Architecture of Bio Data Measurement Model Training by Federated Learning in Raspberry Pi

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Abstract:: With the development of intelligent services and applications enabled by Artificial Intelligence (AI), the Internet of Things (IoT) is infiltrating many aspects of our everyday lives. The growing need for the remote caring of patients at home combined with the ever-increasing popularity of mobile devices due to their ubiquitous nature has resulted in many apps being developed to enable mobile telecare. The Cloud, in combination with mobile technologies has enabled doctors to conveniently monitor and assess a patient' s health while the patient is at the comfort of their own home. According to the existing conditions, I integrated the existing biosensor into the Raspberry Pi environment. Because the wired data transmission of the Raspberry Pi is inconvenient and the wireless data transmission will reduce the data collection rate, resulting in a decrease in the accuracy of subsequent data analysis. And the data storage cost of high collection rate is also relatively huge. And, data can often be highly private or sensitive. This is especially the case with data collected from medical sensors. For this reason, I learned about federated learning, and built a framework through federated learning to perform model training while measuring data to solve the problem of data transmission and storage.

Keywords:

Federated Learning, Raspberry Pi,, IoT, AI, Bio Snesor, Health care

I. Introduction

With the development of smart services and applications powered by artificial intelligence (AI), the Internet of Things (IoT) is permeating every aspect of our daily lives. There is a great need to advance the field of health informatics [2]. The world's population is aging due to increased life expectancy, which has put pressure on governments to finance expenditures related to population aging, especially in healthcare expenditures [3]. As a result, the need to reduce healthcare costs has increased, There is an increasing need to care for patients remotely from home, especially the elderly and those with physical disabilities. By leveraging the power of mobile technology and cloud computing, one can develop a health monitoring system where doctors can evaluate patients remotely from the comfort of their home. There is an increasing need to share health data among healthcare teams including doctors, nurses and family members. Some of the benefits of sharing health information include greater patient safety and better health outcomes, as health professionals gain a more complete picture of medical histories. However, medical data is relatively private and inconvenient to be transmitted online, and for the accuracy of diagnosis and treatment, the data collection rate is high, and the cost of data transmission and storage is relatively high. These problems can be solved by FL, which keeps both data and computation in distributed silos, and aggregates local computation results to train a global predictive model. All the data is stored locally, analyzed while measuring, and an early warning is given when there is an abnormality, so as to facilitate timely treatment. An architecture is proposed here, and the practical feasibility of the architecture is verified by using ECG data for joint learning to identify arrhythmia data.

II. Proposed Method And Result

2.1 Arrhythmia Database

The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample.

The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. Two or more cardiologists independently annotated each record; disagreements were resolved to obtain the computer-readable reference annotations for each beat (approximately 110,000 annotations in all) included with the database.

2.2 Data process

The EGG signal is weak, low-amplitude, low-frequency, and random, and is easily disturbed by noise. The noise may come from the living body, such as breathing and muscle tremors, or it may cause external interference due to poor contact. The main three types of noise in the ECG signal are power frequency interference, myoelectric interference and baseline drift 3, which are also the noise interference that needs to be suppressed and removed in the filtering process.

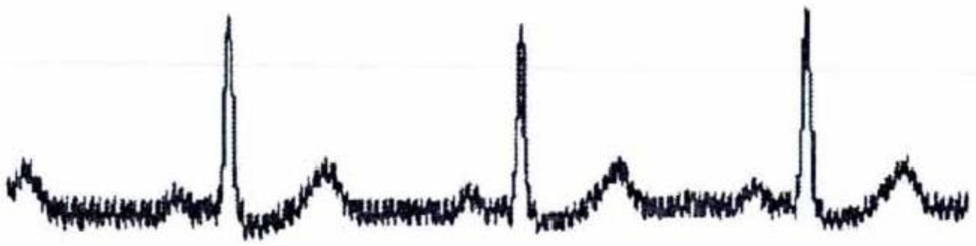


Fig.1. Power frequency interference: It is electromagnetic interference caused by the power supply environment around the equipment that collects ECG signals. The amplitude is low, and the noise frequency is about 50Hz. Its waveform is very similar to a sinusoidal signal. It also affects the detection of P and T waves.

