CardioLearn: A Cloud Deep Learning Service for Cardiac Disease Detection from Electrocardiogram

Shenda Hong\textsuperscript{1}, Zhaoji Fu\textsuperscript{1,2}, Rongbo Zhou\textsuperscript{1}, Jie Yu\textsuperscript{1}, Yongkui Li\textsuperscript{1}, Kai Wang\textsuperscript{1}, Guanlin Cheng\textsuperscript{1}
\textsuperscript{1}HeartVoice Medical Technology, Hefei, China
\textsuperscript{2}University of Science and Technology of China, Hefei, China

ABSTRACT
Electrocardiogram (ECG) is one of the most convenient and non-invasive tools for monitoring peoples’ heart condition, which can use for diagnosing a wide range of heart diseases, including Cardiac Arrhythmia, Acute Coronary Syndrome, et al. However, traditional ECG disease detection models show substantial rates of misdiagnosis due to the limitations of the abilities of extracted features. Recent deep learning methods have shown significant advantages, but they do not provide publicly available services for those who have no training data or computational resources.

In this paper, we demonstrate our work on building, training, and serving such out-of-the-box cloud deep learning service for cardiac disease detection from ECG named CardioLearn. The analytic ability of any other ECG recording devices can be enhanced by connecting to the Internet and invoke our open API. As a practical example, we also design a portable smart hardware device along with an interactive mobile program, which can collect ECG and detect potential cardiac diseases anytime and anywhere.

KEYWORDS
Deep learning, Healthcare, Electrocardiogram

1 INTRODUCTION
The Electrocardiogram (ECG) is one of the most convenient and non-invasive tools for monitoring peoples’ heart condition. It is a kind of physiological signal that records electrical activities of cardiac muscle over a period of time by placing electrodes and leads on the human body. ECG can use for diagnosing a wide range of heart diseases, including Cardiac Arrhythmia, Acute Coronary Syndrome, et al [2, 18]. It is estimated that more than 300 million ECGs are recorded worldwide every year [4], which is a tremendous amount of data for Cardiologists to analyze. Thus, many computer-aided ECG disease detection methods based on feature extraction and machine learning have been proposed over the past 50 years, and they have been used in commercial medical devices. However, existing commercial ECG disease detection methods still show substantial rates of misdiagnosis [3, 13, 14], due to the limitations of the abilities of extracted features, and the lack of generalizability which are tuned for their specific medical devices.

Recently, deep learning methods have shown great potential in healthcare and medical area [11, 16]. Specifically, there are some pioneer works that show successes of deep learning methods on ECG disease detection [1, 4, 6, 7, 15, 17, 19] (see [8] for a survey). However, these methods are still far away from practical applications because none of these models have been deployed for providing publicly available ECG disease detection services. Besides, most of these models only trained on single lead\textsuperscript{1} ECG data thus, they only support single lead ECG disease detection, which is insufficient in most medical area applications.

This demonstration provides CardioLearn, a publicly available out-of-the-box cloud deep learning service that can be used for cardiac disease detection from ECG. Any existing ECG recording devices can be enhanced with cardiac disease detection ability by connecting to the Internet and invoke our open API. To further demonstrate such practical usage, we also design a portable smart hardware device along with an interactive mobile program, so that people can easily collect their ECG records and detect potential cardiac diseases anytime and anywhere.

2 SYSTEM DESIGN
This section introduces our system in detail. We first introduce the details of our deep learning model and the performance tested on a publicly available open-source dataset. Then we show how we deploy the model and serve it as a cloud service.

The framework of CardioLearn is shown in Figure 1. We first build and train two deep neural network models to support applications in the healthcare environment (outside the hospital, usually single lead) and medical environment (inside the hospital, usually 12-lead). We are then serving the model by providing an open API using the HTTP protocol. Moreover, we also design a portable hardware device along with an interactive mobile program as a practical application.

\textsuperscript{1}Here “lead” means “channel”.

