

Classifying Working Memory Performance Using Whole-Block Functional Connectivity in the N-Back Task

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Background & Motivation

- ❑ Working memory (WM) is crucial for reasoning, learning, and goal-directed behaviour
- ❑ Working memory performance depends on sustained coordination between brain regions and networks
- ❑ Current behavioural assessments are vulnerable to non-cognitive factors like fatigue or motivation.
- ❑ Traditional neuroimaging methods often miss sustained task-related network interactions essential for understanding cognitive performance

Research Question & Hypotheses

Main Research Question

- Can block-level functional connectivity patterns during the N-back task classify individuals as high vs. low performers based on their behavioral accuracy?

Hypotheses

- *H1* – Predictive FC Patterns Exist
High performers will show distinct whole-brain and between-network connectivity, especially in frontoparietal and task-positive systems, enabling accurate classification ($\geq 70\%$).
- *H0* – No Distinctive Patterns
No significant FC differences between groups; classification accuracy remains near chance level (50–55%).

Methods

Dataset

- Human Connectome Project (HCP) – 100 healthy adults
- Task-fMRI during N-back (2-back) with faces, places, tools
- Behavioural accuracy scores used to label performance

Functional Connectivity Extraction

- Parcellation: 360-ROI atlas (Glasser et al., 2016)
- Block Timing: Extracted from EV files (start time + duration)
- Connectivity Types: Whole-brain FC + Between-network FC

Classification Pipeline

- Feature Extraction: Upper triangle of FC matrices
- Modeling: Classical ML: SVM, Random Forest, Logistic Regression, Gradient Boosting

Analytical Pipeline & Modeling Approach

Features & Targets

- Whole-Brain FC: Z-scored upper-triangle Functional connectivity across all parcels
- Between Network FC: Z-scored upper-triangle Functional connectivity between 12 Networks
- Targets: Mean accuracy of 2 runs on four 2-back tasks for 100 samples (BP, Faces, Places, Tools)

Preprocessing

- StandardScaler → PCA (retain 95% variance)

Classification Pipeline

- **Labeling methods:** Median split / 67th-percentile / GMM clustering
- **Models:** SVM | Logistic Regression | Random Forest | Gradient Boosting
- **Validation:** GridSearchCV over 3-fold stratified CV (scoring = accuracy)

Regression Pipeline (Exploratory)

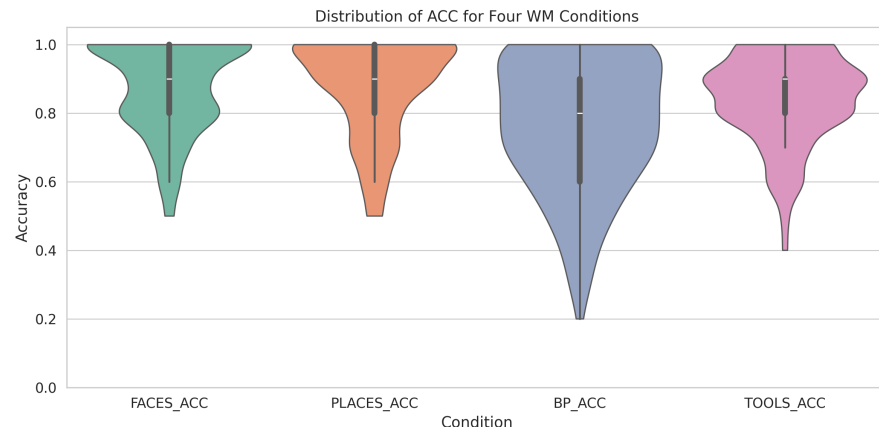
- Models: SVR | Ridge | Lasso | RF-Regressor | GB-Regressor | KNN-Regressor
- Validation: GridSearchCV with 5-fold CV (scoring = neg-MSE)
- Output: True vs. Predicted scatter, R^2 / MSE / MAE, best-params table

