Library Progress International
Vol.44 No. 3, Jul-Dec 2024: P. 16800-16815

Print version ISSN 0970 1052
Online version ISSN 2320 317X

Original Article

Available online at www.bpasjournals.com

Evaluating Yolov7, Yolov8, Adaboost, And RCNN For Object Detection In Dental Prosthetic Imaging

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How to cite this article: Ashwini D. Khairkar*, Sonali Kadam, Kanchan Warke, Waghisha Raj, Shraddha Tandel, Sanchita Ola, Shrikala Deshmukh (2024) Evaluating Yolov7, Yolov8, Adaboost, And RCNN For Object Detection In Dental Prosthetic Imaging. *Library Progress International,* 44(3), 16800-16815

Abstract - The integration of artificial intelligence (AI) into prosthodontics has significantly improved diagnostic accuracy and treatment planning precision. This research evaluates the efficacy of four prominent object detection algorithms—YOLOv7, YOLOv8, AdaBoost, and RCNN—in identifying dental implants from radiographic images. Using a custom dataset containing over 5000 images collected from dental clinics, the study conducts a thorough assessment of each algorithm's performance. The proposed approach involves data processing and model training. This comparative analysis provides valuable insights into the performance characteristics of each algorithm, particularly regarding dental implant identification. Such insights can assist prosthodontists in making informed decisions regarding algorithm selection for clinical implementation, ultimately enhancing patient care and treatment outcomes in the field of dental prosthetics. Findings suggest that YOLOv7 and YOLOv8 excel in both speed and accuracy of dental implant identification, with AdaBoost also performing admirably, although with slightly slower processing times. However, RCNN, despite its precise localization capabilities, demonstrates relatively slower processing speeds. Evaluation metrics unveil varying levels of accuracy among the models, ranging from 77% to 92%. Furthermore, these findings contribute to the ongoing advancements in AI-assisted dental care, promising improved efficiency and precision in treatment planning and execution for better patient outcomes.

Keywords - AdaBoost, artificial intelligence, dental implants, prosthodontics, radiographic images, RCNN, YOLOv7, YOLOv8

1. Introduction

Artificial intelligence (AI) has become a cornerstone in the realm of dentistry, particularly in the field of prosthodontics, where it has revolutionized diagnostic precision and treatment planning. One area where AI excels is in the recognition and characterization of dental implants, which have been transformative in dental care for over half a century. Implants for dental reasons, also referred to as oral or endosseous implants, are an efficient way to replace lost teeth because they integrate easily with the surrounding tissue and imitate the functionality and looks of natural teeth [16][17].

Nevertheless, the success of dental implants hinges on several elements, such as the prosthetic material, the condition and quantity of accessible bone, and the stresses imposed on the prosthetic [18][19]. To address a wide range of clinical scenarios and patient needs, various dental implant options have been created, including endosteal, subperiosteal, zygomatic, and transosteal implants. Each variety is designed for applications and necessitates thoughtful evaluation based on the unique characteristics of each patient [20][21].

Dental bridges provide a budget-friendly way to restore dental functionality and appearance, but dental implants are favored for their enhanced stability, durability, and bone-stimulating properties [22][25]. With the growing popularity of dental implants, dental practitioners frequently see patients with restorations supported or anchored by implants. Regular evaluations of both the dental prosthesis and the associated peri-implant tissues are critical for early detection and management of any problems that may emerge[15][26].
Historically, dentistry's diagnostic approaches have heavily depended on human skills, yet the emergence of deep learning algorithms has introduced exciting opportunities in biomedical imaging [23][24]. These algorithms have shown impressive performance across multiple medical imaging fields, including dentistry, leading to better patient diagnosis and therapeutic results [14].
Among the deep learning algorithms, YOLOv7, YOLOv8, AdaBoost, and RCNN stand out for their effectiveness in dental implant recognition. YOLO (You Only Look Once) algorithms, particularly YOLOv7 and YOLOv8, provide real-time object identification capabilities, allowing dentists to quickly and reliably analyze many aspects of dental implants. AdaBoost leverages ensemble learning for robust classification, while RCNN employs region-based convolutional neural networks for precise localization.

The YOLO (You Only Look Once) algorithm has revolutionized dental implantology, equipping dentists with a highly effective instrument to improve oral health care [27][28]. YOLO's real-time object detection feature enables rapid and precise evaluations of various dental implant parameters such as bone density, tooth positioning, and potential problems [29][30]. By offering vital information on implant positioning and customizing implant designs to fit unique oral structures, this technology substantially alters treatment strategies, guaranteeing greater implant stability [31][32]. With the latest versions, YOLOv7 and YOLOv8, significant strides have been made to further enhance dental implant recognition [33][34]. YOLOv7 incorporates anchor boxes, and pre-defined shapes with varying dimensions, to identify objects of diverse forms. Utilizing nine anchor boxes, YOLOv7 broadens its capacity to recognize a broader spectrum of object sizes and shapes with heightened precision, significantly diminishing false detections. Furthermore, YOLOv7 works at a higher resolution than its previous versions, with images measuring 608 × 608 pixels. This upgrade improves YOLOv7's ability to detect tiny items, increasing its accuracy in recognizing dental implants[35][36].

