

Hybrid YOLOv8-ResNet50 Model for Diabetic Oral Ulcer Severity

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How to cite this article: Sanjay D, Sarvesh S, Aswanth R, Deepan S. Hybrid YOLOv8-ResNet50 Model for Diabetic Oral Ulcer Severity. *Int J Drug Deliv Technol.* 2026;16(37s): 70-77. DOI: 10.25258/ijddt.16.37s.12

Abstract

The metabolic disorder diabetes mellitus affects people worldwide and it results in various oral health problems which include ulcers that develop from wounds which do not heal properly and people who have weakened immune systems. Dental professionals need to identify ulcers early and monitor them throughout time because this practice helps to stop secondary infections from occurring and protects the patient from oral health decline. The process of assessing dental conditions requires extensive time and effort because dentists use traditional diagnostic methods which depend on visual inspection to assess dental conditions through their experienced skills. The research team created a two-stage deep learning system which automatically detects and assesses the severity of diabetic ulcers in intraoral pictures. The YOLOv8 object detection framework achieves accurate ulcer localization through its bounding box estimation method which enables subsequent lesion severity classification via morphological and textural analysis of detected lesions using the ResNet50 convolutional neural network model. The model's ability to generalize to new data improves through data pre-processing procedures which include resolution uniformity and pixel normalization and data augmentation. The proposed hybrid model demonstrates better classification performance with the capacity for rapid preliminary evaluation which enables accurate telemedicine monitoring and risk assessment of diabetic oral lesions through computer-based systems.

Keywords: Deep Learning, Diabetic Oral Ulcer, Medical Imaging, YOLOv8, ResNet50, Lesion Severity Classification

I. INTRODUCTION

The dental health of people with diabetes mellitus systemic disease has widespread oral symptoms because diabetes mellitus functions as a major health risk for their dental condition. People who experience

poor blood sugar control face increased chances of developing persistent mouth sores and gum disease

and their bodies will take longer to heal. These health problems will develop into serious infections or permanent disability if people do not treat them.

Diabetic patients require continuous monitoring of their ulcer development and severity to achieve complete assessment of their dental health. The existing oral ulcer assessment process requires clinicians to conduct direct visual examinations which are affected by their individual biases and the surrounding light conditions. The situation becomes more complicated because advanced technology systems require both specialized equipment and expert knowledge to operate their systems. AI-powered technologies which contain deep learning capabilities now support medical professionals in their medical imaging analysis work by providing enhanced tools for detecting medical conditions that have seen rapid development in recent years.

The research creates a two-part deep learning system which detects and evaluates diabetic oral ulcers through its analysis of intraoral photos. The system operates in three key functions which involve detecting ulcer locations and assessing their severity under real world conditions.

II. LITERATURE SURVEY

The research in dental and medical image analysis evaluated two analysis methods which included traditional techniques and data-driven methods. The first systems used handcrafted feature representations which included:

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The system used Histogram of Oriented Gradients and Local Binary Patterns and colour histograms as its feature set while it employed Support Vector Machines and Random Forests as its default classifiers. The experimental testing of pipelines produced satisfactory outcomes although their performance decreased when tested under different imaging conditions and with multiple lesion types.

Deep convolutional neural networks (CNNs) established a new approach through their capability to train networks for acquiring distinct features from raw image input. Research studies proved that the techniques correctly detect oral mucosal abnormalities and OSCC and dental irregularities through clinical imaging. The common method to address the problem of limited annotated medical datasets combines transfer learning with pre-trained models which include those trained on ImageNet.

Medical imaging now uses single-stage detectors more frequently because YOLO (You Only Look Once) and its following versions can detect and classify target regions in real-time processing. ResNet50 serves as the popular backbone for classification tasks because its residual skip-connection design prevents deep training from encountering vanishing gradient problems. The current research combines both systems because their strengths require development into a single detection-and-classification system.

III. PROPOSED SYSTEM

The presented architectural design operates as a sequential processing system which executes information processing in two distinct phases. The initial phase of YOLOv8 processes intraoral photographs by examining the complete image to find ulcerated tissue while producing bounding box coordinates that indicate the size of detected areas.

