

We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

5,900

Open access books available

145,000

International authors and editors

180M

Downloads

Our authors are among the

154

Countries delivered to

TOP 1%

most cited scientists

12.2%

Contributors from top 500 universities



WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com



Introductory Chapter: The “DNA Model” of Neurosciences and Computer Systems

Manish Putteeraj and Shah Nawaz Ali Mohamudally

1. Introduction

The technological advances made in the recent years have moved beyond the conventional research and design framework that used to singularly focus on the problem at hand and resolve it using the best approaches within the same field. Current systems cater for crossbridges across disciplines for problem solving, a process that creates multiple opportunities toward sustainable and cutting-edge innovations. This design of inter-relationality across dimensions has served well in developing modern techniques such as the use of brain waves to understand human behavior and similar methods toward the introduction of machine learning (ML) stemming from artificial intelligence (AI). This has also led to popular and insightful methods such as brain-computer interfaces (BCI) that are gaining much momentum especially in modern medicine. However, much needs to be done in the field of neurosciences and computer systems to exploit the resources for their respective progression and nurture the existing ecosystem. This chapter will provide an overview of a “DNA model” concept that shows the relative interdependence of brain sciences and computer systems in research and unravel unexplored areas for probing scientists.

1.1 Demystifying the brain

The mammalian brain is arguably the most complex organ of the body with over 100 billion neurons and glial cells which are scattered across the lobes for specific functionality. The neurodevelopmental process consists of multiple stages inclusive of migration, differentiation, maturation, synaptogenesis, pruning, and myelination, among others, which provides the basis for brain development [1]. ML and AI are overlap constructs of neurocomputing, which can be said to be founded on principles of synaptogenesis, a biological process forming the basis of signal integration at the brain level. In a simplistic overview, the mammalian body responds to the environment based on a sensory input integrated at the neuronal level to trigger relevant output. This is also reflected in the decision-making process, whereby the brain computes multiple scenarios for comparison based on the information crunched in different brain regions before initiating the action for the desired value [2]. Applicability of this type of brain process has been made possible using modern noninvasive neuroimaging techniques such as electroencephalograms (EEGs), enabling the visualization and patterning of brain activity for informed decisions. Research by Poli et al. (2013) [3] has effectively demonstrated such applicability of BCI using a neuroscience platform to enhance noncommunicative group-based decision-making process solely relying on a supervised machine learning platform

with an eightfold cross-validation approach. Although at its embryonic stage, this type of research can be further exploited in real-life settings to exclude the argumentative part and enhance the time taken for group-based decision-making process.

1.2 Brain circuitry and artificial neural networks

Brain circuitry, i.e., the synaptic connectivity of individual neurons in one or more brain regions, is vital for a potent signal integration and transmission. Similarly, neuronal interaction via synapses has been shown to be critical for memory recall and learning, via recurrent signal generation at those areas of connectivity [4, 5]. This is comparable to the application of artificial neural networks (ANN) using soft fuzzy logic to compute multiple variables to autonomously generate tailored solutions based on adaptability as well as the governance of signal transmission via weights, a feature that to a certain extent mimics synaptic plasticity of the brain in memory formation and recall [6, 7]. The crossbridge between neurosciences and computer systems is not only reflected in the setup/programming of the system but also in terms of information being fed in real time for fine-tuning of outputs. Using supervised learning algorithms such as the back-propagation algorithm is necessary to assist in marginalizing the gap between expected and actual outputs and render information parsing and predictability meaningful [8]. This physiologic term is termed as the feedback loop system enabling the correction of any deviations at the systemic level or normalization of neuromodulatory signals via neurofeedback systems. Interestingly, ANN also recreates a biological neuronal system via its “artificial firing at the nodal region” akin to action potentials, mediating passage of signals downstream for a source to its effector region [9]. This feed-forwarding process in artificial setups also termed as axonal saltatory conduction in the brain has been found to be efficient for the speed of signal transmission.

1.3 Analysis of brain signals

Innovations have demonstrated the use of brain waves and software recreated from a biological system, to enhance modern medicine for better diagnostic and treatment possibilities. As reviewed by Guggisberg, Koch's [10] probabilistic tractography algorithms can be used to determine the extent of damage to neuronal connectivity following a stroke episode among other rehabilitative techniques such as repetitive transcranial electric stimulation. Of interest, EEG-based BCI architecture has been a tremendous asset in patients suffering from neuromuscular disorders, hence facilitation of simple movement/locomotor remission aided by neuro-prosthetics. Such feats have been developed using noninvasive methods for signal acquisition, bio-signal amplifier and filter to increase the signal-to-noise ratio, exclusion of physiological artifacts, EEG feature extraction and classification as the cue for output using linear or nonlinear classifiers in the form of support vector machines (SVMs), or ANNs, among others [11, 12]. While research is at full steam with respect to BCI-controlled prosthetics, much has been done in terms of platforms used to increase accuracy of the artificial limbs as demonstrated by the application of analyzing the EEG signals using a quadratic time-frequency distribution (QTFD) coupled with a two-layer classification framework to distinguish between individual finger movement within the same hand, hence increasing the resolution and specificity of finger control [13]. Within those lines, Lange et al. [14] processed EEG data using spectrally weighted common spatial patterns (spec-CSP) for feature extraction to correlate it with electromyogram (EMG) recordings for more potent data classification and refined movements. The application of such technology with a neuroscience platform in modern age medicine is inexhaustive.

