Supplementary Resources II:

Public EEG-based motor imagery (MI) datasets.

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

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

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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	# trials per subject	# trials 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.*

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

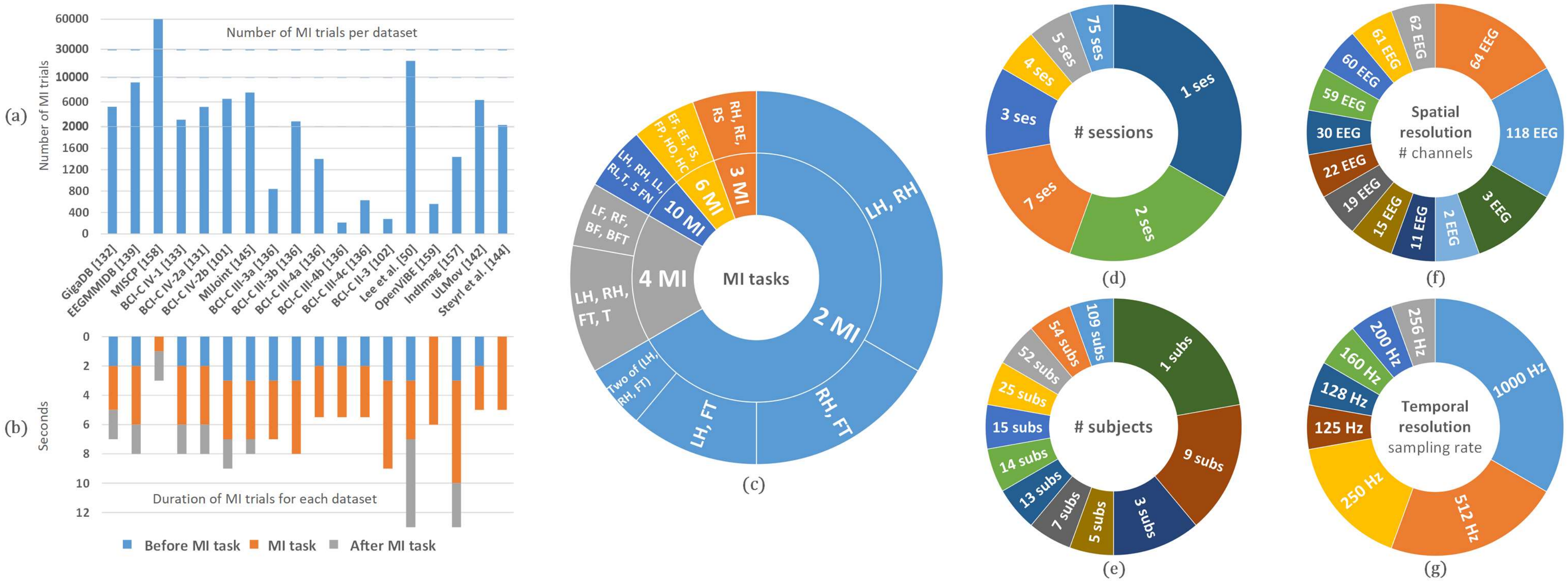
*<u>MI tasks (18)</u>: **LH**: left hand, **RH**: right hand, **LF**: left fist, **RF**: right fist, **BF**: both fists, **HO**: hand open, **HC**: hand close, **LL**: left leg, **RL**: right leg, **FT**: foot/feet, **BFT**: both foot, **T**: tongue, **FN**: finger, **RE**: right elbow, **EF**: elbow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

*<u>Non-MI tasks</u>: **AM**: Actual motor movement, **MWS**: mental word association, **MS**: mental subtraction, **SN**: spatial navigation, **ERP**: event-related potential, **SSVEP**: steady-state visually evoked potentials.*
*<u>Non-task-related (Non-TR) EEG</u>: **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.*

*<u>**SW**: software</u>, S1: BCI2000, S2: Neurofax, S3: g.tec GAMMAsys system*
*<u>**HW**: hardware (equipment)</u>*
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)

<u>Signal quality validation (during recording)</u>
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.

