Brain Challenge Events in Explorations of Neuroscience for Consumers

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Abstract— **The last 4 years of IEEE Brain exploratory events in the form of hackathon, challenge or competition, regarding brain signal datasets have touched on brain computer interface and brain data analytics, making use of neural network /AI modeling. These exploratory efforts span from investigation of individual EEG profiles, to multi-user and multi-modal physiological signal interactions. Some advancements are destined for IoT, to benefit consumers**.

Keywords — BDB, Brain Data Analytics and Usability, neural network, multi-task brain performance assessment, epilepsy prediction.

1. INTRODUCTION

Brain data analytics and tools simplification was at its infancy in the late 2015. No easy means existed to decode brain data in a public or private setting. We contemplated brain hackathons and challenges, within the IEEE Brain Initiative, to educate, with hands-on experiments, to guide work in progress, to share research insights, with the goal to understand brain reactions for consumer usage. This goal was deemed possible as sales of consumer-grade EEG headsets reached 1 million units in 2016. With the advent of affordable EEG headsets, virtual reality manifestation, and open-source EEG datasets[1,2], it behooves us to spread neuroscience benefits across the Internet for user-friendly access of brain computer interface and brain image data, which should no longer be restricted to capital-intensive and specialized hospital/ laboratory environment. Thus, a series of exploratory events were started in 2016. These explorations have been held at universities and IEEE technical conferences around the world with recognizable track records posted on the IEEE Brain website[3]. They are listed below in chronological order.

2016-2019: Brain Computer Interface (BCI) Hackathons were kicked off in 2016, from San Diego, Philadelphia, and Budapest. These hackathons have continued around the world and a wide range of attendance has shown up for education and experimentation in neuroscience applications[4].

2017–2019: Brain Data Bank Challenges (BDBC) were held in St. Petersburg, Glasgow, Boston, Xi'an, Tokyo, Seattle, Montreal, and Los Angeles.

This paper is focused on the findings from the eight BDBC.

Why is it named Brain Data Bank? instead of Data Base, or simply, Data Set (DS)? Measuring brain signals is a daunting task requiring significant resource commitment. Thus, the intention is to access open-source brain datasets as if they were assets scientists could deposit in a reservoir, like one deals with a public trusted bank. Let the asset's value accumulate; allow the brain dataset to be checked in and out based on well-understood rules and support; protect its privacy and security.

How would the value of brain datasets be derived and accumulated? We look for in-depth analysis and usability of open-source brain datasets posted on the Internet. Exploratory projects are presented at the BDBC for in-depth discussion about their on-going trial of newly created value proposition. The exploratory work might not necessarily be ready for prime-time publishing. However, they could represent the current thinking in neuroscience data-oriented research. Thus, a BDBC presentation is not meant work hatched on-site in a typical hackathon time of a day or 2, rather work in progress for a period (probably 6 months or longer,) seeking for feedbacks to continue enhancing its research.

Students, faculty and entrepreneurs with multi-facet research interests formed interdisciplinary teams to compete in BDBC. Photos and instructional materials for reporting have been catalogued in the Brain Initiative website[3] and other websites including the IEEE Dataport[5], which posted the first EEG dataset (from UCSF[6]) for BDBC, as the baseline datasets to draw "Big Data" analytics; for the combined brain data in the public was estimated reaching terabytes in 2015[1,2].

After the BDBC, presenters were encouraged to update their work for peer-reviewed publications. Indeed, 3 papers subsequently appeared in the Journals of EMBS[12] and SC[13], and the Proceedings of the IEEE BBC-MLESP[14], in addition to several prompt reports in the CE Magazine, ICCE, etc. Much efforts have also been dedicated to neurotechnology development, benefiting consumers.

2. BDBC PROJECTS

To show these BDBC projects in progress, each year's winning entries are labeled with a descriptive phrase in italic, to highlight the new techniques advanced from the prior years.

