Non-Invasive Disease Prediction Using Tongue Images

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Abstract

Disease diagnosis at an early stage is extremely important for enhancing the treatment efficacy and decreasing costs of medical treatment. The tongue appearance is one of the non-invasive ways of detecting diseases as its appearance reflects some health disorders. This study proposes a deep learning framework for non-invasive disease prediction based on tongue images. The system uses the YOLOv8 model for detecting tongue regions, as well as the CNN model for feature extraction and disease classification. Tongue images from TMC-Tongue dataset are preprocessed by performing image resizing, normalization, and noise filtering to improve their quality and model performance. YOLOv8 detects the tongue region, whereas CNN extracts features related to different tongue diseases. The developed framework provides users with an application allowing uploading images, analyzing them in real time, and generating reports. Experimental evaluation achieved a classification accuracy of 84.2%, demonstrating the effectiveness of the proposed framework.

Keywords: Tongue Image Analysis, YOLOv8, Convolutional Neural Network (CNN), Disease Prediction, Medical Image Processing, Deep Learning, Non-Invasive Diagnosis, Artificial Intelligence.

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1. Introduction

Early detection of disease is important to increase treatment efficacy, to reduce health care costs, and in some cases even avoid development of advanced medical diseases. The existing methods of diagnostics include laboratory tests, imaging techniques, and invasive examination, which can be costly, time consuming, and unaffordable in low-resource settings. This has led to the need for developing new technologies that will help healthcare specialists in performing diagnostics in an intelligent and non-invasive manner.

Tongue examination has been widely used in traditional Chinese medicine and clinical practice as an important measure to determine general condition of the body. Tongue features, including color, texture, coating, moisture, and fissures can tell a lot about internal physiological processes. On the other hand, manual tongue inspection depends on the experience of the clinician and is influenced by subjective interpretation and lighting. Consequently, computer-based tongue image analysis became an important topic of study in medical image processing and artificial intelligence.

Recent advances in deep learning provided a significant improvement to the prediction capabilities of medical image analysis systems. In particular, Convolutional Neural Networks (CNN) show impressive performance in feature extraction, and current object detection frameworks, such as YOLOv8, are capable of localizing regions of interest in real-time manner. Making use of these advancements, this research proposes to develop a non-invasive disease prediction model based on tongue image analysis.

2. Literature Survey

Tongue image analysis has emerged as a critical non-invasive diagnostic approach based on the assessment of multiple health conditions. Initial studies have been dedicated to creating computer-assisted devices which would be able to capture tongue features and help in diagnosing various diseases. One of the first computer-assisted tongue diagnosis systems was proposed by Zhang et al. [1], which was based on image processing technologies allowing to capture features such as tongue color and texture.

The development of mobile health-care technologies led to the creation of mobile tongue diagnosis system by Hu et al. [2] which would be able to acquire and process tongue images using portable devices. While the technology has shown its potential in real-time health-care, problems with low quality images and different illuminations persisted. Moreover, Li et al. [3] studied the integration of artificial intelligence technologies in TCM tongue diagnosis.

Deep Learning further improved tongue image analysis capabilities. Sashikala and Rajakumaran [4] introduced an image based deep learning approach to analyze tongue color images and identify diseases using depthwise separable convolutional neural network. At the same time, Jiang et al. [5] presented a deep learning-based framework for multi-label tongue image analysis, which was capable of detecting several different tongue-related pathologies at once. Thus, the use of deep neural networks proved to be effective in solving complex diagnostic tasks. Proper tongue segmentation is required for accurate disease prediction.

For this purpose, JiaHong et al. [6] developed a deep learning-based framework for tongue image segmentation, which improved the precision of tongue contour detection and decreased background interference in the process. Recently, researchers paid attention to the problem of object detection, which helped improve tongue localization. In particular, Zhang et al. [7] proposed an improved YOLOv5s-based tongue coating diagnosis system, which was efficient in terms of detection and classification of tongue coating features. Following that research, Ji et al. [9] developed an improved YOLOv8 framework for multi-feature tongue image detection.

Apart from the use of detection methods, deep convolutional neural networks have been extensively used for tongue disease classification. In their research, Tiryaki et al. [8] introduced a model based on CNNs for classifying normal tongue images and pathological tongue lesions. The study produced satisfactory results, demonstrating the potential of deep learning algorithms for automated tongue disease diagnosis.

