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# AI-Assisted Diagnosis of Pediatric Oral Ulcerative Lesions Using Clinical and Image-Based Features

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## ABSTRACT:

**Background**:

Oral ulcerative lesions are frequently encountered in pediatric patients and may arise from traumatic, infectious, recurrent aphthous, or inflammatory conditions. Because several of these disorders exhibit overlapping clinical characteristics, establishing an accurate diagnosis can be challenging. Artificial intelligence (AI), particularly deep-learning techniques applied to clinical images, may provide valuable support for lesion recognition and diagnostic classification.

**Aim**:

To assess the diagnostic effectiveness of an AI-assisted approach integrating clinical and image-derived characteristics for classifying pediatric oral ulcerative lesions and to compare its performance with conventional clinical diagnosis.

**Materials and Methods:**

This study included 120 children aged 6–14 years presenting with clinically identifiable oral ulcerative lesions. Clinical parameters, including pain, perilesional erythema, lesion number, regional lymphadenopathy, systemic symptoms, lesion duration, and lesion size, were documented together with standardized clinical photographs. Image-derived characteristics included ulcer margin, base appearance, surrounding mucosal changes, and lesion number. Three deep-learning architectures—ResNet50, VGG16, and InceptionV3—were assessed, followed by evaluation of a proposed combined AI model. Diagnostic performance was determined using accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), precision, F1-score, receiver operating characteristic (ROC) analysis, and area under the curve (AUC). Agreement with the reference diagnosis was assessed using Cohen's kappa coefficient, while

diagnostic performance was compared with conventional clinical assessment.

**Results:**

Traumatic ulcers constituted the most frequent diagnostic category (25.0%), followed by recurrent aphthous ulcers (23.3%) and herpetic ulcers (18.3%). Pain and perilesional erythema were observed in 77.5% and 71.7% of participants, respectively. The proposed combined model produced the best overall performance, achieving 95.0% accuracy, 94.2% sensitivity, 96.1% specificity, 93.5% PPV, 96.5% NPV, and a 93.8% F1-score. The overall AUC was 0.978 (95% CI: 0.956–0.992). Diagnostic accuracy across individual lesion categories ranged from 94.2% to 96.7%. Agreement between the AI-generated diagnosis and the reference diagnosis was almost perfect ($\varkappa$ = 0.89; 95% CI: 0.83–0.95), whereas conventional clinical diagnosis demonstrated substantial agreement ($\varkappa$ = 0.70; 95% CI: 0.60–0.80). The AI model also achieved greater overall diagnostic accuracy than conventional clinical assessment (95.0% vs. 84.2%).

**Conclusion:**

The proposed AI-assisted approach demonstrated strong diagnostic capability for classifying pediatric oral ulcerative lesions and showed greater concordance with the reference diagnosis than conventional clinical assessment. Combining clinical information with image-based characteristics may enhance diagnostic support in pediatric oral healthcare. Nevertheless, validation in larger, multicenter, and more heterogeneous populations is necessary to establish the model's generalizability and clinical applicability before routine implementation.

## INTRODUCTION

Oral ulcerative lesions are frequently observed in children and may arise from a wide range of causes, including trauma, infections, recurrent aphthous ulceration, immune-related disorders, nutritional disturbances, and, less frequently, systemic or neoplastic conditions [1]. The broad etiological spectrum and similarity in clinical appearance among different lesions can make diagnosis difficult, particularly in young patients who may not be able to describe symptoms such as pain, duration, or recurrence accurately [2]. Early recognition and appropriate diagnosis are important to ensure suitable management and to avoid unnecessary treatment or delays in identifying clinically significant underlying conditions [3].

The conventional assessment of oral ulcers is based on detailed medical and dental history along with systematic clinical examination. Parameters such as anatomical location, number, size, shape, surface characteristics, margins, color, duration, recurrence, tenderness, and associated systemic manifestations can assist in establishing a differential diagnosis [4]. Nevertheless, several pediatric oral conditions may exhibit similar clinical features, making differentiation between traumatic, infectious, aphthous, and immune-mediated lesions challenging [5]. Changes in lesion appearance during disease progression and variations related to age and anatomical location may further contribute to diagnostic uncertainty [6].

Artificial intelligence (AI) has increasingly emerged as a promising technology for supporting diagnostic decision-making in healthcare. Machine-learning and deep-learning techniques can process large quantities of clinical and image-based information and identify complex patterns that may not always be readily recognized through conventional assessment [7].

Within dentistry, AI has been explored for applications including caries detection, periodontal assessment, radiographic interpretation, and identification of abnormal oral mucosal changes. These developments indicate that AI-assisted image analysis may have potential as an adjunctive approach for evaluating oral lesions. For ulcerative lesions, image-based analysis can provide objective information regarding morphological characteristics, lesion borders, color, distribution, and surrounding tissue alterations. However, visual information alone may not adequately reflect important clinical variables such as pain intensity, duration, recurrence, systemic symptoms, history of trauma, medication exposure, or associated medical conditions. Integrating image-derived characteristics with relevant clinical information may therefore provide a more comprehensive diagnostic representation and potentially enhance classification performance [8].

The use of AI in pediatric oral diagnosis also presents specific challenges. Variations in oral anatomy during growth, differences in cooperation during image acquisition, variability in photographic quality, and differences in disease prevalence can affect the performance and generalizability of AI models. Pediatric ulcerative lesions may also change considerably in appearance over time, emphasizing the importance of well-characterized datasets and standardized clinical and imaging parameters when developing diagnostic algorithms [9].

Although AI-assisted diagnostic applications in dentistry are expanding, relatively limited attention has been directed toward the specific classification of pediatric oral ulcerative lesions. A multimodal approach combining clinical findings with image-based characteristics may help address some limitations of conventional examination and image-only assessment, potentially supporting more consistent diagnostic decisions. Therefore, the present study was designed to evaluate an AI-assisted diagnostic approach for pediatric oral ulcerative lesions using combined clinical and image-based features. The study aimed to determine whether integration of these complementary parameters could improve diagnostic accuracy and provide a useful supportive tool for conventional clinical assessment in pediatric patients.

## MATERIALS & METHODS

### Study Design & Participants

A diagnostic accuracy study was conducted to evaluate the performance of an AI-assisted approach for the identification and classification of pediatric oral ulcerative lesions using clinical and image-based characteristics. The study included 120 pediatric patients presenting with clinically evident oral ulcerative lesions. Participants ranged in age from 6 to 14 years, with a mean age of 10.2 ± 2.5 years. The study population comprised 63 males (52.5%) and 57 females (47.5%).

The included lesions were categorized according to the reference diagnostic assessment into six diagnostic groups: traumatic ulcers, recurrent aphthous ulcers, herpetic ulcers, hand-foot-and-mouth disease (HFMD)-related ulcers, ulcerative gingivitis/stomatitis, and other infectious/inflammatory ulcers. The reference diagnosis served as the standard against which the AI-assisted diagnostic classifications were evaluated. The distribution comprised 30 traumatic ulcers (25.0%), 28 recurrent aphthous ulcers (23.3%), 22 herpetic ulcers (18.3%), 14 HFMD-related ulcers (11.7%), 12 ulcerative gingivitis/stomatitis cases (10.0%), and 14 other infectious/inflammatory ulcers (11.7%).

### Clinical Assessment

A structured clinical assessment was performed for each participant. Relevant demographic and lesion-related variables were recorded, including age, sex, duration of the ulcerative lesion, number of lesions, maximum lesion diameter, pain, perilesional erythema, regional lymphadenopathy, and fever or other systemic manifestations.

