Indian Institute of Technology, Gandhinagar

SwitchBraidNet: Quantisation-aware lightweight architecture for hybrid brain-computer interface

Gourav Siddhad, Yogesh Kumar Meena

Human-AI Interaction (HAIx) Lab, IIT Gandhinagar, India

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Outline

Challenges and Motivation

- **Heterogeneous Signals:** MI and SSVEP occupy different spectral, spatial, and temporal subspaces.
- **Hardware Constraints:** Practical deployment targets microcontrollers or wearables with severely restricted memory, power, and compute.
- **Quantisation Degradation:** Low bit-width quantisation (e.g., INT8) introduces noise that disproportionately degrades sensitive models.

Gap in Literature

Existing benchmarks focus on single-paradigm FP32 evaluation; few address QAT for hybrid BCIs.

Our Contributions

1. **SwitchBraidNet**: A novel lightweight EEG deep learning architecture designed for physiological and hardware constraints with end-to-end quantisation robustness.
2. **Quantisation-Aware Benchmark**: The first systematic QAT benchmark on the OpenBMI dataset, evaluating 5 architectures at FP32, FP16, and INT8 across MI, SSVEP, and hBCI paradigms.

Dataset and Preprocessing

- **OpenBMI Dataset [1]:**
  - 54 healthy subjects, 2 sessions.
- **Motor Imagery (MI):**
  - 2 classes (left/right hand).
  - 20 motor-cortex channels, 8–30 Hz.
- **SSVEP:**
  - 4 classes (5.45, 6.67, 8.57, 12 Hz).
  - 10 occipital channels, 4–40 Hz.
- **Preprocessing:**
  - Downsampled 1000→256 Hz.
  - 1 s windows, 0.5 s overlap.
  - Input shape: $(1 \times C \times 256)$.

Experimental Setup

- PyTorch + MNE-Python
- 50 epochs, AdamW (LR=1e-3)
- Nvidia RTX A2000 12 GB
- 5-fold cross-validation

5 Baselines

DeepConvNet [2], EEGNet [3], ShallowConvNet [2], TSception [4],

Proposed Architecture: SwitchBraidNet

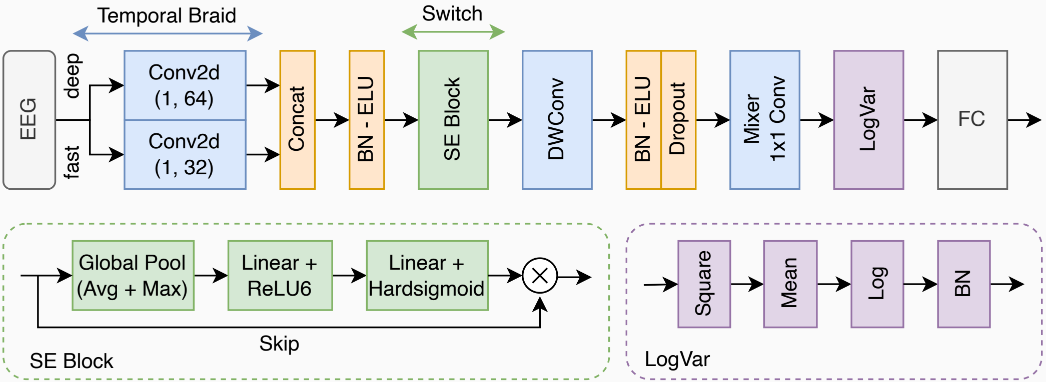


Figure 1: SwitchBraidNet Architecture

SwitchBraidNet: Three-Stage Pipeline

EEG →

Dual-Path Temporal Braid

Deep: 1×64 conv

Fast: 1×32 conv

Concat → BN → ELU

→

Spatial Switch (SE Block)

Avg + Max pool

Hardsigmoid gating

Depthwise conv → BN

→

Log-Variance Readout

$v = \log(E_t[x^2] + \epsilon)$

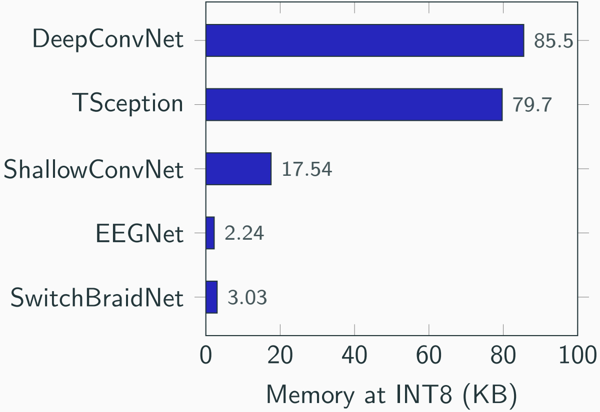
BN → Linear head

→ *Class*

SwitchBraidNet: Design Rationale

- **Dual-Path Temporal Braid:**
  - Deep path captures slow μ/β-band envelopes; fast path captures transients.
  - Joint multi-scale representation without explicit filter banks.
- **Spatial Switch (SE Block):**
  - Learns to gate electrode contributions by global relevance.
  - Hardsigmoid: piecewise-linear, ideal for 8-bit quantisation.
- **Log-Variance Readout:**
  - Replicates log band-power computation in a differentiable layer.
  - Batch Normalisation stabilises dynamic range for low-bit precision.

