

## DAFTAR PUSTAKA

- [1] A. Apicella, F. Isgrò, A. Pollastro, and R. Prevete, “On the effects of data normalisation for domain adaptation on eeg data,” 2023.
- [2] C. Brunner, R. Leeb, G. Müller-Putz, A. Schlögl, and G. Pfurtscheller, “Bci competition 2008–graz data set a,” *Institute of Knowledge Discovery, Graz University of Technology*, vol. 16, pp. 1–6, 2008.
- [3] H. Altaheri, G. Muhammad, and M. Alsulaiman, “Physics-informed attention temporal convolutional network for eeg-based motor imagery classification,” *IEEE Transactions on Industrial Informatics*, 2022.
- [4] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Kaiser, and I. Polosukhin, “Attention is all you need,” in *Advances in neural information processing systems*, 2017, pp. 5998–6008.
- [5] 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,” *Journal of Neural Engineering*, vol. 15, no. 5, p. 056013, 2018. [Online]. Available: <http://stacks.iop.org/1741-2552/15/i=5/a=056013>
- [6] K. M. Ting, *Confusion Matrix*. Boston, MA: Springer US, 2017, pp. 260–260. [Online]. Available: [https://doi.org/10.1007/978-1-4899-7687-1\\_50](https://doi.org/10.1007/978-1-4899-7687-1_50)
- [7] 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,” *Journal of Healthcare Engineering*, vol. 2018, pp. 1–10, 2018.
- [8] 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.
- [9] 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.
- [10] 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.
- [11] A. Fernández-Rodríguez, F. Velasco-Alvarez, and R. Ron-Angevin, “Review of real brain-controlled wheelchairs,” *J Neural Eng*, vol. 13, no. 6, p. 61001, 2016.
- [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. Agarwala and S. Dhage, “Feature extraction methods for electroencephalography based brain-computer interface: a review,” *IAENG International Journal of Computer Science*, vol. 47, no. 3, 2020.

- [14] M. R. N. Kousarrizi, A. A. Ghanbari, M. Teshnehlab, M. A. Shorehdeli, and A. Ghavari, "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*. IEEE, 2009.
- [15] L. Zhang, D. Wen, C. Li, and R. Zhu, "Ensemble classifier based on optimized extreme learning machine for motor imagery classification," *Journal of Neural Engineering*, vol. 17, no. 2, p. 026004, 2020.
- [16] K. Wang, D. Zhai, and Y. Xia, "Motor imagination eeg recognition algorithm based on dwt, csp and extreme learning machine," in *2019 Chinese Control Conference (CCC)*. IEEE, 2019, pp. 4590–4595.
- [17] Z. Jin, G. Zhou, D. Gao, and Y. Zhang, "Eeg classification using sparse bayesian extreme learning machine for brain-computer interface," *Neural Computing and Applications*, vol. 32, pp. 1–9, 2018.
- [18] 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," *Frontiers in Neuroscience*, vol. 6, p. 39, 2012.
- [19] W. Samek, C. Vidaurre, K.-R. Muller, and M. Kawanabe, "Stationary common spatial patterns for brain-computer interfacing," *Journal of Neural Engineering*, vol. 9, no. 2, p. 26013, 2012.
- [20] W. Samek, M. Kawanabe, and K.-R. Muller, "Divergence-based framework for common spatial patterns algorithms," *IEEE Reviews in Biomedical Engineering*, vol. 7, pp. 50–72, 2013.
- [21] W. Wu, Z. Chen, X. Gao, Y. Li, E. N. Brown, and S. Gao, "Probabilistic common spatial patterns for multichannel eeg analysis," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 37, no. 3, pp. 639–653, 2014.
- [22] J. Fan, Y. Li, Q. Liu, and N. Sarkar, "Adversarial domain adaptation for eeg-based emotion recognition," in *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2020, pp. 5032–5035.
- [23] H. Chen, S. Sun, J. Li, R. Yu, N. Li, X. Li, and B. Hu, "Personal-zscore: Eliminating individual difference for eeg-based cross-subject emotion recognition," *IEEE Transactions on Affective Computing*, 2021.
- [24] A. Apicella, P. Arpaia, M. Frosolone, G. Improta, N. Moccaldi, and A. Pollastro, "Eeg-based measurement system for monitoring student engagement in learning 4.0," *Scientific Reports*, vol. 12, no. 1, pp. 1–13, 2022.
- [25] J. Fernandez, N. Guttenberg, O. Witkowski, and A. Pasquali, "Cross-subject eeg-based emotion recognition through neural networks with stratified normalization," *Frontiers in Neuroscience*, vol. 15, p. 11, 2021.
- [26] J. Fan, J. W. Wade, A. P. Key, Z. E. Warren, and N. Sarkar, "Eeg-based affect and workload recognition in a virtual driving environment for asd intervention," *IEEE Transactions on Biomedical Engineering*, vol. 65, no. 1, pp. 43–51, 2017.

