NAFLD Study Summary

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1 Introduction

The distribution of steatosis in Nonalcoholic Fatty Liver Disease (NAFLD) can be categorized into Panacinar, Azonal, Zone 1 and Zone 3. Although Focal Zone 1 pathology is rare in adults with NAFLD (<1%), it has been reported in children with NAFLD. We hypothesized that focal Zone 1 steatosis and focal Zone 3 steatosis are two distinct subphenotypes of pediatric NAFLD.

1.1 Research Purpose

In order to better understand the potential differences between NAFLD histologic phenotypes of children, we performed multi-center cohort study. Our research aims to determine the relationship between the zonality of steatosis and demographic/clinical/histologic features of children with NAFLD.

1.2 data

A total number of 813 children (younger than 18 years old) with biopsy-proven NAFLD enrolled in the NASH Clinical Research Network. 165 charactistics were measured at different aspects. Liver histology was reviewed by the Central Pathology Committee based on NASH CRN scoring system. For each biopsy, the predominant location of the fat droplets was recorded at Zone 1 and Zone 3.

1.2.1 Data issue

Over 50 measurements contain missing values exceeding 60% and were excluded from data. After removing 60 irrelevant variables, 42 variables of diesease NAFLD were reserved for the following factor analysis.

2 Methods

Descriptive statistics were generated for the remaining 42 characteristics, which were not illustrated here.

2.1 Factor analysis for reducing matrix dimension

Factor analysis was used to reduce the dimension of predictor matrix.

2.2 Random Forest for identify final variables

Random forest method was used to identify the essential variables for reconstructing the final model.

2.3 Decision tree for constructing preliminary classifier for NAFLD

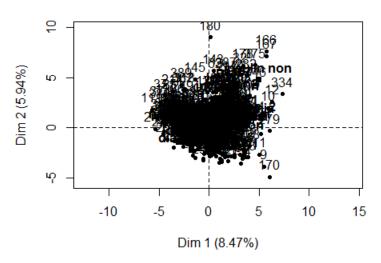
Decision tree was used to build up the preliminary model for zonality partition.

3 Results

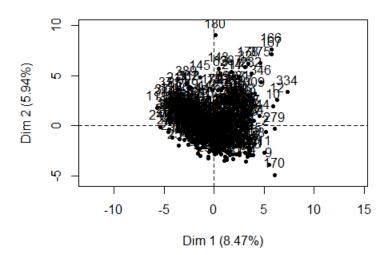
3.1 Factor analysis for reducing matrix dimension

3.1.1 Individual factor map (in dim1 and dim2)

Individual factor map

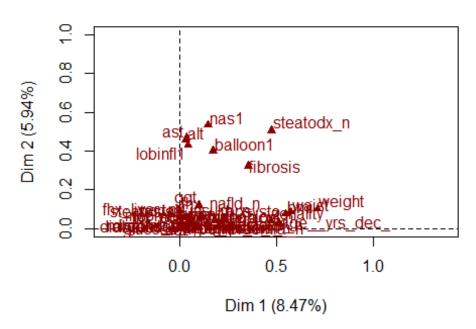


Individual factor map



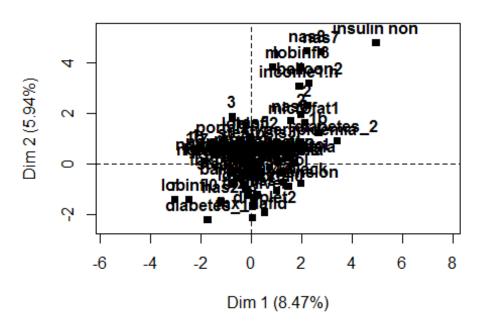
3.1.2 All variables projection (in dim1 and dim2)

Graph of the variables



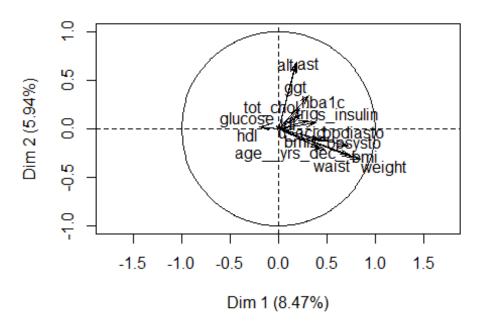
3.1.3 Categorical variables (in dim1 and dim2)

Individual factor map



3.1.4 Numeric variables (in dim1 and dim2)

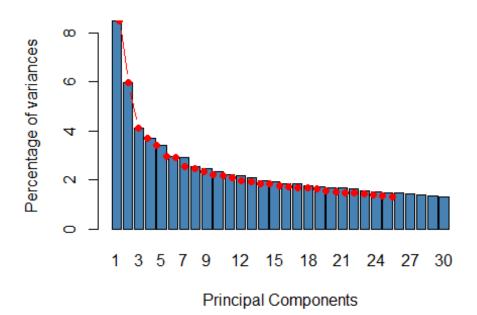
Graph of the quantitative variables



3.1.5 Bar plot

Bar plot shows that \sim 92% of the information (variances) contained in the data are retained by the first two principal components.

