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RESEARCH ARTICLE

Web-Based Application for Tongue Shape and Color Detection Using Artificial Intelligence Techniques: Preliminary Results

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Abstract

Tongue diagnosis is an important method in both Traditional Chinese Medicine (TCM) and Western Medicine (WM), as the tongue's appearance can reflect a person's overall health. Among the key features observed, tongue shape and color play a major role in identifying certain diseases and tracking their progression. This study focuses on the tongue image analysis method of artificial intelligence (AI) to detect shapes and colors of tongue for fast health screening without any need for human intervention. The proposed system firstly used the You Only Look Once version 10 model (YLOVv10) a deep learning object detection system on 750 tongue images in four tasks. The first task used the YOLOv10 model to detect and isolate the entire tongue region from the input image to ensure that the following tasks focus only on the tongue region. The second task was to accurately classify the tongue into seven shape categories, including normal, geographic, fissured, scalloped, thin, swollen, and deviated tongues. Thirdly the system detected crack types associated with fissured tongue, including side cracks, vertical cracks, deep cracks and irregular cracks. Lastly, the system detected whether the tongue contains ulcers or spots or not. The study also used the machine learning CatBoost model to train 5550 color images captured at different color saturations and under different light conditions and classified into seven classes (red, yellow, green, blue, gray, white, and pink) using several color space models, including (RGB, YcbCr, HSV, LAB, and YIQ) as input features to analyze and extract tongue color. The WebApp was developed using Streamlit to offer an easy-to-use graphical interface and provides an automatic tongue shape and color detection tool and compares results based on both TCM and WM perspectives, thus supporting early screening and medical analysis in a fast and reliable way (https://ai-linguasense-version2025.streamlit.app/).

Keywords: Tongue diagnosis; Artificial intelligence; Computer vision systems; YOLO deep learning; CatBoost Machine learning.

1. Introduction

Diagnosing diseases through the tongue is an important method in both TCM and WM. The tongue provides clear indications of internal organ functions and reflects internal health conditions based on its shape, color, and texture [1-3]. Tongue shape and color, in particular, have received increasing attention from scientists and researchers because they provide important diagnostic information about related diseases and nutritional deficiencies [4]. Despite its diagnostic potential, traditional tongue examinations are still mostly performed manually by medical staff, making the process inaccurate, inconsistent, and prone to errors [5]. Furthermore, the diagnostic process requires time and requires highly trained and experienced medical staff [6]. AI techniques can help reduce diagnostic time and automate the process, thus providing more accurate and quick results and addressing the problems associated with human intervention, leading to smart healthcare systems that are easy to access, fast, and accurate.

In the field of tongue diagnosis, two studies [7, 8] used image processing to classify tongue images under fixed light conditions to detect tongue color related to specific health conditions using a predefined condition range; however, they were limited when results fell outside that range. A later study [9] further developed the above studies by involving machine learning algorithms, including naïve Bayes (NB), support vector machine (SVM), k-nearest neighbors (KNN), decision trees (DTs), random forest (RF), and Extreme Gradient Boost (XGBoost) to classify tongue colors from 5,260 images captured under different lighting conditions and color saturations. Although the study demonstrated that the system could support real-time diagnosis with high performance, its limitation was the reliance on color features alone without considering other tongue characteristics. As deep learning became more accessible and outperforms traditional methods in medical image analysis, Yang et al. (2022) [10] developed an intelligent tongue diagnosis system based on deep learning models, including YOLOv5 for tongue detection, U-Net for segmentation, and MobileNetV3 for tongue feature classification (tooth marks, spots and fissured tongues). Their study achieved high classification accuracy with 93.33%, 89.60%, and 97.67% for tooth marks, spots and fissures, respectively. Although their system offered strong performance, a limitation was its dependence on predefined feature categories without considering the tongue color and without including any disease classification.

Okawa et al. (2024) [11] developed two deep learning models, including YOLOv2 with ResNet-50 for tongue detection and ResNet-18 for tongue coating classification. The study performed manual annotation on 443 images using the MATLAB computer vision toolbox and manually drawing the entire tongue region. The detection model achieved high accuracy, resulting in a reliable tongue coating assessment system despite relying on manually labeled data and the lack of tongue color analysis. Another study by Kang et al. (2024) [12] proposed a two-stage tongue image segmentation to accurately detect and segment the tongue region despite background interference using YOLOv5 for coarse detection and LA-UNet for fine segmentation images. Their results showed that the proposed model achieved high performance with an accuracy of approximately 97%, whereas a limitation was the focus on segmentation only without considering tongue characteristics (shape or color) or direct disease classification. Chen et al. (2025) [13] proposed an automated tongue analysis system based on deep learning techniques to improve the accuracy of TCM diagnosis. They used a semi-supervised U2Net model for tongue segmentation, a gated shape CNN model for coating and a Vision Transformer (ViT) model for classifying tooth marks, cracks, and moisture levels. The system achieved high performance in segmentation and classification and addressed challenges of lighting conditions variations and coating texture complexity; however, it needs a high-quality image acquisition hardware and the complexity of handling background tongue conditions. All the abovementioned studies were promising as computerized tongue analysis systems. However, these studies often used small datasets, lacked generalization across a wide range of tongue shapes and colors, or required manual preprocessing steps. In addition, many of the existing tools were not user-friendly or suitable for non-technical users, which limited their use in clinical or community health settings and without provided a comparative analysis of diagnostic results from TCM and WM. There is still a gap in developing a fully automated, accessible, and high-performing WebApp that combines tongue region detection with detailed shape/color classification and comparison between TCM and WM diagnostic interpretations. This study addresses this gap by creating a complete AI framework tongue shape/color classification using Streamlit.

The remainder of this paper is summarized as follows. Section 2 explains the materials and methods used in this study, including the tongue image dataset and the classification categories. It also describes preprocessing steps, and labeling process used to train and validate the deep learning models, the proposed framework that covers the YOLOv10 and CatBoost model training process, and Streamlit Platform. Section 3 presents the results, including detection accuracy, classification performance, and visualization outputs from the WebApp and discusses the significance of the results and the diagnostic interpretations from both TCM and WM perspectives. Finally, Section 4 concludes the paper by summarizing the contributions and potential future directions.

