An Optimized Update Method for Atrial Fibrillation Detection for Wearable Devices

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Abstract. Atrial fibrillation (AF) is a disease of the elderly with high rates of disability and mortality. In order to solve the problems of missed early AF diagnosis and wearable device AF data analysis not fast and accurate enough, this paper uses deep incremental learning to train AF signals as a capture model based on AF data and normal ECG data in public databases and so on. Capturing atrial fibrillation signals from early stage clinical atrial fibrillation patients is considered as a new task, and the established capture model for the old task is updated and learned online, including the online update algorithm of multi-task atrial fibrillation signal capture model based on knowledge distillation and knowledge verification. Finally, the model parameters are adaptively optimised to solve the problems of time-consuming online updating and poor diagnostic performance of the model. The experimental results show that the diagnostic result of AF based on knowledge review is 0.94, and the diagnostic result of AF based on multi-task incremental learning is 0.88 after adding new samples from the clinic. In summary, the results of this research can improve the ability of early detection of AF, which can help promote the practical process of AF diagnostic technology in the clinic.

1. Introduction

Atrial fibrillation (AF) is a kind of arrhythmia caused by irregular atrial contraction, which is easy to induce serious complications such as stroke, arterial embolism, and sudden cardiac death, and has a high disability and mortality rate. The early manifestations of atrial fibrillation are insidious, and clinical diagnosis is difficult and easy to miss [1,2]. At present, 12-lead resting electrocardiogram (ECG) and ambulatory electrocardiogram (Holter ECG) are ideal screening methods for atrial fibrillation, but due to the high cost of detection, inconvenient wearing, and limited recording time, the screening of atrial fibrillation cannot be popularized [3-8]. In recent years, with the integration of the medical field and the mobile Internet field, wearable ECG monitoring devices such as smart bracelets, watches, and wristbands have provided a possibility for early screening of atrial fibrillation due to their advantages of portability, low load, long-term monitoring and real-time wireless data transmission, effectively alleviating the current shortage of medical resources.

It is worth noting that the data detected by the current wearable ECG detection devices such as smart bracelets is of poor quality, and the discrimination accuracy of atrial fibrillation is not high, which cannot meet the requirements of diagnosis and treatment of diseases. In recent years, artificial intelligence technology, especially deep Xi, has also made many remarkable advances in automatic ECG diagnosis. Its excellent performance is mainly due to the multi-level neural network structure, which can automatically extract ECG features, omit the more complex and cumbersome and subjective feature extraction steps, and directly simplify to end-to-end atrial fibrillation signal capture, and has good generalization performance. Current deep learning-based AF signal capture models all adopt batch learning, which means that the data distribution of the model training set is consistent and does not take into account the data distribution differences caused by the large individual differences of different patients. Once a new AF patient appears, the AF signal capture model needs to be re-trained by fusing new samples, which will inevitably waste a lot of time and computational resources, and does not meet the demand for rapid AF detection [9-12].

Incremental learning, as a way of machine learning, which can learn new knowledge from continuously emerging sample data and retain and update the old knowledge that has been learned, is a process of continuously updating and expanding the knowledge system online [13-18]. Therefore, oriented to the single-lead ECG signals collected by wearable devices such as smart bracelets, and targeting the problems of large amount of ECG signal data, strong concealment, and different data distribution due to individual differences, a set of fast and accurate early diagnosis algorithms of atrial fibrillation is researched, so as to push forward the process of practicalization of the atrial fibrillation signal capture technology in the clinic.

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2. Multidimensional feature fusion for early AF detection based on single-lead signal

2.1. Designing a multi-dimensional feature fusion unit

The single-lead ECG signal data undergoes a layer of convolutional preprocessing to extract the shallow morphological features of the signal, and a feature incremental learning block (FIB) is designed to fuse the features. The shallow features are convolved with a 1*1 convolution kernel through the FIB, which adopts the idea of dense network feature enhancement to achieve the effect of multi-dimensional fusion feature incremental learning of ECG signals through cascading in the local network. The effective features of the ECG signals are extracted, screened, and enhanced.

