SUMMARY AND FUTURE TRENDS

Sena Egeli

3 December 2019

Department of Biomedical Technologies, The Graduate School of Natural and Applied Sciences, Izmir Katip Celebi University

Outlines

OVERVIEW OF PROGRESS

Overview of Progress

Why CI applications needed for healthcare?

- Replicate the diagnostic skill of the medical specialist
- Provide more reliable diagnosis

Overview of Progress

In general;

- Classification of the disease:
  From ophthalmology to radiology

- Opthalmology applications

Computational Intelligence for Medical Knowledge Acquisition with Application to Glaucoma

Nicolae Varachiu, Cynthia Karanicolas and Mihaela Ulieru
Faculty of Engineering
University of Calgary
2500 University Dr. NW, Calgary, Alberta T2N 1N4 CANADA
Tel. (403) 210-5404; Fax: (403) 282-6855; e-mail: varachiu@ucalgary.ca
http://isg.enme.ucalgary.ca/People/Ulieru/Default.htm

Abstract

This paper presents an approach that integrates computational intelligence/soft computing paradigms with clinical investigation methods and knowledge. Computational intelligence methods (including fuzzy logic, neural networks and genetic algorithms) deal in a suitable way with imprecision, uncertainty and partial truth. These aspects can be found quite often in practical medical activities and in medical knowledge. The proposed approach uses a knowledge discovery process in order to develop an intelligent system for diagnosis and prediction of glaucoma. The knowledge acquired is embedded in a fuzzy logic inference system. The resulting Neuro-fuzzy Glaucoma Diagnosis and Prediction System is expected to lower the effort, difficulties and risk cost related to this disease (the leading cause of blindness in North America.)

Key words: Computational intelligence, fuzzy logic, knowledge discovery, glaucoma, risk evaluation, prediction

principle asks for robust methods/algorithms to be used. The implementation of these two principles can be expressed in a natural way by using the fuzzy paradigm and classifications approaches [2].

The diagnosis as a medical activity will state if a patient suffers of a specific disease, and if the answer is yes, the specialist will provide a specific treatment.

Despite the difficulties, the diagnosis of glaucoma is solved for the majority of cases. An important challenge for an ophthalmologist remains on the evaluation of the risk of occurrence and the prediction of progression to establish the suitable follow up and treatment accordingly.

A major concern is the reliability of the diagnostic tools used by the physician. There is usually low confidence in these rules mainly due to their negative prediction rate[1]. One of the glaucoma characteristics is that it can be "triggered" in very short periods of time (one hour for example) and without notice – which makes evident the challenge facing any attempt to predict it. Our goal is to face this challenge in developing a machine that can evaluate more precisely the risk factors.

According to the Mars' "Principle of Least

Figure: CI Application Example for Glaucoma

Overview of Progress

- Opthalmology applications

12th International Conference on Application of Fuzzy Systems and Soft Computing, ICAFS 2016, 29-30 August 2016, Vienna, Austria

Intelligent eye tumour detection system

Kamil Dimililer[a]*, Yoney Kirsal Ever[b], Haithm Ratemi[c]

[a]Near East University, Department of Electrical and Electronic Engineering, Near East Boulevard, P.O.Box:99138, Nicosia, TRNC, Mersin 10, Turkey.
[b] Near East University, Department of Software Engineering, Near East Boulevard, P.O.Box:99138, Nicosia, TRNC, Mersin 10, Turkey.
[c] Near East Boulevard, Department of BiomedicalEngineering, Near East Boulevard, P.O.Box:99138, Nicosia, TRNC, Mersin 10, Turkey.

Abstract

In order to diagnose cancer, huge biomedical machines such as PET-CT machines are used. Image fusion is an efficient image processing method for detecting different types of tumours. In this paper an image analysis system for the eye tumour detection will be designed. In this system, different image processing methods are used to extract the tumour and mark it on the original image. The images are first smoothed using median filtering. The background of the image is subtracted, to be then added to the original, results in a brighter area of interest or tumor area.The experimental results show that the suggested system based on image fusion, is capable of detecting tumour in the eye. The proposed research consists of two phases naming, Eye Tumour Detection System and Intelligent Eye Tumour Detection System. Results will be compared accordingly in search for eye cancer.

