Supplementary Resources II:

Public EEG-based motor imagery (MI) datasets.

The content of this document is part of the following review paper:

Deep learning techniques for classification of electroencephalogram (EEG) motor imagery (MI) signals: a review

https://doi.org/10.1007/s00521-021-06352-5

For the details, the reader can refer to the above paper.

If you use the data in this document, please cite the original review paper as:

H. Altaheri, G. Muhammad, M. Alsulaiman, et al. "Deep learning techniques for classification of electroencephalogram (EEG) motor imagery (MI) signals: a review". Neural Comput. Appl., vol. 35, no. 20, 14681–14722, 2023. https://doi.org/10.1007/s00521-021-06352-5

Summary of public EEG-based motor imagery (MI) datasets released between 2002 and 2020, arranged from newest to oldest.

Name [ref.] URL Pub. Year	Key features	# MI classes (Type)	Non-MI	Non-EEG	# Non-TR EEG (Rest/Noise) (Type)	# subjects	# trials total	per subject	per class	# sessions (duration) (time between sessions)	#runs per session (duration) (rest between runs)	# trials per run (# MI in a trial)	Trial duration [B | MI | A] (s)	SW / HW	# electrodes (type)	Sampling rate (Freq. band) (Hz)	Voltage resolution	Signal quality validation (during recording)	MI data validation (after recording)
MIJoint [145] 7 2020	Different joints (same limb), Raw data, pre-processed, and direct trials	3 RH, RE, RS	–	EMG EOG	1 RS	25 19 M 6 F	7500 300×25	300 100×3	2500 100×25	7 MI:5, RS:2 (MI: 320s, RS: 400s) (5-10 min)	1	MI: 40 RS: 50 (ST)	8 [2+1 | 4 | 1]	E7	64 EEG (Gel)	1000 (0.5-100)	–	SQV-1 (≤ 5 kΩ) SQV-4	MIV-4 MIV-5
Lee et al. [50] 2019	Three BCI paradigms: MI, ERP, and SSVEP.	2 LH, RH	ERP, and SSVEP paradigms	EMG	–	54 25 F	21600 TD: 10800 ED: 10800	400 TD: 100×2 ED: 100×2	10800 200×54	2 (51 min) (DD)	2 (offline/online) (22 min) (7 min)	100 (ST)	13±1.5 [3 | 4 | 6±1.5]	E6, E11	62 EEG 4 EMG	1000	–	SQV-1 (≤ 10 kΩ)	–
MISCP [158] 3 2018	Many MI classes and a large number of trials	10 LH, RH, LL, RL,T, 5 FN	Press two keys on keyboard	–	1 RS	13 8 M 5 F	~60,000	~4600	–	75 (50-55 min) (_)	3 (15 min) (2 min)	300 (OT)	3±0.5 [- | 1 | 2±0.5]	S2, E3	19 EEG (Gel)	200 (0.53-70) 1000 (0.53-100)	24 bit (0.1 uV)	SQV-1 (≤ 10 kΩ) SQV-2 (within ± 0.25 cm)	MIV-4 MIV-5
GigaDB [132] 1 2017	Many subjects, different signals: MI/Non-MI, EEG/Non-EEG/Non-TR EEG	2 LH, RH	AM (1-run, same as MI tasks)	EMG	6 EB, EUD, ELR, HM, JC, RS	52 33 M 19 F	~5200-6240 (AM: ~1040)	100-120 (AM: 20)	~2600-3120 (AM: ~520)	1 (50 min) (_)	5-6 MI:4-5, AM:1 (140 s) (4 min max)	20 (OT)	7 [2 | 3 | 2]	S1, E1, E2	64 EEG 2 EMG	512	–	–	MIV-1 (Amp>±100μV) MIV-2, MIV-3, MIV-4
ULMov [142] 15, 17 2017	Upper limb MI movements	6 EF, EE, FS, FP, HO, HC	AM (1-run, same as MI tasks)	EOG, GS, ES	1 RS	15 9 F	6300 420×15 (AM: 6300)	420 10×42 (AM: 420)	900 60×15 (AM: 900)	2 (AM:1, MI:1) (_) (DD)	10	42 (ST)	7.5±0.5 [2 | 3 | 2-3]	E14	61 EEG 3 EOG 19 GS 13 ES	512 (0.01-200)	–	–	–
