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Deep Learning–Based Classification of Impacted Teeth from Panoramic Radiographic Images

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Abstract –Impacted teeth are dental conditions in which the eruption process is obstructed by surrounding teeth, bone, or soft tissue. Manual examination of panoramic radiographs to identify impacted teeth is time-consuming and prone to human error. This study aims to develop an automated classification system capable of distinguishing impacted and non-impacted teeth using a Convolutional Neural Network (CNN). The novelty of this work lies in the implementation of an optimized CNN architecture combined with comprehensive preprocessing and augmentation workflows to enhance classification performance on panoramic dental images. The dataset consisted of 2,000 panoramic radiographs sourced from Prof. Dr. Margono Soekarjo Regional General Hospital (Purwokerto, Indonesia) and a public dental image repository. Preprocessing included image resizing, grayscale conversion, and normalization. To increase data diversity, several augmentation techniques—such as Gaussian noise, Gaussian blur, histogram equalization, CLAHE, and sharpening—were applied. The trained CNN achieved high performance, with an accuracy of 94.65%, precision of 94.68%, recall of 94.63%, and an F1-score of 94.65%. These results demonstrate that augmentation plays a critical role in improving the model's generalization capability. Overall, the integration of an optimized CNN with structured preprocessing and augmentation strategies shows strong potential as a clinical decision-support tool for detecting impacted teeth, contributing to improved diagnostic accuracy and efficiency in dental imaging.

Keywords: CNN, panoramic radiograph, impacted teeth, image augmentation, deep learning, image classification.

I. INTRODUCTION

Impacted teeth represent a common dental anomaly in which teeth eruption is hindered by adjacent teeth, bone, or soft tissue, most frequently affecting the third molars. This condition may lead to complications such as pain, infection, or resorption of neighboring roots if left untreated. Panoramic radiography remains the preferred imaging modality for assessing impacted teeth due to its ability to visualize the full dentition and surrounding structures in a single scan[1]. However, manual interpretation of panoramic images is highly dependent on clinical expertise, often subjective, and prone to inconsistencies. As a result, there is a growing need for a reliable computer-aided diagnostic (CAD) system to support clinicians in accurately identifying impacted teeth [2], [3].

Advancements in artificial intelligence, particularly in deep learning, have greatly enhanced medical and dental image analysis. Convolutional Neural Networks (CNNs) have become the leading method because of their capacity to automatically learn meaningful visual features. Prior studies have demonstrated the effectiveness of CNNs in various dental imaging tasks—including wisdom teeth detection, localization, angulation prediction, and teeth labeling—achieving encouraging performance across multiple datasets [4], [5]. These findings establish CNNs as a powerful approach for complex diagnostic applications in dentistry.

To address these challenges, this study introduces a CNN-based automatic classification framework designed to distinguish impacted from non-impacted teeth. The approach incorporates structured preprocessing techniques—including resizing, grayscale conversion, and normalization—to enhance visual clarity and emphasize key dental features. A comprehensive augmentation

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pipeline, involving Gaussian blur, Gaussian noise, sharpening, histogram equalization, and Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to increase image diversity and strengthen model resilience against variations in exposure and brightness [6], [7], [8].

The dataset consists of 2,000 panoramic radiographs sourced from Prof. Dr. Margono Soekarjo Hospital and a Kaggle repository, offering substantial variability for training and validation. By combining carefully designed preprocessing and augmentation workflows, this research aims to produce a highly accurate and generalizable CNN classifier capable of supporting clinical diagnostic processes.

II. THEORETICAL FRAMEWORK

1. Convolutional Neural Network

Convolutional Neural Network (CNN) is a deep learning architecture widely applied in image analysis tasks due to its ability to automatically learn discriminative features directly from raw visual data. Unlike traditional machine learning approaches that rely on handcrafted features, CNNs perform end-to-end learning by extracting relevant spatial patterns through multiple processing layers [9], [10].

