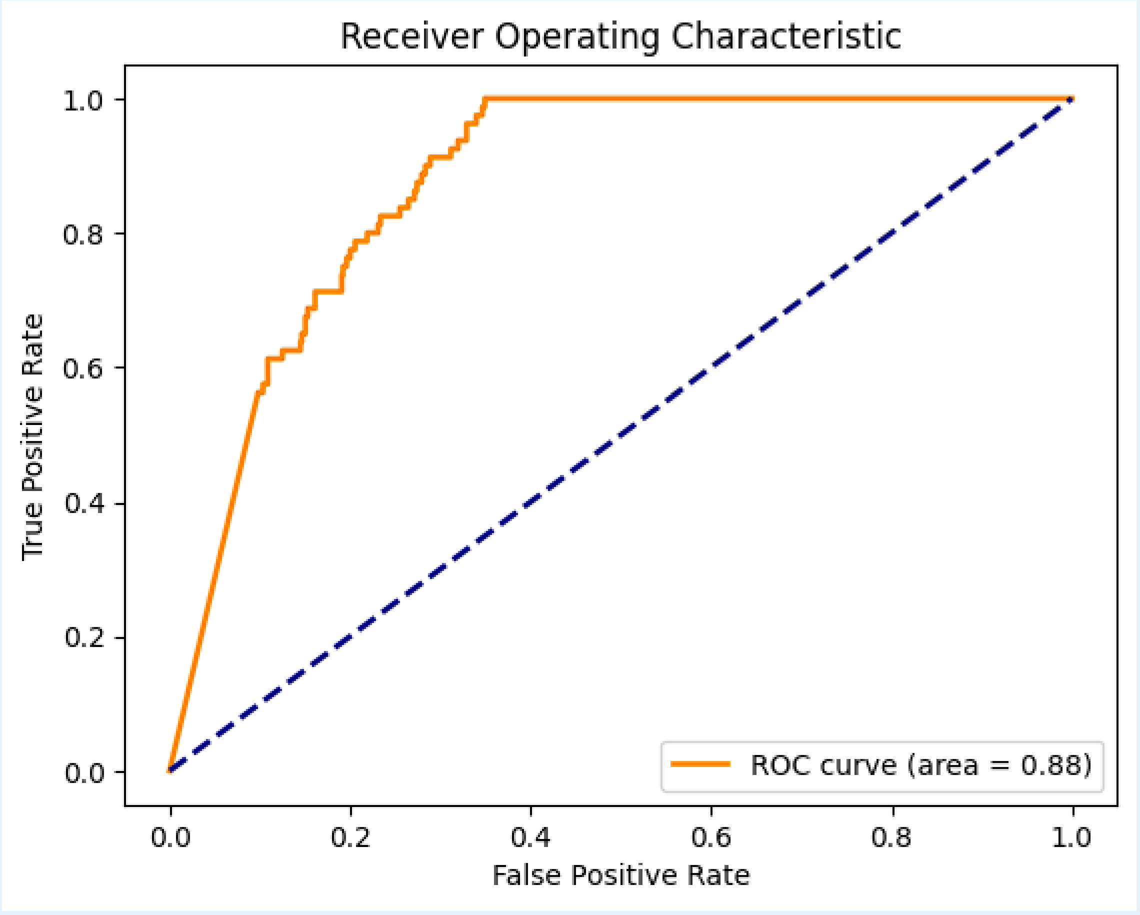
```
# Training for bank dataset
model_bank = create_model(X_train_bank.shape[1])
model_bank.fit(X_train_bank, y_train_bank, epochs=50, batch_size=10, verbose=0)
y_pred_bank = (model_bank.predict(X_test_bank) > 0.5).astype("int32")
print("Classification Report for Bank Marketing Dataset:")
print(classification_report(y_test_bank, y_pred_bank))
```

```
Classification Report for Bank Marketing Dataset:
              precision    recall  f1-score   support

           0       0.95      0.90      0.92       744
           1       0.37      0.56      0.45        80

    accuracy                           0.86       824
   macro avg       0.66      0.73      0.68       824
weighted avg       0.89      0.86      0.88       824
```

```
# Plot ROC Curve
y_scores_bank = model_bank.predict(X_test_bank).ravel()
plot_roc_curve(y_test_bank, y_scores_bank)
```