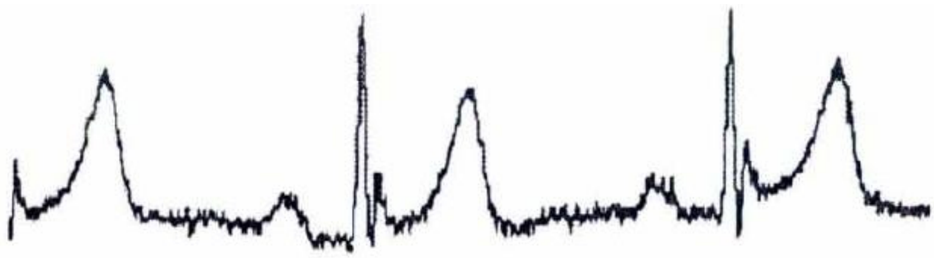


Fig.2. Electromyographic interference: In the process of ECG acquisition, it is caused by the involuntary trembling of human body muscles. This kind of interference is irregular. The waveform shape will change rapidly, the frequency is high, and the distribution is wide. The range is within 0-2000Hz. Concentrated within 30-300Hz, the duration is generally 50ms, and EMG and ECG signals will overlap together, which will cause subtle changes in useful ECG signals to be overlooked.

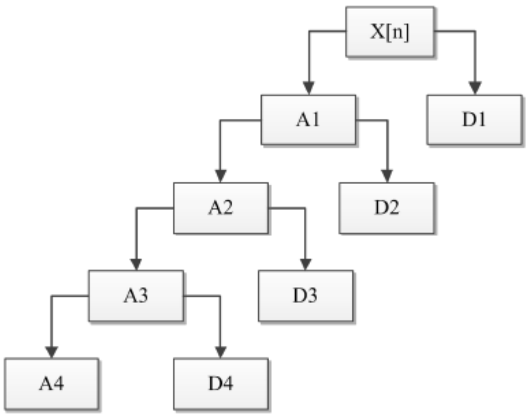
Fig.3. Baseline drift: It belongs to low-frequency interference, and the frequency distribution is within 0.15-0.3Hz. Due to the sliding change of the electrode position or the breathing movement of the human body, the ECG signal changes slowly over time and deviates from the normal baseline position to produce baseline drift. The amplitude and frequency will change all the time. with. The PR band and ST band in the ECG signal are very susceptible to distortion.

Wavelet Transform (WT) can perform time-frequency transformation, and is the most ideal tool for time-domain and frequency-domain analysis of signals. In this paper, the denoising processing method based on wavelet transform is used for the noisy ECG signal, which is divided into the following three steps:

Because the noise and the signal are mixed together, a wavelet basis function is selected first. Because the noise and the signal are mixed together, the wavelet transform is used to decompose the noisy ECG signal at a certain scale to obtain the wavelet coefficients on each scale.

After the ECG signal is decomposed by the wavelet transform scale, the wavelet coefficient with a relatively large amplitude is a useful signal, and the wavelet coefficient with a relatively small amplitude is noise. According to the frequency distribution of the ECG signal and mixed noise, the wavelet coefficient on each scale Threshold processing is performed, and the wavelet coefficients smaller than the threshold are set to zero or processed with a threshold function.

After processing the low-frequency coefficients and high-frequency coefficients after wavelet scale decomposition, the signal is reconstructed.



	Frequency Range (Hz)
D1	90~180
D2	45~90
D3	22.5~45
D4	11.25~22.5
D5	5.625~11.25
D6	2.8125~5.625
D7	1.40625~2.8125
D8	0.703125~1.40625
D9	0.3515625~0.703125
A9	0~0.3515625

Fig.4. 9 scale wavelet decomposition

After decomposing the original signal, we can know that the energy of the detail component of layer 1-2 is consistent with the high-frequency interference of the original signal. It shows that the 1-2 layer is the main place where high-frequency noise (power frequency interference and myoelectric noise) concentrates. Therefore, we need to filter out the detail components of the D1 layer and the D2 layer, and achieve the purpose of removal by setting them to 0. Then, the 3~9 layers of wavelet coefficients obtained by decomposing the signal are processed by the soft threshold formula to process the threshold of the signal.

