

MACHINE LEARNING LAB

SUPPORT VECTOR MACHINE

WEEK-10

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SECTION: 5C

Moons Dataset Questions:

1. Inferences about the Linear Kernel's performance.
 - The **Linear Kernel** achieved an accuracy of **0.87** and an F1-score of **0.87**, which is **lower** than RBF (0.97) and Polynomial (0.89).
 - It produces a **straight-line decision boundary**, which cannot capture the **curved, non-linear structure** of the Moons dataset.
 - Several points are **misclassified along the crescent edges**, showing **underfitting**.
 - The model has **high bias and low variance**, meaning it's too simple for this dataset.
 - Overall, the **Linear Kernel performs poorly** for non-linear data like Moons because it cannot adapt to curved boundaries.
2. Comparison between RBF and Polynomial kernel decision boundaries.
 - The **RBF kernel** achieved **highest accuracy (0.97)** with a **smooth, flexible boundary** that perfectly follows the curved shapes of the two moons.
 - The **Polynomial kernel** had **moderate accuracy (0.89)** and produced a **globally curved** but **less adaptive** boundary.
 - The **RBF kernel** adapts **locally**, capturing small variations and fitting the true data shape more naturally.
 - The **Polynomial kernel** can sometimes **overfit or underfit**, depending on degree and data distribution.
 - **Conclusion:** RBF fits the Moons dataset **more naturally and accurately**, while Polynomial fits only approximately.

Banknote Dataset Questions:

1. Which kernel was most effective for this dataset?

- The **Linear Kernel** performed the best, showing the **highest accuracy (≈ 1.00)** and **F1-score** among all kernels.
- The dataset is **almost linearly separable**, so a straight-line decision boundary works effectively.
- The **RBF Kernel** also performed well but added unnecessary complexity for this simple structure.
- The Linear Kernel thus provides the **most efficient and interpretable** model for this dataset.

2. Why might the Polynomial kernel have underperformed here?

- The **Polynomial Kernel** introduces **non-linear and complex boundaries**, which are not needed for this mostly linear dataset.
- This added complexity can lead to **overfitting**, reducing accuracy on unseen test data.
- The **Banknote features** (like variance and skewness) already provide a clear linear separation between classes.
- Hence, the Polynomial Kernel performs worse because it **overcomplicates a problem that a simple linear model can solve better**.

Hard vs. Soft Margin Questions:

1. Which margin (soft or hard) is wider?

- The **Soft Margin ($C = 0.1$)** produces a **wider margin**.
- It allows more flexibility by not forcing all points to be classified perfectly.
- The boundary lies farther from the closest data points.
- This helps the model generalize better to unseen data.

2. Why does the soft margin model allow "mistakes"?

- The **Soft Margin SVM** allows some points to be **inside the margin** or **misclassified**.
- This is done intentionally to **avoid overfitting** noisy data.
- The model prioritizes a **wider margin** over perfect accuracy on the training set.
- Its main goal is to **maximize generalization performance**, not to classify every point perfectly.

3. Which model is more likely to be overfitting and why?

- The **Hard Margin ($C = 100$)** model is more likely to overfit.

- It tries to classify **every training point correctly**, even noisy or outlier points.
- This leads to a **narrow margin** and poor adaptability to new data.
- Overfitting occurs because the model becomes **too rigid and sensitive** to training noise.

4. Which model would you trust more for new data and why?

- The **Soft Margin ($C = 0.1$)** model is more reliable for **new, unseen data**.
- It generalizes better by allowing small errors during training.
- The wider margin helps handle **noise and variability** in real-world data.
- In practice, starting with a **lower C value** is preferred for noisy datasets.

