Evolving Health Consultancy by Predictive Caravan Health Sensing in Developing Countries

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Abstract
In this paper, we introduce the predictive way to evolve the process of the health consultancy by predictive methods with machine learning. We have tried health consultancy for over 22,000 patients with caravan health sensing in Bangladesh during 2012-2014. In health consultancy with caravan health sensing, doctors' task becomes the bottleneck of the whole process because of the cost and the huge workload, and we try to delegate some of them to health workers who are less skilled. In this paper, we propose a method to predict the advices of doctors from the inquiry, vital data, and the chief complaints of the patients, and to delegate the task to health workers, resulting in eliminating the bottleneck. We also evaluate the accuracy of the prediction of advices from the 931 patients who have taken the doctors' consultancy out of the above experiment. We got the predict accuracy 76.24% with inquiry and vital data, and 82.55% with adding chief complaints data.

Author Keywords
Pervasive Healthcare; Caravan Health Sensing; Remote Healthcare Consultancy; Preventive Healthcare in Developing Countries; Electronic Health Records (EHR); Clinical Decision Support; Machine Learning

Introduction

In a developing county, its health/medical infrastructure has many problems. It is difficult for people in the country, especially lived in rural area to access a medical service [17] because doctors do not find their livelihood requirements fulfilled and do not want to stay in the village. On the other hand, the mobile network spread rapidly in developing countries. Health consultancy over the mobile phone is popular in developing countries such as Bangladesh and provides an alternative solution for partial healthcare delivery [3]. However, these mobile health services do not test the patient against a diagnosis process or use Electronic Health Records and this reduces the impact of the diagnosis.

A caravan-style health checkup, called Portable Health Clinic [11, 13] is one of the solution. Health workers without doctors bring a medical attache case to the checkup site including rural area. The attache case includes tablet PCs, medical sensors and measuring equipment. The worker takes subjects' physical checkup using the attache case and the tablet PC of the case classifies subjects into four colors. The orange (affected) and red (emergency) marked subjects consults with a call center doctor using Skype. The call center doctor gives advices to the subjects based on the checkup result, Question sheet, and tele-conversation.

Although the activity of caravan health sensing produces good evidence for improving the health of the patients [10], it has a bottleneck on the work of remote doctors whose salary and costs are relatively higher than other health workers who works in the local area. From the experimental data analysis, the remote doctors spend about 14 minutes for each patient. The minutes include mostly to listen the Chief Complaints (*CC*s) of patients, and also advices to them. The problem is that while the doctors have these work, other health workers have less tasks. Delegating the task of doctors to other health workers with the doctor's knowledge transferring to the health worker assisted with data analysis is highly demanded.

We attempt to delegate part of doctor's tasks to health workers by two methods of the proposed system: (method 1) predicting advices from inquiry data and vital data which are already collected in the existing caravan health sensing, and (method 2) enhancing the predictability by also collecting CCs by health workers. These methods enable health worker to give the advices to the patients instead of the doctors. Method 1 provides an algorithm to predict the advice from the inquiry data and vital data. Even if the system fails the prediction, the doctor can follow up later by checking whether the predicted advice is correct or not and giving or revising the advice for each advise. Method 2 provides the algorithm to improve the prediction accuracy adding the CC data. This method increases the tasks of the health workers, but aims at reducing total cost of the process by reducing the doctor's labor.

In this paper, we introduced the predictive way to evolve the process of the health consultancy by predictive methods with machine learning. Using the health checkup and health consultancy data held for around 22,000 patients with caravan health sensing in Bangladesh. We proposed a method to predict the advices of doctors from the inquiry, vital data, and the Chief Complaints of the patients, and achieved 76.24% with inquiry and vital data, and 82.55% with adding Chief Complaints data. This result can be utilized to delegate the doctors' task to health workers, resulting in eliminating the bottleneck of the whole process of caravan health sensing.

Related Work

There have been a lot of effort for the improvement of healthcare in developing countries. In Bangladesh, it has gained a large progress in the past decade [5], including A proposal of multi-paths of services to people [4], generating communities to deliver health services to more people [7], and a challenge for universal health coverage [1], which also reached on healthcare for children [2], public health activities which helped to mitigate the health effect of natural disasters [14].

In such a developing country, mobile computing, technology provides an innovation in public healthcare. Ramachandran et al. [16] did a trial to prevent diabetes by mobile phone messaging about lifestyle modification.

