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Predictive YOLO V7 Model of Dental Implant for Radiographic Images

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Abstract: Artificial intelligence (AI) has become integral in prosthodontics, revolutionizing patient diagnoses and communication between prosthodontists and patients. AI systems exhibit remarkable efficiency, often rivaling or surpassing expert prosthodontists. This study focuses on utilizing YOLOv7, an advanced YOLO algorithm, for real-time object detection in dental radiographic images. The algorithm, known for its speed and accuracy, proves valuable in identifying missing teeth and determining dental implant types and dimensions. Leveraging a dataset of 4,000 annotated dental radiographic scans, the YOLOv7 model is trained, customized for direct prediction of dental implant dimensions, and adapted loss functions to ensure accuracy. Additionally, it classifies dental implant types, facilitating precise placement within a patient's oral cavity. Evaluation metrics include an impressive overall accuracy of approximately 89%, with a recall of 0.61, precision of 1 at a confidence of 0.895, and an F1-score of 0.35 at a confidence of 0.292. This underscores the model's efficacy in prosthodontic imaging. The study highlights AI's contemporary role in dental prosthetics, emphasizing its effectiveness in diagnosing conditions and creating customized dental prostheses. Ultimately, the integration of AI, exemplified by YOLOv7, contributes significantly to advancing prosthodontic care. The model's architecture, tailored for dental implant prediction and type classification, presents promising results, and further optimization holds the potential for increased precision and reliability in clinical applications.

Keywords: *Artificial Intelligence, Deep Learning, Dental Implants, Prosthodontics, Radiographic Images, YOLOv7*

1. Introduction

Dental implants known as oral or endosseous implants have been a transformative element in the field of dentistry for over half a century. They represent a significant leap in dental care by providing a highly effective means of replacing missing teeth. The success of dental implants hinges on their ability to seamlessly integrate with the surrounding tissue mimicking the natural tooth's functionality and aesthetics. However, this integration process can be influenced by several factors including the type of implant material used the quality and quantity of available bone and the loading conditions placed on the implant.

There are diverse types of dental implants, each created to cater to certain clinical circumstances and patient demands. Dental implants come in four basic categories: endosteal, subperiosteal, zygomatic and transosteal. The most popular kind of dental implants, endosteal implants, are inserted surgically right into the jawbone. These implants, which are frequently shaped like screws, cylinders, or blades, provide a secure base for false teeth. For individuals with sufficient bone volume and density to sustain them, they are a well-liked option. Subperiosteal implants, in contrast, are positioned on top of the jawbone, slightly below the gingival tissue. Only patients with insufficient bone volume for endosteal implants should use this method. Subperiosteal implants are used to anchor replacement teeth using metal posts or frames that pass through the gums. For those with significant upper jawbone loss, zygomatic implants are a specialised treatment. When traditional procedures may not be possible, these implants provide a stable foundation for dental restorations by anchoring in the cheekbone rather than the jawbone. Even though they are less frequent, transosteal implants are special in that they go all the way through the upper and lower jawbones. They should only be used in certain circumstances and dental practitioners should carefully assess and prepare ahead. These diverse dental implant varieties offer versatility in addressing a range of patient requirements, guaranteeing that tooth replacement may be tailored to fit varied clinical settings and individual preferences.

Dental bridges are dental prosthetics used to replace missing teeth by anchoring artificial teeth (pontics) between existing natural teeth. While bridges offer a cost-effective solution for restoring dental function and aesthetics, dental implants are often preferred for several reasons. Dental implants provide superior stability and longevity, as they are surgically anchored into the jawbone, mimicking natural tooth roots. They do not require the alteration of adjacent teeth, preserving their integrity. Implants also stimulate bone growth, preventing jawbone loss. Additionally, dental implants offer a more natural look and feel, making them popular

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for those seeking a long-term and highly aesthetic tooth replacement option.