Variances



Numeric variables and category variables selected from the factor analysis are listed as followings. All the selected variables have p-values less than 0.01. Among them, 28 variables are reserved in the next analysis. Numeric variables (first 16 selected): weight, bpsysto, bpdiasto, uacid, hba1c, ast, alt, tot_chol, ldl, glucose, bmiz, age, ggt, waist, trig, and hdl. Categories variables (first 14 selected): gender, nas, race, hispanic, hba1c, steatosis, fibrosis, lobinfl, portal, balloon, sinsulin and nash.

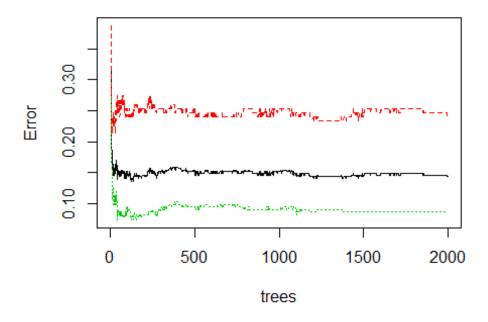
```
## $quanti
##
                 correlation
                                    p.value
## weight
                   0.8442461 3.822462e-107
## waist
                               4.091437e-74
                   0.7583611
## bmi
                   0.7415995
                               2.917777e-69
                   0.7169356
                               9.093304e-63
## age yrs dec
## u_acid
                   0.5130195
                               1.449202e-27
## bpsysto
                   0.4810663
                               5.553538e-24
## bpdiasto
                               1.543188e-20
                   0.4468289
## bmiz
                   0.4300402
                               5.499137e-19
## s insulin
                   0.3872886
                               2.094763e-15
## ggt
                   0.3153869
                               1.868946e-10
## trig
                   0.3093852
                               4.262230e-10
## tot chol
                   0.2343967
                               2.876385e-06
## hba1c
                   0.2268703
                               6.037083e-06
## ldl
                   0.2036934
                               5.072266e-05
## ast
                   0.1890050
                               1.737137e-04
## alt
                   0.1787241
                               3.899607e-04
## hdl
                   -0.1991580 7.489567e-05
```

```
##
## $quali
                          R2
##
                                   p.value
## zonality
                  0.47334031 5.562401e-56
## steatodx_n
                  0.47553270 8.740758e-54
## fibrosis
                  0.35464630 8.998332e-34
## balloon1
                  0.17448912 7.688870e-17
## hispanic
                  0.14437496 7.885964e-14
## nas1
                  0.14726840 2.415324e-11
## diabetes 2 n
                  0.09823338 2.452995e-10
## race
                  0.08639149 4.744673e-06
## portal1
                  0.05252270 2.924595e-05
## insulin n
                  0.04186270 4.685685e-05
## hypertension n 0.03584691 1.691719e-04
## lobinfl1
                  0.04566724 4.262764e-04
## steatosis1
                  0.02670442 5.313243e-03
## microfat n
                  0.01771760 8.489750e-03
## income1
                  0.04342366 8.952898e-03
```

3.2 Random Forest for identify final variables

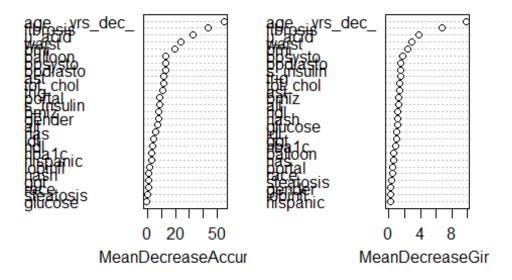
The following plot indicates that the average error rate is 0.15, while the difference between the error rate of zone1 and zone3 is 0.2. The difference between error rates is likely to reduce if an increasing amount of data was used to train the model.

