Heart Disease Classifier

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Abstract

Heart disease is one of the most serious health problems for people nowadays. To detect heart disease in a faster and more accurate way can help Singaporeans increase health standard. Based on the aforementioned consideration, we propose an application which is meant for analysing and predicting the heart disease. To implement this application, we trained specific machine learning models on three different datasets. In overall, we tried five models including LTSM, GBDT, Naive Bayes, SVM and Logistic Regression, and picked GBDT for the first and second datasets and LSTM for the third dataset based on their better performance. Our application is believed to have good performance and reliability based on the experiments we have done so far, and thus might help Singaporeans to live a better life with respect to heart disease issue.

Introduction

Health is always the most concerned topic of people. A statistical data collected from more than 190 countries shows that every year 17.3 million deaths are related with heart disease, which remains the No. 1 global cause of death (Heart Disease and Stroke Statistics 2015). According to a study, Singaporeans suffer heart failure about 10 years earlier than Americans and Europeans, and nearly 1 in 3 Singaporeans are dying from heart disease. In order to increase the average health standard for Singaporeans, one of the best way is to examine peoples heart condition early and find the pathogeny accurately. In this report we are going to introduce an application which can help analysing and predicting the heart disease in two specific aspects: Cardiac Arrhythmia and Cardiovascular diseases. We first collect the basic information about patients such as age, gender, resting blood pressure and so on give a general diagnosis (first step). Then we will further examine the heart rhythm (second step) and heart sounds (third step) of patients. The diagnosis of heart rhythm is classified into 13 classes and diagnosis of heart sounds is classified into 3 classes. Based on these 3 steps and detailed classifications, doctors can have more confidence to give a accurate analysis result, which also help curing patients correctly and effectively.

To achieve this goal we use 3 datasets, one dataset for each step. The first dataset dates from 1988 and consists of four databases: Cleveland, Hungary, Switzerland, and Long Beach VA. Each database provides 76 attributes, including the predicted attribute. The second dataset are based on the Electrocardiogram (ECG) readings and other attributes. There are 279 attributes in total and grouped into 5 blocks: features concerning biographical characteristics, features concerning average wave durations of each interval, features concerning vector angles of each wave, features concerning widths of each wave and features concerning amplitudes of each wave. The third dataset are all WAV files gathered from two sources: (A) from the general public via the iStethoscope Pro iPhone app, provided in Dataset A, and (B) from a clinic trial in hospitals using the digital stethoscope DigiScope, provided in Dataset B. Some of the attributes value are missing in these three datasets, so we do some pre-handling process with each dataset. After comparing different machine learning models and adjusting parameters related, we use Gradient Boosting Decision Tree (GBDT) for the first and second datasets, and Long Short-Term Memory (LSTM) for the third dataset because of their good performance.

Model In Application

Application Implementation

Model Description

LSTM Long Short-Term Memory is a variant of recurrent neural network, which uses special units that can maintain information in memory for long periods of time in addition to standard units, which allows for a better control over the gradient flow and enable better preservation of long-range dependencies. The key point for implementing LSTM is to figure out what to forget, save and ignore as a memory cell. Since LSTM is a state-of-art deep learning method and has been widely used on different topics with great performance, we picked this model to see how it works for our application.

GBDT Gradient boosting is a machine learning technique for regression, classification and sorting tasks. It belongs to boosting algorithm family, which can enhance a weak learner to a strong learner. Boosting algorithms are based on the idea that it?s better to get a result by synthesizing many experts? judgements than getting it from only one of them. Gradient boosting, same as other boosting algorithms, constructs the final prediction model with an ensemble of many weak learners, usually decision tree. This is what we call Gradient Boosting Decision Tree(GBDT).

Boosting is one of the major methods of ensemble learning. It constructs model using a stage-wise iterative method. The weak learner constructed at every step of iteration is designed to make up for the deficiency of the existing model. Gradient boosting does it by construct a learner that reduces the loss along the steepest gradient in each step. Gradient boosting has an enormous scope of application since it is capable of processing all kinds of learning tasks by setting different loss functions. It can resist noise in training data effectively as well.

Gradient boosting algorithm tends to use decision tree because this algorithm is easy to understand and has strong interpretability and rapid forecasting speed. Also, decision tree algorithm can process data with missing fields well and do not need to consider interdependence between features.