As the utilization of dental implants has become more prevalent, dental professionals are increasingly encountering patients with implant-supported or retained restorations. While offering a reliable solution for tooth replacement, these implants are not immune to issues afflicting natural teeth. Diseases and complications can affect dental implants, leading to failures that may occur months or even years after their placement. Consequently, it is prudent to advocate for routine examinations of both the implant and the surrounding peri-implant tissue, analogous to the regular periodontal assessments performed for natural teeth. Identifying any deviations from the norm in a timely manner is crucial, as it enables appropriate treatment interventions to be administered, whether within the dental practice or through specialists, depending on the severity of the condition. Thus, it is imperative for dentists to possess a fundamental understanding of dental implants, not only to ensure their success but also to address any potential issues that may arise.[5] The field of prosthodontics, specializing in dental prostheses, occupies a pivotal position within the realm of dental sciences. Dental prostheses play a crucial role in several aspects of human life. Firstly, the absence of teeth can lead to compromised physical, mental and emotional well-being. It can affect an individual's ability to chew properly, potentially causing dietary and nutrition changes. Secondly, tooth loss can instill feelings of isolation due to concerns about social acceptance. Aesthetic considerations are paramount, as individuals seek a harmonious appearance, with teeth and related soft tissues playing a central role in facilitating social interactions. Lastly, the presence of teeth in the oral cavity maintains proper tongue positioning, the alignment of lips and cheek support, contributing significantly to facial structure.[6]

Traditional diagnostic methods in dentistry have relied primarily on human expertise, involving visual and tactile examinations for diagnosis. However, the advent of deep learning-based algorithms has ushered in a new era in biomedical imaging. These algorithms have demonstrated remarkable capabilities in various medical imaging domains, including radiology, pathology, brain imaging, breast cancer diagnosis and even COVID-19 detection. The success of deep learning in medical imaging opens exciting possibilities for addressing recognition needs related to dental implants.[1]

Many research studies have confirmed that the application of artificial intelligence can lead to improved patient diagnoses and treatment outcomes, making this technology highly valuable in medical settings. In dental clinics, several models and techniques have been developed to provide medical consultations and assess a patient's dental condition. It is crucial to leverage technology that enhances the quality of care while also managing costs effectively within a dental clinic.

Furthermore, AI applications have extended to the development of prediction models aimed at determining the success of osteointegration and implant prognosis. These models incorporate patient-specific risk factors and ontology criteria. Additionally, AI has been employed to optimize dental implant designs by combining finite element analysis (FEA) calculations with AI-driven approaches. However, a comprehensive analysis of AI methodologies' performance and potential impact in implant dentistry is currently lacking. This systematic paper seeks to fill this gap by evaluating the effectiveness of AI models in various aspects of implant dentistry. Specifically, the paper assesses the ability of AI models to identify implant types using periapical and panoramic radiographs, develop prediction models for osteointegration and implant success and optimize implant designs.[2]