Figure 1: The workflow of CardioLearn ECG disease detection cloud deep learning service.
2.1 A Deep Learning Model for ECG Disease Detection

The ECG data usually has two forms of inputs, which are single lead (inside the hospital, see Figure 5) and 12-lead (outside the hospital, see Figure 6). Here “lead” has the same meaning as “channel”. To handle them both, we build two deep neural network models for each kind using TensorFlow. Their input layers are different, while the other layers remain the same. In detail, as shown in Figure 2, the input ECG recording is segmented into several short segments, and each segment goes through 32-layers of stacked one-dimensional convolutional layers (CNN) to capture local ECG patterns and shifts. One recurrent layer (RNN) is then built on top of the convolutional layers to capture long term variations. Finally, the model applies multiple dense layers (Dense) on the output of the recurrent layer to get the predictions of each disease. The objective of the model is a multi-label learning task because multiple diseases might occur in the same ECG recording. Moreover, we also introduce shortcut connections [5] at every two convolutional layers to address the problems of vanishing/exploding gradients when training a very deep neural network. The input dimension is downsampled at every four convolutional layers, and the number of filters increases at every eight convolutional layers. The CNNs have shared weights between segments.

![Figure 2: Model architecture.](image)

To train the deep model, we collected the training data from several hospitals, which are 12-lead ECG recordings lasting from 20 s to several minutes. The corresponding diagnosis results were written by cardiologists using narrative language; we extract keywords and integrate them into diagnostic labels based on standard ECG disease detection systems like [10]. We use Lead I as single lead data while also collect extra single lead data from mobile devices. Finally, our 12-lead model can support 43 types of diseases, and a single-lead model can support 18 types of diseases, both covering over 99% of total abnormalities in our training data. We optimize the loss function by reducing the learning rate by a factor of 0.1 when the validation performance is not improving for 5,000 batches of each task. We are continuously saving and updating the best model for each label as the final model.

We tested our model on a publicly available open-source dataset from 2018 China Physiological Signal Challenge [2] [9]. The challenge ECG recordings were collected from 11 hospitals sampled as 500 Hz, which contains 6,877 (3178 female, 3699 male) 12-lead ECG recordings lasting from 6 s to just 60 s. These recordings are never being used to train our model. We test the model performance on detecting Atrial fibrillation (AF), First-degree atrioventricular block (AVBI), Left bundle branch block (LBBB), Right bundle branch block (RBBB), Premature atrial contraction (PAC) and Premature ventricular contraction (PVC). We report the Receiver Operating Characteristic curve (ROC curve) and the area under ROC (ROC-AUC score) for each disease. The results are shown in Table 1 and Figure 3. We can see that both models achieve higher than 0.93 ROC-AUC scores on almost all diseases. We also notice that AF detection is even higher than 0.97.

![Figure 3: ROC curves on 2018 China Physiological Signal Challenge dataset.](image)

### Table 1: ROC-AUC scores on 2018 China Physiological Signal Challenge dataset.

|                | AF   | AVBI | LBBB | RBBB | PAC | PVC |
|----------------|------|------|------|------|-----|-----|
| Single Lead    | 0.957| 0.9508| 0.9597| 0.8927| 0.9343| 0.9578|
| 12-lead        | 0.9789| 0.9579| 0.9385| 0.9655| 0.9462| 0.9609|

2.2 Serving Deep Model as a Cloud Engine

We deploy our models using TensorFlow Serving [12] on four cloud servers. Specifically, we use the Java Client TensorFlow Serving gRPC API. Each cloud server is equipped with 4-core Intel Xeon Skylake 6146 3.2 GHz CPU 16GB RAM, and 3 Tesla P4 GPU for model inference. The information transmission between servers and clients is based on HTTP protocol. One request of HTTP including HEADER and POST. The HEADER includes content type like “JSON” and authorization information. The authority is a unique token given by the server. The POST is content type format includes sampleRate (HZ, sample frequency of ECG signal), adcGain (Analog-to-Digital Converter gain), dataI, dataII, dataIII, dataAVR, dataAVL, dataAVF, dataV1, dataV2, dataV3, dataV4, dataV5, dataV6 represents 12 standard leads. One can only fill in dataI and leave others null for requesting single lead model. The returned result is also in JSON format. One can easily parse the JSON result and integrate to their own systems.

The master server maintains a global task queue $Q$, which consists of all requests from clients. The task queue implements the First In First Out (FIFO) order. Each request contains authorization token $T$, analysis parameters $P$ (sampling rate, for example), and ECG data $D$. The disease detection process includes three steps: (1) authorization, (2) preprocessing, and (3) invoking deep model. Authorization validates the legality of the request by checking its unique token $T$. Once authorization success, the requests are added
into the $Q$ and wait for the computation resources. Then, the engine resamples the original ECG and removes high-frequency noise as well as low frequency wandering by band-pass filters. After that, the engine invokes GPU and inference to get the results. If any step raises exception due to some errors, the request is added into task queue $Q$ again and wait for the next round analysis. If the process fails or timeout, the server returns a failure execution information. Notice that models are served by multiple concurrent processes so that the time delay of retry is expected to be short.

