Research Article

ROC-Boosting: A Feature Selection Method for Health Identification Using Tongue Image

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Objective. To select significant Haar-like features extracted from tongue images for health identification. Materials and Methods. 1,322 tongue cases were included in this study. Health information and tongue images of each case were collected. Cases were classified into the following groups: group containing 148 cases diagnosed as health; group containing 332 cases diagnosed as ill based on health information, even though tongue image is normal; and group containing 842 cases diagnosed as ill. Haar-like features were extracted from tongue images. Then, we proposed a new boosting method in the ROC space for selecting significant features from the features extracted from these images. Results. A total of 27 features were obtained from groups A, B, and C. Seven features were selected from groups A and B, while 25 features were selected from groups A and C. Conclusions. The selected features in this study were mainly obtained from the root, top, and side areas of the tongue. This is consistent with the tongue partitions employed in traditional Chinese medicine. These results provide scientific evidence to TCM tongue diagnosis for health identification.

1. Introduction

As society continues to develop, health status problems have become the main focus of studies in recent years, and health identification has been one of the most important problems. Health identification is a procedure of identifying the condition of a subject as healthy or ill. Western medicine diagnoses a person’s health condition based on a series of laboratory examinations. However, these examinations are invasive and time-consuming and require a number of laboratory experiments. As an alternative diagnostic method, traditional Chinese medicine (TCM) proposes Su Wen (Plain Questions) as a concept for the preventive treatment of diseases. Plain Questions is part of a classical text written during the Zhanguo period of ancient China, which claims that TCM identifies the health status of a person before diagnosing the decease. Health identification is one of the most fundamental diagnostic methods applied in the preventive treatment of diseases in TCM [1]. Compared with Western medicine, TCM uses noninvasive, time-saving methods including tongue and pulse to identify the health status of an individual. In recent years, Western medicine has also begun to focus on establishing preventive treatments for diseases such as health identification, because these results can save medical time, effort, and cost [2].

However, tongue diagnosis in TCM has been criticized due to its subjective diagnostic criteria. Several studies have focused on tongue image diagnosis, and computer image processing has contributed to tongue criteria objectification. Color is the most common feature in tongue diagnosis due to its intuitiveness. The study of Pang et al. introduced lower order moments such as the mean value and standard deviation of color features to diagnose appendicitis [3]. The study of Zhao et al. found color differences between patients with and without chronic hepatitis B [4]. In the current study, tongue coating color features were extracted. For color
that if a classification model with high predictive accuracy 
learnable were defined. Schapire was able to prove that these 
results is better than a single classifier. The reason why this 
boosting method has a better performance can be explained 
youthingfeaturesexists,anensembledoofaweakmodelsisequivalentto 
it, even if their predictive results are only slightly better than 
a random guess.
Viola and Jones used a boosting algorithm in face 
detection [13] and demonstrated that this algorithm can be 
employed to cope with both feature selection and classi-
fication. However, this algorithm is only suitable for face 
detection, because the eyes and nose are naturally identifiable. 
Mamitsuka proposed a boosting algorithm based on the ROC 
curve for microarray classification [21]. Komori and Eguchi 
and Long and Servedio also proposed boosting algorithms 
for maximizing the area under the ROC (AUC) [22, 23]. 
These studies were able to partly solve the small observation 
problem but were not used in unbalanced sample problems. 
In our problem, the number of features is much larger than 
the number of examples. Fan and Lv proposed a theoretical 
guarantee for screening features from ultrahigh feature spaces 
[24].

In order to address this limitation, we propose a ROC-
Boosting approach for TCM tongue diagnosis in health 
identification. This method first screens the features using 
t-test. Then, a Haar-like feature is selected using several 
different conditions and sends this feature to the ensemble 
classifier. Our method is generic compared to previous meth-
ods, because its conditions include the AUC value, sensitivity, 
specificity, and their combinations. It can also use positive-
negative sample ratio conditions to deal with unbalanced 
sample problems. We name this method ROC-Boosting, 
because its feature selection conditions are all relative to the 
ROC space. Moreover, our method avoids the usage of TCM a 
priori, and its result is consistent with TCM tongue partitions.

