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RESEARCH LETTER

Machine Learning Driven Improvement of Signal Detection by Implantable Cardiac Monitors

Implantable cardiac monitors (ICMs) are small, single-lead devices implanted subcutaneously that are capable of monitoring cardiac rhythms for months to years. The main advantages of ICMs include longer monitoring duration and the ability to provide early notifications. However, the single-lead recordings, percutaneous placement, and possibility of device movement can compromise data quality leading to reduced signal-to-noise ratio and increased false-positive readings.[1] To address this, a software program has been designed to aid in signal processing.[2] Recent studies however have shown that false positives continue to burden device clinics and care teams, with important health economic implications.[1] Here, we present an artificial intelligence (AI)-driven solution to improve the accuracy of arrhythmia classification from ICM signals.

Thirty-three patients with hypertrophic cardiomyopathy were referred to our Heart Rhythm clinic in Vancouver, British Columbia, for sudden cardiac death risk stratification and management. Consecutive patients considered to be at low or moderate risk of sudden cardiac death according to recent guidelines were enrolled in a prospective study employing Bluetooth-enabled Confirm Rx ICMs (Abbott Medical).[3,4] Study protocols were approved by the UBC Providence Health Care Research Institute Office of Research Ethics (study ID: H17-02707).

We developed a predictive model for arrhythmia classification using a recently published deep neural network (DNN).[5] A DNN is a type of machine learning method consisting of multiple data-processing layers. DNNs are unique because they can accept raw and unprocessed data to produce customized specific outcomes. Training a DNN describes the process whereby abstract inputs undergo sequential calculations to produce desired specific results.

We trained and subsequently validated this model using distinct data sets composed of electrogram (EGM) transmissions from ICMs. The model was trained to identify cardiac rhythms of 5 categories: supraventricular tachycardia (SVT), ventricular tachycardia (VT), sinus bradycardia (SB), atrial fibrillation (AF), and normal sinus rhythm (NSR). EGM transmissions were annotated by expert technicians from Abbott Laboratories using a combination of software and manual review. Annotated transmissions were spliced into 20-second segments (n = 1,639) and grouped into 1 of the 5 aforementioned categories. For the training data set, 1,147 EGM-annotated segments were provided in random order to the DNN to train the model in classifying raw EGM traces. Next, the model was validated using 492 new EGM segments to evaluate its classification accuracy. The overall accuracy of the DNN was 94%, defined as the overall proportion of correctly classified signals. We also calculated the sensitivity and positive predicted value of the DNN as they are gold standard measures of diagnostic performance (**Figures 1A and 1B**). The model's sensitivity in identifying SVT, VT, SB, and AF was 95.5%, 100%, 94.4%, and 100%, respectively. The specificity was 89.5%, defined as (model predicted true SNR)/(true SNR). All model training and analyses were performed using Python 3.5.

A prototype rule-based predictive algorithm used in a recent clinical trial of novel ICMs found positive predictive values of 4.3%, 30.2%, and 84.1% for AF, tachyarrhythmias (including SVT and VT), and SB, respectively.[4] Positive predictive values estimated with our new algorithm suggest performance improvements compared to traditional rule-based algorithms. Our application of a recently developed DNN to develop a predictive model with ICM data is a practical example of using clinical data to pilot test and improve machine learning tools. Utilizing real-world data to inform machine learning models can increase the translational potential of tools developed from such models. This approach however also has limitations, including the quality and quantity of the data generated. Clinical data are rarely collected with the intention of generating high-quality and abundant data for basic science experimentation. Therefore, certain subsets of clinically irrelevant data may

FIGURE 1 **Performance Characteristics of a Deep Neural Network Model for Classifying Arrhythmias**

A

Category	Sensitivity (95% CI)	Positive Predictive Value (95% CI)
supraventricular tachycardia (n = 134 transmissions)	0.955 (0.919 - 0.990)	0.970 (0.941 - 0.999)
ventricular tachycardia (n = 28 transmissions)	1 (1 - 1)	1 (1 - 1)
sinus bradycardia (n = 143 transmissions)	0.944 (0.906 - 0.982)	0.957 (0.924 - 0.990)
atrial fibrillation (n = 53 transmissions)	1 (1 - 1)	0.869 (0.777 - 0.961)
normal sinus rhythm (n = 134)		

B

		DNN classification					
		supraventricular tachycardia	**ventricular tachycardia**	**sinus bradycardia**	**atrial fibrillation**	**normal sinus rhythm**	
Expert annotation	**supraventricular tachycardia**	128 (0.260)	0	0	4 (0.008)	2 (0.004)	134
	ventricular tachycardia	0	28 (0.057)	0	0	0	28
	sinus bradycardia	0	0	135 (0.274)	0	8 (0.016)	143
	atrial fibrillation	0	0	0	53 (0.108)	0	53
	normal sinus rhythm	4 (0.268)	0	6 (0.012)	4 (0.008)	120 (0.244)	134
		132	28	141	61	130	492

(A) Summary of prediction performance of a deep neural network-powered prediction model for classification of arrhythmias from implantable cardiac monitor recordings. Sensitivity is defined as: (model predicted true arrhythmia)/(true arrhythmia + false negative). Positive predictive value is defined as: (model predicted true arrhythmia)/(total model predicted arrhythmia). **(B)** Confusion matrix for DNN classification vs expert annotation of ICM-derived EGM segments. CI = confidence interval; DNN = deep neural network; EGM = electrogram; ICM = Implantable cardiac monitor.

be less prioritized and not as available. Confounds may be introduced into the data set that can be difficult to reduce or control because of the real-world nature of clinical data. In this study, the NSR subset of our data set was from segments that were labeled as not containing an arrhythmia. This suggests that the true EGM signal may be NSR but may also be uninterpretable noise or artifact. Therefore, our model's true accuracy and generalizability of identifying NSR requires further testing and validation.

This report describes a novel application of an AI-driven improvement to automated classification of ICM recordings. The DNN used was originally applied to single-lead ECG data, and our results suggest the presence of translatability of AI tools designed for 1 data set toward other similar data sets.[5] Accordingly, it is probable that this model can be applied to other yet untested data sets such as recordings from cardiac telemetry or Holter monitoring to improve signal detection and classification. This presents 1 future direction for this work. Other important avenues of research include demonstration of the generalizability of this predictive model. This would require external validation with data sets consisting of larger and more heterogeneous samples. Moreover, other DNN or machine learning tools should be used to power the predictive model and assess whether further improvements in classification can be made.

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