Machine Learning Integration in Cardiac Electrophysiology

Yashbir Singh, Department of Biomedical Engineering, Chung Yuan Christian University, Zhongli, Taiwan.

Heenaben Patel, West Virginia University, U.S.A.

Deepa, Department of Biomedical Engineering, Chung Yuan Christian University, Zhongli, Taiwan.

Joao Manuel R.S. Tavares, Universidade do Porto, Portugal.

Krit Salahddine, Ibn Zohr University Agadir Morocco.*

Parag Chatterjee, National Technological University, Argentina.

Weichih Hu, Department of Biomedical Engineering, Chung Yuan Christian University, Zhongli, Taiwan.

Abstract--- Atrial fibrillation is a disorder in which there is a chaotic fire of electrical signals from the upper chambers of the heart. The identification of the location of the myocardium responsible for firing these signals and ablation of the area may potentially cure the problem. The electrophysiologists may have to insert the probes or catheters and do the cardiac mapping to identify and analyze the complex heart signals patterns and to identify the location of AF responsible electrical foci. Nowadays, machine learning has become crucial in every technology field. Automation with software using machine-learning algorithms may aid electrophysiologists to do cardiac mapping without struggle and detecting electrical foci by computers. ML algorithms may identify arrhythmia compared to a board-certified cardiologist and can be developed as a very fast and reliable diagnostic tool.

Keywords--- Machine Learning, Cardiac Remodeling, Atrial Fibrillation, Electrical Conduction, Electrophysiology.

I. Introduction

Here in this article, we plan to give a small picture of what modalities we are now using, those that may turn into significant, and for what indications we may use them for minimally invasive cardiac electrophysiology. Furthermore, we would like to provide some light on why people are stuck with these approaches and what data is accessible and what are some of their potential advantages and disadvantages. When people read this article some might ask why more machine learning is needed than that supplied by a standard artificial intelligence (AI) system. We aim to answer this as well in the next few paragraphs. There is not any extensive review research where we can get some further clues but we shall try to provide a sampler, what modalities are at present available or in development and how these might be able to aid us in the field of cardiac electrophysiology. We are focused on minimally invasive cardiac electrophysiology and thus we consider cardiac imaging modalities for use in the evaluation of cardiac synchrony and for optimization of resynchronization devices [1, 2].

II. Why do we need to Advance Machine Learning Techniques?

The devices are often implanted in case of major rhythm problems such as pacemakers, loop recorders and defibrillators. The role of ML is also identified in identifying a manufacturer of a such devices such as pacemakers or defibrillators where the physicians or the staff who interrogates or program these devices usually have difficulty to know unless prior records exist or unless patient informs them or if they can identify the name of implanting facility from visually from chest radiographs [3]. Machine learning along with predictive models can be very useful to develop personalized therapy [4].

This time has been led to an explosion of advance techniques especially to do machine learning. The rapid increase in collected biological data captured with different dimensions and acquisition rates can be analyzed using conventional analysis strategies [5]. Modern machine learning methods are like deep learning and convolutional neural network, promise to influence very large data sets for finding hidden arrangements within them, and for making more precise predictions. Nowadays cardiac electrophysiologists are handling more complex procedures that involve very complex anatomy. The goals of the newer techniques are to decrease radiation exposure to patients and physicians, to improve the efficacy of the procedures, their outcomes, safety, and to allow electrophysiologists to tackle more complex procedures [6,7].

DOI: 10.5373/JARDCS/V12SP4/20201565
ISSN 1943-023X

Received: 17 Feb 2020/Accepted: 16 Mar 2020

III. Which Dataset for Cardiac Electrophysiology Machine Learning?

In medical research, we usually choose a medical image dataset for a Machine learning application that has adequate data volume, annotation, and reusability. Each cardiac imaging data object consists of data elements, metadata, and an identifier and such combination exhibits an imaging examination. The dataset must have sufficient imaging assessments to answer the question being asked. To maximize algorithm development, both the dataset itself and each imaging examination must be described and labeled accurately [8,9].

IV. What New Machine Learning Techniques are Available?

Deep learning has become one of the most dynamic fields in machine learning that mimics the cognitive processing of the human brain using neural networks with multiple hidden layers. Deep architectures trained on millions of medical images can do a better job in detecting objects in particular images than human eyes can do. All present cutting edge models in image classification, the discovery of objects, retrieval of images, and semantic segmentation may utilize neural network systems. The convolution operation scans the image with a given pattern as well as identify a pixel value and calculates the strength of the match for every position [10,11]. There are also various medical imaging modalities obtained during a procedure, such as those obtained utilizing catheter movement the so-called non-fluoroscopic mapping systems, those obtained using some form of ultrasound, such as transesophageal (TEE) and intracardiac (ICE) echocardiography, in either 2D or 3D form, and various forms of cardiac MRI, either intracardiac catheter-based MRI or utilizing experimental MRI EP laboratories [12,13,14,15]. Pooling determines the presence of the pattern in a region, for example by calculating the maximum pattern match in smaller patches (max-pooling), thereby aggregating region information into a single number. The successive application of convolution and pooling operations is at the core of the most network architectures used in image analysis [16].

Artificial Neural Network

An artificial neural network consists of layers of interconnected compute units. The depth of a neural network corresponds to the number of hidden layers and the width of the maximum number of neurons in one of its layers. The artificial neural networks are rebranded to “deep networks” once networks are trained by numerous data with hidden layers. The data receives information in inner layer first in case of the canonical configuration, which ultimately transformed via multiple hidden layers in a non-linear fashion before computation of final outputs in the final layer. [17].