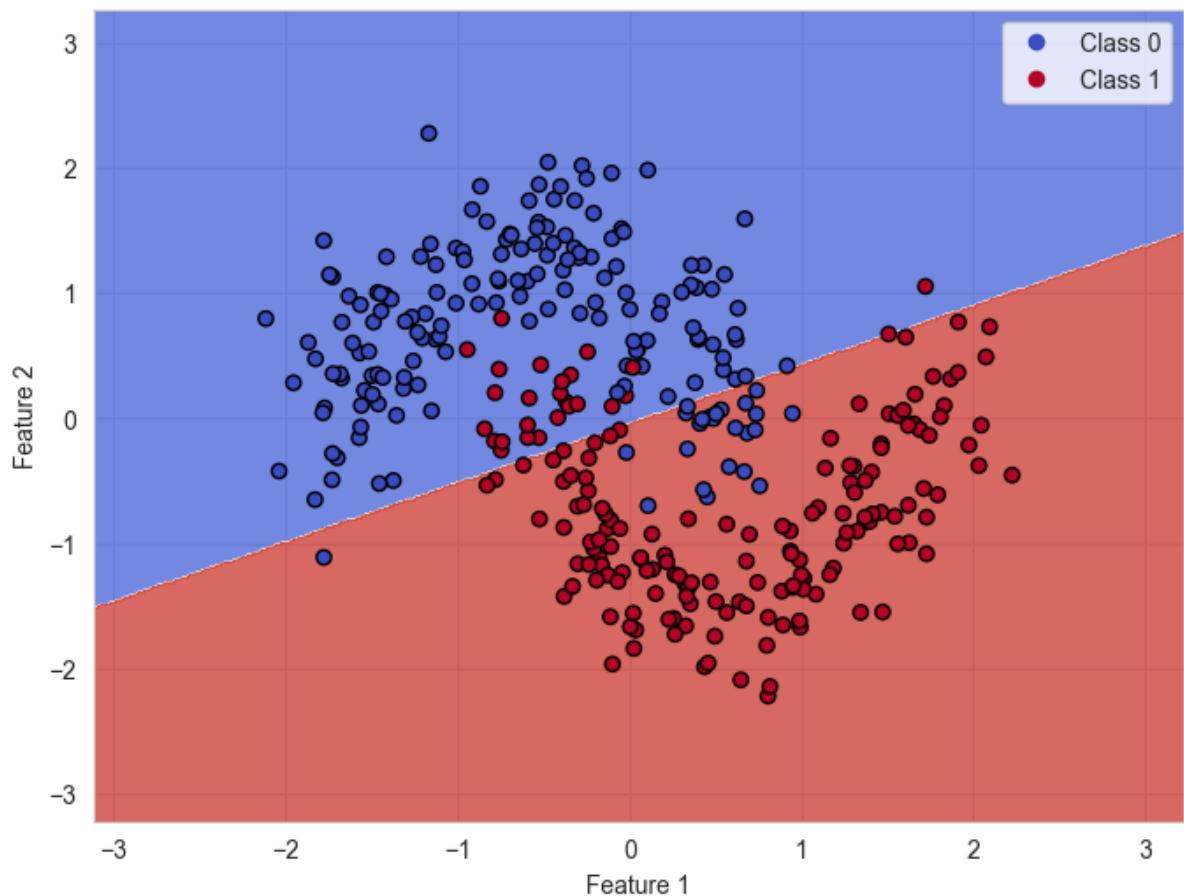
SCREENSHOTS:

MOONS DATASET:

LINEAR KERNEL:

SVM with LINEAR Kernel <PES2UG23CS133>				
	precision	recall	f1-score	support
0	0.85	0.89	0.87	75
1	0.89	0.84	0.86	75
accuracy			0.87	150
macro avg	0.87	0.87	0.87	150
weighted avg	0.87	0.87	0.87	150