IndImag [157] 15, 16 2015	Several mental tasks performed by disabled peoples.	2 RH, FT	Mental activities: SN, MWS, and MS	–	–	9 (disabled) 7 F	1440 160×9	160 80×2	720 80×9	2 (_) (DD)	8 (_) (4)	25 (10 for MI) (ST)	13±0.5 [3 | 7 | 3±0.5]	S3, E13	30 EEG	256 (0.5-100)	–	–	–
Steyrl et al. [144] 15, 18 2014	Two class motor imagery	2 RH, FT	–	–	–	14	2240 TD: 1400 ED: 840	160 TD: 50×2 ED: 30×2	1120 TD: 50×14 ED: 30×14	1 (_) (same session)	8 (TD: 5, ED: 3)	20 (ST)	5 [- | 5 | -]	E15	15 EEG	512	–	–	–
OpenViBE [159] 14 2012	Individual imagery	2 LH, RH	–	–	–	1	560	560	280	3 (_) (DD)	4-5 (total 14 runs)	40 (ST)	6 [- | 6 | -]	E12	11 EEG	512	–	–	–
EEGMMIDB [139] 2 2009	Many subjects	4 LF, RF, BF, and BFT	AM (6-runs, same as MI tasks)	–	2 EO, EC	109	~9156 84×109 (AM: ~9156)	84 21×4 (AM: 84)	~2289 21×109 (AM: ~2289)	1 (26 min) (_)	14 BL: 2, MI: 6, AM: 6 (BL: 1, MI: 2, AM: 2 min)	14 (ST)	8 [2 | 4 | 2]	S1	64 EEG	160	–	–	–
BCI-C IV-1 [133] 4 2008	Uncued classifier application (classification of continuous EEG)	2 Two of 3 classes (LH, RH, FT)	–	–	IS	7 3 AR	3080 TD: 1400 ED: 1680	440 TD: 200 ED: 240	1540 TD: 100×7 ED: 120×7	1	6 TD: 2, ED: 4 (_) (5–15 min)	TD: 100 ED: 60 (ST)	TD: 8 [2 | 4 | 2] ED: 8 [- | 1.5-8 | 1.5-8]	E4, E5	59 EEG	1000 (0.05-200)	16 bit (0.1 uV)	–	–
BCI-C IV-2a [131] 5 2008	Continuous classifier application and eye movement artifacts	4 LH, RH, FT, T	–	EOG	3 EO, EC, EM	9	5184 (4800 valid)	576 TD: 288 ED: 288	1296 TD: 72×9 ED: 72×9	2 (_) (DD)	6 (~ 6 min) (short break)	48 (ST)	8±0.5 [2 | 4 | 2±0.5]	E6	22 EEG 3 EOG	250 (0.5-100)	–	SQV-3	–
BCI-C IV-2b [101] 6 2008	Session-to-session transfer and eye movement artifacts	2 LH, RH	–	EOG	3 EO, EC, EM	9	6480 (720×9)	720 SP: 120×2 FP: 160×3	3240 SP: 120×9 FP: 240×9	5 SP:2, FP:3 (_) (5 days)	10 SP: 6, FP: 4	SP: 20 FP: 40 (ST)	SP: 9±0.5 [3 | 4 | 2±0.5] FP: 9±0.5 [3 | 4.5 | 1.5±0.5]	–	3 EEG 3 EOG	250 (0.5-100)	–	SQV-3	–
BCI-C III-3a [136] 8 2004	Multi-class problems	4 LH, RH, FT, T	–	–	–	3	840	sub1: 360 sub2: 240 sub3: 240	~210 90+60×2	1	6 - 7	40 (ST)	7 [3 | 4 | -]	E8	60 EEG	250 (1-50)	–	–	–
BCI-C III-3b [136] 9 2004	Non-stationarity problems	2 LH, RH	–	–	–	3	2800	sub1: 640 sub2: 1080 sub3: 1080	~1400 320+540×2	3	4 - 9	–	8 [3 | 5 | -]	E9	2 EEG	125 (0.5-30)	–	–	–
BCI-C III-4a [136] 10 2004	Small training sets, (subject-to-subject transfer)	2 RH, FT	–	–	–	5	1400 TD: 560 ED: 840	280 140×2	700 140×5	4	–	–	5.5±0.25 [2±0.25 | 3.5 | -]	E10	118 EEG	1000 (0.5-200)	16 bit (0.1 uV)	–	–
BCI-C III-4b [136] 11	classification of continuous EEG without trial structure	2 LH, FT	–	–	–	1	TD: 210	TD: 210	–	7 TD :3 ED: 4	–	–	TD: 5.5±0.25 [2±0.25 | 3.5 | -]	E10	118 EEG	1000 (0.5-200)	16 bit (0.1 uV)	–	–

