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Artificial Intelligence In Cardiovascular Medicine

Artificial Intelligence and Machine Learning in Cardiac Electrophysiology

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Cardiac electrophysiology requires the processing of several patient-specific data points in real time to provide an accurate diagnosis and determine an optimal therapy. Expanding beyond the traditional tools that have been used to extract information from patient-specific data, machine learning offers a new set of advanced tools capable of revealing previously unknown data patterns and features. This new tool set can substantially improve the speed and level of confidence with which electrophysiologists can determine patient-specific diagnoses and therapies. The ability to process substantial amounts of data in real time also paves the way to novel techniques for data collection and visualization. Extended realities such as virtual and augmented reality can now enable the real-time visualization of 3-dimensional images in space. This enables improved preprocedural planning and intraprocedural interventions. Machine learning supplemented with novel visualization technologies could substantially improve patient care and outcomes by helping physicians to make more informed patient-specific decisions. This article presents current applications of machine learning and their use in cardiac electrophysiology. ***(Tex Heart Inst J 2022;49(2):e217576)***

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Machine learning (ML) provides new tools for analyzing data with use of advanced signal-processing and statistical techniques. Cardiac electrophysiologists use signal-processing tools to interpret real-time data and to help them diagnose, treat, and manage abnormal cardiac rhythms. These data can include 12-lead electrocardiograms (ECGs), intracardiac electrograms, fluoroscopic images, 3-dimensional (3D) electroanatomic maps, and several other types of patient-specific data. Machine learning algorithms are capable of interpreting these heavily intertwined data to assist the physician in making more informed decisions.

Implicit in ML methods is that relevant features of the input data that are indicative of class (for example, QRS widths, PR intervals, and waveform morphologies on ECG tracings) are known. These features are often empirically or analytically derived by experts in the field who use traditional signal-processing techniques and who understand well the electrophysiologic behaviors underlying cardiac function. However, it is often unclear what features of the data are most important for predicting the desired output. The best features can be determined through informed guesses or directly learned from the data, accurate classification being the end goal. The most advanced supervised learning methods, such as deep neural networks and convolutional neural networks (CNNs), use this idea to achieve state-of-the-art results in ML.[1] These algorithms can be applied to classification and regression tasks, making them highly versatile and adaptable. Although the algorithms provide excellent accuracy, they do so by learning features of the data that can be difficult to interpret and provide little insight into the underlying problem. These methods also require considerable input-output pairs to properly train the networks to learn a function between an input and an output.

This article presents current applications of ML in electrophysiology and their use in cardiac electrophysiology. A schematic summary is provided in Figure 1.[2]

Machine Learning Applications in Electrophysiology

Predictive Diagnosis from Surface Leads

A 12-lead ECG provides important information about the health of the heart and contains clues about how to treat cardiac disease. Interpreting electrograms is an art that relies on the science of measuring several ECG intervals and the intricate interdependence among the 12 channels. The current methods for interpreting an ECG are rule-based and can be challenging to implement in a standard and uniform way because of patient-specific differences. Machine learning algorithms can provide quick, accurate diagnoses and can interpret ECGs more efficiently than a clinician can. For example, a deep neural network trained on 91,232 single-lead ECGs from 53,549 patients was shown to classify rhythms with sensitivity greater than that of cardiologists.[3] Other CNNs and recurrent neural networks have been applied to smaller ECG datasets to classify atrial fibrillation (AF) and flutter[4-6] and to distinguish them from other rhythms, with sensitivities ranging from 80% to 95%.

Structural changes in the heart indicative of disease onset can cause subtle changes on recorded ECGs. Using these changes, ML algorithms can predict the onset of disease. In a study that included 180,922 patients, a CNN was able to predict the onset of AF by processing sinus rhythm electrograms before the detection of AF.[7] The authors reported a sensitivity of 82.3% (range, 80.9%–83.6%) and specificity of 83.4% (range, 83.0%–83.8%) when using all sinus rhythm electrograms obtained before the detected fibrillatory event. Impressively, when using only 10 seconds of sinus rhythm, the algorithm was able to predict the onset of AF with a sensitivity of 79.0% (range, 77.5%–80.4%) and specificity of 79.5% (range, 79.0%–79.9%).

Another CNN that was developed to estimate the age and sex of a patient by using 10 seconds of ECG recordings was able to predict age with 90.4% accuracy and predict age within 7 years of the patient's actual age.[7] Marked deviations, such as in older patients, could be indicative of comorbidities. Therefore, the network may serve as a metric for evaluating overall health, thus highlighting the potential for gaining interesting new insights with ML.