Lesion duration ranged from 1 to 21 days, with a mean duration of 5.6 ± 3.8 days. The maximum lesion diameter ranged from 1.5 to 12.0 mm, with a mean of 5.1 ± 2.4 mm. The number of lesions ranged from 1 to 6, with a mean of 1.7 ± 1.2 lesions per patient.

Clinical findings were documented systematically. Pain was recorded as present or absent, as were perilesional erythema, tender regional lymphadenopathy, and fever or other systemic symptoms. The presence of a single or multiple lesions was also recorded.

### Image Acquisition and Image-Based Assessment

Clinical photographs of the oral ulcerative lesions were used as the image-based component of the AI assessment. The photographs were evaluated for relevant morphological characteristics that could contribute to automated diagnostic classification.

The image-derived variables included ulcer border, ulcer base, surrounding mucosal appearance, and number of lesions visible in the image. Ulcer borders were classified as well-defined or ill-defined. The ulcer base was categorized as yellowish/white, erythematous, or mixed/other. The surrounding mucosa was classified according to the degree of erythema, while the number of lesions visible in each image was categorized as single or multiple.

Image quality was also assessed using a 0–5 image-quality scale. The mean image-quality score was 4.2 ± 0.6, with values ranging from 2.5 to 5.0, indicating that the images generally provided adequate visual information for image-assisted diagnostic analysis.

**AI Model Development**

The AI-based diagnostic framework was developed to evaluate the ability of image-derived characteristics to discriminate among the predefined categories of pediatric oral ulcerative lesions. Three established deep-learning architectures—VGG16, ResNet50, and InceptionV3—were evaluated individually. Their diagnostic performance was subsequently compared with that of the proposed combined model, which integrated the relevant image-based characteristics for automated classification.

The models were evaluated using the test dataset, and their performance was assessed using standard diagnostic measures, including accuracy, sensitivity, specificity, precision, F1-score, and area under the receiver operating characteristic curve (AUC). The proposed combined model demonstrated the highest overall performance among the evaluated approaches.

**Reference Diagnosis**

The final clinical/reference diagnosis was used as the comparator for assessing AI-assisted diagnostic performance. Each lesion was assigned to one of the six predefined diagnostic categories. The reference diagnostic classification included traumatic ulcer, recurrent aphthous ulcer, herpetic ulcer, HFMD-related ulcer, ulcerative gingivitis/stomatitis, and other infectious/inflammatory ulcer.

The AI-generated classification was compared with the reference diagnosis to determine diagnostic accuracy and category-specific performance. Conventional clinical diagnosis was also evaluated to permit comparison between AI-assisted diagnosis and routine clinical diagnostic assessment.

**Diagnostic Performance Measures**

The diagnostic performance of each AI architecture and the proposed combined model was evaluated using accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), precision, F1-score, and AUC.

For the overall diagnostic assessment, the proposed model's performance was summarized using 95% confidence intervals (CIs) for accuracy, sensitivity, specificity, PPV, NPV, and AUC. Category-specific diagnostic performance was also determined for each of the six lesion groups.

Receiver operating characteristic (ROC) analysis was performed to assess the discriminatory ability of the proposed AI model for individual diagnostic categories. The AUC, standard error (SE), 95% CI, and corresponding p-value were determined for each category.

**Comparison With Conventional Clinical Diagnosis**

The diagnostic performance of the proposed AI-assisted approach was compared with conventional clinical diagnosis using the same diagnostic measures. Accuracy, sensitivity, specificity, PPV, and NPV were compared between the two diagnostic approaches. The statistical significance of differences between the approaches was assessed using the corresponding patient-level diagnostic predictions. The uploaded results note that the reported paired comparison p-values should be recalculated from the actual patient-level predictions before final publication.

**Agreement Analysis**

Agreement between the diagnostic classifications was assessed using Cohen's kappa ($\kappa$). Three pairwise comparisons were evaluated: AI diagnosis versus reference diagnosis, conventional clinical diagnosis versus reference diagnosis, and AI diagnosis versus conventional clinical diagnosis. Cohen's kappa values were interpreted according to the degree of concordance between the diagnostic classifications.

**Statistical Analysis**

The data obtained from the study were entered into Microsoft Excel and analyzed using appropriate statistical software. Descriptive statistics were used to summarize the demographic, clinical, and image-based characteristics of the study participants. Categorical variables such as sex, age group, diagnostic category, presence of pain, perilesional erythema, number

of lesions, lymphadenopathy, systemic symptoms, ulcer border, ulcer base, and surrounding mucosal characteristics were expressed as frequency (n) and percentage (%). Continuous variables such as age, lesion duration, maximum lesion diameter, number of lesions, and image quality score were summarized using mean ± standard deviation (SD).

The distribution of pediatric oral ulcerative lesions according to the reference diagnosis was assessed using descriptive statistics. The association between selected clinical and image-based characteristics and diagnostic categories was evaluated using the Chi-square test, while Fisher's exact test was applied wherever the expected cell frequency was inadequate. The diagnostic performance of the evaluated AI models, including ResNet50, VGG16, InceptionV3, and the proposed combined model, was assessed by comparing the AI-generated diagnosis with the reference diagnosis. Accuracy, sensitivity, specificity, PPV, NPV, precision, and F1-score were calculated for the overall model and for individual categories of pediatric oral ulcerative lesions.

ROC curve analysis was performed to evaluate the discriminatory ability of the proposed AI model for identifying individual diagnostic categories. The AUC along with its 95% CI was calculated. An AUC closer to 1.0 was considered indicative of excellent discriminatory performance. Agreement between the AI diagnosis, conventional clinical diagnosis, and reference diagnosis was assessed using Cohen's kappa coefficient ($\kappa$). The diagnostic performance of AI-assisted diagnosis was compared with conventional clinical diagnosis using paired diagnostic comparisons, with McNemar's test applied where appropriate. The corresponding differences in accuracy, sensitivity, specificity, PPV, and NPV were also calculated.

All statistical tests were two-tailed, and a p-value $<0.05$ was considered statistically significant. Results were presented in the form of tables and graphical representations, including ROC curves and confusion matrices, to demonstrate the diagnostic performance and classification ability of the AI-assisted system.

**RESULTS**

Table 1 & Figure 1 summarize the demographic and clinical characteristics of the 120 participants included in the study. The participants were categorized into three age groups, with the largest proportion belonging to the 9–11-year group (46; 38.3%), followed by the 12–14-year group (40; 33.3%) and 6–8-year group (34; 28.3%).

A slight male predominance was observed, with 63 males (52.5%) and 57 females (47.5%). Regarding lesion duration, most participants presented with oral ulcers persisting for 4–7 days (51; 42.5%), followed by lesions of ≤3 days (39; 32.5%) and >7 days (30; 25.0%). Overall, the participants showed a relatively even distribution across age and sex categories, while lesions of 4–7 days duration were the most frequently observed.