2. Conclusion

Much progress has been made in the cardiovascular area for coronary abnormality detection inclusive of arrhythmias and infarctions [15, 16], splicing circadian patterns with respect to sleep [17] and fatigue detection [18], prosthetic vision [19], and deep brain stimulators [20], among others. The human-robotic collaboration also forms an intricate and well-established research area for such application, given that commercialization of such products assisting production plants and surgeries are well documented. However, as with all technological innovations, there are certain limitations which are yet to be addressed. Using ML in the field of diagnostic and treatment is always accompanied by the dataset limitation such that the decreased availability of features to be fed into the system can impact on ML performance, especially in disease diagnostics [21]. This is further reinforced by the vulnerability of the system given its dependence on the data used for training; hence, erroneous or biased data will result in flawed outputs. In the case of using machine learning for psychological profiling, the fact that shared symptoms are common across certain mental illnesses, accuracy of predictability would be affected given the nuanced symptomatic classifications [22]. Aside from common methodological factors such as confounding variables and transboundary access to datasets for training algorithms, the major limitation still remains that machine learning cannot as yet include sentient features and thus in the context of robotics-human collaboration or even medical-related decision-making process, implementation of such technology requires further research.

IntechOpen

Author details

Manish Putteeraj and Shah Nawaz Ali Mohamudally*
University of Technology, Mauritius

*Address all correspondence to: alimohamudally@umail.utm.ac.mu

IntechOpen

© 2020 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/3.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. 

References

- [1] Gibb R, Kovalchuk A. Chapter 1 - brain development. In: Gibb R, Kolb B, editors. *The Neurobiology of Brain and Behavioral Development*. Amsterdam, Netherlands: Elsevier, Academic Press; 2018. pp. 3-27
- [2] Wunderlich K, Rangel A, Doherty JP. Neural computations underlying action-based decision making in the human brain. *Proceedings of the National Academy of Sciences of the United States of America*. 2009;**106**(40):17199
- [3] Poli R, et al. Improving decision-making based on visual perception via a collaborative brain-computer interface. In: 2013 IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support (CogSIMA); 2013
- [4] Hasselmo ME, Schnell E, Barkai E. Dynamics of learning and recall at excitatory recurrent synapses and cholinergic modulation in rat hippocampal region CA3. *The Journal of Neuroscience*. 1995;**15**(7):5249
- [5] Silva AJ. Molecular and cellular cognitive studies of the role of synaptic plasticity in memory. *Journal of Neurobiology*. 2003;**54**(1):224-237
- [6] Pagel JF, Kirshtein P. Chapter six - neural networks: The hard and software logic. In: Pagel JF, Kirshtein P, editors. *Machine Dreaming and Consciousness*. San Diego: Academic Press; 2017. pp. 83-92
- [7] Neves G, Cooke SF, Bliss TVP. Synaptic plasticity, memory and the hippocampus: A neural network approach to causality. *Nature Reviews Neuroscience*. 2008;**9**:65
- [8] Chen Y-PP et al. 9.15 - bioinformatics. In: Liu H-W, Mander L, editors. *Comprehensive Natural Products II*. Oxford: Elsevier; 2010. pp. 569-593
- [9] Faber TL, Chen JI, Garcia EV. Chapter 4 - SPECT processing, quantification, and display. In: Zaret BL, Beller GA, editors. *Clinical Nuclear Cardiology*. Fourth ed. Philadelphia: Mosby; 2010. pp. 53-71
- [10] Guggisberg AG et al. Brain networks and their relevance for stroke rehabilitation. *Clinical Neurophysiology*. 2019;**130**(7):1098-1124
- [11] Bansal D, Mahajan R. Chapter 2 - EEG-based brain-computer interfacing (BCI). In: Bansal D, Mahajan R, editors. *EEG-Based Brain-Computer Interfaces*. Amsterdam, Netherlands: Elsevier, Academic Press; 2019. pp. 21-71
- [12] Kumar DK et al. Prosthetic hand control: A multidisciplinary review to identify strengths, shortcomings, and the future. *Biomedical Signal Processing and Control*. 2019;**53**:101588
- [13] Alazrai R, Alwanni H, Daoud MI. EEG-based BCI system for decoding finger movements within the same hand. *Neuroscience Letters*. 2019;**698**:113-120
- [14] Lange G et al. Classification of electroencephalogram data from hand grasp and release movements for BCI controlled prosthesis. *Procedia Technology*. 2016;**26**:374-381
- [15] Acharya UR et al. Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals. *Information Sciences*. 2017;**415-416**:190-198
- [16] Majumdar A, Ward R. Robust greedy deep dictionary learning for ECG arrhythmia classification. In:

2017 International Joint Conference on
Neural Networks (IJCNN); 2017

[17] Bin X, et al. Electrooculogram based
sleep stage classification using deep
belief network. In: 2015 International
Joint Conference on Neural Networks
(IJCNN); 2015

[18] Du L, et al. Detecting driving
fatigue with multimodal deep learning.
In: 2017 8th International IEEE/EMBS
Conference on Neural Engineering
(NER). 2017

[19] Ge C et al. A spiking neural network
model for obstacle avoidance in
simulated prosthetic vision. *Information
Sciences*. 2017;**399**:30-42

[20] Benabid AL et al. Chapter 5 - deep
brain stimulation: BCI at large, where
are we going to? In: Schouenborg J,
Garwicz M, Danielsen N, editors.
Progress in Brain Research. Amsterdam,
Netherlands: Elsevier, Academic Press;
2011. pp. 71-82

[21] Alizadehsani R et al. Machine
learning-based coronary artery disease
diagnosis: A comprehensive review.
Computers in Biology and Medicine.
2019;**111**:103346

[22] Walter M et al. Translational
machine learning for psychiatric
neuroimaging. *Progress in Neuro-
Psychopharmacology and Biological
Psychiatry*. 2019;**91**:113-121