Similarly, YOLOv8 builds upon these enhancements with further improvements in object detection performance. Continuing to utilize anchor boxes for enhanced detection accuracy, YOLOv8 incorporates additional optimizations to boost speed and efficiency [27][28]. With its refined architecture and optimization techniques, YOLOv8 provides dentists with a more robust tool for precise and efficient dental implant recognition [37]. Together, YOLOv7 and YOLOv8 represent cutting-edge advancements in dental implantology, empowering dentists with state-of-the-art technology to deliver superior patient care. By seamlessly integrating these advanced algorithms into clinical practice, dentists can optimize treatment planning, ensure accurate implant placement, and ultimately enhance outcomes in oral healthcare [38][39].

AdaBoost (Adaptive Boosting) is a method of collaborative learning that combines numerous novice learners, such as decision trees or other classifiers, to form a robust classifier. In the context of dental implant recognition, AdaBoost can leverage various weak classifiers trained on features extracted from radiographic images to classify implant types accurately [40][41]. AdaBoost works by iteratively adjusting the weights of misclassified samples to focus on challenging instances, ultimately improving classification performance [42][43]. For dental implants, AdaBoost can analyze features such as implant shape, size, and orientation extracted from radiographic images to classify implants into different categories, such as endosteal, subperiosteal, zygomatic, or transosteal implants [44][45]. By combining the predictions of multiple weak classifiers, AdaBoost can effectively classify dental implants, even in cases where individual classifiers may struggle to make accurate predictions [46][47]. This ensemble approach enhances the robustness of the classification model, ensuring reliable performance across diverse implant types and imaging conditions [48][49].

RCNN (Region-based Convolutional Neural Network) is a sophisticated algorithm for object detection tasks that operates in two stages: region proposal and object classification. In the region proposal stage, RCNN generates candidate object regions within the image using selective search or similar algorithms. These candidate regions are then fed into a convolutional neural network (CNN) for feature extraction and object classification [50] [51]. In the context of dental implant recognition, RCNN excels in the precise localization of implants within radiographic images. By generating candidate regions and leveraging the powerful feature extraction capabilities of CNNs, RCNN can accurately identify dental implants, regardless of their position or orientation within the image[52][53]. The two-stage architecture of RCNN allows for efficient and accurate object detection, making it well-suited for complex recognition tasks such as dental implant recognition. By combining region proposal and object classification in a unified framework, RCNN achieves state-of-the-art performance in identifying dental implants, contributing to improved patient care and treatment outcomes in prosthodontics.

In summary, each of these algorithms - YOLOv7, YOLOv8, AdaBoost, and RCNN - offers unique strengths and capabilities that contribute to the accurate recognition of dental implants in radiographic images. By leveraging the advancements in AI and machine learning, dental professionals can develop robust and reliable systems for dental implant recognition, ultimately enhancing patient care and treatment planning in prosthodontics

2. Literature Survey

Aviwe Kohlakala et al. presented two fully convolutional network (FCN) models. FCN-1 automatically categorizes dental implant connection types from X-ray images, achieving a 98% validation accuracy in simulated images. FCN-2 identifies relevant Regions of Interest (ROIs) containing dental implants, achieving accuracies of 90.43% and 94.06% for foreground and background pixels in different datasets, respectively [1]. Zhang Chunan's investigation integrated outward and 360-degree images through an integrated approach, resulting in exceptional precision for diagnosis and demonstrating the value of combining methods for predicting implant results [2]. Additionally, Jae-Hong Lee's research highlighted significant enhancements in the accuracy of dental implant system classifications by utilizing a deep learning technique, providing dental practitioners with significant assistance in implant categorization [3][54]. In this study, Kurt Bayrakdar developed an AI system that used a deep convolutional neural network and exhibited different levels of accuracy for various measurements. Additionally, the AI algorithm detected 72.2% of canals, 66.4% of sinusitis and fossae, and an astonishing 95.3% of empty tooth areas. This suggests that while the AI system performed well in identifying missing tooth regions, there were variations in its accuracy for bone measurements depending on the specific region [4]. Mostafa Sabzekar's study addressed the issue of uneven data for estimating the efficacy of dental implants. He proposed an ensemble method enhanced with genetic algorithm optimization, which notably boosted essential performance indicators over standalone classifiers. This article highlights the breakthrough contribution made by computational intelligence in improving the analysis and categorization of dental implants [5].

Kim HS's research presented a Deep Convolutional Neural Network (DCNN) built on the YOLOv3 framework, which showed exceptional skill in distinguishing various types of dental implants. It achieved its best results after undergoing 200 training cycles, notably in identifying Bone Level Implant fixtures. The evaluation criteria were based on sensitivity and specificity. This innovation underscores the capabilities of artificial intelligence in accurately analyzing dental implants and pinpointing implant areas within X-ray images [6]. In this paper, Alharbi implemented various machine learning algorithms for predicting dental implants, focusing on ensemble learning methods. They investigated four popular algorithms: Bayesian network, random forest, AdaBoost, and an enhanced version of AdaBoost. The study evaluated and contrasted various collaborative learning techniques for identifying dental implants, where AdaBoost emerged as the top performer with an accuracy rate of 91.7%. These findings indicate that ensemble learning has the potential to boost the predictive power of models used in dental implant analysis [7]. Lee DW's research highlighted the strong capabilities of deep convolutional neural networks, specifically a computerized variant of DCNN, in spotting and categorizing damaged dental implants. This underscores the possibility of optimizing diagnostic processes in evaluating dental implants [8].