- [27] M. Arevalillo-Herráez, M. Cobos, S. Roger, and M. García-Pineda, "Combining inter-subject modeling with a subject-based data transformation to improve affect recognition from eeg signals," *Sensors*, vol. 19, no. 13, p. 2999, 2019.
- [28] H. Altaheri, G. Muhammad, M. Alsulaiman, S. U. Amin, G. A. Altuwaijri, W. Abdul, M. A. Bencherif, and M. Faisal, "Deep learning techniques for classification of electroencephalogram (eeg) motor imagery (mi) signals: a review," *Neural Computing and Applications*, pp. 1–42, 2021.
- [29] 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," *Concurrency and Computation: Practice and Experience*, vol. 30, no. 23, p. e4413, 2018.
- [30] Y. R. Tabar and U. Halici, "A novel deep learning approach for classification of eeg motor imagery signals," *Journal of Neural Engineering*, vol. 14, no. 1, p. 016003, 2016.
- [31] 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," *Journal of Engineering*, vol. 2019, no. 23, pp. 8641–8645, 2019.
- [32] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," in *International Conference on Machine Learning*, 2015, pp. 448–456.
- [33] T. M. Ingolfsson, M. Hersche, X. Wang, N. Kobayashi, L. Cavigelli, and L. Benini, "Eeg-tcnnet: An accurate temporal convolutional network for embedded motor-imagery brain-machine interfaces," *arXiv Prepr. arXiv2006.00622*, 2020.
- [34] F. Chollet, "Xception: Deep learning with depthwise separable convolutions," *CoRR*, vol. abs/1610.02357, 2016. [Online]. Available: <http://arxiv.org/abs/1610.02357>
- [35] M. Dyrholm, C. Christoforou, and L. C. Parra, "Bilinear discriminant component analysis," *Journal of Machine Learning Research*, vol. 8, no. May, pp. 1097–1111, 2007.
- [36] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: A simple way to prevent neural networks from overfitting," *Journal of Machine Learning Research*, vol. 15, pp. 1929–1958, 2014.
- [37] J. T. Springenberg, A. Dosovitskiy, T. Brox, and M. Riedmiller, "Striving for simplicity: The all convolutional net," 2015.
- [38] Z. Lan, O. Sourina, L. Wang, R. Scherer, and G. R. Müller-Putz, "Domain adaptation techniques for eeg-based emotion recognition: a comparative study on two public datasets," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 11, no. 1, pp. 85–94, 2018.
- [39] J. Li, S. Qiu, C. Du, Y. Wang, and H. He, "Domain adaptation for eeg emotion recognition based on latent representation similarity," *IEEE Transactions on Cognitive and Developmental Systems*, vol. 12, no. 2, pp. 344–353, 2019.

- [40] H. Zhao, Q. Zheng, K. Ma, H. Li, and Y. Zheng, "Deep representation-based domain adaptation for nonstationary eeg classification," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 2, pp. 535–545, 2020.
- [41] Y. Ganin, E. Ustinova, H. Ajakan, P. Germain, H. Larochelle, F. Laviolette, M. Marchand, and V. Lempitsky, "Domain-adversarial training of neural networks," *The Journal of Machine Learning Research*, vol. 17, no. 1, pp. 2096–2030, 2016.
- [42] E. Tzeng, J. Hoffman, K. Saenko, and T. Darrell, "Adversarial discriminative domain adaptation," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2017, pp. 7167–7176.
- [43] S. J. Pan, I. W. Tsang, J. T. Kwok, and Q. Yang, "Domain adaptation via transfer component analysis," *IEEE Transactions on Neural Networks*, vol. 22, no. 2, pp. 199–210, 2010.
- [44] B. Schölkopf, A. Smola, and K.-R. Müller, "Nonlinear component analysis as a kernel eigenvalue problem," *Neural Computation*, vol. 10, no. 5, pp. 1299–1319, 1998.
- [45] I. Ahmed, G. Jeon, and F. Piccialli, "From artificial intelligence to explainable artificial intelligence in industry 4.0: A survey on what, how, and where," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 8, pp. 5031–5042, 2022.
- [46] L. J. Greenfield, J. D. Geyer, and P. R. Carney, *Reading EEGs: A Practical Approach*. Philadelphia: Lippincott Williams & Wilkins, 2012.
- [47] 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.
- [48] E. R. Kandel, J. H. Schwartz, T. M. Jessell, S. Siegelbaum, A. J. Hudspeth, and S. Mack, *Principles of Neural Science*. New York: McGraw-Hill, 2000.
- [49] S. Lacey and R. Lawson, *Multisensory Imagery*. Berlin: Springer Science and Business Media, 2013.
- [50] A. Rezeika, M. Benda, P. Stawicki, F. Gembler, A. Saboor, and I. Volosyak, "Brain-computer interface spellers: a review," *Brain Sciences*, vol. 8, no. 4, p. 57, 2018.
- [51] 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.
- [52] A. Assanpour, M. Moradikia, H. Adeli, S. R. Khayami, and S. Shamshirband, "A novel end-to-end deep learning scheme for classifying multi-class motor imagery electroencephalography signals," *Expert Systems*, vol. 36, no. 6, p. e12494, 2019.
- [53] G. Pfurtscheller, C. Brunner, A. Schloßgl, 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.
- [54] Y. Wang, M. Nakanishi, and D. Zhang, "Eeg-based brain-computer interfaces," in *Neural Interface: Frontiers and Applications*. Berlin: Springer, 2019, pp. 41–65.