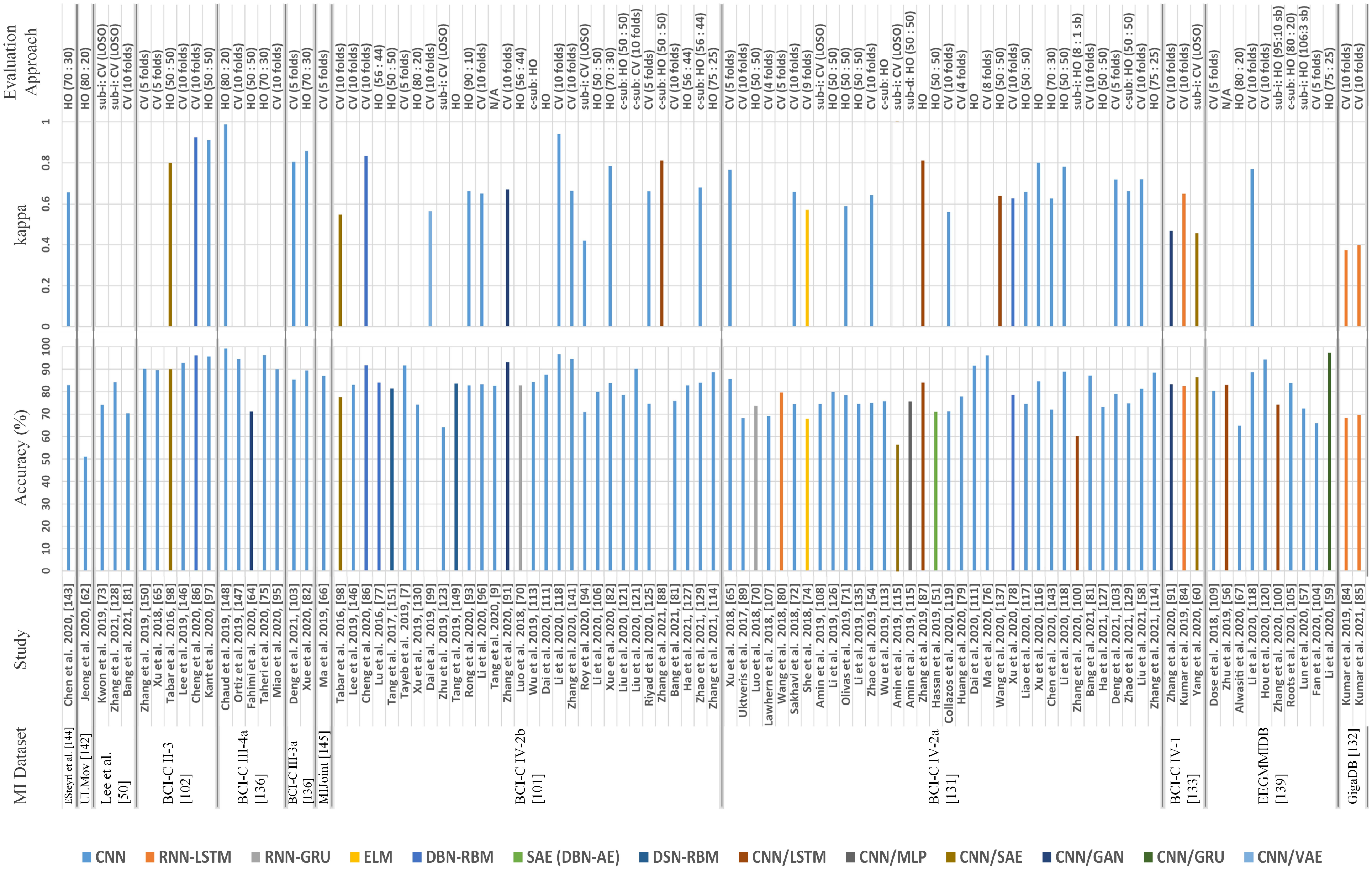
<u>MI data validation (After recording)</u>
MIV-1: Mark bad trials.
MIV-2: EMG/EEG correlation.
MIV-3: Spectral analysis (ERD/ERS).
MIV-4: Classification of MI tasks.
MIV-5: Examining ERP curves.



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*



References

[1] F. Alshehri and G. Muhammad, "A comprehensive survey of the Internet of Things (IoT) and AI-based smart healthcare," *IEEE ACCESS*, vol. 9, pp. 3660–3678, 2021.

[2] M. Masud *et al.*, "A lightweight and robust secure key establishment protocol for internet of medical things in COVID-19 patients care," *IEEE Internet Things J.*, 2020.

[3] G. Muhammad, F. Alshehri, F. Karray, A. El Saddik, M. Alsulaiman, and T. H. Falk, "A comprehensive survey on multimodal medical signals fusion for smart healthcare systems," *Inf. Fusion*, 2021.

[4] J. Cantillo-Negrete, R. I. Carino-Escobar, P. Carrillo-Mora, D. Elias-Vinas, and J. Gutierrez-Martinez, "Motor imagery-based brain-computer interface coupled to a robotic hand orthosis aimed for neurorehabilitation of stroke patients," *J. Healthc. Eng.*, vol. 2018, 2018.

[5] E. López-Larraz, A. Sarasola-Sanz, N. Irastorza-Landa, N. Birbaumer, and A. Ramos-Murguialday, "Brain-machine interfaces for rehabilitation in stroke: A review," *NeuroRehabilitation*, vol. 43, no. 1, pp. 77–97, 2018.

[6] M. S. Al-Quraishi, I. Elamvazuthi, S. A. Daud, S. Parasuraman, and A. Borboni, "EEG-based control for upper and lower limb exoskeletons and prostheses: A systematic review," *Sensors*, vol. 18, no. 10, p. 3342, 2018.

[7] Z. Tayeb *et al.*, "Validating deep neural networks for online decoding of motor imagery movements from EEG signals," *Sensors*, vol. 19, no. 1, p. 210, 2019.

[8] Á. Fernández-Rodríguez, F. Velasco-Álvarez, and R. Ron-Angevin, "Review of real brain-controlled wheelchairs," *J. Neural Eng.*, vol. 13, no. 6, p. 61001, 2016.

[9] X. Tang, W. Li, X. Li, W. Ma, and X. Dang, "Motor imagery EEG recognition based on conditional optimization empirical mode decomposition and multi-scale convolutional neural network," *Expert Syst. Appl.*, vol. 149, p. 113285, 2020.

[10] J. Li, J. Liang, Q. Zhao, J. Li, K. Hong, and L. Zhang, "Design of assistive wheelchair system directly steered by human thoughts," *Int. J. Neural Syst.*, vol. 23, no. 03, p. 1350013, 2013.

[11] L. Cao, B. Xia, O. Maysam, J. Li, H. Xie, and N. Birbaumer, "A synchronous motor imagery based neural physiological paradigm for brain computer interface speller," *Front. Hum. Neurosci.*, vol. 11, p. 274, 2017.

[12] D. Das Chakladar and S. Chakraborty, "Multi-target way of cursor movement in brain computer interface using unsupervised learning," *Biol. Inspired Cogn. Archit.*, vol. 25, pp. 88–100, 2018.

[13] A. Delorme, T. Sejnowski, and S. Makeig, "Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis," *Neuroimage*, vol. 34, no. 4, pp. 1443–1449, 2007.

[14] A. Jafarifarmand and M. A. Badamchizadeh, "EEG artifacts handling in a real practical brain–computer interface controlled vehicle," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 6, pp. 1200–1208, 2019.

[15] D. Pawar and S. Dhage, "Feature Extraction Methods for Electroencephalography based Brain-Computer Interface: A Review.," *IAENG Int. J. Comput. Sci.*, vol. 47, no. 3, 2020.

[16] E. C. Djamal, M. Y. Abdullah, and F. Renaldi, "Brain computer interface game controlling using fast fourier transform and learning vector quantization," *J. Telecommun. Electron. Comput. Eng.*, vol. 9, no. 2–5, pp. 71–74, 2017.