Akhilanand Chaurasia et al. conducted a comprehensive study and meta-analysis to investigate the accuracy of deep learning (DL) algorithms in recognising and classifying dental implant systems (DISs) using dental imaging. By scanning databases from January 2011 to March 2022, nine relevant studies were identified for analysis. The DL-based implantation accuracy for classification ranged from 70.75% to 98.19%, with an overall accuracy of 92.16% While DL models demonstrated great accuracy, the danger of bias and application problems were raised, notably regarding data selection and reference standards. Even with these drawbacks, DL models are still a promising tool and decision-making assistance for dentists, but further study is needed to fully understand how they may be used in clinical situations [9]. Mona Alsomali et al. developed a supervised artificial intelligence (AI) model that could automatically detect radiographic stent gutta-percha (GP) markers in cone beam computed tomography (CBCT) images, making it easier to identify possible implant sites. The model was trained, validated, and tested on 34 CBCT datasets from patients who received radiographic stents as part of implant therapy planning. For item detection and recognition, GP markers in axial pictures were manually labeled. In terms of identifying GP markers, the AI model produced an 83% true positive rate and a 2.8% false positive rate. It suggested that the use of only axial images for training an AI program for the localization of GP markers is not enough to give an accurate AI model performance [10].Huiting Hu et al. studied the initial mortality rates of dental implants in China (from 2006 to 2017). It focused on 1078 cases with 2053 implants with a high early survival rate of 96.15%. Factors linked to favorable early survival rates were patient age (30–60 years), bone quality, bone augmentation, rapid implantation, and shorter implant lengths (<10 mm). The results highlighted how crucial it is to take these parameters into account when placing implants to increase success rates [11]. Mehdi Hadj Saïd et.al in this study aimed to develop a deep convolutional network to identify the model of a dental implant from a radiographic image. Pre-processing and transfer learning was applied to a pre-trained GoogLeNet Inception CNN network.

Model performance was assessed using accuracy, sensitivity, specificity, the Receiver Operating Characteristic (ROC) curve, and the Area under the ROC Curve. The deep CNN model performed exceptionally well in recognizing dental implants from radiographs. These findings support the notion that artificial intelligence can assist practitioners in their medicinal operations [12]. Sanjeev B. Khanagar et.al highlighted the widespread adoption of AI technologies, focusing on convolutional neural networks (CNNs) and artificial neural networks (ANNs) in their research. These artificial intelligence models have proved useful in identifying and diagnosing numerous dental disorders such as dental caries, cracks, infections, and illnesses, as well as predicting treatment outcomes and doing studies like cephalometry and age/gender determination. Notably, AI-based automated systems demonstrate excellent performance, often surpassing that of certified professionals. Some research even indicates these technologies outperform professionals in dentistry in terms of exactness and precision, emphasizing their potential as valuable tools in clinical practice [13]. images based on dental abnormalities, adding annotations, and ensuring adherence to quality control procedures.

Data Collection- The dataset of dental records was gathered from various dental clinics in Pune, India. Panoramic radiographs were chosen due to their comprehensive coverage of the upper and lower jaw regions