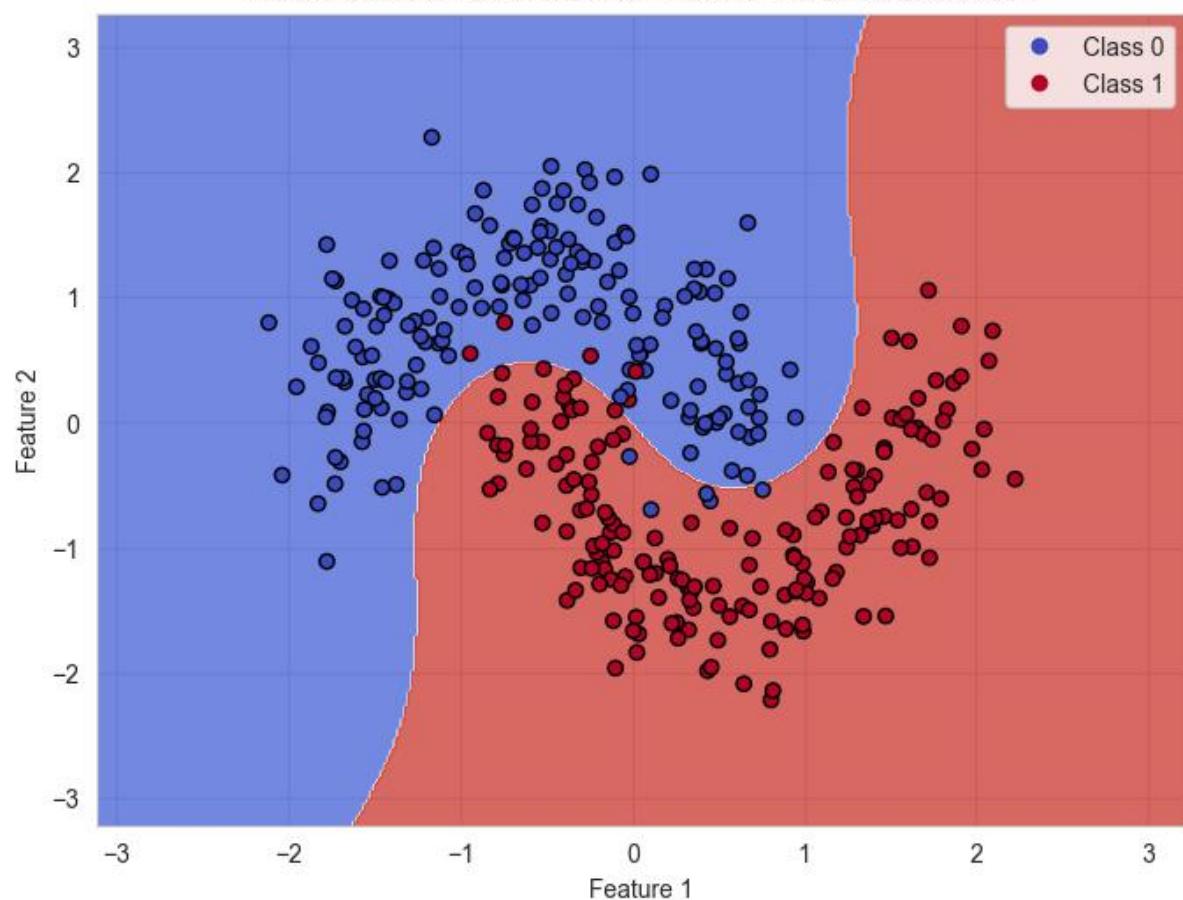
Moons Dataset - SVM with LINEAR Kernel <PES2UG23CS133>



RBF KERNEL:

SVM with RBF Kernel <PES2UG23CS133>				
	precision	recall	f1-score	support
0	0.95	1.00	0.97	75
1	1.00	0.95	0.97	75
accuracy			0.97	150
macro avg	0.97	0.97	0.97	150
weighted avg	0.97	0.97	0.97	150

