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Comparative Analysis of Pixel-Based Segmentation Model for Accurate Detection of Impacted Teeth

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Abstract- Impacted teeth, particularly third molars that fail to erupt properly due to insufficient space or improper angulation, represent a common dental condition that can lead to severe complications including infection, cyst formation, and damage to adjacent structures. Traditional diagnosis relies heavily on manual interpretation of panoramic dental X-ray images by clinicians, a process that is time-consuming, subject to human variability, and lacks pixel-level precision. This paper presents an AI-based impacted tooth detection system using the U-Net deep learning architecture, a convolutional neural network specifically designed for biomedical image segmentation. The proposed system performs pixel-level segmentation of impacted tooth regions from panoramic dental X-ray images, providing precise boundary delineation that conventional object detection methods cannot achieve. The system integrates data annotation, model training using PyTorch, and deployment via a Flask-based web application into a unified end-to-end pipeline. Preprocessing steps including grayscale conversion, resizing to 256 × 256 pixels, and pixel normalization ensure consistent input quality. The trained model achieved an overall segmentation accuracy of approximately 87%, with precision of 85%, recall of 89%, and an F1-score of 87%. Experimental results and confusion matrix analysis confirm that the proposed system reliably detects impacted tooth regions while maintaining a low rate of false predictions. The system demonstrates strong real-time performance through a user-friendly web interface, making it a practical diagnostic support tool for dental professionals.

Keywords- Impacted teeth detection, U-Net, image seg-mentation, panoramic dental X-ray, deep learning, pixel-based segmentation, convolutional neural network, medical image analysis, Flask, PyTorch.

I. INTRODUCTION

The integration of artificial intelligence with medical imaging has opened powerful avenues for enhancing diagnostic accuracy and efficiency in healthcare. Among the dental conditions that benefit from such advances, impacted teeth stand out as a preva-lent problem where timely and accurate identification directly impacts patient outcomes. Impacted teeth, most commonly third molars, fail to erupt into the dental arch due to insufficient space, improper angulation, or obstruction by adjacent teeth. If left undiagnosed, they can cause pain, infection, cyst formation, and damage to neighboring teeth [2].

Despite the widespread use of panoramic dental X-rays (orthopantomograms), the analysis of these images still relies largely on manual examination by trained dental profession-als. This dependency introduces challenges related to time consumption, inter-examiner variability, and limited precision in boundary delineation [5]. Basic computer-aided detection systems that exist today employ general-purpose object detec-tion techniques that are insufficient for the pixel-level accuracy required in surgical planning and clinical decision-making.

Deep learning, and specifically convolutional neural networks (CNNs), have transformed medical image analysis by enabling automated detection of abnormalities with accuracy that rivals or surpasses human experts [3]. The U-Net architecture, originally proposed by Ronneberger et al. [1], has become the de facto standard for biomedical image segmentation owing to its encoder–decoder structure and skip connections, which allow precise localization even when training data is limited. This paper proposes an end-to-end AI-based impacted tooth detection system built on the U-Net segmentation model. The system accepts panoramic dental X-ray images, preprocesses them, performs pixel-level segmentation to identify impacted tooth regions, and visualizes the result via an OpenCV-generated overlay. A Flask web application provides the user-facing interface, enabling real-time predictions accessible to clinicians without requiring specialist machine-learning knowledge.

The remainder of this paper is organized as follows. Sec-tion II reviews related work. Section III states the problem formally. Section IV describes the proposed methodology. Section V covers the implementation and experimental setup. Section VI presents results and discussion. Section VII con-cludes the paper, and Section VIII outlines future directions.

II. LITERATURE REVIEW

Ronneberger et al. [1] introduced the U-Net architecture for biomedical image segmentation, demonstrating high accu-racy on medical image datasets even with limited annotated examples. The encoder–decoder design with skip connections allows precise spatial localization, making it highly suitable for detecting structures such as tumors, organs, and dental abnormalities.

Lee et al. [2] reviewed deep learning applications in dental imaging, covering CNN-based detection of cavities, tooth structures, and impacted teeth. Their study confirms that AI-based systems can assist dentists in achieving faster and more reliable diagnoses. However, performance depends critically on dataset quality and size.

Minaee et al. [4] provided a comprehensive survey of pixel-based image segmentation techniques, emphasizing the importance of precise boundary detection in medical applica-tions. Their work validates the use of pixel-level analysis for improving automated diagnostic reliability, while noting that such methods can be computationally intensive.

Litjens et al. [3] demonstrated that CNN-based systems outperform traditional methods in detecting medical image abnormalities with reduced human effort. Their survey supports the adoption of advanced architectures such as U-Net for dental applications, while highlighting the need for large annotated datasets.

Chen et al. [5] presented an automated system for detecting dental pathologies from radiographic images using deep learning, showing high reliability in identifying abnormalities and reducing manual effort. Performance was noted to decrease with low-quality X-ray inputs.

Irvin et al. [6] discussed the role of high-quality annotations in training deep learning models for medical imaging, explain-ing how accurate segmentation masks improve model accuracy and learning efficiency.