2017 – *Multi-user, multi-modal physiological sensing*

(1) Cloud Analysis of EEG/ECG for Opposite Mood Detection (remote processing of multi-modal data)
(2) Multi-user Motor Imagery BCI for Cooperative and Competitive Interaction
(3) BCI Interface for Data Labeling
(4) Readability Analysis based on Cognitive Assessment using Physiological Sensing (human comprehension assessment)
(5) Eliminating Individual Bias to Improve Stress (frustration) Detection from Multimodal Physiological Data
(6) Benefits of Intelligence Training are Marked by Individual Differences in Brain Network Efficiency

2018 – *Machine Learning to improve dataset performance*

(1) Spatial Correlation Preserving EEG Dimensionality Reduction Using Machine Learning
(2) Brain Insight - 3D Display of Brain Reacting to NeuroRacer– 6 months after and 6 years after[13], for Aging Multi-tasking Performance Assessment
(3) A Novel Application of Deep Learning to Predict Cognitive Control in Older Adults using EEG Data

2019 – *AI/Neural Network for detection of brain disorder*

(1) AI and Advanced Signal Processing: Accurate Classification of Epileptic Brain States
(2) Epileptic Seizure Detection with Neural Networks for Medical Implants
(3) High-Performance, High Resolution Brain Network Analysis using Graph-centric Metrics (for schizophrenia diagnosis)
(4) Neuroplastic - Resin MRI for Brain Tumor Visualization.

Not exactly AI related, Project 2019-(4) showed a resin MRI brain with tumor, created from 3D Printing technology to improve gaps and resolution over the conventional brain MRI.

One can find more detailed information (slides and source contact emails to request the full content) of these BDBC projects in Section 6 – Appendix.

3. Brain Datasets

Datasets used throughout the BDBC are summarized below:

Designated Brain Datasets:

i. UCSF NeuroRacer[6] Multi-tasking brain signal datasets, 350 GB. EEG signals (64-channels) from 185 participants, ages 20 – 80, with 47 qualified entries. The target population, ages 60 - 79, was divided into 3 groups for performance comparison: each with about 12 subjects – original measurements were published in 2013 with follow-up measurements in 2018.

ii. UIUC INSIGHT project[7] - dataset on "Cognitive and anatomical data in a healthy cohort of adults." The BOLD fMRI images, under multi-session cognitive training, involved 110 participants, ages 18 - 44, dataset size: 11.59 GB. The qualified sample size was narrowed down to 25 subjects, 2016.

Datasets of Contestant's Choice:

iii. P. L. Lee, et al., "Cloud Analysis of EEG/ECG for Opposite Mood Detection – 8 channels (4 EEG, 4 other optional physiological signals, 20 subjects, each watched 5-minute videos to register a subject's mood of either "like" or "dislike", 2016.

iv. M. S. Treder, et al. "attention"[11], containing 600 trials for each of 8 healthy subjects, 62 channels (60 EEG and 2 EOG) were recorded, 2011.

v. Jadavpur University dataset, 337 MB, 2017.
https://github.com/Rikayan/Multi-Sensor-Data-Student
   a. Reading material – three passages each for easy (T1) and difficult (T2) text
   b. For T1, 15 seconds as baseline -> 1st passage -> 2nd passage -> 3rd passage
   c. Break of 2-3 minutes -> Repeat for T2 (Randomized the sequence: T1 and T2)
   d. 9 subjects, ages 21-44 years (6 males, 3 females.)

vi. AffPac Dataset[8], 2009.
10 subjects who played 15 Pacman game blocks - 2 minutes each, including 5 random blocks tagged with the emotion "frustration":
   a. Self-reported Valence, Arousal, Dominance, using 9-point Likert scale
   b. EEG – 32 channels
   c. GSR, PPG – 1 channel each
   d. EOG, EMG – 4 channels each

vii. Melbourne NeuroVista Seizure Prediction Database[9], 31 GB, 2013.
iEEG recordings of 2,988 seizures selected from 12 participants in this unique long-term in-man trail.

viii. CHB-MIT Dataset[10], 2009.
EEG data from people within tractable seizures: 23 recordings selected from 22 epileptic patients: 5 males, ages 3 - 22; and 17 females, ages 1 - 19.

ix. From SCANLab Stress and Anxiety Study, UNO, 2017~2019.
10 channels, containing sMRI and DTI data of 35 children, ages 7-16: 13 children with 22q11.2DS (schizophrenia vulnerable) and 22 children with growth developmental issues.