According to above, Gradient Boosting Decision Tree is one of the best, state-of-the-art machine learning algorithms. Therefore, we choose it for our first two datasets.

Application Training result

UCI Dataset Result There are many missing attribute values in UCI dataset. In addition, the Cleveland data set became corrupted after the loss of a computing node, and the surviving data set contains only 14 attributes per instance(shown at Figure 1). Therefore, we constructed a 14 attributes UCI dataset with 920 instances, and the last row ("num") is the attribute to be predicted. In these instances, some of them also have unobserved attributes, for all of unobserved attributes, we replaced them to a certain number "-69" which means unobserved, and we divide the whole dataset into training data and test data with a proportion of 4:1. All model used in UCI dataset will use this processed dataset.

	attribute	description	type
1.	age	Age in years	int
2.	sex	Female or male	bin
3.	cp	Chest pain type (typical angina, atypical angina, non-angina, or asymptomatic angina)	cat
4.	trestbps	Resting blood pressure (mm Hg)	con
5.	chol	Serum cholesterol (mg/dl)	con
6.	fbs	Fasting blood sugar (< 120 mg/dl or > 120 mg/dl)	bin
7.	restecg	Resting electrocardiography results (normal, ST-T wave abnormality, or left ventricular hypertrophy)	cat
8.	thalach	Max. heart rate achieved during thalium stress test	con
9.	exang	Exercise induced angina (yes or no)	bin
10.	oldpeak	ST depression induced by exercise relative to rest	con
11.	slope	Slope of peak exercise ST segment (upsloping, flat, or downsloping)	cat
12.	ca	Number of major vessels colored by fluoroscopy	int
13.	thal	Thalium stress test result (normal, fixed defect, or reversible defect)	cat
14.	num	Heart disease status: number of major vessels with >50% narrowing (0,1,2,3, or 4)	int

Figure 1: Attributes

UCI dataset was used at the first step of our application, it provides basic information. Because UCI dataset's attributes are limited and could be commonly measured, our application uses UCI dataset to train a general classifier. We have trained it with five models, they are GBDT in LightGBM, Naive Bayes, SVM, Neural Network and Logistic Regression. After comparing the accuracy between these models with tried every model's best performance in this dataset(will be shown in next chapter) and every member of our group developed one of models in this dataset. Finally we found that GBDT had highest and stable accuracy about 89.57%. As a result, we chose LightGBM as our final training library. LightGBM is efficient, low memory usage and better accuracy with a gradient boosting method. Additionally, LightGBM can be used for nearly all regression problems, our classifier is exactly one of them.

In LightGBM, we have taken a lot of time in reading the documentation and trying to understand the principle of GBDT, such as what is gradient and boosting. Besides, when using default parameters in LightGBM model, we got an accuracy 82.83% which is too low. Therefore, we tried to improve the accuracy of model's performance. On the one hand, we eliminated some least important attributes in this model by using Pandas, the importance of every attributes using in LightGBM are shown at Figure 2, we attempted to eliminate FBS and RESTECG, but the accuracy dropped, so we didn't modify attributes using this model. On the other hand, we modified LightGBM model's attributes by using a script, this script continuously modifies parameters of model's like number of leaves, minimum data in a leaf, learning rate and so on, then find the parameters result with best accuracy. Finally, we got a optimal result with accuracy 89.57%.