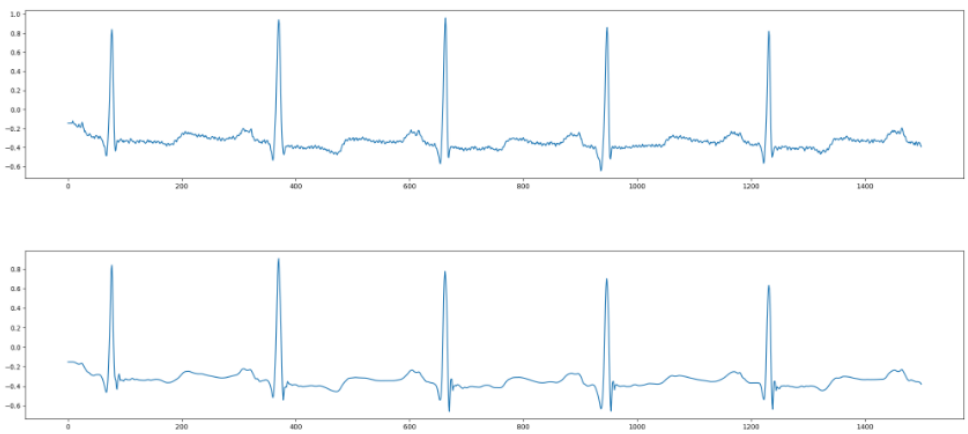


Fig.5. Noise reduction effect comparison

There are already preprocessed ECG data, but such data cannot be directly used for classification learning. So we need to first build a dataset that fits the deep learning model. The conversion process is to first cut out the heartbeat that meets the requirements from an ECG signal as a sample, and then go through disorder and segmentation to finally form a data set that can be used for deep learning.

Syncopation of heart beats requires finding where the QRS peaks are located. Since we only train the network model, we directly use the manual annotation provided by the MIT-BIH dataset, and take 99 signal points forward and 200 signal points backward at the peak to form a complete heart beat. If it is necessary to identify and classify the real measured signals, and design a heartbeat detection algorithm, I may continue to do it later.

The data set is divided into training set, verification set and test set according to the purpose. The training set is used to train the parameter model, the verification set is used to test the accuracy and error (loss function) of the model training, and the test set is used for the final test of the training effect after the training is completed. An analogy can be made to studying, quizzes, and exams. The data structures of the three are the same, but the content of the data contained is different. Each training set contains two parts: data and labels. The data is a list of several heart beats after preprocessing, and the label is the ECG type corresponding to each heart beat sample.

2.3 Deep Learning Neural Network (CNN)

An array of 92192 (total number of heart beats) is generated, each element is 300 signal points of one heart beat, and each element in lable Set is the label value corresponding to an array in dataSet (N (normal beat), L (left bundle branch block), R (right bundle branch block), A (atrial premature contraction), and V (ventricular premature contraction) corresponds to 01234).

The local model is constructed using a CNN model with a total of four convolutional layers each followed by a pooling layer.

```
=================================================================
Layer (type:depth-idx)                   Param #
=================================================================
EcgConv1d                                --
├─Conv1d: 1-1                            88
├─MaxPool1d: 1-2                         --
├─Conv1d: 1-3                            1,488
├─MaxPool1d: 1-4                         --
├─Conv1d: 1-5                            12,832
├─AvgPool1d: 1-6                         --
├─Conv1d: 1-7                            55,360
├─Flatten: 1-8                           --
├─Linear: 1-9                            311,424
├─Dropout: 1-10                          --
├─Linear: 1-11                           645
=================================================================
Total params: 381,837
Trainable params: 381,837
Non-trainable params: 0
=================================================================
```

Fig.6. CNN Model params

2.4 Federated Learning

Multiple existing studies have evaluated the applicability of installing FL on resource-constrained IoT devices such as Raspberry Pi. The results show that complex models (e.g., MobileNet) with millions of parameters are infeasible for such devices. For distributed learning or training of resource-constrained IoT devices, it is feasible to use 1D CNN models with fewer parameters to process sequential data. And it just so happens that ECG data is exactly 1D time series data. Therefore, I want to use FL to solve data transmission storage costs and privacy issues.