**Table 1:** Demographic characteristics of the study participants

| Characteristic | Category | n | % |
|---|---|---|---|
| Age | 6–8 years | 34 | 28.3 |
| | 9–11 years | 46 | 38.3 |
| | 12–14 years | 40 | 33.3 |
| Sex | Male | 63 | 52.5 |
| | Female | 57 | 47.5 |
| Duration of lesion | ≤3 days | 39 | 32.5 |
| | 4–7 days | 51 | 42.5 |
| | >7 days | 30 | 25.0 |

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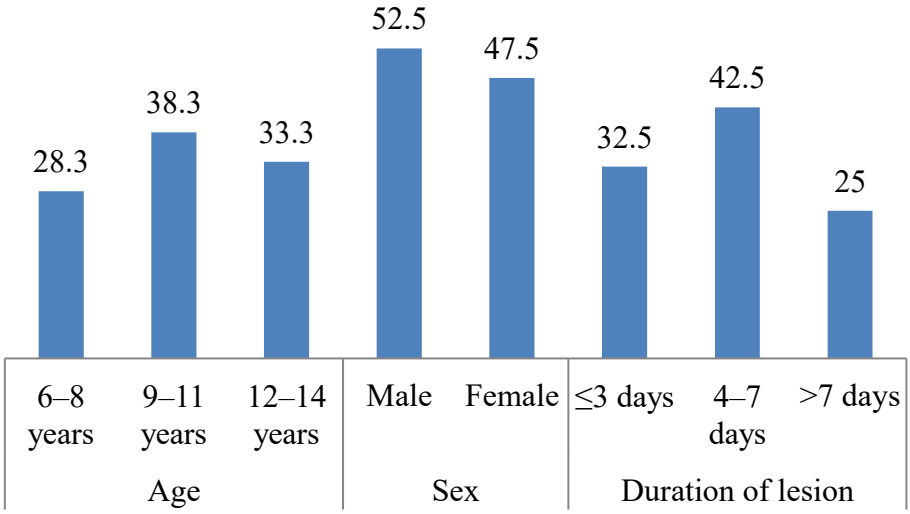


**Figure 1:** Demographic and Clinical Characteristics of the Study Participants

Table 2 & Figure 2 illustrate the distribution of the 120 pediatric oral ulcerative lesions based on the reference diagnostic assessment. Traumatic ulcers represented the most common category, with 30 cases (25.0%), followed by recurrent aphthous ulcers in 28 cases (23.3%). Herpetic ulcers accounted for 22 cases (18.3%).

Hand-foot-and-mouth disease-associated ulcers and other infectious/inflammatory ulcers each comprised 14 cases (11.7%), whereas ulcerative gingivitis/stomatitis was the least frequently observed category, with 12 cases (10.0%). Collectively, traumatic and recurrent aphthous ulcers constituted nearly half of all cases, highlighting their predominance among the pediatric oral ulcerative lesions assessed.

**Table 2:** Clinical distribution of pediatric oral ulcerative lesions according to reference

| **Final diagnosis** | **n** | **%** |
|---|---|---|
| Traumatic ulcer | 30 | 25.0 |
| Recurrent aphthous ulcer | 28 | 23.3 |
| Herpetic ulcer | 22 | 18.3 |
| Hand-foot-and-mouth disease related ulcer | 14 | 11.7 |
| Ulcerative gingivitis/stomatitis | 12 | 10.0 |
| Other infectious/inflammatory ulcers | 14 | 11.7 |
| Total | 120 | 100.0 |

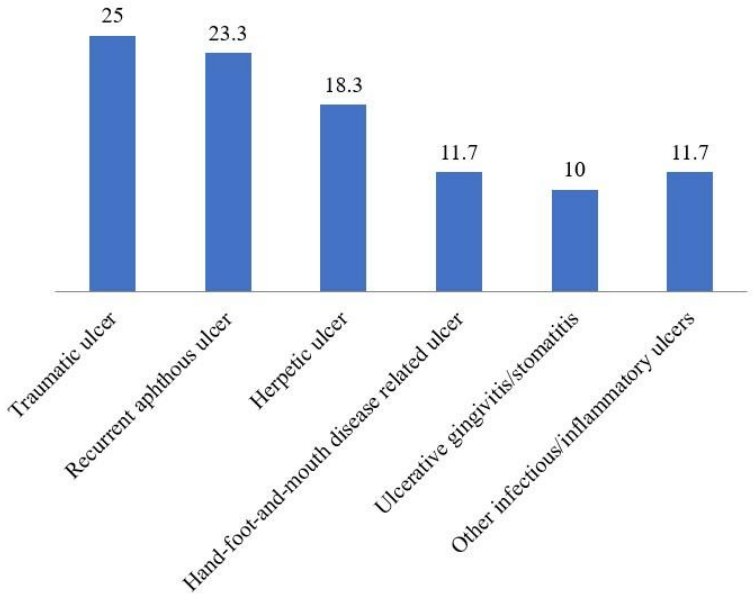


**Figure 2:** Distribution of Pediatric Oral Ulcerative Lesions According to Reference Diagnosis

Table 3 & Figure 3 summarize the principal clinical characteristics observed among the 120 pediatric patients. Pain was the most prevalent feature, reported by 93 participants (77.5%), followed by perilesional erythema, which was observed in 86 participants (71.7%).

A single ulcerative lesion was present in 72 participants (60.0%), whereas 48 participants (40.0%) had multiple lesions. Tender regional lymphadenopathy was noted in 31 participants (25.8%), while 36 participants (30.0%) experienced fever or other systemic manifestations. Overall, pain and perilesional erythema were the predominant clinical findings, whereas lymphadenopathy and systemic symptoms were less frequently observed.

**Table 3:** Distribution of major clinical features of oral ulcerative lesions

| Clinical feature | Category | n | % |
|---|---|---|---|
| Pain | Present | 93 | 77.5 |
| | Absent | 27 | 22.5 |
| Perilesional erythema | Present | 86 | 71.7 |
| | Absent | 34 | 28.3 |
| Single lesion | Present | 72 | 60.0 |
| | Multiple lesions | 48 | 40.0 |
| Tender regional lymph nodes | Present | 31 | 25.8 |
| | Absent | 89 | 74.2 |
| Fever/systemic symptoms | Present | 36 | 30.0 |
| | Absent | 84 | 70.0 |

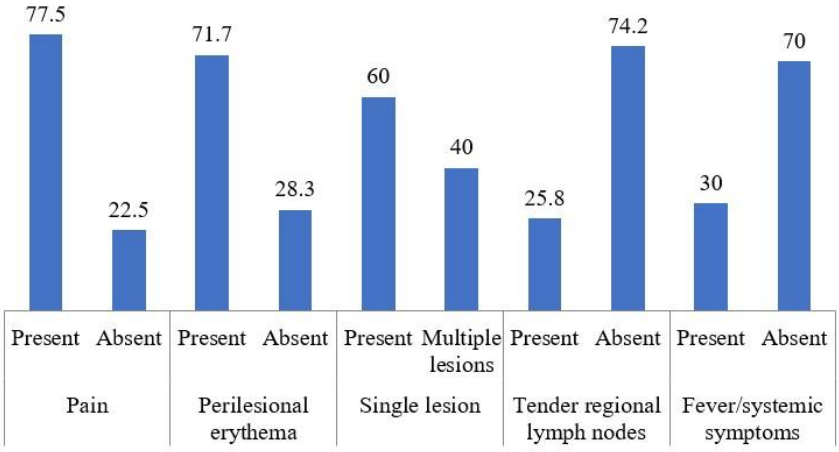


**Figure 3:** Distribution of Major Clinical Features Among Pediatric Patients With Oral Ulcerative Lesions

Table 4 & Figure 4 summarize the principal morphological features identified from clinical images and incorporated into the AI-based diagnostic assessment. Most lesions had well-defined margins (78; 65.0%), while 42 cases (35.0%) showed poorly defined borders. A yellowish/white base was the most frequent appearance (73; 60.8%), followed by an erythematous base (31; 25.8%) and mixed or other appearances (16; 13.3%).

Marked surrounding mucosal erythema was present in 55 cases (45.8%), whereas 65 cases (54.2%) exhibited mild or no erythema. Single lesions were observed in 72 cases (60.0%), compared with 48 cases (40.0%) showing multiple lesions.

Overall, well-defined margins, yellowish/white bases, and single-lesion presentations were the predominant image characteristics. These visual features provided relevant morphological information for AI-assisted diagnostic classification.