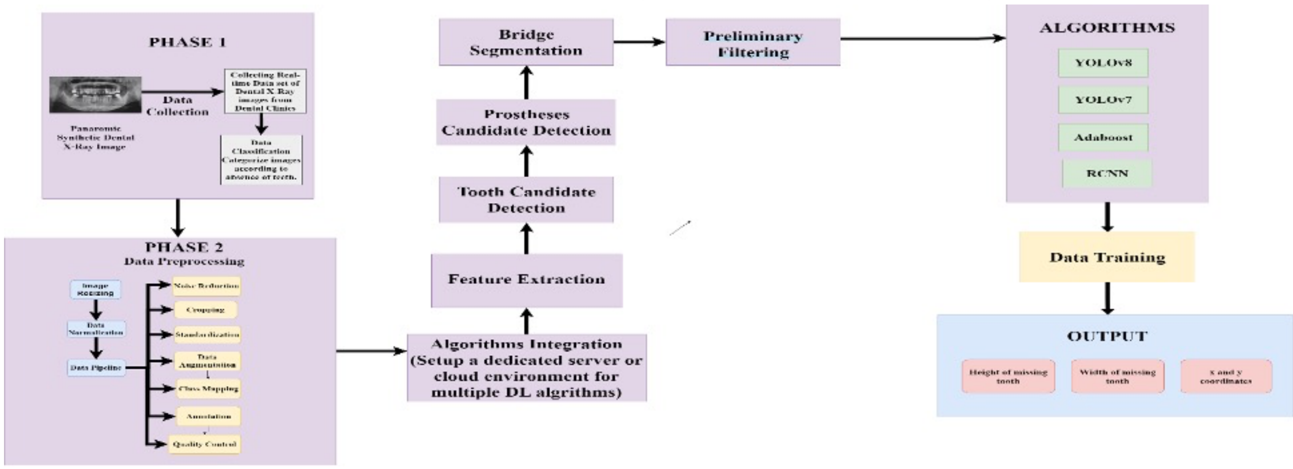


Fig 1. System Architecture

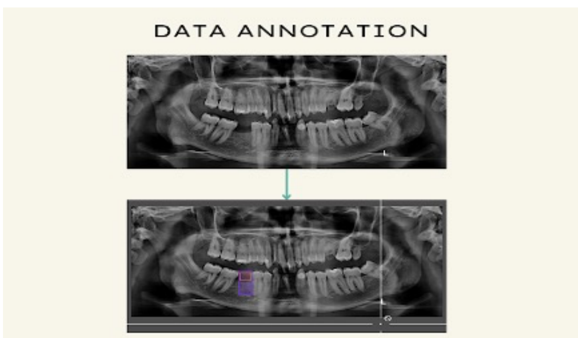


Fig 2. Data Collection and Processing

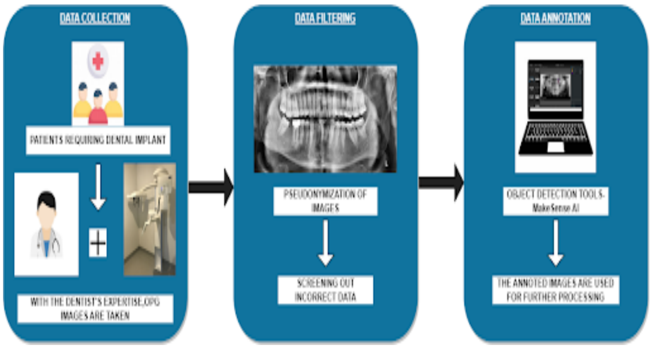


Fig 3. Data Annotation

3. Proposed Methodology

Figure 1 explains the system architecture of our model. The proposed system consists of three main phases. Initially, real-time data is collected from several dental clinics, and the specific location of teeth that are absent in everyone's jaw is determined and categorized.

In the second phase, data pre-processing is conducted, which involves several tasks such as resizing images, normalizing data, reducing noise, cropping images, standardizing formats, augmenting data, classifying in a single film. We collected around 5865 dental scans.

Data Filtering- The dental dataset underwent thorough scrutiny to ensure the legitimacy and reliability of each section. Panoramic radiographs were meticulously reviewed to identify and remove any images displaying poor quality or errors. This rigorous screening process maintained the integrity and accuracy of the dataset, enhancing its utility for future dental research and clinical applications.

Data Annotation- MakeSense.ai provided an important role in annotating the dataset by creating exact bounding box annotations on dental radiography pictures. These annotations accurately delineated the implant placement sites and provided contextual information about surrounding tissues, such as gums and adjacent teeth. This comprehensive annotation approach facilitated precise implant positioning and supported a deeper analysis of dental radiographs. The annotated dataset serves as the foundation for our research efforts, enabling the training of deep learning models to independently analyze dental radiographs and improve the efficiency and accuracy of implant planning procedures.

In the final phase of the proposed system, the deep learning model YOLO is utilized for object detection tasks related to identifying missing teeth and dental abnormalities from panoramic dental X-rays. Using YOLOv7 and YOLOv8, the panoramic X-ray images are processed to extract features and identify potential tooth candidates. Each tooth type is treated as an individual object for accurate detection. Additionally, a separate detector is incorporated specifically for identifying prosthesis candidates, thereby enhancing the detection performance for full dental restorations. YOLO's real-time object detection capabilities and accuracy make it well-suited for this task.

Alternatively, the RCNN (Region-based Convolutional Neural Network) approach can also be employed in this phase. RCNN operates by generating region proposals and then classifying each proposed region to determine if it contains a tooth or a dental abnormality. Although RCNN has been effective in object detection tasks, it is computationally intensive and may not be as efficient for real-time applications compared to YOLO.

Another option that is discussed is to use AdaBoost, a machine-learning algorithm which incorporates inadequate classifiers to build a powerful classifier. In this context, AdaBoost could be trained to identify specific features or patterns associated with missing teeth or dental abnormalities in panoramic X-ray images. However, AdaBoost may require more manual feature engineering compared to deep learning models like YOLO and may not be as effective for complex object detection tasks.

Ultimately, the use of YOLOv7 and YOLOv8 in the final phase of the system offers a robust and efficient solution for identifying missing teeth, dental abnormalities, and prosthesis candidates from panoramic dental X-ray images, providing detailed information about the location and dimensions of the missing teeth.

4. Implementation

In our research initiative dedicated to advancing the analysis and classification of dental implants, we undertook a thorough exploration of machine learning and deep learning methodologies. Our primary objective was to improve the accuracy and effectiveness of detecting and classifying dental implants. To achieve this goal, we customized and applied four unique model architectures: YOLOv8, YOLOv7, Adaboost, and RCNN.

These model architectures were meticulously selected for their diverse strengths and capabilities, each offering unique advantages in the realm of object detection and classification. Leveraging a dataset comprising 5500 images, sourced in real-time from dental scan centers, we tailored our implementations to harness the full potential of each model architecture. This ensured that our models were trained and fine-tuned on data representative of real-world scenarios, thus facilitating optimal performance in the context of dental implant analysis.

In the studies we conducted, MakeSense.ai was essential for generating comprehensive bounding boxes on dental radiation images. These annotations provided a dual purpose: they precisely defined the spot for dental implant installation while also including the surrounding areas including gums and neighboring teeth. This annotated dataset has tremendous importance because it serves as the foundation for training our deep learning models. These models are anticipated to autonomously examine dental X-rays, thereby simplifying and boosting the accuracy and efficiency of dental implant planning.

