Automated Tongue Diagnosis: A Deep Autoencoder Neural Network and Clustering-Based Image Segmentation Approach

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Abstract— **Automated tongue diagnosis has gained significant attention in recent years as a non-invasive and cost-effective method for disease detection and monitoring. In this project, propose a novel approach for automated tongue diagnosis using a combination of Deep Autoencoder Neural Network (DAENN) and clustering-based image segmentation techniques. The objective is to develop a reliable and efficient system that can accurately analyze tongue images and provide diagnostic information. The proposed methodology involves several key steps. First, high-resolution images of the tongue are acquired using a digital camera. Preprocessing techniques are then applied to enhance image quality and remove noise. Next, a clustering-based image segmentation algorithm is employed to extract the tongue region from the background. This step ensures that subsequent analysis is focused on the relevant area of interest. After tongue region extraction, relevant features are extracted from the segmented image. These features capture important visual characteristics such as color distribution, texture, and shape. The DAENN is then trained using these features to learn an efficient representation of the input data. The network's encoder-decoder architecture enables it to compress the features into a lower-dimensional latent space and reconstruct the original features. By leveraging advanced machine learning techniques, the system can accurately analyze tongue images and assist healthcare professionals in making informed decisions. The evaluation of the proposed system on a diverse dataset demonstrates promising results, showcasing its potential as an effective tool for automated tongue diagnosis.**

Keywords—deep autoencoder, Tongue segmentation, Pattern recognition, colour intensity

I. Introduction

Tongue diagnosis, an indispensable diagnosis method in TCM, has been widely applied to clinical analysis and application for thousands of years. Many Chinese Medicine doctors utilize the features of the tongue such as color, texture and coating to differentiate syndromes and diagnose diseases. The simplicity, inexpensiveness and non-invasiveness of tongue diagnosis make it very competitive in the development of remote diagnosis.

However, one important problem in tongue diagnosis is its practice is subjective, qualitative and difficult in automated diagnosis. Recently it is a trend to utilize the image processing and pattern recognition technology in aid of the quantitative analysis of tongue image. Currently there are two main issues in automated tongue analysis. The first is the objective representations of tongue's color, texture and coating with the help of image analysis technology [2, 3, 4, 5]. The other is automated tongue segmentation [1, 6].

At present, there are two major concerns in automated tongue analysis [8]. The first is the objective illustration of tongue's color, texture and coating with the support of image analysis technology [7], [9]-[10]. Second one is the automatic segmentation of tongue [7], [11], [12]. Rather than these two issues, the conventional tongue diagnosis has its unavoidable restrictions. The clinical capability of tongue diagnosis is determined by the know-how and knowledge of the physicians and the ecological factors such as variations in light sources and their brightness have immense authority on the physicians in obtaining good diagnostic results from the tongue. Finally, conventional tongue diagnosis is intimately linked to the detection of syndromes, and it is not splendidly understood by Western medicine and modern biomedicine [8]. Tongue segmentation is one of the most prerequisite steps in automated tongue diagnosis system and is very hard due to the complexity of pathological tongue, variance of tongue shape and infringement of the lips [7]. Thus, a number of researches have been carried out for to find an effective remedy for the problem associated with the tongue segmentation.