A typical CNN consists of convolutional layers for feature extraction, non-linear activation functions such as ReLU, pooling layers for spatial dimensionality reduction, and fully connected layers for classification. Owing to these characteristics, CNNs have been extensively utilized in medical and dental imaging applications—including detection, segmentation, and classification—demonstrating high accuracy and robustness in real-world diagnostic scenarios [11].

2. Impacted Teeth

Impacted teeth refer to teeth that fail to erupt into their proper functional position within the dental arch due to physical obstruction by adjacent teeth, dense bone, or overlying soft tissue. This condition most commonly affects the mandibular and maxillary third molars, but can also involve canines, premolars, or supernumerary teeth. Impaction may be classified based on angulation, depth, or spatial position, such as mesioangular, distoangular, vertical, or horizontal impactions. If left untreated, impacted teeth can lead to various complications, including pericoronitis, caries on adjacent teeth, periodontal defects, cystic formations, and resorption of neighboring roots. Because of these potential risks, early and accurate identification of impacted teeth is essential for proper treatment planning [12], [13].

The assessment of teeth impaction is typically performed using panoramic radiographs, which provide a comprehensive view of the dentition and surrounding anatomical structures. Radiographic evaluation allows clinicians to analyze the angulation, positioning, and relationship of the impacted teeth to vital structures such as the mandibular canal or maxillary sinus. Examples of panoramic radiographs containing multiple impacted teeth with different angulations are shown in Figure 1, where the red bounding boxes highlight vertically, horizontally, and mesioangularly impacted third molars**.** These variations illustrate the complexity of impaction patterns and the challenges faced during manual interpretation [14]. However, interpretation of radiographs depends heavily on clinical expertise and may vary between practitioners, leading to inconsistencies in diagnosis. As a result, research has increasingly focused on developing automated and objective methods—such as computer-aided diagnostic systems and deep learning models—to improve the accuracy, reliability, and efficiency of impacted teeth detection in dental imaging [15].

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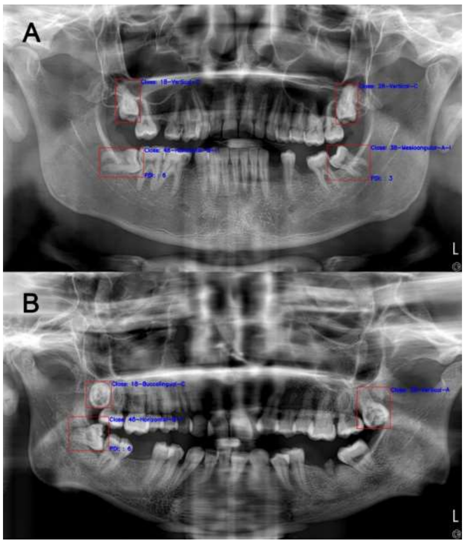

Figure 1. Panoramic radiographs demonstrating various types of impacted third molars. Red bounding boxes indicate vertical, horizontal, and mesioangular impactions, showing the diversity of teeth angulations encountered in clinical diagnosis.

III. METHODOLOGY

1. Materials

The materials used in this study consist of panoramic dental radiographs serving as the primary dataset, obtained from two sources: Prof. Dr. Margono Soekarjo Hospital and a publicly available Kaggle repository. The dataset comprised a total of 2,000 panoramic radiographic images, including 1,000 impacted and 1,000 non-impacted cases. Of these, 1,200 images were retrospectively collected from the hospital clinical database, while the remaining 800 images were obtained from the Kaggle repository.

All hospital radiographs were fully anonymized prior to analysis, and no personally identifiable patient information was accessible during this study. The use of retrospective and anonymized data ensured patient confidentiality throughout the research process. Ethical approval was waived due to the retrospective nature of the study and the exclusive use of anonymized radiographic data.