1. RCNN:

- Region Proposal Network (RPN): RCNN starts with an RPN, accountable for creating region recommendations or potential boxes with boundaries that may contain elements of interest.
- Feature Extraction Layers: These layers extract features from the proposed regions using a convolutional neural network (CNN). These features capture essential information about the proposed regions.
- Region-based CNN: The extracted features are then fed into another CNN, often pre-trained on large datasets like ImageNet, for object classification and localization.
- Output Layer: RCNN concludes with an output layer that produces the final bounding box coordinates and class possibilities for the detected objects.

The mathematical formulae typically associated with RCNN (Region-based Convolutional Neural Network) are:

i. Region Proposal Network (RPN):

- P(object)- Probability of an object being present within a region proposal.
- $\Delta(x,y,w,h)$ - Box regression parameters for adjusting the bounding box coordinates.
- Lcls - Classification loss term.
- Lreg - Regression loss term.
- Ltotal=Lcls+λLreg- Total loss, where λ is a balancing parameter.

ii. Bounding Box Regression:

- x^=x+wΔx- Predicted x-coordinate of the bounding box.
- y^=y+hΔy- Predicted y-coordinate of the bounding box.
- w^=weΔw- Predicted width of the bounding box.
- h^=heΔh - Predicted height of the bounding box.

iii. Loss Functions:

- Classification Loss Lcls:
- The cross-entropy loss function is used to determine the difference between predicted class probability and ground truth labels.
- Regression Loss Lreg:
- Typically, smooth L1 loss or another regression loss function is used to calculate the variance between estimated and ground truth bounding box coordinates.

These formulae are central to the training process of RCNN, facilitating the optimization of the network parameters to accurately detect and classify objects within images.

```
# Preprocess the data
images, labels = preprocess_data(image_folders, label_folders)

from sklearn.metrics import accuracy_score

# Predict the test data
y_pred = model.predict(X_test)

# Convert the predicted values to labels
y_pred_labels = lenc.inverse_transform(y_pred)

# Calculate the accuracy
accuracy = accuracy_score(y_test, y_pred_labels)

# Print the accuracy
print("Accuracy: {:.2f}%".format(accuracy * 100))

# Print the accuracy
print("Accuracy: {:.2f}%".format(accuracy * 100))

Accuracy: 77.46%
```

Fig 4. Accuracy for RCNN-77.4%

Data processing for RCNN includes:

- Region Proposal Generation: The dataset undergoes preprocessing to generate region proposals or candidate bounding boxes using selective search or similar methods.
- Feature Extraction: Features are extracted from the proposed

regions using CNNs, ensuring that essential information is captured for accurate object detection and classification.

Training and Testing: Similar to YOLOv7 and Adaboost, RCNN is trained on a portion of the dataset and evaluated on a separate testing set to assess its performance accurately.

2. Adaboost:

- Base Classifiers: Adaboost operates through a series of base classifiers, each focusing on different features or aspects of the data. These classifiers are typically simple decision trees or weak learners.
- Weighted Combination: The predictions of these base classifiers are combined with weights based on their performance, leading to a final prediction. This weighted combination ensures that more accurate classifiers contribute more to the final prediction, enhancing overall accuracy.

In AdaBoost, the mathematical formulation involves the calculation of the average weighted error of each inadequate classifier, the determination of their contribution to the final strong classifier, and the update of sample weights based on their classification performance. Here are the key equations used in AdaBoost:

i. Weighted Error for Weak Classifier hi:

Where:
- ϵi is the weighted error for weak classifier hi.
- wi are the sample weights.
- xi is the input feature vector.
- yi is the true label.
- II is the indicator function.

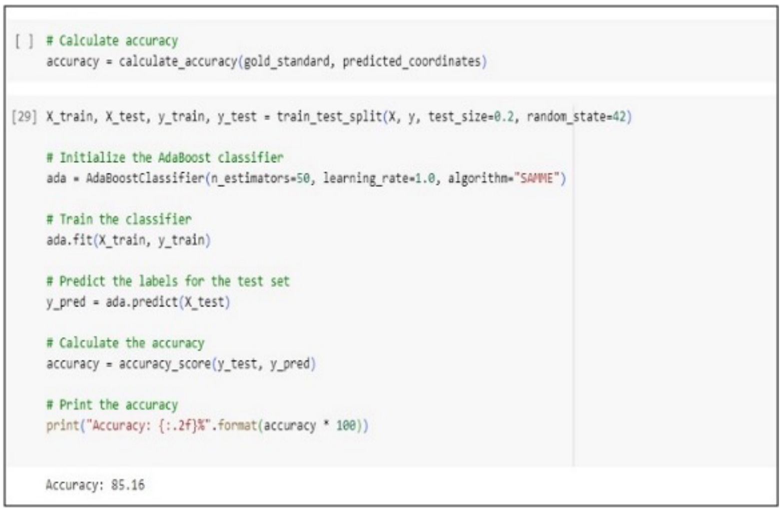
ii. Classifier Weight:

Where:
- αi is the weight associated with weak classifier hi.
- ϵi is the weighted error of weak classifier hi.

iii. Update Sample Weights:

Where:
- wi+1 are the updated sample weights for the next iteration.
- Z is the normalization factor to ensure the sum of weights remains 1.
- αi is the weight of weak classifier hi.
- yi is the true label.
- hi(xi) is the prediction of weak classifier hi for input xi.

