Building Electronic Health Record using Voice Recognition and Big Data Techniques

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Keywords: EHR, Voice Recognition, Microsemi, Raspberry Pi, Text mining, Classification

Abstract: Electronic Health Record (EHR) is a foundation for any intelligent diagnose and medical data analytics. In our previous research, we discovered that the existing EHR in clinic mainly manually created by physicians are seriously fraud. They are too sample, containing serious mistakes and far from accurate. It causes great difficulties for any intelligent diagnose and medical data analyses. This paper reports our efforts in an attempt to automatic and semi-automatic EHR creation. We have adopted an advance AI techniques in voice recognition and text mining in order to build a prototype of "doctor's assistant", which can record conversations between a doctor and a patient, then the recorded voice file is further converted into a text file. With text mining techniques, the key symptom described by a patient is abstracted and converted into structured data. EHR will be generated automatically for doctors' approval. This will greatly reduce doctors' workload and increase the accuracy and quality of EHR.

1. Introduction

In our previous research on "Efficiency of TIVPDS Treatment on Cancer Patients and the Impact on Patients' quality of life through BDA" [1, 2], we have discovered that the most authentic and initial data which is the patients' health records, are seriously fraud. They content inaccurate data, missing information and even serious wrong data. This is because, firstly, doctors have no motivation to fill detailed records after a conversion with a patient, secondly, doctors under huge pressure both in time and responsibility. Among a 10 minutes time slut for a patient, doctors only have maximum of 3 minutes to fill a page long EHR, where the patients' description of an illness may take half page. Thirdly, the doctor can only do it after a patient left the office by memory. Lastly, it is a boring, tedious and repeated action. Doctors' normal practice is copy-and-paste from an existing EHR. These all together make EHR have no meaningful usage. To improve the quality and accuracy of EHR for any further clinical and medical analyses and treatment improvements. Automatic or semi-automatic EHR creation is vital. There are some approaches have been taken in this front. Baowaly, Mrinal Kanti et al implement a synthetic method including medical Wasserstein GAN with gradient penalty (medWGAN) and medical boundary-seeking GAN (medBGAN) to improve EHR quality [3]. Murray, Sara G et al adopt a machine leaning method, which allow for automated "noisy labeling" of positive and negative controls to create a "silver standard" in EHR [4]. Walonoski, Jason et al create an open source software called Synthea, which can auto generate synthetic patients' EHR for the 10 most frequent reasons for primary care encounters and the 10 chronic conditions with the highest morbidity. They can be sued for research and insurance claims analyses [5]. These research have one thing in common is that the recognition of the poor quality and inaccuracy of the existing EHR and trying to improve them.

2. Design of Doctors' Assistant

To construct a doctor's assistant, a prototype has been designed. The overall goal of the system is to automatically or semi-automatically generate a patient's EHR. For normal illness the EHR should be generated automatically and in some special case it can generate up to 80% of the required fields, doctor can edit and modify inaccurate part. Once a doctor made a modification the system should learn from it and make use of it in the next EHR generation. The system architecture is illustrated in Figure 1. It has three major components: voice recording device, voice-to-text convertor and text mining module.

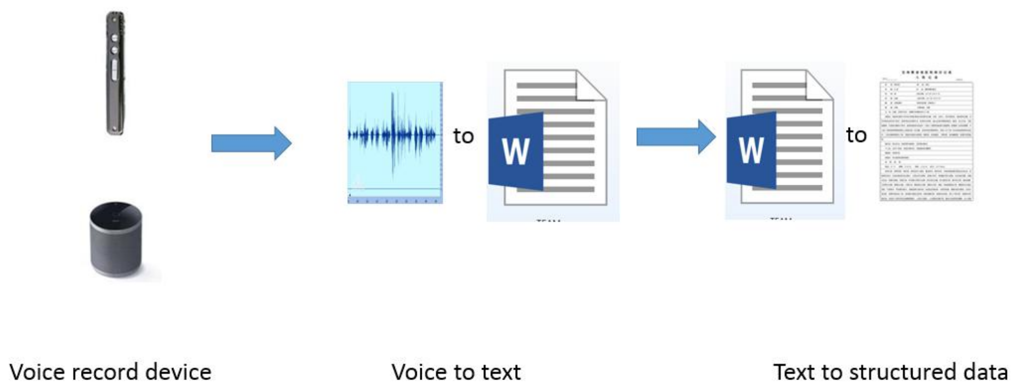

Figure 1. The structure of the doctor's assistant

2.1. Voice Record Device

To record doctor-patient voice conversation, we have used Microsemi ZLK38AVS. It is a developing environment supporting programming in voice recording, sound signal filtering and noise removal. In addition, it can link to Amazon Alexa, the voice recognition module. ZLK38AVS includes serval functions illustrated in Figure 2. It is used a sandbox for testing English voice recognition. Microsemi ZLK38AVS can record voice conversation up to 30 minutes and translate them into text in an internet-connected computer.