2. Subjects and Methods

Tongue images and health information of 1,426 cases from 
2011 to 2012 were collected. ROC-Boosting was employed 
to select Haar-like features extracted from tongue images. 
Natural partition tongue image features are selected. Then, 
partitions on the tongue image confirm the TCM diagnosis 
method. This procedure is illustrated in Figure 1.

2.1. Subjects. Tongue images and health information of 1,426 
cases from 2011 to 2012 were obtained from the Teaching 
Hospital of Tianjin University of Traditional Chinese 
Medicine (TJUTCM). Among these 1,426 cases, 96 cases 
were excluded due to low quality or duplicate images and 
health records with missing values. Then, TCM students and 
experts were employed to discuss the tongue images and 
health information collected. During this discussion, eight 
additional duplicate images were found. An outpatient doctor 
confirmed that these duplicates resulted from the abuse of 
health insurance ID usage. Hence, these eight images were 
excluded. Finally, a total of 1,322 cases were included into 
this study. TCM diagnoses health/illness status before the specific 
disease, because TCM focuses on the preventive treatment 
of diseases [8]. For this reason, we focused on the health 
identification problem in this study, and all subjects were 
diagnosed as healthy or ill. The 1,322 cases were classified in 
the following groups: group A, diagnosed as healthy based on
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Tongue images and health status

Feature extracting and screening

Haar-like features

Feature selection

Selected Haar-like features

Feature partition

Selected Haar-like feature partitions

TCM tongue partitions

Comparing

Figure 1: Study procedure. Haar-like features are extracted from tongue images and screened. Then, partitions on the tongue image confirm the TCM diagnosis method.

| Group | Status                                           | Number of cases |
|-------|-------------------------------------------------|-----------------|
| A     | Healthy, diagnosed based on tongue image and health information | 148             |
| B     | Ill, diagnosed based on health information, but tongue image is normal | 332             |
| C     | Ill, diagnosed based on both tongue image and health information | 842             |
| Total |                                                 | 1,322           |

both tongue image and health information (n = 148 cases); group B, diagnosed as ill based on health information, even if tongue images are normal (TCM considers that tongue changes do not reflect all illnesses, n = 332 cases); and group C, diagnosed as ill based on both tongue image and health information (n = 842 cases). The number of cases in each group is summarized in Table 1. Before the features were extracted, all images were scaled to 120 × 100 and segmented from the background to exclude the impact of the background to the feature extraction and selection process, as shown in Figure 2.

2.2. Methods

2.2.1. Improved Haar-Like Feature Extraction. Usually, color features are extracted from the whole tongue and Haar-like features are extracted from partitions. We improved the Haar-like feature to have five partitions, considering that humans focus their view at the center of the target at first glance, as shown in Figure 3. In comparison, the original Haar-like feature was considered as the difference of the sum of the color values between two horizontal or vertical partitions. The center partition of this feature has two parameters: W and H. These parameters represent the width and height of this partition. The other four surrounding partitions have three parameters: T, X, and Y. T represents the width of these four partitions, while X and Y represent the position of the top-left corner of the Haar-feature. Considering that humans usually focus their view at the center partition and the other four partitions, the number of pixels at the center partition and the other four partitions in the improved Haar-like feature should be equal. To ensure that the number of pixels at the center partition is equal to the other four partitions, T is given by \[ WH/(2W+2H) \], where \[ \lceil \rceil \] represents the maximum integer number smaller than the calculated real number. Parameters X and Y represent the position of the left-top corner of this feature. The improved Haar-like feature uses the difference between the sum of the pixel color values at the center partition and the other four partitions.

Every improved Haar-like feature is composed of five partitions (1–5). This Haar-like feature has five parameters: X, Y, W, H, and T. W and H represent the width and height of the center partition. T represents the width of the other partitions. X and Y represent the position of the Haar-like feature. The feature value can be computed by the difference between the sum of the pixel values at center partition and the other four partitions.