These equations are iteratively applied to train multiple weak classifiers and combine them into a strong classifier with improved performance.



```
[ ] # Calculate accuracy
    accuracy = calculate_accuracy(gold_standard, predicted_coordinates)

[29] X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    # Initialize the AdaBoost classifier
    ada = AdaBoostClassifier(n_estimators=50, learning_rate=1.0, algorithm="SAMME")

    # Train the classifier
    ada.fit(X_train, y_train)

    # Predict the labels for the test set
    y_pred = ada.predict(X_test)

    # Calculate the accuracy
    accuracy = accuracy_score(y_test, y_pred)

    # Print the accuracy
    print("Accuracy: {:.2f}%".format(accuracy * 100))

    Accuracy: 85.16
```

Fig 5. Accuracy for Adaboost- 85.16%

Data processing for Adaboost involves:
- Feature Engineering: Adaboost relies on carefully engineered features to train its base classifiers effectively. These features are selected or engineered to capture relevant information about the data.

Training and Testing: Similar to YOLOv7, the dataset is divided into training and testing sets, allowing Adaboost to learn from the training data and evaluate its performance on unseen data during testing.

3. YOLOv7 Architecture:
- Backbone Network: Similar to YOLOv8, YOLOv7 employs a backbone network, like CSPDarknet53, for extracting characteristics from the input images.
- Feature Pyramid Network (FPN): YOLOv7 could potentially integrate FPN to gather attributes at various dmensions, facilitating multi-scale feature extraction for object detection..
- Detection Head: YOLOv7's detection head consists of convolutional layers tasked with examining features and producing forecasts, encompassing bounding box locations, objectness probabilities, and class identifiers.
- Anchor Boxes: Similar to YOLOv8, YOLOv7 employs anchor boxes to adjust predictions, accommodating differences in various proportions and dimensions found in the data.
- Loss Function: YOLOv7 employs various loss functions to guide model training, similar to YOLOv8, ensuring accurate prediction of object properties.

Data processing for YOLOv7 follows a similar approach to YOLOv8, including data preprocessing steps such as standardizing image sizes and normalizing pixel values. Additionally, the dataset is divided into testing and training sets for evaluation purposes and model training.

The mathematical formulae associated with YOLO (You Only Look Once) are:

i. Bounding Box Prediction:
- bx, by - Center coordinates of the bounding box.

- bw, bh - Width and height of the bounding box.
- ^bx, ^by - Predicted center coordinates of the bounding box.
- ^bw, ^bh - Predicted width and height of the bounding box.

ii. Objectness Score:
- po - Probability that an object is present within the bounding box.
- ^po - Predicted probability that an object is present within the bounding box.

iii. Class Prediction:
- c1, c2, ..., cn - Class probabilities for each class.
- c^1, c^2, ..., c^n - Predicted class probabilities for each class.
- iv. Loss Function:
- Combines localization loss, confidence loss, and classification loss:

Where:
- λcoord and λnoobj are hyperparameters to balance the loss terms.
- 1ijobj and 1ijnoobj are indicator functions indicating whether an object is present in the bounding box.
- pijo is the predicted objectness score.
- pi(c) and p^i(c)are predicted and ground truth class probabilities respectively.

These formulae encapsulate the core components of the YOLO algorithm, facilitating object detection and classification within images.

These architectural components and data processing strategies are pivotal in the successful implementation and deployment of YOLOv8 and YOLOv7 for dental implant analysis and classification, contributing to improved efficiency and accuracy in the detection of dental implants from radiographic images

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4. YOLOv8 Architecture:
- Backbone Network: YOLOv8 uses a robust backbone network, such as CSPDarknet53, to extract intricate details from input images. This network design plays a critical role in seizing high-level features necessary for precise object detection.
- Feature Pyramid Network (FPN): Certain iterations of YOLOv8 incorporate FPN, enabling multi-scale feature extraction. FPN gathers features at multiple scales, supporting the detection of objects of differing sizes and ensuring thorough examination of the input image.
- Detection Head: The detection head in YOLOv8 consists of a sequence of convolutional layers tasked with scrutinizing the extracted features and producing forecasts. These forecasts encompass bounding box positions, objectness probabilities, and class tags for identified objects.
- Anchor Boxes: YOLOv8 employs anchor boxes to adjust predictions, accommodating differences in various proportions and dimensions found in the data. These anchor boxes play a crucial role in honing predictions and boosting the model's precision.
- Loss Function: YOLOv8 leverages multiple loss functions to optimize for bounding box localization, object presence, and class probabilities. These loss functions direct model training by measuring the discrepancy between forecasted and actual values, thereby improving prediction accuracy.

Data processing for YOLOv8 includes:
- Data Preprocessing: To prepare data for YOLOv8, preprocessing is crucial. This involves ensuring images have a consistent size, adjusting pixel values to a specific range, and formatting annotations with bounding box locations and class identifications.

- Training and Testing: We split the data into training and testing sets. 60% is used to train a YOLOv8 model to identify and predict the properties of dental implants. The remaining 40% is used to evaluate the model's performance and accuracy

Each model architecture serves a unique purpose in dental implant analysis, and their tailored designs are essential for achieving accurate detection and classification results.

5. Results and Discussion

In this section, we assess the efficacy of the proposed systems and conduct a thorough analysis of the results obtained. Table 1 outlines the statistical measures utilized in this study for evaluation purposes.