We run the stress test to validate the performance of cloud serving using Apache Jmeter. We prepare 20,000 samples 12-lead 30 seconds ECG recordings. The number of concurrent processes of each server is set to 15. The results are shown in Figure 4. The left figure shows the distribution of process time, and we can see that almost 99% of requests can be returned within 2.5 seconds. This time cost shows a promising real-world application because it reduces one report of ECG disease detection from minutes (by Cardiologists) to seconds. The right figure shows the test summary. We can see that the total throughput is 11.5 records per second, which means CardioLearn can analyze nearly 1 million 30-second ECG recordings per day. Notice that when handing long term ECG recordings, we can still keep a comparable execution time, by cutting long term ECG recordings into short recordings and batching them, where each batch can contain hundreds of short recordings.

3 DEMONSTRATION

Our demonstration consists of two parts: 1) a website of an ECG analytic tool that provides an out-of-the-box cloud deep learning service, and 2) a portable hardware device to record ECG as well as an interactive mobile application to display results.

Figure 5 shows the webpage of the ECG analytics tool. It consists of three steps to get analysis results. First of all, users should provide necessary parameters of their ECG data, including sampling frequency, ADC Gain, and baseline voltage. Then, users have two ways to upload their ECG data: 1) upload comma-separated values (CSV) file from their computer or 2) copy and paste CSV file into the website textbox directly. Besides, we also provide a variety of ECG records as example data. Finally, after clicking “Analysis” button, the formatted ECG report, including ECG records and analysis results, shows on the bottom as in Figure 5. In the ECG report, the middle main part shows ECG recordings, with pink mesh grid background that helps cardiologists to measure and review the reports. The left bottom shows disease detection results given by CardioLearn, which is Atrial Fibrillation in this case. The upper part shows ECG measurements like PR interval, QRS width, et al., which also help cardiologists for a better review.

Figure 6 shows our portable hardware device and interactive mobile application. The portable hardware device weighs around 10 g, and the size is 75 mm length, 25 mm width, and 4.5 mm height, which is very convenient to carry on in daily life. A Bluetooth module is equipped on the chip for connecting with a mobile phone. The interactive mobile application is developed based on WeChat Mini Program so that it can support any mobile phone, including Android or iOS, if they can install WeChat. The usage is simplified to only one step: just put the user’s fingers on the metal electrodes and wait for 30 seconds. The device records ECG and sends the data to the application via Bluetooth transmission, the mobile application then sending the request to CardioLearn for analysis, and finally display the returned results on the user's mobile phone. The ECG records and results can also be retrospected from the mobile application.

4 CONCLUSION

In this paper, we introduce CardioLearn, a publicly available out-of-the-box cloud deep learning service for cardiac disease detection from ECG, which can help improve the analytic ability of existing ECG recording devices. Besides, we also design a portable
smart hardware device along with an interactive mobile program to demonstrate such practical usage. We wish everyone can easily and early detect potential cardiac diseases anytime and anywhere.

REFERENCES

[1] Zach I Atta, Suraj Kapa, Francisco Lopez-Jimenez, Paul M McKie, Dorothy J Ladewig, Gaurav Satam, Patricia A Pelikka, Maurice Enriquez-Sarano, Peter A Noseworthy, Thomas M Munger, et al. 2019. Screening for cardiac contractile dysfunction using an artificial intelligence–enabled electrocardiogram. Nature medicine 25, 1 (2019), 70.

[2] Tomas B Garcia. 2014. Introduction to 12-lead ECG: The art of interpretation. Jones & Bartlett Publishers.

[3] Maya E Guglin and Deepak Thatai. 2006. Common errors in computer electrocardiogram interpretation. International journal of cardiology 106, 2 (2006), 212–217.

[4] Awni Y Hannun, Pranav Rajpurkar, Masoumeh Haighpanahi, Geoffrey H Tison, Codie Bourn, Mintu P Taranakhi, and Andrew Y Ng. 2019. Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. Nature medicine 25, 1 (2019), 65.