4. Discussion & Summary

Table I describes, in perspective, the BDBC datasets used in the associated presentations.

Table I. Datasets used in BDBC Presentations

BDBC Year	Presenter's Affiliations	Presentation Title in short	Brain Dataset	Dataset Year
2016	NCU, Taiwan CWL, USA	Cloud Analysis to detect mood	NCU "Mood"	2016
2017	HSE, RAS, Russia	Brain Wrestling	NFB Lab	2017
2017	Pavlov Inst. RAS, Russia	BCI data labeling	Trender's "Attention"	2011
2017	TCS, India	Readability; easy / difficult	Jadavpur University	2017
2017	TCS, India	Stress - bias, frustration	AffPAC	2009
2017	GIT & CRA, USA	Intelligence Training	INSIGHT	2016
2018	UMKC, USA	Dimensionality	NeuroRacer	2013 &2018
2018	UMKC, USA	Brain Insight 3D Display	NeuroRacer	2013 &2018
2018	SUNY-B,UCB & UNT, USA	Deep Learning	NeuroRacer	2013 &2018
2019	Polytech Montreal / CHUM, CND	AI to predict epilepsy	Melborne	2013
2019	U-Kiel, Germany	CNN to predict epilepsy	CHB-MIT	2009
2019	UNO & SUND, USA	Graphic-Brain Network	SPANLab	2017-2019

Some datasets are recent, some dated 10 years ago where interpretations of the brain actions and reactions might carry a different connotation. Thus, understanding of dataset idiosyncrasy can impact the confidence level projected by the investigation. Table II characterizes 10 datasets used in the BDBC projects. The size of the datasets is shown in GBytes in

Column 2. The number of channels for EEG signal acquisition is shown in Column 3, followed by the number of qualified subjects (smaller than the total subjects invited) in Column 4. Column 5 lists various physiological signals or brain images considered. Column 6 is checked when AI/Deep Learning algorithms are applied. The last column shows the confidence in terms of accuracy, sensitivity, or success rate projection, against the known response, as a result of the analytics.

Table II. Characteristics of Datasets & Analytics

Brain Dataset	Size (GB)	No. of Chanl.	No. Subj.	Signals	AI/ DL	Projected Confidence
NeuroRacer	350	64	47	EEG	√	87%
CHB-MIT (epilepsy)	43	4	22	EEG	√	90%
Melborne (epilepsy)	31	16	12	iEEG	√	86%
NCU "Mood"	<1	8	20	EEG,ECG PPG		80%
Trender's "Attention"	<1	62	8	EEG EOG	√	76%
AffPAC "Frustration"	<1	37	10	EEG,GSR PPG,EOG EMG		68% ~ 76%
INSIGHT	12	Head scan	25	fMRI/ DTI	√	65% ~ 77%
NFB Lab	<1	32	2	EEG,MEG		By Demo.
Jadavpur University	.337	4	9	EEG,Eye-tracking		Comprehend by entropy
SPANLab - schizophrenia	WiP	10	35	sMRI-DTI		WiP

BDBC projects have shown progressive efforts in brain dataset analytics and usability for the last 4 years:

- **i.** EEG measurements migrated from single-subject focus to multi-subject correlation.
- **ii.** The number of subjects gathered for brain signal measurements ranged from 8 to 185. However, subjects qualified to dataset assessment was, at best, 47.
- **iii.** The largest brain datasets used was 350 GB. Advanced schemes for feature selection and classification states are required and a data compression factor of 280 was demonstrated.
- **iv.** AI techniques have applied to brain image data analytics since the last BDBC in 2017, which demonstrated 15% improvement over dataset accuracy[21]. The small number of subjects (25) remains uninsured results, particularly comparing with the conventional average of 7%. Namely,
    - a. EEG dataset processed over Cloud computing, with longer training samples, reached 80% success rate for predicting emotions in contrast (i.e., "like" vs. "dislike.")
    - b. Applying ML for logic reasoning and multi-tasking performance improved confidence level of the dataset to 87%.
    - c. Applying AI/CNN, the latest epilepsy prediction showed 90% sensitivity @ 1.5 minutes before a seizure happened.
- **v.** The number of EEG channels used in these datasets varied from 4 to 64. Specifically aimed for consumer applications, 3D CNN modeling displayed spatio-temporal EEG imagine dynamic changes to suggest a reduction from 64 to 31 (possibly to 12) channels with only 10% penalty in accuracy for assessing multi-task performance level in senior citizens.
- **vi.** Supplementing MRI with resin brain tumor models manufactured from 3D Printing technology showed promises for improved cost, resolution and brain image coverage over the conventional MRI utilization.

As we have learned from these past investigations, we suggest future BDBC entries to consider:

- ✓ Brain Image Processing – enhancing feature selection schemes and classification states
- ✓ AI/DL/ML/Neural Network algorithms to address brain dataset idiosyncrasy
- ✓ 3D spatial and temporal visual display for dynamic brain image interpretation
- ✓ Graphic-centric Neural Network Analysis for user-friendly diagnosis
- ✓ Standardization of dataset performance, accuracy, success rate, sensitivity, confidence, and reliability.

5. ACKNOWLEDGMENT

The author wishes to acknowledge the endorsement and support from the IEEE Brain Management and Core Team, the Conference Organizers from SPCN, SC and Big Data and numerous members of interest from around the world who joined BDBC in the organizing efforts and presentations. Their names are too many to list here. However, one can find these front runners in neuroscience/neurotechnology from the Brain website[11] under the Competition tab, with running photos and BDBC descriptions.

6. APPENDIX

Highlights of salient BDBC projects are listed below with the title, authors, a representative slide and contact email address noted for individual content acquisition.

1. "Cloud Analysis of EEG/ECG for Opposite Mood Detection,[10]" by P. Lee, et al., NCU, Taiwan, 2016.

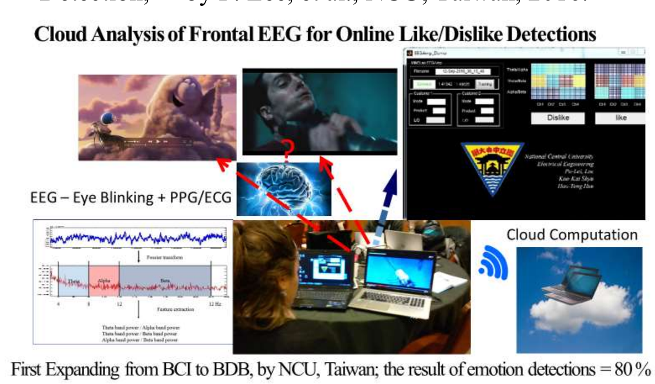


Figure 1. inMEx multi-physiological measurement instrument expanding BCI local data for cloud computing BDB

analysis and display. For details, contact: nchu@cwlab.com

2. “Multi-user Motor Imagery BCI for Cooperative and Competitive Interaction”, by D. Altukhov, N. Smetanin, and A. Kuznetsova, Higher School of Economics, RAS, 2017.

