Results and explanations

Note: before reading this, please read the file I attached named "Clarification of Approach Regarding Prompt Ambiguities"

Results table:

Category	Model / Method	Metric	Result	Source Notebook
Baseline Performance	Dummy Classifier (Most Frequent)	Mean Acc (+/- Std)	0.5143 (+/- 0.0286)	notebook_1
		Mean Prec (+/- Std)	0.0000 (+/- 0.0000)	notebook_1
Task 1: Classic ML	**SVM (Polynomial Kernel)**	**Mean Acc (+/- Std)**	**0.6129 (+/- 0.1477)**	notebook_1
	(Best Classic Model)	**Mean Prec (+/- Std)**	**0.6600 (+/- 0.2066)**	notebook_1
	SVM (RBF Kernel)	Mean Acc (+/- Std)	0.5329 (+/- 0.0703)	notebook_1
		Mean Prec (+/- Std)	0.5103 (+/- 0.0462)	notebook_1
	SVM (Linear Kernel)	Mean Acc (+/- Std)	0.5214 (+/- 0.0825)	notebook_1
		Mean Prec (+/- Std)	0.5067 (+/- 0.0557)	notebook_1
	k-Nearest Neighbors	Mean Acc (+/-	0.5071 (+/- 0.1005)	notebook_1

		Std)		
		Mean Prec (+/- Std)	0.5118 (+/- 0.1409)	notebook_1
	Logistic Regression	Mean Acc (+/- Std)	0.5143 (+/- 0.0286)	notebook_1
		Mean Prec (+/- Std)	0.0000 (+/- 0.0000)	notebook_1
Task 2A: Feat. Sel.	UFS (f_classif)	Top 5 Features	delta41, delta51, beta23, theta23, delta23	notebook_1
(Original Features)	RFE (LogReg Estimator)	Top 5 Features	delta40, delta58, delta60, theta55, gamma63	notebook_1
	PCA (Loadings PC1)	Top 5 Features	beta32, beta27, beta26, beta30, beta28	notebook_1
	PCA (Loadings PC2)	Top 5 Features	alpha44, alpha42, alpha46, alpha16, alpha45	notebook_1
Task 2B: Feat. Sel.	UFS (f_classif)	Top 5 Features	temp_left_delta_mean, cent_L_cent_R_delta_asym, front_left_delta_mean, delta42, delta24	notebook_1
(Task 1 Features)	RFE (Best Linear SVM Estimator)	Top 5 Features	delta42, theta12, theta24, temp_left_delta_mean, front_left_delta_mean	notebook_1
	PCA (Loadings PC1)	Top 5 Features	cent_L_cent_R_delta_asym, delta24, front_left_delta_mean, front_L_front_R_theta_asym, par_L_par_R_delta_asym	notebook_1
	PCA (Loadings PC2)	Top 5 Features	delta42, theta24, cent_L_cent_R_theta_asym, temp_L_temp_R_delta_asym, theta12	notebook_1
GNN Approach	Best Single Config (CV)	Mean Acc (+/- Std)	0.7250 (+/- 0.0935)	notebook_2
	Final GNN Ensemble	**Accuracy**	**0.7750**	notebook_2

	(OOF)			
		F1 Score (Macro)	**0.7749**	notebook_2

Reasoning for Model Performance Differences (Task 1 - notebook_1.ipynb)

- **Best Performer (SVM (Polynomial Kernel) - Accuracy: ~0.61):** This model likely performed best because the polynomial kernel is effective at capturing **complex, non-linear relationships and interactions** between the input features. The combination of raw channel data, regional averages, and asymmetry ratios used might have patterns that are only separable when considering these higher-order feature combinations, which the polynomial kernel explicitly models.
- **Moderate/Baseline Performers (Logistic Regression, Linear SVM, RBF SVM, kNN - Accuracy: ~0.51-0.53):**
  - Logistic Regression and Linear SVM are linear models. Their lower performance suggests the boundary between the two neural states is likely **not linearly separable** using the selected features.
  - SVM (RBF Kernel), while capable of non-linearity, might not have found the optimal hyperparameters within the search grid, or its specific way of mapping data (Gaussian-based) wasn't as effective as the polynomial approach for this particular dataset's structure.
  - kNN relies on the proximity of data points in the feature space. Its near-baseline performance suggests that samples from the two classes are highly intermingled, making classification based purely on nearest neighbors difficult with this feature set.
- **Note:** The relatively high standard deviation across models highlights the challenge of the **small dataset size (N=40)**. Performance can be sensitive to the specific samples included in each cross-validation fold.

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2. Explanation for Feature Selection Differences (Task 2 - notebook_1.ipynb)

The top features identified by Univariate Feature Selection (UFS), Recursive Feature Elimination (RFE), and Principal Component Analysis (PCA) often differ because they evaluate feature importance based on fundamentally different criteria.

Why Differences Occur:

- A feature might have a strong individual correlation with the target (high UFS score) but be redundant when combined with others in a model (low RFE importance).
- A feature might be crucial for a specific model's decision boundary (high RFE importance) but not explain much overall variance (low PCA loading).
- A feature might explain a lot of data variance (high PCA loading) but not be strongly related to the class separation itself (low UFS/RFE score).