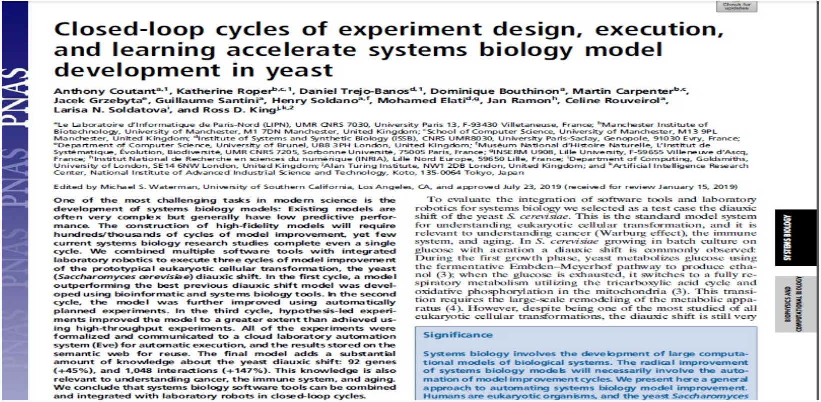
Peer-review under responsibility of the Organizing Committee of ICAFS 2016

Keywords: Artificial neural networks; image fusion; eye tumour detection; canny operators.

Figure: CI Application for Eye Tumour Detection System

Overview of Progress

- Modeling of biological systems



PNAS

Check for updates

Closed-loop cycles of experiment design, execution, and learning accelerate systems biology model development in yeast

Anthony Coutant[a,1], Katherine Roper[b,c,1], Daniel Trejo-Banos[d,1], Dominique Bouthinon[a], Martin Carpenter[b,c], Jacek Grzebyta[e], Guillaume Santini[a], Henry Soldano[a,f], Mohamed Elati[d,g], Jan Ramon[h], Celine Rouveirol[a], Larisa N. Soldatova[i], and Ross D. King[j,k,2]

[a]Le Laboratoire d'Informatique de Paris-Nord (LIPN), UMR CNRS 7030, University Paris 13, F-93430 Villetaneuse, France; [b]Manchester Institute of Biotechnology, University of Manchester, M1 7DN Manchester, United Kingdom; [c]School of Computer Science, University of Manchester, M13 9PL Manchester, United Kingdom; [d]Institute of Systems and Synthetic Biology (iSSB), CNRS UMR8030, University Paris-Saclay, Genopole, 91030 Evry, France; [e]Department of Computer Science, University of Brunel, UB8 3PH London, United Kingdom; [f]Muséum National d'Histoire Naturelle, L'Institut de Systématique, Évolution, Biodiversité, UMR CNRS 7205, Sorbonne Université, 75005 Paris, France; [g]INSERM U908, Lille University, F-59655 Villeneuve d'Ascq, France; [h]Institut National de Recherche en sciences du numérique (INRIA), Lille Nord Europe, 59650 Lille, France; [i]Department of Computing, Goldsmiths, University of London, SE14 6NW London, United Kingdom; [j]Alan Turing Institute, NW1 2DB London, United Kingdom; and [k]Artificial Intelligence Research Center, National Institute of Advanced Industrial Science and Technology, Koto, 135-0064 Tokyo, Japan

Edited by Michael S. Waterman, University of Southern California, Los Angeles, CA, and approved July 23, 2019 (received for review January 15, 2019)