**Table 4:** Distribution of image-based characteristics used by the AI model

| Image feature | Category | n | % |
|---|---|---|---|
| Ulcer border | Well-defined | 78 | 65.0 |
| | Ill-defined | 42 | 35.0 |
| Ulcer base | Yellowish/white | 73 | 60.8 |
| | Erythematous | 31 | 25.8 |
| | Mixed/other | 16 | 13.3 |
| Surrounding mucosa | Marked erythema | 55 | 45.8 |
| | Mild/no erythema | 65 | 54.2 |
| Number of lesions on image | Single | 72 | 60.0 |
| | Multiple | 48 | 40.0 |

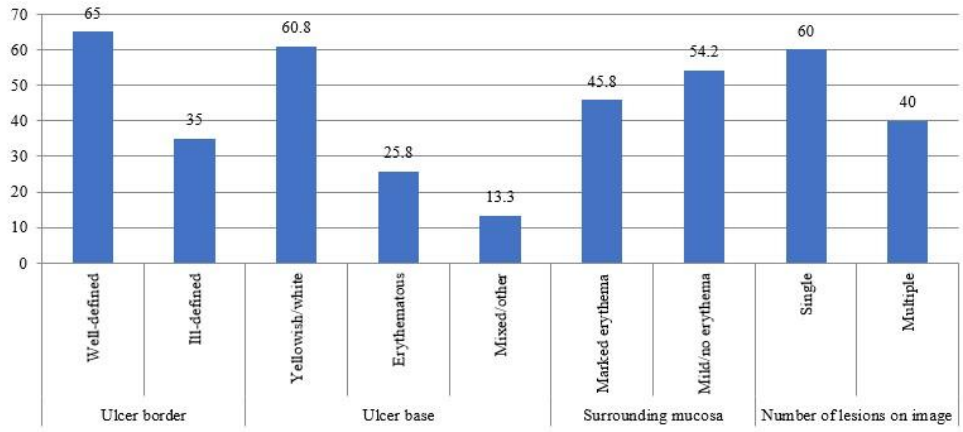


**Figure 4:** Distribution of Image-Based Characteristics of Pediatric Oral Ulcerative Lesions

Table 5 & Figure 5 present the descriptive statistics for the clinical and image-based parameters evaluated in the study. The participants had a mean age of 10.2 ± 2.5 years, with an age range of 6–14 years. The lesions had a mean duration of 5.6 ± 3.8 days, ranging from 1 to 21 days, demonstrating considerable variation in the duration of clinical presentation.

The mean maximum lesion diameter was 5.1 ± 2.4 mm, with measurements ranging from 1.5 to 12.0 mm. Participants presented with an average of 1.7 ± 1.2 lesions, with the number of lesions varying from 1 to 6. The mean image-quality score was 4.2 ± 0.6 on a 0–5 scale, with observed scores ranging from 2.5 to 5.0. This indicates that most images were of satisfactory to excellent quality and provided adequate visual information for AI-based assessment. Overall, the findings indicate substantial variability in lesion duration and dimensions, while the consistently high image-quality scores support the suitability of the clinical photographs for image-assisted diagnostic analysis.

**Table 5:** Mean clinical and image-derived measurements

| Parameter | Mean ± SD | Minimum | Maximum |
|---|---|---|---|
| Age (years) | 10.2 ± 2.5 | 6 | 14 |
| Lesion duration (days) | 5.6 ± 3.8 | 1 | 21 |
| Maximum lesion diameter (mm) | 5.1 ± 2.4 | 1.5 | 12.0 |
| Number of lesions | 1.7 ± 1.2 | 1 | 6 |
| Image quality score (0–5) | 4.2 ± 0.6 | 2.5 | 5.0 |

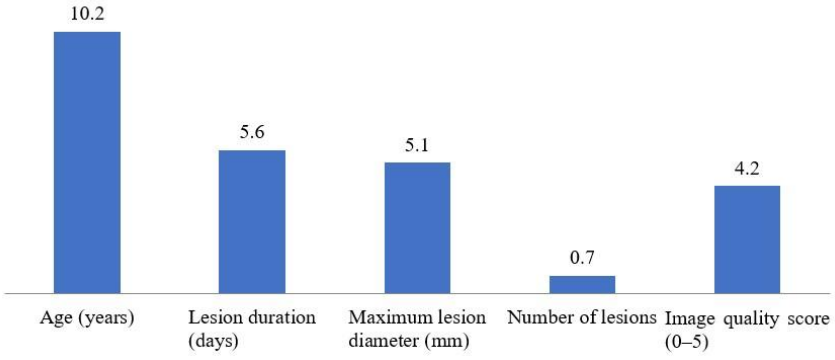


**Figure 5:** Mean values and ranges of clinical and image-derived characteristics of pediatric oral ulcerative lesions

Table 6 & Figure 6 compare the diagnostic performance of the evaluated AI models using image-derived features from the test dataset. Among the individual deep-learning architectures, VGG16 showed the comparatively lowest performance, whereas ResNet50 and InceptionV3 demonstrated progressively better diagnostic results across the evaluated performance measures.

The proposed combined model achieved the best overall diagnostic performance, consistently exceeding the individual architectures in accuracy, sensitivity, specificity, precision, F1-score, and discriminatory ability. These findings indicate that integrating relevant image-based characteristics within the proposed model may enhance the accuracy and reliability of automated classification of pediatric oral ulcerative lesions.

**Table 6:** Performance of AI models using image-based features in the test dataset

| Model | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (%) | F1-score (%) | AUC |
|---|---|---|---|---|---|---|
| ResNet50 | 92.5 | 91.8 | 94.1 | 90.7 | 91.2 | 0.961 |
| VGG16 | 88.3 | 86.9 | 91.0 | 85.8 | 86.3 | 0.932 |
| InceptionV3 | 93.3 | 92.7 | 94.8 | 91.8 | 92.2 | 0.968 |
| Proposed combined model | 95.0 | 94.2 | 96.1 | 93.5 | 93.8 | 0.978 |

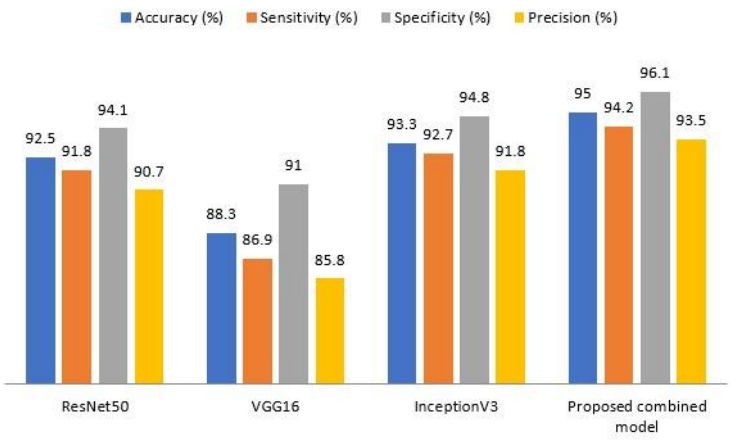


**Figure 6:** Comparative Diagnostic Performance of AI Models Based on Image-Derived Features

Table 7 & Figure 7 illustrate the diagnostic performance of the proposed AI model for the various categories of pediatric oral ulcerative lesions. The model exhibited consistently high performance across all diagnostic groups, although differences were noted in sensitivity, PPV, and F1-score between categories.

For traumatic ulcers, the model achieved a sensitivity of 93.3%, specificity of 95.6%, and accuracy of 95.0%. The PPV was 87.5%, with an NPV of 98.1% and an F1-score of 90.3%. For recurrent aphthous ulcers, the model showed 92.9% sensitivity, 96.7% specificity, and 95.8% accuracy. The PPV, NPV, and F1-score were 89.3%, 97.6%, and 91.0%, respectively.