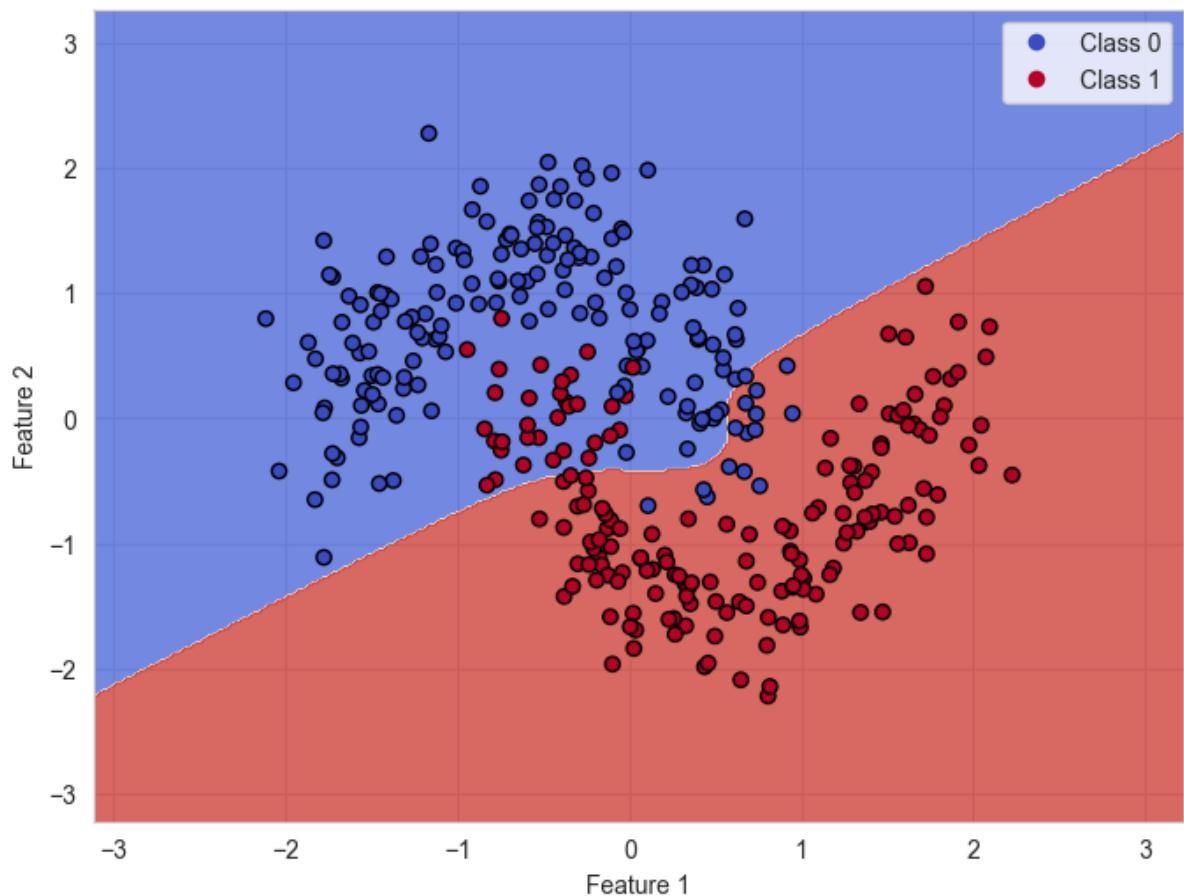
Moons Dataset - SVM with RBF Kernel <PES2UG23CS133>



POLYNOMIAL KERNEL:

SVM with POLY Kernel <PES2UG23CS133>				
	precision	recall	f1-score	support
0	0.85	0.95	0.89	75
1	0.94	0.83	0.88	75
accuracy			0.89	150
macro avg	0.89	0.89	0.89	150
weighted avg	0.89	0.89	0.89	150