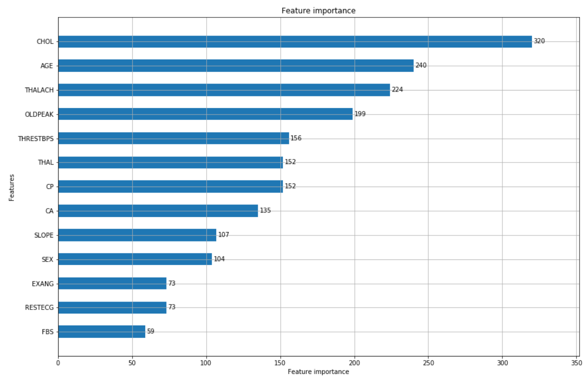


Figure 2: Importance of attributes in LightGBM

Dataset2 Result

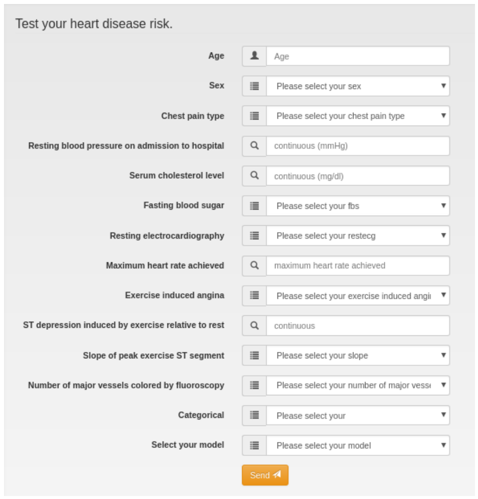
Dataset3 Result

Application Display

We design a web application with Bottle[] as the back-end framework of our application and Bootstrap[] as the front-end library. We provide two functions for our users:

- Predict the risk of heart disease based on most attributes same as UCI dataset
- Predict murmur or extrastole risk of heart based on heart sound wav file

For the first function, users have to fill 14 attributes such as age, sex and so on to get better accurate prediction. We use models on dataset1 and dataset2 then we compare results from different model and get a ranking of the risk. We'll return a result based on the ranking for users to show if they have a risk of heart disease or not. The user interface is showed in Figure 3.



Test your heart disease risk.

Age	Age
Sex	Please select your sex
Chest pain type	Please select your chest pain type
Resting blood pressure on admission to hospital	continuous (mmHg)
Serum cholesterol level	continuous (mg/dl)
Fasting blood sugar	Please select your fbs
Resting electrocardiography	Please select your restecg
Maximum heart rate achieved	maximum heart rate achieved
Exercise induced angina	Please select your exercise induced angi
ST depression induced by exercise relative to rest	continuous
Slope of peak exercise ST segment	Please select your slope
Number of major vessels colored by fluoroscopy	Please select your number of major vess
Categorical	Please select your
Select your model	Please select your model

Figure 3: User interface for the first function

For the second function, users have to upload their heart sound wav files recorded from their mobile to predict the risk of two heart diseases, murmur and extrastole. We use models on dataset3 to predict in back-end. We'll get two problities of murmur and extrastole. If the probablities are too high, then we'll tell users they may have the risk. The user interface is showed in Figure 4.

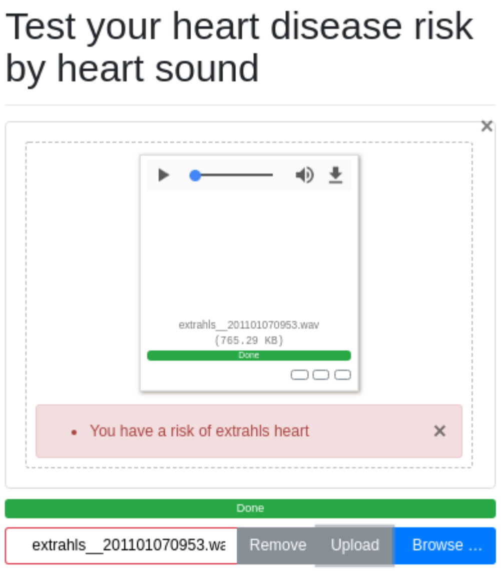
Experiment

Experiment Setup

We have pushed our project into Github, and to see more details about our application, you could setup an experiment by yourself. Our project is running as a website. To setup the service, first you should ensure you have installed Anaconda3 and python library LightGBM. Second, you should install front-end framework package Bootstrap and back-end framework package Bottle. Then you could run the service in our repository.

Model Comparison

The information we can derive the heart sound is limited as it is prone to be contaminated by environment noise. Basically, we are able to observe two types of abnormalities in a piece of heart sound: murmur, which indicates the blood reverse flow caused by mitral insufficiency, and extra systole,



Test your heart disease risk by heart sound

extrahls__201101070953.wav
(765.29 KB)

You have a risk of extrahls heart

extrahls__201101070953.wa

Figure 4: User interface for the second function

which indicates myocardial injury. These two kinds of abnormalities are independent, so we extract the starting part of Fourier transform power (frequency lower than 470Hz) and a binary sequence marking the existence of heart beat pulse in 0.075s time interval (about the width of a pulse) as sequential features for murmur heart sound and extra systole respectively. We built two two-layer LSTM model to classify these sequential features. The evaluation of the two models are shown below:

TO BE ADDED

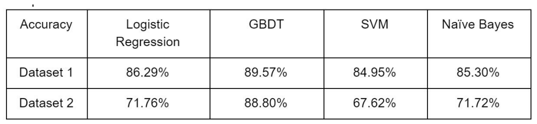
[insert table here]

As explained above, our heart disease testing based on three data sources: biographical information, ECG and heart sound.

