Advances in Tongue Diagnosis Objectification of Traditional Chinese Medicine

ZHANG Zhidong[1], ZHU Xiaolong[1], CAO Xiyuan[1], LI Bo[2], ZANG Junbin[1], GUO Dong[3], MEN Jiuzhang[3], XUE Chenyang[1]

(1. *Key Laboratory of Instrumentation Science and Dynamic Measurement of Ministry of Education, North University of China, Taiyuan 030051*; 2. *School of Software*, *North University of China, Taiyuan 030051*; 3. *College of Basic Medical Science*, *Shanxi University of Chinese Medicine*, *Taiyuan 030051*)

Abstract: Tongue diagnosis is a non-invasive, efficient, and accurate method for determining a person's physical condition, and plays an essential role in disease diagnosis and health management. However, tongue diagnosis is easily influenced by the subjective experience of the practitioner and the light environment. In addition, tongue diagnosis lacks clear quantitative indicators and objective records. This all limits the transmission and development of tongue diagnosis. Therefore, the acquisition and analysis of tongue information using image equipment, image processing and computer vision have become a hot research topic for the objectification of tongue diagnosis. This paper reviews the research progress of tongue diagnosis objectification in Traditional Chinese medicine. The tongue image acquisition, color correction, segmentation, feature extraction and analysis, and disease prediction included in the study of tongue diagnosis objectification are reviewed. The shortcomings of current automated tongue diagnosis systems and future research ideas are also summarized to provide a reference for further development of tongue diagnosis objectification.

Keywords: Tongue Diagnosis, Tongue Diagnosis Objectification, Image Processing, Automated Tongue Diagnosis Systems

1 Introduction

Traditional Chinese medicine (TCM) is an empirical science. The medical theory system gradually formed and developed through long-term medical practice under the guidance of ancient simple materialism and spontaneous dialectics, which is take the holistic view of similarity as the dominant idea. After thousands of years of medical practice and improvement, TCM has formed a special and independent medical theory system with Chinese culture. The theory of traditional Chinese medicine has been valued and recognized by more and more countries[1-2].

Tongue diagnosis is one of the essential diagnostic methods in TCM, it is help TCM practitioners to diagnose diseases according to the characteristics of tongue coating[3]. The process of tongue diagnosis in TCM includes observation of the patient's tongue texture and tongue coating. The tongue texture is the muscle and collateral tissue of the tongue, and the tongue coating is a layer of thin or thick coating attached to the tongue surface. The tongue belongs to a terminal organ of the human body, which is involved in human activities and metabolism. The tongue is closely related to the state of human health from the perspective of holistic view of TCM[4]. Therefore, the doctor can comprehensively judge the disease condition based on the shape and size of the tongue, the color of the tongue coating, the coating quality and other characteristics of the patient[5]. The features changes of the tongue, color change, thickness increment, coating changes, and cracks on the tongue of the tongue, can imply the patient's overall health status[6]. TCM practitioners can distinguish patients' disease location, disease nature and disease degree according to their tongue features and TCM theories.

TCM diagnosis of tongue diagnosis is highly subjective. It relies on the physician's subjective experience and expertise. Because of these factors, it is difficult for TCM practitioners to accurately record and preserve tongue data. This dilemma has caused inconveniences to clinical teaching and research and is not conducive to the transmission and development of TCM. Therefore, it is meaningful to establish objective and quantitative indicators for tongue diagnosis to reflect the functional status of the human body more accurately and objectively. The digitization of tongue diagnosis has important implications for the development of traditional Chinese medicine.

With the development of modern photography technology, image processing technology and deep learning computer technology, the digitalization of tongue diagnosis has become possible. The digitalization of tongue diagnosis mainly includes the process of tongue photography by camera, digital image feature extraction, deep learning feature annotation, model training. Tongue diagnosis is easily disturbed by the environment, such as light source and brightness have a substantial influence on the TCM practitioner's observation of tongue features, especially on color features. Therefore, this paper systematically introduces the development status and latest research progress of tongue diagnosis digital technology.

2 The Research Development of Tongue Diagnosis System

In recent years, various types of tongue diagnostic systems are designed. These systems digitize the physiological characteristics of the tongue, reducing the diagnostic error caused by the doctor's visual analysis and making the diagnosis more objective and scientific. The critical technologies for building the tongue diagnosis system include tongue image acquisition, automatic segmentation of the tongue region, and tongue feature analysis. Among them, the advanced technology mainly used in tongue diagnosis is image processing technology. Fig.1 shows flow chart of tongue diagnosis system.

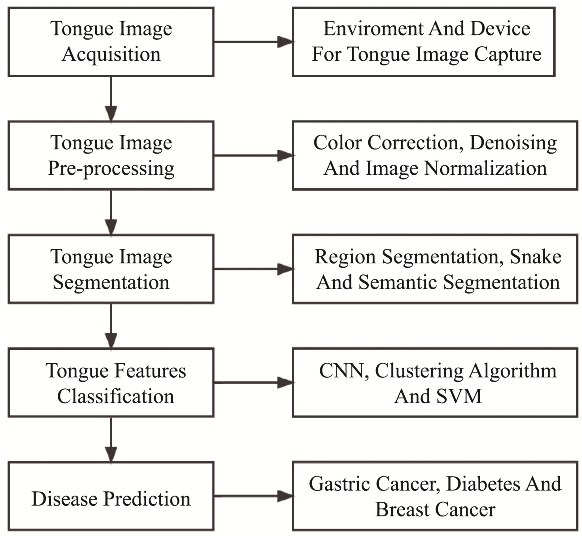


Fig.1 Flow Chart of Tongue Diagnosis System

The tongue image can reflect the health status of the human body, and provide a diagnostic basis for the qualitative positioning and prognosis of the disease. The image processing can capture the physical characteristics from the picture but the eyes of the human are difficult to sense these little bits of information. This information will is beneficial to improving the accuracy of tongue diagnosis[8]. The maturity of image processing technology has greatly promoted the development of digital tongue diagnosis technology. It has realized the classification of tongue shape, tongue color, tongue state, tongue coating, and other characteristics through image processing technology and artificial intelligence technology[9].

3 Tongue Image Capture Device

High quality tongue photographs are the basis for improving the accuracy of digital tongue diagnosis. To ensure the effectiveness of image acquisition, a stable and standard lighting environment for image acquisition needs to be constructed[10]. The tongue diagnostic image acquisition system include image acquisition device, illumination device, and control module.