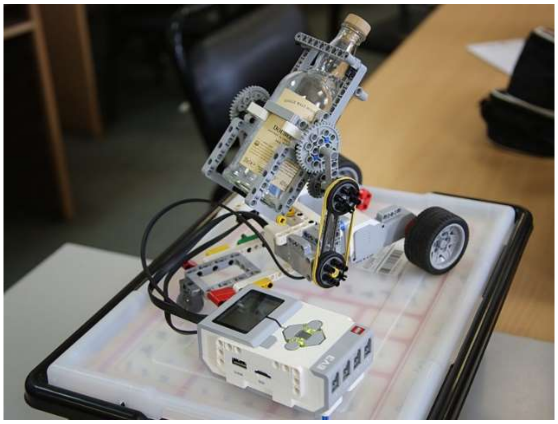


Figure 2. Lego mobile directed by EEG signals from 2 contestants, respectively. Video : https://yadi.sk/i/x1t-i5BP3KUkPf, contact <kuznesashka@gmail.com>, http://nfb-lab.readthedocs.io/en/latest/.

3. “BCI Interface for Data Labeling”, by R. O. Malashin, et al., Pavlov Institute of Physiology, RAS, Russia, 2017.

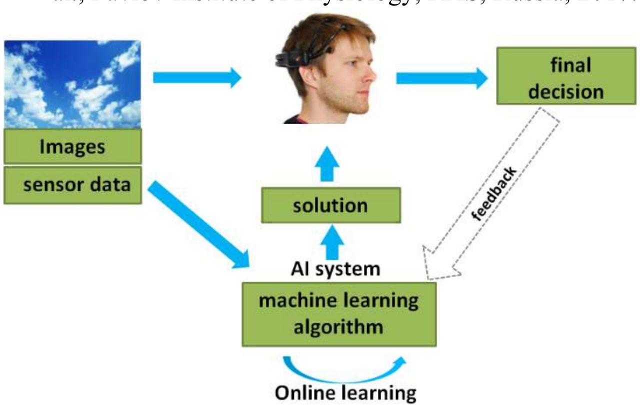
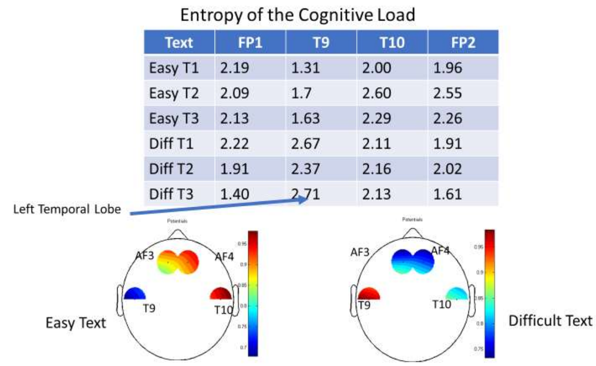


Figure 3. The EEG-based BCI for reinforcement of attention. For details, contact <malashinroman@mail.ru>

4. “Readability Analysis based on Cognitive Assessment using Physiological Sensing”, by A. Sinha, D. Roy, R. Chaki, B. K. De, & S. K. Saha, TCS, India, 2017.



Entropy of the Cognitive Load

Text	FP1	T9	T10	FP2
Easy T1	2.19	1.31	2.00	1.96
Easy T2	2.09	1.7	2.60	2.55
Easy T3	2.13	1.63	2.29	2.26
Diff T1	2.22	2.67	2.11	1.91
Diff T2	1.91	2.37	2.16	2.02
Diff T3	1.40	2.71	2.13	1.61

Figure 4. Electrophysiological signal analysis during silent reading. For details, contact: <aniruddha.s@tcs.com>

5. “Eliminating Individual Bias to Improve Stress Detection from Multimodal Physiological Data," by D. Das, S. Datta, T. Bhattacharjee, A. D. Choudhury, and A. Pal, TCS, India, 2017. https://ieeexplore.ieee.org/abstract/document/8513680.