One of the most challenging tasks in modern science is the development of systems biology models: Existing models are often very complex but generally have low predictive performance. The construction of high-fidelity models will require hundreds/thousands of cycles of model improvement, yet few current systems biology research studies complete even a single cycle. We combined multiple software tools with integrated laboratory robotics to execute three cycles of model improvement of the prototypical eukaryotic cellular transformation, the yeast (*Saccharomyces cerevisiae*) diauxic shift. In the first cycle, a model outperforming the best previous diauxic shift model was developed using bioinformatic and systems biology tools. In the second cycle, the model was further improved using automatically planned experiments. In the third cycle, hypothesis-led experiments improved the model to a greater extent than achieved using high-throughput experiments. All of the experiments were formalized and communicated to a cloud laboratory automation system (Eve) for automatic execution, and the results stored on the semantic web for reuse. The final model adds a substantial amount of knowledge about the yeast diauxic shift: 92 genes (+45%), and 1,048 interactions (+147%). This knowledge is also relevant to understanding cancer, the immune system, and aging. We conclude that systems biology software tools can be combined and integrated with laboratory robots in closed-loop cycles.

To evaluate the integration of software tools and laboratory robotics for systems biology we selected as a test case the diauxic shift of the yeast *S. cerevisiae*. This is the standard model system for understanding eukaryotic cellular transformation, and it is relevant to understanding cancer (Warburg effect), the immune system, and aging. In *S. cerevisiae* growing in batch culture on glucose with aeration a diauxic shift is commonly observed: During the first growth phase, yeast metabolizes glucose using the fermentative Embden–Meyerhof pathway to produce ethanol (3); when the glucose is exhausted, it switches to a fully respiratory metabolism utilizing the tricarboxylic acid cycle and oxidative phosphorylation in the mitochondria (3). This transition requires the large-scale remodeling of the metabolic apparatus (4). However, despite being one of the most studied of all eukaryotic cellular transformations, the diauxic shift is still very

SYSTEMS BIOLOGY

BIOPHYSICS AND COMPUTATIONAL BIOLOGY

Significance

Systems biology involves the development of large computational models of biological systems. The radical improvement of systems biology models will necessarily involve the automation of model improvement cycles. We present here a general approach to automating systems biology model improvement. Humans are eukaryotic organisms, and the yeast *Saccharomyces*

Figure: Biology Model Development in Yeast

Overview of Progress

CI applications are successfull in Cardiovascular Diseases, why?

Focused on QRS wave complex, which is easily measured and this waveform is understood well = accurate algorithms

An advantage: tests on publicly available databases

Overview of Progress

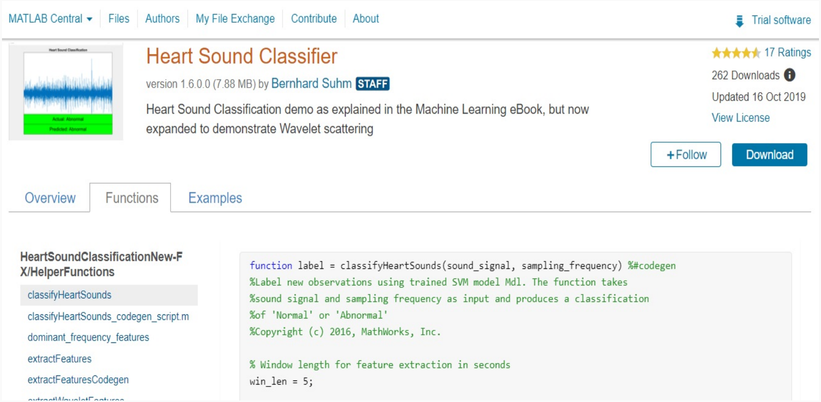


Figure: Heart Sound Classifier Application with MATLAB

Overview of Progress

Neuromuscular disease

Obtained wave forms not clear and isolated due to action potentials from muscle fibers

Overview of Progress

Computational Intelligence in Gait Research

Problems of gait researches

- Large volume of recorded data
- Lengthy assessment times in gait laboratories

Solution : CI technology

Overview of Progress

Computational Intelligence in Gait Research

CI is a fusion of learning mechanisms and computing specifically suited for powerful decision systems capable of interpreting and processing large volumes of data.
Thanks to CI applications in gait analysis;

- more robust, efficient, and cost-effective diagnostic, monitoring, and control systems are built.