[17] M. R. N. Kousarrizi, A. A. Ghanbari, M. Teshnehlab, M. A. Shorehdeli, and A. Gharaviri, "Feature extraction and classification of EEG signals using Wavelet transform, SVM and artificial neural networks for brain computer interfaces," in *2009 International Joint Conference on Bioinformatics, Systems Biology and Intelligent Computing*, 2009, pp. 352–355.

[18] L. Wang, Z. Lan, Q. Wang, R. Yang, and H. Li, "ELM_Kernel and Wavelet Packet Decomposition Based EEG Classification Algorithm," *Autom. Control Comput. Sci.*, vol. 53, no. 5, pp. 452–460, 2019.

[19] H. Ramoser, J. Muller-Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Trans. Rehabil. Eng.*, vol. 8, no. 4, pp. 441–446, 2000.

[20] L. Zhang, D. Wen, C. Li, and R. Zhu, "Ensemble classifier based on optimized extreme learning machine for motor imagery classification," *J. Neural Eng.*, vol. 17, no. 2, p. 26004, 2020.

[21] K. Wang, D.-H. Zhai, and Y. Xia, "Motor Imagination EEG Recognition Algorithm based on DWT, CSP and Extreme Learning Machine," in *2019 Chinese Control Conference (CCC)*, 2019, pp. 4590–4595.

[22] Z. Jin, G. Zhou, D. Gao, and Y. Zhang, "EEG classification using sparse Bayesian extreme learning machine for brain–computer interface," *Neural Comput. Appl.*, pp. 1–9, 2018.

[23] K. K. Ang, Z. Y. Chin, C. Wang, C. Guan, and H. Zhang, "Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b," *Front. Neurosci.*, vol. 6, p. 39, 2012.

[24] C.-Y. Chen, C.-W. Wu, C.-T. Lin, and S.-A. Chen, "A novel classification method for motor imagery based on Brain-Computer Interface," in *2014 International Joint Conference on Neural Networks (IJCNN)*, 2014, pp. 4099–4102.

[25] M. Arvaneh, C. Guan, K. K. Ang, and C. Quek, "Optimizing the channel selection and classification accuracy in EEG-based BCI," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 6, pp. 1865–1873, 2011.

[26] W. Samek, C. Vidaurre, K.-R. Müller, and M. Kawanabe, "Stationary common spatial patterns for brain–computer interfacing," *J. Neural Eng.*, vol. 9, no. 2, p. 26013, 2012.

[27] W. Samek, M. Kawanabe, and K.-R. Müller, "Divergence-based framework for common spatial patterns algorithms," *IEEE Rev. Biomed. Eng.*, vol. 7, pp. 50–72, 2013.

[28] W. Wu, Z. Chen, X. Gao, Y. Li, E. N. Brown, and S. Gao, "Probabilistic common spatial patterns for multichannel EEG analysis," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 37, no. 3, pp. 639–653, 2014.

[29] M. Rashid *et al.*, "Current Status, Challenges, and Possible Solutions of EEG-Based Brain-Computer Interface: A Comprehensive Review," *Front. Neurorobot.*, 2020.

[30] X. Zhang, L. Yao, X. Wang, J. J. M. Monaghan, D. Mcalpine, and Y. Zhang, "A survey on deep learning-based non-invasive brain signals: recent advances and new frontiers," *J. Neural Eng.*, 2020.

[31] H. Altaheri, M. Alsulaiman, and G. Muhammad, "Date Fruit Classification for Robotic Harvesting in a Natural Environment Using Deep Learning," *IEEE Access*, vol. 7, no. 1, pp. 117115–117133, Aug. 2019.

[32] M. Qamhan, H. Altaheri, A. H. Meftah, G. Muhammad, and Y. A. Alotaibi, "Digital Audio Forensics: Microphone and Environment Classification Using Deep Learning," *IEEE Access*, vol. 9, pp. 62719–62733, 2021.

[33] G. Muhammad, M. S. Hossain, and N. Kumar, "EEG-based pathology detection for home health monitoring," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 2, pp. 603–610, 2020.

[34] G. Muhammad, M. F. Alhamid, and X. Long, "Computing and processing on the edge: Smart pathology detection for connected healthcare," *IEEE Netw.*, vol. 33, no. 6, pp. 44–49, 2019.

[35] G. Muhammad, S. K. M. M. Rahman, A. Alelaiwi, and A. Alamri, "Smart health solution integrating IoT and cloud: A case study of voice pathology monitoring," *IEEE Commun. Mag.*, vol. 55, no. 1, pp. 69–73, 2017.

[36] F. Lotte *et al.*, "A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update," *J. Neural Eng.*, vol. 15, no. 3, p. 31005, 2018.

[37] A. Craik, Y. He, and J. L. Contreras-Vidal, "Deep learning for electroencephalogram (EEG) classification tasks: a review," *J. Neural Eng.*, vol. 16, no. 3, p. 31001, 2019.

[38] N. Padfield, J. Zabalza, H. Zhao, V. Masero, and J. Ren, "EEG-based brain-computer interfaces using motor-imagery: Techniques and challenges," *Sensors*, vol. 19, no. 6, p. 1423, 2019.

[39] S. Aggarwal and N. Chugh, "Signal processing techniques for motor imagery brain computer interface: A review," *Array*, vol. 1, p. 100003, 2019.

[40] Z. Wan, R. Yang, M. Huang, N. Zeng, and X. Liu, "A review on transfer learning in EEG signal analysis," *Neurocomputing*, vol. 421, pp. 1–14, 2020.

[41] E. Lashgari, D. Liang, and U. Maoz, "Data augmentation for deep-learning-based electroencephalography," *J. Neurosci. Methods*, p. 108885, 2020.

[42] D. Moher, A. Liberati, J. Tetzlaff, D. G. Altman, and P. Group, "Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement," *PLoS med*, vol. 6, no. 7, p. e1000097, 2009.

[43] J. del R. Millán *et al.*, "Combining brain–computer interfaces and assistive technologies: state-of-the-art and challenges," *Front. Neurosci.*, vol. 4, p. 161, 2010.