Ground truth labels for impacted and non-impacted teeth were determined based on radiographic diagnosis and available clinical records. The labeling process was conducted by at least one licensed dentist with experience in interpreting panoramic radiographs. Each image was reviewed and assigned to either the impacted or non-impacted category according to standard clinical criteria. Inter-rater agreement analysis was not performed in this study, which is acknowledged as a limitation.

To minimize potential distributional differences between data sources, all images were resized and preprocessed using the same standardized preprocessing pipeline. The complete dataset was subsequently divided into three subsets: 70% for training, 20% for validation, and 10% for testing to ensure balanced and reliable model evaluation.

The equipment used in this research included a personal computer or laptop for image processing tasks, the Python programming language as the primary development environment for implementing the deep learning algorithms, and Google Colab as the cloud-based computing platform used to train and evaluate the Convolutional Neural Network (CNN) model. These tools collectively supported data preparation, model development, training, and performance evaluation throughout the study.

2. Preprocessing Image

The image preprocessing phase was carried out to ensure consistency in both spatial dimensions and intensity values before the images were introduced to the CNN model. This stage included several essential operations, namely grayscale conversion, image resizing, and normalization. Converting the images to grayscale reduced redundant information by transforming RGB inputs into a single intensity channel. All radiographs were then resized to 224 × 224 pixels to maintain uniform dimensions compatible with convolutional processing. Normalization was further applied to scale pixel values within the 0–1 range, promoting stable model training and numerical consistency. These preprocessing steps form a crucial component of digital image preparation, enhancing computational efficiency and supporting optimal CNN performance.

3. Augmentation

To enhance the generalization capability of the CNN model and reduce the risk of overfitting, a series of data augmentation techniques were applied exclusively to the training dataset. The validation and testing datasets were not augmented to ensure an unbiased and reliable evaluation of model performance.

The applied augmentation techniques were designed to simulate common variations observed in clinical panoramic radiographs, including differences in image quality, contrast, and noise. These techniques included Gaussian noise injection to model sensor noise, Gaussian blur to simulate reduced image sharpness, and image sharpening to enhance edge details. In addition, histogram equalization and Contrast Limited Adaptive Histogram Equalization (CLAHE) were employed to improve local and global contrast, particularly in underexposed regions of dental radiographs.

The augmentation operations were applied randomly during the training process, ensuring that the model was exposed to diverse image representations across epochs. While the exact number of augmented samples was not fixed, this on-the-fly augmentation strategy effectively increased sample variability and encouraged the CNN to learn robust and invariant feature representations. The parameter ranges for augmentation were selected conservatively to preserve clinically meaningful anatomical structures while introducing sufficient variability for effective model training.

4. CNN Architecture

The developed CNN architecture was designed to efficiently extract discriminative dental features while maintaining optimized computational performance. The network consists of multiple convolutional blocks incorporating convolutional layers, batch normalization, max-pooling, and dropout operations. An initial convolutional layer with a larger kernel size is applied to capture low-level spatial features from panoramic radiographs, followed by deeper convolutional layers to learn hierarchical representations. Batch normalization is employed to stabilize training, while dropout layers are applied after pooling and fully connected layers to reduce overfitting. The extracted feature maps are flattened and passed through two fully connected layers before the final softmax-activated output layer, enabling binary classification of impacted and non-impacted teeth [16]. The detailed architecture of the proposed CNN model is summarized in Table 1, while the overall structural design is illustrated in Figure 2.