On the other hand, in the medical research field, Clinical Decision Support System (*CDSS*) has been proposed and developed for long years [8], for effective and precise medical service. One of the challenges of CDSS is to automatically diagnose patients' diseases. In the early stage it was designed by static rule-based approaches [9].

Additionally, recently, there are increasing number of works for automatically modeling the rules or projections, by machine learning or data mining techniques [12, 15, 19].

Furthermore, natural language processing techniques are expected to be utilized for clinical data analysis [6, 18].

Predictive Method for Caravan Health Sensing and Consultancy

In this section, we introduce our approach to predict the advices and to improve the prediction accuracy rate. We apply the machine learning method to predict the advices from inquiry data, vital data and the chief complaints of the patients which were archived by caravan healthcare sensing project. The final goal of this research is to delegate the task to health workers, reducing the hard work of remote doctor which becomes a bottleneck of the whole process. Breaking the bottleneck, we attempt to improve the efficiency of caravan healthcare sensing.

How it works?

We attempt to delegate part of doctor's tasks to health workers by two methods of the proposed system: (method 1) predicting advices from inquiry data and vital data which are already collected in the existing caravan health sensing, and (method 2) enhancing the predictability by also collecting CCs by health workers. These methods enable health worker to give the advices to the patients instead of the doctors. Method 1 provides an algorithm to predict the advice from the inquiry data and vital data. Even if the system fails the prediction, the doctor can follow up later. Method 2 provides the algorithm to improve the prediction accuracy adding the CC data. This method increases the tasks of the health workers, but aims at reducing total cost of the process by reducing the doctor's labor.

Fig.1 is the overview of the proposed method. We assume the health workers and the doctors to use our methods in the following way:

1. First, a health worker gets CCs from the patients, in addition to inquiry data and vital data in the current process. We assume to prepare specific questions for each CC word which is extracted from the dataset. For example, if "pain" is the effective CC word, we include "Do you have any pain in your body?" in advanced questionnaire. Thus, a health

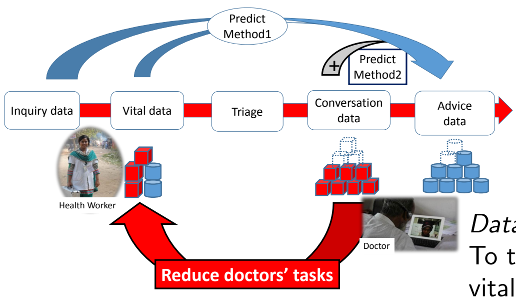

Figure 1: Proposed solution

worker can ask advanced questionnaire based on the selected CC words.

2. Next, the proposed system predicts whether the patient needs the advice or not based on the predictive model trained by the dataset of the past inquiry, vital, and selectively CC words.
3. Health worker can give the advice to the patients following the prediction of the system.
4. The doctor can skip the advices which are correctly predicted by the system and given by the health worker. S/he can be OK with checking the advice was correct, and compensate if there is a false in the given / ungiven advices. This compensation is expected to be lighter than the traditional consultation, given the accurate prediction rate than specific level.

Dataset and environment of experiment
To train the model for predicting advices from inquiry, vital, and CC data, we utilize the dataset collected in the experiments in the large-scale field in Bangladesh. Here, we explain about the dataset.

We archived 8527 patient records from the caravan health sensing project in 2012. 1635 patients were categorized into the more risky group who need the remote healthcare. Our research use 931 records our of 1635 records which archived all healthcare records.

Data types
We mainly archived 4 types of data. We summarize and describe the preprocessing of data as followings:

1. Inquiry data: containing lifestyle or past disease information We asked 32 questions for the patients.

   The answers contain categorical data. For instance, "Q: Do you take any of the following medicines periodically?Anti hypertensive?" and the answer is either "Yes" or "No". We factored these categorical data into a boolean.
2. Vital data: collected by the system equipped with vital measures. We recorded 19 checkup items. Some of the results are continuous data such as blood pressure, and the others are categorical data such as urine test result.
3. Conversation data between a patient and a doctor: We also archived the conversation data as free text data. These data are text, so the analysis is not straightforward. We extract each word from the text data and make it a word vector for analysis.