- [55] M. C. Chen, R. L. Ball, L. Yang *et al.*, “Deep learning to classify radiology free-text reports,” *Radiology*, vol. 286, pp. 845–852, 2018.
- [56] D. H. Hubel and T. N. Wiesel, “Receptive fields and functional architecture of monkey striate cortex,” *The Journal of Physiology*, vol. 195, pp. 215–243, 1968.
- [57] R. Yamashita, M. Nishio, R. K. G. Do *et al.*, “Convolutional neural networks: an overview and application in radiology,” *Insights Imaging*, vol. 9, no. 4, pp. 611–629, 2018.
- [58] C. Farabet, C. Couprie, L. Najman, and Y. LeCun, “Learning hierarchical features for scene labeling,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 35, no. 8, pp. 1915–1929, 2013.
- [59] A. Krizhevsky and G. E. Hinton, “Using very deep autoencoders for content-based image retrieval,” in *ESANN*, 2011, pp. 1–7.
- [60] S. Ren, K. He, R. Girshick, and J. Sun, “Faster r-cnn: Towards real-time object detection with region proposal networks,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 6, pp. 1137–1149, 2017.
- [61] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan, “Show and tell: A neural image caption generator,” in *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, 2015, pp. 3156–3164.
- [62] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf, “Deepface: Closing the gap to human-level performance in face verification,” in *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. Columbus, OH: IEEE, 2014, pp. 1701–1708.
- [63] D. H. Hubel and T. N. Wiesel, “Receptive fields of single neurons in the cat’s striate cortex,” *Journal of Physiology*, pp. 574–591, 1959.
- [64] K. Fukushima, “Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position,” *Biological Cybernetics*, pp. 193–202, 1980.
- [65] Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel, “Handwritten digit recognition with a back-propagation network,” in *NIPS*, 1989, pp. 1–9.
- [66] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in *Advances in Neural Information Processing Systems*, 2012, pp. 1097–1105.
- [67] V. Nair and G. E. Hinton, “Rectified linear units improve restricted boltzmann machines,” in *International Conference on Machine Learning*, 2010, pp. 807–814.
- [68] A. Kulkarni, D. Chong, and F. A. Batarseh, “5 - foundations of data imbalance and solutions for a data democracy,” in *Data Democracy*, F. A. Batarseh and R. Yang, Eds. Academic Press, 2020, pp. 83–106. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/B9780128183663000058>

- [69] J. Brownlee, *Better Deep Learning: Train Faster, Reduce Overfitting, and Make Better Predictions*. Machine Learning Mastery, 2018. [Online]. Available: <https://books.google.co.id/books?id=T1-nDwAAQBAJ>
- [70] J. Hu, L. Shen, S. Albanie, G. Sun, and E. Wu, “Squeeze-and-excitation networks,” 2019.
- [71] S. Woo, J. Park, J.-Y. Lee, and I. S. Kweon, “Cbam: Convolutional block attention module,” 2018.
- [72] A. Bartoli and A. Fusiello, *Computer Vision – ECCV 2020 Workshops: Glasgow, UK, August 23–28, 2020, Proceedings, Part V*, ser. Lecture Notes in Computer Science. Springer International Publishing, 2021. [Online]. Available: <https://books.google.co.id/books?id=EmcYEAAAQBAJ>