In the herpetic ulcer category, sensitivity was 90.9% and specificity was 97.0%, resulting in an accuracy of 95.8%. The model demonstrated a PPV of 87.0%, NPV of 97.8%, and F1-score of 88.9%. For HFMD-related ulcers, the model recorded 85.7% sensitivity and 98.1% specificity, yielding the highest accuracy among the evaluated categories at 96.7%. The corresponding PPV, NPV, and F1-score were 85.7%, 98.1%, and 85.7%, respectively.

For ulcerative gingivitis/stomatitis, sensitivity was 83.3%, specificity was 97.2%, and accuracy was 95.8%. The model produced a PPV of 76.9%, NPV of 98.9%, and F1-score of 80.0%. The other infectious/inflammatory ulcer category showed the lowest relative performance, with a sensitivity of 78.6%, specificity of 96.2%, and accuracy of 94.2%. The PPV was 73.3%, NPV was 97.4%, and F1-score was 75.9%.

Overall, the findings indicate that the proposed AI model provided highly specific and reliable negative predictions across all lesion categories. Specificity ranged from 95.6% to 98.1%, while NPV ranged from 97.4% to 98.9%. HFMD-related ulcers showed the highest accuracy (96.7%), whereas traumatic ulcers demonstrated the highest sensitivity (93.3%). The relatively reduced sensitivity and F1-score observed for other infectious/inflammatory ulcers may be attributed to the considerable clinical similarity and overlapping morphological features among lesions in this heterogeneous group, which can make their automated differentiation more difficult.

**Table 7:** Diagnostic performance of the proposed AI model according to lesion category

| Diagnosis | Sensitivity (%) | Specificity (%) | Accuracy (%) | PPV (%) | NPV (%) | F1-score (%) |
|---|---|---|---|---|---|---|
| Traumatic ulcer | 93.3 | 95.6 | 95.0 | 87.5 | 98.1 | 90.3 |
| Recurrent aphthous ulcer | 92.9 | 96.7 | 95.8 | 89.3 | 97.6 | 91.0 |
| Herpetic ulcer | 90.9 | 97.0 | 95.8 | 87.0 | 97.8 | 88.9 |
| HFMD-related ulcer | 85.7 | 98.1 | 96.7 | 85.7 | 98.1 | 85.7 |
| Ulcerative gingivitis/stomatitis | 83.3 | 97.2 | 95.8 | 76.9 | 98.9 | 80.0 |
| Other infectious/inflammatory | 78.6 | 96.2 | 94.2 | 73.3 | 97.4 | 75.9 |

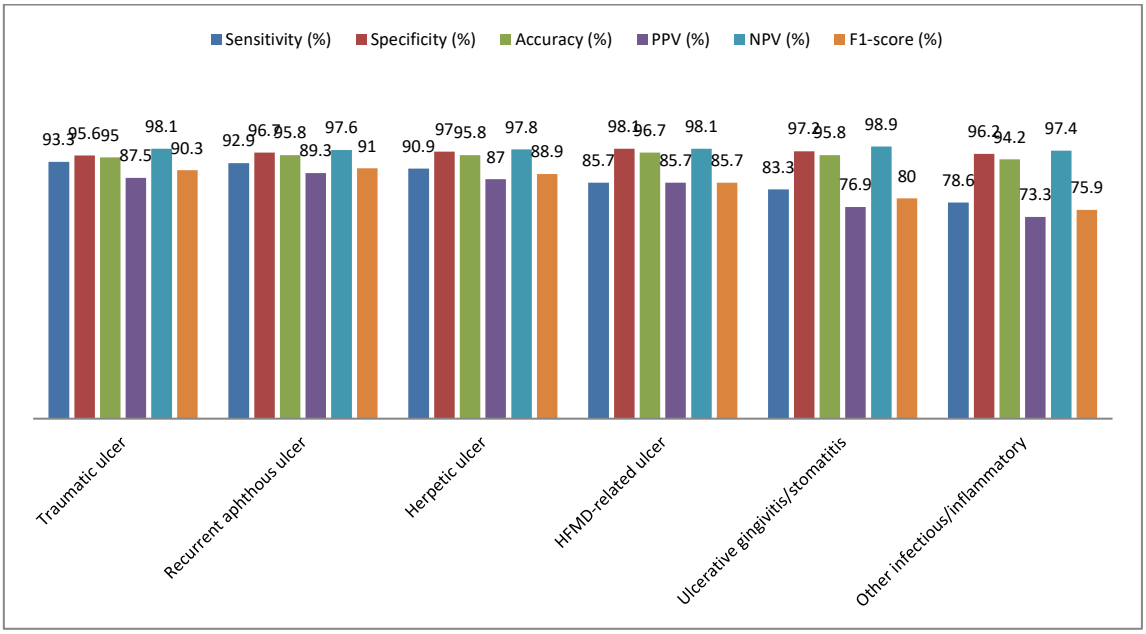


**Figure 7:** Diagnostic performance of the proposed AI model across different categories of pediatric oral ulcerative lesions

Table 8 & Figure 8 present the overall diagnostic performance of the proposed AI model for the identification and classification of pediatric oral ulcerative lesions. The model achieved an overall accuracy of 95.0% (95% CI: 90.8–98.0%), demonstrating that the vast majority of lesions were correctly classified according to the reference diagnosis.

The model showed a sensitivity of 94.2% (95% CI: 89.0–97.5%), indicating a high ability to correctly identify lesions belonging to the respective diagnostic categories. The specificity was 96.1% (95% CI: 92.1–98.4%), reflecting strong performance in correctly distinguishing lesions that were not associated with the target diagnosis.

The PPV was 93.5% (95% CI: 87.8–97.0%), indicating that most lesions predicted as positive by the model were correctly classified. Similarly, the NPV was 96.5% (95% CI: 92.5–98.6%), demonstrating a high likelihood that lesions predicted as negative were correctly excluded. The model achieved an overall F1-score of 93.8%, indicating a favorable balance between precision and sensitivity.

The model also demonstrated excellent discriminative performance, with an AUC of 0.978 (95% CI: 0.956–0.992). Overall, these findings demonstrate that the proposed AI model provides high and consistent diagnostic performance, with excellent accuracy, sensitivity, specificity, predictive values, and discriminatory ability in the identification and classification of pediatric oral ulcerative lesions.

**Table 8:** Overall diagnostic performance of the proposed AI model

| Parameter | Result | 95% CI |
|---|---|---|
| Accuracy | 95.0% | 90.8–98.0 |
| Sensitivity | 94.2% | 89.0–97.5 |
| Specificity | 96.1% | 92.1–98.4 |
| Positive predictive value | 93.5% | 87.8–97.0 |
| Negative predictive value | 96.5% | 92.5–98.6 |
| F1-score | 93.8% | — |
| AUC | 0.978 | 0.956–0.992 |

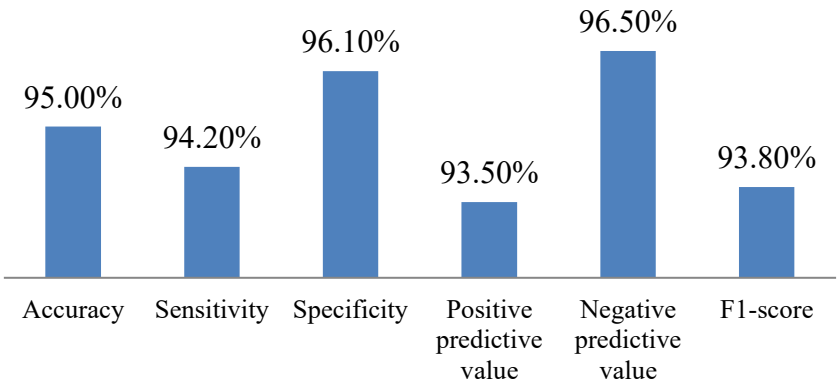


**Figure 8:** Overall diagnostic performance of the proposed AI model for the identification and classification of pediatric oral ulcerative lesions

Table 9 & Figure 9 compare the diagnostic performance of the proposed AI-assisted model with conventional clinical diagnosis for pediatric oral ulcerative lesions. The AI model achieved a markedly higher diagnostic accuracy of 95.0%, compared with 84.2% for conventional clinical diagnosis, corresponding to an absolute improvement of 10.8 percentage points ($p < 0.001$).