2.2. Designing fusion feature incremental learning blocks

The electrical signal multi-dimensional fusion feature is extracted through the multi-dimensional feature fusion unit (MFU) which is shown in Figure 1. The unit extracts spatial and temporal features using CNN and BiLSTM, respectively, and fuses them to reduce or suppress the influence of random interference and other uncertain factors by adding new dimensional information, thus improving the effectiveness of the features. Subsequently, the multi-dimensional fusion features are also reduced using a 1*1 convolution layer. The 1*1 convolution kernel not only does not significantly increase the number of parameters, but also further enhances the mapping potential of the network and reduces the instantaneous memory consumption. It also effectively fuses the multi-dimensional feature output. At this point, the feature extractor design is complete. Then, a Softmax classifier is used to construct an atrial fibrillation diagnosis network, and the entire network is fine-tuned using a stochastic gradient descent algorithm. Finally, the network model is validated using a test set.

Fig. 1. Network model structure for atrial fibrillation diagnosis based on feature enhancement

3. On-line training algorithm for deep atrial fibrillation early detection network model based on multi-task incremental learning

The deep atrial fibrillation diagnosis model established based on the internationally authoritative open ECG dataset is regarded as an old task. Due to the large individual differences among different patients, their data distributions are not the same. If the atrial fibrillation diagnosis model is to have the same atrial fibrillation recognition ability for different atrial fibrillation patients, that is, for new tasks, it is necessary to perform online updating learning on the established old task atrial fibrillation diagnosis model based on the atrial fibrillation sample data of the new task. This project intends to study the online training algorithm of multi-task incremental learning atrial fibrillation early detection network based on knowledge distillation and knowledge review, aiming to achieve a balance between maintaining the performance of old tasks and learning new task knowledge. The update process of multi-task incremental learning atrial fibrillation early detection network is shown in Figure 2.

Fig. 2. Update process of atrial fibrillation diagnosis network based on multi-task incremental learning
3.1. New task knowledge learning algorithm based on knowledge distillation

The knowledge distillation method transfers learned knowledge to an old model to achieve online updating. Compared to directly training the model with new atrial fibrillation samples for a new task, this method makes it easier for the old task model to learn new knowledge, while also maintaining the performance of the old task model. The specific steps of the algorithm are as follows:

- Based on the feature-enhanced atrial fibrillation diagnosis framework, only the new task failure samples are used to train an atrial fibrillation diagnosis model under a new task, where the loss function is a standard cross-entropy loss function.
- Calculate the output probability $\hat{y}_n$ of the new task model for the new task atrial fibrillation sample data $X_n$, the category prediction probability for each new task sample, as the supervision information for the new task data.
- Calculate the output probability $\hat{y}_n^{(i)}$ of the new task model for the new task data and the prediction probability $p_n^{(i)}$ of the multi-task model for the new data belonging to the new task. The calculation method is as follows:

$$\hat{y}_n^{(i)} = \frac{\hat{y}_n^{(i)}}{\sum \hat{y}_n^{(i)}} = \frac{1}{\sum \hat{y}_n^{(i)}}$$

- Construct a knowledge distillation loss function $L^D_{new}(X_n, \hat{y}_n)$ for new task knowledge learning, as follows:

$$L^D_{new}(X_n, \hat{y}_n) = -\frac{1}{|N_n|} \sum_{i=1}^{K_n} \sum_{k=1}^{K_n} \hat{y}_n^{(i)} \log (p_n^{(i)})$$

where $n$ is the new task; $N_n$ is the total number of new task samples; $K$ is the number of ECG signal annotation categories, and $K_n$ is the number of new categories; $L^D_{new}$ is to make the multi-task model's prediction probability for the new categories close to that of the new model for the new task categories, allowing the multi-task model to learn knowledge on the new task.