Convolutional Designs

More recent work using convolutional neural networks (CNNs) allows to greatly reducing the number of model parameters compared to a fully connected network by applying convolutional operations to only small regions of the input space and by sharing parameters between regions [18]. Convolutional Neural Networks (CNNs) contain a convolutional part where hierarchical feature extraction arises and a fully connected part for classification can occur, depending on the nature of the output.

V. Challenges

The challenge with all these modalities is to confirm that they are actually helpful. Researches evaluating a number of these modalities have sometimes shown conflicting results and this may well depend on what each modality is compared to and where the studies are performed. The initial studies were performed in low complexity substrates and therefore cost-effectiveness proved very difficult to demonstrate. It is also often difficult to show that something is cost-effective in high volume centers where the success rates in complex procedures are already fairly good and the complication rates are low. It is important to remember that with the use of CT scanning there is still considerable radiation exposure, at least to the patient and that catheter-based technology is expensive and invasive. However, the non-radiation based modalities have been associated with a significant reduction in radiation exposure for patients and physicians and a tendency to increased success rates and lower complication rates, especially in more complex procedures.

VI. Conclusion

We hope that we are able to shed light on the kind of modalities available and applications of machine learning in cardiac electrophysiology. In addition, we hope that as AI advances, it may aid in learning cardiac

DOI: 10.5373/JARDCS/V12SP4/20201565
ISSN 1943-023X

Received: 17 Feb 2020/Accepted: 16 Mar 2020

electrophysiology by allowing us to identify the visualization of the lesions as they are formed and better-automated software may become available in future for cardiac mapping to guide ablation.

Acknowledgements

We are thankful to the Department of Biomedical Engineering, Chung Yuan Christian University, Taiwan and special thanks to Weichihhu lab members.

References

[1] Lickfett L, Mahesh M, Vasamreddy C, et al. Radiation exposure during catheter ablation of atrial fi brillation. *Circulation.* 2004 Nov 9;110(19):3003-10.

[2] Zhu, Xiaojin. "Machine Teaching: An Inverse Problem to Machine Learning and an Approach Toward Optimal Education." *AAAI*. 2015.

[3] Howard, J. P., Fisher, L., Shun-Shin, M. J., Keene, D., Arnold, A. D., Ahmad, Y., ... & Cole, G. D. (2019). Cardiac rhythm device identification using neural networks. *JACC: Clinical Electrophysiology*, *5*(5), 576-586.

[4] Cantwell, C. D., Mohamied, Y., Tzortzis, K. N., Garasto, S., Houston, C., Chowdhury, R. A., ... & Peters, N. S. (2019). Rethinking multiscale cardiac electrophysiology with machine learning and predictive modelling. *Computers in biology and medicine*, *104*, 339-351.

[5] Bengio, Yoshua, Aaron Courville, and Pascal Vincent. "Representation learning: A review and new perspectives." *IEEE transactions on pattern analysis and machine intelligence* 35.8 (2013): 1798-1828.

[6] LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." *Nature* 521.7553 (2015): 436-444.

[7] Schmidhuber, Jürgen. "Deep learning in neural networks: An overview." *Neural networks* 61 (2015): 85-117.

[8] Rahman, Md Mahmudur, Prabir Bhattacharya, and Bipin C. Desai. "A framework for medical image retrieval using machine learning and statistical similarity matching techniques with relevance feedback." *IEEE transactions on Information Technology in Biomedicine* 11.1 (2007): 58-69.

[9] Kononenko, I. (2001). Machine learning for medical diagnosis: history, state of the art and perspective. *Artificial Intelligence in medicine*, 23(1), 89-109.

[10] Avery, T. E., & Burkhart, H. E. (2015). Forest measurements. *Waveland Press.*

[11] Li, H., Handsaker, B., Wysoker, A., Fennell, T., Ruan, J., Homer, N., ... & Durbin, R. (2009). The sequence alignment/map format and SAMtools. *Bioinformatics*, 25(16), 2078-2079.

[12] Jongbloed MR, Bax JJ, Lamb HJ, et al. Multislice computed tomography versus intracardiac echocardiography to evaluate the pulmonary veins before radiofrequency catheter ablation of atrial fi brillation: a head-to-head comparison. *J Am Coll Cardiol.* 2005 Feb 1;45(3):343-50.

[13] Packer DL. Three-dimensional mapping in interventional electrophysiology: techniques and technology. *J Cardiovasc Electrophysiol.* 2005 Oct;16(10):1110-6.

[14] Kistler PM, Earley MJ, Harris S, et al. Validation of three-dimensional cardiac image integration: use of integrated CT image into electroanatomic mapping system to perform catheter ablation of atrial fi brillation. *J Cardiovasc Electrophysiol.* 2006 Apr;17(4):341-8.

[15] Dong J, Calkins H, Solomon SB, et al. Integrated electroanatomic mapping with three dimensional computed tomographic images for real-time guided ablations. *Circulation.* 2006 Jan 17;113(2):186-94.

[16] Cireşan, D. C., Giusti, A., Gambardella, L. M., & Schmidhuber, J. (2013, September). Mitosis detection in breast cancer histology images with deep neural networks. In *International Conference on Medical Image Computing and Computer-assisted Intervention* (pp. 411-418). Springer, Berlin, Heidelberg.

[17] Singh, Y., Wu, S. Y., Friebe, M., Tavares, J. M. R., & Hu, W. (2018). Cardiac Electrophysiology Studies *Based on Image and Machine Learning.*

[18] Singh, Y., Deepa, S., Wu, S. Y., Tavares, J. M. R., Friebe, M., & Hu, W. (2018). Effect of left ventricular longitudinal axis variation in pathological hearts using Deep learning (No. 648). *EasyChair.*

DOI: 10.5373/JARDCS/V12SP4/20201565
ISSN 1943-023X

Received: 17 Feb 2020/Accepted: 16 Mar 2020