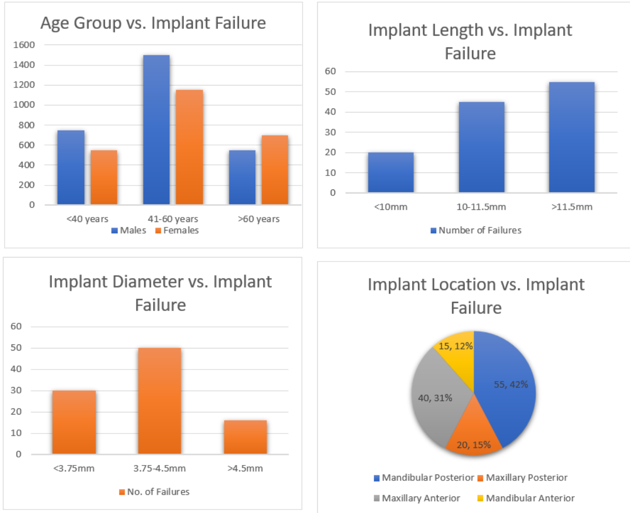

Fig 1. Graphs depicting the Implant failure statistics in various regions

The YOLO (You Only Look Once) algorithm is a game-changer in dental implantology, offering a versatile tool to enhance oral healthcare. YOLO's real-time object detection capabilities empower dentists to swiftly and accurately assess various aspects of dental implants, such as bone density, tooth alignment and potential issues. This technology improves treatment planning, providing valuable insights into implant placement. YOLO also contributes to optimizing implant designs, tailoring specifications to individual oral anatomy for enhanced stability. During surgery, it aids in precise implant placement, minimizing errors. Furthermore, YOLO facilitates patient education by visually explaining procedures and expected outcomes. Post-implantation, supports quality assurance and early issue detection, ensuring long-term implant success, resulting in improved outcomes in oral healthcare. YOLOv7, the latest iteration of the YOLO series, contributes significantly to this progress. One major advancement is the integration of anchor boxes, predefined boxes with various aspect ratios aimed at detecting objects of different shapes. YOLOv7 utilizes nine anchor boxes, a notable increase from its predecessors, expanding its capability to detect a broader range of object sizes and shapes with greater accuracy. This enhancement effectively reduces false positives in object detection tasks, rendering YOLOv7 a valuable tool across diverse applications, particularly in recognizing objects within complex scenarios. Another pivotal enhancement in YOLOv7 lies in its adoption of the "focal loss" function. Unlike previous YOLO versions that employed standard cross-entropy loss, which struggled with small object detection, focal loss addresses this challenge by assigning lower weight to well-classified examples while emphasizing the more challenging instances—the objects that are inherently difficult to detect. Additionally, YOLOv7 operates at a higher resolution compared to its predecessors. Processing images at 608 by 608 pixels, an upgrade from YOLOv3's 416 by 416 resolution, grants YOLOv7 the ability to detect smaller objects and overall enhances its accuracy. These advancements make YOLOv7 an invaluable tool across diverse applications, particularly in recognizing objects within complex and intricate scenarios in the realm of dental implantology.

Sr. No.	*Algorithm used for dental implantation*	*Accuracy obtained*
1.	Bayesian network	72.8%
2.	Random Forest	77.8%
3.	AdaBoost Algorithm	86.1%
4.	Improved AdaBoost Algorithm	91.7%

Table 1. Accuracy Comparison of prediction of dental implants using machine learning algorithms

Accurate recognition of dental implants is pivotal across various dental applications, from forensic identification to restoring compromised dental connections. Within implant dentistry, these devices provide promising solutions for prosthetic restorations. However, accurately categorizing a previously placed dental implant in a patient's jaw becomes a complex challenge when their dental records are inaccessible. Deep learning methods offer a potential solution by automating and enhancing the recognition process, ultimately improving patient care and treatment planning within prosthodontics. This paper delves into the application of deep learning to address these challenges, aiming to advance the understanding and application of cutting-edge technologies in prosthodontic practices. The integration of deep learning is anticipated to enhance the accuracy of dental implant recognition methodologies, contributing to the ongoing evolution of prosthodontic care for more efficient and precise outcomes.

2. Related Work

Dong-Woon Lee *et.al* aimed to assess the reliability and validity of three different deep convolutional neural networks (DCNN) architectures (VGGNet-19, GoogLeNet Inception-v3and an automated DCNN) for detecting and classifying fractured dental implants (DI) using panoramic and periapical radiographic images. A dataset of 251 intact and 194 fractured DI radiographic images, gathered from the evaluation of 21,398 DIs at two dental hospitals, was employed. All three DCNN architectures exhibited robust performance in fractured DI detection and classification, achieving an accuracy of over 0.80 in the Area Under the Curve (AUC). The automated DCNN architecture, when applied to periapical images, demonstrated the highest and most reliable detection (AUC = 0.984, 95% CI = 0.900–1.000) and classification (AUC = 0.869, 95% CI = 0.778–0.929) accuracy compared to the fine-tuned and pre-trained VGGNet-19 and GoogLeNet Inception-v3 architectures. These findings indicate that all three DCNN architectures exhibit acceptable accuracy in the detection and classification of fractured DIs, with the automated DCNN architecture using only periapical images achieving the best performance.[10]