The integration of tongue localization, deep feature extraction, disease prediction and real-time user interaction in one framework has rarely been reported. Hence, in this paper, we propose a combined non-invasive disease prediction system that uses tongue localization via YOLO, feature extraction via CNNs, and disease classification using the TMC-Tongue dataset [10].

3. Methodology

The proposed disease prediction system based on a non-invasive approach uses tongue images to detect the possible diseases using object detection and image classification algorithms. The whole process involves image acquisition, image pre-processing, tongue detection, feature extraction, disease classification, and visualization of results. The entire process of the proposed system is presented in Figure. 1.

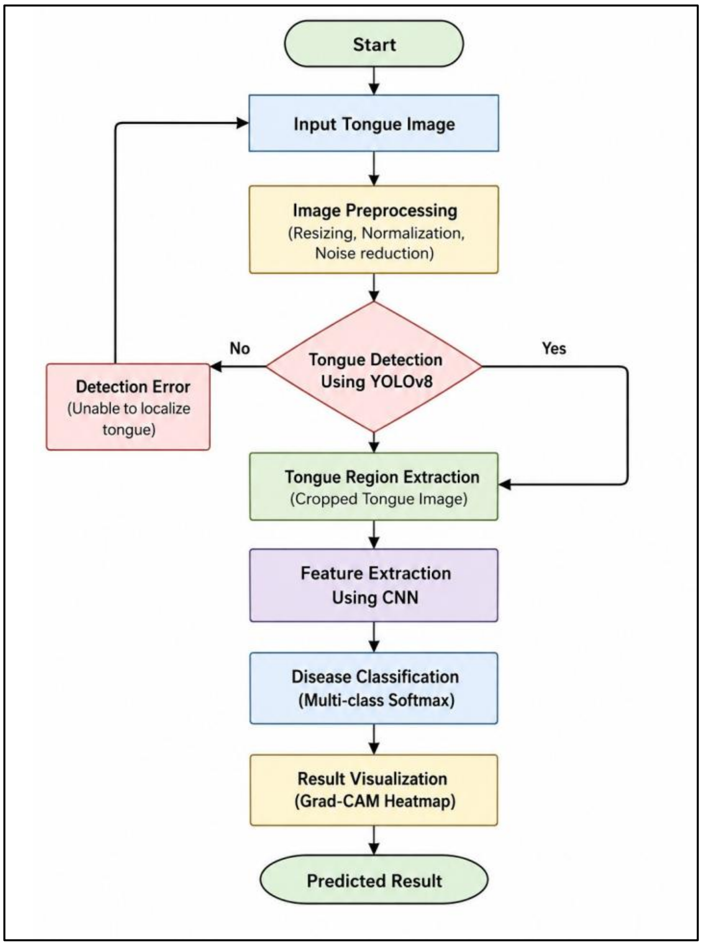

Figure 1. Overall Workflow of the Proposed Non-Invasive Disease Prediction

The experiments were performed on the TMC-Tongue database [10] for AI-assisted diagnosis of Traditional Chinese Medicine (TCM). The database consists of 6,719 high-quality tongue images captured under standardized conditions and annotated based on pathological characteristics of tongues. This dataset encompasses both healthy tongue samples and several pathological categories that depict variations in tongue color, coating, fissures, shape and other clinically relevant attributes. Each tongue image is annotated and clinically validated based on

TCM criteria. The database comprises 5,594 training images, 572 validation images, and 553 testing images. Some examples of tongue images used in the database are given in Figure. 2.