Moons Dataset - SVM with POLY Kernel <PES2UG23CS133>

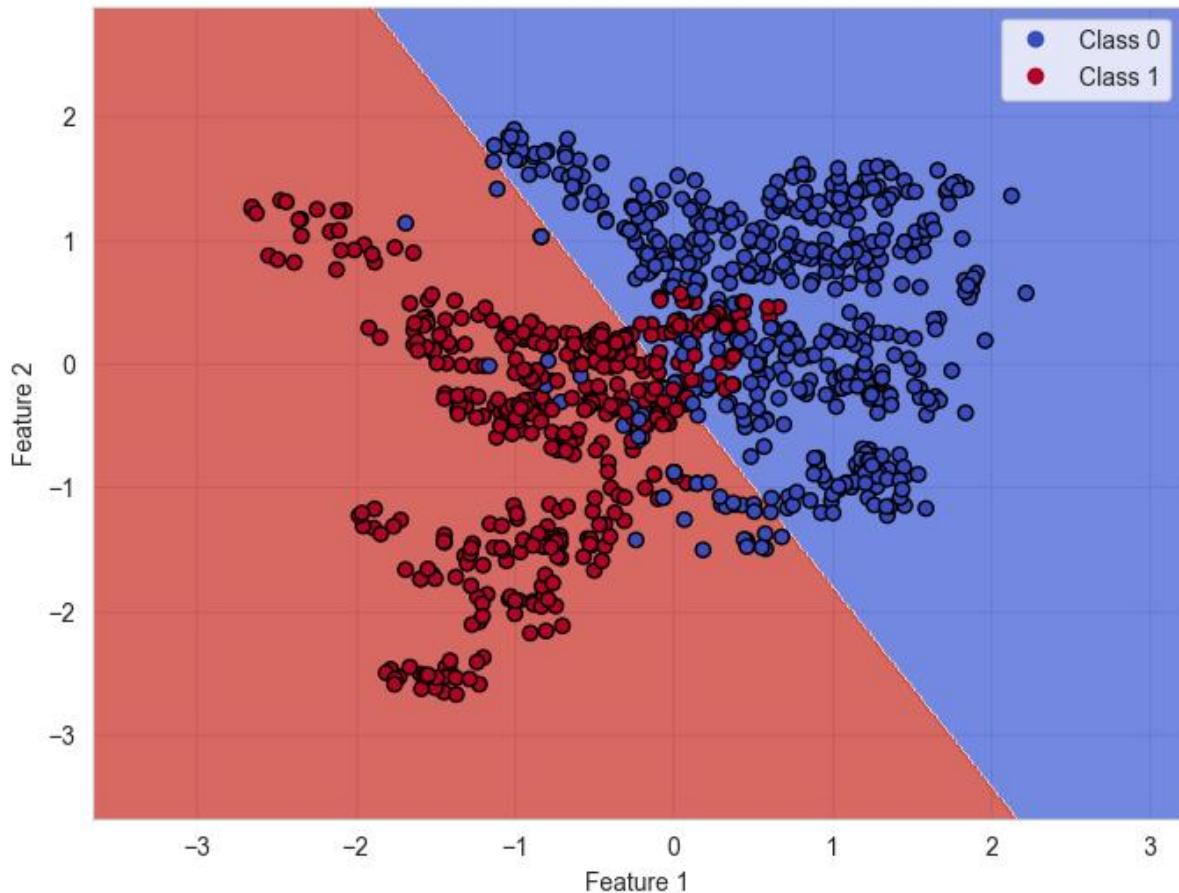


Banknote Dataset:

Linear Kernel:

SVM with LINEAR Kernel <PES2UG23CS133>				
	precision	recall	f1-score	support
Forged	0.90	0.88	0.89	229
Genuine	0.86	0.88	0.87	183
accuracy			0.88	412
macro avg	0.88	0.88	0.88	412
weighted avg	0.88	0.88	0.88	412