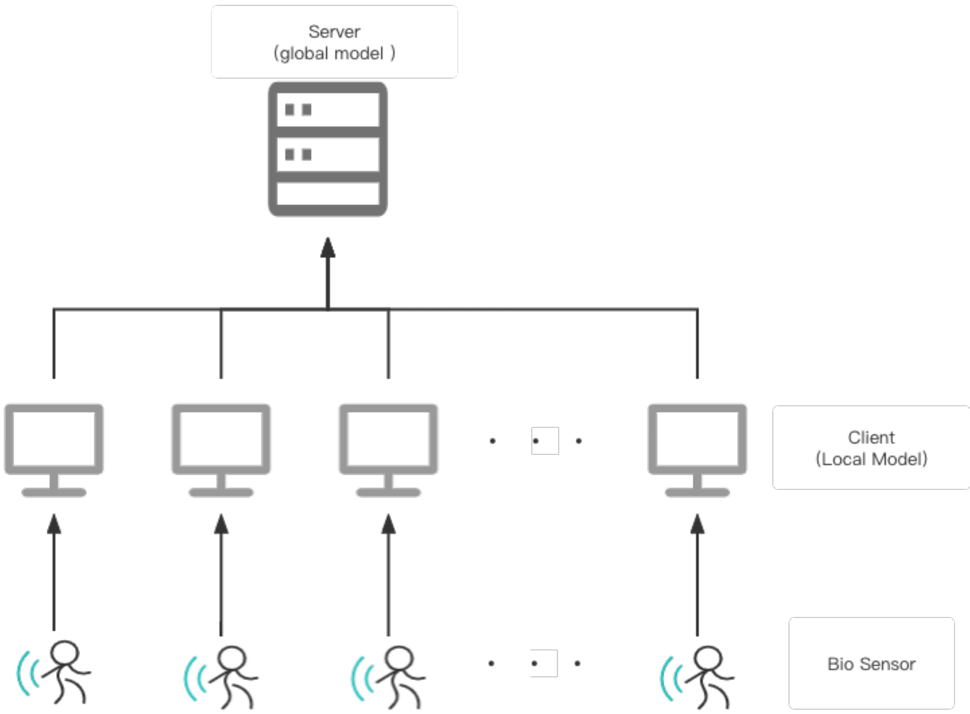


Fig.7. Schematic diagram of federated learning architecture

The FL is illustrated in Fig. 7. During the training process, the server first initializes the global model and sends it to all participating clients. After receiving the model, each client trains the global model by client. Afterward, each client returns the updated model to the server. The server then aggregates all those models to update the global model to get. The above process (often called round) repeatedly continues until the model converges. Here, in order to verify the feasibility, a simulation test is first carried out, using the ECG data prepared in advance instead of the data collected by the sensor in real time.

2.5 Result

After testing, the total communication data size is 45604046 bytes in the case of simulating five clients and one server. Compared with transmitting data, performing deep learning on the server effectively reduces the cost of transmission. After 400 rounds of training, the test results are (Accuracy of N: 99%, Accuracy of L: 99%, Accuracy of R: 99%, Accuracy of A: 59%, Accuracy of V: 98%). It can be seen that the ECG waveform classification results are not degraded much.

III. Conclusion

This paper proposes a deep federated learning framework for ECG heartbeat waveform data classification using IoT without sharing private data, thus protecting user privacy. And effectively reduce the cost of data communication. The results show a good percentage of classification accuracy for the model after the joint round. The goal of not sharing data and reducing the cost of data transmission and storage is achieved. And because people's physical state will continue to change, subsequent research on whether the accuracy of ECG classification will be affected can also be studied through this framework.

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