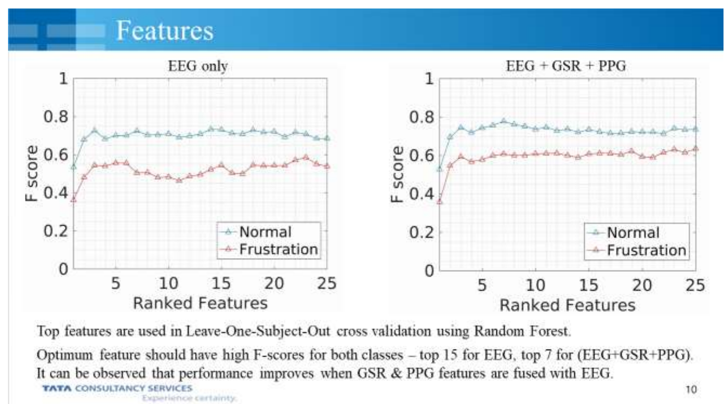


Figure 5. Affpac Dataset accuracy improves when GSR & PPG features are fused with EEG. For details, contact: <anirban.duttachoudhury@tcs.com>.

6. “Benefits of Intelligence Training are Marked by Individual Differences in Brain Network Efficiency”, by T. Curley, GIT, and B. Bauchwitz, CRA, USA, 2017.

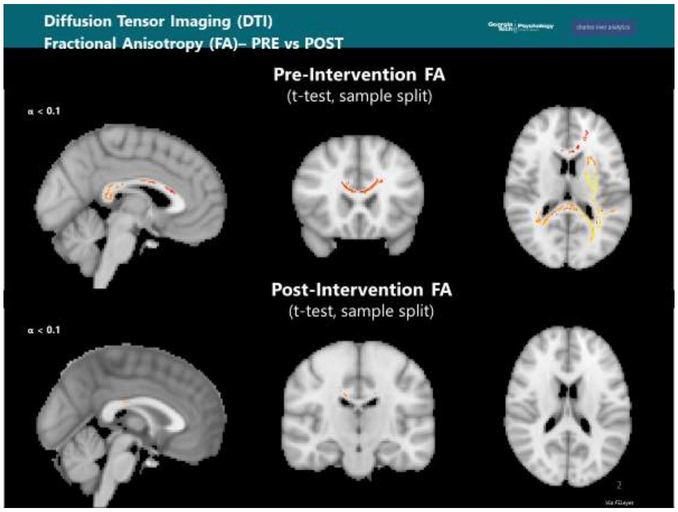


Figure 6. Diffusion Tensor Imaging Fractional Anisotropy.For details, contact: <taylor.curley@gatech.edu>.

7. "Spatial Correlation Preserving EEG Dimensionality Reduction Using Machine Learning", by H. Gebre-Amlak, H. Nguyen, J. Lowe, & A. Nabulsi of UMKC and N. Chu of CWLab Int'l, USA, 2018. https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8621106.

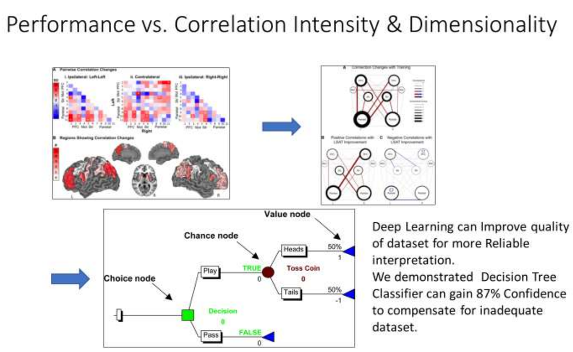


Figure 7. Confidence gain of 87% using Decision Tree Classifier against NeuroRacer dataset. For details, contact: <hhgc77@mail.umkc.edu>.

8. "Brain Insight, extracted from UCSF NeuroRacer Datasets – 6 months after and 6 years after[13], for Aging Multi-tasking Performance Assessment," by J. Lowe, A. Nabulsi, et al., UMKC, USA, 2018.