2. Materials and Methods

2.1. Tongue Image Datasets

The study was conducted in accordance with the Declaration of Helsinki and approved by the Human Research Ethics Committee at the Ministry of Health and Environment, Training and Human Development Centre, Iraq (Protocol ID 201/21) for studies involving humans. This study used two groups of datasets. The first group contained 750 tongue images, collected to represent various tongue shapes commonly observed in both clinical and traditional diagnostic practices. All images were collected from publicly available sources (Roboflow datasets) or captured with a digital camera under controlled light conditions, when the tongue was fully visible and in focus. No personal identifiers were included during images capture to ensure privacy and ethical considerations. Each collected image was then annotated using a free online tool for labeling image datasets, called MakeSense AI platform (https://www.makesense.ai/). Image annotation and labeling were manually drawn around the tongue region to define the ROI that corresponds to tongue shape category. To ensure effective training of YOLO models, each image was assigned to different categories, including the entire tongue region, tongue shapes (normal, geographic, fissured, scalloped, thin, swollen, and deviated tongues), crack types (side crack, vertical crack, deep crack and irregular crack) and ulcers or spots existing, as shown in Figure 1.

Fig. 1. An example of the tongue shapes, ulcers and spots.

The second group contains a dataset of 5,550 color images to support tongue color classification [9, 14]. These images were captured under various lighting conditions and color saturations, and analyzed using five color space models (RGB, YCbCr, HSV, LAB, and YIQ), as shown in Figure 2.

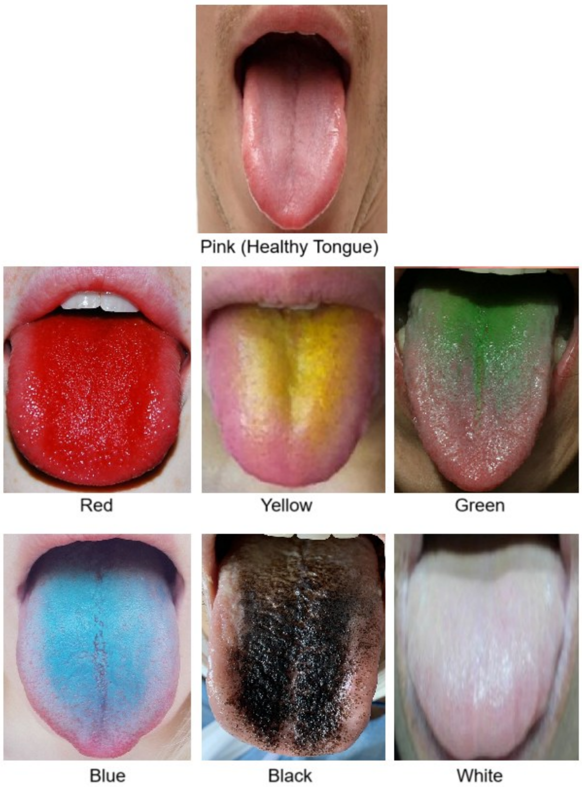


Fig. 2. An example of tongue colors.

2.2. Pre-processing

Before training the models, several preprocessing steps were performed to improve the quality and consistency of the dataset:

- Resizing: All images were resized to a uniform dimension of 640 × 640 pixels to match the input requirements of the YOLOv10 model.
- Normalization: Pixel values were scaled between 0 and 1 to reduce computational complexity and ensure stable learning.
- Data Augmentation: To increase the robustness of the model and prevent overfitting, augmentation techniques such as horizontal flipping, brightness adjustment, and rotation were applied. This process generated additional training examples and helped simulate real-world variations in tongue position and lighting conditions.

2.3. The Proposed Framework

The proposed framework of AI-based system for automated tongue analysis is shown in Figure 3. The proposed system combines deep learning and machine learning techniques. A YOLOv10 deep learning model [15, 16] is used to perform four sequential tasks: Task (T0) detects and isolates the entire tongue region as the main region of interest (ROI) from the input image, removing background elements, such as face, lips and teeth to improve analysis accuracy. Next, Task (T1) classifies the tongue shape into seven categories, including normal, geographic, fissured, scalloped, thin, swollen, or deviated tongue. For fissured tongues, T2 identifies the specific crack type, including vertical, side, deep, or irregular cracks. T3 then detects the presence of ulcers or spots, which may indicate infections or systemic diseases. In parallel, the system uses a machine learning algorithm based on the CatBoost model [17, 18] to perform Task (T4), which classifies tongue color under various lighting conditions based on color features from RGB, YCbCr, HSV, LAB, and YIQ to extract detailed color features.

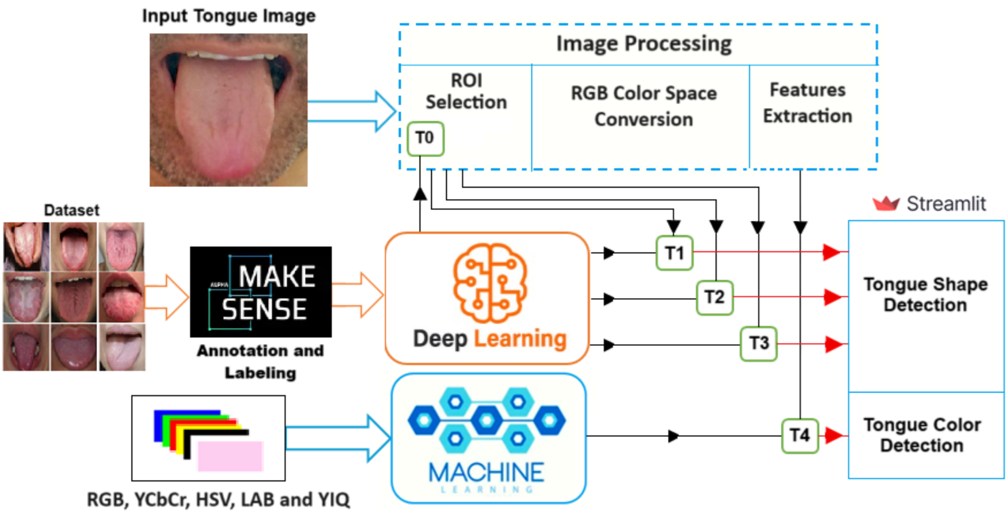


Fig. 3. The proposed framework for AI-based system for automated tongue analysis.

