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Classification of normal and abnormal ECG records using lead convolutional neural network and rule inference

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With the improvement of living standards, more and more people pay attention to their own health problems and performing an ECG test is the preferred selection for preventing cardiovascular disease. Although it is easy to sample ECG now, diagnostic conclusion cannot be made because of the lack of domain experts, especially in the basic community medical insurance system (BCMIS) of China. A feasible solution is to send ECG records to a cloud-computing platform monitored by ECG physicians, and send back the results to users. In fact, such institutions are common in China now, for instance, Shanghai Aerial Hospital Network. However, there are a large number of ECG records needing to be interpreted and the workload of physicians will be very heavy considering the huge possible audience. For ECG records are mainly collected from people attending physical examinations, their diagnostic conclusion is likely to be "normal". If a computer-aided ECG diagnostic tool filters out most normal records while physicians only focus on interpreting the remaining abnormal ones, i.e., man-machine integration [1], the diagnostic efficiency will be greatly increased and the social benefits will be significant.

Different from heartbeat classification [2], we should provide a classification result for each ECG record. However, due to the limitations of standard ECG databases, there is less research work concerning this subject [3]. For this, we constructed the Chinese Cardiovascular Disease Database (CCDD) [4] containing standard 12-lead ECG records with about 10–20 s in duration. Based on it, both Zhu [5] and Wang [6] have proposed methods for classification of normal and abnormal ECG records with short duration (record classification), but their classifiers were far from meeting the demand. Our prior work [7] applied a lead convolutional neural network (LCNN) on the 12-lead ECG and achieved by far the best results ever reported on the CCDD. To improve the performance further, this study proposes a novel model for record classification, which integrates two LCNNs and four rule-based classifiers.

Figure 1 shows the overall framework of the proposed model. As we can see, it consists of three parts, namely, statistical learning, rule inference as well as summarizing. In the part of statistical learning, the ECG record is first preprocessed by two different methods respectively, and then two probability values are outputted by using LCNNs and the multipoint-prediction technology. After that, we employ the Bayesian fusion method to incorporate the two outputs. In the part of rule

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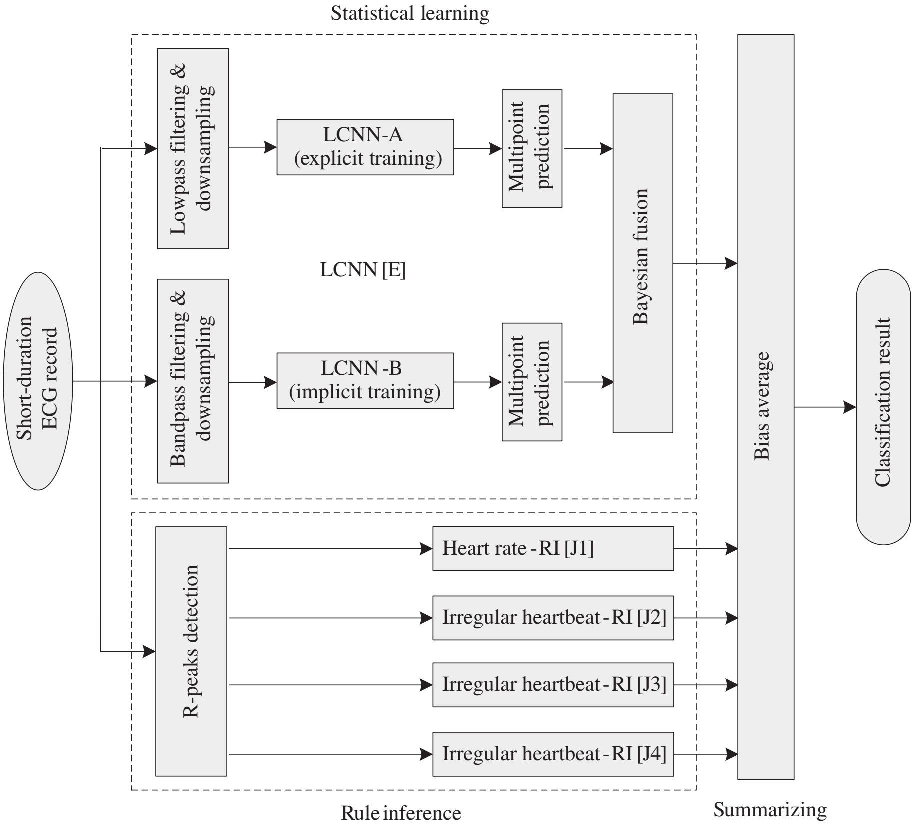

Figure 1 Overall framework of the proposed model.

inference, all R-peak positions in the ECG record are detected first [8], and then four disease rules based on them are used for further analysis. Finally, in the part of summarizing, we utilize the bias-average method to determine the result, i.e., "normal (0-class)" or "abnormal (1-class)".

The part of statistical learning (denoted as LCNN[E]) describes a homogeneous ensemble in nature, and our approach has certain advantages over some well-known ensemble methods such as Bagging and AdaBoost. Please refer to [9] for more information. Next, we will introduce the remaining two parts in detail.