Model Size Comparison



Model	Params	INT8
DeepConvNet	87,552	85.50
TSception	81,617	79.70
ShallowConvNet	17,962	17.54
EEGNet	2,292	2.24
SwitchBraidNet	**3,106**	**3.03**

Key Insight

SwitchBraidNet is **28**× smaller than DeepConvNet and **26**× smaller than TSception at INT8.

MI Results Across Precisions

Table 1: Motor Imagery classification (2-class: left/right hand)

	DeepConvNet			EEGNet			ShallowConvNet			TSception			**SwitchBraidNet**		
	32	16	8	32	16	8	32	16	8	32	16	8	32	16	8
Acc	68.57	68.75	68.39	69.08	68.67	68.04	68.29	68.58	63.79	65.73	66.09	65.48	**69.33**	**69.49**	**69.12**
F1	67.91	68.44	68.35	69.06	68.46	68.02	68.08	68.58	62.50	65.65	66.05	65.47	**69.23**	**69.27**	**68.92**
ITR	6.12	6.24	5.99	6.46	6.18	5.76	5.93	6.12	3.33	4.36	4.56	4.22	**6.64**	**6.75**	**6.50**
κ	0.37	0.38	0.37	0.38	0.37	0.36	0.37	0.37	0.28	0.31	0.32	0.31	**0.39**	**0.39**	**0.38**

- SwitchBraidNet achieved **highest accuracy at all precisions**, peaking at 69.49%.
- Statistically significant improvements over EEGNet ($p < 0.001$) and DeepConvNet ($p < 0.001$).

SSVEP Results Across Precisions

Table 2: SSVEP classification (4-class: 5.45, 6.67, 8.57, 12 Hz)

	DeepConvNet			**EEGNet**			ShallowConvNet			TSception			SwitchBraidNet		
	32	16	8	32	16	8	32	16	8	32	16	8	32	16	8
Acc	93.32	93.26	93.24	**93.65**	**93.71**	**93.67**	86.77	86.33	83.02	92.21	91.99	91.66	93.48	93.42	93.40
F1	93.33	93.29	93.25	**93.67**	**93.73**	**93.69**	86.78	86.34	82.80	92.24	92.01	91.66	93.49	93.44	93.41
ITR	92.42	92.21	92.15	**93.49**	**93.70**	**93.57**	73.58	72.46	64.42	88.90	88.22	87.22	92.94	92.74	92.69
κ	0.91	0.91	0.91	**0.92**	**0.92**	**0.92**	0.82	0.82	0.77	0.90	0.89	0.89	0.91	0.91	0.91

- EEGNet leads marginally; SwitchBraidNet is highly competitive (**0.17% gap**).
- ShallowConvNet shows the **largest INT8 degradation** (−3.75%).

Table 3: Hybrid MI-SSVEP / SSVEP-MI performance (8-class)

	DeepConvNet			EEGNet			ShallowConvNet			TSception			**SwitchBraidNet**		
	32	16	8	32	16	8	32	16	8	32	16	8	32	16	8
Acc	63.99	64.12	63.77	64.69	64.35	63.73	59.25	59.20	52.96	60.61	60.79	60.01	**64.81**	**64.92**	**64.56**
κ	0.59	0.59	0.59	0.60	0.59	0.59	0.53	0.53	0.46	0.55	0.55	0.54	**0.60**	**0.60**	**0.60**
ITR_{Seq}	31.39	31.53	31.14	32.16	31.79	31.11	26.42	26.38	20.46	27.81	28.00	27.20	**32.29**	**32.41**	**32.02**
ITR_{Sim}	62.78	63.05	62.29	64.32	63.58	62.22	52.85	52.75	40.91	55.62	55.99	54.40	**64.58**	**64.82**	**64.04**

- SwitchBraidNet achieves the **highest hybrid ITR**: 64.82 bpm (simultaneous).
- Simultaneous mode ITR is 2$\times$ sequential ($p < 0.001$).

Why Use a Hybrid Approach?

Practical Advantages

- **8 commands** from 2×4 paradigm fusion.
- **Reduced fatigue:** MI offloads sustained SSVEP fixation.
- **Resilience:** Functional fallback if one modality is impaired.

Trade-off

- Best hBCI accuracy (64.92%) is lower than single-modality SSVEP (93.65%).
- Expected: fusing the harder MI task across a higher-dimensional decision boundary increases errors.

Limitations & Future Work

Limitations

- In noisy environments or for subjects with subtle neural features, INT8 precision may cause feature collapse.
- Results validated only on OpenBMI; generalisation to other datasets (e.g., BCI Competition IV 2a/2b) remains to be confirmed.
- Translating high offline accuracies to online usage presents challenges due to noise, attention variability, and impedance degradation.

Future Work

- Incorporate P300 to expand the command space further.
- Explore attention-based adaptive weighting for optimal signal combination.
- Real-time closed-loop validation on ARM Cortex-M / FPGA hardware.

Conclusion

- **SwitchBraidNet:** A three-stage architecture (temporal braid + spatial switch + log-variance readout) optimized for edge-deployed hybrid BCIs.
- **Robustness:** INT8 degradation of only 0.21% (MI) with a 3.03 KB memory footprint.
- **Performance:** State-of-the-art MI accuracy; highly competitive SSVEP performance (0.17% gap to best).
- **Hybrid BCI:** Validated sequential and simultaneous paradigms; simultaneous achieves 64.82 bpm ITR.
- **Benchmark:** First systematic QAT benchmark for hybrid BCIs on OpenBMI across 5 architectures and 3 precisions.

Thank You!

Follow HAIx Lab on LinkedIn for updates

https://github.com/HAIx-Lab/SwitchBraidNet

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