Under this setup, the number of improved Haar-like features is very large. Considering that the number of significant features is very small in our previous study, we reduced the number of features similar to our previous study [14].
In this study, the density of the parameter grid is reduced to lower the number of improved Haar-like features. We set \( W \in \{10, 12, 14, \ldots, 60\}, \ H \in \{10, 12, 14, \ldots, 72\}, \ X \in \{1, 6, 11, \ldots, [100-W-2*T+1]\}, \) and \( Y \in \{1, 7, 13, \ldots, [120-H-2*T+1]\} \) experimentally. After this simplification, the number of features is 98,592 in red, green, and blue color plains, respectively. These features are parts of the inputs of the ROC-Boosting algorithm.

2.2.2. ROC-Boosting. Concerning the difference between improved Haar-like feature values of the healthy and ill population, three tests were designed. The first test investigates the difference between the healthy group (group A) and the ill group diagnosed solely based on health information (group B). Cases in group B were diagnosed as healthy, because differences in tongue images cannot be observed by using the human eye. This test would prove whether a difference exists between these two groups. The second test is designed to verify the difference between the healthy and ill groups (groups A and C), because the difference between these two groups can be observed by using the human eye. The third test is designed to verify the difference between the healthy (A) and ill groups (B and C). As the number of improved Haar-like features becomes very large in comparison to the number of examples, \( t \)-tests were used to screen the improved Haar-like features in the first instance before applying our method. We reduced the number of improved Haar-like features to approximately \( 10^6 \) through the \( P \) value of the \( t \)-test. The \( P \) value and number of filtered features are listed in Table 2. These features are inputs of our method.

Our method, ROC-Boosting, is illustrated in Algorithm 1. This algorithm calculates the AUC value of all features in every loop. The AUC value would be set to its negative value when the ROC curve is concave; that is, the ROC curve is flipped around the random guess line. This flipping is designed to deal with the reversed prediction feature. Then, ROC-Boosting selects the feature through some conditions, which would be discussed later. After the correctly classified examples and selected features are removed, the loop is restarted. When conditions for selecting features no longer meet, the algorithm stops and presents all selected features. ROC-Boosting selects the most significant features on the tongue images to diagnose subjects from different groups in each step. These features can be used to build classifiers for identifying the health status of subjects from different groups. Verification of conformance between the positions of these features and TCM tongue partitions provides scientific evidence for TCM tongue diagnosis.

As described before, this algorithm is a generic version of the algorithm used by Yang et al. [12]. Viola’s method only applies to situations when features with extremely high sensitivity exist such as features that describe the eyes and nose of a human face detection problem. When the condition in step 9 is changed to the highest sensitivity and specificity, ROC-Boosting would be similar to Viola’s algorithm. The procedure for running Viola’s algorithm has shown that such features do not exist in our problem. This is the reason why we generalized Viola’s method.

In our problem, we use the next two conditions in step 9. The first is a negative/positive ratio condition. We compute \( r = p/n \) and \( r' = p'/n' \), where \( p \) is the number of positive examples, \( n \) is the number of negative examples, \( p' \) is the number of positive examples correctly classified by one feature, and \( n' \) is the number of negative examples correctly classified by one feature. This condition is \(|r-r'|\). The second condition is the AUC \( \left| a - 0.5 \right| \) value, where \( a \) is the AUC of this feature. We used these two conditions, because we did not find any significant feature existing in our problem, and the positive/negative examples are not balanced.

2.3. Statistical Analysis Software. We extracted the ROC-Boosting features using a DELL PC (OptiPlex 7020, i5-4590; Quad-Core with 8 GB RAM). The R 2.15.2 64 bit version was the statistical software used [25]. AUC values were calculated using the ROCR package. The code for feature extraction and ROC-Boosting was programmed as a script in R.

3. Results and Discussions

3.1. Results. For Test 1, only eight features are selected. The ninth feature condition is \( |a - 0.5| = 0.00943 \). For Test 2, 25 features are selected. The 26th feature condition is \( |a - 0.5| = 0.00687 \). In these two tests, the algorithm comes to its end, because a feature that is better than the guess could no longer be found. For Test 3, 27 features are selected. The 28th feature exceedingly concerns the disease examples than the healthy
The problems of health identification is the use of Haar-like features even when high sensitivity features do not exist. One of the conditions to select features. ROC-Boosting also works well and sensitivity can be relatively low. It can also use other specificity and select features simultaneously, and the value of specificity is increased. ROC-Boosting can also use specificity from high sensitivity features. A high performance classifier would be built when high sensitivity is maintained and specificity is increased. ROC-Boosting can also use specificity and sensitivity simultaneously, and the value of specificity and sensitivity can be relatively low. It can also use other conditions to select features. ROC-Boosting also works well even when high sensitivity features do not exist. One of the problems of health identification is the use of Haar-like features on tongue images. In a preexperiment, we tested all features in this study. No high sensitivity feature exists in our data, and we confirmed that Viola's method works. ROC-Boosting was able to select the features.