[44] L. J. Greenfield, J. D. Geyer, and P. R. Carney, *Reading EEGs: A practical approach*. Lippincott Williams & Wilkins, 2012.

[45] T. Ball, M. Kern, I. Mutschler, A. Aertsen, and A. Schulze-

Bonhage, "Signal quality of simultaneously recorded invasive and non-invasive EEG," *Neuroimage*, vol. 46, no. 3, pp. 708–716, 2009.

[46] E. R. Kandel, J. H. Schwartz, T. M. Jessell, S. Siegelbaum, A. J. Hudspeth, and S. Mack, *Principles of neural science*, vol. 4. McGraw-hill New York, 2000.

[47] "CHB-MIT Scalp EEG Database." [Online]. Available: https://archive.physionet.org/physiobank/charts/chbmit.png. [Accessed: 12-Apr-2020].

[48] S. Lacey and R. Lawson, *Multisensory imagery*. Springer Science & Business Media, 2013.

[49] A. Rezeika, M. Benda, P. Stawicki, F. Gembler, A. Saboor, and I. Volosyak, "Brain–computer interface spellers: A review," *Brain Sci.*, vol. 8, no. 4, p. 57, 2018.

[50] M.-H. Lee *et al.*, "EEG dataset and OpenBMI toolbox for three BCI paradigms: an investigation into BCI illiteracy," *Gigascience*, vol. 8, no. 5, p. giz002, 2019.

[51] A. Hassanpour, M. Moradikia, H. Adeli, S. R. Khayami, and P. Shamsinejadbabaki, "A novel end-to-end deep learning scheme for classifying multi-class motor imagery electroencephalography signals," *Expert Syst.*, vol. 36, no. 6, p. e12494, 2019.

[52] G. Pfurtscheller, C. Brunner, A. Schlögl, and F. H. L. Da Silva, "Mu rhythm (de) synchronization and EEG single-trial classification of different motor imagery tasks," *Neuroimage*, vol. 31, no. 1, pp. 153–159, 2006.

[53] Y. Wang, M. Nakanishi, and D. Zhang, "EEG-Based Brain-Computer Interfaces," in *Neural Interface: Frontiers and Applications*, Springer, 2019, pp. 41–65.

[54] X. Zhao, H. Zhang, G. Zhu, F. You, S. Kuang, and L. Sun, "A multi-branch 3D convolutional neural network for EEG-based motor imagery classification," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 10, pp. 2164–2177, 2019.

[55] O. Avilov, S. Rimbert, A. Popov, and L. Bougrain, "Optimizing Motor Intention Detection with Deep Learning: Towards Management of Intraoperative Awareness," *IEEE Trans. Biomed. Eng.*, 2021.

[56] K. Zhu, S. Wang, D. Zheng, and M. Dai, "Study on the effect of different electrode channel combinations of motor imagery eeg signals on classification accuracy," *J. Eng.*, vol. 2019, no. 23, pp. 8641–8645, 2019.

[57] X. Lun, Z. Yu, T. Chen, F. Wang, and Y. Hou, "A simplified CNN classification method for MI-EEG via the electrode pairs signals," *Front. Hum. Neurosci.*, vol. 14, 2020.

[58] T. Liu and D. Yang, "A Densely Connected Multi-Branch 3D Convolutional Neural Network for Motor Imagery EEG Decoding," *Brain Sci.*, vol. 11, no. 2, p. 197, 2021.

[59] Y. Li, H. Yang, J. Li, D. Chen, and M. Du, "EEG-based intention recognition with deep recurrent-convolution neural network: Performance and channel selection by Grad-CAM," *Neurocomputing*, vol. 415, pp. 225–233, 2020.

[60] J. Yang, Z. Ma, J. Wang, and Y. Fu, "A Novel Deep Learning Scheme for Motor Imagery EEG Decoding Based on Spatial Representation Fusion," *IEEE Access*, vol. 8, pp. 202100–202110, 2020.

[61] Y. Chu, X. Zhao, Y. Zou, W. Xu, J. Han, and Y. Zhao, "A decoding scheme for incomplete motor imagery EEG with deep belief network," *Front. Neurosci.*, vol. 12, p. 680, 2018.

[62] J.-H. Jeong, B.-H. Lee, D.-H. Lee, Y.-D. Yun, and S.-W. Lee, "EEG classification of forearm movement imagery using a hierarchical flow convolutional neural network," *IEEE Access*, vol. 8, pp. 66941–66950, 2020.

[63] J. Yang, S. Yao, and J. Wang, "Deep fusion feature learning network for MI-EEG classification," *IEEE Access*, vol. 6, pp. 79050–79059, 2018.

[64] F. Fahimi, S. Dosen, K. K. Ang, N. Mrachacz-Kersting, and C. Guan, "Generative Adversarial Networks-Based Data Augmentation for Brain-Computer Interface," *IEEE Trans. neural networks Learn. Syst.*, 2020.

[65] B. Xu *et al.*, "Wavelet transform time-frequency image and convolutional network-based motor imagery EEG classification," *IEEE Access*, vol. 7, pp. 6084–6093, 2018.

[66] X. Ma, S. Qiu, W. Wei, S. Wang, and H. He, "Deep Channel-Correlation Network for Motor Imagery Decoding From the Same Limb," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 1, pp. 297–306, 2019.

[67] H. Alwasiti, M. Z. Yusoff, and K. Raza, "Motor imagery classification for brain computer interface using deep metric learning," *IEEE Access*, vol. 8, pp. 109949–109963, 2020.

[68] R. Alazrai, M. Abuhijleh, H. Alwanni, and M. I. Daoud, "A deep learning framework for decoding motor imagery tasks of the same hand using eeg signals," *IEEE Access*, vol. 7, pp. 109612–109627, 2019.

[69] G. Gómez-Herrero *et al.*, "Automatic removal of ocular artifacts in the EEG without an EOG reference channel," in *Proceedings of the 7th Nordic Signal Processing Symposium-NORSIG 2006*, 2006, pp. 130–133.

[70] T. Luo and F. Chao, "Exploring spatial-frequency-sequential relationships for motor imagery classification with recurrent neural network," *BMC Bioinformatics*, vol. 19, no. 1, p. 344, 2018.