Table 1. Detailed Architecture of the Proposed CNN Model

No.	Layer Type	Filters / Units	Kernel Size	Stride	Activation	Output Size
Input	Input Layer	–	–	–	–	224 × 224 × 1
1	Zero Padding	–	–	–	–	234 × 234 × 1
2	Convolutional	16	11 × 11	2	–	117 × 117 × 16
3	Batch Normalization	–	–	–	–	117 × 117 × 16
4	Convolutional	32	3 × 3	1	ReLU	117 × 117 × 32
5	Batch Normalization	–	–	–	–	117 × 117 × 32
6	Max Pooling	–	2 × 2	2	–	58 × 58 × 32

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7	Dropout	–	–	–	–	58 × 58 × 32
8	Convolutional	32	3 × 3	2	ReLU	29 × 29 × 32
9	Batch Normalization	–	–	–	–	29 × 29 × 32
10	Max Pooling	–	2 × 2	2	–	14 × 14 × 32
11	Dropout	–	–	–	–	14 × 14 × 32
12	Convolutional	64	3 × 3	1	ReLU	14 × 14 × 64
13	Batch Normalization	–	–	–	–	14 × 14 × 64
14	Max Pooling	–	2 × 2	2	–	7 × 7 × 64
15	Dropout	–	–	–	–	7 × 7 × 64
16	Flatten	–	–	–	–	3,136
17	Fully Connected (Dense)	64	–	–	ReLU	64
18	Dropout	–	–	–	–	64
19	Fully Connected (Dense)	128	–	–	ReLU	128
Output	Fully Connected (Dense)	2	–	–	Softmax	2

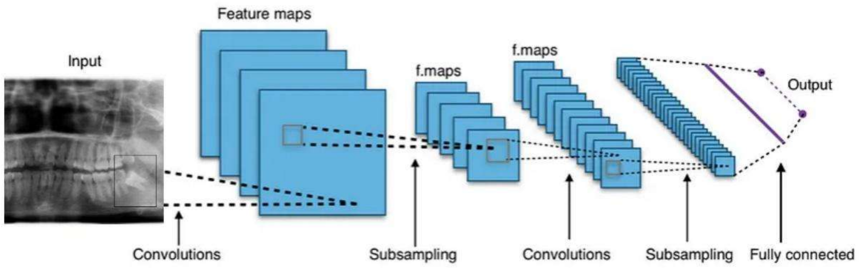

Figure 2. Overview of the proposed CNN architecture for impacted teeth classification. The network consists of an input layer followed by convolutional layers with batch normalization, max-pooling, and dropout operations for hierarchical feature extraction. The extracted feature maps are flattened and passed through two fully connected layers before the final softmax output layer, enabling binary classification of impacted and non-impacted teeth from panoramic radiographs.

5. Training dan Evaluation

The training process of the CNN model was conducted through iterative learning across multiple epochs using the preprocessed and augmented dataset, which was divided into 70% training, 20% validation, and 10% testing portions. Data augmentation was applied exclusively to the training set, while the validation and testing sets were kept unchanged to ensure unbiased performance evaluation. At the start of training, the network weights were initialized randomly. Each epoch consisted of mini-batches with a batch size of 32, which were passed through the network to generate predictions.

The loss function quantified the discrepancy between predicted and actual labels and guided the adjustment of model weights to minimize classification errors. Binary cross-entropy was employed as the loss function, as the task involves binary classification between impacted and non-impacted teeth. The Adam optimizer, operating with a learning rate of 0.0001, was selected for its adaptive moment estimation and stable convergence properties. The model was trained for a maximum of 50 epochs, and early stopping was applied when the validation loss failed to improve for five consecutive epochs to prevent overfitting.

Model training and evaluation were performed using Google Colab as the computing platform, utilizing a standard GPU environment to accelerate the training process. Training and validation performance were monitored continuously throughout the learning process.

The model's performance was assessed using accuracy, precision, recall, and F1-score, which collectively measure the reliability and generalization ability of the classifier. Accuracy, defined in Eq. (1), represents the proportion of correct predictions relative to the entire dataset:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Precision, shown in Eq. (2), quantifies the proportion of predicted positives that are correctly identified:

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

Recall, given in Eq. (3), reflects the model's sensitivity in detecting all true positive cases, which is essential for identifying impacted teeth:

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

The F1-score, expressed in Eq. (4), is the harmonic mean of precision and recall, offering a balanced measure of performance:

$$F1-score = 2 \times \frac{Precision \times Recall}{Precision+Recal} \tag{4}$$

Here, TP, TN, FP, and FNdenote true positives, true negatives, false positives, and false negatives, respectively. Throughout training, these metric values were compared between training and validation sets to ensure stable learning behavior.