2.4. Streamlit Platform

Streamlit is an open source user-friendly interface platform designed to help researchers create and share their Web-apps based on a Python programming environment [19, 20]. Streamlit supports user interface elements, such as multi-page app support, a dropdown menu, a sidebar, and input widgets. The proposed system was developed using Streamlit, as shown in Figure 4. The proposed WebApp is called AI LinguaSense that enables users to analyze the shape/color of their tongue in images immediately. The WebApp allows users to select an indicator type "Shape or Color" from a dropdown menu and then uploads an image of a tongue using a drag-and-drop panel or browse image files in different formats, including PNG, JPG, JPEG, AVIF, WEBP, BMP, TIFF and TIF. Once an image is uploaded, the system processes it immediately and displays the detected tongue region with a highlighted bounding box. After detecting the tongue, the system performs shape/color classification using the trained models (T0-T4) and presents medical insights from both TCM and WM. The processed image with the annotated detection is shown below the result, enabling users to visually verify the classification. This WebApp inferences visual output and comparative medical interpretation which makes the application useful for educational, diagnostic, and research purposes. To provide a deeper understanding of each detected tongue shape/color, a predefined dictionary was created to map each shape/color to descriptions from both TCM and WM. For instance, a scalloped tongue is interpreted in TCM as a sign of “qi deficiency or stagnation,” while WM may relate it to “pressure from teeth or swelling”. These explanations are shown alongside the detection result to support medical understanding for both practitioners and users.

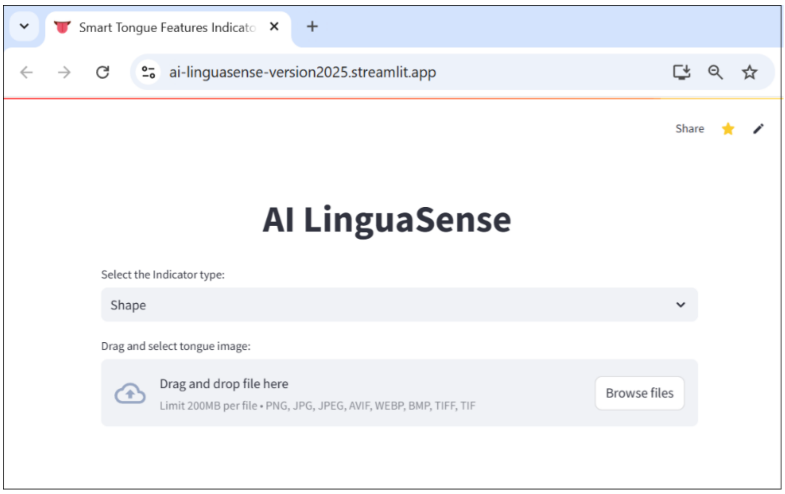


Fig. 4. Screen capture of the proposed Streamlit WebApp for detecting tongue shape and color.

3. Results

3.1. Training and Validation for YOLO (T0)

The YOLO models were trained and validated on a computer with Windows 11, 16 GB of DDR5 RAM, and an Nvidia RTX 4060 GPU with 6 GB of memory. The annotated images, along with their corresponding labels in YOLO format, were divided into training, validation, and testing sets. Approximately 80% of the images were used for training, 10% for validation, and 10% for testing. This split ensured that the model was trained on a large portion of the data while still being tested on unseen examples to measure generalization performance. The performance results of the T0, which was used to detect and isolate the tongue region from input images, is shown in

Figure 5. The T0 model was trained for 300 epochs to achieve these results. The bar chart in the top-left corner shows that more than 700 tongue instances were detected. The Precision-Recall curve in the top-right indicates a high detection accuracy, with an average precision (mAP@0.5) of 0.995. The two lower scatter plots in Figure 5 provide further insight, including the bottom-left chart that shows the density of object centers (x, y), mostly concentrated around the middle of the images, while the bottom-right chart illustrates the correlation between bounding box width and height. These patterns confirm that the labeled data is well-centered and consistently annotated, supporting robust model training.

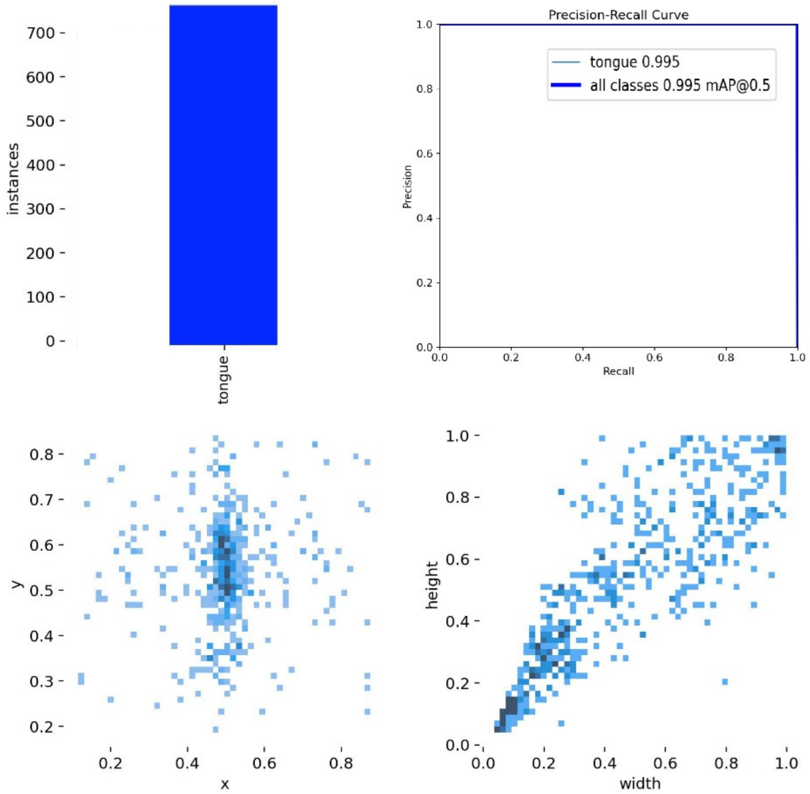


Fig. 5. Performance metrics of the YOLOv10 (T0) model trained for 300 epochs to detect tongue regions, showing high precision (mAP@0.5 = 0.995), for 750 labeled instances and well-distributed bounding box positions and sizes.