[71] B. E. Olivas-Padilla and M. I. Chacon-Murguia, "Classification of multiple motor imagery using deep convolutional neural networks and spatial filters," *Appl. Soft Comput.*, vol. 75, pp. 461–472, 2019.

[72] S. Sakhavi, C. Guan, and S. Yan, "Learning temporal information for brain-computer interface using convolutional neural networks," *IEEE Trans. neural networks Learn. Syst.*, vol. 29, no. 11, pp. 5619–5629, 2018.

[73] O.-Y. Kwon, M.-H. Lee, C. Guan, and S.-W. Lee, "Subject-independent brain–computer interfaces based on deep convolutional neural networks," *IEEE Trans. neural networks Learn. Syst.*, vol. 31, no. 10, pp. 3839–3852, 2019.

[74] Q. She, B. Hu, Z. Luo, T. Nguyen, and Y. Zhang, "A hierarchical semi-supervised extreme learning machine method for EEG recognition," *Med. Biol. Eng. Comput.*, vol. 57, no. 1, pp. 147–157, 2018.

[75] S. Taheri, M. Ezoji, and S. M. Sakhaei, "Convolutional neural network based features for motor imagery EEG signals classification in brain–computer interface system," *SN Appl. Sci.*, vol. 2, no. 4, pp. 1–12, 2020.

[76] X. Ma, D. Wang, D. Liu, and J. Yang, "DWT and CNN based multi-class motor imagery electroencephalographic signal recognition," *J. Neural Eng.*, vol. 17, no. 1, p. 16073, 2020.

[77] N. Lu, T. Li, X. Ren, and H. Miao, "A deep learning scheme for motor imagery classification based on restricted Boltzmann machines," *IEEE Trans. neural Syst. Rehabil. Eng.*, vol. 25, no. 6, pp. 566–576, 2016.

[78] J. Xu, H. Zheng, J. Wang, D. Li, and X. Fang, "Recognition of EEG signal motor imagery intention based on deep multi-view feature learning," *Sensors*, vol. 20, no. 12, p. 3496, 2020.

[79] W. Huang, Y. Xue, L. Hu, and H. Liuli, "S-EEGNet: Electroencephalogram Signal Classification Based on a Separable Convolution Neural Network With Bilinear Interpolation," *IEEE Access*, vol. 8, pp. 131636–131646, 2020.

[80] P. Wang, A. Jiang, X. Liu, J. Shang, and L. Zhang, "LSTM-based EEG classification in motor imagery tasks," *IEEE Trans. neural Syst. Rehabil. Eng.*, vol. 26, no. 11, pp. 2086–2095, 2018.

[81] J.-S. Bang, M.-H. Lee, S. Fazli, C. Guan, and S.-W. Lee, "Spatio-spectral feature representation for motor imagery classification using convolutional neural networks," *IEEE Trans. Neural Networks Learn. Syst.*, 2021.

[82] J. Xue *et al.*, "A Multifrequency Brain Network-Based Deep Learning Framework for Motor Imagery Decoding," *Neural Plast.*, vol. 2020, 2020.

[83] X. Zhao, J. Zhao, C. Liu, and W. Cai, "Deep neural network with joint distribution matching for cross-subject motor imagery brain-computer interfaces," *Biomed Res. Int.*, vol. 2020, 2020.

[84] S. Kumar, A. Sharma, and T. Tsunoda, "Brain wave classification using long short-term memory network based OPTICAL predictor," *Sci. Rep.*, vol. 9, no. 1, pp. 1–13, 2019.

[85] S. Kumar, R. Sharma, and A. Sharma, "OPTICAL+: a frequency-based deep learning scheme for recognizing brain wave signals," *PeerJ Comput. Sci.*, vol. 7, p. e375, 2021.

[86] L. Cheng, D. Li, G. Yu, Z. Zhang, X. Li, and S. Yu, "A Motor Imagery EEG Feature Extraction Method Based on Energy Principal Component Analysis and Deep Belief Networks," *IEEE Access*, vol. 8, pp. 21453–21472, 2020.

[87] R. Zhang, Q. Zong, L. Dou, and X. Zhao, "A novel hybrid deep learning scheme for four-class motor imagery classification," *J. Neural Eng.*, vol. 16, no. 6, p. 66004, 2019.

[88] R. Zhang, Q. Zong, L. Dou, X. Zhao, Y. Tang, and Z. Li, "Hybrid deep neural network using transfer learning for EEG motor imagery decoding," *Biomed. Signal Process. Control*, vol. 63, p. 102144, 2021.

[89] T. Uktveris and V. Jusas, "Application of convolutional neural networks to four-class motor imagery classification problem," *Inf. Technol. Control*, vol. 46, no. 2, pp. 260–273, 2017.

[90] Z. Wang, L. Cao, Z. Zhang, X. Gong, Y. Sun, and H. Wang, "Short time Fourier transformation and deep neural networks for motor

imagery brain computer interface recognition," *Concurr. Comput. Pract. Exp.*, vol. 30, no. 23, p. e4413, 2018.

[91] K. Zhang *et al.*, "Data augmentation for motor imagery signal classification based on a hybrid neural network," *Sensors*, vol. 20, no. 16, p. 4485, 2020.

[92] N. Shajil, S. Mohan, P. Srinivasan, J. Arivudaiyanambi, and A. A. Murrugesan, "Multiclass Classification of Spatially Filtered Motor Imagery EEG Signals Using Convolutional Neural Network for BCI Based Applications," *J. Med. Biol. Eng.*, vol. 40, no. 5, pp. 663–672, 2020.

[93] Y. Rong, X. Wu, and Y. Zhang, "Classification of motor imagery electroencephalography signals using continuous small convolutional neural network," *Int. J. Imaging Syst. Technol.*, vol. 30, no. 3, pp. 653–659, 2020.

[94] S. Roy, A. Chowdhury, K. McCreadie, and G. Prasad, "Deep learning based inter-subject continuous decoding of motor imagery for practical brain-computer interfaces," *Front. Neurosci.*, vol. 14, 2020.