   For example, The sentence of "occasional headache for 1 year" becomes the vector which has a positive value corresponding to the dimension of "occasional", "headache", "for", "1", and "year". After that, we count the frequency of each word, took the 131 words which has more than 5 times frequency by heuristics, and constructed the binary word vectors for 131 words.

   But there are many meaningless words such as 'after', 'ho', and 'with' in the 131 words, For simplicity, we didn't apply any algorithm to filter out these words, but in a future work, it will be a possibility to improve the performance of our methods.
4. Advice data: that has been suggested by the doctor to the patient. The system which is used by remote doctor can provide the selection for the advice in Bengali language. The remote doctor can select the

Words

abdomen, abdominal, acidity, after,
alergy, allergy, anorexia, antihtn,
antihypertensive, anxiety, appetite,
asthma, back, bleeding, blood, body,
bodyache, both, bp,
burningsensation, case, chest, cold,
complaints, constipation, cough,
days, decrease, discharge,
discomfort, distress, dm, drug,
drugs, duration, during, easy,
epigastric, eye, feet, fever,
feverish, frequency, from, g,
gastritis, generalized, glucose,
grade, hand, headache, headeche,
heart, high, hip, ho, hot, htn,
hypertension, increase, increased,
insomnia, insulin, irregular, is,
itching, joint, joints, knee, known,
lbp, left, leg, leucorrhoea, level,
limb, loss, low, lower, medication,
menstrual, micturation, micturition,
mild, month, months, multiple, n,
nausea, neck, nocomplain,
nocomplaints, noho, nospecific, not,
obesity, occasional, occasionally,
oha, or, oral, over, pain,
palpitation, pattern, per, pressure,
problem, pt, pud, pv, region,
respiratory, right, same, several,
side, skin, sleep, sometimes,
sweating, swelling, taking, times,
to, uncontrolled, upper, urine, uti,
vertigo, weakness, weight, which,
whitish, whole, with, work, year

Figure 2: Chief Complaints word list

common advice and give it to patient easily thanks to this advice-selection system. We hereby consider these selection types of advice as advice data. On the other hand, the doctor sometimes adds the free text data to give the advice for the patient. We hereby show an example which is mixed selection type and free text advice type: "Go through the following checkup/test and if needed to see the nearest specialist doctor —Fasting Blood Sugar". The sentence without underline is the selected part, and the one with underline is a free text.

Method 1: Prediction for Advice
We try to predict the advice with method 1 using the inquiry data and the vital data as input data and advice data as output data. The machine learning algorithm can be applied for the prediction of advices. We show the procedure for the Method 1 as followings.

1. Prepare the dataset. It consists of 32 inquiry variables and 19 vital variables for input, and 21 advice variables.
2. For each advice variable,
   (a) train the SVM model to predict the advice by linear kernel, by 2-fold cross validation. Meanwhile, the positive training data are augmented (copied) to balance between the number of negative data.
   (b) Calculate the accuracy rate as the following, after reducing the number of positive data to the original:

$$Accuracy = (\frac{TN}{TN+FP}+\frac{TP}{TP+FN})\times\frac{1}{2}\times 100 \quad (1)$$

   where TP, TN, FP, FN is the rate of each cell in the confusion matrix.

We get the prediction accuracy score for each of 21 advices. When predicting advices, we can apply the trained model for each advice for the input inquiry and vital variables.

Method2: Improve the prediction accuracy, using CC data
We expand the Method 1 to improve the prediction accuracy adding CC data to input data.

1. Calculate the Odds ratio and rank the importance of CC words
2. Prepare CC data by extracting words in the way explained in the previous section.
3. Add CC word one by one to the dataset which is used for Method 1. As well, 32 inquiry variables,19 vital varies, CC variables, and 21 advice variables are used.
4. For each advice variable, By logistic regression, estimate the advice variese, and calculate the odds ratio for each CC variable out of 137 by the following formula.

$$Odds\ ratio = \frac{TP/FN}{FP/TN} \quad (2)$$

   where TP, TN, FP, FN is the rate of each cell in the confusion matrix.
5. Get the mean odds ratio among 21 CC variables.
6. Order the CC variables by the mean odds in the decreasing order.