Fig. 6. Detected tongue regions using T0 with high confidence across various tongue images.

Figure 6 shows the visual performance of the T0 model in detecting and isolating the tongue region from various input images during the training process. This demonstrates the system's ability to detect tongues of various shapes, sizes, and lighting conditions in various scenarios. These results reflect the model's effectiveness after training over 300 epochs, making it a reliable step in detecting and isolating the tongue from background noise before engaging in subsequent training models that focus solely on the tongue region.

3.2. Training and Validation for YOLO (T1)

Figure 7 shows the performance results of the trained model (T1), which was used to classify the tongue into seven shape categories, including normal, geographic, fissured, scalloped, thin, swollen, and deviated tongues. The Trained T1 provides an average precision for all classes of 0.832 with good correlation between bounding box width and height. Figure 8 shows the visual performance of the T1 model in detecting tongue shapes during the training process (300 epochs) under different scenarios.

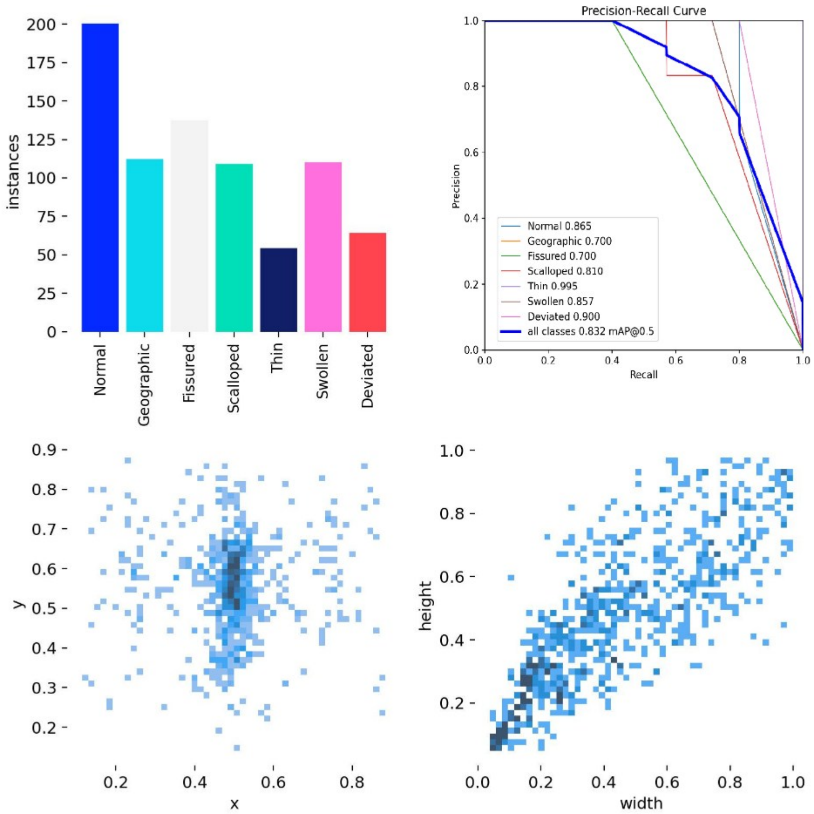


Fig. 7. Performance metrics of the T1 model trained for 300 epochs to detect tongue shapes, showing high precision (mAP@0.5 = 0.832), for 750 labeled instances.

Fig. 8. Detected tongue shapes using T1 with high confidence across various tongues.

3.3. Training and Validation for YOLO (T2)

Figure 9 shows the performance results of the T2 model, which was used to classify tongue cracks into four categories, including side crack, vertical crack, deep crack and irregular crack. The trained T2 model achieved an average accuracy of 0.756 for all categories, with a good correlation between the width and height of the bounding box. Figure 10 shows the visual performance of the T2 model in detecting cracks during the training process (300 epochs) under different scenarios.