IV. RESULTS AND DISCUSSION

1. Model Training Result

The training process using the augmented dataset produced highly satisfactory performance. As illustrated in Figure 3, the loss curves for both the training and validation sets exhibit a steady downward trend, reaching a final value of approximately 0.1. This pattern indicates that the model was able to learn effectively without showing signs of significant overfitting. Conversely, the accuracy curve demonstrates a consistent upward trend, with validation accuracy surpassing 0.93. This suggests that the model maintained strong predictive ability when evaluated on previously unseen data. Overall, these results confirm that data augmentation successfully increased dataset variability, enabling the CNN to generalize more effectively across different radiographic conditions.

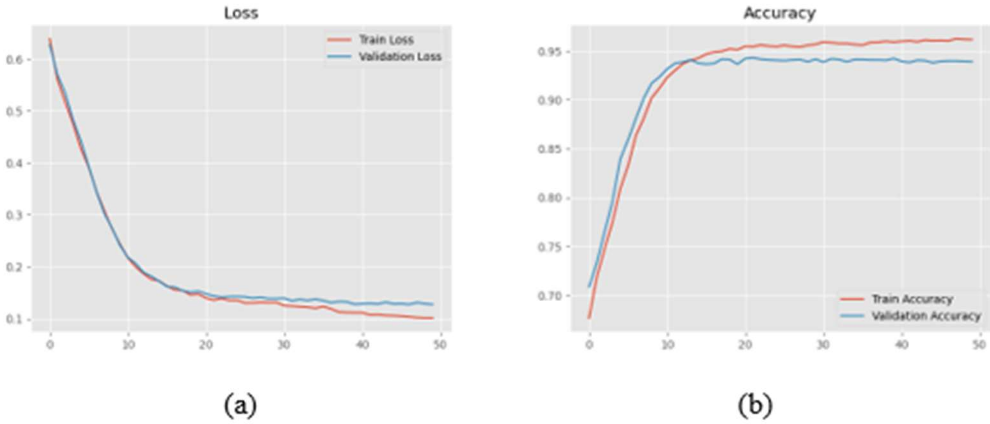

Figure 3. Training curves of the augmented CNN model: (a) loss graph and (b) accuracy graph.

Further evaluation using the confusion matrix presented in Table 2 shows that the model achieved a classification accuracy of 95% for impacted teeth and 93% for non-impacted teeth. The relatively low misclassification rates indicate that the model is robust and reliable in distinguishing between the two categories. This balanced performance across both classes is particularly important, as it suggests that the model does not disproportionately favor one category over the other. Such consistency reinforces the suitability of the augmented CNN model for practical applications, where radiographic quality and clinical variability may differ from sample to sample.

Table 2. Confusion Matrix of the CNN Training Model (Normalized Values)

		Predicted	
		Impacted	Non-Impacted
Actual	Impacted	0.95	0.05
	Non-Impacted	0.07	0.93

Quantitative performance indicators for the augmented model are summarized in Table 3. The accuracy, precision, recall, and F1-score all fall within the range of 0.93, reflecting excellent overall classification capability. The high recall value demonstrates that the model is highly effective in detecting impacted teeth, while the strong precision score indicates that most positive predictions are correct. The close alignment among precision, recall, and F1-score further confirms the model's balanced performance. These findings collectively strengthen the evidence that augmentation techniques significantly enhanced the CNN's effectiveness in impacted teeth classification.