2004													ED: 3.25-10.25 [2±0.25 | 1.5-8 | -]						
BCI-C III-4c [136] 12 2004	Non-stationarity problems	2 LH, FT	–	–	–	1	630 TD: 210 ED: 420	630	–	7 TD :3 ED: 4	–	–	TD: 5.5±0.25 [2±0.25 | 3.5 | -] ED: 3±0.25 [2±0.25 | 1 | -]	E10, E11	118 EEG	1000 (0.5-200)	16 bit (0.1 uV)	–	–
BCI-C II-3 [102] 13 2002	First public MI dataset	2 LH, RH	–	–	–	1 F	280 TD: 140 ED: 140	280	140	1	7 (_) (several minutes)	40 (ST)	9 [3 | 6 | -]	E6, E9	3 EEG	128 (0.5-30)	–	–	–

***BCI-C**: BCI Competition*
1 http://gigadb.org/dataset/100295
2 https://www.physionet.org/content/eegmmidb/1.0.0/
3 https://doi.org/10.6084/m9.figshare.c.3917698
4 http://www.bbci.de/competition/iv/#dataset1
5 http://www.bbci.de/competition/iv/#dataset2a
6 http://www.bbci.de/competition/iv/#dataset2b
7 https://doi.org/10.7910/DVN/RBN3XG
8 http://bbci.de/competition/iii/#data_set_iiia
9 http://bbci.de/competition/iii/#data_set_iiib
10 http://bbci.de/competition/iii/#data_set_iva
11 http://bbci.de/competition/iii/#data_set_ivb
12 http://bbci.de/competition/iii/#data_set_ivc
13 http://www.bbci.de/competition/ii/
14 http://openvibe.inria.fr/datasets-downloads/
15 http://bnci-horizon-2020.eu/database/data-sets
16 https://lampx.tugraz.at/~bci/database/004-2015/description.pdf
17 https://lampx.tugraz.at/~bci/database/001-2017/dataset_description.pdf
18 https://lampx.tugraz.at/~bci/database/002-2014/description.pdf

***MI**: motor imagery, **F**: female, **M**: male, **TD**: training data, **ED**: evaluation data, **A**: after MI trial, **B**: before MI trial, **SP**: screening paradigm, **FP**: feedback paradigm, **BL**: baseline, **s**: seconds, **OT**: one-MI per trial, **ST**: Sustained (several/long) MIs per trial, **DD**: different days.*

*Sensors: **EEG**: electroencephalogram, **EOG**: electrooculography, **EMG**: electromyography, **GS**: glove sensors, **ES**: exoskeleton sensors.*

