A PROJECT REPORT

on

"Automated Identification of Faulty Teeth in CBCT Images Using Deep Learning"

Submitted to

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In Partial Fulfillment of the Requirement for the Award of

BACHELOR'S DEGREE IN COMPUTER SCIENCE AND ENGINEERING

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CERTIFICATE

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"Automated Identification of Faulty Teeth in CBCT Images Using Deep Learning"

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This a record of bonafide work carried out by them, in the partial fulfillment of the requirement for the award of Degree of Bachelor of Engineering (Computer Science & Engineering) at KIIT Deemed to be university, Bhubaneswar. This work is done during year 2024-2025, under our guidance.

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ABSTRACT

Teeth segmentation and classification in CBCT is a critical task in dental diagnostics. The complex structure of dental anatomy and overlapping nature of teeth in CBCT make manual segmentation time-consuming and error-prone. This report presents a deep learning-based approach for automatic teeth segmentation and classification. We employ the YOLOv8 framework to segment individual teeth from CBCT images and assign unique labels for easy identification. The segmented teeth are then cropped and stored in separate folders. Following this, a Sequential Convolutional Neural Network (CNN) is used to classify each tooth as normal or abnormal. Two datasets were utilized for training and evaluation. The first dataset comprises 1,022 annotated CBCT slices (X-ray projections), providing a diverse range of cases to enhance model generalization. The second dataset consists of 682 individual CBCT images, categorized into normal and abnormal cases to facilitate robust classification and anomaly detection.

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Chapter 1

Introduction

In recent years, digital dentistry has undergone rapid advancements, driven by innovations in artificial intelligence (AI) and the development of Cone-Beam Computed Tomography (CBCT).

CBCT has become an essential tool in modern dentistry, widely utilized for diagnosing bony and dental pathological conditions. It plays a crucial role in detecting fractures, analyzing structural maxillofacial deformities, assessing impacted teeth preoperatively, and imaging the temporomandibular joint. Additionally, CBCT provides highly detailed diagnostic images, making it indispensable in dental applications. Based on detector types, CBCT units are categorized into two groups: those utilizing an image intensifier tube/charge-coupled device (IIT/CCD) combination and those employing a flat-panel imager. One of the primary advantages of CBCT in dentistry is its compact design, which reduces the physical footprint while delivering high-resolution images that enhance tooth visualization.[1]

Despite these advancements, segmenting teeth from CBCT images remains a challenging task due to several factors. The primary difficulties include the similarity in brightness between tooth roots and adjacent jawbones, as well as the connected edges between neighboring teeth near the crowns. As a result, automatic individual tooth identification remains a complex problem. Recent research has explored convolutional neural networks (CNNs) for this purpose; however, these methods often encounter classification inaccuracies due to the high visual resemblance between neighboring teeth.[2]

This research focuses on developing a specialized deep-learning model for CBCT image analysis, with an emphasis on individual tooth segmentation and classification. The model categorizes teeth into 32 predefined classes corresponding to standard human dentition, making it a highly specialized tool for dental applications as shown in Fig. 1. By leveraging advanced image processing and deep learning techniques, the system ensures precise tooth identification, which is crucial for various dental fields.[3][4]