Overview of Progress

Computational Intelligence in Gait Research

Gait data are obtained from;

- Motion analysis systems
- Force Platforms
- Foot Pressure
- Electromyography

Overview of Progress

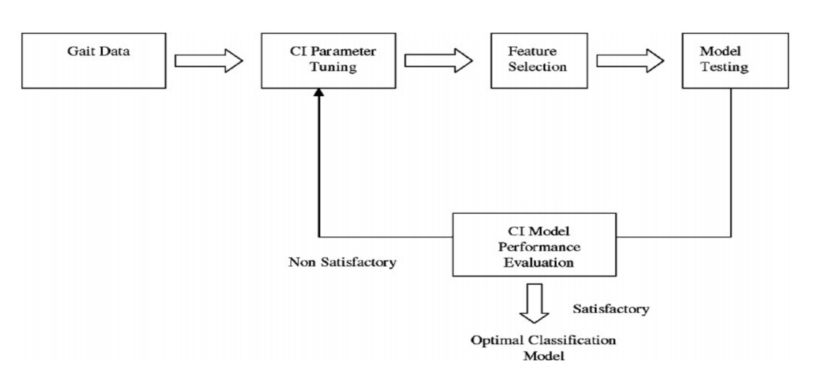


Figure: Flowchart depicts design of the CI model in a general intelligent gait system.

Overview of Progress

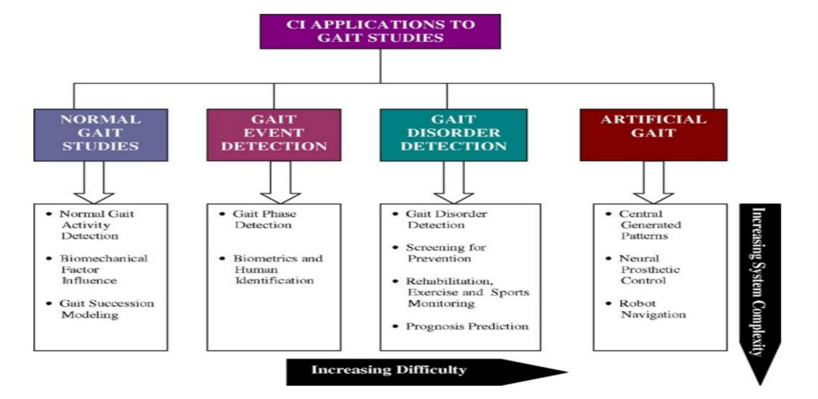


Figure: Current and future CI applications in gait studies

Overview of Progress

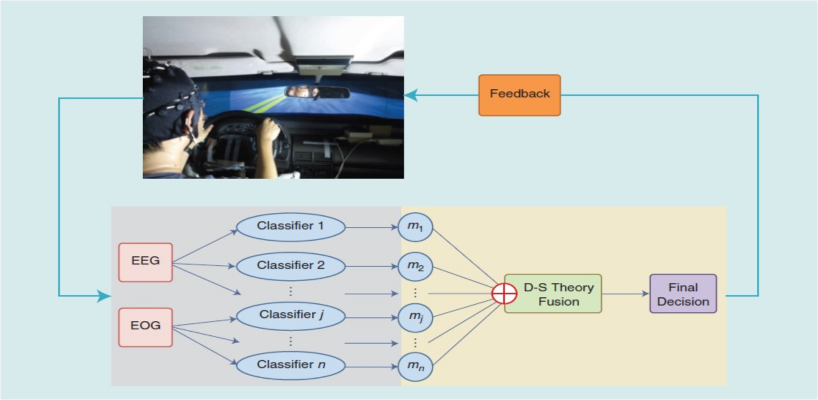


Figure: The multimodal fusion of EEG and EOG signals for a hybrid Brain - Computer Interface using the D-S theory.