Between Network

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BP_ACC: upper triangle z-FC features shape: (100, 66)
FACES_ACC: upper triangle z-FC features shape: (100, 66)
PLACES_ACC: upper triangle z-FC features shape: (100, 66)
TOOLS_ACC: upper triangle z-FC features shape: (100, 66)
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Whole Brain

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faces_up shape: (100, 64620)
places_up shape: (100, 64620)
body_up shape: (100, 64620)
tools_up shape: (100, 64620)
```

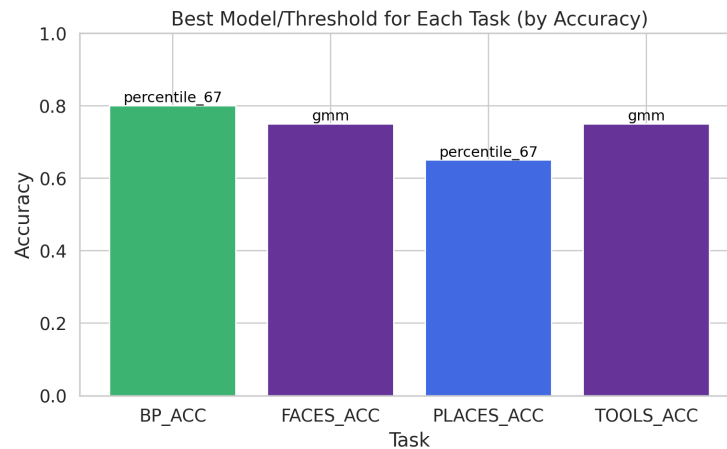
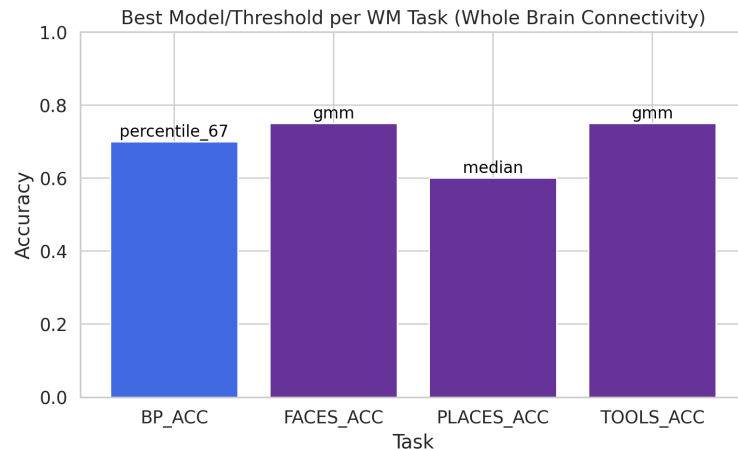
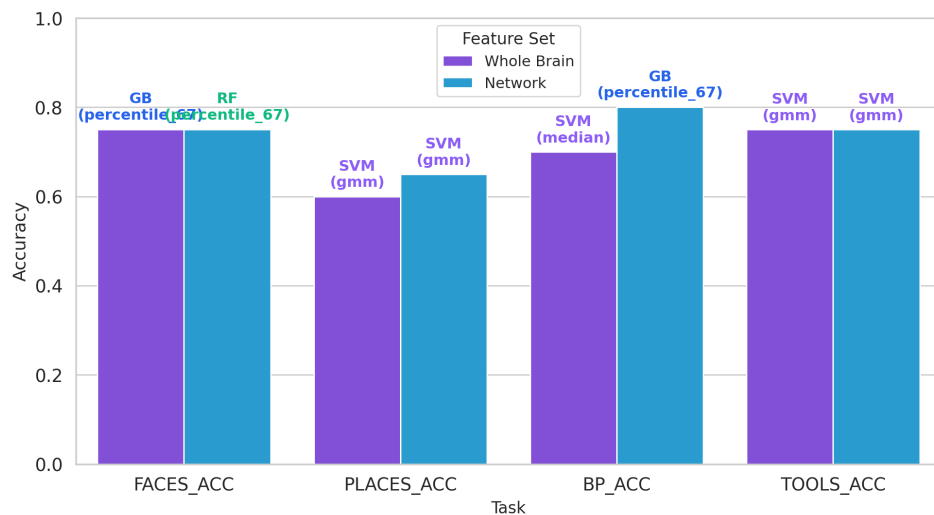


Results & Key Findings

Classification → Best Model Performance

1. Network FC: BP_ACC (percentile_67 split) → Random Forest, Accuracy ≈ 0.80
2. Whole FC: FACES_ACC/TOOLS_ACC (GMM split) → SVM, Accuracy ≈ 0.75

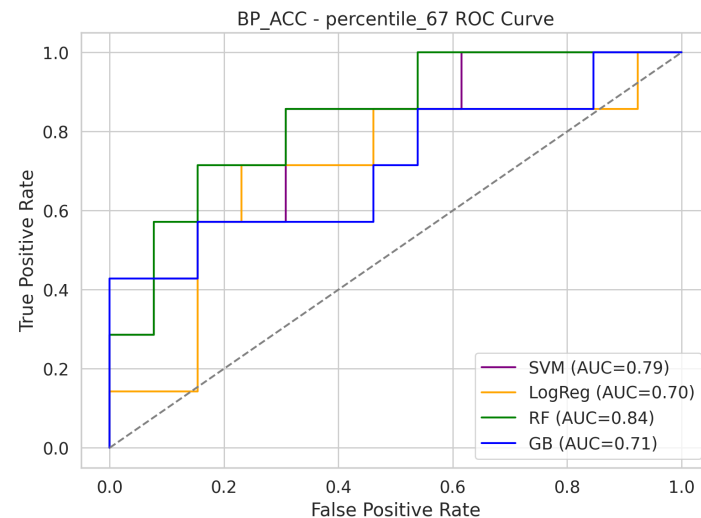
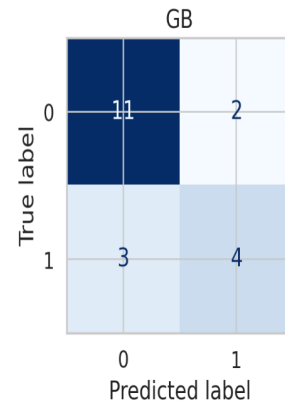
Best Classification Model & Threshold - Whole Brain vs Network



Results & Key Findings

Key Findings:

- **SVM**, **RF**, and **GB** consistently emerged as the top-performing models across different tasks and feature sets.
- **GMM** and **percentile_67** proved to be the most effective methods for binarizing performance labels.
- In the figures, The **ROC curve** and **Confusion Matrix** for the task with the best performance demonstrate strong predictive power, with high true positive and true negative rates.
- The PLACES task showed the lowest classification performance (accuracy ≈ 0.65), likely due to limited relevance of FPN features for spatial processing, higher noise and variability, and imbalanced class splits.

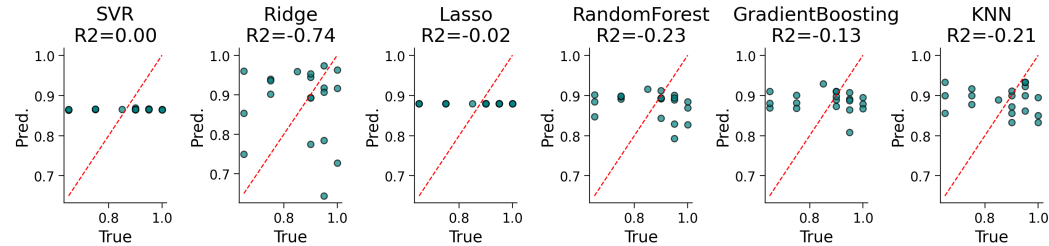


Results & Key Findings

Exploratory Regression Analysis Outcome:

- The regression models **failed to reliably predict continuous accuracy scores**. This was indicated by consistently low or negative R^2 values across all tasks and models, suggesting a weak linear relationship between the features and continuous performance.

FACES_ACC Prediction: True vs Predicted (each model)



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===== Model Comparison Across All Tasks & Thresholds =====

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	Task	ThreshMethod	SVM_Acc	LR_Acc	RF_Acc	GB_Acc	SVM_AUC	\
0	BP_ACC	median	0.55	0.60	0.40	0.60	0.520000	
1	BP_ACC	percentile_67	0.65	0.35	0.55	0.70	0.500000	
2	BP_ACC	gmm	0.55	0.60	0.40	0.60	0.520000	
3	FACES_ACC	median	0.60	0.40	0.60	0.40	0.500000	
4	FACES_ACC	percentile_67	0.60	0.55	0.55	0.45	0.500000	
5	FACES_ACC	gmm	0.75	0.70	0.75	0.75	0.500000	
6	PLACES_ACC	median	0.60	0.35	0.45	0.50	0.500000	
7	PLACES_ACC	percentile_67	0.55	0.45	0.25	0.35	0.500000	
8	PLACES_ACC	gmm	0.60	0.35	0.45	0.50	0.500000	
9	TOOLS_ACC	median	0.60	0.45	0.60	0.70	0.500000	
10	TOOLS_ACC	percentile_67	0.60	0.45	0.60	0.65	0.500000	
11	TOOLS_ACC	gmm	0.75	0.65	0.65	0.75	0.500000	
12	BP_ACC	median	0.55	0.65	0.55	0.55	0.655000	
13	BP_ACC	percentile_67	0.70	0.70	0.80	0.75	0.791209	
14	BP_ACC	gmm	0.55	0.65	0.55	0.55	0.655000	
15	FACES_ACC	median	0.40	0.55	0.55	0.60	0.260417	
16	FACES_ACC	percentile_67	0.60	0.40	0.50	0.50	0.489583	
17	FACES_ACC	gmm	0.70	0.50	0.75	0.70	0.573333	
18	PLACES_ACC	median	0.55	0.40	0.45	0.60	0.552083	
19	PLACES_ACC	percentile_67	0.55	0.50	0.55	0.65	0.363636	
20	PLACES_ACC	gmm	0.55	0.40	0.45	0.60	0.552083	
21	TOOLS_ACC	median	0.75	0.75	0.60	0.65	0.656250	
22	TOOLS_ACC	percentile_67	0.50	0.50	0.40	0.35	0.395833	
23	TOOLS_ACC	gmm	0.75	0.45	0.75	0.70	0.373333	

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===== Model Comparison Across All Tasks & Thresholds =====