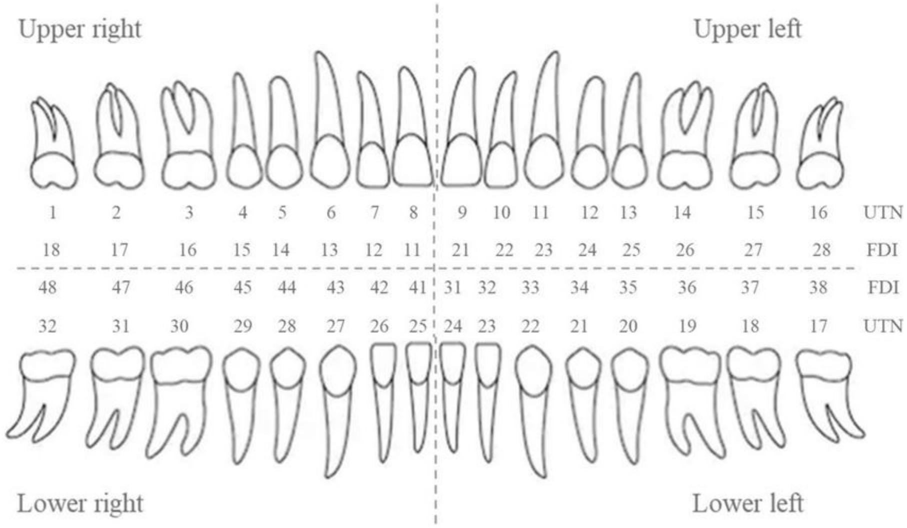

Fig. 1: Teeth Numbering in Fédération Dentaire Internationale (FDI) system

The primary objective of this research is to design an automated deep learning-based system for detecting faulty teeth in CBCT images. This study utilizes the YOLOv8 architecture to achieve accurate classification and anomaly detection within dental imagery. Convolutional Neural Networks (CNNs) have emerged as a powerful deep-learning approach for image analysis, excelling in feature extraction and classification tasks. Among various CNN-based models, the You Only Look Once (YOLO) series has gained prominence for real-time object detection due to its efficiency and accuracy. YOLOv8, the latest version introduced by Ultralytics, exhibits significant improvements in speed and precision, making it particularly well-suited for medical image analysis.[5]

Chapter 2

Literature Review

This section provides a detailed overview of the literature on teeth segmentation. Recently Deep learning methods have developed in recent years and achieve accurate classification in dental image analysis using various Machine Learning and Deep Learning algorithms, such as YOLO, R-CNN, and NASNet. Below is the brief summary of the taxonomic division of the reviewed literature.

Beser et al. (2024) proposed a deep learning-based framework using YOLO-v5 for automatic tooth detection and segmentation in pediatric panoramic radiographs. The classification involved detecting deciduous and permanent teeth in 3854 images of pediatric patients with mixed dentition. Using expert-labeled data, the YOLO-v5x model achieved a sensitivity of 0.99, precision of 0.99, and F1 score of 0.99 for tooth detection, and 0.98 for segmentation. The framework results were validated by comparing them with expert annotations, demonstrating its potential to automate and enhance diagnostic efficiency in pediatric dentistry.[6]

Jader et al. (2018) developed a deep learning-based framework for the instance segmentation of teeth in panoramic X-ray images using Mask R-CNN architecture. The dataset consisted of 193 annotated images, which were expanded by leveraging transfer learning from the MSCOCO dataset. The segmentation classified images into individual teeth regions and achieved an accuracy of 98%, precision of 94%, and specificity of 99%. The framework demonstrated superior results compared to unsupervised segmentation methods, showcasing its effectiveness for detailed dental structure analysis.[7]

Al-Ghamdi et al. (2022) proposed a CNN-based framework using a Neural Search Architecture Network (NASNet) for detecting dental diseases through panoramic X-ray images. The classification categorized images into three classes: cavity, filling, and implant. From an initial dataset of 83 images, 245 images were generated through data augmentation and preprocessing techniques to improve model performance. The proposed framework achieved an accuracy of over 96%, outperforming other traditional diagnostic methods. The results were validated by comparing them with manual interpretations, highlighting the potential of deep learning for improving diagnostic consistency in dental radiology.[8]

Budagam et al. (2024) approached a framework for Teeth segmentation and recognition using two deep learning models, U-Net and YOLOv8 where classification and segmentation of teeth in panoramic X-rays are performed. The dataset contained 425 images and achieved a precision of 94.3, a recall of 92.3, and a mAP of 72.9 and a mean average precision at 50 (AP50) of 94. The results indicated a balance between precision and recall and achieved an excellent mAP.[9]

Zhang et al. applied a deep learning approach in order to detect and classify teeth of dental periapical radiographs. The combination of faster R-CNN and region based fully convolutional neural networks (R-FCN) were used to identify problems such as tooth loss, decayed tooth and filled tooth, which frequently appear on patients.[10]

Chapter 3

Methodology

3.1 Model Architecture

3.1.1 YOLO Architecture

You Only Look Once (YOLO) is a deep learning-based object detection architecture designed for real-time applications. Unlike traditional methods that use region proposals followed by classification, YOLO treats object detection as a single regression problem, making it exceptionally fast and efficient. This will help us in detection and segregation of different tooth in an X-ray into 32 different kinds.

YOLO divides an input image into a grid of S × S cells, where each cell predicts bounding boxes and class probabilities. The network processes the entire image in one forward pass, unlike region-based methods that analyze multiple segments separately.