Advice No.	Advice
Ad1	Walk or do physical exercise regularly
Ad2	Check blood pressure every week regularly. If pressure is not normal for a few weeks, see the nearest doctor.
Ad3	Check diabetes every month and if not normally see the nearest specialist doctor.
Ad4	Drink lots of water
Ad5	Continue current medicine as usual
Ad6	Walk 30 minutes regularly
Ad7	Take the medicine regularly as per instruction
Ad8	Go through the following checkup/test and if needed to see the nearest specialist doctor.
Ad9	Do not bend down to work
Ad10	Do not smoke
Ad11	Avoid tension and live easy
Ad12	Avoid oily food; eat less fat and less spicy foods
Ad13	Take FBS (Fasting Blood Sugar) test to confirm diabetes. If needed see the nearest specialist doctor.
Ad14	Comply with the diabetes diet plan.
Ad15	Do not take raw salt with meal.
Ad16	Use high commode in toilet
Ad17	Eat more vegetables
Ad18	Avoid soft bed and prefer hard mattress
Ad19	Check your pressure after 7 days. If the pressure is not normal, see the nearest doctor.
Ad20	Do not eat sweets.
Ad21	Do not lift heavy weight

Table 1: Advice list

7. Predict advices with inquiry, vital, and CCs
8. For k in 1 to the number of CC words,
   (a) picks up the CC words of the top k odds rates.
   (b) applies the same steps with method 1 adding the picked CC words.

We get the prediction accuracy score for each of 21 advices, for increasing numbers of added CC words. When predicting advices, we can apply the trained model for each advice for the input inquiry, vital, and CC variables.

Evaluation

In this section, we try to evaluate the our approach by simulating doctors' time when they have the conversation with the patient and give advice to them. We can get the

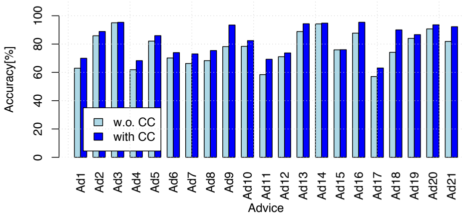

Figure 3: Accuracy of predicting each advices by method 1 and 2

result that the PHC process will be improved by our approach.

Fig.3 (w.o. CC) is the accuracy of predicting each advices from inquiry and vital data by method 1. On average, it achieved 76.24% ($\sigma = 11.43$), with 56.80% of minimum and 94.41% of maximum.

We look the trends in the accuracy rate looking into each advice. Predicting by only inquiry data and vital data, Ad2, Ad3, Ad5, Ad16, Ad19 and Ad20 marked high score. (more than 80%) Almost all advices (extracting Ad16 and Ad 20) are for high blood pressure. These types of advices can be easily predicted by only inquiry data and vital data.

Improvement by adding CCs
Fig.3 (with CC) is the accuracy of predicting each advices from inquiry and vital data by method 1. On average, it achieved 82.65% ($\sigma = 10.48$), with 61.72% of minimum and 95.44% of maximum. Compared to method 1, it outperformed 6.41% on average.

Fig.4 is the improvement of predicting each advice with gradually adding CC. From the figure, several advices remains low accuracy around 60%, but some improves by adding CCs up to around 20 CCs. On average, it reaches over 80% around CCs.

We look the trends of the accuracy rate in detail. Predicting by the method 2, Ad9, Ad18 and Ad21 improved a lot compared to Method1.(more than 5%). All the advices are related to the pain.

In the end, we can say that it is possible to predict advices with the result of Method1, and the results of Method 2 shows that the better accuracy rate adding CCs.

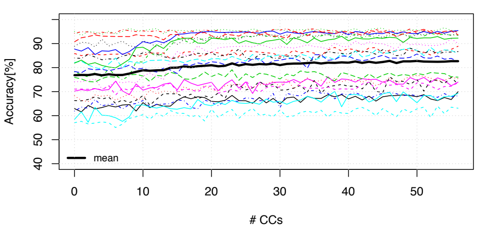

Figure 4: Accuracy of predicting each Advice with CC

Conclusion

In this paper, we introduced the predictive way to evolve the process of the health consultancy by predictive methods with machine learning. Using the health checkup and health consultancy data held for around 22,000 patients by caravan health sensing in Bangladesh, we proposed a method to predict the advices of doctors from the inquiry, vital data, and the chief complaints of the patients, and achieved 76.24% with inquiry and vital data, and 82.55% with adding chief complaints data. This result can be utilized to delegate the doctors' task to health workers, resulting in eliminating the bottleneck of the whole process of caravan health sensing.

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