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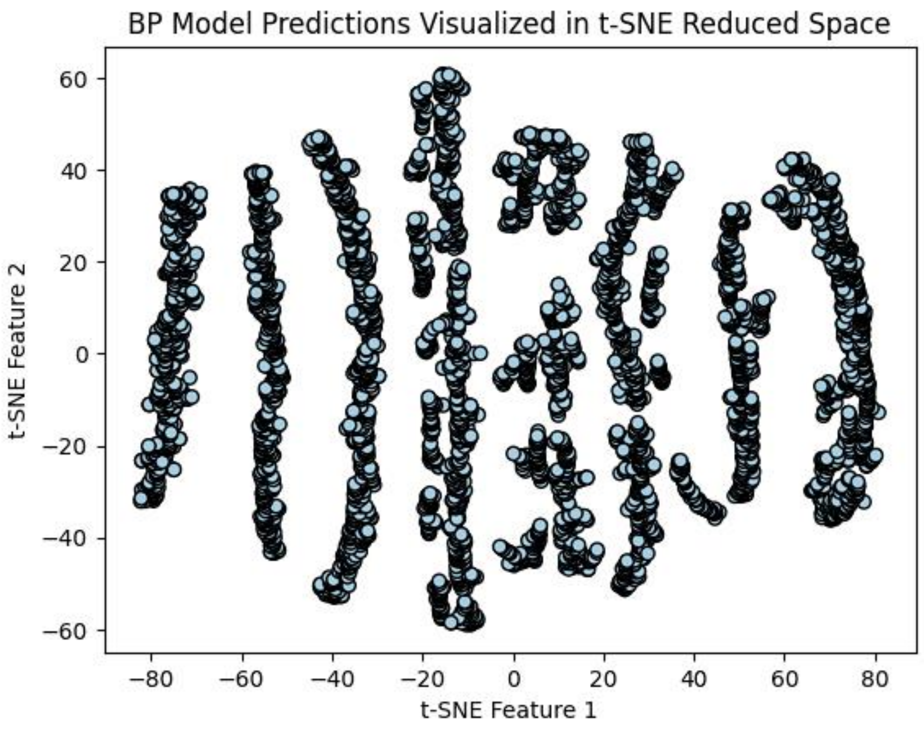
```
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt

# Dimensionality Reduction using t-SNE
tsne = TSNE(n_components=2, random_state=0)
X_reduced = tsne.fit_transform(X_bank)

y_pred = bp_model.predict(X_bank)
y_pred_classes = np.argmax(y_pred, axis=1)

plt.scatter(X_reduced[:, 0], X_reduced[:, 1], c=y_pred_classes, cmap=plt.cm.Paired, edgecolors='k')
plt.xlabel('t-SNE Feature 1')
plt.ylabel('t-SNE Feature 2')
plt.title('BP Model Predictions Visualized in t-SNE Reduced Space')
plt.show()
```



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```python
from sklearn.metrics import confusion_matrix, accuracy_score

def compute_classification_error(y_true, y_pred):
    error = 1 - accuracy_score(y_true, y_pred)
    return error

def generate_confusion_matrix(y_true, y_pred):
    cm = confusion_matrix(y_true, y_pred)
    return cm

y_pred_bp = bp_model.predict(X_bank)
y_pred_bp = (y_pred_bp > 0.5).astype(int)

error_bp = compute_classification_error(y_bank, y_pred_bp)
cm_bp = generate_confusion_matrix(y_bank, y_pred_bp)

print("Classification Error (BP):", error_bp)
print("Confusion Matrix (BP):\n", cm_bp)
```

