Review of: "Automated multilabel diagnosis on electrocardiographic images and signals"

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Potential competing interests: April 30, 2022 Editorial Board Nature Communications Dear Editor: I wish to submit a Comment article for publication in Nature Communications, titled “Artificial intelligence for diagnosis of electrocardiograms, which has more potential, images or signals?.” The paper was coauthored by Fan Lin and Xiaoyun Yang. This paper describes artificial intelligence for diagnosis of ECGs. At present, the types of ECG for deep learning diagnosis are limited. We believe that Sangha and colleagues must have tried more kinds of rhythm disorders with deep learning method for ECG diagnosis. We hope that the authors can present the results of these data more openly, which will be helpful to the future researchers. Given your journal’s commitment to publishing high-quality papers relating to health sciences, we believe that the findings of this study are relevant to the scope of your journal and will be of interest to its readership. This manuscript has not been published or presented elsewhere in part or in entirety and is not under consideration by another journal. We have read and understood your journal’s policies, and we believe that neither the manuscript nor the study violates any of these. There are no conflicts of interest to declare. Thank you for your consideration. I look forward to hearing from you. Sincerely, Xiaoyun Yang Division of Cardiology, Department of Internal Medicine, Tongji Hospital, Tongji Medical College, Huazhong University of Science and Technology No. 1095, Jiefang Avenue, Wuhan, Hubei, China Email: yangxiaoyun321@126.com

Artificial intelligence for automated diagnosis of ECGs, which one has more potential for deep learning, images or signals?

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Electrocardiogram (ECG) has been developed for more than 100 years, and it is an essential tool in the diagnosis and management of cardiovascular diseases. But the experienced cardiologists who have received professional training in ECG are scarce, and artificial intelligence (AI) can make up this deficiency. In recent years, the automatic diagnosis of

ECG has become one of the hot research topics in the fields of computer and medicine.

For a long time, the physicians complete ECG as follows: collecting ECG signals - printing ECG imagings- interpretating ECG. This procedure often takes a long time. For emergency and critical patients, if the ECG cannot be diagnosed accurately in time, the patients may be treated incorrectly or delayed.

Zhu Hongling et al[1] used a deep learning model to predict 21 diagnostic categories arrhythmia from 12-lead ECG, including identifying multi-label arrhythmia, which was better than that of physicians with 6-12 years of training. Weston Hughes et al[2] had predict the presence of 38 diagnostic classes in 5 categories from 12-lead ECG, and the most classes of convolutional neural network (CNN) performed exceeded cardiologist clinical diagnoses and the MUSE (GE Healthcare) system's automated ECG diagnosis. However, the signal-based deep learning models of ECG are facing challenges. At present, the unified storage format of ECG signals from different sources has not been established, and the signal-based mode of single or limited sources limits its application and promotion in ECG signals from other sources.

In February, 2022, Veer Sangha and colleagues[3] reported a comparative study of image-based model and signal-based model in diagnosis. The training data of the study were collected from 2010 to 2017, including 231,704 ECG samples out of 2,228,236 ECG samples of 1,506,112 patients from 811 municipalities in Brazil, including 6 rhythm disorders. The validation data set of the model adopts an internal validation set and two external validation sets, which indicates that ECG image-based model has better performance than signal-based model, and image-based model has more extensive application scenarios.

Different from the previous studies on large ECG data sets, this study only verified six kinds of rhythm disorders, such as atrial fibrillation (AF), right bundle branch block (RBBB), left bundle branch block (LBBB), first-degree atrioventricular block (1 dAVb), sinus bradycardia (SB) and sinus tachycardia (ST). Except AF, the other five rhythm disorders can be diagnosed by two P-QRS-T length of ECG. None of the images in the four formats lost important signal of the rhythm disorders, so the diagnostic accuracy of images in different formats did not change. However, other types of arrhythmia, such as second-degree atrioventricular block, third-degree atrioventricular block, atrial arrhythmia and ventricunal arrhythmia would lose important information after being converted into the above four formats images, and which information are essential for the diagnosis. Gliner Vadim et al[4] were using image-based model to diagnosis of more kinds of rhythm disorders. The accuracy of arrhythmia diagnosis in this study is similar to Veer Sangha and colleagues have reported, but the sensitivity of PAC and PVC diagnosis was low, being 0.33 and 0.65 respectively. However, in other studies the specificity and sensitivity of the signal-based deep learning model in PAC and PVC are all above 0.9.

Therefore, it is reasonable to believe that the most important factor limiting the application of ECG image-method in deep learning is the information contained in the images. If the 10-seconds ECG signal is converted into a 3 * 4 or 2 * 6 image format, some important information will be lost, especially the arrhythmia which requires three or more P-QRS-T length segment of ECG. The loss of this important information may lead to more possibility of lowering the diagnostic accuracy of more kinds of rhythm disorders. On the other hand, for the six kinds of rhythm disorders mentioned in the study, the amount of information is reduced, and made the model focuses on target information. It can improve the efficiency of deep learning training, which is the potential reason why the accuracy rate of image-based models for these six dysrhythmias is higher than that of signal-based models.

Because of the complexity of ECG, there are hundreds of diagnostic terms, such as primary diagnostic statements, secondary diagnostic statements, modifiers, and statements for the comparison of ECGs[5]. At present, the types of ECG for deep learning diagnosis were limited. We believe that the Veer Sangha and colleagues must have tried more kinds of rhythm disorders with deep learning method for ECG diagnosis. We hope that the authors can present the results of these data more openly, which will be helpful to the future researchers.

Reference

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