[95] M. Miao, W. Hu, H. Yin, and K. Zhang, "Spatial-frequency feature learning and classification of motor imagery EEG based on deep convolution neural network," *Comput. Math. Methods Med.*, vol. 2020, 2020.

[96] F. Li, F. He, F. Wang, D. Zhang, Y. Xia, and X. Li, "A novel simplified convolutional neural network classification algorithm of motor imagery EEG signals based on deep learning," *Appl. Sci.*, vol. 10, no. 5, p. 1605, 2020.

[97] P. Kant, S. H. Laskar, J. Hazarika, and R. Mahamune, "CWT Based Transfer Learning for Motor Imagery Classification for Brain computer Interfaces," *J. Neurosci. Methods*, vol. 345, p. 108886, 2020.

[98] Y. R. Tabar and U. Halici, "A novel deep learning approach for classification of EEG motor imagery signals," *J. Neural Eng.*, vol. 14, no. 1, p. 16003, 2016.

[99] M. Dai, D. Zheng, R. Na, S. Wang, and S. Zhang, "EEG classification of motor imagery using a novel deep learning framework," *Sensors*, vol. 19, no. 3, p. 551, 2019.

[100] D. Zhang, K. Chen, D. Jian, and L. Yao, "Motor imagery classification via temporal attention cues of graph embedded EEG signals," *IEEE J. Biomed. Heal. informatics*, vol. 24, no. 9, pp. 2570–2579, 2020.

[101] R. Leeb, C. Brunner, G. Müller-Putz, A. Schlögl, and G. Pfurtscheller, "BCI Competition 2008–Graz data set B," *Inst. Knowl. Discov. Graz Univ. Technol.*, pp. 1–6, 2008.

[102] B. Blankertz *et al.*, "The BCI competition 2003: progress and perspectives in detection and discrimination of EEG single trials," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1044–1051, 2004.

[103] X. Deng, B. Zhang, N. Yu, K. Liu, and K. Sun, "Advanced TSGL-EEGNet for Motor Imagery EEG-Based Brain-Computer Interfaces," *IEEE Access*, vol. 9, pp. 25118–25130, 2021.

[104] C.-C. Fan, H. Yang, Z.-G. Hou, Z.-L. Ni, S. Chen, and Z. Fang, "Bilinear neural network with 3-D attention for brain decoding of motor imagery movements from the human EEG," *Cogn. Neurodyn.*, vol. 15, no. 1, pp. 181–189, 2021.

[105] K. Roots, Y. Muhammad, and N. Muhammad, "Fusion Convolutional Neural Network for Cross-Subject EEG Motor Imagery Classification," *Computers*, vol. 9, no. 3, p. 72, 2020.

[106] D. Li, J. Xu, J. Wang, X. Fang, and J. Ying, "A Multi-Scale Fusion Convolutional Neural Network based on Attention Mechanism for the Visualization Analysis of EEG Signals Decoding," *IEEE Trans. Neural Syst. Rehabil. Eng.*, 2020.

[107] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung, and B. J. Lance, "EEGNet: a compact convolutional neural network for EEG-based brain–computer interfaces," *J. Neural Eng.*, vol. 15, no. 5, p. 56013, 2018.

[108] S. U. Amin, M. Alsulaiman, G. Muhammad, M. A. Bencherif, and M. S. Hossain, "Multilevel weighted feature fusion using convolutional neural networks for EEG motor imagery classification," *IEEE Access*, vol. 7, pp. 18940–18950, 2019.

[109] H. Dose, J. S. Møller, H. K. Iversen, and S. Puthusserypady, "An end-to-end deep learning approach to MI-EEG signal classification for BCIs," *Expert Syst. Appl.*, vol. 114, pp. 532–542, 2018.

[110] Z. Tang, C. Li, and S. Sun, "Single-trial EEG classification of motor imagery using deep convolutional neural networks," *Optik (Stuttg).*, vol. 130, pp. 11–18, 2017.

[111] G. Dai, J. Zhou, J. Huang, and N. Wang, "HS-CNN: a CNN with hybrid convolution scale for EEG motor imagery classification," *J. Neural Eng.*, vol. 17, no. 1, p. 16025, 2020.

[112] B.-H. Lee, J.-H. Jeong, and S.-W. Lee, "SessionNet: Feature similarity-based weighted ensemble learning for motor imagery classification," *IEEE Access*, vol. 8, pp. 134524–134535, 2020.

[113] H. Wu *et al.*, "A Parallel Multiscale Filter Bank Convolutional Neural Networks for Motor Imagery EEG Classification," *Front. Neurosci.*, vol. 13, p. 1275, 2019.

[114] C. Zhang, Y.-K. Kim, and A. Eskandarian, "EEG-inception: an accurate and robust end-to-end neural network for EEG-based motor imagery classification," *J. Neural Eng.*, vol. 18, no. 4, p. 46014, 2021.

[115] S. U. Amin, M. Alsulaiman, G. Muhammad, M. A. Mekhtiche, and M. S. Hossain, "Deep Learning for EEG motor imagery classification based on multi-layer CNNs feature fusion," *Futur. Gener. Comput. Syst.*, vol. 101, pp. 542–554, 2019.

[116] M. Xu *et al.*, "Learning EEG topographical representation for classification via convolutional neural network," *Pattern Recognit.*, vol. 105, p. 107390, 2020.

[117] J. J. Liao, J. J. Luo, T. Yang, R. Q. Y. So, and M. C. H. Chua, "Effects of local and global spatial patterns in EEG motor-imagery classification using convolutional neural network," *Brain-Computer Interfaces*, vol. 7, no. 3–4, pp. 47–56, 2020.

[118] M.-A. Li, J.-F. Han, and L.-J. Duan, "A Novel MI-EEG Imaging With the Location Information of Electrodes," *IEEE Access*, vol. 8, pp. 3197–3211, 2019.

[119] D. F. Collazos-Huertas, A. M. Álvarez-Meza, C. D. Acosta-Medina, G. A. Castaño-Duque, and G. Castellanos-Dominguez, "CNN-based framework using spatial dropping for enhanced interpretation of neural activity in motor imagery classification," *Brain Informatics*, vol. 7, no. 1, pp. 1–13, 2020.