```
Classification Error (BP): 0.29400000000000004
Confusion Matrix (BP):
 [[3530    0]
 [1470    0]]
```

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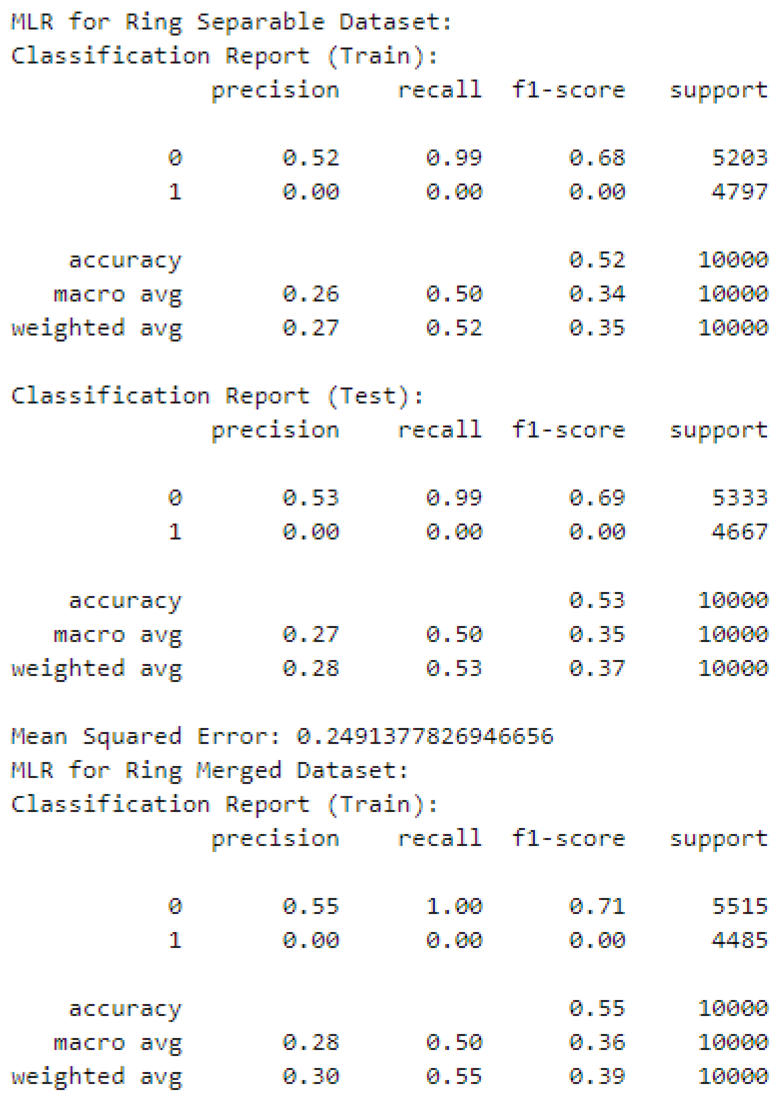
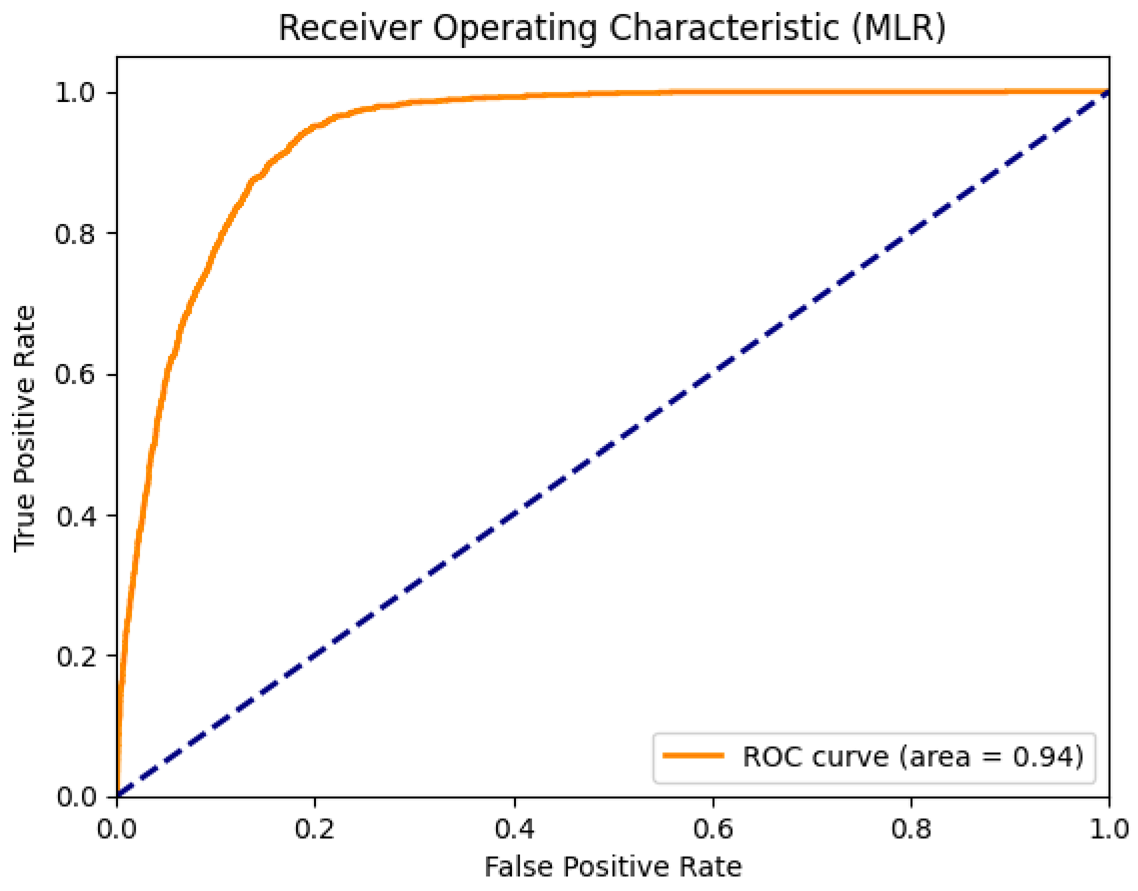