The system extracts the detected lesion patch from the original image after the detection process ends and sends it to the ResNet50 classifier for analysis. The module uses multiple visual factors which include color gradient intensity and edge irregularity and surface texture and structural deformation to assess the distinct area and determine its intensity classification. The classifier results show better diagnostic performance when using lesion-exclusive crop input which improves classification accuracy.

METHODOLOGY

1. Dataset Collection

The research team utilized public resources to obtain their training data from oral health imaging databases which permit public access and from

photographic collections which qualify as public resources. The collection features various diabetic oral ulcers with different severity levels and different types of lesions. The researchers created three dataset sections to use for training and validation and testing purposes which enabled them to conduct impartial evaluations of the research results. The preprocessed images of ulcers which were created for YOLOv8 input are shown in Figure 1 (Dataset Image).



Figure 1. Dataset image

2. Image Preprocessing

The image preprocessing system functioned in a consistent way across all pictures before the model data processing began. The process required standardizing image dimensions because both networks needed specific input resolution standards which required converting pixel intensity values to the $[0, 1]$ range and applying histogram equalization to enhance image sample contrast. The training images received extra augmentation treatment which included random rotation and horizontal and vertical flipping and zoom adjustment to enhance the model's ability to identify various image patterns.

3. Ulcer Detection using YOLOv8

The main detection system utilized YOLOv8 because its anchor-free structure together with its training method effectiveness produced outstanding spatial accuracy results. The team established their intraoral image data training system by starting with ImageNet weights which they obtained from the model. The model successfully identified ulcers across various dimensions because its training utilized real bounding box data. The system applied described bounding box coordinates to determine which regions required further classification processing.

4. Severity Classification using ResNet50

The multi-class classifier based on ResNet50 used isolated ulcer patches as its input for its classification task. The residual architecture of ResNet50, which uses layer-bypassing shortcut connections, provides stable gradient flow during backpropagation, which results in an essential advantage over traditional deep CNNs that experience gradient degradation problems. The top classification layer of the system received a complete replacement with a newly created dense layer which matched the target number of ulcer severity categories.

IV. SYSTEM ARCHITECTURE

The framework operates under its defined operational procedures. The preprocessing module begins its full processing sequence after it receives an intraoral image which results in the image being processed to standard resolution and intensity levels while all noise artifacts get removed. The conditioned image is sent to YOLOv8 which generates accurate bounding box predictions that identify the location of the ulcer. The system establishes an area which contains only the ulcer through bounding box coordinates while it eliminates all background elements that do not pertain to the classification process. The ResNet50 model receives the cropped patch to conduct its analysis which evaluates color distribution and surface texture and structural morphology through its multiple convolutional and residual layers. The network creates a probability vector which contains all severity classes and the prediction process selects the class with the strongest confidence score. System Workflow: Figure 2 System Workflow: The workflow begins when users upload images which process through pre-processing before YOLOv8 starts Ulcer Detection. The system functions through severity classification which implements ResNet50 as its operational method. The system delivers results after it conducts comprehensive ulcer examination of the animated video content. The predictive class label together with its confidence score enables clinicians to determine the ulcer type and clinical severity which assists them in creating effective treatment plans.

Hybrid Model Architecture for Diabetic Oral Ulcer Severity

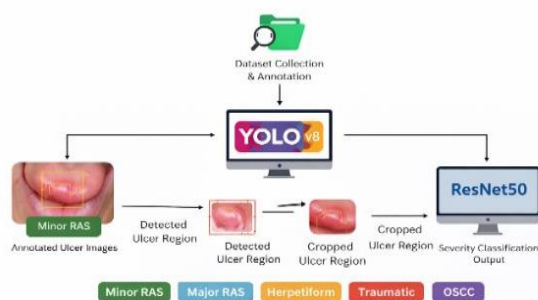


Figure 2. System Workflow

V. IMPLEMENTATION

The researchers constructed the complete pipeline by using Python programming language along with deep learning and scientific computing frameworks which are established standards in the scientific domain. The YOLOv8 detector used the Ultralytics library to create its initial detection framework which depended on COCO-pretrained weights before it became a tool which detects intraoral ulcers.

The training process used the annotation labels which were created through standard image-labeling software as bounding box supervision.