Each grid cell is responsible for detecting objects whose center falls within it, and it predicts:

- Bounding Box Coordinates (x, y, width, height)
- Confidence Score (indicating the likelihood of an object in that box)
- Class Probabilities (identifying the object's category)

Final detections are obtained using Non-Maximum Suppression (NMS), which removes redundant bounding boxes.

3.1.1.1 YOLOv8 Architecture

Many YOLO models have been developed over the years. YOLOv8 (You Only Look Once version 8) is one of the latest iteration in the YOLO family of real-time object detection models. It builds upon the strengths of previous versions while incorporating advanced architectural improvements, making it more efficient and accurate for tasks such as object detection, segmentation, and classification. The architecture of the model is shown in Fig. 2. which includes several new modifications to enhance the quality of processing and outcomes.

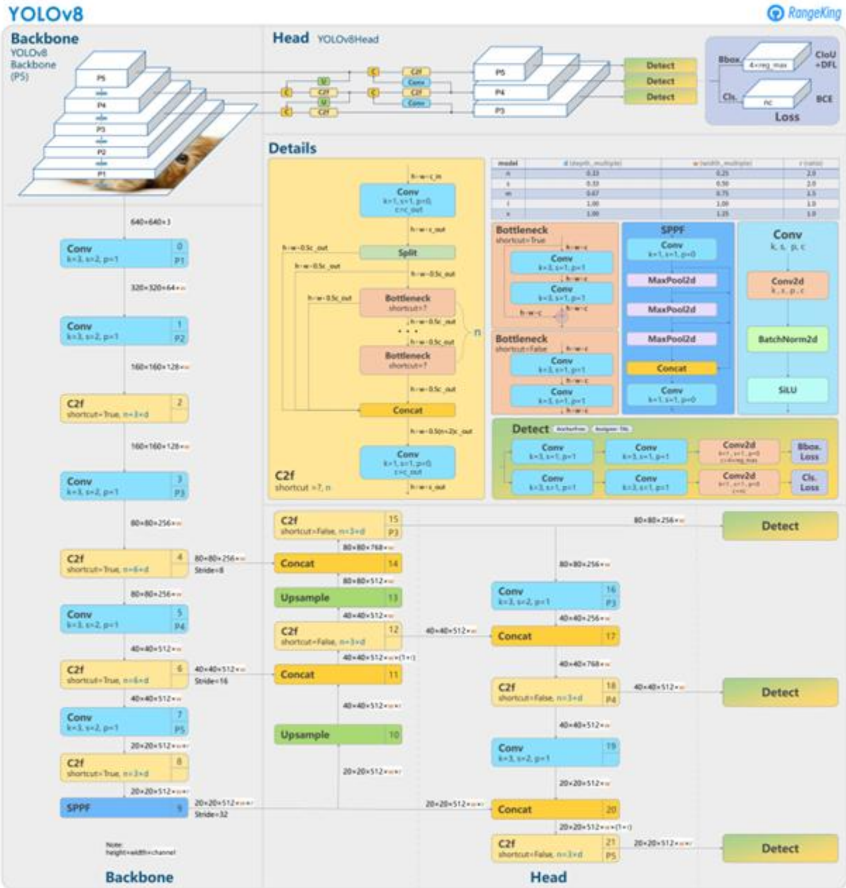

Figure 2: YOLOv8 Architecture

Key Components of YOLOv8 Architecture:

A. Backbone

The backbone is responsible for feature extraction from input images. YOLOv8 employs a CSPDarknet53-based backbone with modifications, including:

- CSP (Cross Stage Partial) connections, which improve gradient flow and reduce computational cost.
- CBS blocks (Convolution + BatchNorm + SiLU activation) for better feature representation.
- Simplicity in design, allowing for improved speed and accuracy compared to previous versions like YOLOv5.
- Efficient Downsampling: The network gradually reduces the spatial dimensions, keeping important information while improving detection accuracy.

B. Neck

The neck aggregates multi-scale features extracted from the backbone and passes them to the detection head. YOLOv8 uses:

- PANet (Path Aggregation Network) for enhanced feature fusion.

- FPN (Feature Pyramid Network) to improve small object detection.
- Spatial pyramid pooling (SPP), which helps capture features at different scales, enhancing generalization.
- ModuleC2f (C2f Block) – A new lightweight module introduced in YOLOv8 that improves feature extraction efficiency while reducing model complexity. It optimizes the Cross Stage Partial (CSP) connections, making computations faster without losing accuracy.