We regard biographical information as a vector indicating a sample in the sample space. And for the ECG data, we use the method introduced by Guvenir et al. in (**?**) to extract a 275 dimensional feature for each sample. For such classification task, we tested four binary classification models: support vector machine (SVM), logistic regression, nave Bayes and gradient boosting decision tree (GBDT). The performance of the four models on dataset1 and dataset2 are shown at Figure 5, we have implemented all of those models into UCI dataset and dataset2(later modify), and the type of UCI dataset and dataset2 are both text(professional word), our process method in processing these two datasets is similar. We will introduce how we get the optimal accuracy of each model.

Optimization method

We used Sklearn to invoke both Logistic Regression, SVM and Naive Bayes models, and logistic regression has the secondly good accuracy in both UCI dataset and dataset2. The optimization method for both of these three method is to select columns to make the cross validation be best, which



Accuracy	Logistic Regression	GBDT	SVM	Naïve Bayes
Dataset 1	86.29%	89.57%	84.95%	85.30%
Dataset 2	71.76%	88.80%	67.62%	71.72%

Figure 5: The result of using different model with optimal attributes

aims to avoid overfit. Excepting for select columns method, we also have different method for different models.

Logistic Regression Optimization

In Logistic Regression, things we should do are to analyse the fit coefficient, and drop columns with negative fit coefficient. In this way, our training time shortened a lot. We also tried some parameters Sklearn provides, we modified penalty parameter to 'l1' to avoid overfit, and we tried C parameter to modify inverse of regularization strength.

SVM Optimization

For SVM we tried 4 different kernel functions.

- Linear Kernel Function:$K(x_i, x_j) = x_i^T x_j$.
- Polynomial Kernel Function: $K(x_i, x_j) = (\gamma x_i^T x_j + r)^d, d > 1$.
- RBF Kernel Function: $K(x_i, x_j) = exp(-\gamma ||x_i - x_j||^2), \gamma > 0$.
- Sigmod Kernel Function: $K(x_i, x_j) = tanh(\gamma x_i^T x_j + r), \gamma > 0, r < 0$.

After comparing different kernel functions, the linear one with the penalty parameter c = 2 gives best expected accuracy 67.62%.

Naive Bayes Optimization

For Nave Bayes, three different algorithms of it are provided in scikit-learn.

- GaussianNB: The prior is Gaussian distribution. It is commonly used when the distributions of most sample features are continuous values.$P(X_j|Y = C_k) = \frac{1}{\sqrt{2\pi\sigma_k^2}} exp(\frac{(x_j - u_k)^2}{2\sigma^2})$.
- MultinomialNB: The prior is Multinomial distribution. It is suitable when the distributions of most sample features are multivariate discrete values.$P(X_j|Y = C_k) = \frac{x_j + \lambda}{M_k + n\lambda}$
- BernoulliNB: The prior is Bernoulli distribution. We choose this when the distributions of sample features are binary discrete values or very sparse multivariate discrete values.$P(X_j = x_j|Y = C_k) = P(j|Y = C_k)x_j + (1 - P(j|Y = C_k))(1 - x_j)$

After comparing the performance of these three distributions, we chose GaussianNB for dataset 1 and BernoulliNB for dataset 2.

Conclusion

We implement an application meant for heart disease detecting, which uses three different aspects including overall healthy condition, cardiac arrhythmia and heartbeat sounds to diagnose the final result step by step. By the end, we obtain relatively reliable performance and provide a platform for other users. It should be noted that we tried several models on three datasets and picked up the optimal model as the final model for our app. Through this project, we learn how to do demand analysis, performance evaluation and also tuning skill, which helps us to understand further for machine learning.

References