ResNet50 was loaded with ImageNet-pretrained weights, and its output head was replaced with a task-specific dense layer sized to the number of severity classes. The dataset was divided into three subsets which included training, validation, and testing at a ratio of 70% for training, 15% for validation, and 15% for testing. The system applied OpenCV and NumPy to perform image transformations and augmentations while it restricted random augmentations to occur only during training time. The training process used GPU hardware to conduct all computations at a faster pace. The system used categorical cross-entropy as its loss objective which it optimized through Adam optimization and a decaying learning rate schedule. The preprocessed OSCC sample shown in Figure 3 (Preprocessed Image) demonstrates how training progressed to reveal the highlighted ulcer area. The model output shown in the figure identifies the OSCC type and reports a confidence level of 0.999971.



Figure 3. Preprocessed image

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image 1/1 /content/462947_1_En_81_Fig13_HTML.jpg: 224x224 OSCC
Speed: 6.1ms preprocess, 4.6ms inference, 0.0ms postprocess per
Predicted Ulcer Type: OSCC
Confidence: 0.9999717473983765
```

Hybrid YOLOv8-ResNet50 Model for Diabetic Oral Ulcer Severity

Figure 4. Output of the above image

VI. PERFORMANCE METRICS

The performance of the proposed YOLOv8-ResNet50 model is evaluated using standard evaluation metrics. These metrics help in measuring the accuracy and effectiveness of the model in detecting and classifying oral ulcers.

Evaluation Metric	Definition	Formula
Accuracy	Overall correct predictions / total	$(TP+TN)/(TP+TN+FP+FN)$
Precision	Correct positive predictions / total positives predicted	$TP / (TP + FP)$
Recall	Correct positives identified / actual positives	$TP / (TP + FN)$
F1-Score	Harmonic mean of Precision and Recall	$2 \times (P \times R) / (P + R)$

Table 1. Evaluation Table

In that the Table 1 Evaluation Table, that explains about the accuracy, precision, recall, f1-score all about the formulas and definitions.

1. Accuracy

Accuracy is the ratio of correctly predicted samples to the total number of samples. It shows the overall performance of the model.

2. Precision

Precision measures how many of the predicted positive cases are actually correct. It indicates the reliability of the model in making positive predictions.

3. Recall

Recall measures how many actual positive cases are correctly identified by the model. It shows the detection capability of the system.

4. F1-Score

The harmonic mean between precision and recall gives F1 score. This takes into consideration both measures equally. The precision and recall metrics have been calculated using numbers that are derived from the confusion matrix that comprises of TP, FP, TN, and FN.

The confusion matrix shown in the above figure Fig 5(Confusion Matrix), showing the comparison between the actual and predicted classes. This shows how accurate the model is in classifying different objects.

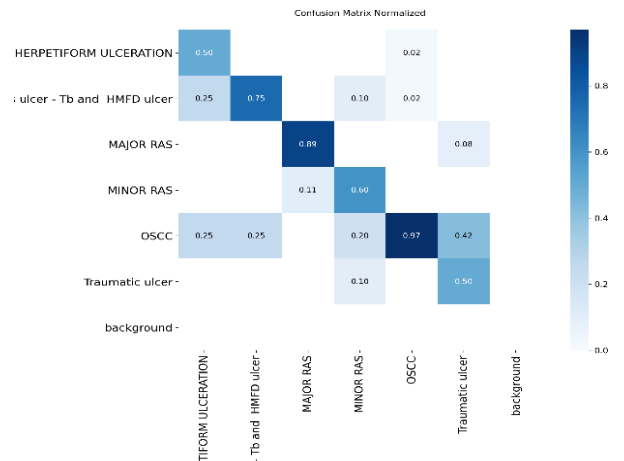


Figure 5. Confusion matrix

VII. FUTURE ENHANCEMENTS

The current system needs to upgrade its operations through multiple potential pathways. The model will achieve better generalization when researchers expand the dataset through additional authentic clinical photographs which come from various patient groups and different imaging techniques. The system would enable clinical specialists to make better diagnoses through the introduction of more specific ulcer subtypes.

Researching EfficientNet or Vision Transformers as advanced backbone architectures might provide minor improvements in accuracy. The system will gain more practical applications when researchers develop its capabilities to perform real-time device-based inference in locations that lack medical facilities. The electronic patient health records system will enhance diagnostic accuracy through the combination of historical records and predictive data which comes from image analysis.