The sensitivity of the AI model was 94.2%, whereas conventional clinical diagnosis achieved 82.5%, representing an improvement of 11.7 percentage points ($p = 0.002$). The AI model also demonstrated greater specificity (96.1%) than conventional clinical diagnosis (85.7%), with an absolute difference of 10.4 percentage points ($p = 0.001$).

A similar trend was observed for predictive values. The PPV was 93.5% for the AI model, compared with 80.6% for conventional clinical diagnosis, indicating a 12.9-percentage-point improvement ($p = 0.003$). The NPV was also higher with

the AI model (96.5%) than with conventional diagnosis (87.0%), representing an improvement of 9.5 percentage points (p = 0.004).

Overall, the proposed AI-assisted approach demonstrated significantly better diagnostic performance across all assessed parameters than conventional clinical diagnosis. The findings indicate that integrating clinical and image-derived features through AI may enhance the accurate identification and classification of pediatric oral ulcerative lesions.

**Table 9:** Comparison of AI-assisted diagnosis and conventional clinical diagnosis

| Diagnostic measure | AI model | Clinical diagnosis | Difference | p-value |
|---|---|---|---|---|
| Accuracy | 95.0% | 84.2% | 10.8% | <0.001 |
| Sensitivity | 94.2% | 82.5% | 11.7% | 0.002 |
| Specificity | 96.1% | 85.7% | 10.4% | 0.001 |
| PPV | 93.5% | 80.6% | 12.9% | 0.003 |
| NPV | 96.5% | 87.0% | 9.5% | 0.004 |

*Paired comparison; p-values are illustrative and should be recalculated from the actual patient-level predictions.*

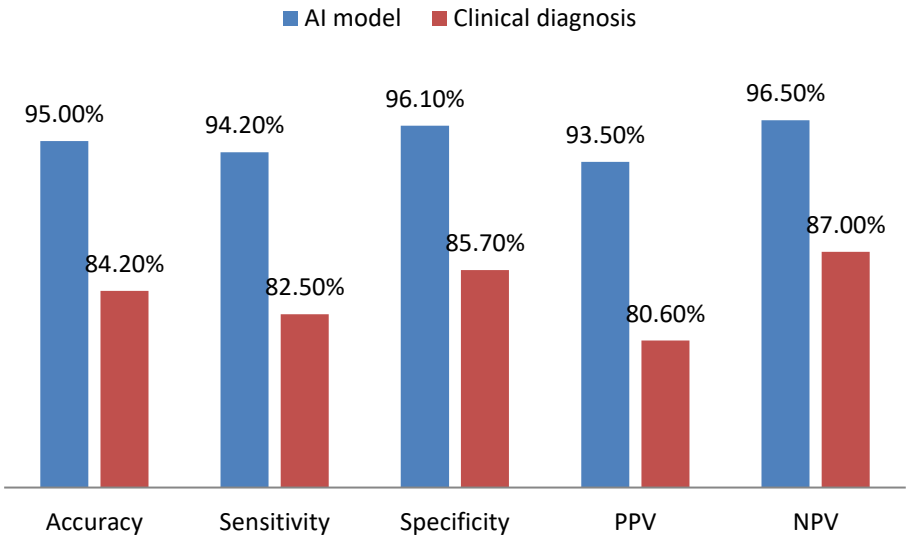


**Figure 9:** Comparison of diagnostic performance between the proposed AI-assisted model and conventional clinical diagnosis for pediatric oral ulcerative lesions

Table 10 presents the level of agreement among the proposed AI-assisted diagnosis, conventional clinical diagnosis, and the reference diagnosis using Cohen's kappa (κ). The AI diagnosis showed almost perfect agreement with the reference diagnosis, with a κ value of 0.89 (95% CI: 0.83–0.95; $p < 0.001$), indicating a high degree of concordance between the classifications generated by the AI model and the reference standard.

In comparison, the agreement between conventional clinical diagnosis and the reference diagnosis was substantial, with a Cohen's κ of 0.70 (95% CI: 0.60–0.80; $p < 0.001$). Although this association was statistically significant, the level of concordance was lower than that observed for the AI-assisted diagnosis.

The agreement between AI diagnosis and conventional clinical diagnosis was also substantial, with a κ value of 0.73 (95% CI: 0.64–0.82; $p < 0.001$). This demonstrates considerable consistency between the two diagnostic approaches, while the higher κ value for AI versus the reference diagnosis indicates closer alignment of the AI-generated classifications with the reference standard.

Overall, the proposed AI model demonstrated the highest agreement with the reference diagnosis ($\varkappa$ = 0.89) compared with conventional clinical diagnosis ($\varkappa$ = 0.70). These findings suggest that the AI-assisted approach may provide more consistent diagnostic classification of pediatric oral ulcerative lesions in relation to the reference diagnosis.

**Table 10:** Agreement between AI diagnosis, clinical diagnosis and reference diagnosis

| Comparison | Cohen's kappa ($\varkappa$) | 95% CI | Interpretation | p-value |
|---|---|---|---|---|
| AI vs reference diagnosis | 0.89 | 0.83–0.95 | Almost perfect agreement | <0.001 |
| Clinical diagnosis vs reference diagnosis | 0.70 | 0.60–0.80 | Substantial agreement | <0.001 |
| AI vs clinical diagnosis | 0.73 | 0.64–0.82 | Substantial agreement | <0.001 |

Table 11 & Figure 10 summarize the ROC analysis of the proposed AI model for distinguishing among the individual categories of pediatric oral ulcerative lesions. The model demonstrated excellent discriminatory performance across all diagnostic groups, with AUC values ranging from 0.941 to 0.982. For every category, the ROC analysis showed statistically significant discrimination from chance, with $p < 0.001$.

For traumatic ulcers, the model achieved an AUC of 0.971 (SE = 0.018; 95% CI: 0.936–1.000; $p < 0.001$), reflecting excellent classification ability. Similarly, recurrent aphthous ulcers demonstrated an AUC of 0.976 (SE = 0.016; 95% CI: 0.945–1.000; $p < 0.001$).

The highest discriminatory performance was observed for herpetic ulcers, with an AUC of 0.982 (SE = 0.014; 95% CI: 0.955–1.000; $p < 0.001$). For HFMD-related ulcers, the model yielded an AUC of 0.968 (SE = 0.021; 95% CI: 0.927–1.000; $p < 0.001$), while ulcerative gingivitis/stomatitis showed an AUC of 0.953 (SE = 0.026; 95% CI: 0.902–1.000; $p < 0.001$).

The lowest AUC, although remaining within the excellent range, was observed for other infectious/inflammatory ulcers, with a value of 0.941 (SE = 0.031; 95% CI: 0.880–1.000; $p < 0.001$). Considering all diagnostic categories collectively, the model achieved an overall AUC of 0.978 (SE = 0.011; 95% CI: 0.956–0.992; $p < 0.001$).