3.2. Old task performance maintenance algorithm based on knowledge review

Retrospection allows the old task model to review a small amount of old task data $X_o$ and review the knowledge that has been learned, ensure that it is not forgotten too quickly, and maintain the performance of the old model without incurring excessive storage costs. The specific steps of the algorithm are as follows:

- Calculate the output $\hat{y}_o$ of the old task model on a small amount of old task data $X_o$, the category prediction probability for each old task sample, as the maintenance information for the performance of the old task.

$$\hat{y}_o = \frac{1}{\sum \hat{y}_o}$$

- Calculate the output probability of the old task model on the old task data $y_o^{(i)} (y_o^{(i)} \in \hat{y}_o)$ as well as the prediction probability of the multi-task model on a small amount of old task data belonging to each category of the old task, calculated as follows:

$$\hat{y}_o^{(i)} = \frac{\hat{y}_o^{(i)}}{\sum \hat{y}_o^{(i)}}$$

$$p_o^{(i)} = \frac{1}{\sum p_o^{(i)}}$$

Usually $c > 1$, the purpose is to increase the influence of smaller probability values on the knowledge review loss function.

- Construct a knowledge review loss function $L^R_{old}(X_o, \hat{y}_o)$ for the performance of the old task, as follows:

$$L^R_{old}(X_o, \hat{y}_o) = -\frac{1}{|N_o|} \sum_{i=1}^{K_o} \sum_{k=1}^{K_o} \hat{y}_o^{(i)} \log (p_o^{(i)})$$

where $K_o$ is the number of old task categories. $L^R_{old}$ ensures that the current model's prediction probability for old task categories is as close as possible to that of the old task model, so that the multi-task model maintains its performance on old tasks. Not all samples in the old task ECG samples will play a significant role in reviewing knowledge, so in order to better maintain the performance of the atrial fibrillation diagnosis model, it is necessary to select valuable ECG sample knowledge for review. Specifically, a fixed number of samples with correct classification and posterior probability greater than 0.9 in each old task atrial fibrillation category sample are selected as samples for maintaining performance.

3.3. Online updating algorithm for multi-task fault diagnosis model based on knowledge distillation and knowledge review

Online updating of the atrial fibrillation diagnosis model mainly involves the design of a loss function for the multi-task atrial fibrillation diagnosis model, while preserving the performance of the old model and learning new sample knowledge. For multi-task atrial fibrillation diagnosis, which mainly involves incremental learning of electrocardiogram samples, knowledge distillation should be used to extract new knowledge and adaptively modify the mapping relationship of the model. Therefore, the loss function expression for multi-task incremental learning is as follows:

$$L_{MFD} = \lambda \cdot L^R_{old}(X_o, \hat{y}_o) + (1 - \lambda) \cdot L^D_{new}(X_n, \hat{y}_n)$$

The $\lambda$ is the weight allocation of the loss function, which dynamically adjusts the proportion of the knowledge distillation loss function and the knowledge review loss function in the total loss function in multi-task learning, effectively alleviating the imbalance in sample
size caused by incremental learning. The \( \lambda \) values are all in the range of \([0, 1]\).

### 4. Experiments

#### 4.1. Dataset

By using Huawei smart watches to collect the ECG signals of 50 AF patients and 70 normal patients, and pre-processing 120 samples such as labelling and wavelet denoising, the training and test sets of the optimised and updated AF detection model were constructed based on the pre-processed data sets. Among them, 50% of the clinical patient data and the public AF database were collected for training and online updating of the AF detection model, and the remaining 50% of the collected clinical data will be used as an external validation set to complete the clinical validation of the algorithm to test the generalisation ability of the model. In the process of ECG data annotation, the clinical cardiologist mainly relies on the method of independent data labelling and cross-validation to calibrate the true value, and finally invites a senior cardiologist as a database review expert to review the AF ECG signal in the database to ensure the accuracy of the data. The before and after comparison of wavelet denoising is shown in Figure 3.