[5] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Identity mappings in deep residual networks. In European conference on computer vision. Springer, 630–644.

[6] Shenda Hong, Meng Wu, Yulin Liu, Caiyun Ma, Shoushu Wei, Zhiqiang He, et al. 2018. An Open Access Database for Evaluating the Algorithms of Electrocardiogram Rhythm and Morphology Abnormality Detection. Journal of Medical Imaging and Health Informatics 8, 7 (2018), 1368–1373.

[7] Yanbo Xu, Siddharth Biswal, Shriprasad R Deshpande, Kevin O Maher, and Jimeng Sun. 2017 Computing in Cardiology (CinC). IEEE, 1–4.

[8] Shenda Hong, Cao Xiao, Edward Choi, and Jimeng Sun. 2018. Opportunities and challenges in developing deep learning models using electronic health records data: a systematic review. Journal of the American Medical Informatics Association 25, 10 (2018), 1419–1428.

[9] Jay W Mason, E William Hancock, and Leonard S Gettes. 2007. Recommendations for the standardization and interpretation of the electrocardiogram: part II: electrocardiography diagnostic statement list a scientific statement from the American Heart Association Electrocardiography and Arrhythmias Committee, Council on Clinical Cardiology; the American College of Cardiology Foundation; and the Heart Rhythm Society Endorsed by the International Society for Computerized Electrocardiography. Journal of the American College of Cardiology 49, 10 (2007), 1128–1135.

[10] Riccardo Miotto, Pei Wang, Shuang Wang, Xiaqian Jiang, and Joel T Dudley. 2017. Deep learning for healthcare: review, opportunities and challenges. Briefings in bioinformatics 19, 6 (2017), 1236–1246.

[11] Christopher Olston, Noah Fiedel, Kiril Gorovoy, Jeremiah Harmsen, Li Lao, Fang-wen Li, Vinu Rajasekhar, Sukriti Ramesh, and Jordan Soyke. 2017. Tensorflow-serving. Flexible, high-performance ml serving. arXiv preprint arXiv:1712.06139 (2017).

[12] Jürg Schläpfer and Hein J Wellens. 2017. Computer-interpreted electrocardiograms: benefits and limitations. Journal of the American College of Cardiology 70, 9 (2017), 1183–1192.

[13] Supreeth P Shashikumar, Amit J Shah, Gari D Clifford, and Shamim Nemati. 2018. Detection of paroxysmal atrial fibrillation using attention-based bidirectional recurrent neural networks. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. ACM, 715–723.

[14] Cao Xiao, Edward Choi, and Jimeng Sun. 2018. Opportunities and challenges in developing deep learning models using electronic health records data: a systematic review. Journal of the American Medical Informatics Association 25, 10 (2018), 1419–1428.

[15] Yangho Xu, Siddharth Biswal, Shriprasad R Deshpande, Kevin O Maher, and Jimeng Sun. 2018. Raim: Recurrent attentive and intensive model of multimodal patient monitoring data. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. ACM, 2563–2573.

[16] Frank G Yanowitz. 2012. Introduction to ECG interpretation. LDS Hospital and Intermountain Medical Center (2012).

[17] Jürg Schläpfer and Hein J Wellens. 2017. Computer-interpreted electrocardiograms: benefits and limitations. Journal of the American College of Cardiology 70, 9 (2017), 1183–1192.

[18] Jürg Schläpfer and Hein J Wellens. 2017. Computer-interpreted electrocardiograms: benefits and limitations. Journal of the American College of Cardiology 70, 9 (2017), 1183–1192.

[19] Supreeth P Shashikumar, Amit J Shah, Gari D Clifford, and Shamim Nemati. 2018. Detection of paroxysmal atrial fibrillation using attention-based bidirectional recurrent neural networks. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. ACM, 715–723.

[20] Cao Xiao, Edward Choi, and Jimeng Sun. 2018. Opportunities and challenges in developing deep learning models using electronic health records data: a systematic review. Journal of the American Medical Informatics Association 25, 10 (2018), 1419–1428.

[21] Yuxi Zhou, Shenda Hong, Junyuan Shang, Meng Wu, Qingyun Wang, Hongyan Li, and Junqing Xie. 2019. K-margin-based residual-convolution-recurrent neural network for atrial fibrillation detection. In Proceedings of the 28th International Joint Conference on Artificial Intelligence. AAAI Press, 6057–6065.