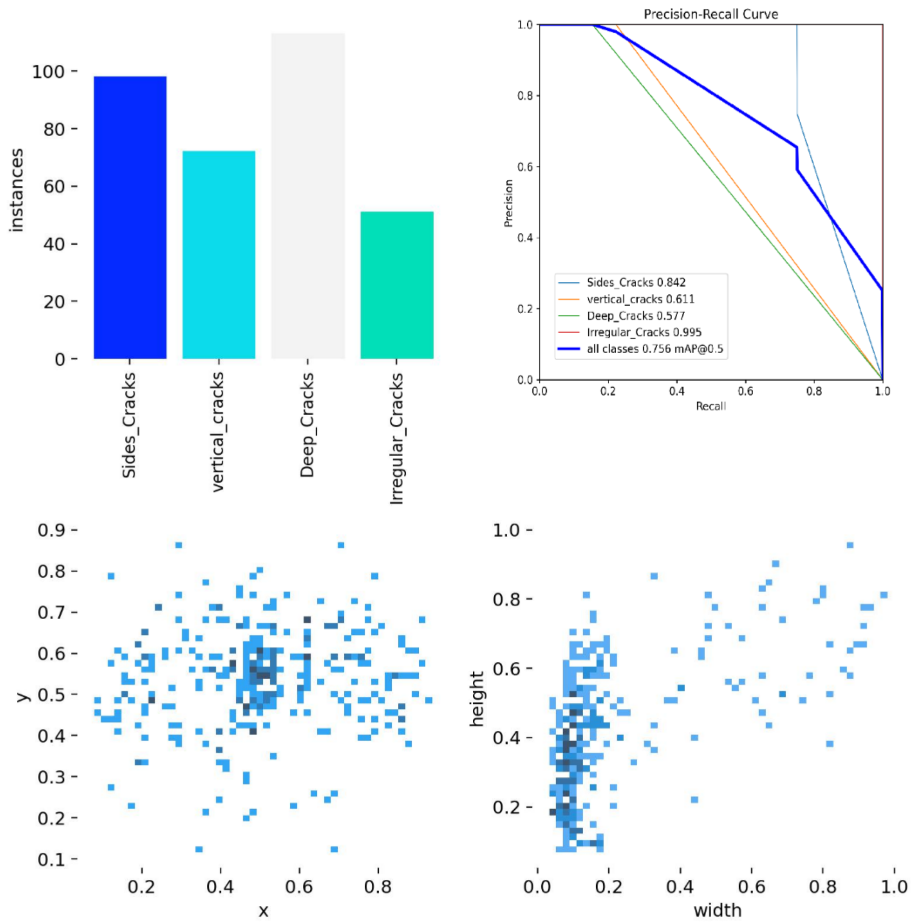


Fig. 9. Performance metrics of the T2 model trained for 300 epochs to detect cracks, showing moderate precision (mAP@0.5 = 0.756).

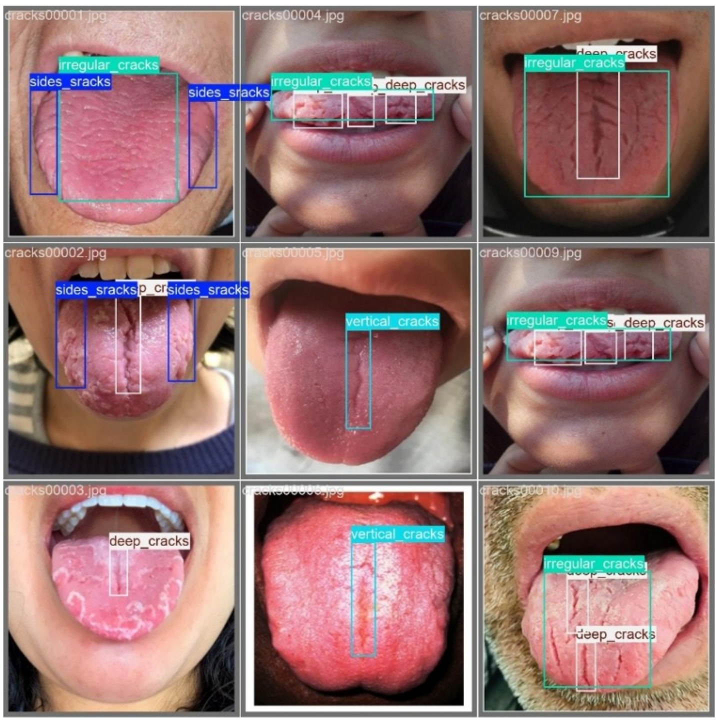


Fig. 10. Detected tongue cracks using T2.

3.4. Training and Validation for YOLO (T3)

Figure 11 shows the performance results of the T3 model, which was used to detect ulcers and spots in the tongue. The trained T3 model achieved an average accuracy of 0.859 for all categories, with a good correlation between the width and height of the bounding box. Figure 12 shows the visual performance of the T3 model in detecting ulcers and spots during the training process (300 epochs) under different scenarios.

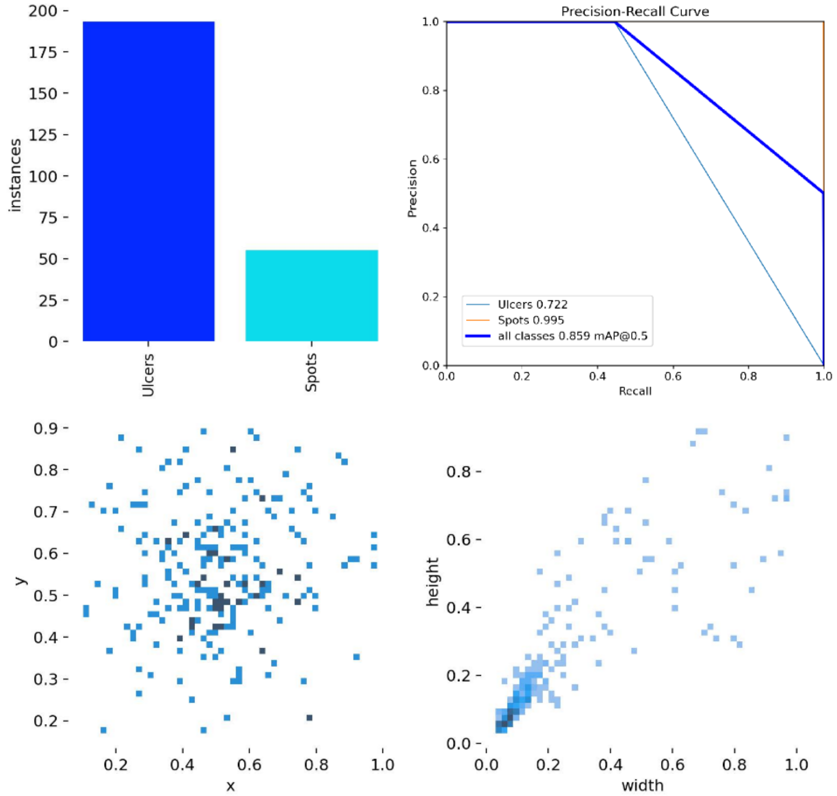


Fig. 11. Performance metrics of the YOLOv10 (T3) model trained for 300 epochs to detect ulcers and spots, showing high precision (mAP@0.5 = 0.859).