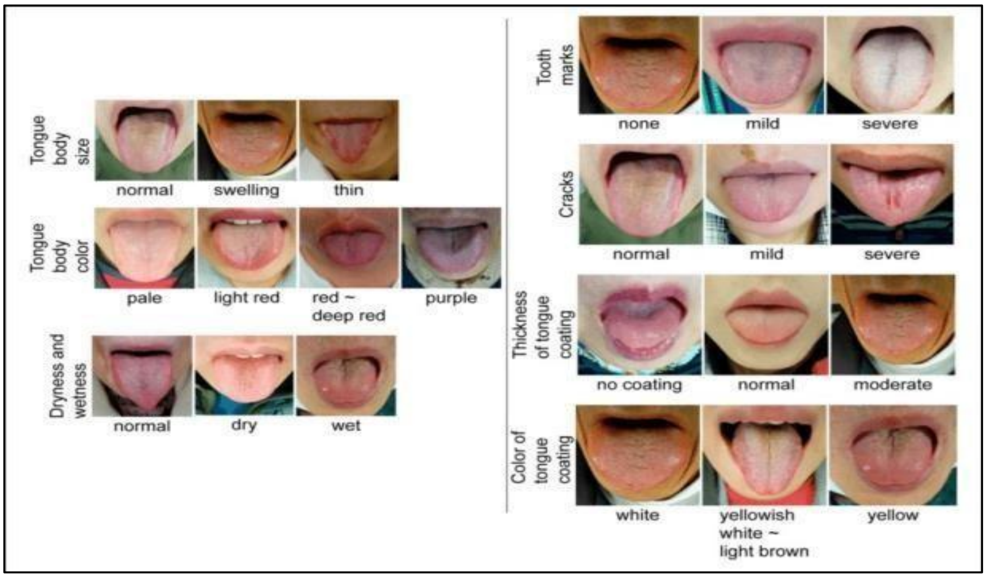

Figure 2. Sample Tongue Images from the TMC-Tongue Dataset

Prior to the training process, all images are preprocessed to enhance image quality and standardize the data. All images are rescaled into size 224 x 224 and normalized to ensure uniformity in the distribution of the pixel intensities. Noise and contrast improvement algorithms are employed to reduce differences in illumination and facilitate visibility of the features.

Following image preprocessing, tongue localization is carried out with the use of the YOLOv8 object detection algorithm. YOLOv8 has been chosen due to its high accuracy, computational efficiency and excellent capability to detect the boundaries of objects. In this study, the tongue region is localized in one step through the generation of bounding boxes and confidence scores. The localization process yields cropping and separation of the tongue region from the background. Only the relevant information is sent to the classification process.

In Figure 3, the localized tongue image is provided as input to a CNN, which automatically extracts the features and classifies the disease. The CNN model is made up of multiple convolutional layers, Rectified Linear Unit (ReLU) activation layers, and max-pooling layers. The CNN automatically learns discriminative features related to tongue color distribution, texture features, fissures, tongue coating, and other pathological features from these layers. A Softmax activation function in the output layer computes the probability of each disease class, and the class with the highest probability is selected as the predicted disease.

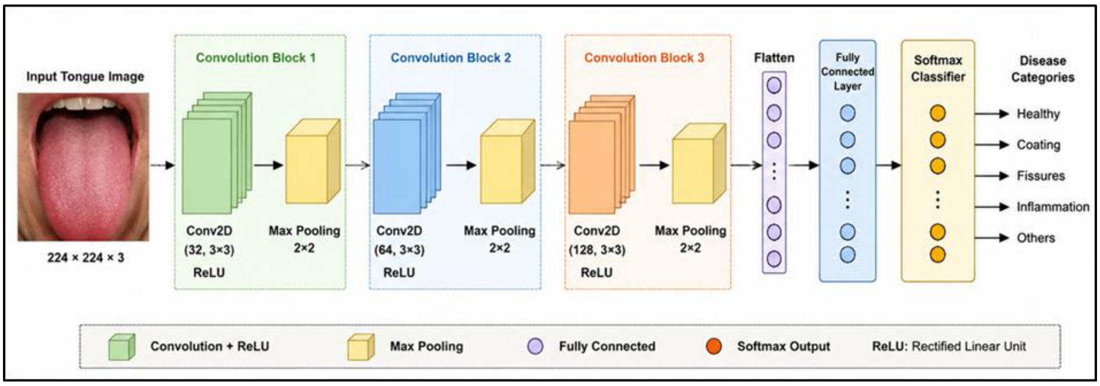

Figure 3. CNN Architecture for Tongue Feature Extraction and Disease Classification

In order to enhance the interpretation capability of the proposed architecture, the gradient-weighted class activation map (Grad-CAM) approach is adopted in the classification stage. The Grad-CAM technique will show the important parts of the tongue image that play the critical role in the prediction task. This enhances the interpretability of the model while boosting the confidence level in the output predictions. The prediction outputs are shown using a user-friendly interface that provides functions of uploading images, live image capturing, and report generation.