FUTURE CHALLENGES AND RESEARCH AREAS

Future Challenges and Research Areas

Next step: Prognosis

Determining the effectiveness of treatment or therapy

Future Challenges and Research Areas

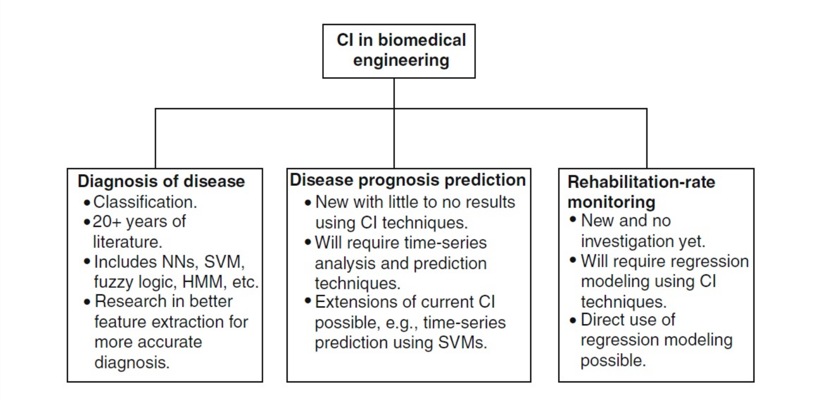


Figure: CI in biomedical engineering

EMERGING AND FUTURE TECHNOLOGIES IN HEALTHCARE

Wireless Healthcare Systems

→Main objective is filling the gap between accessibility and communication, reducing delays and costs.

Wireless Healthcare Systems

Patient Monitoring
One of the first and most common application.

Faster and cost-efficient way to conduct doctor-patient consults to assess the patient's current state and clinical results at a distance.

Example study: Detection of Fetal Electrocardiogram through OFDM, Neuro-Fuzzy logic and Wavelets Systems for Telemetry

Wireless Healthcare Systems

Information Analysis and Collaboration
Collaboration of medical experts but not only for diagnosis also medical data.

Faster and cost-efficient way to conduct doctor-patient consults to assess the patient's current state and clinical results at a distance.

Example study: A Predictive Model for Assistive Technology Adoption for People With Dementia

Wireless Healthcare Systems

Mobihealth: Body Area Networks using Wireless Mobie Phone Technology

Medical devices that can be worn by patient and monitor their vital signals

Wireless Healthcare Systems

Telerehabilitation

Using artificial intelligence techniques such as NNs to carry out routine rehabilitation work allowing the physical therapist to attend to other duties.

Example study: Ankle Rehabilitation System with Feedback from a Smartphone Wireless Gyroscope Platform and Machine Learning Classification

RADIOLOGY APPLICATIONS OF CI

Radiology Applications of CI

Motivation for applications;

- To have greater efficacy and efficiency in clinical care
- To reduce errors Or mainly; work overload of radiologists