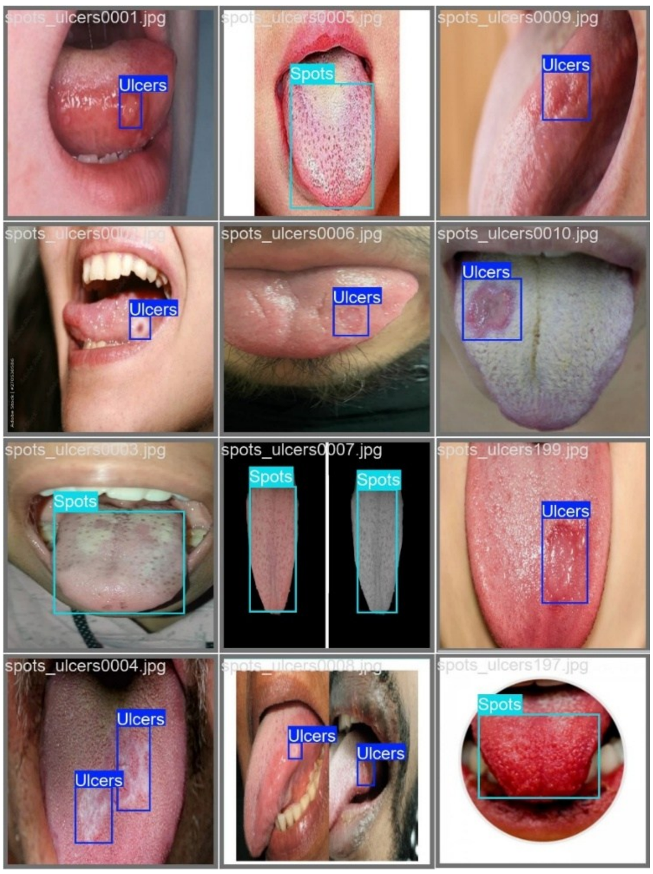
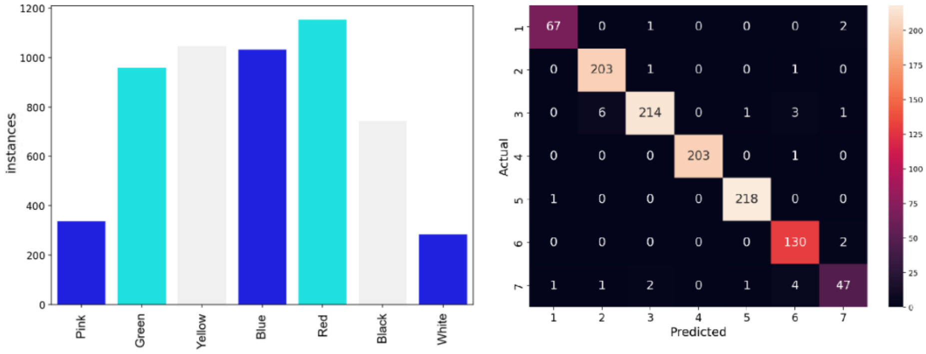


Fig. 12. Detected tongue ulcers and spots using YOLOv10 (T3).

3.5. Training and Validation for CatBoost (T4)

For training CatBoost (T4), 80% of the dataset was employed to train the model, and 20% of the remaining dataset was employed for testing. Figure 13 (a) illustrated number of instances per class, with pink as class 1 with 337, green as class 2 with 959 images, yellow as class 3 with 1046, blue as class 4 with 1032, red as class 5 with 1153, black as class 6 with 742, and white as class 7 with 284 images to cover the abnormal tongue colors. Figure 13 (b) shows the confusion matrix for tongue color classification with a weighted average accuracy of 0.97.



(a) (b)

Fig. 13. (a) Number of instances per class and (b) the confusion matrix for tongue color classification.

3.5. Results from Streamlit

The Streamlit WebApp of the proposed system (AI LinguaSense) will be available to the public by accessing the following link: (https://ai-linguasense-version2025.streamlit.app/). The user can take an image of his/her tongue and upload it to the website to detect health problems related to his/her tongue shape and color. For example, Figure 14 shows a normal tongue, without any cracks or ulcers or spots when the shape indicator is selected. However, when the color indicator is selected, the WebApp shows a greenish color in the middle of the tongue and a pinkish color at the tip. This suggests that this tongue may be related to liver or gallbladder problems according to TCM, or it may indicate a problem with bile pigmentation, liver dysfunction, or infection, according to WM.