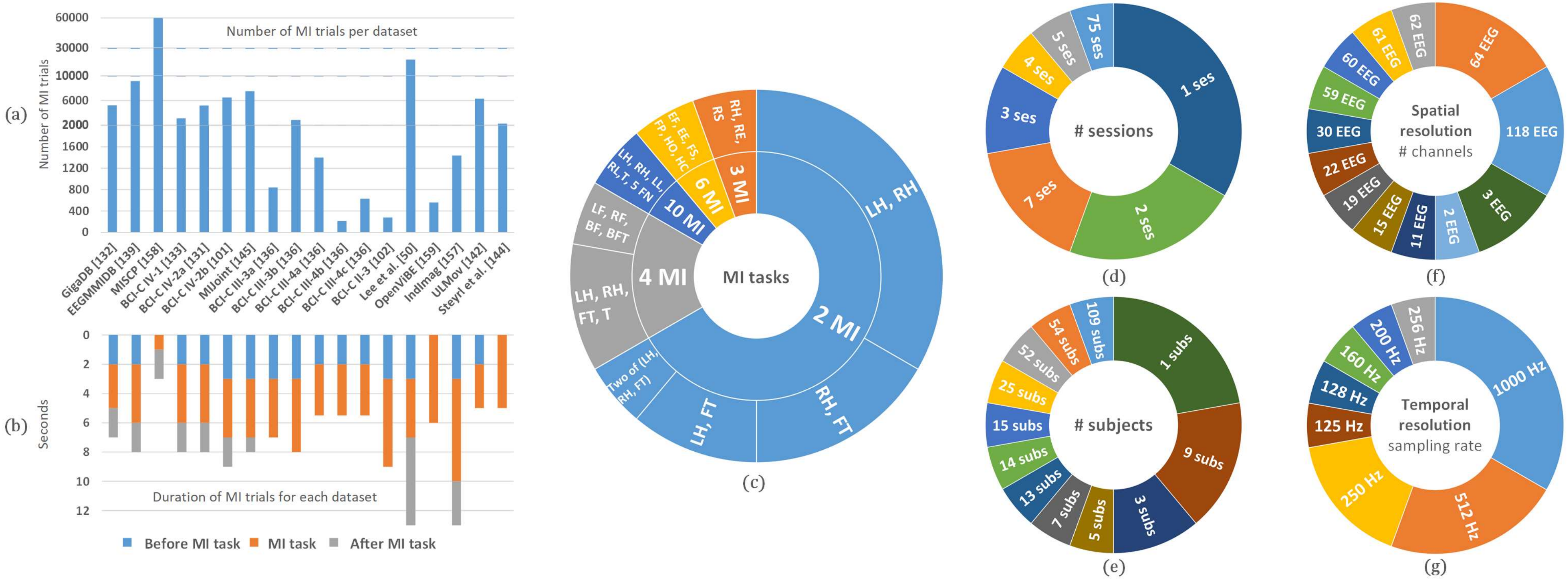
*MI tasks (18): **LH**: left hand, **RH**: right hand, **LF**: left fist, **RF**: right fist, **BF**: both fists, **HO**: hand open, **HC**: hand close, **LL**: left leg, **RL**: right leg, **FT**: foot/feet, **BFT**: both foot, **T**: tongue, **FN**: finger, **RE**: right elbow, **EF**: elbow flexion, **EE**: elbow extension, **FS**: forearm supination, **FP**: forearm pronation.*

*Non-MI tasks: **AM**: Actual motor movement, **MWS**: mental word association, **MS**: mental subtraction, **SN**: spatial navigation, **ERP**: event-related potential, **SSVEP**: steady-state visually evoked potentials.*
*Non-task-related (Non-TR) EEG: **EB**: eye blinking, **EO**: eye-open, **EC**: eye-closed, **EUD**: eyeball up/down, **EM**: eye movement, **ELR**: eyeball left/right, **HM**: head movement, **JC**: jaw clenching, **RS**: resting state, **IS**: idle state.*

***SW**: software, S1: BCI2000, S2: Neurofax, S3: g.tec GAMMAsys system*
***HW**: hardware (equipment)*
E1: Biosemi ActiveTwo. (with Ag/AgCl active electrodes)
E2: 3D coordinate digitizer (Polhemus Fastrak)
E3: EEG-1200 JE-921A (Nihon Kohden, Japan).
E4: BrainAmp MR plus amplifiers (Brain Products GmbH, Munich, Germany)
E5: Ag/AgCl electrode cap (EASYCAP GmbH)
E6: Ag/AgCl electrodes
E7: Neuroscan SynAmps2 amplifier (Neuroscan, Inc.)
E8: 64-channel EEG amplifier from Neuroscan
E9: G.tec amplifier
E10: 128 channel Ag/AgCl electrode cap from ECI
E11: BrainAmp amplifier
E12: Mindmedia NeXus32B amplifier
E13: g.LADYbird active electrodes and two g.USBamp biosignal amplifiers (Guger Technologies, Graz, Austria)
E14: active electrodes (g.tec medical engineering GmbH, Austria)
E15: biosignal amplifier and active Ag/AgCl electrodes (g.USBamp, g.LADYbird, Guger Technologies OG, Schiedlberg, Austria)

Signal quality validation (during recording)
SQV-1: Electrode impedance.
SQV-2: Distances between reference electrodes.
SQV-3: Visual inspection by an expert to detect trials containing artifacts.
SQV-4: EMG Validation to detect actual movements.