Machine learning algorithms have also been used to reconstruct 12-lead ECGs from intracardiac electrograms collected from a single lead.[8] In a retrospective, diagnostic electrophysiologic study of 14 patients, a concurrent electrogram and 12-lead ECG signals were used to compute the transformation from electrogram to ECG and vice versa. The signals were separated into discrete time blocks containing a single heartbeat. The data blocks were then converted into the time-frequency

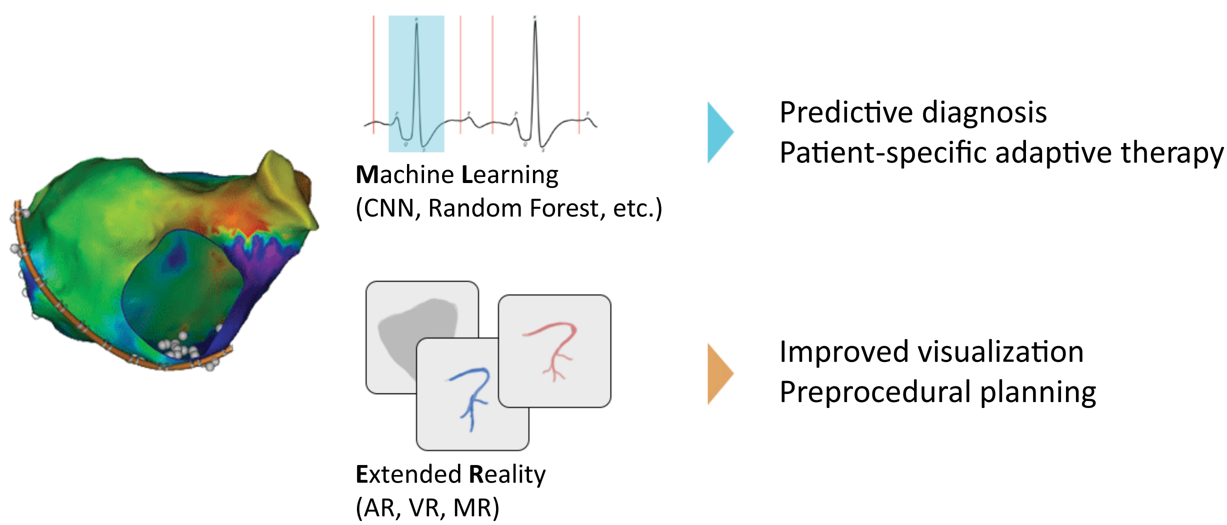

Fig. 1 *Diagram shows roles of machine learning and extended reality in cardiac electrophysiology. Three-dimensional electroanatomic mapping combined with traditional imaging techniques and diagnostic techniques creates a large amount of information that needs to be processed in real time to improve the accuracy of diagnoses and therapies. Machine learning enables the improved accuracy of diagnoses by using a large amount of data obtained during procedures. With use of machine-learning techniques (for example, supervised and unsupervised learning) and convolutional neural networks (CNN), specific, previously unknown features of data can be extracted and used to make a predictive diagnosis and deliver patient-specific therapy. A large amount of data also warrants novel methods of visualization. Extended realities such as augmented reality (AR), virtual reality (VR), and mixed reality (MR) can substantially augment data available to the operator in inpatient and outpatient settings.*

Image of 3-dimensional electroanatomic map adapted with permission from Kim YH, Chen SA, Ernst S, Guzman CE, Han S, Kalarus Z, et al. 2019 APHRS expert consensus statement on three-dimensional mapping systems for tachycardia developed in collaboration with HRS, EHRA, and LAHRS. J Arrhythm 2020;36(2):215-70.[2]

domain to produce image-like spectrograms. These were then fed into a convolutional encoder-decoder neural network model—a specific type of CNN—to learn a function between electrogram and ECG signals. For each patient, the algorithm was trained on a small dataset from 14 patients and validated on the remaining dataset per patient. This enabled the computation of the 12-lead ECG of previously recorded arrhythmic episodes after training the algorithm for a short amount of time in an inpatient setting. From a set of 5 electrogram channels that were obtained from a diagnostic catheter placed in the coronary sinus and used as input, 12-lead ECG signals were reconstructed for 14 patients, with an average Pearson correlation coefficient greater than 0.9 for every patient. The reverse problem of reconstructing 5 electrogram leads from a 12-lead ECG was also shown, with a correlation coefficient greater than 0.9 for most patients.

Patient-Specific Adaptive Therapy

The treatment and management of abnormal heart rhythms with the use of implanted devices, ablative techniques, and drugs can be greatly improved by using ML algorithms. In a retrospective analysis of 481 patients who underwent cardiac resynchronization therapy,[9] a random forest model accurately predicted clinical outcomes after a given therapy by incorporating patient-specific features. In a different study[10] of 1,510 patients undergoing cardiac resynchronization therapy (CRT), random forest classifiers were also used to create a SEMMELWEIS-CRT score that predicted 1- to 5-year all-cause mortality rates. The algorithm using this score performed significantly better than algorithms using other scores, with a mean area under the curve of 0.785. In another study[11] that compared multiple models to improve patient selection for CRT, a naïve Bayes algorithm incorporating patient-specific variables was used to predict the outcomes of a therapy. The algorithm outperformed clinical guidelines in predicting survival free from a composite endpoint of death, heart transplant, or placement of a left ventricular assist device.

