Short Communication

Interventional Cardiology

Artificial intelligence applied to implantable cardiac monitors data

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Received date: 18-Aug-2023, Manuscript No. FMIC-23-110629;
Editor assigned: 21-Aug-2023, PreQC No. FMIC-23-110629 (PQ);
Reviewed date: 04-Sep-2023, QC No. FMIC-23-110629;
Revised date: 11-Sep-2023, Manuscript No. FMIC-23-110629 (R);
Published date: 21-Sep-2023, DOI: 10.37532/1755-5310.2023.15(S18).465

Description

Implantable Cardiac Monitors (ICMs) are an established diagnostic tool for continuous ambulatory monitoring of cardiac arrhythmias in patients with unexplained syncope and in patients with symptoms, such as dizziness, palpitations, chest pain, and shortness of breath, which could be related to unknown arrhythmias [1-4].

ICMs continuously monitor patient's Subcutaneous Electrocardiograms (SECGs) and provide alerts when they detect arrhythmic events, such as asystoles, bradycardia, and both atrial and ventricular tachycardias.

ICMs may transmit large amount of data to clinicians. This on the one hand is positive because it brings opportunities to associate patients' symptoms with cardiac arrhythmias, to detect unknown cardiac conditions, and therefore to derive clinical insight and relevant knowledge to guide medical action. On the other hand, false arrhythmia detections may occur and may cause unnecessary healthcare staff review workload for healthcare staff [5-7].

Artificial Intelligence (AI) already applied to classify cardiac rate and rhythm from electrocardiography and Holter data [8-9], can theoretically be applied to ICM SECGs data. The first proof of this concept has been provided by Mittal, et al., [10], who evaluated AI application to improve ICM accuracy in detecting atrial tachyarrhythmias.

Our group has recently provided new evidence about the capability of AI algorithms to accurately classify ICMs data and reduce false arrhythmia detections [11]. The main finding of our study was that the evaluated AI algorithm accurately classified episodes detected by ICM with 95.4% overall accuracy, in particular with 97.19% sensitivity, 94.52% specificity, 89.74% positive predictive value, and 98.55% negative predictive value. Our data added important insight into the field of applying AI to ICM data because the previous research [10], was limited to AI classification of atrial tachyarrhythmias while we applied AI to the classification of atrial tachyarrhythmias but also of bradycardias, asystoles, and ventricular tachycardias. Another important result of our study was to confirm that AI algorithms can reduce false positive arrhythmia reduction by 98.0% overall and in particular by 99.5% for bradycardia, 98.8% for asystole, 94.0% for atrial tachycardias and 87.5% for ventricular tachycardia. These results have relevant clinical implications since the clinical value of ICM depends on reliable arrhythmia detection. AI may contribute to improving the data triage process, reducing the Hospital staff workload, and providing quick insights from data to support clinicians in taking prompt medical action and improving patient care.

Our more recent publication [12], shows that the evaluated AI algorithm is capable of expanding ICM's detection capacity from the standard 4 cardiac arrhythmias (asystoles, bradycardias, and atrial or ventricular tachycardias) to 25 cardiac rhythm patterns through multi-label classification. For example, atrial tachyarrhythmias as detected by the ICM were sub-classified as atrial tachycardia, and atrial fibrillation with slow ventricular response (40 bpm-59 bpm), atrial fibrillation with controlled ventricular response (60 bpm-120 bpm), atrial fibrillation with rapid ventricular response (>120 bpm). Similarly, bradycardia was classified as mild sinus bradycardia (40 bpm-59 bpm) or severe sinus bradycardia (<40 bpm). Other AI-driven rhythm classifications comprised rS complexes, premature atrial contractions (sub-classified as unifocal, bigeminal, trigeminal, quadrigeminal, couplet, or triplet), premature ventricular contractions (sub-classified as positive, negative, unifocal bigeminy, unifocal trigeminy, unifocal quadrigeminy, couplet or triplet, interpolated), inverted T waves. These classifications and differentiations of the cardiac rhythms are clinically relevant because they allow physicians to better characterize each patient and to personalize patient therapy (anticoagulation, rhythm control strategy, ventricular response control strategy, pacemaker indication, etc.). Even with the significant increase in the number of detected cardiac arrhythmias, the identification precision remained high with a pondered global accuracy of 88%, which is comparable, if not better, than expert cardiologists' performances. Importantly we also estimated the time an AI algorithm takes to access, read, and diagnose ICM episodes. This time on average was as low as 6 seconds suggesting that the introduction of AI algorithms in the clinical practice may reduce the time in heart electrical signal processing and cardiac pattern diagnosis, compared to traditional visual analysis.

AI is progressing from bench to bedside. We know that AI algorithms will soon be integrated with the platforms which allow remote monitoring of patients with implantable cardiac devices. Moreover, we envision that AI in the near future will provide predictive analytics capabilities that will directly benefit patients in real-world clinical practice. AI and in particular Machine Learning (ML) have been applied in ECG and Holter data to identify patients at risk of left ventricular dysfunction [13], atrial fibrillation [14], and mortality [15]. Recently ML has been applied to predict ventricular fibrillation based on electrocardiographic features [16]. These ML algorithms have been tested in preliminary clinical applications with promising results [17-18].

Conclusion

In conclusion, cardiac monitors, both wearable and insertable ones, will be used more and more in the future for monitoring cardiovascular diseases. The development of Bluetooth technology and the application of AI algorithms will result in the capability of detecting cardiovascular events on time, earlier and everywhere. Both wearables and implantable cardiac monitors have pros and cons that need to be fully evaluated; as for implantable cardiac monitors pros comprise the fact that they are easy to implant, minimally invasive, safe and highly effective in providing long-term continuous ambulatory monitoring. The detection accuracy is high and continuously improving with the implementation of new detection algorithms and the application of AI. Implantable cardiac monitors have also cons that have to be evaluated, such as the data volume which may cause Hospital staff work, and possible risks, even if low, of infection, bleeding or bruising after surgery, or discomfort in daily activities, such as taking a shower, a few days after implant.

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