  Advantage : Available large datasets

Radiology Applications of CI

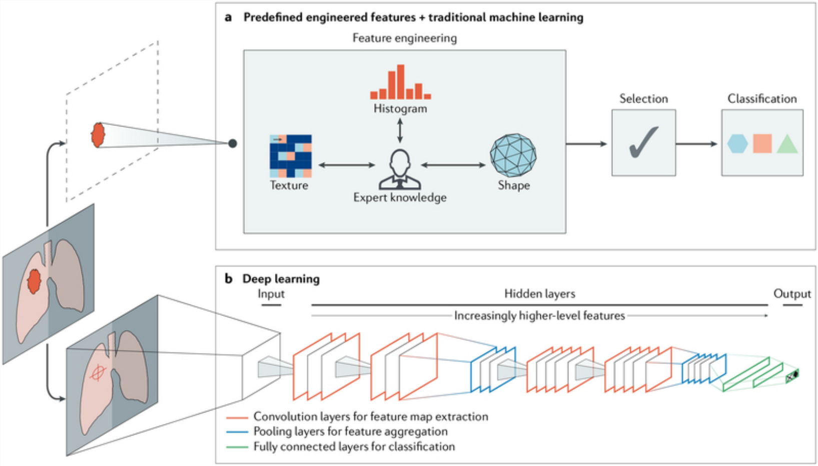


Figure: Widely used artificial intelligence methods

Radiologists vs Artificial Intelligence

Mammography Application

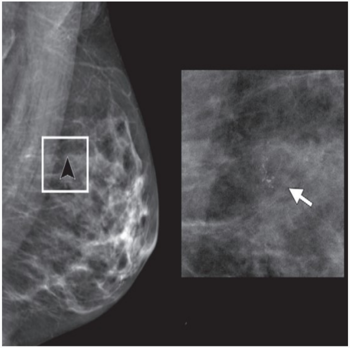


Figure: Left, mediolateral oblique view from screening mammogram in 54-year-old asymptomatic woman. A computer-aided diagnosis (CAD) prompt is present (arrowhead). Right, magnification view of area of interest.

Radiology Applications of CI

- Radiomics : extraction of features from diagnostic images
- Imaging biobanks: “organised databases of medical images, and associated imaging biomarkers (radiology and beyond),shared among multiple researchers, linked to other biorepositories.” defined by the European Society of Radiology.
- Dose Optimization

FPGA APPLICATIONS OF CI

FPGA Applications of CI

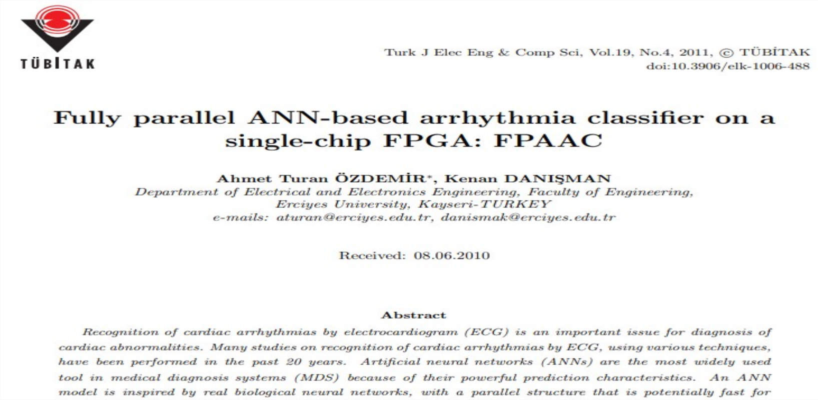
Field **P**rogrammable **G**ate **A**rray

Semiconductor devices that are based around a matrix of configurable logic blocks connected via programmable interconnects.

Why FPGA preferred for Neural Network Application?

- **Reconfigurability**
- Cost
- Speed
- Accuracy
- **Parallelism**

FPGA Applications of CI



TÜBİTAK

Turk J Elec Eng & Comp Sci, Vol.19, No.4, 2011, © TÜBİTAK
doi:10.3906/elk-1006-488

Fully parallel ANN-based arrhythmia classifier on a single-chip FPGA: FPAAC

Ahmet Turan ÖZDEMİR*, Kenan DANIŞMAN
Department of Electrical and Electronics Engineering, Faculty of Engineering, Erciyes University, Kayseri-TURKEY
e-mails: aturan@erciyes.edu.tr, danismak@erciyes.edu.tr

Received: 08.06.2010

Abstract

Recognition of cardiac arrhythmias by electrocardiogram (ECG) is an important issue for diagnosis of cardiac abnormalities. Many studies on recognition of cardiac arrhythmias by ECG, using various techniques, have been performed in the past 20 years. Artificial neural networks (ANNs) are the most widely used tool in medical diagnosis systems (MDS) because of their powerful prediction characteristics. An ANN model is inspired by real biological neural networks, with a parallel structure that is potentially fast for

Figure: Sample study for FPGA Application of CI

FPGA Applications of CI

More sample studies;

- An Overview of MRI Brain Classification Using FPGA Implementation
- A High-Performance FPGA Based Fuzzy Processer Architecture for Medical Diagnosis
- An FPGA Based Coprocessor for Cancer Classification Using Nearest Neighbour Classifier