[120] Y. Hou, L. Zhou, S. Jia, and X. Lun, "A novel approach of decoding EEG four-class motor imagery tasks via scout ESI and CNN," *J. Neural Eng.*, vol. 17, no. 1, p. 16048, 2020.

[121] X. Liu, Y. Shen, J. Liu, J. Yang, P. Xiong, and F. Lin, "Parallel Spatial–Temporal Self-Attention CNN-Based Motor Imagery Classification for BCI," *Front. Neurosci.*, vol. 14, 2020.

[122] S. U. Amin, H. Altaheri, G. Muhammad, M. Alsulaiman, and W. Abdul, "Attention based Inception model for robust EEG motor imagery classification," in *2021 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, 2021, pp. 1–6.

[123] X. Zhu, P. Li, C. Li, D. Yao, R. Zhang, and P. Xu, "Separated channel convolutional neural network to realize the training free motor imagery BCI systems," *Biomed. Signal Process. Control*, vol. 49, pp. 396–403, 2019.

[124] Y. K. Musallam *et al.*, "Electroencephalography-based motor imagery classification using temporal convolutional network fusion," *Biomed. Signal Process. Control*, vol. 69, p. 102826, 2021.

[125] M. Riyad, M. Khalil, and A. Adib, "MI-EEGNET: A novel convolutional neural network for motor imagery classification," *J. Neurosci. Methods*, vol. 353, p. 109037, 2021.

[126] D. Li, J. Wang, J. Xu, and X. Fang, "Densely feature fusion based on convolutional neural networks for motor imagery EEG classification," *IEEE Access*, vol. 7, pp. 132720–132730, 2019.

[127] K.-W. Ha and J.-W. Jeong, "Temporal Pyramid Pooling for Decoding Motor-Imagery EEG Signals," *IEEE Access*, vol. 9, pp. 3112–3125, 2021.

[128] K. Zhang, N. Robinson, S.-W. Lee, and C. Guan, "Adaptive transfer learning for EEG motor imagery classification with deep Convolutional Neural Network," *Neural Networks*, vol. 136, pp. 1–10, 2021.

[129] H. Zhao, Q. Zheng, K. Ma, H. Li, and Y. Zheng, "Deep Representation-Based Domain Adaptation for Nonstationary EEG Classification," *IEEE Trans. Neural Networks Learn. Syst.*, 2020.

[130] G. Xu *et al.*, "A deep transfer convolutional neural network framework for EEG signal classification," *IEEE Access*, vol. 7, pp. 112767–112776, 2019.

[131] C. Brunner, R. Leeb, G. Müller-Putz, A. Schlögl, and G. Pfurtscheller, "BCI Competition 2008–Graz data set A," *Inst. Knowl. Discov. Graz Univ. Technol.*, vol. 16, pp. 1–6, 2008.

[132] H. Cho, M. Ahn, S. Ahn, M. Kwon, and S. C. Jun, "EEG datasets for motor imagery brain–computer interface," *Gigascience*, vol. 6, no. 7, p. gix034, 2017.

[133] B. Blankertz, G. Dornhege, M. Krauledat, K.-R. Müller, and G. Curio, "The non-invasive Berlin brain–computer interface: fast acquisition of effective performance in untrained subjects," *Neuroimage*, vol. 37, no. 2, pp. 539–550, 2007.

[134] D. P. Kingma and M. Welling, "Auto-encoding variational bayes," *arXiv Prepr. arXiv1312.6114*, 2013.

[135] Y. Li, X.-R. Zhang, B. Zhang, M.-Y. Lei, W.-G. Cui, and Y.-Z.

Guo, “A channel-projection mixed-scale convolutional neural network for motor imagery EEG decoding,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 6, pp. 1170–1180, 2019.

[136] B. Blankertz *et al.*, “The BCI competition III: Validating alternative approaches to actual BCI problems,” *IEEE Trans. neural Syst. Rehabil. Eng.*, vol. 14, no. 2, pp. 153–159, 2006.

[137] L. Wang, W. Huang, Z. Yang, and C. Zhang, “Temporal-spatial-frequency depth extraction of brain-computer interface based on mental tasks,” *Biomed. Signal Process. Control*, vol. 58, p. 101845, 2020.

[138] D. Freer and G.-Z. Yang, “Data augmentation for self-paced motor imagery classification with C-LSTM,” *J. Neural Eng.*, vol. 17, no. 1, p. 16041, 2020.

[139] A. L. Goldberger *et al.*, “PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals,” *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000.

[140] L. Xiaoling, “Motor imagery-based EEG signals classification by combining temporal and spatial deep characteristics,” *Int. J. Intell. Comput. Cybern.*, 2020.

[141] K. Zhang *et al.*, “Instance transfer subject-dependent strategy for motor imagery signal classification using deep convolutional neural networks,” *Comput. Math. Methods Med.*, vol. 2020, 2020.

[142] P. Ofner, A. Schwarz, J. Pereira, and G. R. Müller-Putz, “Upper limb movements can be decoded from the time-domain of low-frequency EEG,” *PLoS One*, vol. 12, no. 8, p. e0182578, 2017.

[143] J. Chen, Z. Yu, Z. Gu, and Y. Li, “Deep Temporal-Spatial Feature Learning for Motor Imagery-Based Brain–Computer Interfaces,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 11, pp. 2356–2366, 2020.

[144] D. Steyrl, R. Scherer, O. Förstner, and G. R. Müller-Putz, “Motor imagery brain-computer interfaces: random forests vs regularized LDA-non-linear beats linear,” in *Proceedings of the 6th International Brain-Computer Interface Conference*, 2014, pp. 241–244.

[145] X. Ma, S. Qiu, and H. He, “Multi-channel EEG recording during motor imagery of different joints from the same limb,” *Sci. data*, vol. 7, no. 1, pp. 1–9, 2020.