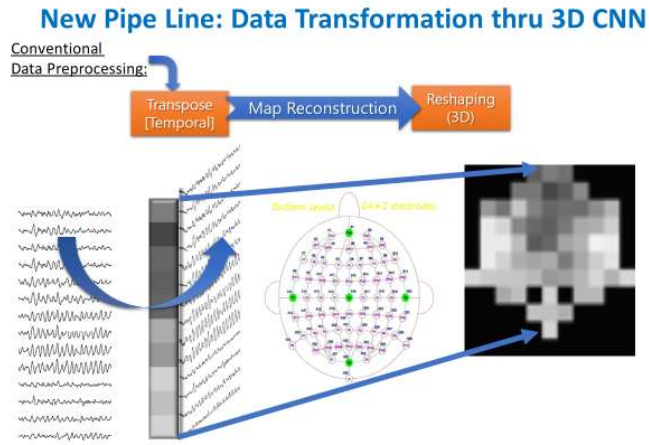


Figure 8. NeuroRacer dataset enhanced through 3D CNN for combined spatial and temporal display. For details, contact: <Jmlkvf@mail.umkc.edu>.

9. "A Novel Application of Deep Learning to Predict Cognitive Control in Older Adults using EEG Data", by A. Vereshchaka, F. Yang and W. Dong, SUNY-Buffalo, A. Suresh, UCB, I. Olokodana, UNT, USA. 2018.

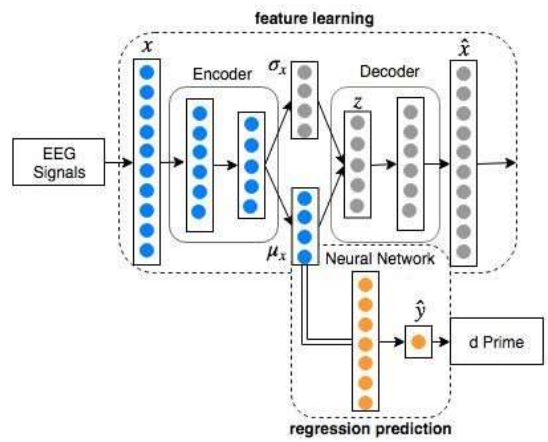


Figure 9. Deep Learning Model for Interpretation of NeuroRacer Datasets. For details, contact: <avereshc@buffalo.edu>.

10. "AI and Advanced Signal Processing: Accurate Classification of Epileptic Brain States," by Laura Gagliano & Elie Bou Assi, Polystim Neurotech Lab, Polytechnique Montreal, and CHUM, Canada, 2019.

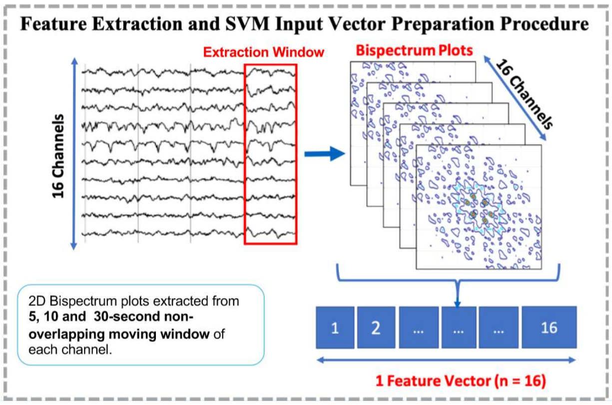


Figure 10. Feature extraction procedure using bispectrum analysis prefers window of 30 sec to reach 86%+ predictability. For details, contact: <laura.gagliano11@gmail.com>.

11. "Epileptic Seizure Detection with Neural Networks for Medical Implants", by Matthias Schneider, Avitha Maria Francis, Hendrik Lehmann, Igor Barg and Andreas Bahr, U. of Kiel, Germany, 2019.