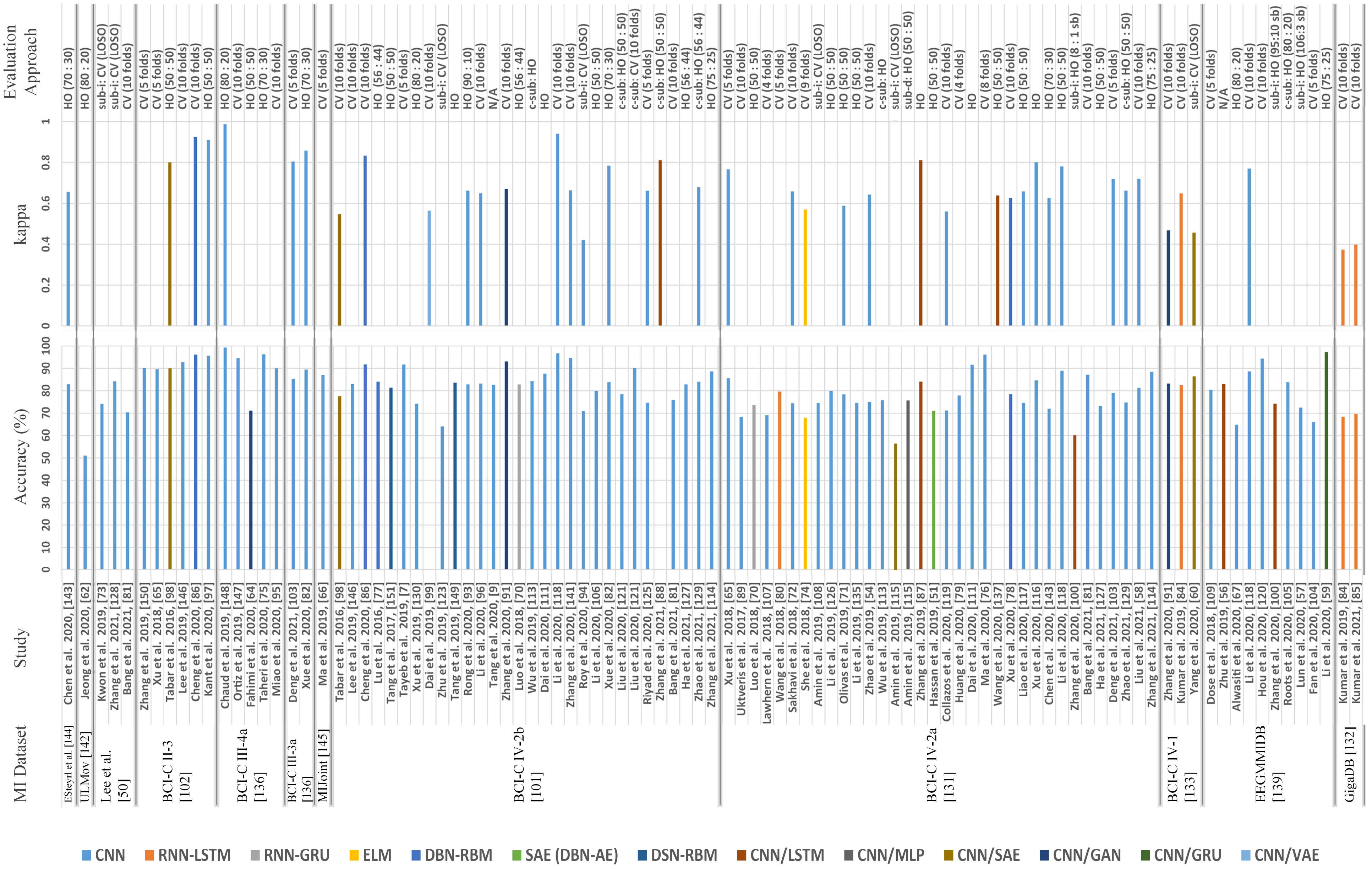
MI data validation (After recording)
MIV-1: Mark bad trials.
MIV-2: EMG/EEG correlation.
MIV-3: Spectral analysis (ERD/ERS).
MIV-4: Classification of MI tasks.
MIV-5: Examining ERP curves.



Visualization of main information for the public MI datasets presented in the previous table, including the number of MI trials per dataset (a), duration of MI trials per dataset (b), proportional representation of MI tasks (c), number of sessions (d), number of subjects (e), number of channels (spatial resolution) (f), and the sampling rate (temporal resolution) (g).

A visualization of the classification accuracy of EEG-based motor imagery (MI) reported by the latest deep learning-based articles for all public MI datasets.

***HO**: Hold-out (train: test), **CV**: Cross-validation, **LOSO**: Leave-one-subject-out, **c-sub**: Cross-subject, **sub-d**: Subject-dependent, **sub-i**: Subject-independent, **sb**: subjects, **"(x : y sb)"**: x subjects for training and y subjects for testing*



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