Table 3. Evaluation Metrics of the CNN Training Model

Metric	**Value**
Accuracy	0.93897
Precision	0.93875
Recall	0.93920
F1-Score	0.93898

2. Model Testing Result

The testing phase using the augmented dataset demonstrated strong overall performance. As shown in Table 4, the confusion matrix indicates that the model successfully classified the majority of impacted and non-impacted teeth images with high accuracy. Only a small fraction of samples were misclassified, highlighting the model's robustness in distinguishing between the two categories. This balanced classification behavior suggests that no dominant bias occurred toward either class. The high correctness rate further confirms that dataset augmentation enriched the variability of training samples, enabling the CNN to generalize effectively to new, unseen radiographs.

Table 4. Confusion Matrix of the CNN Model During Testing (Normalized Values)

	Predicted		
Actual		Impacted	Non-Impacted
	Impacted	0.96	0.04
	Non-Impacted	0.07	0.93

Based on the test dataset consisting of 200 images, these normalized values correspond to 96 correctly classified impacted cases, 4 misclassified impacted cases, 93 correctly classified non-impacted cases, and 7 misclassified non-impacted cases. This clarification provides clearer insight into the absolute classification performance of the proposed model.

The quantitative testing results are summarized in Table 5, showing that the model achieved an accuracy of 0.94647, precision of 0.94683, recall of 0.94633, and an F1-score of 0.94658. These well-balanced metrics indicate that the model not only performs reliably in detecting impacted teeth but also maintains consistent accuracy when classifying non-impacted teeth. The high recall value demonstrates the model's ability to identify most impacted cases, while the strong precision score confirms that most positive predictions are correct. The close alignment among the four metrics underscores the stability and reliability of the augmented model for dental radiograph classification.

Table 5. Evaluation Metrics of the CNN Testing Model

Metric	**Value**
Accuracy	0.94647
Precision	0.94683
Recall	0.94633
F1-Score	0.94658

In addition to numerical results, qualitative examples of model predictions are presented in Figure 4. The first image shows a non-impacted panoramic radiograph correctly classified as non-impacted, while the second example depicts an impacted teeth radiograph that was also accurately identified. These examples illustrate that the augmented model not only performs well in terms of evaluation metrics but also consistently generates accurate predictions on real test data. Such consistency reinforces its suitability for practical clinical applications.

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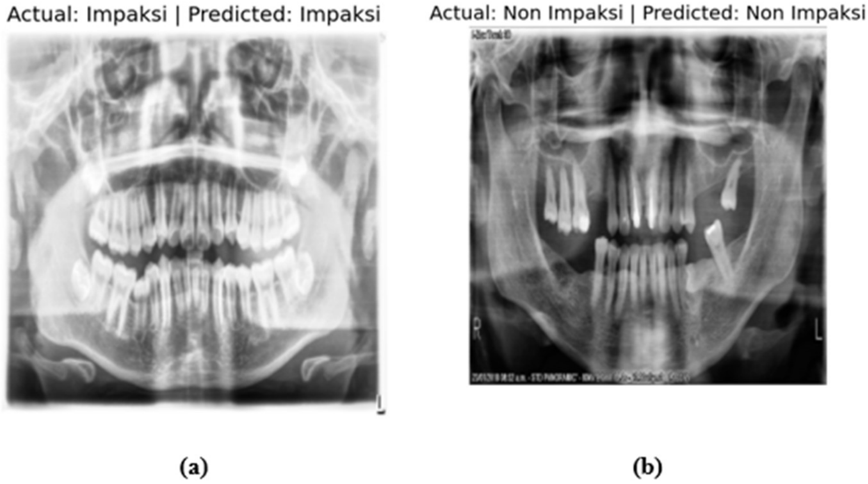

Figure 4. Example predictions on test images with augmentation: (a) correctly predicted non-impacted radiograph, (b) correctly predicted impacted radiograph.