Accurately identifying and ablating the focus of AF could possibly improve patient outcomes and reduce the frequency of recurrent AF. Machine learning strategies have been implemented to better guide physicians in performing cardiac ablations. In a small 5-patient study,[12] electroanatomic mapping data were combined with patients' computed tomographic (CT) scans to identify with high confidence areas for ablation. Electroanatomic maps and magnetic resonance imaging (MRI) data were used to create an augmented set of features that was then used in a random-forest model to identify areas for ablation, with a mean sensitivity of 82.4% and mean specificity of 99.2%. A similar strategy involves use of a multiscale-simulation algorithm to identify optimal ablation sites.[13] This algorithm, called Optimal Target Identification via Modelling of Arrhythmogenesis (OPTIMA), simulates AF on patient-specific maps derived from MRI maps, and it computes the minimum set of ablations needed to extinguish AF in silico.[13] Supervised ML is used in this algorithm to classify areas of atrial fibrosis in late gadolinium-enhanced cardiac magnetic resonance images.[14] This approach has also been used to predict recurrence of AF after pulmonary vein isolation, with a mean sensitivity of 82% and mean specificity of 89%.[15]

An enormous amount of data is generated in both inpatient and outpatient settings. With the advent of leadless systems capable of multisite sensing and pacing,[16] even more data are bound to be generated. These data include patient history; billing data; images obtained from ultrasonographic, CT, and MRI scans; electrophysiologic data obtained invasively or noninvasively; diagnoses; and several other types of patient-specific information. The disconnect between these seemingly disparate datasets may explain why therapy and diagnosis are algorithmic and not necessarily patient-specific. Machine learning algorithms applied to healthcare data may help provide patient-specific care by bridging the gaps in patient data collected from multiple sources.

Machine learning algorithms are trained on large datasets. Newer technologies enable the collection and visualization of data that could not be previously obtained. The combination of 3-dimensional (3D) electroanatomic mapping with use of CT scans and intracardiac echocardiographic imaging may diminish reliance on potentially harmful fluoroscopic imaging during procedures. Although the resulting maps carry a substantial amount of spatiotemporal data, only a projection of such maps can be visualized on a 2-dimensional (2D) monitor. Newer technologies, such as virtual reality (VR), augmented reality (AR), and mixed reality (MR), aim to address this issue.

A New Reality in Visualization

Imaging is an integral part of any electrophysiologic procedure. Traditional fluoroscopic imaging has been associated with an increased risk of tissue damage and cancer for both doctors and patients.[17] In addition, visualizing multiple projections of a 3D object through a 2D image has always been challenging. The combination of 3D electroanatomic mapping with tools such as intracardiac echocardiographic imaging has catalyzed a shift towards nonfluoroscopic procedures.

Because of advances in visualization tools, it is now possible to see and interact with these 3D images. Holographic imaging technology (RealView Imaging) has been used in visualizing and planning cardiac procedures.[18] This technology enables the visualization and viewing of static and dynamic images, as well as interaction with segmented images such as those obtained from a CT scan. During an inpatient procedure, holographic images can be visualized near the patient so that an appropriate diagnosis can be made or an intervention performed in combination with other available data.

Another approach to the visualization of 3D images involves extended realities. Extended realities can include VR, in which a virtual environment is set up for interacting with and visualizing images; AR, in which the visualization is overlaid on the true observable space; and MR, in which a virtual environment and augmented images are overlaid together on the observable space. These extended realities may offer substantial improvements over current visualization capabilities and enable better visualization of human anatomy. For example, in a project by Case Western University, the Stanford Virtual Heart is visualized on VR (Lighthaus, Inc.[19]) and MR (HoloAnatomy[20]) platforms with use of Microsoft HoloLens 2 smartglasses in order to better study, understand, and interact with human anatomy, and in particular cardiac anatomy.

Preprocedural planning can also be substantially enhanced with use of extended realities. In a recent study,[21] the use of VR in preprocedural surgical planning was evaluated in 6 patients. By visualizing and viewing immersive 3D images of segment CT scans through CardioVR technology (Medical VR), cardiothoracic surgeons were able to determine the optimal location for surgical access and the spatial orientation of various organs.

Extended realities could provide valuable information during procedures. The CommandEP system (SentiAR), recently cleared for use by the United States Food and Drug Administration, combines electroanatomic maps with holographic imaging of the heart. In a small prospective study of 10 patients undergoing catheter ablation,[22] the system successfully visualized 3D images of CT scans obtained before the procedure and overlaid them with electroanatomic maps. Using a head-mounted display, the user could also view catheters in real time, which is optimal when navigating catheters and choosing an ablation zone.

Conclusion

As ML algorithms are developed, validated, and implemented in low-power hardware, they will become essential at every step in patients' health management and will lead to the identification of various health conditions and patient-specific therapies. As the use of ML-based tools in the daily practice of cardiologists increases, data-driven methodologies will continue to advance. Moreover, once adequately validated, those ML-based tools will facilitate daily clinical workflows, increase patient satisfaction, and enhance the early detection and correct interpretation of findings, ultimately leading to improved patient outcomes. The same holds true for AR and VR technologies, which have provided exciting new directions for streamlining electrophysiologic procedures.

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