C. Head

The detection head is where final predictions, including bounding boxes, class scores, and objectness scores, are generated. YOLOv8 improves upon previous versions by introducing:

- Decoupled detection heads, which separate classification and regression tasks for improved accuracy.
- Anchor-free design, removing predefined anchor boxes and replacing them with dynamic object center prediction, making it faster and more adaptable.
- Better Loss Functions – Uses DIOU loss (Distance IoU) and focal loss for more precise bounding box predictions.

YOLOv8 stands out as a state-of-the-art object detection model, leveraging an improved CSPDarknet53 backbone, PANet with C2f, and an anchor-free decoupled detection head. These advancements make it faster, more accurate, and ideal for our teeth segmentation system.

3.1.2 CNN Model (Sequential - Keras) Architecture

A Convolutional Neural Network (CNN) is a deep learning model widely used for image classification, object detection, and segmentation tasks. In the case of dental X-ray analysis, a CNN can effectively segment teeth into normal and abnormal types by learning important visual patterns.

In Keras, the Sequential API is a simple yet powerful way to build CNNs, where layers are stacked in a sequential order. This structured approach is particularly useful for tooth segmentation, as it allows for step-by-step feature extraction, classification, and segmentation. The rough architecture of the model is shown in Fig. 3

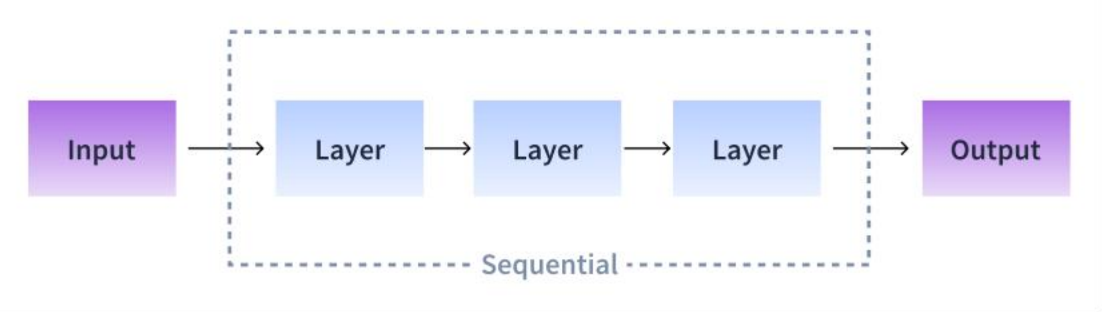

Figure 3: Keras Sequential API Architecture

A CNN for segmenting teeth into normal and abnormal categories typically follows this structure:

A. Input Layer (Preprocessing Stage)

- The input to the CNN is a grayscale or RGB X-ray image, resized to a fixed dimension (e.g., 224×224 pixels).
- Image augmentation (rotation, flipping, contrast adjustment) is applied to improve model robustness.

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

model = Sequential()
```

B. Feature Extraction (Convolutional Layers)

- Convolutional Layers (Conv2D): These layers apply filters (kernels) to detect edges, textures, and patterns in dental X-rays.
- Activation Function (ReLU): Introduces non-linearity to help the model learn complex features.
- Batch Normalization: Normalizes activations to stabilize training and improve convergence.
- MaxPooling Layers: Reduce spatial dimensions, keeping important features while reducing computation.

```
model.add(Conv2D(32, (3,3), activation='relu', input_shape=(224,224,3)))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Conv2D(64, (3,3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Conv2D(128, (3,3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
```

C. Flattening & Fully Connected Layers (Classification Stage)

- Flatten Layer: Converts extracted features into a 1D vector for classification.
- Dense Layers: Fully connected layers help classify the extracted features.

- Dropout: Prevents overfitting by randomly deactivating neurons during training.

```
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(2, activation='softmax'))  # Output: 2 classes (Normal, Abnormal)
```

D. Output Layer (Prediction Stage)

- The final layer uses a softmax activation function to classify teeth as either normal or abnormal.
- The model outputs a probability score for each class.

```
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

The Keras Sequential CNN model effectively segments and classifies teeth as normal or abnormal by using convolutional layers for feature extraction and dense layers for classification. This deep learning approach enhances accuracy, speed, and automation in dental diagnosis, making it a valuable tool in dental radiology and AI-powered healthcare.