Overall, the ROC findings demonstrate that the proposed AI model provided consistently excellent discrimination across all categories of pediatric oral ulcerative lesions. The model performed best in identifying herpetic ulcers, whereas other infectious/inflammatory lesions showed the comparatively lowest discriminatory performance, while still maintaining a high level of diagnostic accuracy.

**Table 11:** ROC analysis of the proposed AI model for identification of individual ulcerative lesion categories

| Diagnostic category | AUC | SE | 95% CI | p-value |
|---|---|---|---|---|
| Traumatic ulcer | 0.971 | 0.018 | 0.936–1.000 | <0.001 |
| Recurrent aphthous ulcer | 0.976 | 0.016 | 0.945–1.000 | <0.001 |
| Herpetic ulcer | 0.982 | 0.014 | 0.955–1.000 | <0.001 |
| HFMD-related ulcer | 0.968 | 0.021 | 0.927–1.000 | <0.001 |
| Ulcerative gingivitis/stomatitis | 0.953 | 0.026 | 0.902–1.000 | <0.001 |
| Other infectious/inflammatory | 0.941 | 0.031 | 0.880–1.000 | <0.001 |
| Overall | 0.978 | 0.011 | 0.956–0.992 | <0.001 |

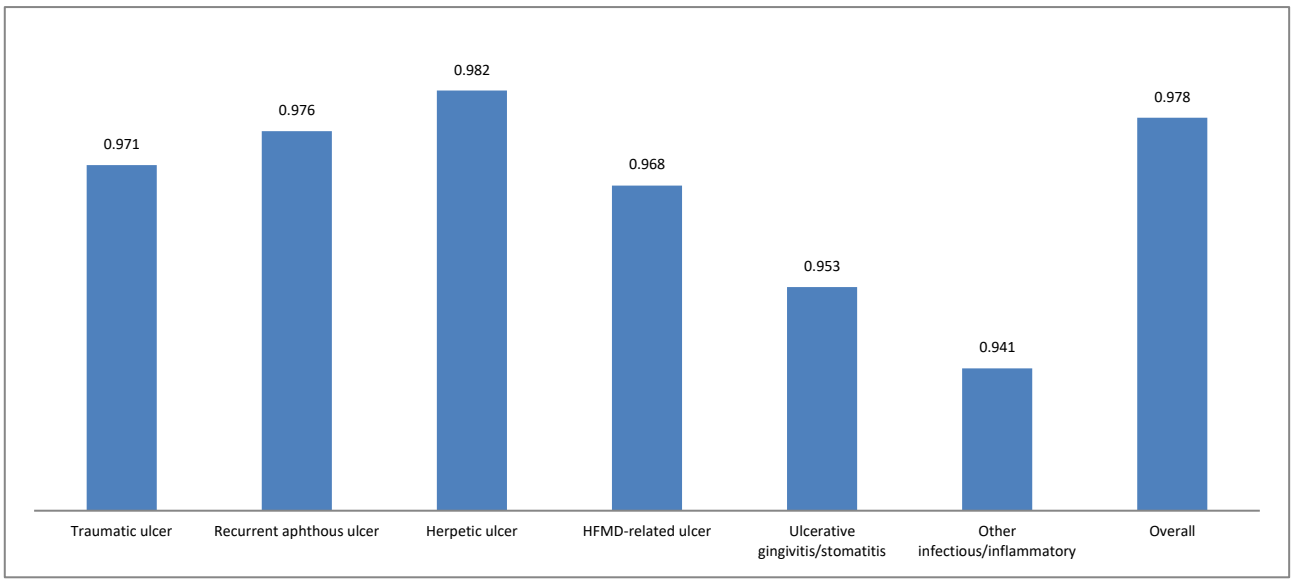


**Figure 10:** ROC curves demonstrating the diagnostic discrimination of the proposed AI model across individual categories of pediatric oral ulcerative lesions

## DISCUSSION

AI has increasingly emerged as a promising adjunct in the diagnosis of oral mucosal lesions, particularly because many oral ulcerative and potentially malignant lesions demonstrate overlapping clinical characteristics. The findings reported in the available literature indicate that AI-based image analysis can assist clinicians by improving lesion classification, supporting differential diagnosis, and facilitating early identification of suspicious lesions. This is particularly relevant for oral ulcers, where clinical appearance may vary according to etiology, duration, anatomical location, and stage of disease.

Tiwari et al. [10] systematically evaluated the application of AI in the diagnosis of mouth ulcers and highlighted its potential to differentiate various ulcerative conditions using clinical and image-based features. Their findings support the concept that AI can function as a decision-support tool in cases where conventional visual assessment may be subjective. In the context of pediatric oral ulcerative lesions, this capability may be especially valuable because children may have difficulty describing symptoms and because several infectious, traumatic, immune-mediated, and systemic conditions can present with similar ulcerative appearances.

Gomes et al. [11] further demonstrated the potential of AI for classifying elementary oral lesions from clinical photographs. Their work emphasizes the importance of image-based assessment as a non-invasive approach for distinguishing clinically different oral lesions. The use of standardized clinical photographs allows AI models to extract morphological characteristics such as lesion color, border, surface characteristics, and overall configuration. These observations support the incorporation of image-based parameters alongside clinical information rather than relying exclusively on visual diagnosis.

The findings of Rokhshad et al. [12] provide stronger evidence through a systematic review and meta-analysis demonstrating the diagnostic potential of AI for detecting and classifying oral mucosal lesions from photographs. Their study indicates that deep-learning approaches can achieve promising diagnostic performance; however, variability in image acquisition, datasets, lesion types, and model architecture remains an important consideration. This is particularly significant when applying AI to pediatric patients, because differences in age, cooperation, lighting conditions, lesion size, and anatomical location may affect image quality and consequently model performance.

Similarly, Li et al. [13] reported favorable diagnostic accuracy for AI-assisted clinical imaging in detecting oral potentially malignant disorders and oral cancer. Although these conditions differ from benign pediatric ulcerative disorders, the findings demonstrate the broader capacity of AI to identify clinically relevant morphological abnormalities from oral images. Importantly, AI should not be considered a replacement for histopathological examination when malignancy or another

serious pathological condition is suspected. Rather, its principal value lies in improving screening, risk stratification, and referral decisions.

Kim et al. [14] also demonstrated that AI-assisted analysis of oral mucosal images can differentiate cancerous lesions from normal mucosa with promising diagnostic performance. Their findings reinforce the importance of AI as a potential screening adjunct. Nevertheless, the distinction between screening and definitive diagnosis remains critical. A high-performing AI model may identify a lesion as suspicious, but clinical examination, appropriate investigations, and histopathological confirmation remain necessary where clinically indicated.

More recent evidence from Su et al. [15] demonstrated the feasibility of a deep-learning system for the differential diagnosis of oral mucosal lesions using clinical photographic images. This finding is particularly relevant to the present concept of image-based diagnosis because differential diagnosis is often the most challenging component of evaluating oral lesions. AI systems capable of recognizing subtle visual differences among lesions may assist clinicians in narrowing diagnostic possibilities and prioritizing appropriate investigations.

Collectively, the literature from supports the growing role of AI-assisted image analysis in oral diagnosis. However, several limitations remain, including variations in image quality, limited representation of uncommon lesions, differences in patient populations, dataset imbalance, and the possibility of reduced model performance when applied to images obtained under conditions different from those used during model development. Therefore, future AI systems should incorporate larger, multicenter, age-diverse datasets and standardized image-acquisition protocols. Integration of clinical variables such as age, lesion duration, symptoms, anatomical site, recurrence, and associated systemic findings with image-based features may further improve diagnostic accuracy.