4. Results and Analysis

For the implementation of the proposed disease prediction system, YOLOv8 was used for localizing the tongue image and CNN for classifying diseases. The model was trained using the dataset of annotated tongue images called TMC-Tongue Dataset. Some data augmentation techniques such as rotation, flipping, scaling, and changing the brightness were used to enhance the performance of the model.

The performance of the proposed model is measured using the following four classification metrics: Accuracy, Precision, Recall, and F1 Score. These metrics measure the capability of the model in correctly predicting the tongue conditions with minimum errors.

Table 1. Classification Performance of the Proposed Model

Metric	Value (%)
Accuracy	84.2
Precision	83.5
Recall	82.7
F1-Score	83.1

Experimental results show that the proposed YOLOv8-CNN framework obtains an overall classification accuracy of 84.2%. An 83.5% precision value indicates that most positive predictions belong to the right disease class, Likewise, a recall value of 82.7% shows that the model can successfully identify the disease cases related to tongue images. The balanced F1-score of 83.1% illustrates that the proposed framework has an acceptable trade-off between precision and recall, thus ensures stable disease prediction performance.

The significance of the YOLOv8 was immense when it comes to increasing the overall accuracy in classification. The object detection step localizes the tongue region and removes irrelevant background information before classification. As a result, the CNN was able to detect only those regions that are diagnostically meaningful. In addition, the features extracted were tongue color distribution, fissures, tongue coating features, and tongue surface texture patterns which are essential in predicting the diseases. Thus, the proposed YOLOv8-CNN combination was much more robust and efficient than other direct image classification methods.

In order to examine the robustness of the proposed method under different environmental imaging situations, experiments were carried out using the tongue images taken in various conditions. The results are shown in Table 2.

Table 2. Performance Under Different Testing Conditions

Test Scenario	Accuracy (%)
Normal Lighting	87
Low Light	79
Blurred Image	76

Noisy Background	78
Different Angles	82
High Quality Image	88

As depicted in Table 2, the maximum classification accuracy of 88% was obtained when high quality tongue images having good visibility and focus were used. On the other hand, tongue images taken in well light conditions produced an accuracy of 87%. In both cases, stable performance was observed. Blurry and poor lighting condition images produced a lower accuracy of 76% and 79%, respectively, owing to less visibility of important features of the tongue. The presence of background noise was also found to cause a decrease in the performance.

The practical implementation of the system described in this research is demonstrated through the application interface presented in Figures. 4-9. These Figures show the entire process from user input to disease prediction and report generation.

Figure 4. Home Page of the Proposed Disease Prediction Application

Figure 4 shows the home page of the created application. Figure 5 depicts the patient data acquisition system. Patient demographics and health-related information are first collected, followed by the disease prediction process.

Figure 5. Patient Data Collection Interface

Figure 6 presents an uploaded tongue image with visible abnormalities. The image undergoes pre-processing and the tongue region is detected using the YOLOv8 algorithm and classified using the CNN classifier.