```

	Task	ThreshMethod	SVM_Acc	LR_Acc	RF_Acc	GB_Acc	SVM_AUC	\
0	BP_ACC	median	0.55	0.60	0.40	0.60	0.52	
1	BP_ACC	percentile_67	0.65	0.35	0.55	0.70	0.50	
2	BP_ACC	gmm	0.55	0.60	0.40	0.60	0.52	
3	FACES_ACC	median	0.60	0.40	0.60	0.40	0.50	
4	FACES_ACC	percentile_67	0.60	0.55	0.55	0.45	0.50	
5	FACES_ACC	gmm	0.75	0.70	0.75	0.75	0.50	
6	PLACES_ACC	median	0.60	0.35	0.45	0.50	0.50	
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10	TOOLS_ACC	percentile_67	0.60	0.45	0.60	0.65	0.50	
11	TOOLS_ACC	gmm	0.75	0.65	0.65	0.75	0.50	



Conclusion

- Task-based functional connectivity can successfully classify high vs. low N-back performers, reaching up to ~80% accuracy for BP_ACC and TOOLS_ACC.
- Whole-brain and between-network connectivity approaches perform similarly, with network-based FC slightly better in some cases.
- Prediction for spatial domain (PLACES_ACC) is weaker (~65% accuracy), suggesting limited FC relevance for spatial working memory.
- Classification outperforms regression models, which fail to capture individual variability.
- Challenges include feature relevance gaps, limited sample size, class imbalance, and possible overfitting.
- Future work should focus on combining multiple network features, exploring cross-network dynamics, increasing sample size, and applying advanced, interpretable machine learning methods.

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