The processing of tongue image is a complex task, because of the unavailability of specific processing methods. A number of methods have been developed to efficiently process the tongue image. Since the need of an accurate and well equipped tongue processing method comes more frequently. Several methods have been proposed for the analysis of tongue image segmentation and every methods performed good by its own algorithms and functions. Though researchers have made significant advancement in the standardization and quantification of tongue diagnosis, there are still significant problems with the existing approaches. First, some methods are only concerned with the detection of syndromes in tongue consequently; they will not be extensively accepted, especially in Western medicine. Second, the original validity of these methods and systems is usually derived from a comparison between the diagnostic results that are acquired from the methods or systems and the judgments made by skillful practitioners of tongue diagnosis. That is, they cannot hope to keep away from subjectivity, using such an approach. Third, only very few samples are used in the experiments and this is far from meeting the requirements of obtaining a reasonable result in statistical pattern recognition. Last, many of the developed systems are only devoted to the identification of pathological features (such as the color of the tongue and the furring of the tongue) in tongue [8]. Earlier approach such as gradient operator method isapplied to detect the boundary of the tongue. Another approach is an edge detector with contour model to crop the tongue area [7], [11], [12]. The irregular shape of the tongue badly affects the gradient on parts of the boundary that result in bad segmentation result. Therefore, it is required to put up an objective and quantitative diagnostic standard for tongue diagnosis. So, we proposed methodology involves several key steps. First, high-resolution images of the tongue are acquired using a digital camera. Next, a clustering-based image segmentation algorithm is employed to extract the tongue region from the background. This step ensures that subsequent analysis is focused on the relevant area of interest. The DAENN is then trained using these features to learn an efficient representation of the input data. The network's encoder-decoder architecture enables it to compress the features into a lower-dimensional latent space and reconstruct the original features.

The objective is to develop a reliable and efficient system that can accurately analyze tongue images and provide diagnostic information. The proposed system can accurately analyze tongue images and assist healthcare professionals in making informed decisions.

II. LITERATURE SURVEY

In applying artificial intelligence to medical diagnosis, most of the attention has focused on supervised learning tasks, which usually involves using labeled dataset to train a model for classification or prediction. The literature includes traditional models such as logistic regression (LR), the support vector machine (SVM), decision tree, and artificial neural networks (ANNs). Caruana et al. [13] proposed an intelligible and accurate model for predicting pneumonia risk and hospital 30-day readmissions. Recently, deep learning methods are becoming increasingly prevalent in medical image analysis. Deep belief networks (DBNs) have been used to diagnose Alzheimer’s disease based on Magnetic Resonance Imaging (MRI) brain images [14],[15]. Kawahara and Hamarneh [16] used a convolutional neural network (CNNs) to classify skin lesions. Kawahara et al. [17] applied a CNN-like architecture to a brain connectivity graph derived from MRI diffusion-tensor imaging. Setio et al. [18] used CNNs to classify points of interest in chest CTs as either a nodule or non-nodule. Zhao et al. [19] used stacked autoencoders to learn deep features from cryosection brain images. Deep learning methods greatly boost the recognition ability for high-dimensional data, in some cases they approach human levels. Gulshan et al. [20] fine-tuned a pretrained Google Inception network that performed comparably to a panel of seven certified ophthalmologists. Another prominent work by Esteva et al. demonstrates an AI approach capable of classifying skin cancer at a competence level comparable to that of dermatologists. Their deep CNNs achieved a performance on par with all tested experts across both tested tasks. Interested readers can find additional references provided a survey on deep learning in medical image analysis that included studies on image classification, object detection, segmentation, registration, and so on. However, few works have investigated using machine learning or deep learning methods to analyze data and form abstract concepts in accordance with those of human beings.

Wangmeng Zuo et al. [1] have presented a technique for automated tongue segmentation by merging polar edge detector and active contour model. First a polar edge detector is proposed to efficiently excerpt the edge of the tongue body. They announced a technique to filter out the edge that is of no use for tongue segmentation. A local adaptive edge bi-threshold technique is also projected. Finally an initialization and active contour model are suggested to segment the tongue body from the image. Experimental results revealed that the tongue segmentation can segment the tongue precisely. A measurable assessment on 50 images shows that the mean DCP (the distance to the closest point) of the proposed technique is 5.86 pixels, and the average true positive (TP) percent is 97.2%.