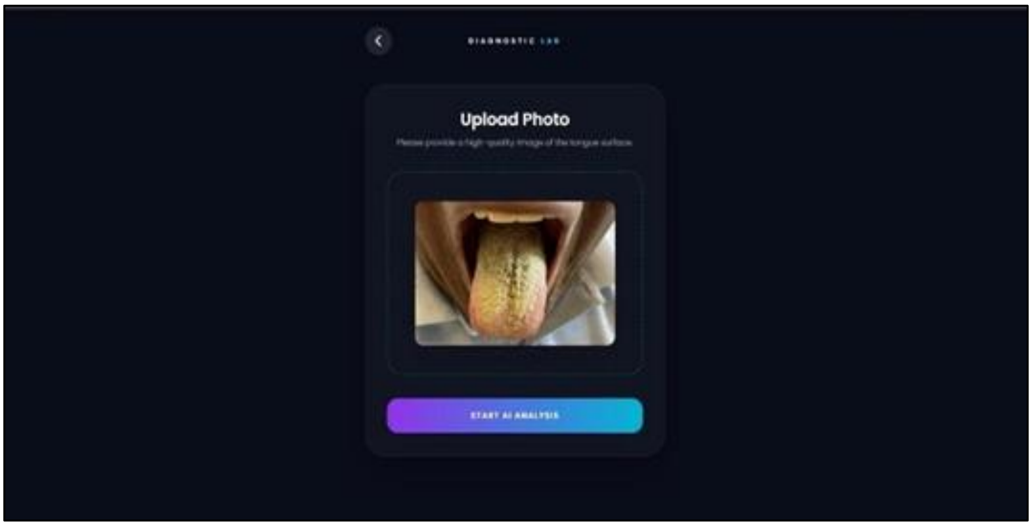

Figure 6. Abnormal Tongue Image Upload

The predicted output by using the proposed model is illustrated in Figure 7. The system automatically classifies the image based on the features of the tongue and provides the disease prediction accordingly.

Figure 7. Disease Prediction Result

Figure 8 shows one of the images of a healthy tongue uploaded in the system. The tongue shows healthy attributes, which is evidence of the success of the classification of healthy tongues by the model.

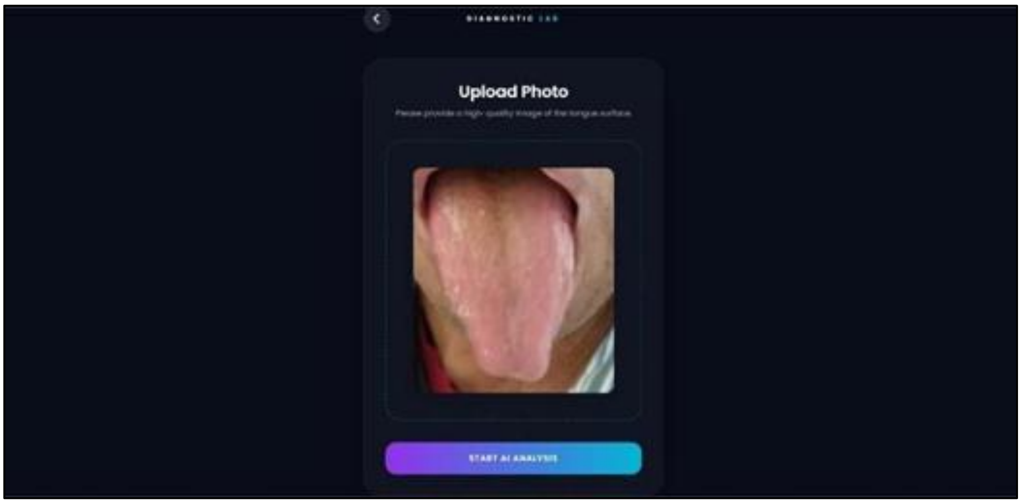

Figure 8. Healthy Tongue Image Uploaded

Figure 9. Medical Diagnostic Report

Figure 9 shows the medical report generated automatically by the system, including the tongue image uploaded, the prediction of the condition, diagnosis and health suggestions.

The integration of tongue detection, feature extraction, disease prediction, and automatic report generation using YOLOv8 and a CNN, it is possible to obtain high accuracy of the disease prediction. Thus, the obtained experimental results prove the efficiency of the proposed system for detecting tongue abnormalities and disease classification.

5. Conclusion

This research work proposed a non-invasive disease prediction model with tongue image analysis based on deep learning approaches. The described technique combines the YOLOv8 algorithm for precise tongue localization and the CNN method for automatic feature extraction and classification. As a result of processing tongue images and the designed technique offers a useful strategy to conduct preliminary health examinations without invasive methods. Image preprocessing and data augmentation contributed to improving model robustness and generalization capacity, whereas YOLOv8 successfully excluded any background noises by accurate isolation of the tongue. On the TMC-Tongue dataset, the experimental evaluation provided the model accuracy of 84.2%. Moreover, the created application allows uploading the image, conducting the analysis and generating the report automatically. The conducted experiment demonstrated that the proposed YOLOv8-CNN framework is an efficient, easily accessible, and cheap solution for intelligent disease prediction and diagnostics.

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