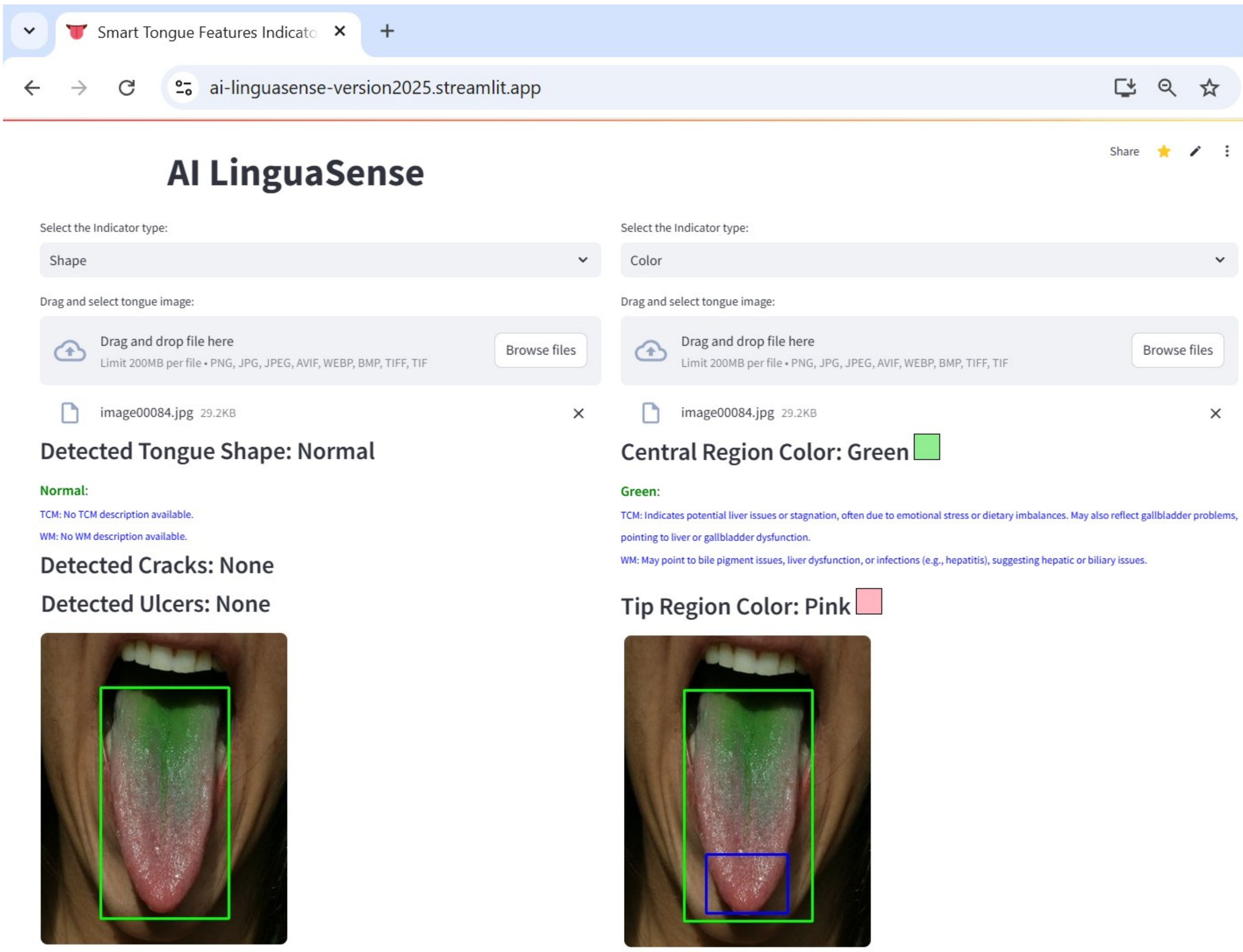


Fig. 14. Screenshot of the AI LinguaSense Webapp analyzing tongue shape and color, indicating a normal shape with no cracks or ulcers, and identifying green and pink regions.

Another example shows a swollen tongue with no cracks, but with ulcers when the shape indicator is selected, as shown in Figure 15. This may indicate dampness or a deficiency in spleen energy, often due to poor digestion or fluid metabolism according to TCM, or it may be related to inflammation, fluid retention, or allergic reactions according to WM. As for the detected ulcer, it may be the result of heat or toxicity in the body, often linked to stomach or heart fire according to TCM, and often due to infection (viral or bacterial), deficiency (such as vitamin B12 and iron), or trauma (such as biting or irritation) according to WM. When the color indicator is selected, the color appears pink in both the middle and tip regions.

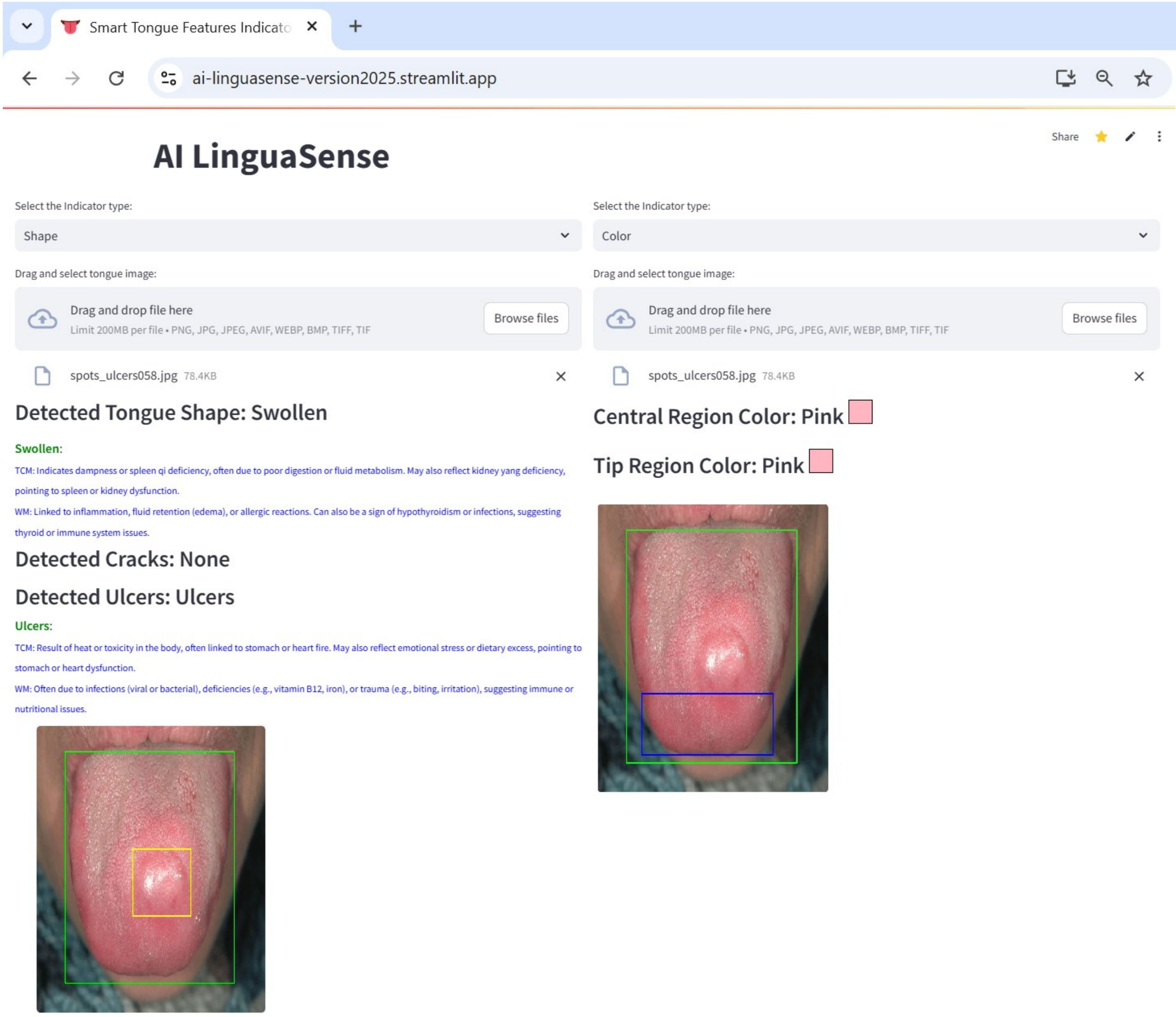


Fig. 15. Screenshot of the AI LinguaSense WebApp analyzing a swollen tongue with ulcers and pink coloration at both middle and tip regions.