In the field of dental implant analysis and classification, an array of innovative machine learning and deep learning models has emerged, each with distinct capabilities and applications. Aviwe Kohlakala et al. introduced two Fully Convolutional Network (FCN) models: FCN-1 for dental implant categorization and FCN-2 for identifying implant regions in X-ray images. These models achieved impressive validation accuracies, indicating their effectiveness in learning key features associated with dental implants.[3] Meanwhile, Hak-Sun Kim's Deep Convolutional Neural Network (DCNN) based on YOLOv3 excelled in classifying different types of dental implants and demonstrated optimal performance after 200 training epochs, particularly in Bone Level Implant fixture classification. These advancements highlight the potential of AI-driven dental implant analysis for precise implant categorization and detection of implant regions in radiographic images.[8]

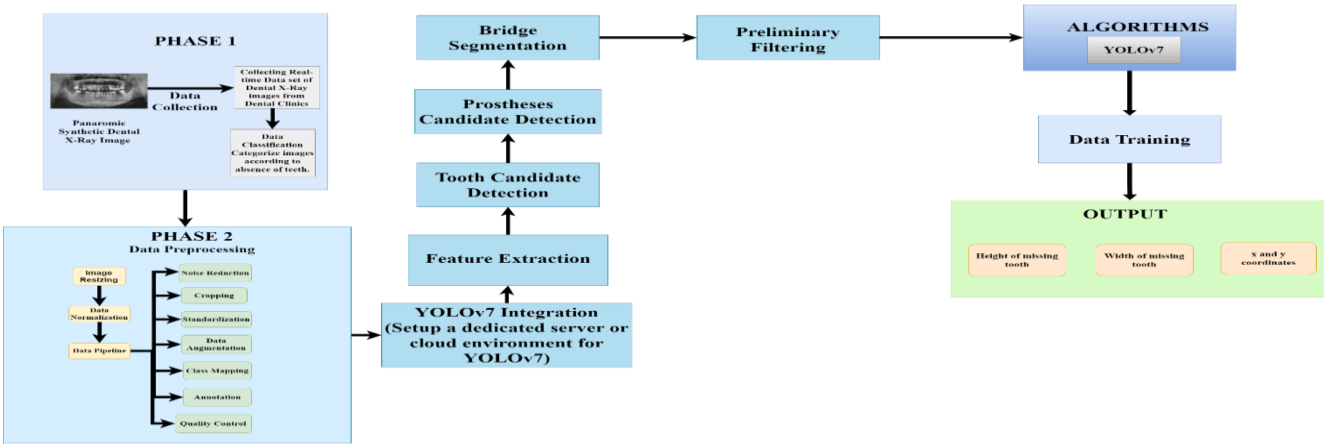

Fig 2. System Architecture

Sevda Kurt Bayrakdar's AI system, despite variations in accuracy for bone measurements, exhibited strong performance in identifying missing tooth regions and showcased the potential for automating certain dental assessments.[9] Mafawez T. Alharbi explored ensemble learning methods for predicting dental implants, with AdaBoost achieving the highest accuracy at 91.7%. These results suggest that ensemble learning can enhance the predictive capabilities of dental implant analysis models.[7] Dong-Woon Lee's research emphasized the robust performance of deep convolutional neural networks, particularly an automated DCNN, in detecting and classifying fractured dental implants, underlining the potential for automating diagnostics in dental implant evaluation.[10]

In addition, Shintaro Sukegawa's work highlighted the importance of network depth and introduced residual learning to enhance image discrimination accuracy, contributing to more precise dental implant analysis.[11] Chunan Zhang's study combined periapical and panoramic images in a hybrid model, achieving remarkable diagnostic accuracies and demonstrating the effectiveness of a combined approach in predicting implant outcomes.[12] Jae-Hong Lee's research showcased the substantial improvement in dental implant system classification accuracy with the incorporation of a deep learning algorithm, offering valuable support to dental professionals in implant classification.[13] Mostafa Sabzekar's study addressed the challenge of imbalanced data in predicting implant success, introducing an ensemble approach with genetic algorithm optimization, which significantly improved key performance metrics when compared to single classifiers. These collective efforts underscore the transformative potential of artificial intelligence in advancing dental implant analysis and classification across various aspects of the field.[14]

3. System Architecture

The proposed system is structured into three main phases. Real-time data is collected in the first stage from different dental clinics. The precise location of the missing teeth in each patient's mouth is then used to categorise this data.