Figure 2. Microsemi ZLK38AVS with the components' explanation

To increase flexibility, we add a temporary storage function so it can also be used off-line. To do this a flashed SD card is installed in the Raspberry pi3 single board computer. With this SD card, voice record device can be used separately. In case a doctor needs to visit a patient where no Internet connection available. The doctor can then record the conversion and bring SD card back to office.

After plug into a computer system the recorded voice file can be converted into text for further process.

2.2. Voice to Text Conversion

To convert voice recording into a text file, instead of using Alexa, a voice recognition module from Iflytek is used. This is because it can recognize Chinese oral language. Iflytek API provides Automatic Speech Recognition (ASR) function both in the Android and Linux systems. We tested both APIs in our application. However, because our application is built based on Raspberry Pi3 which operates on Linux system, we only used Linux API.

2.3. Text to Structured Medical Record

The core part of this research is convert captured text conversation into clinical symptom and finally fill in EHR. The text file obtained from the doctor-patient conversation contains large amount of non-medical description. It needs cleaning, filtering, conversion and text mining. So that a patient self-description of his or her illness can be abstracted. Because of the high rate of semantic ambiguity in Chinese oral language, we have adopted three methods to accomplish this task. The detailed is illustrated in Figure 3.

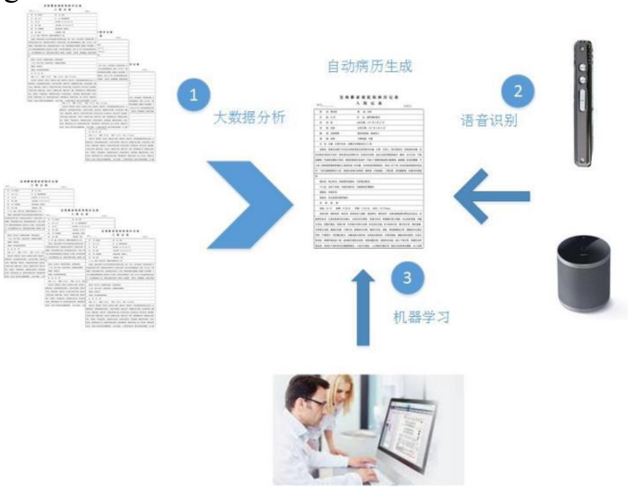

Figure 3. Text to EHR generation

Apart from voice recognition module, we need to build sample EHR from existing medical records which were generated by the physicians. Big data analytics techniques such as classification algorithms were used. We started using words to victor methods and then adopted CART classification algorithm in our approach. To train our classifier, large amount existing medical records (3000) have been used. Among those 3000 cases being collected, we selected 543 cases that were diagnosed as “Obstructive jaundice” and other kinds of biliary diseases. In order to prevent overfitting of the CART algorithm, attributes with 40% noisy data were not selected to the dataset. The analysis of patients’ oral description only 5 categories were focused: “skin”, “appetite”, “mental health”, “abdomen” and “body temperature” as shown in Figure 4.

Skin	Mental	Appetite	Excrement	Urinate	Stomach	Body Temperature	Diagnosis
Skin sclera yellow stain	Weak	Anomaly	Normal	Normal	Normal	Normal	Obstructive jaundice, Pancreatic head occupying
Normal	Normal	Normal	Normal	Normal	Normal	Normal	Obstructive jaundice after PTCD surgery,
Normal	Weak	Anomaly	Normal	Acceptable	Normal	Normal	Cholangiocarcinoma
Skin and sclera yellow stain (Disappear obscurely)	Weak	Acceptable	Normal	Thick	Normal	Normal	Obstructive jaundice, Hepatic hilar cholangiocarcinoma
Yellowish skin (Discharged)	Weak	Slightly	Terracotta	Thick	Pain in the abdomen	Normal	Obstructive jaundice, Hepatic hilar cholangiocarcinoma
Itchy skin	Normal	Acceptable	Normal	Normal	Normal	Normal	Obstructive jaundice, Pancreatic cancer? Bile duct stones? Cholangiocarcinoma?