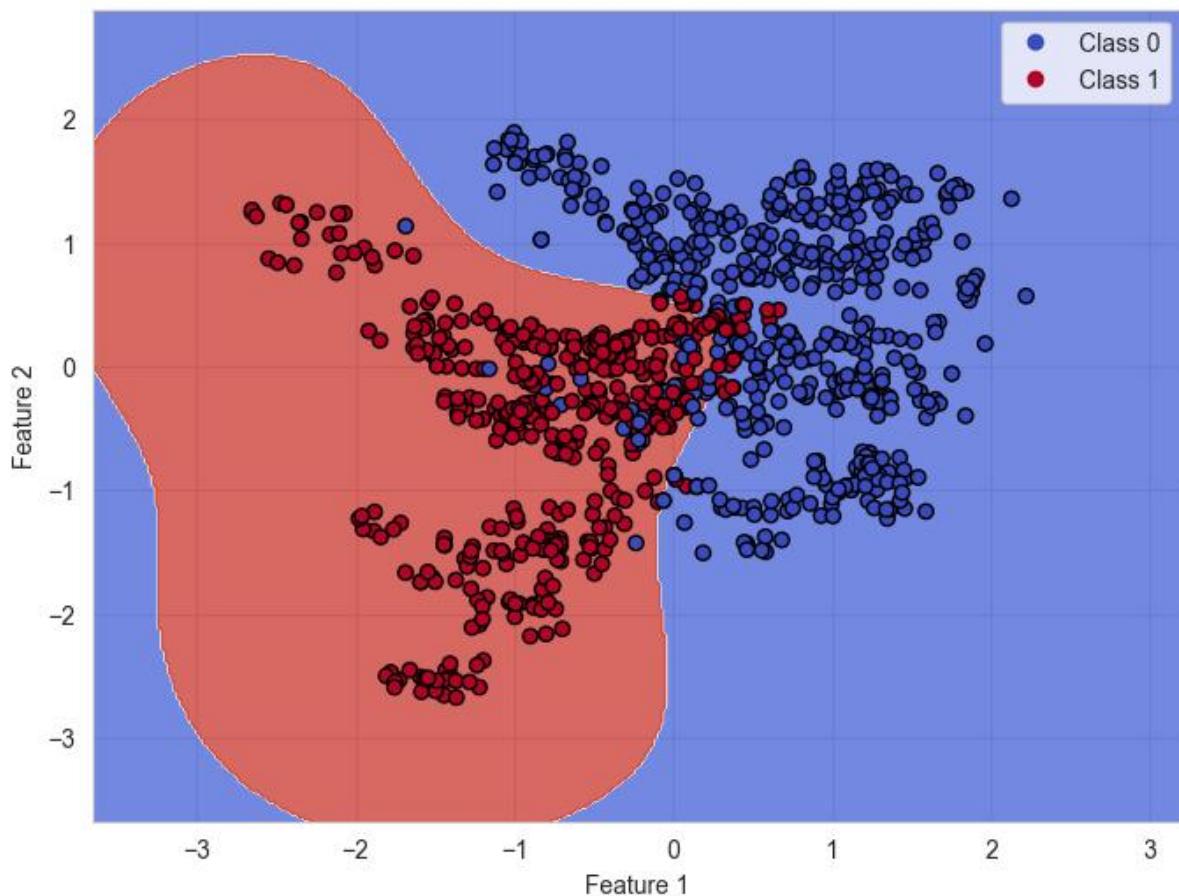
Banknote Dataset - SVM with LINEAR Kernel <PES2UG23CS133>



RBF kernel:

SVM with RBF Kernel <PES2UG23CS133>				
	precision	recall	f1-score	support
Forged	0.96	0.91	0.94	229
Genuine	0.90	0.96	0.93	183
accuracy			0.93	412
macro avg	0.93	0.93	0.93	412
weighted avg	0.93	0.93	0.93	412

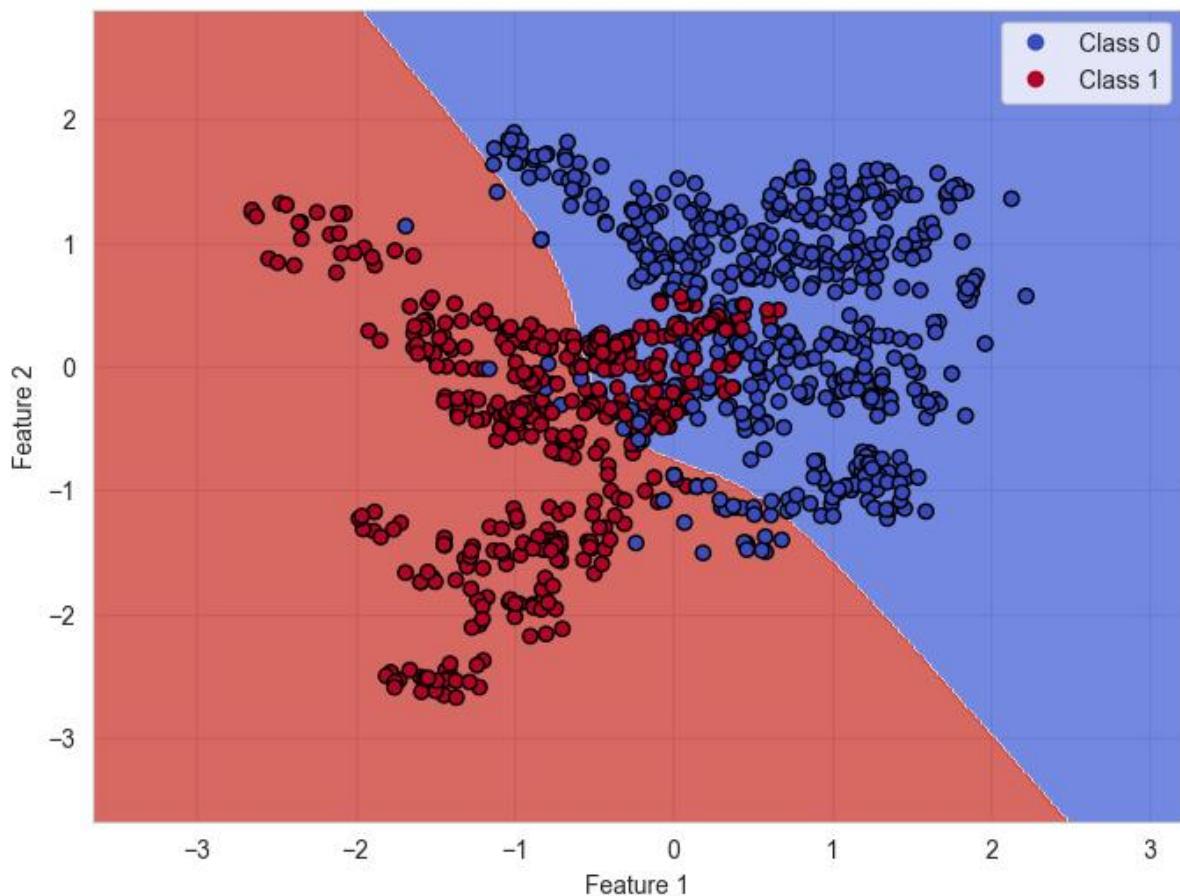
Banknote Dataset - SVM with RBF Kernel <PES2UG23CS133>