3.2 Evaluation Metrics

We have utilized multiple metrics to assess the effectiveness of the proposed method, including accuracy, recall, precision, and mean Average Precision (mAP):

- Accuracy measures the proportion of correctly classified instances out of the total instances.
- Recall evaluates the model's capability to identify all relevant instances of a particular class.
- Precision assesses the correctness of positive predictions, representing the fraction of true positives among all predicted positives.
- mAP (mean Average Precision) calculates the average precision-recall area under the curve for multiple classes at varying confidence thresholds, offering a comprehensive evaluation of model performance.
- AP50 determines the average precision-recall area under the curve for multiple classes at a fixed confidence threshold of 0.5.

These metrics are derived from the confusion matrix. Given N classes and a corresponding confusion matrix M, equations can be applied to compute these evaluation metrics.

$$Accuracy = \frac{\sum_{i=1}^{N} M_{ii}}{\sum_{i=1}^{N} \sum_{j=1}^{N} M_{ij}}$$

$$Precision_i = \frac{M_{ii}}{\sum_{j=1}^{N} M_{ji}}$$

$$Recall_i = \frac{M_{ii}}{\sum_{j=1}^{N} M_{ij}}$$

$$mAP = \frac{1}{N} \sum_{i=1}^{N} AP_i = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{n} (Recall_j - Recall_{j-1}) Precision_j$$

Chapter 4

Implementation

4.1 Teeth Segmentation using Yolov8:

4.1.1 Data Preprocessing:

This report highlights about employment of deep learning method to address the task of teeth segmentation and numbering in CBCT. The dataset was sourced from the publicly available platform Roboflow [9], using only pre-augmented images for segmentation. We utilized a total of 894 images for training and 128 images for testing. Each image was labeled with tooth numbers based on the FDI notation. All of the images are resized to 640x640 pixels to meet the requirements of the YOLO model, and pixel values has been normalized to the range [0,1] to ensure stable training.

4.1.2 Model Pipeline and Training

A pipeline utilizing YOLOv8 is choosen for tooth detection, as illustrated in Fig. 4. The first step involves training the YOLOv8 model to detetect teeth, detect their locations, and extract bounding boxes for each identified tooth.

For YOLOv8 training, images were resized to 640×640 pixels, and histogram equalization was applied to enhance contrast. The dataset was expanded to include 894 training images and 128 validation images through two augmentation techniques: random cropping (0% to 20%) and brightness adjustment (0% to 10%). The training process utilized batch processing with ten images per batch. To prevent overfitting, a dropout rate of 0.6 was applied as a regularization technique. Additionally, the training was optimized using the SGD optimizer with a learning rate of 0.005 to ensure efficient learning.

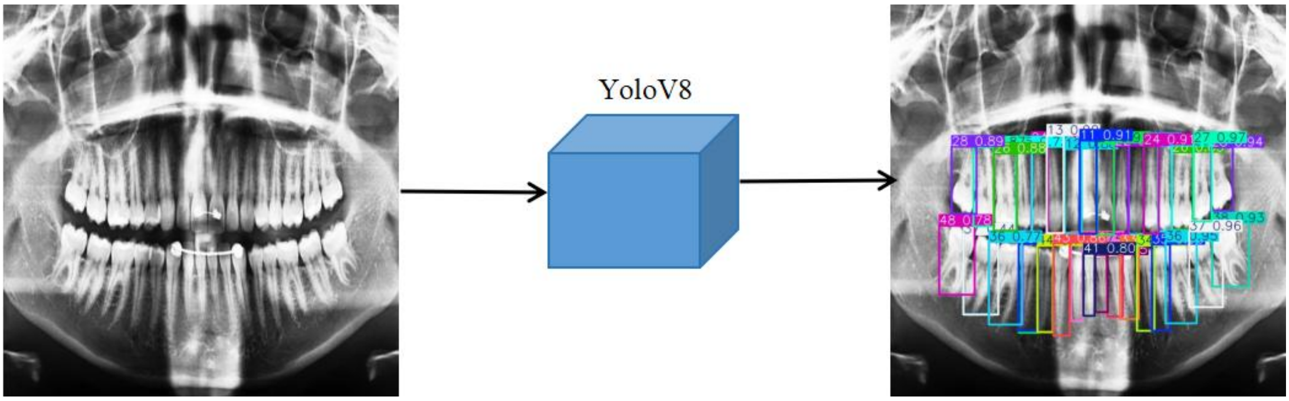

Figure 4: Pipeline of the method

4.1.3 Evaluation

The model has achieved a precision of 94.3%, a recall of 92.3%, and a mean average precision (mAP) of 72.9%, with an AP50 of 94.6% across all tooth classes. These results demonstrate a strong balance between precision and recall, highlighting the model's effectiveness in accurately localizing and identifying teeth within the dataset. Notably, YOLOv8 exhibited high precision in detecting molar teeth, achieving a mAP of nearly 80.0% despite their complex shapes, further reinforcing its robustness in dental image analysis.