Table 1. The statistical performance measures employed

Performance Measure	Definition
Precision(PRE)	TP/(TP+FP)
Recall(REC)	TP/(TP+FN)
Accuracy(ACC)	(TP+TN)/(TP+FN+FP+TN)

This study investigates and compares the performance of four deep-learning algorithms in dental implant sizing. As outlined in the implementation section, the algorithms investigated include YOLOv8, YOLOv7, AdaBoost, and RCNN, each selected for its unique strengths and capabilities in object detection and classification tasks. Leveraging a dataset of dental radiographic images collected from dental clinics, our study sought to evaluate the accuracy and efficiency of these algorithms in accurately sizing dental implants. Through rigorous experimentation and analysis, we aimed to provide valuable insights into the effectiveness of these algorithms in improving dental implant planning and treatment outcomes. The results presented herein shed light on the comparative performance of these algorithms and their potential implications for clinical practice in prosthodontics.

5.1 Precision-

In dental implant sizing, precision reflects the accuracy of predicted implant sizes. It is calculated as the proportion of implants correctly identified (true positives) compared to all implants the model predicted as a specific size (true positives and false positives).

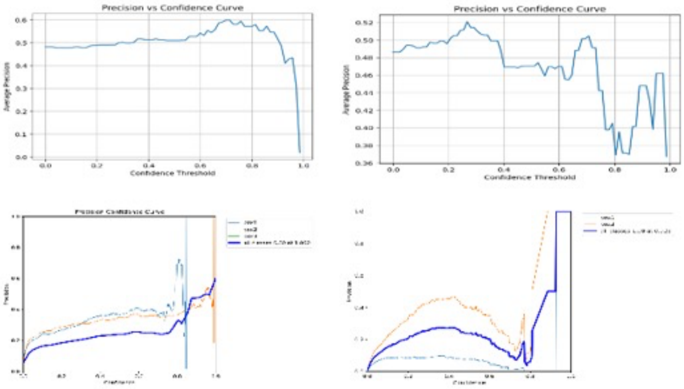

Figure 6. Precision curves (clockwise- RCNN, Adaboost, YoloV7, YoloV8)

5.2 Recall-

It measures the proportion of correctly identified dental implants of a specific size (true positives) out of all implants of that size present in the dataset (true positives plus false negatives).

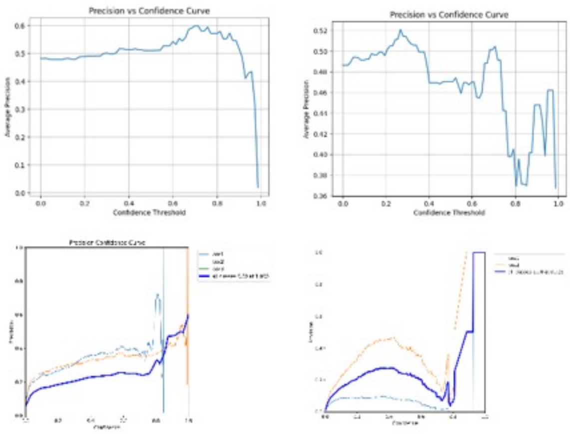

Figure 7. Recall curves (clockwise- RCNN, Adaboost, YoloV7, YoloV8)

5.3 Visualizations and Interpretations-

We've incorporated graphical representations to showcase the efficacy of our YOLOv7 and YOLOv8 models in detecting dental implants. These visual aids highlight the model's accuracy and precision in identifying the precise locations of dental implants within the images.

In these graphs, box 1 and box2 are the bounding boxes of the dental implants.