![Fig. 3. The Result of Wavelet Denoising](image)

#### 4.2. Model evaluation

During the update process of the multi-task incremental learning intelligent fault diagnosis model, the network parameters are updated and learned based on the current diagnosis results. Due to different learning rate settings, the model may converge slowly or quickly and oscillate near the extreme point. However, most learning rates are adjusted based on experience or iteration times, resulting in poor performance. Therefore, this project aims to adaptively optimise the learning rate of the network based on the change in the model’s classification accuracy without introducing new parameters.

\[
\eta_{t+1} = \eta_{t+1} \cdot e^{(acc_{t+1} - acc_t)}
\]

where \((acc_{t+1} - acc_t)\) is the difference in sample classification accuracy obtained during the two iterations. When the model classification accuracy significantly increases, this indicates that the step size should be increased in the gradient direction during this round of iteration to accelerate the convergence rate. When the model classification accuracy oscillates, that is, when the optimal solution approaches the extreme point of the loss function, this indicates that the step size should be decreased in the gradient direction during this round of iteration to reduce the oscillation of the optimal solution near the extreme point to obtain a better optimal solution. In this case, \(e^{(acc_{t+1} - acc_t)} \in (0,1)\), the network learning rate is adaptively decreased.

Under the environment of Windows 10 operating system and Intel(R) Core(TM) i5-8265U CPU @1.60GHz, through the collection of ECG data from early volunteers with clinical atrial fibrillation, we used it to validate and evaluate the atrial fibrillation early detection model based on multi-task deep incremental learning. At the same time, we combined the public database data to evaluate the stability, time complexity, accuracy, sensitivity, and specificity of the atrial fibrillation detection model based on multi-task incremental learning. The results are shown in Table 1.

<table>
<thead>
<tr>
<th>Evaluation index</th>
<th>Atrial fibrillation diagnosis based on multi-task incremental learning</th>
<th>Atrial fibrillation diagnosis based on knowledge review</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>0.86</td>
<td>0.88</td>
</tr>
<tr>
<td>Precision</td>
<td>0.77</td>
<td>0.82</td>
</tr>
<tr>
<td>Recall</td>
<td>0.71</td>
<td>0.80</td>
</tr>
<tr>
<td>F1-score</td>
<td>0.74</td>
<td>0.80</td>
</tr>
<tr>
<td>AUC</td>
<td>0.88</td>
<td>0.94</td>
</tr>
</tbody>
</table>

As shown in Fig. 4 and Fig. 5, the diagnosis result of atrial fibrillation based on knowledge review is 0.94, and after adding new clinical samples, the diagnosis result of atrial fibrillation based on multi-task incremental learning is 0.88.

![Fig. 4. Atrial fibrillation diagnosis based on knowledge review](image)
5. Conclusions

Aiming at the problem of detecting atrial fibrillation based on ECG signals, this project proposes an intelligent detection method of atrial fibrillation for wearable devices, which utilizes deep incremental learning to solve the problem of online updating of atrial fibrillation signal detection model for wearable devices. First, clinical data are collected and labeled using wearable devices such as smartwatches, and at the same time, the training and test sets are divided by combining the data from public databases, and by designing the structure of deep atrial fibrillation detection network containing feature enhancement in order to extract more discriminative and effective features. The AF signal capture model is trained based on AF data and normal ECG data from public databases and so on. Secondly, the capture of AF signals from patients with early clinical AF is considered as a new task, and knowledge distillation and knowledge review are used to realize the performance preservation and online update of the AF signal capture model, so as to achieve the effect that the model is adaptively corrected according to the new samples, and to realize the detection of AF. Finally, the model parameters are designed for adaptive optimization to solve the problem of time-consuming online update of the model and poor diagnostic performance due to incremental learning. The diagnosis result of AF based on knowledge review is 0.94, and the diagnosis result of AF based on multi-task incremental learning is 0.88 after adding new clinical samples.

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References