REFERENCES

References

1. Begg, Rezaul Lai, Daniel Palaniswami, Marimuthu. (2008). Computational Intelligence in Biomedical Engineering. 10.1201/9781420005899. Malik, Sadaf Kanwal, Nadia Asghar, Mamoona Ali, Mohammad Karamat, Irfan Fleury, Martin. (2019). Data Driven Approach for Eye Disease Classification with Machine Learning. Applied Sciences. 9. 10.3390/app9142789.
2. N. Varachiu, C. Karanicolas and M. Ulieru, "Computational intelligence for medical knowledge acquisition with application to glaucoma," Proceedings First IEEE International Conference on Cognitive Informatics, Calgary, Alberta, Canada, 2002, pp. 233-238. doi: 10.1109/COGINF.2002.1039303
3. Kamil Dimililer, Yoney Kirsal Ever, Haithm Ratemi, Intelligent eye Tumour Detection System,Procedia Computer Science, Volume 102, 2016,Pages 325-332, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2016.09.408.(http://www.sciencedirect.com/science/article/pii/S187705091
4. Coutant, Anthony Roper, Katherine Trejo Banos, Daniel Bouthinon, Dominique Carpenter, Martin Grzebyta, Jacek Santini, Guillaume Soldano, Henry Elati, Mohamed Ramon, Jan Rouveirol, Céline Soldatova, Larisa King, Ross. (2019). Closed-loop cycles of experiment design, execution, and learning accelerate systems biology model development in yeast. Proceedings of the National Academy of Sciences. 116. 201900548. 10.1073/pnas.1900548116.
5. Bernhard Suhm (2019). Heart Sound Classifier (https://www.mathworks.com/matlabcentral/fileexchange/65286-heart-sound-classifier), MATLAB Central File Exchange. Retrieved November 22, 2019.

References

6. Lai, Daniel Begg, Rezaul Palaniswami, Marimuthu. (2009). Computational Intelligence in Gait Research: A Perspective on Current Applications and Future Challenges. IEEE Transactions on Information Technology in Biomedicine. 13. 687-702. 10.1109/TITB.2009.2022913.
7. Lin, Chin-Teng Liu, Yu-Ting Wu, Shang-Lin Cao, Zehong Wang, Yu-Kai Huang, Chih-Sheng King, Jung-Tai Chen, Shi-An Lu, Shao-Wei Chuang, Chun-Hsiang. (2017). EEG-Based Brain-Computer Interfaces: A Novel Neurotechnology and Computational Intelligence Method. IEEE Systems, Man, and Cybernetics Magazine. 3. 16-26. 10.1109/MSMC.2017.2702378.
8. Trends in telemedicine utilizing artificial intelligence AIP Conference Proceedings 1933, 040009 (2018); https://doi.org/10.1063/1.5023979
9. P. Kumar, S. K. Sharma and S. Prasad, ”Detection of fetal electrocardiogram through OFDM, neuro- fuzzy logic and wavelets systems for telemetry,” 2015 International Conference on Humanoid, Nanotechnology, Information Technology,Communication and Control, Environment and Management (HNICEM), Cebu City, 2015, pp. 1-3. doi: 10.1109/HNICEM.2015.7393203
10. Á. Garai and A. Adamkó, ”Comprehensive healthcare interoperability framework integrating telemedicine consumer electronics with cloud architecture,” 2017 IEEE 15th International Symposium on Applied Machine Intelligence and Informatics (SAMI), Herl’any, 2017, pp. 000411-000416.doi: 10.1109/SAMI.2017.7880344