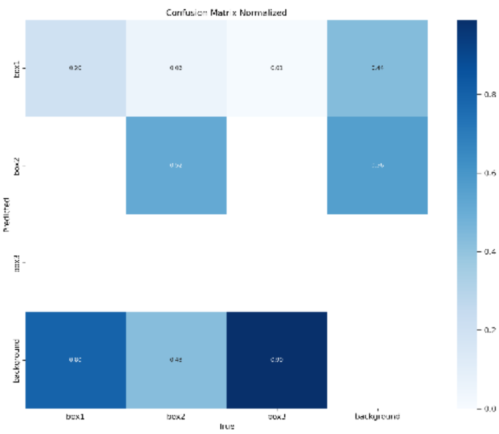

Figure 8. Confusion Matrix- YOLOv7

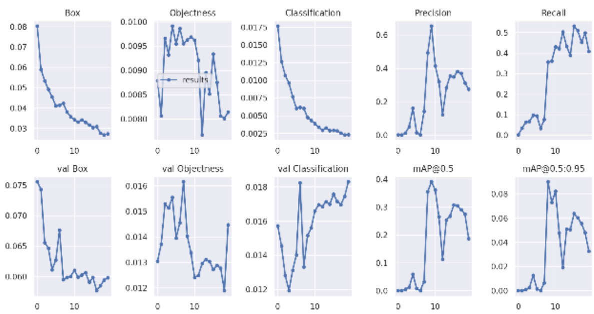

Figure 9. Results- YOLOv7

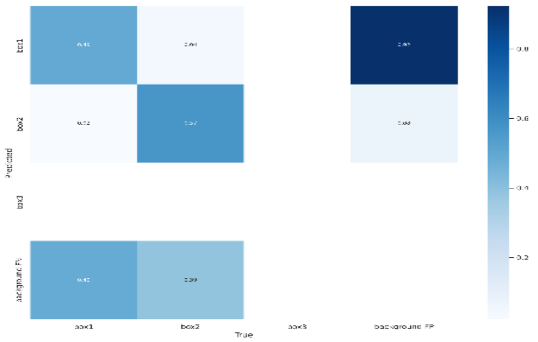

Figure 10. Confusion Matrix- YOLOv8

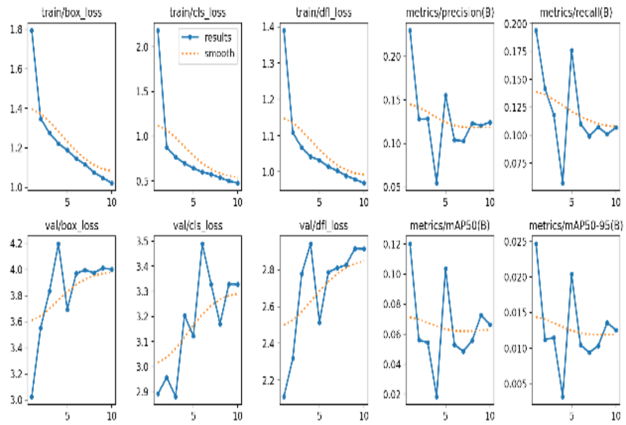

Figure 11. Results- YOLOv8

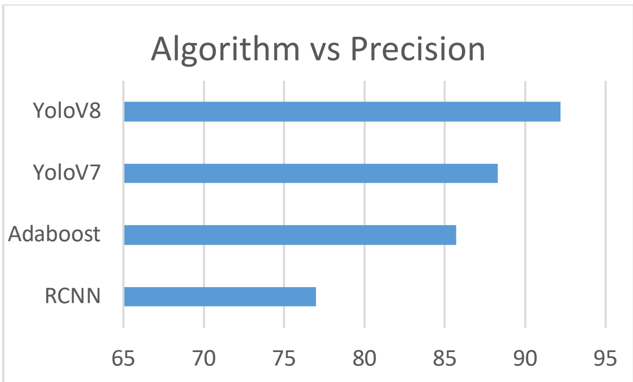

Figure 12. The performance of precision for different algorithms

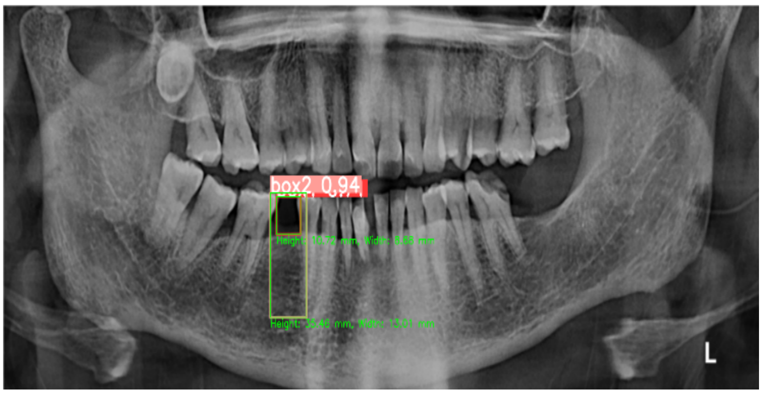

Figure 13. YOLOv8 predicting the bounding boxes and the height and width of the same

5.4 Comparison of the algorithms-

The metrics we acquired are in line with our original research goals, indicating the effectiveness of our models in detecting dental implants. These findings hold substantial importance in dental implant studies as they provide a robust and precise method for localizing implants.

6. Limitations and Future Research

Our study's focus on detecting dental implants limits its ability to discern specific implant types or materials, hindering its applicability in detailed implant characterization. The detection accuracy of these algorithms may be compromised by variations in lighting conditions and implant materials. Future research should address these limitations by exploring methods to classify different implant types accurately and mitigate the impact of lighting variations and material diversity. Enhanced methods for dataset augmentation and feature extraction could bolster the YOLOv8 model's resilience and effectiveness in identifying dental implants, thereby expanding its applicability in clinical environments.

7. Conclusion

In conclusion, this study offers a thorough comparative analysis of four object detection algorithms—YOLOv7, YOLOv8, AdaBoost, and RCNN—within the context of dental implant identification. Leveraging a substantial custom dataset and employing rigorous evaluation metrics, the research sheds light on the strengths and limitations of each algorithm. YOLOv7 and YOLOv8 emerge as top performers, demonstrating swift real-time object detection with high precision rates of 88.83% and 92.2%, respectively. AdaBoost, although slightly slower in processing time compared to YOLO variants, showcases commendable classification performance with a precision of 85.7%. RCNN, while precise in localization, exhibits relatively slower processing times with a precision of 77%. The study underscores the potential for further research by advocating the expansion of datasets to encompass diverse clinical scenarios and modalities, allowing for a more comprehensive evaluation of algorithm capabilities. Moreover, it encourages exploring broader applications of AI algorithms in dental practice beyond implant identification, such as automated assessment of bone quality and predictive modeling for treatment outcomes. By paving the way for future research and implementation of AI-driven solutions, this study promises to advance the field and enhance treatment outcomes for dental patients.

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