Earlier, an improved a handheld color scanner is proposed to capture tongue images by placing a microscope slide on top of the tongue[11]. As the scanner scans the entire tongue surface, a clear color image is captured. This method avoids the primary color calibration and artifact removal efforts. However, the image acquisition process involves touching the patient's tongue with the instrument. This operation may cause the spread of disease. In addition, since each person has a different tongue shape, the hardware needs to be specially designed to accommodate the size of the tongue. To overcome the limitations of a previous hand-held image capture device, they capture the tongue image with a commercial digital camera (640 x 480 pixels) plus a Munsell Color Checker embedded inside the image. o overcome the limitations of a previous hand-held image capture device, he takes picture of the tongue with a commercial digital camera (640 x 480 pixels) plus a Munsell Color Checker embedded inside the image. Cao et al. summed up some critical principles of designing portable tongue image acquisition device[12]. After selecting a more suitable light source and optimizing other hardware structures, a new portable tongue diagnostic device was produced. The whole instrument is modified by drilling through holes in the integrating sphere. There are three holes on the integrating sphere, the luminescence hole, the tongue observation hole, and the camera hole. There is a camera, tungsten halogen lamp, and reflection device inside.

In contrast to others who used portable tongue diagnostic instruments and large tongue diagnostic instruments to capture tongue images, Hu et al.[13] used a smartphone with D50 imaging standard to take tongue pictures. The tongue images they acquired were low resolution and captured under different lighting conditions. Therefore, the traditional tongue diagnostic analysis methods cannot give accurate diagnostic results directly. To address these challenges, they designed an automatic diagnostic tongue image framework. This framework includes tongue image capture guidance, tongue image color correction, and other functions that can solve the above challenges. Han et al.[14] investigated the relationship between tongue microorganisms and colon cancer. They took images of the tongues of 47 patients and 45 healthy individuals using a DS0l-B tongue diagnostic information acquisition system (DAOSH Co., Shanghai, China). This system consists of an image acquisition module and a software analysis module. It incorporates modern technological achievements and can automatically quantify the thickness of the tongue layer. The system photographed the tongue membranes of all subjects and analyzed the thickness of the tongue membranes. The tongue diagnostic information acquisition system has proven to be effective in past clinical applications[15].

Digital cameras can capture high-quality tongue images, but owing to the complexity of tongue image information, changes in external light sources, random noise of the equipment, and other factors, the captured tongue photos are easily disturbed. It can cause interference to the subsequent processing and analysis and restrict the further development of modernization of tongue diagnosis. With the enhancement of the spectral resolution of hyperspectral imaging, initial progress has been achieved in applying hyperspectral technology to tongue diagnosis objectification. Li et al. developed a hyperspectral imaging system to capture tongue images[16]. This system is designed concerning the thrust hyperspectral imager and has high spectral resolution and spatial resolution. It consists of the spectrometer, CCD detector, lateral motion device, and image acquisition and control module. The hyperspectral imaging system can capture hyperspectral images in the tongue 120 bands. Then they verified the effectiveness of the system on captured tongue photos. Zhang et al. used a visible hyperspectral image system in the spectral range of approximately 400-1000 nm to predict tongue color values and tongue location[17]. Hyperspectral images contain rich spectral and spatial information. For accurate prediction, a deep architecture of advanced spectral-spatial features for the hierarchical construction of hyperspectral images was constructed. During the acquisition of tongue photographs with the tongue diagnostic instrument, tongue fluttering or excessive force brings interference to the tongue morphology acquisition. Tongue shape features are crucial elements for tongue diagnosis, but the information acquired through two-dimensional tongue images is insufficient to extract features such as tongue thickness and curvature angle[18].To solve these problems, Liu et al.[19] proposed an image capture system for three-dimensional modeling of the tongue that uses two light sources, four digital cameras, a frame for holding the head, a matrix of adjustable laser beams for generating artificial features on the tongue surface, and a laser device for positioning the tongue. The four cameras were able to adjust the exposure time and the high-speed frame rate. After reconstruction by algorithm, a finite element-based representation of the tongue was acquired. The experimental results validate the effectiveness and importance of the method in further analyzing reasonable tongue morphology for medical diagnosis.

To obtain more comprehensive 3D surface information, Lu et al.[20] propose a 3D reconstruction method of the tongue body. A digital camera was placed in the front of the tongue model, and the positions of the camera and the tongue model were fixed. Eight LED light sources were evenly distributed along the radial direction on a vertical circle. The tongue sequence was acquired under the illumination of the light sources in eight different directions. After pre-processing the lingual image sequence, the lingual body is reconstructed using an algorithm. The accuracy analysis shows that the method is feasible for the reconstruction of the real tongue body. Jung et al. proposed a method for providing frontal and lateral feedback gridlines for the tongue image acquisition process[21]. Two digital cameras and an LCD monitor were used in order to provide frontal and lateral feedback grid lines to the subjects. Three different grid line types were used to acquire tongue images for the analysis of tongue color and tongue shape. It was demonstrated that the proposed tongue image acquisition process with frontal and lateral grid lines improved the reproducibility of color and shape characteristics and potentially improved the accuracy of computerized tongue diagnosis.

4 Light Environment Selection and Color Correction

The light environment during the tongue diagnosis has a significant impact on the diagnostic results. Under different lighting conditions, the tongue will appear in different colors, which will affect the judgment of the tongue color and thus the clinical diagnosis. Therefore, researchers have taken different approaches to solving the problem of the lighting environment. Cao et al.[12] developed the portable device using a 20-watt tungsten halogen lamp, which achieves a color rendering index of 90 but a color temperature of only 2674 k. Compared with a standard D65 light source (color temperature 6174 k), the 20-watt tungsten halogen lamp appears darker and more yellow. The tongue images obtained under this light look dark red and are inconsistent with the tongue color observed in natural daylight. Therefore, it is essential to improve the color temperature of the light source while maintaining the color rendering index. Zhang et al.[22] designed a standard tongue image acquisition device. It has two 70W cool-type halogen lamps with a color temperature of 4800k. To compensate for the high heat dissipation, optical fibers were used as waveguides and a light source separate from the image acquisition part was installed. The acquisition device has been demonstrated by six TCM experts to provide a stable environment for tongue diagnosis. The acquisition of tongue images is the premise of tongue image processing and analysis, and the acquired images are required to have high resolution and excellent color reproduction. The tongue color can best express the physiology and lesions of the tongue. Whether the color of the tongue image is actual or not is very important, which directly affects the accuracy of the automatic analysis of the features of the tongue map. Therefore, the color correction of the tongue image is necessary.