References

11. S. Zhang et al., ”A Predictive Model for Assistive Technology Adoption for People With Dementia,” in IEEE Journal of Biomedical and Health Informatics, vol. 18, no. 1, pp. 375-383, Jan. 2014.doi: 10.1109/JBHI.2013.2267549
12. R. LeMoyne, T. Mastroianni, A. Hessel and K. Nishikawa, ”Ankle Rehabilitation System with Feedback from a Smartphone Wireless Gyroscope Platform and Machine Learning Classification,” 2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA), Miami, FL, 2015, pp. 406-409.
13. Hosny, Ahmed et al. “Artificial intelligence in radiology.” Nature reviews. Cancer vol. 18,8 (2018): 500-510. doi:10.1038/s41568-018-0016-5
14. Rodriguez-Ruiz, Alejandro Lång, Kristina Gubern-Mérida, Albert Broeders, Mireille Gennaro, Gisella Clauser, Paola Helbich, Thomas Chevalier, Margarita Tan, Tao Mertelmeier, Thomas Wallis, Matthew Andersson, Ingvar Zackrisson, Sophia Mann, Ritse Sechopoulos, Ioannis. (2019). Stand-Alone Artificial Intelligence for Breast Cancer Detection in Mammography: Comparison With 101 Radiologists. Journal of the National Cancer Institute. 111. 10.1093/jnci/djy222.
15. Geras, Krzysztof Mann, Ritse Moy, Linda. (2019). Artificial Intelligence for Mammography and Digital Breast Tomosynthesis: Current Concepts and Future Perspectives. Radiology. 293. 182627. 10.1148/radiol.2019182627.

References

16. Neri, Emanuele Regge, Daniele. (2016). Imaging biobanks in oncology: European perspective. Future Oncology. 13. 10.2217/fon-2016-0239.
17. What is an FPGA? Field Programmable Gate Array,https://www.xilinx.com/products/silicon-devices/fpga/what-is-an-fpga.html, (Accessed November 2019)
18. Gomperts, Alexander Ukil, Abhisek Zurfluh, Franz. (2011). Development and Implementation of Parameterized FPGA-Based General Purpose Neural Networks for Online Applications. Industrial Informatics, IEEE Transactions on. 7. 78 - 89. 10.1109/TII.2010.2085006.
19. A. Gomperts, A. Ukil and F. Zurfluh, ”Development and Implementation of Parameterized FPGA-Based General Purpose Neural Networks for Online Applications,” in IEEE Transactions on Industrial Informatics, vol. 7, no. 1, pp. 78-89, Feb. 2011. doi: 10.1109/TII.2010.2085006
20. Ozdemir, Ahmet Danisman, Kenan. (2011). Fully parallel ann-based arrhythmia classifier on a single-chip fpga: Fpaac. Turkish Journal of Electrical Engineering and Computer Sciences. 19. 667-687. 10.3906/elk-1006-488.

References

21. Othman, Fauzi Abdullah, Norarmalina Rusli, Nur. (2010). An overview of MRI brain classification using FPGA implementation. 10.1109/ISIEA.2010.5679389
22. Roy Chowdhury, Shubhajit Saha, Hiranmay. (2008). A High-Performance FPGA-Based Fuzzy Processor Architecture for Medical Diagnosis. Micro, IEEE. 28. 38-52. 10.1109/MM.2008.63.
23. B. Senthilkumar and G. Umamaheswari, ”Improved noise removal algorithm implementation in FPGA for the breast cancer detection,” 2012 IEEE International Conference on Computational Intelligence and Computing Research, Coimbatore, 2012, pp. 1-2.doi: 10.1109/ICCIC.2012.6510298
24. M. I. Ibrahimy, A. F. Ismail, M. B. I. Reaz, F. Mohd-Yasin and T. H. Khoon, ”Fetal QRS Complex Detection Algorithm for FPGA Implementation,” International Conference on Computational Intelligence for Modelling, Control and Automation and International Conference on Intelligent Agents, Web Technologies and Internet Commerce (CIMCA-IAWTIC’06), Vienna, 2005, pp. 846-850. doi: 10.1109/CIMCA.2005.1631370
25. Tahir, Muhammad Bouridane, A.. (2006). An Fpga Based Coprocessor for Cancer Classification Using Nearest Neighbour Classifier. ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings. 3. III - III. 10.1109/ICASSP.2006.1660828.