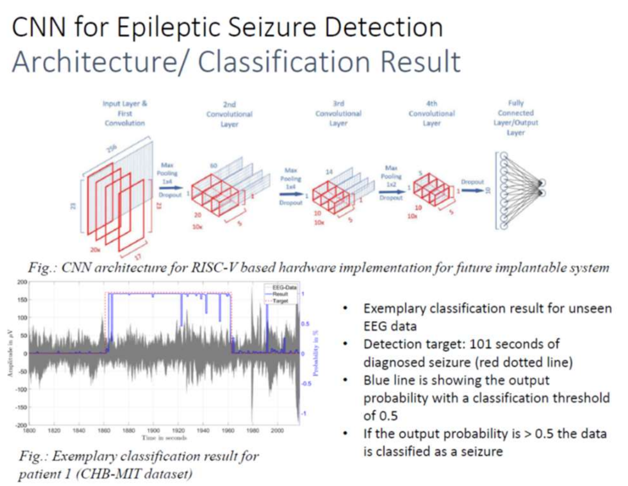


Figure 11. CNN Architecture/Classification prototyped in hardware for epileptic seizure prediction. For details, contact: <andreas.bahr@tf.uni-kiel.de>

12. "High-Performance, High Resolution Brain Network Analysis using Graph-centric Metrics", by S. Arifuzzaman, UNO, and M. Kabir, NDSU, 2019.

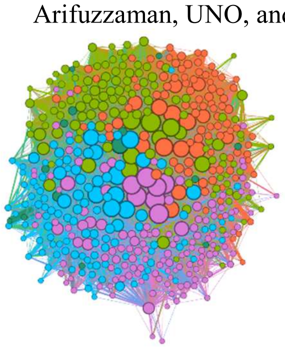


Figure 12. DTI for graphic-centric brain network analysis. For details, contact: smarifuz@uno.edu.

13. "Neuroplastic", by Gregory Taylor, Chapman U., 2019.


Figure 13. Resin MRI for Brain Tumor Visualization, For more details. Contact: <gtyler@chapman.edu>.

7. ACRONYM

AI	Artificial Intelligence
BBC	Bioinformatics & Biomedicine Conference
BCI	Brain Computer Interface
BDB	Brain Data Bank
BDBC	Brain Data Bank Challenges / Competitions
BOLD	Blood Oxygenation Level Dependent
CE	Consumer Electronics
CHB-MIT	Children's Hospital Boston – Massachusetts Institute of Technology
CHUM	University of Montreal Hospital Center
CNN	Convolutional Neural Network
CRA	Charles River Analytics, Inc.
CWL	CWLab International
DL	Deep Learning
DS	Data Set
DTI	Diffusion Tensor Imaging
EEG	ElectroEncephaloGraphy
EMBS	Engineering in Medicine & Biology Society
EMG	ElectroMyoGram
EOG	ElectroOculoGram
ERP	Event Related Potential
FA	Fractional Anisotropy
FS	Figure Series
fMRI	functional MRI
GIT	Georgia Institute of Technology
GSR	Galvanic Skin Response
HSE	Higher School of Economics
ICCE	Int'l Conference on Consumer Electronics
iEEG	intracranial EEG signals
IoT	Internet of Things
LCSM	Latent Change Score Model
LSAT	Law School Admission Test
ML	Machine Learning
MLESP	Machine Learning EEG Signal Processing
MRI	Magnetic Resonance Imaging

NCU	National Central University
PPG	Photoplethysmogram
RAS	Russian Academy of Science
SC	Sensors Council
sMRI	structural MRI
SPCN	Symposium on video & audio Signal Processing in Neurotechnology
SUNY-B	State University of New York at Buffalo
SVM	Support Vector Machine
TCS	Tata Consultancy Service and Technology
UCB	University of Colorado at Boulder
UCSF	University of California at San Francisco
UIUC	University of Illinois at Urbana-Champaign
UMKC	University of Missouri at Kansas City
UNO	University of New Orleans
UNT	University of North Texas
WiP	Work in Progress

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