Figure 4. Final sorted results of different cases

In CART decision tree algorithm Gini index was used. CART is a binary decision tree. To classify multiple labels a recursive process was adopted. Gini index for every attribute were computed and the attribute with the minimum Gini index was selected as the first split and the next minimum and so on to achieve a global optimal. Gini index measures the divergences between the probability distributions of the target attribute's values. To compute Gini index of each attribute, the following equation was used:

$$Gini(y,S) = 1 - \sum_{c_j \in dom(y)} \left(\frac{\left|\sigma_{y=c_j} S\right|}{|S|} \right)^2$$

To select a best split, to following equation was used:

$$GiniGain(a_i,S) = Gini(y,S) - \sum_{v_{i,j} \in dom(a_i)} \frac{\left|\sigma_{a_i=v_{i,j}} S\right|}{|S|} \cdot Gini(y, \sigma_{a_i=v_{i,j}} S)$$

3. Conclusion

This paper reports our effort to solve EHR inaccuracy problem by create a voice recognition based auto EHR generator. With the help of a voice recording device from Microsemi, which provides a native support of connection to an online voice recognition service, in addition with the voice recognition API provided by Iflytek, they enable us to apply big data techniques to convert doctor-patient conversation into structured EHR. Our initial experiments demonstrate the feasibility of the device which can not only record the conversion but also can automatically fill the EHR as medical practice required. However, our initial module demands reliable and fast internet connection. It also requires high quality voice recordings which means the conversion has to be in a quiet and noise free environment. Although it is possible to store a small amount voice recording into a SD card but it is not enough to support doctors' daily practice. However, with our application of CART decision tree classifier, we managed to achieve the accuracy of 72% EHR auto filling. Our plan is to plug in machine learning methods to further increase our accuracy and EHR coverage. After initial clinical trial, it is evident that it can provide a convenience and efficacy in creation of EHR. Compare with manual filling EHR, it can increase efficiency by 82%. We strong believe with machine learning methods, which we plan to do next, the doctors' assistant would achieve its higher usage value.

Acknowledgement

This research project was supported by the fund provided by the Research Institute of Big Data

Analytics (RIBDA), Xi'an Jiaotong-Liverpool University and 2018 Suzhou Science and Technology Development Planning Programme with project number: SYG201840.

References

[1] Li Gangmin, Gu Jianze and Bai Xuming (2018). "*Study of the Effectiveness of TIVAPDS Treatment on Cancer through BD*", ICSAI2018, Nanjing, China, 10-12th Nov, 2018. Due to publish on IEEE Conference Record Number 46413XP, ISBN: 978-1-7281-0119-4.
[2] Li Gangmin and Zhang Shiyang (2018), "*Evaluate Cancer Patients Quality of Life after Receiving TIVAPDS Treatment through Big Data Analytics*", CICET'2018, 29-31 Oct 2018, Tamsui Campus, Tamkang University, New Taipei, Taiwan, paper 28
[3] Baowaly, Mrinal Kanti; Lin, Chia-Ching; Liu, Chao-Lin; Chen, Kuan-Ta. "*Synthesizing electronic health records using improved generative adversarial networks*", Journal of the American Medical Informatics Association. Mar 2019, Vol. 26 Issue 3, p228-241.
[4] Murray, Sara G; Yazdany, Jinoos; Avati, Anand; Schmajuk, Gabriela. "*Automated and flexible identification of complex disease: building a model for systemic lupus erythematosus using noisy labelling*", Journal of the American Medical Informatics Association. Jan2019, Vol. 26 Issue 1, p61-65.
[5] Walonoski, Jason; Kramer, Mark; Nichols, Joseph; Quina, Andre; Moesel, Chris; Hall, Dylan; Duffett, Carlton; Dube, Kudakwashe; Gallagher, Thomas; McLachlan, Scott. "*Synthea: An approach, method, and software mechanism for generating synthetic patients and the synthetic electronic"*, Journal of the American Medical Informatics Association. Mar 2018, Vol. 25 Issue 3, p230-238.