NAFLD random forest error rate plot

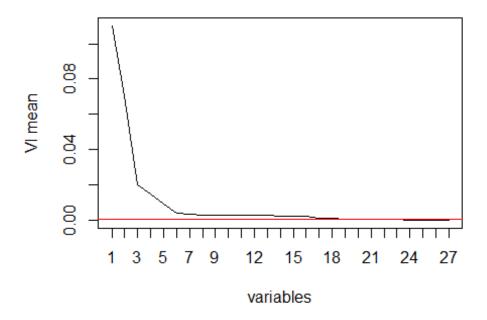


The below plots show the rank of different variables contributing to MeanDecreaseAccurary and MeanDecreaseGini, respectively. The results also indicate that the top four variables have clear impact accuracy and Gini score compared with other variables.

NAFLD random forest important variable plot



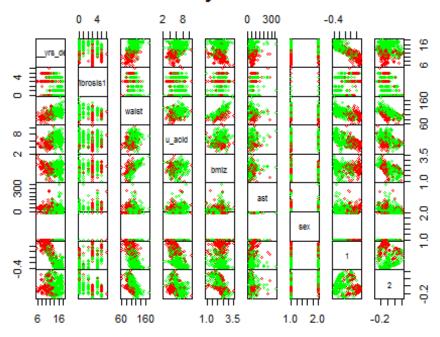
The following analysis automatically outputs sixteen variables, which lie above the threshold (the red line in the plot) and are recognized as important variables. Among them, eight (age, fibrosis, waist, u_acid, bmiz, ast, bmi and bpsysto) are selected as predictors for zonality partition. Since bmiz is the standardization of bmi, bmi can be removed. Random forest also indicates that the top 3 variables have the strongest predicting power.



```
## [1] 16 27 4 19 1 15 6 2 8 20 3 22 13 14 7 17 24 5 9 21 18
## [1] 16 27 4 19 1 15 6 2
## [1] 16 27 2
```

The plot below illustrates the correlation between each pair of important variables. Moreover, it also suggests whether the selected important variables can distinguish the zonality 1 from zonality 3. The results show that bmiz, ast and u_acid can not distinguish these two zonalities. Four variables (age, fibrosis, sex and waist) will be included in the decision tree analysis.

Predictors and Proximity Based on RandomForest



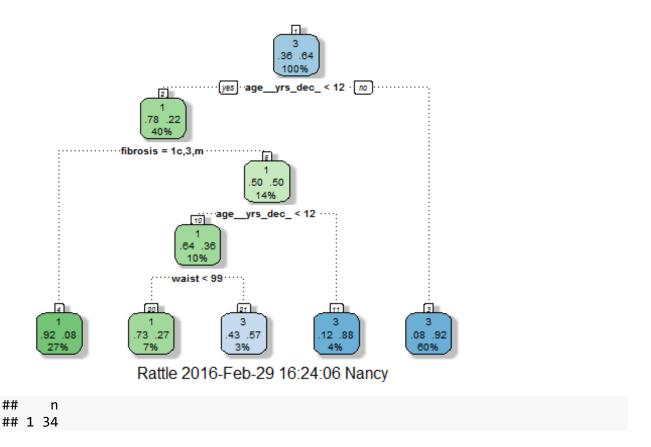
3.3 Construct a preliminary decision tree model

A preliminary decision tree model is build up and will be improved in the following analysis.

• The model is formulated as:

Zonality = Age + Fibrosis + Waist + error

The following plot shows that how the decision tree model split data into zone1 and zone3. This model was parameterized through the training dataset and was validated by the test dataset.



There are 34 observations between predicted zonality and zonality. The error rate for this model is 0.1588235, which means that the model can achieve around 85% accuracy for predicting zonality compared to the original zonality result in the test dataset. Below are the details of the model:

```
## n= 220
##
## node), split, n, loss, yval, (yprob)
       * denotes terminal node
##
##
   1) root 220 79 3 (0.35909091 0.64090909)
##
     2) age yrs dec < 12.44932 89 20 1 (0.77528090 0.22471910)
##
##
      4) fibrosis=1c,3,m 59 5 1 (0.91525424 0.08474576) *
##
      5) fibrosis=0,1a,1b,2 30 15 1 (0.50000000 0.50000000)
       10) age__yrs_dec_< 11.75068 22  8 1 (0.63636364 0.36363636)
##
##
         20) waist< 98.9935 15 4 1 (0.73333333 0.26666667) *
         ##
       ##
##
     3) age__yrs_dec_>=12.44932 131 10 3 (0.07633588 0.92366412) *
```

4 Discussion

The above study are limited in two major aspects: small sample size and many missing values. A large dataset can improve the training of classifier. The removal of missing values further reduced the available data for analysis.