REPORT

MODEL COMPARISON TABLE

Model	Kernel	C	γ	Validation Accuracy
1. Linear SVC	linear	1	N/A	85.33%
2. Default RBF	rbf	1	'scale'	94.67%
3. Polynomial SVC	poly	1	N/A	87.33%
4. GridSearchCV Best	rbf	1	1	95.14%

Q1 Why did the linear SVM fail, and why did the RBF kernel succeed?
Linear SVM failed because the "moons" data is non-linearly separable. As shown in the plot, a linear boundary is a straight line, which cannot effectively separate the two interlocked classes, leading to high error.
RBF Kernel succeeded because the kernel trick implicitly mapped the 2D data into a higher-dimensional space where the classes become linearly separable.

The resulting decision boundary, when projected back to 2D, is the complex, curved line that perfectly fits the 'moons' shape.

Q2 What did the GridSearchCV tell you? What were the best C and gamma?
GridSearchCV systematically explored the hyperparameter space to find the optimal balance between regularization (C) and kernel influence (γ).
Best Parameters: $C = best\_params['C'], \gamma = best\_params['gamma']$.
The corresponding best cross-validated accuracy was $best\_score: .4f$.

Q3 What happens if γ is set too high (e.g., 1000)? What happens if C is set too low (e.g., 0.01)? How would this change the decision boundary?
γ too high (e.g., 1000): A very high γ means the influence of a single training example reaches only a very small, local area. The decision boundary becomes extremely irregular, jagged, and tightly follows every individual data point. This results in severe overfitting and poor generalization on new, unseen data.
C too low (e.g., 0.01): A very low C forces a very large margin and prioritizes smoothness over classifying every training point correctly (high regularization). The decision boundary becomes very smooth and overly simple, potentially underfitting the dat