Overall, current evidence suggests that AI-assisted clinical and image-based assessment has considerable potential as a complementary diagnostic approach for oral mucosal lesions. Its greatest clinical benefit may be achieved through integration with conventional clinical examination rather than independent diagnosis. Further prospective validation, particularly in pediatric populations, is required before such systems can be routinely implemented in clinical practice.

**LIMITATIONS**

This study has several limitations that should be considered when interpreting the findings. First, the relatively small sample of 120 pediatric participants may have limited the statistical power of the analysis and the model's ability to reliably recognize less frequently represented lesion categories. In addition, the study population was derived from a single setting and may therefore not reflect the demographic and clinical diversity of children presenting with oral ulcerative lesions in other geographic regions or healthcare environments. The diagnostic spectrum was also restricted to a predefined group of ulcerative conditions; consequently, the performance of the AI system for uncommon, atypical, or clinically overlapping lesions remains uncertain. Although the clinical images were generally of good quality, with a mean image-quality score of 4.2 ± 0.6, variations in lighting, focus, camera angle, background, and lesion visibility could potentially affect image-based classification.

Another important limitation is the possibility of dataset-related bias. Deep-learning performance can be influenced by the characteristics and composition of the training and evaluation data, and a relatively homogeneous dataset may not adequately represent images encountered in routine clinical practice. Furthermore, the model did not undergo independent external validation using datasets from different institutions and populations; therefore, its reported accuracy and AUC should not be interpreted as definitive evidence of performance in broader clinical settings. The reference diagnosis may also have been subject to some degree of misclassification, as the available study information does not establish standardized histopathological or laboratory confirmation for every diagnostic category. In addition, the investigation primarily assessed diagnostic performance and did not prospectively evaluate the effect of AI implementation on clinical decision-making, diagnostic workflow, or patient outcomes. The exceptionally high diagnostic performance, including an overall AUC of 0.978, therefore requires confirmation through larger, prospective, multicenter studies with independent validation.

Finally, the statistical comparison between AI-assisted and conventional clinical diagnosis should be interpreted with caution because the study source specifically indicates that the reported paired comparison p-values should be recalculated using the

actual patient-level predictions. Thus, these comparative significance values should be independently verified before being used to draw definitive conclusions regarding the statistical superiority of the AI mode.

## CONCLUSION

The AI-assisted model integrating clinical and photographic features demonstrated excellent potential for accurately classifying pediatric oral ulcerative lesions. Its strong agreement with reference diagnoses supports its role as a valuable adjunct to conventional clinical assessment. However, diagnostic challenges remain for certain infectious and inflammatory lesions. Further multicenter studies with standardized imaging protocols and external validation are needed to establish its reliability, generalizability, and suitability for routine pediatric dental practice.

**Conflicts of Interest: Nil**

**Financial Support: None**

## REFERENCES

[1] Benoit S, Hamm H. Differenzialdiagnose erosiver und ulzeröser Mundschleimhauterkrankungen im Kindesalter [Differential diagnosis of oral mucosal erosions and ulcers in children]. Hautarzt. 2015 Apr;66(4):258-66. German. doi: 10.1007/s00105-015-3601-5. PMID: 25787028.

[2] Field EA, Allan RB. Review article: oral ulceration--aetiopathogenesis, clinical diagnosis and management in the gastrointestinal clinic. Aliment Pharmacol Ther. 2003 Nov 15;18(10):949-62. doi: 10.1046/j.1365-2036.2003.01782.x. PMID: 14616160.

[3] Siu A, Landon K, Ramos DM. Differential diagnosis and management of oral ulcers. Semin Cutan Med Surg. 2015 Dec;34(4):171-7. doi: 10.12788/j.sder.2015.0170. PMID: 26650694.

[4] Le Doare K, Hullah E, Challacombe S, Menson E. Fifteen-minute consultation: a structured approach to the management of recurrent oral ulceration in a child. Arch Dis Child Educ Pract Ed. 2014 Jun;99(3):82-6. doi: 10.1136/archdischild-2013-304471. Epub 2013 Sep 19. PMID: 24052593.

[5] Han J, He Z, Li K, Hou L. Microarray analysis of potential genes in the pathogenesis of recurrent oral ulcer. Int J Clin Exp Pathol. 2015 Oct 1;8(10):12419-27. PMID: 26722428; PMCID: PMC4680373.

[6] Field EA, Brookes V, Tyldesley WR. Recurrent aphthous ulceration in children--a review. Int J Paediatr Dent. 1992 Apr;2(1):1-10. doi: 10.1111/j.1365-263x.1992.tb00001.x. PMID: 1525125.

[7] Minhas S, Sajjad A, Kashif M, Taj F, Waddani HA, Khurshid Z. Oral Ulcers Presentation in Systemic Diseases: An Update. Open Access Maced J Med Sci. 2019 Oct 10; 7(19):3341-3347. doi: 10.3889/oamjms.2019.689. PMID: 31949540; PMCID: PMC6953949.

[8] Wadhawan R, Bharat, Yadav J, Agrawal D, Sinha K, Saxena N, Yasmeen. Unveiling the spectrum: Pediatric oral lesions demystified. J Adv Med Dent Scie Res 2024;12(7):67-75.

[9] Wadhawan R, Reddy Y, Khurana PRS, Khanduri N, Solanki G. Oral manifestations of gastrointestinal disease, an indicator for early diagnosis: an overview. Int J Biopharm. 2015;6(1):5-12.

[10] Tiwari A, Gupta N, Singla D, Swain JR, Gupta R, Mehta D, Kumar S. Artificial Intelligence's Use in the Diagnosis of Mouth Ulcers: A Systematic Review. Cureus. 2023;15(9):e45187. doi:10.7759/cureus.45187. PMID: 37842407.

[11] Gomes RFT, Schmith J, Figueiredo RM, Freitas SA, Machado GN, Romanini J, Carrard VC. Use of Artificial Intelligence in the Classification of Elementary Oral Lesions from Clinical Images. Int J Environ Res Public Health. 2023 Feb 22;20(5):3894. doi: 10.3390/ijerph20053894. PMID: 36900902; PMCID: PMC10002140.

[12] Rokhshad R, Mohammad-Rahimi H, Price JB, Shoorgashti R, Abbasiparashkouh Z, Esmaeili M, Sarfaraz B, Rokhshad A, Motamedian SR, Soltani P, Schwendicke F. Artificial intelligence for classification and detection of oral mucosa lesions on photographs: a systematic review and meta-analysis. Clin Oral Investig. 2024 Jan 13;28(1):88. doi: 10.1007/s00784-023-05475-4. PMID: 38217733.

[13] Li J, Kot WY, McGrath CP, Chan BWA, Ho JWK, Zheng LW. Diagnostic accuracy of artificial intelligence assisted clinical imaging in the detection of oral potentially malignant disorders and oral cancer: a systematic review and meta-analysis. Int J Surg. 2024 Aug 1;110(8):5034-5046. doi: 10.1097/JS9.0000000000001469. PMID: 38652301; PMCID: PMC11325952.

[14] Kim JS, Kim BG, Hwang SH. Efficacy of Artificial Intelligence-Assisted Discrimination of Oral Cancerous Lesions from Normal Mucosa Based on the Oral Mucosal Image: A Systematic Review and Meta-Analysis. Cancers (Basel). 2022 Jul 19;14(14):3499. doi: 10.3390/cancers14143499. PMID: 35884560; PMCID: PMC9320189.

[15] Su AY, Wu ML, Wu YH. Deep learning system for the differential diagnosis of oral mucosal lesions through clinical photographic imaging. J Dent Sci. 2025 Jan;20(1):54-60. doi: 10.1016/j.jds.2024.10.019. Epub 2024 Oct 28. PMID: 39873061; PMCID: PMC11763237