To achieve color correction of tongue images, Wang et al.[23] proposed an optimized correction scheme to correct tongue images captured in different device-related color spaces to a target device-independent color space. After capturing tongue images with the same camera and lighting conditions, the relevant parameters were checked using a Munsell color detector and a spectrophotometer. They are fed into different regression algorithms to train the correction parameters. Finally, this color correction algorithm was applied to the tongue image to obtain the corrected tongue image. Hu et al.[13] used a support vector machine (SVM) to predict the illumination conditions and the corresponding color correction matrix based on the color difference of images taken with or without flash. The method can correct the color of tongue images under different lighting conditions (fluorescent, incandescent, halogen, etc.) and provides better accuracy in detecting tongue features with less processing complexity.

5 Tongue Segmentation

In addition to the tongue, the TCM tongue images collected by the tongue scanner often contain background areas, such as lips, teeth, or even facial images, which do not play much of a role in tongue diagnosis. To avoid affecting the subsequent analysis of these regions, segmenting the tongue from the background regions such as the face is a crucial step in automatic tongue analysis. It is an extremely tough process due to tongue pathology, tongue shape variations, and interference from lips and teeth. Meanwhile, the accuracy of automatic tongue segmentation will directly affect the performance of algorithms related to tongue image feature analysis. An accurate tongue image segmentation method is a crucial technique for studying the objectification of tongue diagnosis. The existing automatic tongue segmentation methods can be roughly divided into two categories: Segmentation method based on traditional technology and segmentation method based on deep learning.

The active contour model, also known as Snake, is a complex active contour extraction and image interpretation method[24]. The method has been extensively researched and applied in the research area of image segmentation and contour detection[25]. In the same feature extraction process, the initial estimation of data, target contour, and a priori knowledge is integrated. After the initialization is initiated, a continuous and complete target contour is captured without human intervention. At the same time, the image segmentation process can effectively utilize the image's high-level information and guide and correct the processing of the underlying visual messages. This kind of processing has similarities with the human vision system[26].

As the most fundamental active contour model, the snake model also has defects. Therefore, many researchers have improved and studied based on this model, advancing the research progress of segmentation methods based on traditional techniques. The shapes of tongue bodies collected from different individuals are very different and therefore cannot be correctly described using predefined deformable templates. To address this problem, Pang et al.[27] proposed an original technique based on a combination of a bi-elliptical deformable template (BEDT) and an active contour model, known as bi-elliptical deformable contour (BEDC). The algorithm features a fully automatic interpretation of the tongue image and a consistent combination of global and local control through template forces. Subsequently, BEDC was applied to a mass of clinical tongue images with remarkable segmentation results, enabling the interpretation of tongue images in a fully automated manner.

Ning et al.[28] proposed an automatic tongue segmentation method based on region merging. First, the tongue image is diffused while preserving the edge structure of the tongue. After segmenting the diffused tongue image into multiple small regions, the tongue regions are merged and extracted. Finally, the extracted tongue contour is served as the initial curve, and the region merging results are refined using the snake algorithm. The refined tongue contour is smoother than the result obtained by region merging. Compared with the previous double elliptical deformable contour algorithm based on the active contour model[27], the method significantly improves the segmentation performance and can reliably extract the tongue body from different tongue images.

In contrast to other researchers who used snake-based algorithms for tongue segmentation, shi et al.[29] used the method of saliency object detector proposed by Feng et al.[30]. They used a specific theoretical tool segmentation technique for clinical tongue images. Based on the knowledge of tongue shape and location, the tongue region is initialized into an upper binary part and a lower ensemble matrix. Then the dual geographic vector flow (DGF) method is applied to detect tongue edges and segment the tongue region. Geodesic flow is calculated in the lower part of the image and geographic gradient vector flow is computed in the upper part.

Li et al.[31] used a hyperspectral imaging system instead of a digital camera to acquire tongue images and designed a tongue segmentation algorithm based on hyperspectral images. This algorithm converts the hyperspectral tongue image cube into a spectral angle cube by a spectral angle matching algorithm and then detects the edge information by employing the edge information of the one-dimensional pulse waveform, and finally realizes the tongue segmentation. The experiment shows that this hyperspectral image-based tongue segmentation algorithm can segment the tongue body more accurately.

The segmentation method based on the variable model usually uses the Snakes algorithm, which requires the initial region to be specified first and then fine-grained segmentation with Snakes. However, the selection method of the initial region sometimes has a relatively large error or is more complicated, which significantly reduces the practicability of the algorithm. The TCM tongue image segmentation method uses image pixel value characteristics and some specific algorithms to achieve tongue image segmentation, but the stability and performance of these algorithms are difficult to meet the practical application requirements, these algorithms need human assistance, and the automation effect is poor, the algorithm runs slower. Most of the existing tongue image segmentation methods are proposed for closed collection environments, and the robustness of the algorithms is poor when faced with complex open environments. Therefore, using new image processing techniques to improve the robustness of segmentation methods has important theoretical research significance and practical application value.

In recent years, deep learning has made significant progress in computer vision fields such as semantic segmentation. Among them, the convolutional neural network (CNN)[32] is extensively used in image segmentation due to its robust feature learning and expression capabilities. Deep learning algorithms for tongue segmentation have been explored to reduce computational time and hardware requirements. The tongue image segmentation problem is similar to the image semantic segmentation problem. Semantic segmentation, also known as full-pixel semantic segmentation, labels each pixel in an image with a class label to identify the content and location in the image[33]. Compared with natural image semantic segmentation, tongue image segmentation has the following characteristics[34]:

1. The color and gray values of the tongue are close to those of lips and skin, so they are difficult to distinguish.

2. The tongue surface contains a wealth of features, which have a significant impact on tongue edge extraction. For example, tooth marks on the edge of the tongue body and cracks on the tongue body cause interference to the determination of tongue edges.

3. The edge of the tongue root is fuzziness, and it is difficult to accurately determine the edge of the tongue root by relying on the edge information.

4. The difference between tongues collected from different diseases and different people are distinct, and it is difficult to use a fixed deformation template to solve the problem of tongue morphological differences.

5. The surface of the tongue body reflects many pathological details, which has a significant impact on the edge extraction, such as tooth marks on the edge of

the tongue and cracks on the tongue body.

Lin et al.[35] proposed an end-to-end trainable tongue image segmentation method using a deep convolutional neural network based on ResNet[36] called DeepTongue. Unlike the traditional manual extraction of image features, this method can automatically extract high-level image features for better segmentation. It segments the tongue by using a forward network without image pre-processing. The algorithm has no restrictions on the external illumination, the location of the tongue and the size of the tongue image. Experimental results show that DeepTongue significantly improves the accuracy and speed of segmentation. In addition, it is much faster than existing tongue image segmentation methods.

Xue et al.[37] proposed a deep learning-based tongue image segmentation method. They first applied semantic segmentation to tongue segmentation by using pixel classification, where segmenting the tongue from the original image can be viewed as labeling all pixels belonging to the tongue in the image as the tongue and all other pixels as the background. Then, a fully convolutional network is used to segment the tongue automatically while preserving the semantic information of the tongue shape. In addition, they also tried to combine it with traditional algorithms to optimize the results. The experimental results show that the neural network-based semantic segmentation method outperforms the traditional algorithm in terms of accuracy and efficiency.

Qu et al.[38] proposed a SegNet-based automatic segmentation method for tongue images. In the segmentation method, an image quality evaluation method based on luminance statistics is proposed to determine whether the input image needs to be segmented or not. And SegNet is used to train on a dataset constructed exclusively for tongue image segmentation to obtain a depth model for automatic tongue image segmentation. Compared with the traditional tongue image segmentation methods, it avoids the complicated process of manual feature extraction and has obvious superiority in segmentation performance.

Zhou et al.[39] proposed a new end-to-end model for multi-task learning of tongue localization and segmentation, called TongueNet, based on deep convolutional neural networks that automatically segment the tongue in a pixel-to-pixel manner. In order to extract multi-scale features of tongue images, a feature pyramid network based on context-aware residual blocks is proposed. The network is designed based on the characteristics of tongue images and can effectively extract multi-scale features of the tongue. They conducted a quantitative and qualitative comparison between TongueNet and state-of-the-art methods on commonly used datasets, and the segmentation results showed that TongueNet significantly outperformed other methods.

In tongue segmentation, the differences in the size and shape of the tongue and the similarity of the tongue color to the color of the lips increase the difficulty of tongue segmentation, which makes the traditional tongue image segmentation method in terms of segmentation automation and segmentation accuracy. To be further improved. In addition, the closed environment has a stable lighting environment, which is more beneficial to the tongue segmentation algorithm. The existing automatic tongue image segmentation methods are mainly applied in the closed acquisition environment; the tongue image segmentation problem in the open acquisition environment is affected by the illumination and the image quality impact is more difficult to resolve. Therefore, it is of great significance to use the latest research algorithms in the fields of image processing and machine learning to improve the segmentation accuracy of tongue images. Table 1 summarizes the methods used for tongue segmentation and their advantages.

6 Tongue Feature Extraction Methods

Tongue features, including tongue color, tongue coating, and tongue shape, are an essential basis for TCM doctors to diagnose diseases. The different parts of the tongue correspond to the human organs, and organ changes can be objectively reflected in the tongue, and the doctor can diagnose the patient's physical condition by observing the tongue features.

Table 1 Tongue Segmentation Methods

References	Segmentation Method	Advantages
Pang[27]	Bi-elliptical deformable contour	Model can deform to fit local details
Ning[28]	The proposed method based on region merging	It reduces the interference of strong edges around the tongue body
Shi[29]	The double geo-vector flow	Circumvent the problems of edge enhancement and contour discontinuity
Li[31]	Hyperspectral image based tongue segmentation algorithm	Compared with BEDC, this algorithm is simpler and has better segmentation results
lin[35]	An end-to-end segmentation method based on ResNet	The proposed method segments tongue by using a forward network without preprocessing, and has no restrictions of the illumination and size of tongue images.
Xue[37]	Segmenting the tongue with semantic segmentation	The segmentation method outperforms the traditional algorithm in terms of accuracy and efficiency. The method does not require manual annotation.
Qu[38]	Tongue image segmentation method based on SegNet	The method avoids the complicated process of manual feature extraction and has obvious advantages in segmentation performance.
Zhou[39]	A novel end-to-end model for multi-task learning of tongue localization and segmentation	The model achieves state-of-the-art tongue segmentation performance in terms of robustness and accuracy.
Li[40]	Tongue contour extraction based on improved level set curve evolution	The method considers not only the color information but also the tongue contour shape constraint expressed by the energy function
Huang[41]	A new OET-NET using U-Net	The new model excludes the effects of distance, light and similar objects. Thus, it can quickly and accurately extract the tongue body from the open environment.

The extraction and analysis of tongue features is an essential step in the objective and quantitative application of Chinese medicine tongue diagnosis[42]. Accurate classification is difficult due to the subtle differences between internal categories. With the need for objectivity and standardization in TCM tongue diagnosis, researchers have devoted their work to the automated classification of tongue features.

Huang et al.[43] proposed a classification method for automatic identification and analysis of tongue shapes based on geometric features. The method corrects tongue deflection by using a combination of automatic contour extraction and length, area, and angle criteria. Tongue shape features were defined using seven sub-features defined by length, area and angle information. Experimental results show that this shape correction method reduces the bias of tongue shape. The tongue shape classification method achieved an accuracy of 90.3%.

Zhang et al.[44] used geometric features to quantify the shape of the human tongue and its relationship with patient status. Thirteen geometric features based on measurements, distances, areas and their ratios were extracted from the acquired tongue images by a specially designed color correction device. With these features, five tongue shapes (rectangular, pointed triangle, square and round) were defined based on TCM theory, and these shapes were classified using a decision tree. The experimental results showed that the extracted geometric features were helpful in tongue shape classification with an average accuracy of 76.24% for all shapes.

The teeth-marked tongue, as one of the tongue features, can provide a variety of valuable diagnostic information to TCM practitioners. However, the dentate features of different tongues are diverse, and researchers have investigated dentate tongue identification. The majority of existing methods use concave area information to classify dentate tongue, Shao et al.[45] proposed a dentate tongue recognition algorithm using concave surface and brightness variation of tongue dentate marks. The classification effect has experimented on a test database with a high accuracy rate. However, the classification effect of this algorithm is not stable when the dentition area is not concave. To deal with this problem, Li et al.[46] proposed a three-stage method by which a suspicious region is first proposed using concavity information, then deep features are extracted using convolutional neural networks, and finally, a multi-instance classifier is used for the final decision. Experimental results demonstrate the effectiveness of the method.

According to TCM theory, tongue coating can provide valuable diagnostic information, and its color, shape and location can reflect the internal state of the body and organs[47-48]. However, because the tongue is variable and different tongues have different coating, tongue classification is a challenging task. Most researchers utilize features extracted from a fixed location, which can lead to inconsistent feature extraction when the size or location of the tongue region changes[49]. To address this issue, Tang et al.[50] proposed a new method for tongue feature extraction and classification using artificial intelligence. It first selects suspicious tongue patches using tongue information of decayed and greasy tongue. After that, a convolutional neural network (CNN) is used instead of the manually extracted tongue features. In addition, a multi-instance support vector machine (MI-SVM) is applied to the tongue classification. The experimental results show that the method outperforms existing tongue classification methods.

Liu et al.[51] proposed a new method for analyzing tongue information based on hyperspectral images. Hyperspectral images were acquired using a hyperspectral imaging system in the spectral range of 370.2000 to 992.9560 nm (343 bands). In comparison with the actual tongue, it was found that the spectral images in the 527.5480 nm band reflected the actual tongue information better than the others. The experimental results showed that the hyperspectral imaging technique is useful for tongue information extraction.

Tongue color is one of the features focused on observation during tongue diagnosis in TCM, and high-precision tongue color recognition will help improve the efficiency of TCM diagnosis. Before neural networks were applied to the medical field, common tongue color classification was based on the color space. Wang et al.[52] investigated in detail three features of the tongue color space, namely the tongue color domain that defines the color range, the color centers of 12 tongue color categories, and the color distribution of typical image features in the tongue color domain. Using the obtained tongue color space, they proposed a new color feature extraction method for diagnostic classification, and the experimental results verified the effectiveness of the method.

When the artificial intelligence technology was relatively mature, researchers combined deep learning with tongue color classification. Kawanabe et al.[53] applied the K-means clustering algorithm as a machine learning method to the acquired images to quantify tongue body and coating color information in a clinical setting. Hou et al.[54] proposed a neural network-based method for automatic tongue color classification. The acquired images will be pre-processed and enhanced to be stored in a tongue image database. The images from the database are input to the neural network for training, while the network parameters are adjusted in a targeted manner. The network is trained accurately and then used for tongue color classification. The experimental results show that the method is more practical and accurate than the traditional method.

Hsu et al.[55] studied tongue features in early-stage breast cancer patients and non-breast cancer patients. They used an automated tongue diagnostic system to extract nine tongue features: tongue color, tongue texture, tongue fissures, tongue coating, red spots, petechiae, tooth marks, saliva, and tongue shape. The extracted features were further subdivided according to the localized area by extracting significant tongue features to distinguish early breast cancer patients from non-breast cancer patients.

In the study of tongue classification, some scholars have digitized tongue features and classified them according to specific criteria[43-46]. Some scholars have applied deep learning techniques to tongue feature classification and developed various classification models with high accuracy[50,52,55]. These methods are effective in identifying features such as tongue color, tooth marks, and tongue shape individually. However, these studies focused on only a few features and did not analyze for all tongue features. Therefore, these studies are not effective for clinical applications. In addition, interpretability is important for medical diagnosis results, and these methods, although validated with a large amount of data, do not explain the deep learning training process. To solve these problems, Li et al.[56] used the ResNet network as the backbone feature extraction network to achieve the final classification of 11 tongue features, including tongue texture and tongue coating features, and visualized the classification decisions using GradCAM. The method is similar to the diagnosis of a Chinese medicine practitioner, thus effectively helping and standardizing the diagnosis process. Table 2 summarizes the methods used for tongue feature extraction and their accuracy rates.

7 Disease Prediction

According to traditional Chinese medical theory, the tongue is divided into four sections, which are the tongue tip, tongue margin, tongue center, and tongue root. Fig.2 shows the different regions into which the tongue is divided[57].

The tongue tip corresponds to the heart and lungs, and the tongue margin corresponds to the liver and gallbladder. The tongue center corresponds to the stomach and spleen, and the tongue root corresponds to the kidneys and bladder. According to the theory that the parts of the tongue correspond to the organs, the doctor can understand the pathological changes of the organs and the location of the disease by observing the changes in each part of the tongue. It is an essential reference for clinical treatment.

Table 2 Tongue Feature Extraction Methods

References	Extraction of Tongue Features	Feature Extraction Method	Accuracy
Huang[43]	Tongue shape	Geometric features	90.3%
Zhang[44]	Tongue shape	Geometric features	76.24%
Shao[45]	Teeth-marked tongue	Gradient of Concave Region	83%
Li[46]	Teeth-marked tongue	VGG-16 and multiple-instance support vector machines	72.7%
Zhang[49]	Tongue color and Teeth-Marked Tongue	The clustering method and Graham convex hull algorithm	Not mentioned
Tang[59]	Tongue coating	ResNet and multiple-instance Support Vector Machine	85%
Liu[51]	Tongue coating	Hyperspectral technology	Not mentioned
Wang[52]	Tongue color	One-class SVM	Not mentioned
Cui[42]	Tongue color	ROC-Boosting algorithm	72.7%
Kawanabe[53]	Tongue color	K-means clustering algorithm	Not mentioned
Hou[54]	Tongue color	CaffeNet	83%
Lo[55]	Tongue color, tongue texture, tongue fissures, tongue coating, red spots, petechiae, tooth marks, saliva, and tongue shape.	The Mann–Whitney test and logistic regression	early BC patients:60%, Normal:80%
Li[56]	11 features including: tongue color, tongue coating, tooth marks, Rough and tender tongue, Puffy and thin tongue, Fissured tongue and so on	ResNet	86%

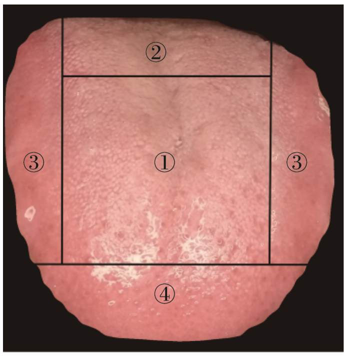


Fig.2 Region 1 is the center of the tongue, corresponding to the stomach and spleen. Region 2 is the root of the tongue and corresponds to the kidney and bladder. Area 3 is the edge of the tongue and corresponds to the liver and gallbladder. Area 4 is the tip of the tongue and corresponds to the heart and lungs.

The surface of the tongue contains many features such as teeth marks, fissures, and color. Different diseases correspond to different tongue features, and researchers have made disease predictions based on different tongue features or established direct links between tongue features and diseases. Kim et al.[58] explored the usefulness of the Tongue Diagnostic System as a diagnostic tool for assessing tongue thickness. The clinical trial included 60 patients with functional dyspepsia. The percentage of tongue moss measured by the tongue diagnosis system correlated significantly with the actual amount of tongue moss, indicating that the tongue diagnosis system can measure the percentage of tongue coating quantitatively.

As tongue color is an important feature to identify diseases during tongue diagnosis in TCM, Zhang et al.[59] proposed a tongue color analysis system. This system was built based on a dataset consisting of 143 tongues of healthy individuals and 902 tongues of patients with different diseases. The system was able to distinguish between healthy and diseased when detecting new tongue images. The average accuracy of the system recognition was 91.99%.The experimental results show that there exists a relationship between tongue color and human status, which can be used for detecting diseases in medical applications.

The significant link between the tongue microbiome and conventional tongue diagnosis has been demonstrated in previous studies[60]. Hu et al.[61] investigated the relationship between the tongue and oral microbiota of patients with gastric cancer. The tongue thickness of gastric cancer patients and healthy controls were analyzed using a tongue collection instrument, and high-throughput sequencing was used to characterize the microbial community of the tongue. The bacterial community of the tongue was correlated with the appearance of the tongue moss. The experimental results suggest that the tongue may be a potential way to diagnose gastric cancer, but its sensitivity needs further improvement.

Since the diagnosis of gastric cancer is time-consuming and gastric cancer detection is invasive, it tends to cause repercussions for patients. With the rapid development of artificial intelligence technology, researchers have proposed various methods to diagnose cancer. Gholami et al.[62] improved the accuracy of gastric cancer diagnosis by using a combination of deep neural networks based on the tongue surface and color features, support vector machines, and deep convolutional neural networks. According to the results, the use of DenseNet architecture in the proposed method has higher accuracy compared to other architectures, with 91% accuracy observed in the diagnosis of gastric cancer.

The traditional breast cancer diagnosis has other drawbacks besides invasive or radioactive, such as false-negative mammograms and ultrasound's inability to detect breast calcifications. Lo et al.[63] used an automated tongue diagnostic system to extract tongue features from breast cancer patients and non-breast cancer patients for non-invasive identification with the aim of early detection of breast cancer and timely treatment. Afterward, they analyzed the results by methods such as the Mann-Whitney test and logistic regression, and the experimental results demonstrated that tongue diagnosis can be used as a preliminary screening procedure for early detection of breast cancer.

To investigate the tongue characteristics of lung cancer patients with different TCM syndromes, Su et al.[64] used a tongue digital analyzer to detect tongue parameters and analyzed the qualitative, tongue color, and quantitative tongue images separately. The experimental results revealed statistically significant differences in tongue color, tongue color, and tongue thickness among different lung cancer syndrome groups.

Diabetes mellitus is a metabolic disease characterized by high blood sugar. Patients with diabetes without early diagnosis or standard treatment can lead to serious multisystem complications. The features of the tongue are closely associated with diabetes mellitus. Objectifying tongue characteristics and developing predictive models for diabetes risk has become an important research direction for researchers[65]. Hsu et al.[66] used an automated tongue diagnostic system to extract tongue images from 199 type 2 diabetic patients and 372 non-diabetic patients. Subsequently, tongue characteristics of different groups were analyzed and compared using methods such as independent t-test for continuous variables and chi-square test for categorical variables. The results showed that the prevalence of thick coating, yellow coating and blue tongue was significantly higher in type 2 diabetic patients compared to the control group.

Li et al.[67] used the application of the TFDA-1 tongue diagnostic instrument to collect tongue images. Then tongue features including color and texture features were extracted using the tongue diagnostic system, and advanced tongue features were extracted using the ResNet-50 network. Finally, a non-invasive diabetes risk prediction model was developed to predict the risk of pre-diabetic patients and diabetic patients. The model can detect pre-diabetic patients and diabetic patients non-invasively. The accuracy of the model was 0.929. In addition, their study fully demonstrated the correlation between tongue features and glucose metabolism. The methods used for disease prediction are summarized in Table 3.

8 Conclusion

This paper introduces the research progress of the automated tongue diagnosis system in the past 20 years. With the advancement of technology, acquisition devices have evolved from simple cameras to high-precision and high resolution digital cameras; tongue segmentation algorithms and tongue feature recognition algorithms have evolved from traditional algorithms requiring human intervention to artificial intelligence algorithms that automatically learn deep features; and the focus of research efforts has shifted from manufacturing acquisition instruments and processing tongue images to disease prediction.

With the improvement of image capture equipment and image processing methods, automatic tongue diagnosis provides more accurate and objective clinical diagnosis results and plays an essential role in Chinese medicine[69]. However, the following shortcomings of current tongue objectification research limit its further development.

Table 3 Disease Prediction Methods

References	Disease	Prediction Algorithm	Accuracy
Kim[58]	Functional dyspepsia	Pearson's correlation	The agreement: 0.84
Zhang[59]	Illness	k-NN and SVM	91.99%
Hu[61]	Gastric cancer	Student-Newman-Keuls	Not mentioned
Gholami[62]	Gastric cancer	DenseNet	91%
Lo[63]	Early-stage breast cancer	The Mann–Whitney test and logistic regression	Early BC patients:60%, Normal:80%
Su[64]	Lung cancer	Discriminant analysis method	65.7%
Li[65]	Diabetes	Stacking model and ResNet50	87%
Hsu[66]	2 Diabetes	ResNet50	87%
Li[67]	Diabetes	ResNet-50	92.9%
Zhao[68]	Hypertension	BP Neural Network	84.78%

1. Tongue features are susceptible to factors such as diet, medications, and personal habits, and changes in features may lead to erroneous results in subsequent studies.

2. There is no standard tongue database. During tongue objectification studies, researchers have used different collection devices and different collection environments. This leads to the inability to generalize the captured tongue photos, the lack of a large amount of data, and the difficulty in recognizing the accuracy and interpretability of the algorithm.

3. The research process focuses more on the data acquisition and analysis techniques themselves, ignoring the real needs of clinical research, and the technical tools provided lack TCM guidance and have limited significance in assisting clinical diagnosis.

In response to these problems, further research on tongue diagnosis objectification should focus on the integration with clinical diagnosis and listen to clinicians' know opinions during the research process[70]. In addition, with the help of modern advanced science and technology, a unified standard way of collecting tongue photographs should be established, and the promotion of a standard tongue image database and various disease prediction models based on tongue diagnosis analysis should be promoted.

References

[1] Normile, D. The new face of traditional Chinese medicine[J]. Science 2003; 299(5604): 188–190.

[2] Wang, Y. H., Xu, A. L. Zheng: A systems biology approach to diagnosis and treatments[J]. Science 2014, 346, S13–S15.

[3] Kim, S. R., Choi, W., Yeo, I. & Nam, D. H. Comparative Analysis of Tongue Indices between Patients with and without a Self-Reported Yin Deficiency: A Cross- Sectional Study[J]. Evid Based Complement Alternat Med 2017, 1279052.

[4] Matos, L. C., Machado, J. P., Monteiro, F. J. & Greten, H. J. Can Traditional Chinese Medicine Diagnosis Be Parameterized and Standardized? A Narrative Review[J]. Healthcare 2021, 9.

[5] Maciocia, G. Tongue Diagnosis in Chinese Medicine[M]. Eastland Press, Seattle, WA, 1995.

[6] Jung, C. J., Jeon, Y. J., Kim, J. Y. & Kim, K. H. Review on the current trends in tongue diagnosis systems[J]. Integr Med Res 2012, 1, 13-20.

[7] Huang, J. et al. Detection of Diseases Using Machine Learning Image Recognition Technology in Artificial Intelligence[J]. Comput Intell Neurosci 2022, 5658641.

[8] Zhou, Z., Peng, D., Gao, F. & Lu, L. Medical Diagnosis Algorithm Based on Tongue Image on Mobile Device[J]. Journal of Multimedia Information System 2019, 6, 99-106.

[9] Ma, J., Wen, G., Wang, C. & Jiang, L. Complexity perception classification method for tongue constitution recognition[J]. Artif Intell Med 2019, 96.

[10] Gareus, I. et al. Introducing a computer-assisted, digital tongue-imaging device for standardization of traditional tongue diagnosis[J]. Forsch Komplementmed 2014, 21, 190-196.

[11] Cai, Y. A novel imaging system for tongue inspection[C]. //19th IEEE Instrumentation and Measurement Technology Conference (IMtc 2002), vol.1. 2002: 159-163.

[12] Cao, M., Cai, Y., Liu, C., et al. Recent Progress in New Portable Device for Tongue Image Analysis[C]. //2008 International Conference on Neural Networks and Signal Processing. [v.2].: IEEE, 2008: 488-492.

[13] Hu, M. C., Cheng, M. H. & Lan, K. C. Color Correction Parameter Estimation on the Smartphone and Its Application to Automatic Tongue Diagnosis. J Med Syst 2016, 40, 18.

[14] Han, S., Chen, Y., Hu, J. & Ji, Z. Tongue images and tongue coating microbiome in patients with colorectal cancer[J]. Microb Pathog 2014, 77, 1-6.

[15] Kim, J., Han, G., Ko, SJ., et al. Tongue diagnosis system for quantitative assessment of tongue coating in patients with functional dyspepsia: a clinical trial[J]. Ethnopharmacol. 2014 Jun 13.

[16] Li, Q., Liu, J., Xiao, G., Xue, Y. Hyperspectral tongue imaging system used in tongue diagnosis[J]. ICBBE 2008: 2579–81.

[17] Zhang, D., Zhang, J., Wang, Z. & Sun, M. Tongue colour and coating prediction in traditional Chinese medicine based on visible hyperspectral imaging[J]. IET Image Processing 2013, 2265-2270.

[18] Yang, Y. et al. Nonlinearity of Degenerately Doped Bulk-Mode Silicon MEMS Resonators[J]. Journal of Microelectromechanical Systems 2016, 25, 859-869.

[19] Zhi, L., Wang, H., Hui, X., et al. 3D Tongue Reconstruction Based on Multi-view Images and Finite Element[J]. Advances in Information Sciences & Service Sciences 2011.

[20] Lv, H., Cai, Y., Song, G. 3D reconstruction of tongue surface based on photometric stereo[C]// IEEE International Conference on Signal Processing. IEEE, 2013.

[21] Jung, C. J., Kim, K. H., Jeon, Y. J. & Kim, J. Improving color and shape repeatability of tongue images for diagnosis by using feedback gridlines[J]. European Journal of Integrative Medicine 2014, 6, 328-336.

[22] Zhang, H. Z., Wang, K. Q., Zhang, D., et al. Computer aided tongue diagnosis system. [C]// International Conference of the Engineering in Medicine & Biology Society. IEEE, 2006.

[23] Wang, X. & Zhang, D. An optimized tongue image color correction scheme[J]. IEEE Trans Inf Technol Biomed 2010, 14, 1355-1364.

[24] Michael, K., Andrew, W.. Snakes: Active contour models[J]. International Journal of Computer Vision 1988, 1(4).

[25] Bai, X. & Wang, W. Saliency Snake: A unified framework with adaptive initial curve[J]. Optik 2014, 125, 6972-6976.

[26] Mesejo, P., Ibáñez, Ó., Cordón, Ó. & Cagnoni, S. A survey on image segmentation using metaheuristic-based deformable models: state of the art and critical analysis[J]. Applied Soft Computing 2016, 44, 1-29.

[27] Pang, B., Zhang, D. & Wang, K. The bi-elliptical deformable contour and its application to automated tongue segmentation in Chinese medicine[J]. IEEE Trans Med Imaging 2005, 24, 946-956.

[28] Ning, J., Zhang, D., Wu, C. & Yue, F. Automatic tongue image segmentation based on gradient vector flow and region merging[J]. Neural Computing and Applications 2010, 21, 1819-1826.

[29] Shi, M., Li, G., Li, F., Xu, C. Computerized tongue image segmentation via the double geo-vector flow[J]. Chinese medicine 2014,9(1).

[30] Feng, J., Wei, Y., Tao, L., et al. [C]. //2011 International Conference on Computer Vision. [v.2].: IEEE, 2011: 1028-1035.

[31] Li, Q., Xue, Y., Wang, J., et al. Automated tongue segmentation algorithm based on hyperspectral image[J]. Journal of Infrared & Millimeter Waves 2007, 26(1): 77-8.

[32] Liu, Q., Zhang, N., Yang, W., et al. A Review of Image Recognition with Deep Convolutional Neural Network[J]. Springer Cham, 2017.

[33] Michael, S., Guo, Y., Theodoros, G., & Liu,Y.. A review of semantic segmentation using deep neural networks[J]. Int J Multimed Info Retr2018, 7, 87–93.

[34] Lu, Y., Li, X., Zhang, H., et al. Review on tongue image segmentation technologies for traditional Chinese medicine: Methodologies performances and prospects[J]. Acta Automatica Sinica (in Chinese) 2019, 4: 1-12.

[35] Lin, B., Xie, J., Li, C., et al. Deeptongue: Tongue Segmentation Via Resnet[C]// 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2018.

[36] He, K., Zhang, X., Ren, S., et al. Deep Residual Learning for Image Recognition[C]// 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). IEEE, 2016.

[37] Xue, Y., Li, X., Wu, P., et al. Automated Tongue Segmentation in Chinese Medicine Based on Deep Learning: 25th International Conference, ICONIP 2018, Siem Reap, Cambodia, December 13–16, 2018, Proceedings, Part VII[M]. 2018.

[38] Qu, P., Zhang, H., Zhuo, L., Zhang, J. & Chen, G. in Intelligent Computing Theories and Application Lecture Notes in Computer Science Ch [M]. Chapter 23, 247-259 (2017).

[39] Zhou, C., Fan, H. & Li, Z. Tonguenet: Accurate Localization and Segmentation for Tongue Images Using Deep Neural Networks[J]. IEEE Access 2019, 148779-148789.

[40] Li, W., Hu, S,, Wang, S., et al. Towards the objectification of tongue diagnosis: Automatic segmentation of tongue image[C]// Conference of the IEEE Industrial Electronics Society. 2010.

[41] Huang, Z., Miao, J., et al. A novel tongue segmentation method based on improved U-Net[J]. Neurocomputing 2022, 500.