The confusion matrix in Fig. 5 illustrates YOLOv8's predictions at a confidence threshold of 0.5 and an IoU threshold of 0.5. The final row, which represents unclassified tooth instances, suggests that while YOLOv8 accurately identified most teeth with minimal misclassifications, it failed to detect certain instances above the confidence threshold. This implies a lack of sufficient knowledge about some tooth instances in specific images from the dataset.

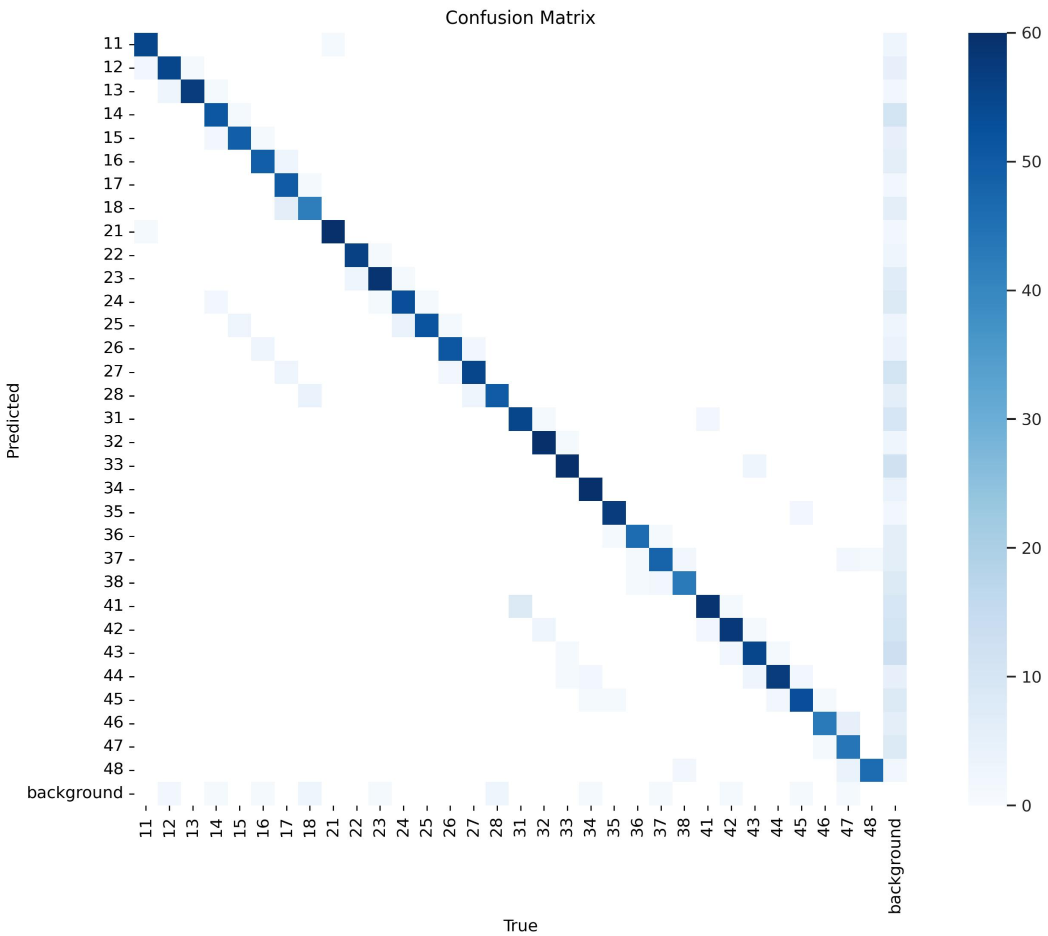

Figure. 5: Confusion matrix for YOLOv8 predictions

4.1.4 Tooth Label Correction

In the mentioned model, classification errors occur due to the identical visual resemblance between adjacent teeth. The FDI notation system standardizes labeling through quadrant-based mapping, where teeth in Quadrant 1 are paired with their counterparts in Quadrant 2, and Quadrant 3 with Quadrant 4. By applying predefined FDI mappings, this process updates incorrect labels, improving classification accuracy and maintaining consistency across different imaging conditions. The corrected labels are displayed and stored as shown in the Fig. 6, serving as a reliable preprocessing step for further analysis. This approach enhances automated dental analysis, minimizes misdiagnoses, and boosts the model's overall performance.