[146] H. K. Lee and Y.-S. Choi, “Application of continuous wavelet transform and convolutional neural network in decoding motor imagery brain-computer interface,” *Entropy*, vol. 21, no. 12, p. 1199, 2019.

[147] C. J. Ortiz-Echeverri, S. Salazar-Colores, J. Rodríguez-Reséndiz, and R. A. Gómez-Loenzo, “A new approach for motor imagery classification based on sorted blind source separation, continuous wavelet transform, and convolutional neural network,” *Sensors*, vol. 19, no. 20, p. 4541, 2019.

[148] S. Chaudhary, S. Taran, V. Bajaj, and A. Sengur, “Convolutional neural network based approach towards motor imagery tasks EEG signals classification,” *IEEE Sens. J.*, vol. 19, no. 12, pp. 4494–4500, 2019.

[149] X.-L. Tang, W.-C. Ma, D.-S. Kong, and W. Li, “Semisupervised deep stacking network with adaptive learning rate strategy for motor imagery EEG recognition,” *Neural Comput.*, vol. 31, no. 5, pp. 919–942, 2019.

[150] Z. Zhang *et al.*, “A novel deep learning approach with data augmentation to classify motor imagery signals,” *IEEE Access*, vol. 7, pp. 15945–15954, 2019.

[151] X. Tang, N. Zhang, J. Zhou, and Q. Liu, “Hidden-layer visible deep stacking network optimized by PSO for motor imagery EEG recognition,” *Neurocomputing*, vol. 234, pp. 1–10, 2017.

[152] L. Deng, Jia and Dong, Wei and Socher, Richard and Li, Li-Jia and Li, Kai and Fei-Fei, “Imagenet: A large-scale hierarchical image database,” in *IEEE Conference on Computer Vision and Pattern Recognition*, 2009, pp. 248–255.

[153] H. Altaheri, M. Alsulaiman, G. Muhammad, S. U. Amin, M. Bencherif, and M. Mekhtiche, “Date fruit dataset for intelligent harvesting,” *Data Br.*, vol. 26, p. 104514, Oct. 2019.

[154] M. Alsulaiman, G. Muhammad, M. A. Bencherif, A. Mahmood, and Z. Ali, “KSU rich Arabic speech database,” *Inf.*, vol. 16, no. 6 B, pp. 4231–4253, 2013.

[155] Graz University of Technology, “Data sets - BNCI Horizon 2020.” [Online]. Available: http://bnci-horizon-2020.eu/database/data-sets. [Accessed: 05-Feb-2021].

[156] F. Lotte, “Fabien Lotte’s professional homepage - Links.” [Online]. Available: https://sites.google.com/site/fabienlotte/bci-community/links?authuser=0#h.p_ID_172. [Accessed: 05-Feb-2021].

[157] R. Scherer *et al.*, “Individually adapted imagery improves brain-computer interface performance in end-users with disability,” *PLoS One*, vol. 10, no. 5, p. e0123727, 2015.

[158] M. Kaya, M. K. Binli, E. Ozbay, H. Yanar, and Y. Mishchenko, “A large electroencephalographic motor imagery dataset for electroencephalographic brain computer interfaces,” *Sci. data*, vol. 5, p. 180211, 2018.

[159] N. Brodu, F. Lotte, and A. Lécuyer, “Exploring two novel features for EEG-based brain–computer interfaces: Multifractal cumulants and predictive complexity,” *Neurocomputing*, vol. 79, pp. 87–94, 2012.

[160] A. Ramos-Murguialday *et al.*, “Brain–machine interface in chronic stroke rehabilitation: a controlled study,” *Ann. Neurol.*, vol. 74, no. 1, pp. 100–108, 2013.

[161] X. Zhang, L. Yao, Q. Z. Sheng, S. S. Kanhere, T. Gu, and D. Zhang, “Converting your thoughts to texts: Enabling brain typing via deep feature learning of eeg signals,” in *2018 IEEE international conference on pervasive computing and communications (PerCom)*, 2018, pp. 1–10.

[162] J. Van Erp, F. Lotte, and M. Tangermann, “Brain-computer interfaces: beyond medical applications,” *Computer (Long. Beach. Calif).*, vol. 45, no. 4, pp. 26–34, 2012.

[163] R. Yuste *et al.*, “Four ethical priorities for neurotechnologies and AI,” *Nat. News*, vol. 551, no. 7679, p. 159, 2017.

[164] K. LaFleur, K. Cassady, A. Doud, K. Shades, E. Rogin, and B. He, “Quadcopter control in three-dimensional space using a noninvasive motor imagery-based brain–computer interface,” *J. Neural Eng.*, vol. 10, no. 4, p. 46003, 2013.

[165] Y. Yu *et al.*, “Toward brain-actuated car applications: Self-paced control with a motor imagery-based brain-computer interface,” *Comput. Biol. Med.*, vol. 77, pp. 148–155, 2016.

[166] X. Zhang, L. Yao, C. Huang, Q. Z. Sheng, and X. Wang, “Intent recognition in smart living through deep recurrent neural networks,” in *International Conference on Neural Information Processing*, 2017, pp. 748–758.

[167] T. Li, J. Zhang, T. Xue, and B. Wang, “Development of a novel motor imagery control technique and application in a gaming environment,” *Comput. Intell. Neurosci.*, vol. 2017, 2017.

[168] A. Kreilinger, H. Hiebel, and G. R. Müller-Putz, “Single versus multiple events error potential detection in a BCI-controlled car game with continuous and discrete feedback,” *IEEE Trans. Biomed. Eng.*, vol. 63, no. 3, pp. 519–529, 2015.

[169] X. Zhang, L. Yao, S. S. Kanhere, Y. Liu, T. Gu, and K. Chen, “Mindid: Person identification from brain waves through attention-based recurrent neural network,” *Proc. ACM Interactive, Mobile, Wearable Ubiquitous Technol.*, vol. 2, no. 3, pp. 1–23, 2018.

[170] X. Zhang, L. Yao, C. Huang, T. Gu, Z. Yang, and Y. Liu, “DeepKey: An EEG and gait based dual-authentication system,” *arXiv Prepr. arXiv1706.01606*, 2017.