Nickolls et al. [7] explained how GPU-based parallel computing significantly accelerates deep learning training, supporting the use of GPU acceleration for the proposed system. Taha and Hanbury [8] evaluated metrics such as accuracy, Dice coefficient, and IoU for segmentation models, informing the evaluation framework used in this work.

Table I summarizes the key contributions, methods, and limitations of the reviewed works.

TABLE I
COMPARATIVE STUDY OF RELATED WORKS

Ref.	Key Contribution	Method	Limitation
[1]	U-Net for biomedical segmentation	Encoder–decoder CNN	High resource requirement
[2]	DL review for dental imaging	CNN	No specific im-plementation
[4]	Pixel segmentation survey	Pixel-based techniques	Not dental-specific
[3]	CNNs in medical imaging	CNN analy-sis	Large dataset needed
[5]	Automated dental pathology detec-tion	DL radiographic analysis	Degrades on noisy images
[6]	Annotation tech-niques for medi-cal DL	Mask genera-tion	Time-consuming annotation
[7]	GPU-accelerated DL training	Parallel com-puting	Expensive hard-ware
[8]	Segmentation evaluation metrics	Statistical metrics	Evaluation only

III. PROBLEM STATEMENT

Despite advances in panoramic dental imaging, the detection of impacted teeth remains largely dependent on expert manual interpretation, giving rise to four key challenges:

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- Lack of Automation: No widely adopted automated system exists for detecting impacted teeth with pixel-level precision.
- Time-Consuming Analysis: Manual examination of X-ray images demands significant time and specialized expertise.
- Human Error and Variability: Diagnostic outcomes vary between practitioners due to subjective interpretation.
- Limited Precision in Existing Systems: Traditional ob-ject detection methods fail to delineate accurate boundaries of impacted teeth, which is essential for surgical planning.

The central research question addressed in this work is: How can an AI-based system be developed to accurately detect and segment impacted teeth from panoramic dental X-ray images using pixel-level precision, while providing real-time, reliable, and clinically interpretable results?

IV. METHODOLOGY / PROPOSED SYSTEM

A. System Overview

The proposed system follows a three-tier client–server architecture comprising a Presentation Layer (web interface), an Application Layer (Flask backend), and a Model Layer (U-Net segmentation model). Supporting utilities include OpenCV, NumPy, PIL, and PyTorch. The end-to-end workflow is illustrated in Fig. 1.

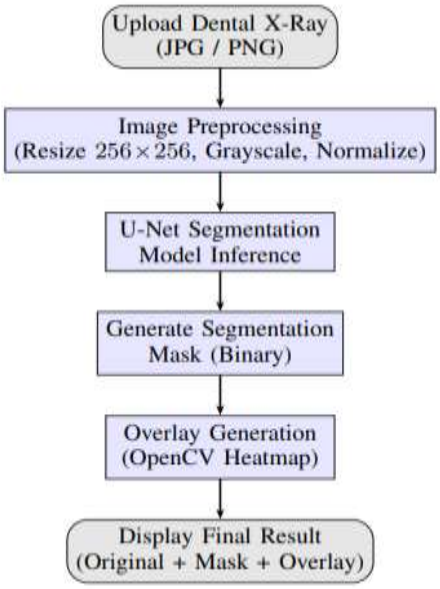

Fig. 1. System workflow for impacted tooth detection

B. U-Net Architecture

U-Net [1] is a fully convolutional network whose architecture resembles the letter "U". It comprises three parts:
Contracting Path (Encoder): Successive blocks apply two 3 × 3 convolutions with ReLU activation followed by 2 × 2 max pooling. Spatial dimensions are halved at each step while the feature channel depth doubles, enabling the network to capture progressively abstract representations.

Bottleneck: The deepest layer retains the most semantically rich, spatially compressed representation, connecting encoder and decoder.

Expansive Path (Decoder): Transposed convolutions up-sample feature maps back to the original resolution. Skip con-nections concatenate encoder feature maps with corresponding decoder feature maps, restoring fine spatial details lost during downsampling.

Output Layer: A 1 × 1 convolution maps the final feature map to a single-channel binary segmentation map. A sigmoid activation assigns each pixel a probability of belonging to the impacted tooth class.

C. Loss Function

Training minimizes a combined loss:

$$L = LDice + LBCE \qquad (1)$$

where Dice loss addresses class imbalance and Binary Cross-Entropy loss ensures pixel-wise fidelity.

D. Image Preprocessing Pipeline

All input images undergo: (1) reading via OpenCV, (2) conversion to grayscale, (3) resizing to 256 × 256 pixels, (4) normalization of pixel values to [0, 1], and (5) conversion to a PyTorch tensor for model inference.

V. IMPLEMENTATION / EXPERIMENTAL SETUP

A. Development Environment

The system was developed using Python 3.10 with PyTorch as the deep learning framework, Flask for backend API development, and OpenCV for image processing and overlay generation. Model training utilized CUDA GPU acceleration on an NVIDIA GPU. All other software dependencies were managed via standard Python package tools.