```
MLR for Ring Separable Dataset:
Classification Report (Train):
              precision    recall  f1-score   support

           0       0.52      0.99      0.68      5203
           1       0.00      0.00      0.00      4797

    accuracy                           0.52     10000
   macro avg       0.26      0.50      0.34     10000
weighted avg       0.27      0.52      0.35     10000

Classification Report (Test):
              precision    recall  f1-score   support

           0       0.53      0.99      0.69      5333
           1       0.00      0.00      0.00      4667

    accuracy                           0.53     10000
   macro avg       0.27      0.50      0.35     10000
weighted avg       0.28      0.53      0.37     10000

Mean Squared Error: 0.2491377826946656
MLR for Ring Merged Dataset:
Classification Report (Train):
              precision    recall  f1-score   support

           0       0.55      1.00      0.71      5515
           1       0.00      0.00      0.00      4485

    accuracy                           0.55     10000
   macro avg       0.28      0.50      0.36     10000
weighted avg       0.30      0.55      0.39     10000
```


Receiver Operating Characteristic (MLR)
True Positive Rate
False Positive Rate
ROC curve (area = 0.94)
0.0
0.2
0.4
0.6
0.8
1.0

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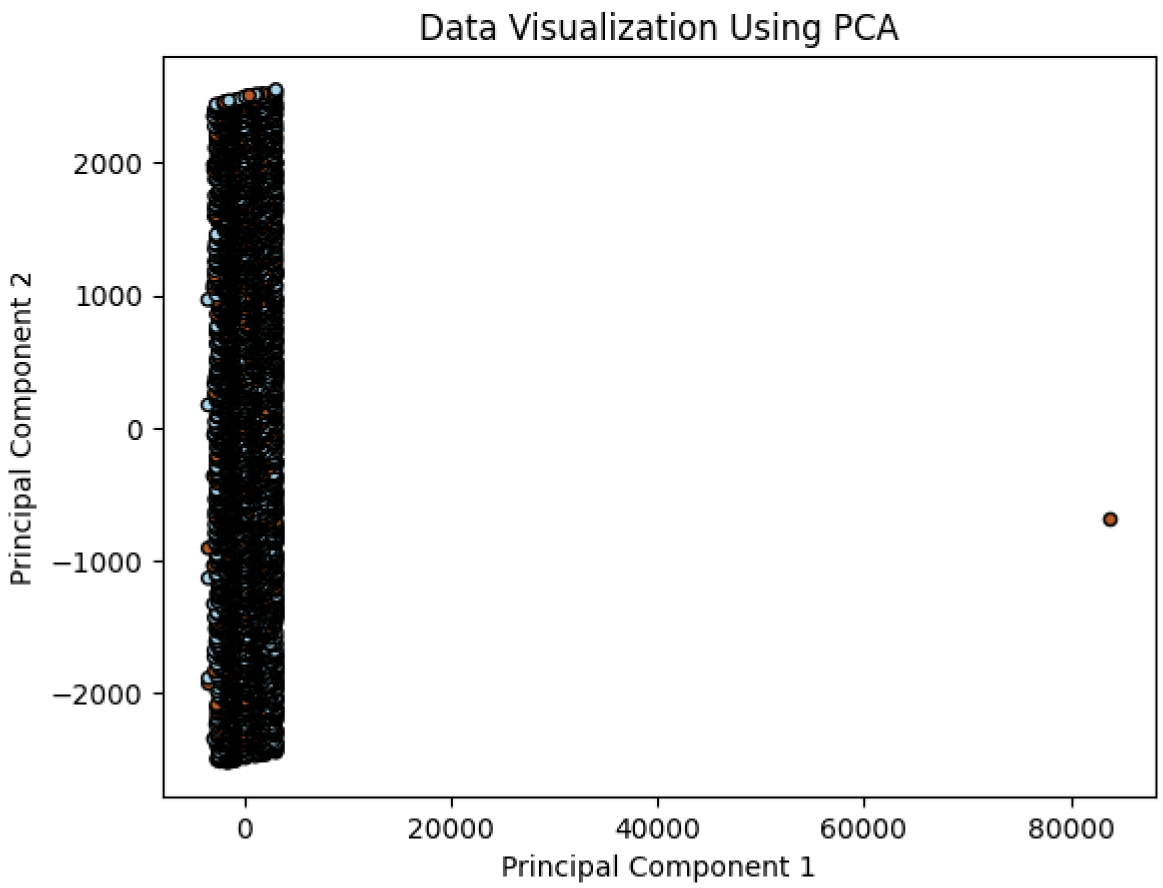

Data Visualization Using PCA
Principal Component 2
Principal Component 1
2000
1000
0
−1000