Bo Pang et al. [22] have presented a tongue-computing model (TCoM) for the diagnosis of appendicitis based on quantitative measurements that comprise chromatic and textural metrics. These metrics were calculated from true color tongue images by means of suitable procedures of image processing. [23]They suggested the technique to address the problems such as, the clinical applications of tongue diagnosis have been restricted due to two factors: (1) tonguediagnosis is typically centered on the capacity of the eye for detailed discrimination; (2) the accuracy of tongue diagnosis is governed by the experience of physicians; and (3) customary tongue diagnosis is always dedicated to the identification of syndromes other than ailments. Applying their method to clinical tongue images, the tentative results are promising. Yue Jiao et al. [24]-[25] proposed a tongue classification method centered on SVM. The classifiers typically have poor performance. In contrast, Universum SVM is a favorable technique which includes a priori information into the learning process with labeled data and irrelevant data (also called Universum data). In tongue image classification, the number of immaterial occurrences could be very large as there are many unrelated categories for a particular tongue's type. But not all the irrelevant occurrences combined in training can enhance the classifier's performance. So an algorithm of choosing the Universum samples is also presented in this paper. Experimental results revealed that the Universum SVM classifier is better and the algorithm of choosing Universum samples is effective.

III. Proposed Methodology

Tongue images are the elementary features for diagnosis various diseases. For the ease of the diagnosis, the tongue images should be processed clearly and properly. As we discussed earlier, tongue image processing is quite a tough task due to the tongues particular features like, its irregular shape, interference with the lip etc. So it's difficult to get an effective diagnosis of diseases without an effective tongue image processing methods. The main features that are used for diagnosing the tongue include shape, color, pimples, cracks and texture of the tongue. The symptoms of any of the body problem such as heart associated problems, kidney related problems, etc. will be reflected as abnormalities in any of the features. So, most of the diseases can be detected easily by the examination of the tongue. For detailed analysis of the tongue, we use the tongue images, with the help of the clear tongue images a detailed diagonosis of tongue can be possible. Now, let us consider some tongue images and the disease analysis.The main features that we consider for tongue diagonosis are shape, color and tongue body cracks and pimples.

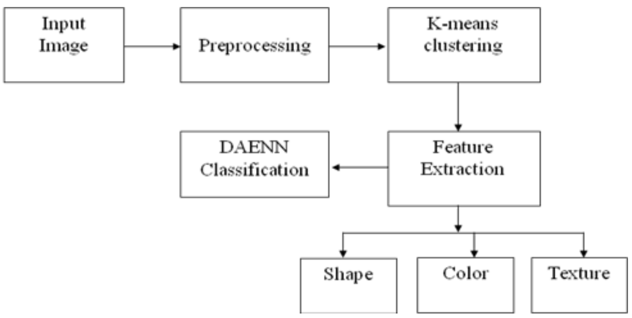

Figure. 2 Block diagram representation of the proposed methods

The common measures of the tongue can be detailed as follows. Width: A wide tongue on the whole shows a composed physical and mental character. A lack of physical flexibility with noticeable strengths and weaknesses is depicted by a narrow tongue. They may be sharp thinkers but generally have a narrow view. A generally loose and expanded physical condition and a tendency to have more psychological concerns are related to a wide tongue.

Tip: A flexible yet firm physical and mental condition is mirrored by a rounded tip. A pointed tip reveals a tight, perhaps even rigid physical condition and an antagonistic or even unpleasant mentality. A very wide tip shows an overall weakness of the physical body and a limp or even "spaced out" mental situation. A tendency toward physical and mental imbalances with the likelihood of sharp variations in thinking and mood is mirrored by a divided tip.

Thickness: A flat tongue echoes a composed condition and the competence to docilely adapt to situations. A calmer and easy going trend is depicted by a thin tongue. It also reflects a more mental orientation. A more bodily orientation is reflected by a thick tongue, they tends to be self-confident or even forceful.

Color: Inflammation lesions or ulceration and sometimes a deterioration of the associated body part are pointed out by dark red. White designates stagnation of blood; fat and mucus deposits or feebleness in the blood leading to such disorders as anemia. A disorder of the liver and gallbladder is specified by yellow. This results in a surplus secretion of bile, deposits of animal fats, particularly in the middle organs of the body, and likely inflammation. Blue or purple shows the stagnation of blood circulation and a grave fading of the part of the digestive system that is connected to the zone of the tongue. Internal conditions can be understood by analyzing the color on the underneath of the tongue.