Data pre-processing, which takes place in the second phase,

includes a number of tasks like resizing images, normalising data, minimising noise, cropping images, standardising the format, augmenting the data, classifying images based on dental abnormalities, adding annotations and making sure quality control procedures are followed.

The next stage involves setting up a specific environment for using the deep learning model YOLOv7. This setting is used to extract features from panoramic dental X-rays and identify possible tooth candidates. For accurate detection, each of the 32 different types of teeth is handled as an individual object. An additional detector is added especially for prosthesis candidates to improve detection performance for full dental restorations. Bridge identification, which entails identifying the denture portions as well as the supporting teeth, is also included in this detection process.

Following this, a YOLOv7 model is established, and the data is trained using this model. The desired output from this phase includes the dimensions of the missing tooth (height and width),

the tooth number and the X and Y coordinates, providing detailed information about the missing tooth's location.

4. Implementation

In the practical implementation phase of our research, we harnessed a dataset comprising nearly 4,000 dental radiographic scans as a foundational resource. To equip these scans with the necessary information for our deep learning project, we opted for the versatile and highly capable data annotation tool known as MakeSense.ai. This tool boasts an array of features, each of which is tailored to facilitate different aspects of the data labelling process.

For our research, MakeSense.ai was instrumental in creating precise bounding box annotations on dental radiographic scans. These annotations served a dual purpose: firstly, they identified the exact cavity for dental implant placement with precision and secondly, they extended to include the surrounding area, encompassing the gums and adjacent teeth. The annotated dataset is of paramount importance as it forms the foundation for training our deep learning models. These models will be able to automatically analyse dental radiographs, making dental implant planning more efficient and accurate.

In YOLOv7, the layers consist of:

- Backbone Network: YOLOv7 utilizes a backbone network, such as CSPDarknet53, to extract features from input images.
- Feature Pyramid Network (FPN): Some versions of YOLOv7 incorporate FPN, which captures features at different scales to aid in detecting objects of various sizes.
- Detection Head: The detection head comprises a series of convolutional layers that analyse the extracted features and produce predictions for bounding box coordinates, objectness scores and class labels.
- Anchor Boxes: YOLOv7 makes use of anchor boxes to fine-tune predictions, accounting for variations in aspect ratios and scales in the data. This data was provided using the MakeSense.ai tool.
- Loss Function: YOLOv7 employs various loss functions, including those for localization, objectness and classification, to guide model training and enhance prediction accuracy.

Data processing in YOLOv7 involves:

- Data Preprocessing: Before inputting data into YOLOv7, it's crucial to preprocess it. This typically includes standardizing image sizes, normalizing pixel values and structuring annotations to include the coordinates of the missing tooth.
- Training and Testing: The 60-40 train-test split implies that 60% of the dataset is used for training the model, allowing YOLOv7 to learn to predict the missing tooth's coordinates. The remaining 40% is reserved for testing, where the model's performance and accuracy are assessed.

Crucially, we have adjusted YOLOv7's output layer structure to regress length and width measurements alongside its regular predictions for object detection. This structural modification equips the model with the capability to directly predict these essential dental implant dimensions.

To train the model effectively, we've adapted the loss function to account for errors in these new measurements. This ensures that the model is penalized for inaccuracies, promoting precise length and width predictions. An accurately annotated dataset, which incorporates correct measurements for dental implant length and width, is paramount in this process, serving as the foundation for training the model to achieve accuracy. Following model training, post-processing may be necessary to extract the predicted length and width dimensions from the model's output.