−2000
0
20000
40000
60000
80000

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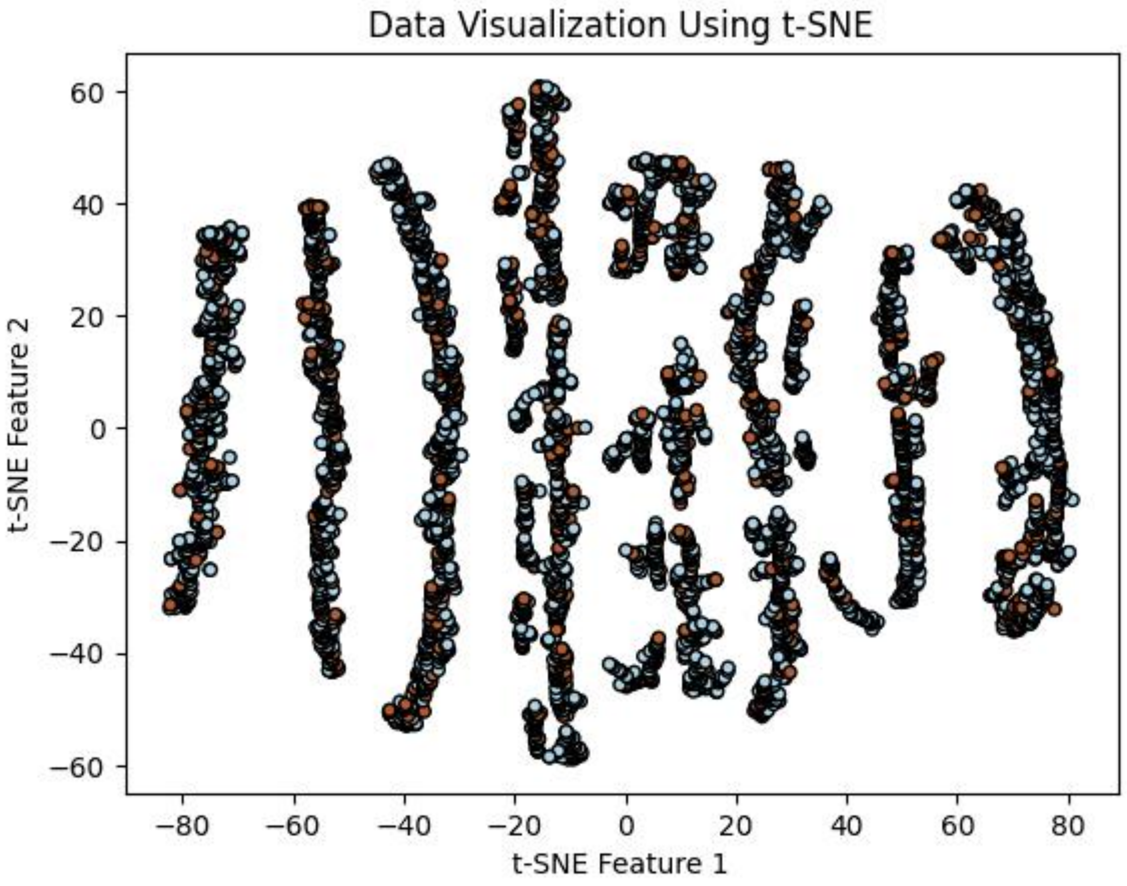
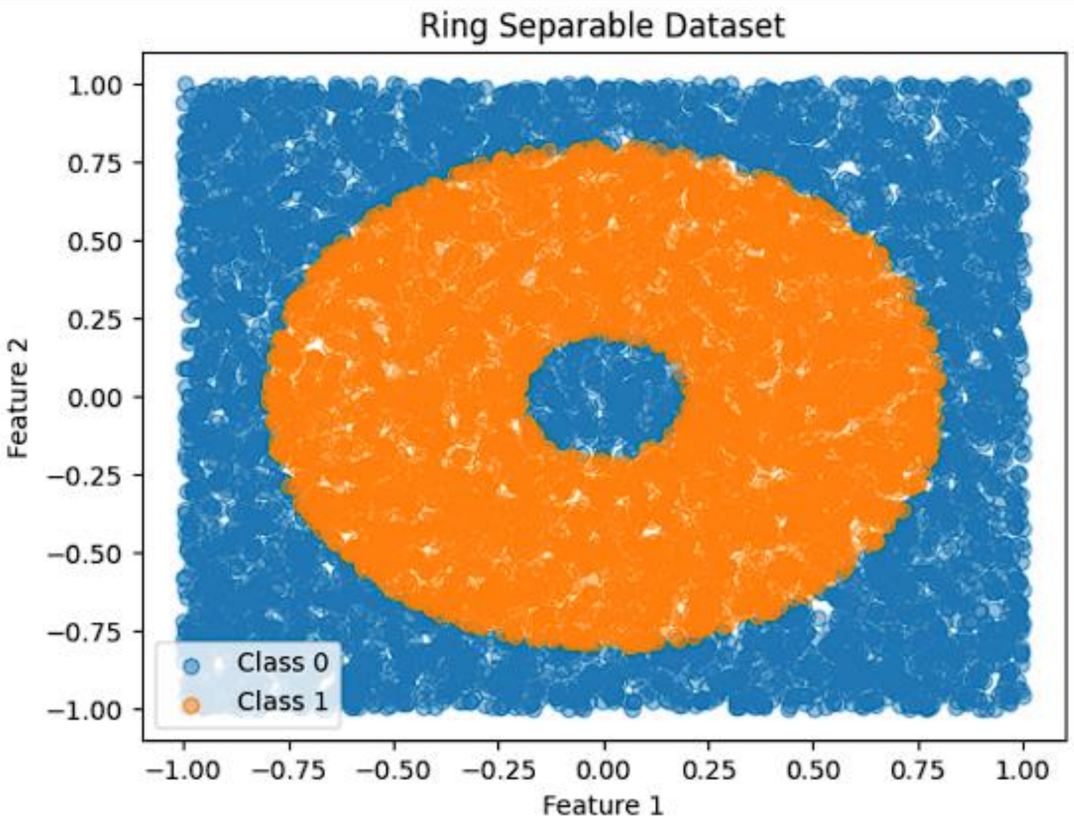
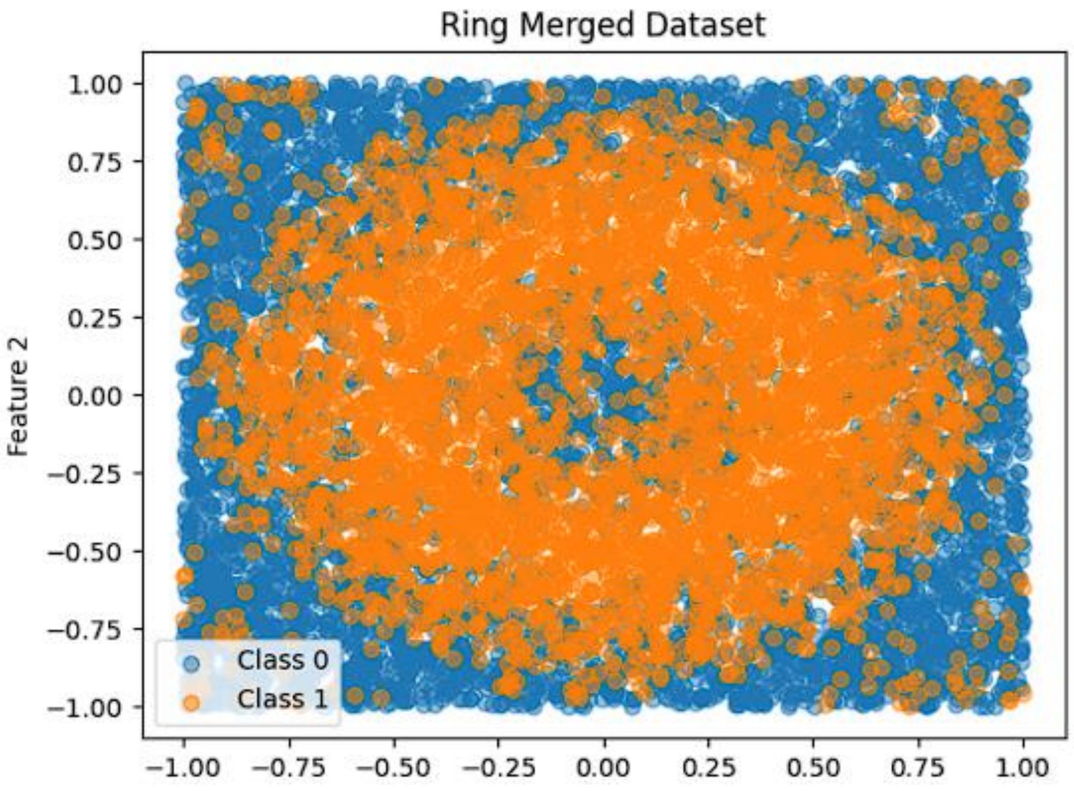

Data Visualization Using t-SNE
t-SNE Feature 2
t-SNE Feature 1
60
40
20
0
−20
−40
−60
−80
−60
−40
−20
0
20
40
60
80


Ring Separable Dataset
Feature 1
Feature 2
Class 0
Class 1
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


Ring Merged Dataset
Feature 2
Class 0
Class 1