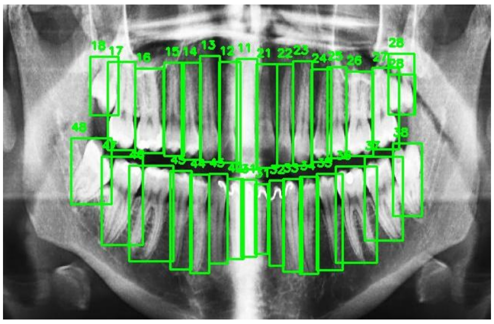

Figure 6: Correct Leveling

After detecting teeth, individual tooth regions were segmented and cropped from the original image using the bounding box coordinates provided by the YOLOv8 model. These extracted teeth images were stored as a structured dataset for further classification.

4.2 Tooth Classification Model

4.2.1 Data Preparation:

CBCT images of both Normal and Abnormal teeth images has been collected from dental doctors. Normal and Abnormal teeth having 353 and 329 images respectively. Then cropped and resized to 224×224 pixels and converted to PNG, JPG format. For prepossessing, a pretrained CNN network was utilized, and data augmentation was performed using the Keras framework with the Image Data Generator function. The CBCT image dataset we divide into training and test sets. The training and test sets were utilized to examine the PCT and supporting structures while optimizing the weights for a deep CNN model.

4.2.2 Evaluation

The test dataset was used to evaluate the model's performance, achieving an accuracy of 77.22%. The evaluation metrics included precision, recall, and F1-score. For the Normal class, the model achieved a precision of 0.69, recall of 0.78, and an F1-score of 0.74 (support = 32). For the Abnormal class, the precision was 0.84, recall was 0.77, and the F1-score was 0.80 (support = 47).

Chapter 5

Applications

Teeth segmentation in X-ray images using YOLOv8 has numerous applications in dentistry, enhancing diagnostic accuracy and efficiency.

- Treatment Planning: Precise tooth segmentation aids in orthodontic and surgical procedures by providing detailed visualization of dental structures.
- Disease Detection: It supports the identification of dental caries, fractures, and other abnormalities.
- Digital Record Management: Automated segmentation helps maintain accurate and organized dental records.
- Education and Training: It serves as a tool for training dental students with real-world scenarios.
- AI-Powered Assistance: Integration with AI systems enables real-time analysis for quicker decision-making in clinical settings.

Chapter 6

Conclusion

This project highlights the potential of YOLOv8 as a cutting-edge framework for medical image segmentation, particularly in the domain of CBCT based dental imaging. By achieving high accuracy in tooth segmentation, the system effectively addresses the challenges posed by complex dental structures and overlapping anatomy in CBCT scans. Automating the segmentation process significantly reduces the time and effort required for manual annotation, providing a more efficient and consistent approach to dental diagnostics.

Furthermore, the integration of a Sequential Convolutional Neural Network (CNN) for tooth classification enhances the system’s capabilities by distinguishing normal and abnormal teeth. The use of a dataset containing 598 annotated CBCT slices (or X-ray projections) ensures the model is trained on diverse cases, improving its reliability and generalization. This dual-stage system—combining segmentation and classification—lays the foundation for streamlined diagnostic workflows, enabling precise identification of individual teeth and detailed analyses for treatment planning.

Chapter 7

Future Work

Future developments for this project can focus on expanding the dataset to include panoramic X-rays dental scans, offering a more comprehensive representation of dental cases. Incorporating these modalities would enhance the model's capability to handle diverse imaging formats and improve its applicability in real-world scenarios. Additionally, the segmentation can be extended to include other dental structures, such as gums, jawbones, and surrounding tissues, enabling a more holistic analysis of dental health and facilitating more detailed treatment planning. To improve accessibility and usability, the model can be optimized for deployment on edge devices, such as tablets or portable systems commonly used in clinics. This would allow for real-time processing and diagnostics, empowering dental professionals with advanced tools at their fingertips.

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