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B. Dataset and Annotation

Panoramic dental X-ray images containing impacted teeth were collected and organized into training, validation, and testing splits. Impacted tooth regions were annotated at the pixel level using tools such as LabelMe and CVAT, producing binary segmentation masks where white pixels denote impacted tooth regions and black pixels denote the background.

C. Training Configuration

The U-Net model was trained using the Adam optimizer with the parameters listed in Table II.

TABLE II
MODEL TRAINING PARAMETERS

Parameter	Value
Epochs	50–100
Batch Size	8 or 16
Optimizer	Adam
Learning Rate	0.001
Loss Function	Dice Loss + Binary Cross-Entropy
Input Size	256 × 256
Framework	PyTorch

D. Web Application

A Flask-based web application exposes a /predict API endpoint. On receiving a POST request containing a dental X-ray image, the backend preprocesses the image, performs model inference, generates the binary segmentation mask, applies an OpenCV JET colormap overlay, and returns the result as a base64-encoded image. The frontend (HTML/CSS/JavaScript) provides an upload interface and renders the original image, segmentation mask, and overlay side-by-side.

E. System Architecture Diagram

Fig. 2 shows the data flow between system components.

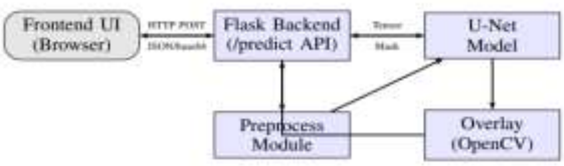

Fig. 2. Component-level architecture of the proposed system

VI. RESULTS AND DISCUSSION

A. Performance Metrics

The trained U-Net model was evaluated on the test set using standard segmentation metrics. Results are summarized in Table III.

TABLE III
SEGMENTATION PERFORMANCE ON TEST SET

Metric	Value (%)
Accuracy	87
Precision	85
Recall	89
F1-Score	87

Each metric is computed at the pixel level using the standard formulas:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}$$

$$F_1 = 2 \cdot \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

B. Confusion Matrix

Table IV presents the pixel-level confusion matrix obtained on the test set. The model correctly identified 890 out of 1,000 impacted tooth pixel groups (TP) and 870 out of 1,000 background pixel groups (TN), with only 110 false negatives and 130 false positives, confirming reliable detection with low erroneous predictions.

TABLE IV
PIXEL-LEVEL CONFUSION MATRIX

Actual \ Predicted	**Impacted Tooth**	**Background**
Impacted Tooth	TP = 890	FN = 110
Background	FP = 130	TN = 870

C. Discussion

The 87% segmentation accuracy demonstrates the viability of pixel-based U-Net segmentation for impacted tooth detection. Pixel-level boundary delineation offers a marked improvement over traditional bounding-box object detection methods, which cannot provide the precise contours required for surgical planning.

The high recall of 89% is particularly important in a clinical context: it indicates that the system misses very few actual impacted regions, reducing the risk of under-diagnosis. The slightly lower precision (85%) reflects a moderate number of false positives, which can serve as conservative diagnostic flags for clinician review.

Real-time inference through the Flask web interface, with predictions delivered within 2–5 seconds, demonstrates practical clinical usability. Testing confirmed correct operation of all modules including preprocessing, prediction, mask generation, overlay visualization, and graceful error handling for invalid inputs.

A notable limitation is reduced performance on low-quality or noisy X-ray images. The system does not currently support multi-class segmentation of other dental structures. These limitations motivate the future enhancements described in Section VIII.

VII. CONCLUSION

This paper presented an AI-based impacted tooth detection system using the U-Net deep learning architecture for pixel-level segmentation of panoramic dental X-ray images. The system integrates dataset annotation, model training, and web-based deployment into a complete, end-to-end pipeline that significantly reduces the need for manual clinical analysis.

The proposed system achieved an accuracy of 87%, precision of 85%, recall of 89%, and an F1-score of 87%, demonstrating its effectiveness in real-world scenarios. The combination of pixel-based segmentation, OpenCV overlay visualization, and a Flask-based interface makes the system both technically robustand practically accessible for dental professionals.

The work highlights the transformative potential of deep learning in dental diagnostics and contributes a reproducible, modular framework that can be extended to broader dental imaging applications.

VIII. FUTURE WORK

Several directions are identified for future enhancement of the proposed system:

- Extended Datasets: Training on larger, more diverse datasets across multiple dental conditions to improve generalization and robustness.
- Multi-Class Segmentation: Extending the model to simultaneously detect cavities, root structures, bone loss, and other dental pathologies.
- Advanced Architectures: Exploring attention-based U-Net variants, Transformer-based segmentation models, and hybrid architectures for higher precision.
- Mobile and Cloud Deployment: Developing cross-platform mobile and cloud-based versions to improve accessibility for remote dental healthcare settings.
- Explainable AI: Incorporating Grad-CAM or similar techniques to provide interpretable visualizations that help clinicians understand model decisions.
- Clinical Integration: Interfacing with hospital and dental management systems for seamless incorporation into existing clinical workflows.
- Automated Annotation: Developing semi-automated annotation pipelines to reduce the manual effort required in building training datasets.

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