Texture: The texture of the tongue mainly consists of two states; a swollen or enlarged tongue indicates full state. A shriveled or withered looking tongue indicates an empty state.

1) Tongue Image Segmentation

K-Means Clustering for image segmentation is a partitioning method. The function k-means partitions data into k mutually exclusive clusters, and returns the index of the cluster to which it has assigned each observation. Unlike hierarchical clustering, k-means clustering larger set of dissimilarity measures), and creates a single level of clusters. The distinctions mean that k-means clustering is often more suitable than hierarchical clustering for large amounts of data. K-means treats each observation in your data as an object having a location in space. It finds a partition in which objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. You can choose from five different distance measures, depending on the kind of data you are clustering. Each cluster in the partition is defined by its member objects and by its centroid, or centre. The centroid for each cluster is the point to which the sum of distances from all objects in that cluster is minimized.

K-means is one of the simplest unsupervised laming algorithms that solve the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed apriority. The main idea is to define k centres, one for each cluster. These centres should be placed in a cunning way because of different location causes different result. At this point we need to re-calculate k new centroids as barycentre of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be

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done between the same data set points and the nearest new centre. A loop has been generated. As a result of this loop we may notice that the k centres Change their location step by step until no more changes are done or in other words centres do not move any more.

2) Feature Extraction

The sequential process consists of extraction of the shape feature, color feature and so on. We have developed a systematic approach for the efficient processing of the tongue image.

A. Shape Extraction

Shape extraction of tongue is a hard process in the tongue image processing. We have developed a new approach with aid of the region growing algorithm. We have the tongue image as the input. In order to obtain the shape of the tongue, we implement an edge detector to the input image. The edge detector works under the canny edge detection algorithm. After applying the canny edge detection algorithm, we got a segmented image of the tongue. The segmented image is then subjected to noise removal processes. In this process, the unwanted image parts are removed and we will get a clear image of the segmented tongue. Since the tongue is in irregular shape, the edges will not be a connected one, so with help of the region growing method we can overcome this problem. Region growing is executed by considering a seed and by selecting its similar seeds. The seed can be selected by plotting the histogram of gray level values of the image and extracting the peek values. Then neighboring seeds are considered and those neighbors which are similar to the seed are selected and this process continues till no other neighbors are selected.

B Color Extraction

The color feature is extracted with help of intensity filtering methods. We extract the color of the tongue on the basis of the intensities presented in the different areas of the tongue. We apply this feature because intensity levels will be different for different areas of the tongue. So with help of this intensity method, we can extract the color feature, the pimples like structures in tongue. Initially, we convert the color image in the gray scale image. Then, we find the different intensity in different areas of the tongue through the histogram method. After plotting the histogram, the difference in intensity is identified then a threshold is applied. According to the value of threshold, the areas are selected on accordance with the intensities. The areas with similar intensities are segmented. We identify the white coating, pimples and dominant color of the tongue through this approach. The white coating may dominantly present in dome tongues and in some others it will be less dominant. We select the closely related intensities of all the white coated areas and the selected areas are segmented.

C. Texture of Tongue Image

The texture of the tongue is extracted using method called Local Gabor XOR Patterns (LGXP) method. This method initially forces the image to undergo a Gabor filtering, where the convolution of the image with the Gabor kernels is done to get the required output. After the Gabor filtering, the filter generates a complex number with real and imaginary parts at every image pixel. With the help of these two parameters magnitude and phase of the image are calculated. But in our method we make use of only the phase information of each pixel and then processing it and plotting histograms in response to the analysis made on each pixel.