The adoption of pixel-level segmentation frameworks such as U-Net will lead to precise lesion boundary delineation which replaces the current bounding-box crop method. Systematic hyperparameter optimization through grid search or Bayesian methods combined with stratified cross-validation would yield statistically rigorous performance estimates. The combination of cloud deployment with explanation techniques which include Grad-CAM will enable transparent model decision-making through visual evidence which clinicians can use to validate each prediction.

The framework enables its users to expand its functions for detecting early-onset OSCC and other mucosal pathologies. The medical model requires protection

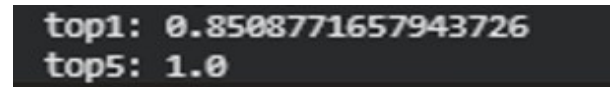
against adverse imaging conditions through model compression which enables its use in edge deployment to achieve clinical deployment across various healthcare settings. The dental clinician needs multilingual user interfaces to conduct prospective validation studies that will assess the system's real-world diagnostic performance capabilities.

Figure 6 Result

Accuracy of Mouth Ulcer Model

Top1 accuracy = 85%

Top 5 accuracy = 99 to 100%



VIII. RESULT & DISCUSSION

The researchers used the complete dataset of oral ulcers to evaluate and train their YOLOv8-ResNet50 system. The training loss curve showed a continuous downward trend which indicated that the model was achieving its planned performance targets. The system proved its ability to differentiate between various severity levels because the classification accuracy persisted until it reached its highest point.

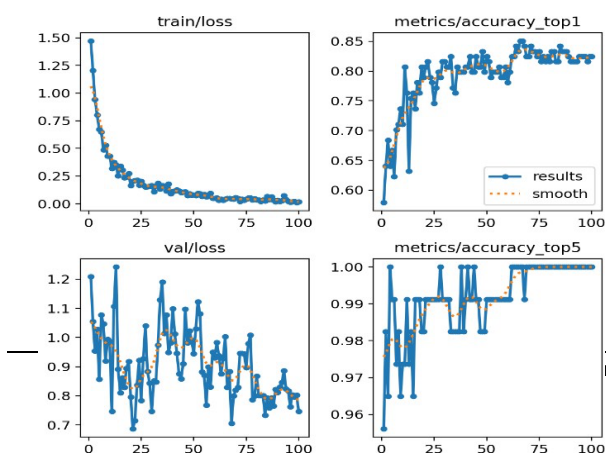
The validation loss showed small variations in its pattern yet it decreased throughout the testing which demonstrated the model's ability to generalize without overfitting because of the implemented augmentation methods and the selected ROI crop inputs. The sample-level testing confirmed that YOLOv8 accurately located ulcers through its precise bounding box measurements which the ResNet50 classifier used to deliver accurate severity assessment results. The model achieved correct labeling results at extremely high confidence near 0.9997 which demonstrated how residual feature representations enable the model to distinguish between high-severity lesions. The results shown in Figure 6 (Result) demonstrate that training periods create loss progression which leads to smooth convergence while avoiding overfitting issues.

The research findings support the design decision of the proposed two-stage model because the study shows that the sequence of localization followed by classification will produce better results than whole-image classification methods which distract from diagnosis through their background elements. The system serves as a practical tool for preliminary screening in both in-person and telehealth settings. The system improves diagnostic accuracy through its new capabilities. Figure 6. Result Figure Fig 7 (Accuracy)

Figure 7. Accuracy

IX. CONCLUSION

The research presents an automated system which employs YOLOv8 for location tracking and ResNet50 for evaluating diabetes-related oral lesions. The system uses detected lesion areas to classify data because these areas contain the medically important features which doctors need to see. The system demonstrates strong classification results and maintains training consistency through experimental results which provide evidence of its clinical decision support tool value. The research accomplishes a significant achievement by developing AI systems which researchers improved through their specific methods to handle diabetes-related oral health problems.



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