In addition to dental implant length and width measurements, our YOLOv7 model also yields valuable information regarding the implant's location. Specifically, it categorizes implants into different types, including endosteal, subperiosteal, zygomatic and transosteal. This classification is a crucial component of our research, as it assists in specifying the exact placement and type of dental implant needed in a patient's oral cavity. Our deep learning model excels in not only measuring the dimensions but also providing comprehensive information about implant location, contributing to the precision and accuracy of dental implant planning.

5. Results

In this section, we present the results of our dental implant research using YOLOv7. The objective of our study was to detect and analyze dental implant positions using YOLOv7 object detection.

5.1. Accuracy and Confidence

Our model achieved an overall accuracy of approximately 89% when evaluating dental implant positions. The accuracy metric is calculated as:

Accuracy = (True Positives + True Negatives) / (True Positives + True Negatives + False Positives + False Negatives)

5.2. Recall and Precision

When we set a confidence threshold of 0.895, the recall of our model was 0.61, and the precision was 1. These metrics are calculated as follows:

Recall = True Positives / (True Positives + False Negatives)

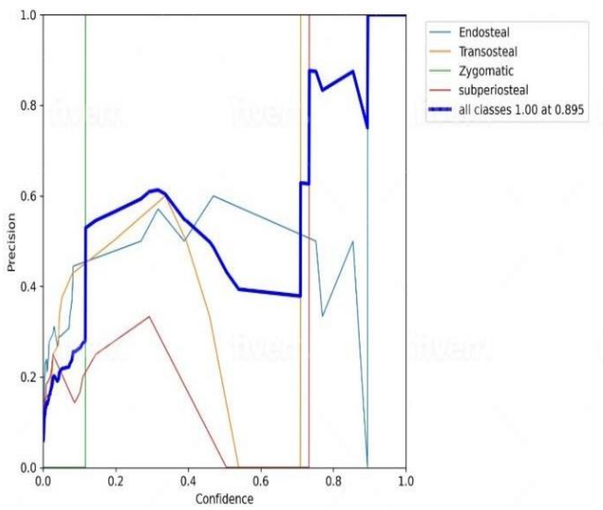

Fig 3. Recall vs Confidence for the 4 types of implants

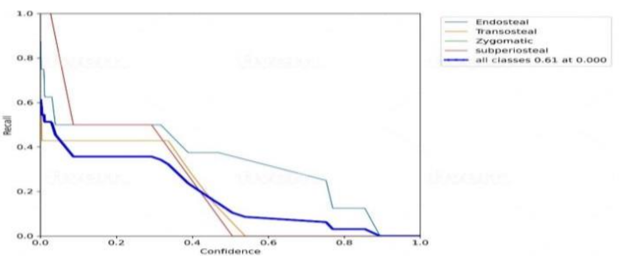

Fig 4. Precision vs Confidence for the 4 types of implants

Precision = True Positives / (True Positives + False Positives)

5.3. F1-Score

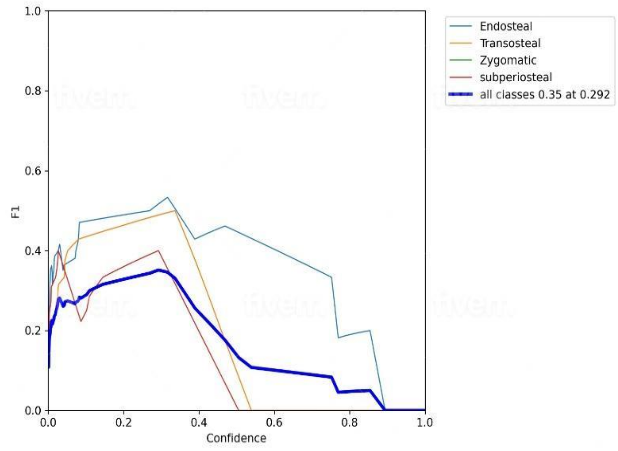

Fig 5. F1 vs Confidence for the 4 types of implants

At a confidence threshold of 0.292, our model achieved an F1-Score of 0.35. The F1-Score is calculated as:

*F1-Score = 2 * (Precision * Recall) / (Precision + Recall)*

5.4. Visualizations and Interpretation

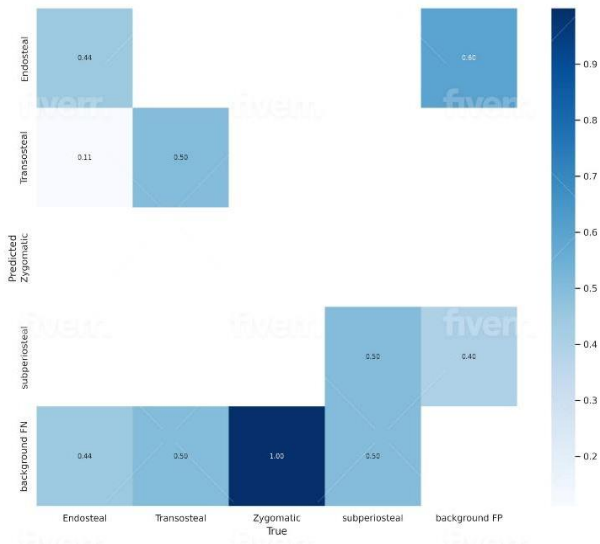

Fig 6. Heatmap

We have included visualizations to illustrate the performance of our YOLOv7 model in dental implant detection. These visualizations demonstrate the accuracy and precision of our model in locating dental implants within images.

The results indicate that high precision (Precision = 1) is achieved when a high confidence threshold is set (0.895). However, this comes at the cost of reduced recall (Recall = 0.61). Conversely, when the confidence threshold is lowered to 0.292, the F1-Score decreases to 0.35, reflecting the trade-off between precision and recall.

5.5. Comparison with Research Objectives

The obtained metrics align with our initial research objectives, showcasing the success of our YOLOv7 model in dental implant detection. These results have significant implications for the field of dental implant research by offering a powerful and accurate tool for implant localization.

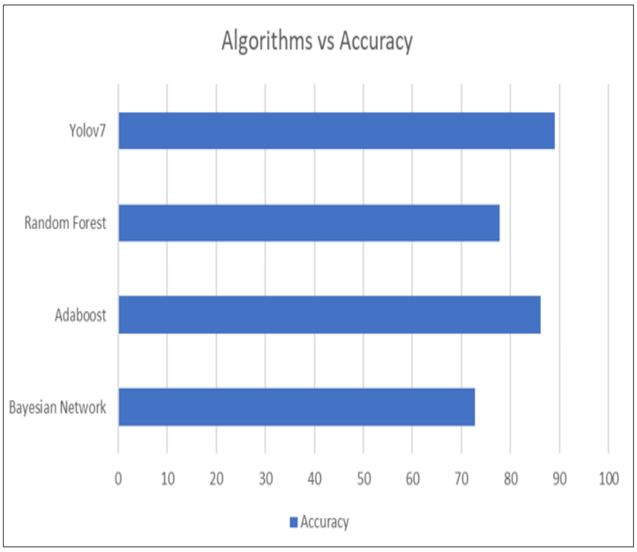

Fig 7. The performance of accuracy for different algorithms

6. Limitations and Future Research

While our findings show promise, it is crucial to recognize the constraints inherent in our study, including potential difficulties arising from diverse lighting conditions or variations in implant materials. Subsequent investigations could prioritize overcoming these limitations and advancing the YOLOv7 model's efficacy in dental implant detection. Despite the encouraging outcomes observed, it is imperative to underscore the study's limitations, notably the potential challenges posed by fluctuating lighting conditions and diverse implant materials. Subsequent research endeavors may concentrate on mitigating these constraints, aiming to enhance and refine the YOLOv7 model's capabilities in detecting dental implants.

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