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

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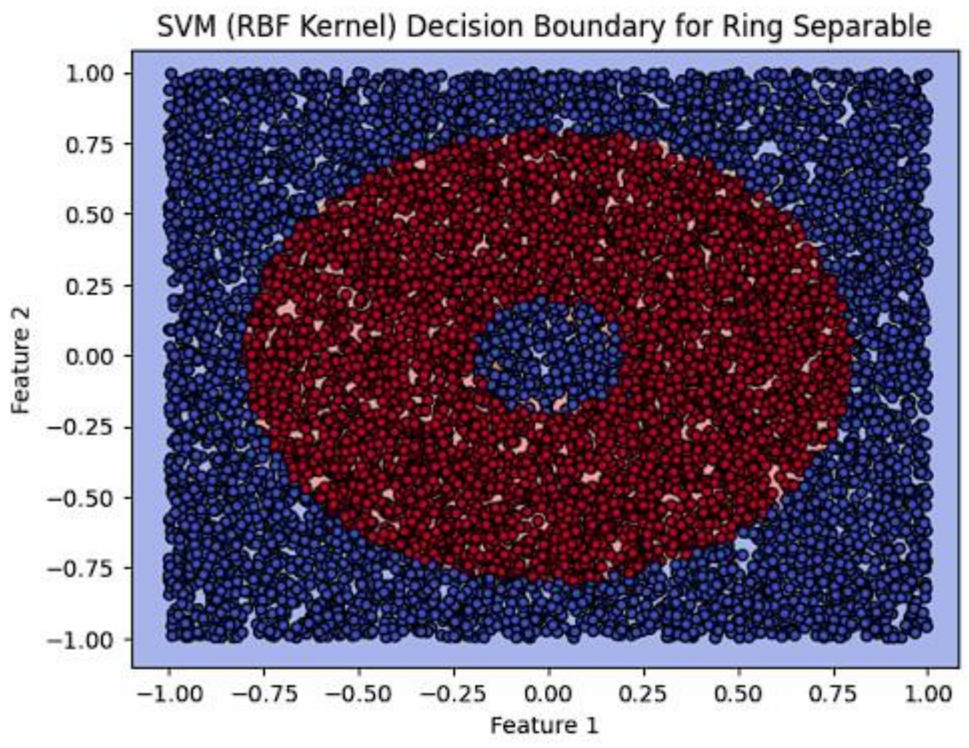
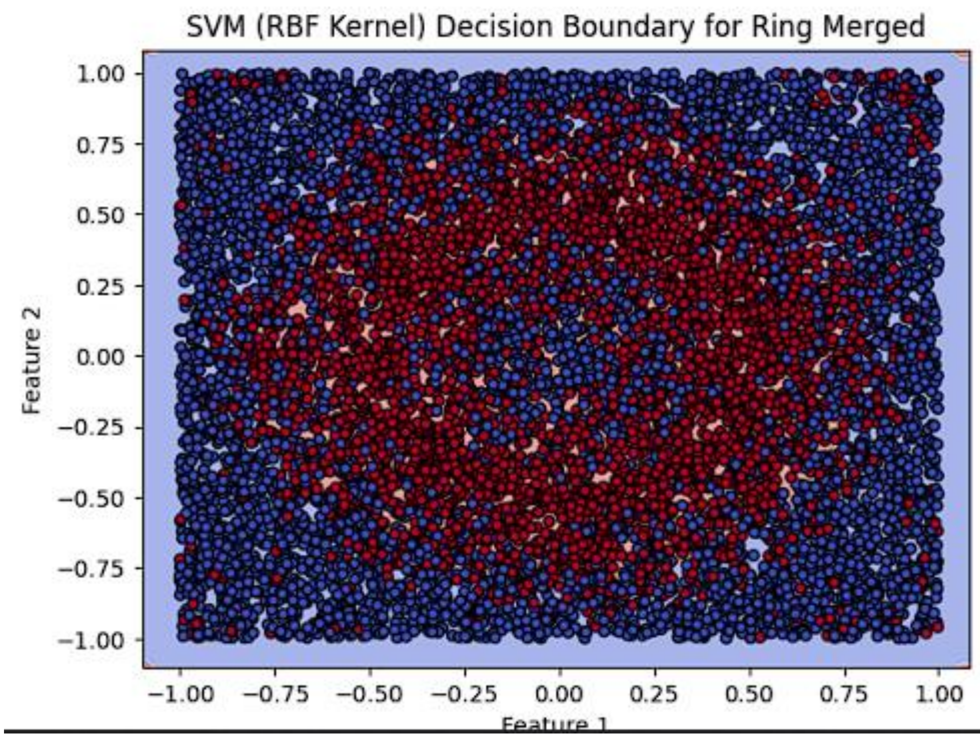


```
# Train SVM with RBF kernel and plot decision boundary for merged dataset
svm_merged_rbf = SVC(kernel='rbf')
svm_merged_rbf.fit(X_merged, y_merged)
plot_decision_boundary(X_merged, y_merged, svm_merged_rbf, "SVM (RBF Kernel) Decisio
```


SVM (RBF Kernel) Decision Boundary for Ring Merged
Feature 2
Feature 1