Rule inference. Let fs be the sampling frequency, R_i ($1 <= i <= n$) be the i-th R-peak position in an ECG record and std($\cdot$) be the function of calculating the standard deviation. The formula for calculating the average RR interval is given by

$$\mathrm{AvgRR} = \frac{1}{n-1}\sum_{i=2}^{n}(R_i - R_{i-1}),$$

the four disease rules are defined as follows:

- RI[J1]. The rule for detecting abnormal heart rate is defined as follows. The heart rate (HR) given by the following formula is less than 59 or greater than 101:

$$\mathrm{HR} = \frac{60 \times fs \times (n-1)}{R_n - R_1}.$$

- RI[J2]. The first rule for detecting irregular heartbeat is defined as follows. Three successive RR intervals exceed the average RR interval by 15%, i.e., $\exists k \in [1, n-3], \forall j \in [1, 3]$ satisfies

$$\left|\frac{(R_{k+j} - R_{k+j-1}) - \mathrm{AvgRR}}{\mathrm{AvgRR}}\right| > 0.15.$$

- RI[J3]. The second rule for detecting irregular heartbeat is defined as follows. One RR interval exceeds the average RR interval by 15% and the standard deviation of the rates between two neighboring RR intervals is greater than 0.05, i.e., $\exists k \in [1, n-1]$ satisfies

$$\begin{cases} \left|\dfrac{(R_{k+1} - R_k) - \mathrm{AvgRR}}{\mathrm{AvgRR}}\right| > 0.15, \\ \mathrm{std}\left(\left\{\dfrac{R_{i+2} - R_{i+1}}{R_{i+1} - R_i} \middle| 1 \leqslant i \leqslant n-2\right\}\right) > 0.05. \end{cases}$$

- RI[J4]. The last rule for detecting irregular heartbeat is defined as follows. The standard deviation of RR intervals is greater than

$(0.05 \times \mathrm{AvgRR})$, i.e.,

$$\frac{\mathrm{std}\left(\{R_{i+1}-R_i|1 \leqslant i \leqslant n-1\}\right)}{\mathrm{AvgRR}} > 0.05.$$

Different from LCNN[E] that outputs a probability value, the four rule-based classifiers (namely RI[J1], RI[J2], RI[J3] and RI[J4]) will output 1 if an ECG record is identified as abnormal heart rate or irregular heartbeat, otherwise 0 is the result.

Summarizing. There is no doubt that an ECG record is abnormal if it is identified as a specific disease type. With this in mind, we develop a novel fusion technology, namely the bias-average method, given by

$$\begin{cases} \mathrm{ro} = \max(\mathrm{ro}_1, \mathrm{ro}_2, \mathrm{ro}_3, \mathrm{ro}_4), \\ \mathrm{output} = \begin{cases} \dfrac{\mathrm{ro}+\mathrm{nno}}{2}, & \mathrm{ro} == 1, \\ \mathrm{nno}, & \text{otherwise}, \end{cases} \end{cases}$$

where ro_1, ro_2, ro_3, ro_4 and nno are the outputs of the RI[J1], RI[J2], RI[J3], RI[J4] and LCNN[E] classifiers, $\max(\cdot)$ is to choose the maximum value. If we use the first three rule-based classifiers, just replace "$\max(\mathrm{ro}_1, \mathrm{ro}_2, \mathrm{ro}_3, \mathrm{ro}_4)$" with "$\max(\mathrm{ro}_1, \mathrm{ro}_2, \mathrm{ro}_3)$". The final classification result is "normal" if output is less than 0.5, otherwise it is "abnormal".

Evaluation. The CCDD contains 193690 standard 12-lead ECG records at present. To make a fair comparison, the same training ($n = 12320$), validation ($n = 560$) and testing samples ($n = 151274$) from it as well as the same performance metrics including specificity, sensitivity, accuracy, NPV (negative predictive value), AUC (area under the ROC curve) and TPR95 (specificity under the condition of NPV being equal to 95%) [7, 9] were used to evaluate the proposed model. With the 151274 testing samples, although the sensitivity and NPV were slightly lower, LCNN[E] outperformed our prior work [7] in all other metrics. On this basis, when RI[J1], RI[J2] and RI[J3] were added, most metrics continued to increase. The specificity, sensitivity, accuracy, NPV, AUC and TPR95 were 86.03%, 86.46%, 86.22%, 89.11%, 0.9322 and 65.4% respectively at this point. When RI[J4] was added further, the sensitivity, NPV and TPR95 increased to 89.82%, 91.04% and 67.9% respectively while the specificity, accuracy and AUC started to decrease. It is worth noting that TPR95 is the key indicator in our application scenarios [10]. Compared with our prior work with a TPR95 of 26.7%, the proposed model significantly improved the performance. Although it exhibits an increase in terms of computational complexity with respect to our prior work, there is no problem if we apply it in practical applications. The total computing time for an ECG record is about 125 ms on an Intel Core 2 CPU@2.93 GHz, 2 GB RAM, 32 bit Window 7 OS.

Conclusion. Aiming to lessen the workload of physicians, this study presents a systematic approach for record classification. Our results show that deep neural networks (LCNN) can achieve better performance when used together with rule-based classifiers. Specifically, the proposed model yields an accuracy of 86.22% and 0.9322 AUC on the CCDD, which is an significant improvement on previously reported results [5–7, 9]. Moreover, TPR95 can reach 67.9%, which means that the workload of physicians can be decreased by ($N\% \times 67.9\%$) in a clinically acceptable scope (especially in the BCMIS of China) if the percentage of normal ECG records is $N\%$. In general, at least $70\% \times 67.9\% = 47.53\%$ of workload can be reduced since $N\%$ can be more than 70% in our application scenario. We have deployed the proposed model on the real-time cloud platform http://www.kzyyw.com/.

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