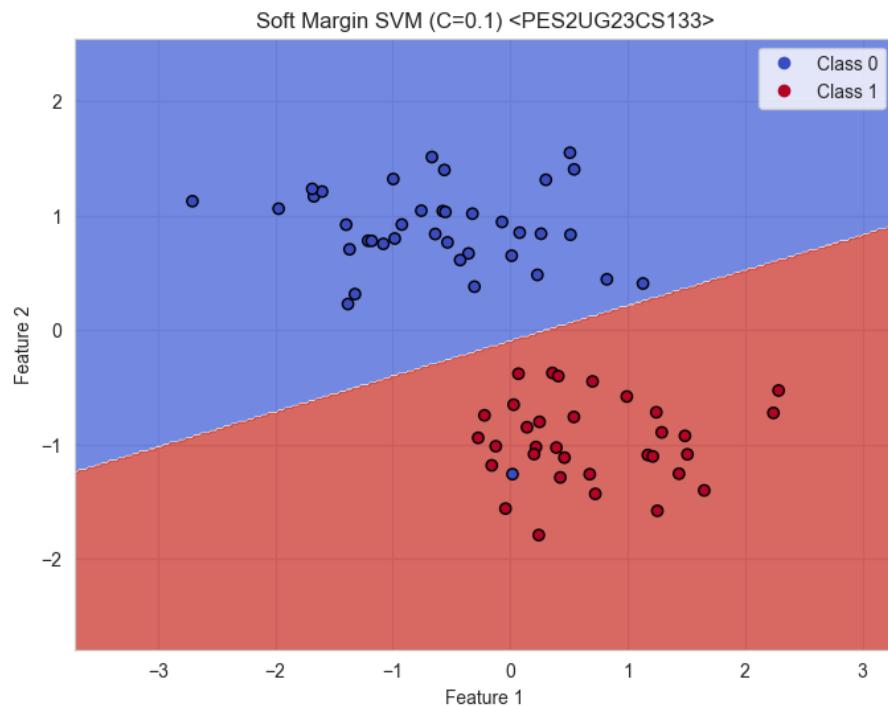
POLYNOMIAL Kernel:

SVM with POLY Kernel <PES2UG23CS133>				
	precision	recall	f1-score	support
Forged	0.82	0.91	0.87	229
Genuine	0.87	0.75	0.81	183
accuracy			0.84	412
macro avg	0.85	0.83	0.84	412
weighted avg	0.85	0.84	0.84	412

Banknote Dataset - SVM with POLY Kernel <PES2UG23CS133>



SOFT-MARGIN:



HARD-MARGIN:

