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Tongue Image Diagnosis System using Machine Learning with Hand-Crafted Features

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***Abstract:** Traditional Chinese Medicine theorizes a clear relationship between the visual characteristics of the tongue and the operational condition of the body's organs. The visual characteristics of the tongue can offer important indications for diagnosing diseases. Investigating tongue image processing methods for automated disease identification is a flourishing field of study in the modernization of Traditional Chinese Medicine. Although autonomous extraction of high-dimensional features is inherently more beneficial in deep learning than in conventional methods, its usefulness in medical image analysis, notably in tongue images, is restricted by the need for extensive training data. This limitation arises from the need for more labeled images. This paper demonstrated the automated diagnosis of tongue photos by analyzing digital images utilizing Image Processing techniques and using Machine Learning using major image-based features. The performance simulation and analysis of the suggested system are conducted using MATLAB Software.*

***Keywords:** Tongue Image Classification, Morphological Features, Image Processing, Machine Learning*

I. INTRODUCTION

To obtain information about the state of organs, meridians, and the flow of blood and qi, traditional medical practitioners employ four diagnostic techniques: observation, auscultation and olfaction, interrogation, and pulse feeling and palpation. They extrapolate pathological and physiological changes from this data and suggest appropriate courses of action. Typically, the human tongue exhibits a range of properties that aid in diagnosing diseases, with color attributes being particularly significant. Tongue diagnosis is a crucial component of traditional medicine's inspection methods. It serves as a vital means to understand the physiological functions and pathological changes in the human body, as well as to diagnose diseases. This is achieved by closely observing and analyzing variations in tongue images [3]. Tongue fissures are cracks on the surface of the tongue that vary in number, depth, and shape. These fissures provide objective information about the body's energy, the extent and type of disease-causing factors,

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and the patient's overall condition. They can also be used to assess the outcomes and prognosis of diseases. Changes in the dimensions and quantity of these fissures are crucial factors in their diagnosis and prognosis [4]. Typically, the tongues of healthy individuals appear smooth, whereas the development of multiple fissures on the tongue usually indicates the presence of health issues. For instance, a fissured tongue may signify problems with the spleen or stomach, as well as a lack of blood and body fluids. Consequently, identifying fissures in the tongue can help patients recognize their health issues and prevent spleen- and stomach-related disorders [6].

Finding a reliable method to recognize fissured tongues is essential because it is a key component of tongue diagnostics. Computer and image processing techniques have been employed to make conventional tongue analysis more objective, advancing the field of tongue diagnosis technology. A critical aspect of this research is the examination of fissured tongues. Constructing an artificial intelligence model using previously diagnosed tongue images can provide a more objective interpretation of new tongue images in clinical practice and reduce human interpretation errors. Additionally, computer-assisted tongue analysis is highly valued in traditional medicine for its accurate, reliable, and objective medical analysis [8]. This advancement has been made possible through digital clinical imaging technologies and pattern recognition models [10].

This paper is structured as follows: Related work regarding this research is elaborated in Section II. The methodology for tongue image diagnosis is presented in Section III. The experimental result analysis of the proposed work is discussed in Section IV. Finally, the conclusion is provided in the last section.

II. LITERATURE REVIEW

The The majority of research utilizes tongue image classification techniques founded on image processing and artificial intelligence methodologies, which are elaborated upon in the following sections. A novel computer identification technique was introduced for diagnosing fissured tongue [1]. This method identifies the presence of fissures and measures their severity based on factors such as the number of fissures, their breadth, length, and depth. Initially, tongue photos were gathered from the hospital and provided to three Chinese clinical specialists, who are top physicians, for identification [2]. The primary focus is the identification of fissured tongues. First, median filtering, histogram averaging, and tongue segmentation were used to preprocess images of fissured and non-fissured tongues [3]. Input vectors were extracted using local binary patterns (LBP), histogram of

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oriented gradients (HOG), and Haar-like feature extraction techniques due to distinct differences in texture and grayscale between fissured and non-fissured portions of the images [4]. Deep convolutional neural network algorithms were utilized for tongue area detection, tongue area calibration, and constitution categorization [5]. Uneven picture distribution, caused by fluctuating environmental conditions, negatively impacts classification effectiveness. The technique involves dividing the dataset into two groups and classifying them independently, enhancing classification accuracy [6]. Three different sizes of tongue datasets were used. For each dataset, both deep convolutional neural networks and typical digital image processing methods were employed to extract features from tongue photos [7]. The novel technique was integrated with base classifiers Softmax, SVM, and Decision Tree. The CHDNet model was introduced to acquire advanced features and enhance categorization during training [8]. As a result, testing sample predictions became more accurate. A control group of 48 healthy volunteers and a cohort of 267 gastritis-diagnosed patients were used to assess the methodology. Test results indicate that CHDNet is a promising method for identifying tongue images in Traditional Chinese Medicine (TCM) research [9]. A private cloud-based telemedicine solution was developed to integrate Chinese medicine and traditional tongue examination. The YOLO v4 framework was modified to include a dual-backbone structure to identify and segment tongue images from videos [10]. Additionally, an image collector was designed to acquire pictures, calibrate light sources, and standardize picture data [11]. To ensure compatibility with data usage and transplantation, the system transfers image candidates from the private cloud platform to the database. Chinese medicine professionals analyze tongue pictures, classify suspected lesions, and provide labeled findings and suggestions to the database [12]. Preliminary testing confirmed the practicality of the telemedicine system. The Deep Color Correction Network (DCCN) was introduced to acquire a mapping model that relates distorted color images captured under various lighting conditions to desired visually perceived colors. This network ensures color consistency across different cameras or capture devices. Experimental results demonstrate that the DCCN model achieves high accuracy and resilience in both objective and subjective measures for correcting tongue image colors [13]. TongueNet, a highly accurate and efficient automated tongue segmentation technique, was introduced [14]. The U-net architecture was employed as the segmentation framework with a limited image dataset. Additionally, a morphological layer was suggested in the later construction phases [15]. When tested on a dataset of 1,000 tongue images, the system achieved a Pixel Accuracy of 98.45% with an average processing time of 0.267 seconds per image. This performance surpassed that of conventional state-of-the-art tongue segmentation methods in accuracy and speed [16]. Comprehensive qualitative and quantitative trials demonstrated the robustness of the system across various positions, poses, and shapes. Results suggest significant progress toward developing a fully automated tongue diagnosis system [17]. The model identifies tongue fissures and pinpoints their specific locations. To replicate the true color distribution of tongue images, the gray-world method adjusts color values [18]. The method was evaluated using qualitative and quantitative analyses, demonstrating favorable outcomes [19]. The conceptual alignment deep auto-encoder (CADAE) approach was proposed to assess tongue pictures representing different body composition (BC) types, core concepts of TCM. CADAE encodes tongue images in the first stage and decodes patterns in the second [20]. Tests show CADAE effectively learns representations consistent with BC types [21]. The representation space of hidden conceptual neurons can be observed using the decoder network [22]. Tests indicate artificial neural networks (ANNs), trained with different loss functions, acquire unique perspectives on data [23]. Unexplored ANN representation spaces suggest AI's potential to assist in medical progress and reduce professionals' workloads [24]. A novel deep learning (DL) method was developed for analyzing tongue color images to diagnose and classify diseases [25]. This method includes distinct steps for feature extraction, classification, and preprocessing. The model uses Gaussian filtering (GF) and data augmentation techniques to eliminate noise during preprocessing [26]. Feature vectors are extracted using the convolutional neural network (CNN) Visual Geometry Group (VGG 19) model. Classification tasks are performed using Gaussian Naive Bayes (GNB) and random forest (RF) classifiers [27]. Experimental findings show the VGG19-RF model achieved F1-Score, recall, accuracy, and precision values of 93.80%, 93.70%, 93.70%, and 93.68%, respectively [28]. On a mobile device, digital image processing and pattern recognition methods classify tongue pictures from different medical situations. The tongue body is located by identifying the trough using grayscale integral projection processing [29]. The tongue body image is transformed from RGB to HSV color space, with average hue and saturation values as color attributes. Diagnosis outcomes are determined by the relationship between bodily complaints and color features. Deep transfer learning was established for tongue image classification [30]. Pre-trained networks like ResNet and Inception_v3 extract tongue properties, and classification results are obtained using a fully connected layer and global average pooling [31]. A dataset of 2,245 tongue images from specialist TCM healthcare facilities was used for classification assessment [34]. Experimental findings validate the proposed deep transfer learning strategy's usefulness for tongue image classification, outperforming current deep learning methods [32]. An automated tongue diagnosis system for mobile-enabled platforms is suggested by the conceptual framework [35]. The integration of tongue diagnostics into next-generation point-of-care healthcare systems is facilitated by this design [36]. MATLAB is used to quantify three quantitative attributes: geometry, color, and texture. The images are classified using SVM and CNN classifiers, with CNN achieving better prediction accuracy [33].

III. REVIEW

The complete operational procedure of the method being discussed is illustrated in Figure 1. The model described comprises a sequence of processes, which will be

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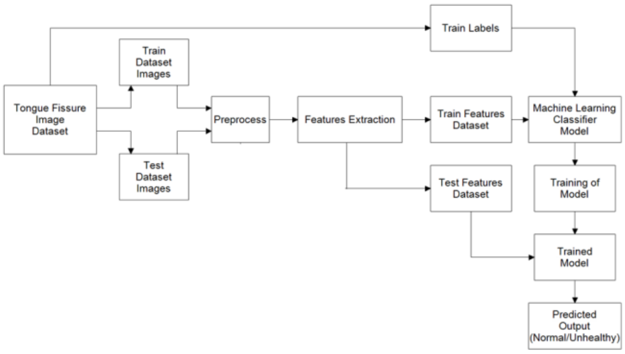
discussed in detail below.



[Fig.1: Tongue Image Diagnosis System]

A. Tongue Image Dataset, Dataset Splitting

The suggested technique utilizes a common benchmark image database for the diagnosis of tongue images [6]. The dataset is a compilation of color photographs divided into two categories: unhealthy and healthy. Training and testing are the two main phases in which the project operates. As a result, it is essential to split the dataset images into two halves. Using a machine learning classifier, training aims to produce a trained model. The training photos are extracted and then preprocessed to achieve this. In contrast, testing entails enhancing the learned model with test characteristics to evaluate or predict the incoming test picture.

B. Pre Process

During the picture preparation phase, we improved the quality of our images by eliminating minute instances of noise. This was performed to identify the targeted regions in the tongue image accurately. Our methodology entails adopting an image as input and adjusting its dimensions. Next, we employed a median filter to remove unwanted noise and provide an image devoid of noise. The median filtering system improves the magnitude value of the image by compensating for the strength value of adjacent pixels that may include noise. Furthermore, we improved the contrast of the image to pinpoint the most suitable location of the lesion. The work utilizes several initial processing techniques, which include:

a) Image Resizing: It is an essential procedure for maintaining the uniform dimensions of photographs without any reduction. Following preprocessing, the next step is background subtraction, namely the segmentation of the region of interest from the captured image. To isolate the particular area of interest from the surrounding background, the enhanced image is partitioned into segments.

b) Contrast Enhancement: It is specifically intended for commonly encountered scenarios. Various stretching strategies have been devised to expand the limited range to encompass the entire dynamic range that is accessible.

c) HSV Colour Space Conversion: It employs the principles of Hue, Saturation, and Value to define colors. The HSV color model is often favored over the RGB model in cases where accurate color description is crucial. The term "Hue" refers to the precise color, "Saturation" indicates the degree to which that color is blended with white, and "Value" indicates the degree to which that color is blended with black (Gray level). The isolation of color data from brightness is not feasible within the RGB color paradigm. Hue Saturation Value (HSV) is a technique employed to differentiate the brightness of an image from its component color information. Consequently, the RGB image undergoes conversion into an HSV image.

C. Feature Extraction

Extraction of features is the first step in the image categorization process. Occasionally, the volume of the input data is extraordinarily large, making it extremely difficult to handle in its raw form. One approach to address this issue is to transform the input data into a collection of features. It is the process of isolating and extracting distinct characteristics from tongue pictures. This approach mitigates the intricacy of classification difficulties. The objective of the process is to reduce the size of the original dataset by measuring particular attributes, known as features, that distinguish one input pattern from another. In the suggested model, two to three attributes are primarily taken from images to identify their properties.

a) Color Histogram: A collection of bins is constructed, where each bin corresponds to the probability of pixels in the image having a particular color. A color histogram for a specific image is defined as a rectangular array in one dimension.

b) Color Moments: These are quantitative metrics employed to distinguish photographs based on their color characteristics. Once computed, these three metrics\u2014mean, standard deviation, and skewness\u2014offer a quantification of color similarity between photographs. These similarity values can be compared to the indexed values of photos in a database for activities such as image retrieval. An image is defined by nine moments, with three moments for each of the three color channels. The ith color channel at the jth picture pixel will be denoted as pij. The mean and standard deviation can be precisely described as follows:

c) Haralick Features: These characteristics are obtained using a Gray Level Co-occurrence Matrix (GLCM), which measures the frequency of neighboring gray levels in the image. The GLCM is a square matrix where the dimensions are equivalent to the number of gray levels N in the relevant region of interest (ROI). The graph linear correlation model (GLCM) quantifies the texture of an image by calculating the frequency of pixel pairs with exact values and spatial correlations

D. Classification - Ensemble Bagging Classifier

An ensemble classifier is employed to categorize images of ill tongues from tongue images. We employed a machine learning technique to categorize feature data into a specified number of classes. The ensemble bagging classifier is utilized to train the tongue pictures in this study. A classifier is a program that takes a collection of photos, creates a model based on that collection, and then guesses which category each input image belongs to, either healthy or unhealthy. Ensemble methods, in the field of statistics and machine learning, employ numerous learning algorithms to provide superior prediction performance compared to individual learning algorithms used in isolation. Bootstrap Aggregation, also referred to as Bagging, is a simple and extraordinarily efficient ensemble technique. Bagging applies the Bootstrap technique to a machine learning system, typically decision trees, involving significant variances. Let's assume there are N observations and M features. Bootstrapping involves randomly selecting a sample from a larger population, with the possibility of selecting the same observation multiple times. A model is created by selecting a subset of features from a sample of observations. The feature that provides the most optimal division of the training data is selected from the subset. Multiple models are generated by repetition, with each model being trained simultaneously. The prediction is derived by aggregating the predictions from all the models. When employing bagging with decision trees, our primary concern is not the individual trees overfitting the training data. To ensure both effectiveness and efficiency, the individual decision trees are grown to a significant depth, with just a small number of training samples at each leaf node of the tree, and pruning is not performed on the trees.

IV. RESULT AND DISCUSSION

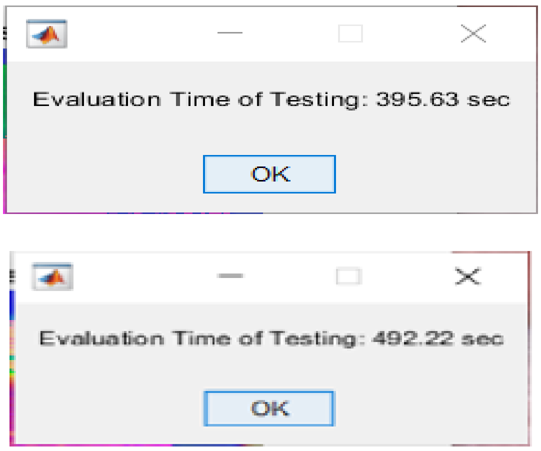
The proposed system implemented and studied on Intel CORE i3 processor, 8GB of RAM, and operates on the Windows 10 operating system platform. The MATLAB R2018b Software is utilized for writing programming code. We have utilized the Image Processing and Statistics and Machine Learning toolkit for this purpose. The training and testing photos are sourced from a standardized Dataset for experimental analysis [6]. Performance evaluation of the system is conducted by analyzing parameters obtained from the confusion matrix and receiver operating characteristics (ROC), as described below.

Accuracy (ACC) $= \frac{TP+TN}{TP+TN+FP+FN}$

True Positive Rate (TPR) $= \frac{TP}{TP+FN}$

True Negative Rate (TNR) $= \frac{TN}{TN+FN}$

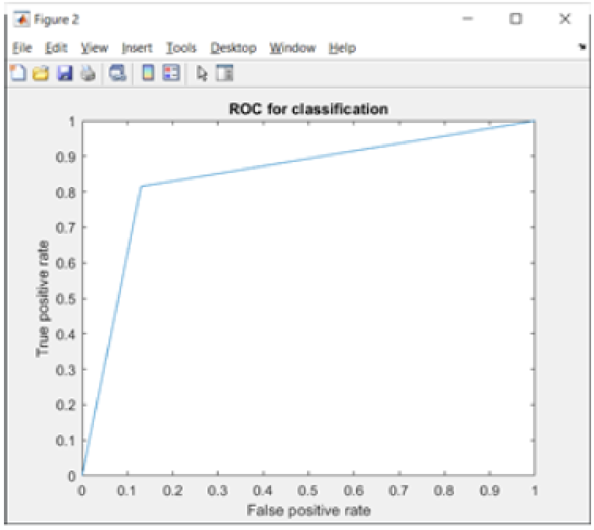
F1 score (F1) $= 2.\frac{PPV.TPR}{PPV+TPR} = \frac{2TP}{2TP+FP+FN}$



[Fig.2: Duration of Evaluation for Test Images of a Normal and Unhealthy Tongue]

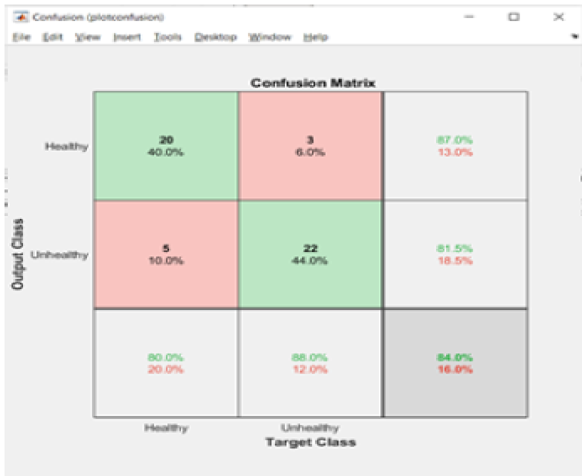
Figure 2 indicates the test evaluation time for healthy and unhealthy tongue image diagnosis. Following the examination of all test images from the dataset to obtain the system performance parameters, the following parameters are examined to assess system efficiency.

Figure 3 represents the confusion matrix result evaluation for binary classification which defines the relationship between actual output and predicted output.



[Fig.3: Result Evaluation using Test Confusion Matrix]

The results parameters evaluation on test dataset samples are shown in table 1 with ROC curve analysis shown in figure 4which shows the best true positive rate and lower false positive rate.



[Fig.4: Result Evaluation using Test Confusion Matrix]

Table 1: Analysis of Performance Metrics of all Test Images

Result Parameters	Accuracy	Error Rate	Sensitivity	Specificity	F-Score
Values	84%	16%	81.48%	86.95%	86.61%

V. CONCLUSION

The utilization of machine learning with manually designed characteristics for diagnosing tongue illnesses is a highly interesting field of study that has the potential to enhance diagnostic precision and availability. Through continuous progress and interdisciplinary cooperation, this technique has the potential to become a conventional instrument in the field of medical diagnostics. This research presents a method for diagnosing tongue illnesses using machine learning algorithms and manually designed characteristics. This method utilizes the abundant visual data, like as color and texture, present in tongue pictures to accurately identify different medical diseases. The method we present demonstrates outstanding performance in classifying tongue image diseases, with an average accuracy of 84% through the use of ensemble bagging classification. Hence, it is evident that the utilization of machine learning techniques effectively addresses the issue of tongue picture classification, so significantly advancing the intelligent and unbiased progression of Traditional Chinese Medicine (TCM) tongue diagnosis.

Additionally, the development of novel techniques with distinct characteristics and evaluation parameters can aid in addressing new findings, such as different illness categories related to tongue images. Furthermore, employing a GPU can significantly decrease the training time required for dataset characteristics. The same algorithm can be utilized for classifying datasets related to other diseases as well.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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- **Funding Support:** This article has not been sponsored or funded by any organization or agency. The independence of this research is a crucial factor in affirming its impartiality, as it has been conducted without any external sway.
- **Ethical Approval and Consent to Participate:** The data provided in this article is exempt from the requirement for ethical approval or participant consent.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Authors Contributions:** The authorship of this article is contributed equally to all participating individuals.

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