[42] Cui, Y., Liao, S. & Wang, H. ROC-Boosting: A Feature Selection Method for Health Identification Using Tongue Image[J]. Comput Math Methods Med 2015, 362806.

[43] Huang, B., Wu, J., Zhang, D. & Li, N. Tongue shape classification by geometric features[J]. Information Sciences 2010, 180, 312-324.

[44] Zhang, B. & Zhang, H. Significant Geometry Features in Tongue Image Analysis[J]. Evid Based Complement Alternat Med 2015, 897580.

[45] Shao, Q., Li, X., Fu, Z. Recognition of teeth-marked tongue based on gradient of concave region[C]// 2014 International Conference on Audio, Language and Image Processing. IEEE, 2014.

[46] Li, X., Zhang, Y., Cui, Q., Yi, X. & Zhang, Y. Tooth-Marked Tongue Recognition Using Multiple Instance Learning and CNN Features[J]. IEEE Trans Cybern 2019, 49, 380-387.

[47] Wei, B., Shen, L., Cai, Y., et al. Research on Curdy and Greas Tongue Fur Analysis for Traditional Chinese Medicine[J]. Acta Electronica Sinica 2003, 31(S1): 2083-2086.

[48] Sun, S. et al. Biology of the Tongue Coating and Its Value in Disease Diagnosis[J]. Complement Med Res 2018, 25, 191-197.

[49] Zhang, J., Hu, G., Zhang, X. Extraction of tongue feature related to TCM physique based on image processing[C]// 2015 12th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP). IEEE, 2015.

[50] Tang, Y., Sun, Y., Chiang, J. Y. & Li, X. Research on Multiple-Instance Learning for Tongue Coating Classification[J]. IEEE Access 2021, 9, 66361-66370.

[51] Liu, M., Zhao, J., et al. Tongue Coat Information Extraction of the Traditional Chinese Medicine with Hyperspectral Image. [J], Guang Pu Xue Yu Guang Pu Fen Xi. 2017 Jan; 37(1):162-5. Chinese. PMID: 30195286.

[52] Wang, X., Zhang, B., Yang, Z., Wang, H. & Zhang, D. Statistical analysis of tongue images for feature extraction and diagnostics[J]. IEEE Trans Image Process 2013, 22, 5336-5347.

[53] Kawanabe, T. et al. Quantification of tongue colour using machine learning in Kampo medicine[J]. European Journal of Integrative Medicine 2016, 8, 932-941.

[54] Hou, J., Su, H., Yan, B., et al. Classification of Tongue Color Based on CNN[C]//. Proceedings of 2017 IEEE 2nd International Conference on Big Data Analysis （ICBDA 2017）,2017: 745-749.

[55] Hsu, P., Wu, H., Chang, H., Chen, J., et al. A Perspective on Tongue Diagnosis in Patients with Breast Cancer[J]. Evid Based Complement Alternat Med 2021 Dec 26; 2021: 4441192.

[56] Li, J. et al. Automatic Classification Framework of Tongue Feature Based on Convolutional Neural Networks[J]. Micromachines (Basel) 2022, 13.

[57] Lozano, F. (2014). Basic Theories of Traditional Chinese Medicine. In: Lin, YC., Hsu, EZ. (eds) Acupuncture for Pain Management[M]. Springer, New York, NY.

[58] Kim, J. et al. Tongue diagnosis system for quantitative assessment of tongue coating in patients with functional dyspepsia: a clinical trial[J]. J Ethnopharmacol 2014, 155, 709-713.

[59] Zhang, B., Wang, X., You, J. & Zhang, D. Tongue color analysis for medical application[J]. Evid Based Complement Alternat Med 2013, 264742.

[60] Jiang, B. et al. Integrating next-generation sequencing and traditional tongue diagnosis to determine tongue coating microbiome[J]. Sci Rep 2012, 2, 936.

[61] Hu, J., Han, S., Chen, Y. & Ji, Z. Variations of Tongue Coating Microbiota in Patients with Gastric Cancer[J].

Biomed Res Int 2015, 173729.

[62] Gholami, E., Kamel Tabbakh, S. R. & kheirabadi, M. Increasing the accuracy in the diagnosis of stomach cancer based on color and lint features of tongue[J]. Biomedical Signal Processing and Control 2021, 69.

[63] Lo, L. C., Cheng, T. L., Chen, Y. J., Natsagdorj, S., Chiang, J. Y.. TCM tongue diagnosis index of early-stage breast cancer[J]. Complementary Therapies in Medicine 2015, 23(5), 705-713.

[64] Su, W., Xu, Z. Y., Wang, Z. Q. & Xu, J. T. Objectified study on tongue images of patients with lung cancer of different syndromes[J]. Chin J Integr Med 2011, 17, 272-276.

[65] Li, J. et al. Establishment of noninvasive diabetes risk prediction model based on tongue features and machine learning techniques[J]. Int J Med Inform 2021, 149, 104429.

[66] Hsu, P. C. et al. The tongue features associated with type 2 diabetes mellitus[J]. Medicine (Baltimore) 2019, 98, e15567.

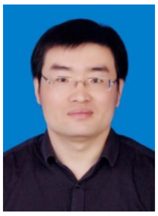
[67] Li, J., Yuan, P., Hu, X., et al. A tongue features fusion approach to predicting prediabetes and diabetes with machine learning[J]. Journal of Biomedical Informatics 2021, 115(2): 103693.

[68] Zhao, J., Ma, B., Liu, M., et al. Screening method for combined coronary artery disease in hypertensive patients by tongue hyperspectroscopy[J]. Spectroscopy and Spectral Analysis 2022, 42(02): 512-516.

[69] Meng, D. et al. Tongue Images Classification Based on Constrained High Dispersal Network[J]. Evid Based Complement Alternat Med 2017, 7452427.

[70] Chen, L., Wang, B., Zhang, Z., Lin, F. & Yihan, M. Research on Techniques of Multifeatures Extraction for Tongue Image and Its Application in Retrieval[J]. Comput Math Methods Med 2017, 8064743.

Author Biographies



ZHANG Zhidong is an associate professor and master's supervisor of North University of China. His main research interests include digitalization of Traditional Chinese medicine and ocean observation instruments.

E-mail: zdzhang@nuc.edu.com

ZHU Xiaolong is a M.Sc. candidate of North University of China. His main research interests include digitalization of tongue diagnosis and image processing algorithms.

E-mail: zxldtc112233@163.com

XUE Chenyang is a professor and doctoral supervisor of North University of China. His main research interests include optical acoustic sensors, intelligent Chinese medical treatment, and marine observation instruments, etc.

E-mail: xuechenyang@nuc.edu.com