As a last example, Figure 16 shows a thin tongue with no cracks, ulcers, or spots when the shape indicator is selected. This shape may indicate blood deficiency and dehydration, often associated with heart or spleen dysfunction according to TCM, and anemia, malnutrition, or chronic dehydration when the WM is taken into account. When the color indicator is selected, the WebApp shows a white color in the middle of the tongue, reflecting cold or dampness in the body, often associated with an imbalance of the spleen or lung according to TCM, or associated with dehydration, a fungal infection (such as oral thrush), or anemia according to WM. The WebApp also shows a white color at the tip of the tongue, which may indicate cold or dampness in the lungs or heart, often associated with poor circulation or chronic colds according to TCM, or associated with dehydration, a fungal infection, or anemia when the WM is taken into account.

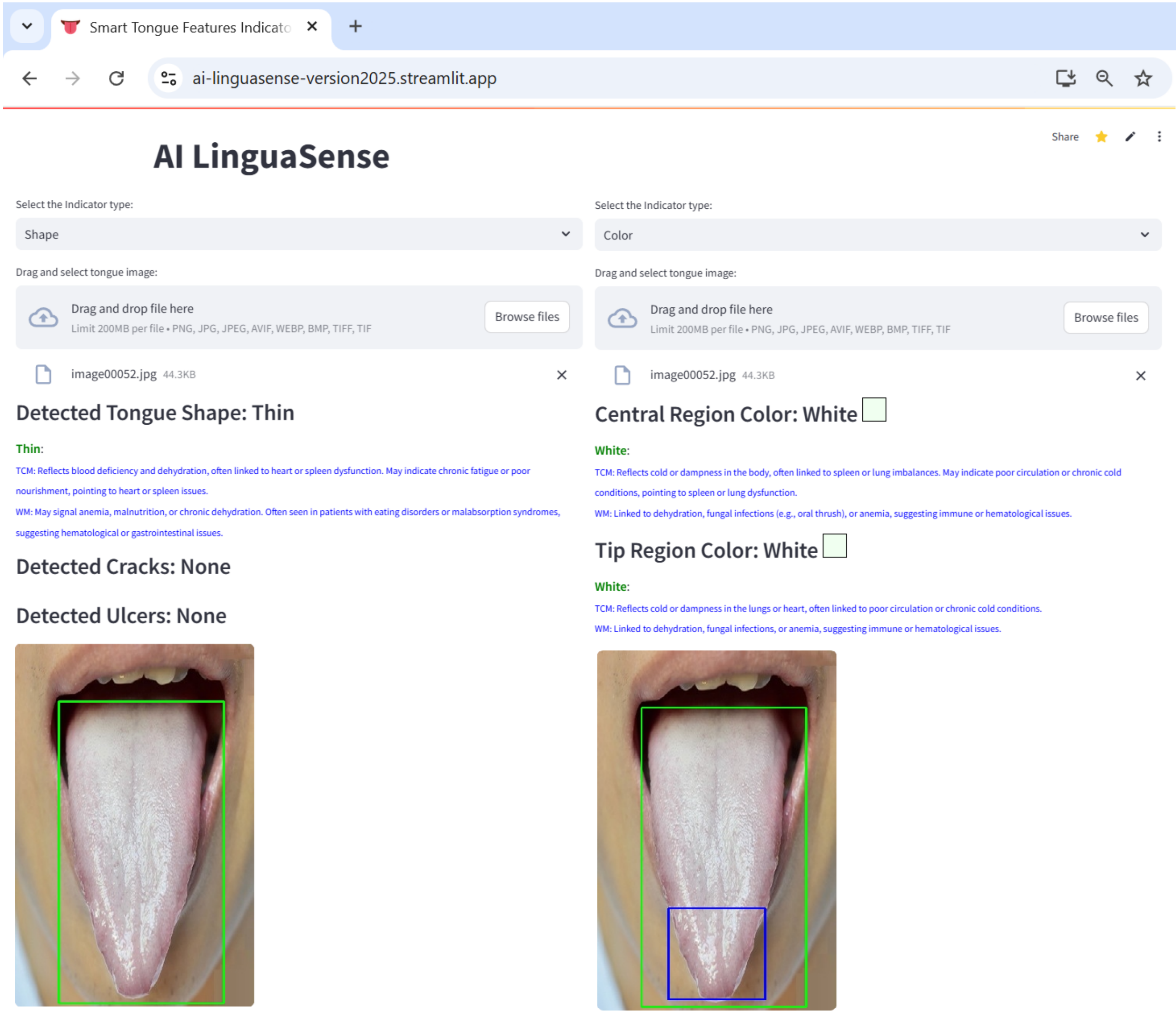


Fig. 16. Screenshot of the AI LinguaSense WebApp analyzing a thin tongue without cracks, ulcers and spots and white coloration at both middle and tip regions.

4. Conclusion

The main contribution of this research paper is the design of an AI WebApp that can quickly detect tongue shape and color and predict related health problems according to both traditional Chinese medicine and Western medicine without any human intervention. In the proposed system, the tongue region was first detected using a trained YOLO model T0, which identified only the tongue area and removed background noise to ensure that the tongue region was the main ROI for subsequent AI models. The proposed system then trained three YOLO models (T1, T2, and T3) to detect tongue shapes, cracks, and ulcers/spots. The proposed system also used T4 as a machine learning model to examine tongue color and diagnose related diseases. The AI WebApp allows rapid and rolling deployment of research techniques into fieldable prototypes. Furthermore, by integrating clinical knowledge from both traditional and modern medicine, the system provides more useful feedback, making it a reliable and effective tool for examining and diagnosing tongue health. This proposed system is expected to be integrated into fixed and mobile computer-aided tongue diagnosis systems in the future.

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