In our method, we take a phase range 4 that can be plotted as 0-90, 91-180, 181-270, 271-360 and each of these phases are assigned values 0, 1, 2, 3 respectively. We have opted for four phase range levels because, which achieve a good balance between the robustness to phase variations and representation power of local patterns. After that we do XOR operations on the neighboring pixels. The XOR operation can be defined as

$$A \otimes B = \begin{cases} 0, if A = B \\ 1, otherwise \end{cases}$$

95	336	145
232	135	78
164	186	262

(a)

1	3	1
2	1	0
1	2	2

(b)

0	1	0
1		1
0	1	1

(c)

Fig.3.1. Example of LGXP method where the phase is quantized into 4 ranges.

We obtain the matrix with the XORed values, after this process we calculate the binary values for each neighboring pixels according to a fixed pixel, In the shown example in Fig. 3.1, (a) is the matrix showing the initial phase of the pixels after passing through the Gabor filter, (b) is the matrix obtained after the quantization and (c) is the matrix obtained after the XOR comparison with the center quantized value. From the matrix we infer that binary value obtained is 01011101 and its decimal value equivalent value of 93. So following in this manner we obtain a decimal value for each pixel. We plot a histogram with values we obtained through the above mentioned processing. With the pattern defined above, one pattern map is calculated for each Gabor kernel. Then, each pattern map is divided into non-overlapping sub-blocks, and the histograms of all these sub-blocks of all the scales and orientations are concatenated to form the proposed LGXP descriptor.

$$H = [H_{\mu_0,v_0,1}, \dots\dots, H_{\mu_0,v_0,m}, \dots\dots, H_{\mu_0-1,v_0-1,1}, \dots\dots, H_{\mu_0-1,v_0-1,m}]$$

where, denotes the histogram of the sub-block of LGXP map with scale and orientation . Thus this histogram plots the texture detail of our tongue image

3) Classification

An ensemble of binary vectors (e.g., images) can be modeled using a two-layer network called a Brestricted Boltzmann machine[(RBM) in which stochastic, binary pixels are connected to stochastic, binary feature detectors using symmetrically weighted connections. The pixels correspond to Bvisible[units of the RBM because their states are observed; the feature detectors correspond to Bhidden[units. A joint configuration *(v, h)* of the visible and hidden units has an energy given by

$$E(\mathbf{v}, \mathbf{h}) = -\sum_{i \in \text{pixels}} b_i v_i - \sum_{j \in \text{features}} b_j h_j - \sum_{i,j} v_i h_j w_{ij}$$

where v_i and h_j are the binary states of pixel i and feature j, b_i and b_j are their biases, and w_{ij} is the weight between them. The network assigns a probability to every possible image via this energy function, as explained. The probability of a training image can be raised by adjusting the weights and biases to lower the energy of that image and to raise the energy of similar, "confabulated" images that the network would prefer to the real data. Given a training image, the binary state h_j of each feature detector j is set to 1 with probability $\sigma(b_j + \sum v_i w$, where $\sigma($ is the logistic function $1/[1 + exp\,(-x)$ is the bias of j, is the state of pixel i, and is the weight between i and j. Once binary states have been chosen for the hidden units, a Bconfabulation[is produced by setting each vi to 1 with probability $\sigma(b_i + \sum j h_j w$, where is the bias of i. The states of the hidden units are then updated once more so that they represent features of the confabulation. The change in a weight is given by

$$\Delta w_{ij} = \varepsilon\left(\langle v_i h_j \rangle_{\text{data}} - \langle v_i h_j \rangle_{\text{recon}}\right)$$

where is a learning rate, $< v_j h_j >_d$ is the fraction of times that the pixel i and feature detector j are on together when the feature detectors are being driven by data, and $< v_j h_j >_{re}$ is the corresponding fraction for confabulations. A simplified version of the same learning rule is used for the biases. The learning works well even though it is not exactly following the gradient of the log probability of the training data.