Learnability theory guarantees the effectiveness of the ROC-Boosting algorithm. If a high performance classifier exists in a health identification problem using Haar-like features on the tongue image, which is the basic hypothesis of this study, an ensemble of weak classifiers whose performance is better than the random guess would be equivalent to it. In ROC-Boosting, the condition \(|a - 0.5| > 0\) keeps every weak classifier better than the random guess.

Furthermore, weak classifiers should focus on both negative and positive examples. As shown in Figure 5, even though these two features (181,520 in the left subfigure and 188,479 in the right subfigure) were \(|a - 0.5| > 0, 188,479\) is excluded, because it focuses on the positive example only. In ROC-Boosting, \(|r - r'|\) excludes these features.

We also compared the two different conditions of ROC-Boosting for Test 3. The first condition is the negative/positive ratio and the \(|a - 0.5| > 0\), 188,479 is excluded, because it focuses on the positive example only. In ROC-Boosting, \(|r - r'|\) excludes these features.

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Test 1 has a poor performance due to insignificant differences between groups A and B. Even the human eye cannot identify the health status of group B. Test 2 had the best result, because group A is composed of healthy subjects and group C is composed of ill subjects. The shape of the overlaid feature is distributed around the tongue. The difference between these two groups is the most significant among the three tests. The overlaid features for Test 2 are concentrated at the center of the tongue. The overlaid features in the last figure consist of three areas: root, center, and top of the tongue image. We marked these three areas in the last figure. Its performance is slightly worse than Test 2 due to the interference of group B.

3.2. Discussions. Our method is more generic than previous studies. Viola's method is only applicable to situations where high sensitivity features exist [13]. In this situation, the algorithm selects features with increasing specificity from high sensitivity features. A high performance classifier would be built when high sensitivity is maintained and specificity is increased. ROC-Boosting can also use specificity and sensitivity simultaneously, and the value of specificity and sensitivity can be relatively low. It can also use other conditions to select features. ROC-Boosting also works well even when high sensitivity features do not exist. One of the problems of health identification is the use of Haar-like features on tongue images. In a preexperiment, we tested all features in this study. No high sensitivity feature exists in our data, and we confirmed that Viola's method works. ROC-Boosting was able to select the features.

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Relatively, the negative/positive ratio and $|d - d'|$ condition are associated with both positive and negative classes, while obtaining a similar AUC value. The correct prediction of both healthy and ill subjects is equally important in health identification.

4. Conclusion

We propose the application of the ROC-Boosting algorithm for health identification. This algorithm uses filtered Haar-like features and selects features from both positive and negative examples. The features selected for diagnosing
**Figure 5:** Two features of the AUC value larger than 0.5 are shown. Feature 181,520 in the left is selected, because the whole ROC curve is laid upward the random guess line. Feature 188,479 in the right is excluded, because its ROC curve crosses the random guess line at the corners of the ROC space.

**Figure 6:** Comparative results of the negative/positive ratio and $|d - d'|$ conditions, as well as the solely AUC value condition. Although the AUC value on the right image (0.727) is slightly larger than the left image (0.723), the solely AUC value condition obtains this superiority, because it is inclined to predict all subjects as with disease. When the number of positive and negative subjects is unbalanced, prediction tending to the major class is the most common phenomenon.
health and ill subjects are concentrated in the root, center, and top partitions of the tongue images. Unlike previous studies, these partitions are not results of preexperience. A deterministic algorithm presents these partitions. These results provide scientific evidence to TCM tongue diagnosis for health identification.

Conflict of Interests

The authors declare no conflict of interests in this work.

Authors’ Contribution

Yan Cui completed the algorithm and wrote the paper. Hongwu Wang and Shizhong Liao performed the mathematical models and methods of this study.

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