3. Discussion

The results from both the training and testing phases demonstrate that the augmented CNN model exhibits strong and consistent performance in classifying impacted and non-impacted teeth from panoramic radiographs. The steadily decreasing loss curves and increasing accuracy values observed during training indicate that the model successfully learned discriminative features without exhibiting overfitting. This behavior is further supported by the balanced confusion matrices and consistently high performance metrics, including accuracy, precision, recall, and F1-score.

The testing results further confirm the model's ability to generalize effectively to unseen data, as evidenced by the near-identical performance metrics obtained during training and testing. The minimal misclassification rates across both classes suggest that the applied data augmentation strategies played a significant role in enhancing model robustness, enabling the CNN to handle variations in image quality, anatomical structures, and contrast commonly encountered in panoramic radiographs.

Qualitative evaluation using representative test samples also reinforces the reliability of the proposed approach, demonstrating accurate identification of both impacted and non-impacted teeth in real clinical images. These findings indicate that the integration of structured preprocessing and comprehensive augmentation techniques contributed to increased feature diversity and strengthened the model's diagnostic capability, supporting its potential application as a practical computer-aided decision-support tool in clinical dental imaging.

Several previous studies have reported the use of pre-trained deep learning architectures such as VGG, ResNet, and DenseNet for dental image classification tasks, often achieving high classification accuracy. However, these state-of-the-art architectures typically require large-scale annotated datasets and substantial computational resources. In contrast, the proposed custom CNN architecture is lightweight and specifically designed for panoramic radiographic images, making it more suitable for limited datasets and practical clinical implementation while maintaining competitive performance.

The use of binary classification in this study was intentionally designed as an initial screening approach to distinguish between impacted and non-impacted teeth. From a clinical perspective, this distinction represents a fundamental diagnostic step that can assist clinicians in rapidly identifying cases that require further assessment or intervention. Although impacted teeth can be further categorized based on angulation, depth, or spatial position, such detailed subclassification generally requires larger annotated datasets and more complex labeling protocols. Therefore, this study prioritizes robust and reliable binary detection as a foundational stage toward automated clinical screening. Future work will extend the proposed framework to multi-class classification to enable more detailed characterization of impaction types and provide enhanced diagnostic support for clinical decision-making.

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Limitations and Future Work

Although the proposed model demonstrated promising and consistent performance, several limitations should be acknowledged. First, the evaluation was restricted to internal validation using a single combined dataset sourced from one institution and a public repository, which may limit the generalizability of the findings. External validation using independent datasets from multiple institutions is therefore recommended to further assess clinical applicability. Second, while the proposed lightweight CNN architecture was designed to suit limited datasets and computational resources, this study did not include direct experimental comparisons with state-of-the-art pre-trained models such as VGG, ResNet, or EfficientNet. Future work may explore such comparisons to systematically evaluate performance–efficiency trade-offs. In addition, model evaluation relied on a single train–validation–test split; future studies may incorporate k-fold cross-validation and statistical significance analysis to provide more robust and comprehensive performance assessment. Addressing these aspects would further strengthen the reliability and clinical relevance of the proposed approach.

V. CONCLUSION

This study demonstrates that an optimized Convolutional Neural Network enhanced with structured preprocessing and comprehensive augmentation techniques can effectively classify impacted and non-impacted teeth from panoramic radiographs with high accuracy and stability. By integrating grayscale conversion, resizing, normalization, and augmentation methods such as Gaussian noise, Gaussian blur, sharpening, histogram equalization, and CLAHE, the model developed robust feature representations capable of handling variations in radiographic quality. Both training and testing results consistently showed strong performance, with accuracy, precision, recall, and F1-scores exceeding 94%, and confusion matrices indicating minimal misclassification across classes. These findings confirm that augmentation plays a critical role in improving generalization, while the proposed CNN architecture reliably identifies clinically relevant dental patterns. Overall, the system demonstrates significant potential as a computer-aided diagnostic tool, offering improved efficiency, objectivity, and accuracy in detecting impacted teeth within clinical dental imaging workflows.

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