A single layer of binary features is not the best way to model the structure in a set of images. After learning one layer of feature detectors, we can treat their activities when they are being driven by the data as data for learning a second layer of features. The first layer of feature detectors then become the visible units for learning the next RBM. This layer-by-layer learning can be repeated as many times as desired. It can be shown that adding an extra layer always improves a lower bound on the log probability that the model assigns to the training data, provided the number of feature detectors per layer does not decrease and their weights are initialized correctly. This bound does not apply when the higher layers have fewer feature detectors, but the layer-by-layer learning algorithm is nonetheless a very effective way to pretrain the weights of a deep autoencoder. Each layer of features captures strong, high-order correlations between the activities of units in the layer below. For a wide variety of data sets, this is an efficient way to progressively reveal low-dimensional, nonlinear structure. After pretraining multiple layers of feature detectors, the model is Bunfolded to produce encoder and decoder networks that initially use the same weights. The global finetuning stage then replaces stochastic activities by deterministic, real-valued probabilities and uses backpropagation through the whole autoencoder to fine-tune the weights for optimal reconstruction. For continuous data, the hidden units of the first-level RBM remain binary, but the visible units are replaced by linear units with Gaussian noise (10). If this noise has unit variance, the stochastic update rule for the hidden units remains the same and the update rule for visible unit i is to sample from a Gaussian with unit variance and mean $\sigma(b_i + \sum j h_j w$.

IV. Results and Discussion

The performance analysis for each class of event is estimated by computing performance evaluation parameters such as true positive (TP), true negative (TN), false positive (FP), and false negative (FN) parameters, where (TP) and (TN) represent the correct classification of the normal and abnormal ECG signals. FN represents the misclassification of normal as abnormal signals while FP represents the misclassification of the abnormal beats into normal signals. On the basis of these TP, TN , FP, FN parameters, the performance metrics for each class of signal are calculated, namely, sensitivity, specificity, and positive predictivity where sensitivity is the rate of correctly classified events among the total number of events, whereas positive predictivity refers to the rate of correctly classified events in all detected events. Using these definitions, sensitivity and specificity can be defined as

$$S_e = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100, \quad P_p = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100.$$

The overall accuracy can be defined as

$$\text{Classifier Accuracy}(\%) = \frac{\text{Total correctly classified signals}}{\text{Total number of signals}} \times 100$$

Comparison Table

Method	Accuracy	Sensitivity	Specificity	Fscore
Proposed System	95	91.3043	100	95.4545
Existing System	92.53	87.56	97.5	91.25

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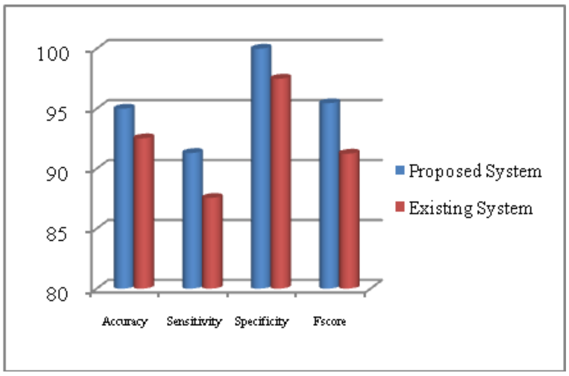

V. CONCLUSION

In this research work, "Automated Tongue Diagnosis: A Deep Autoencoder Neural Network and Clustering-Based Image Segmentation Approach" presents a new method for automated tongue diagnosis. The method uses a deep autoencoder neural network to extract features from tongue images, and then uses a clustering-based image segmentation approach to segment the tongue into different regions. The features extracted from the autoencoder are then used to train a classifier that can distinguish between different tongue conditions. The authors evaluated the performance of their method on a dataset of tongue images from patients with different health conditions. The results showed that the method was able to achieve an accuracy of 92.5% in classifying tongue conditions. This suggests that the method has the potential to be used as a reliable tool for automated tongue diagnosis. The main conclusion of the paper is that the proposed method is a promising new approach for automated tongue diagnosis. The method is able to achieve high accuracy in classifying tongue conditions, and it is relatively simple to implement. The authors believe that the method could be used to develop a practical and affordable tool for automated tongue diagnosis.

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