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# Orthodontic Malocclusion Detection on Clinical Images using Ml Techniques

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**Abstract:** Teeth are an important part of the human system. Malocclusion is the second most frequent oral disease following dental caries and periodontal disease. Malocclusion or misalignment of the teeth, is a common dental condition, this is caused by the shape of jaws or birth defects and other kinds of childhood habits. In this project, we developed a deep learning algorithm to automatically detect malocclusion in dental clinical images. Our algorithm was trained on a dataset of labeled image and achieved high accuracy in identifying malocclusion in a variety of intraoral photographs. Our algorithm is trained to work on a large dataset and achieve high accuracy in classifying images. In Dentistry, deep learning techniques have been used for automatic cephalometric landmark detection and teeth segmentation in a panoramic X-ray. Previous papers have used datasets where images are not very high quality. Hence we have used YOLO V5 to improve the picture quality and also improve the time consumed saving time. The past algorithms put constraints on the amount of dataset, whereas we implemented an algorithm such that it does not restrict dataset limits. Our project has succeeded in providing results that is efficient from other models by approximately 1%. The widespread use of intraoral photos as an analytical tool for malocclusion facilitates communication between different dental specialties for the assessment of patient treatment needs. This approach has the potential to improve the time efficiency in dentistry.

## I. Introduction

The main aim of our algorithm is to train the system to identify the datasets that are given as input. The result of this training process is to deliver an efficient and well-developed model that can classify malocclusion of teeth. We take the leverage of deep learning to train the system for classifying. The consistency in our algorithm is bought by its high accuracy in classifying images. The main task of the system is to distinguish types of malocclusion patterns. This produces significant advancement in the field of dentistry. This can replace traditional diagnostic methods of examining teeth which may be time-consuming and inefficient. [5] Deep Learning methods have already proved successful over the years in various fields, so this technique can be seen as a story of success in the field of dentistry, as seen previously in automatic cephalometric landmark detection and teeth segmentation in panoramic X-rays [7] . Our project has built up flexible boundaries that can be pushed for what can be achieved by these advanced technologies. The new advanced equipment to capture intraoral photos which is used as a screening tool is an important aspect of our method. This method also provides an added benefit of communication in different specialties in dentistry. This technique also improves the assessment and treatment of patients, by reducing the time consumed. In hindsight, our deep learning algorithm provides an optimistic road toward improving time and diagnostic accuracy in the field of dentistry. By combining current advanced technologies we aim to harness the outcomes and develop the realm of malocclusion detection using artificial intelligence. We aspire to revolutionize how dental professionals approach and address this prevalent oral health concern.

## II. Literature Review

A comprehensive survey of literature has disclosed that the automatic identification of teeth malocclusion is carried out broadly by machine learning and deep learning-based methos. The following sections present a review of recent literature on the topic Zhi Li et.al [6] Previous epidemiological studies on malocclusion among global populations have primarily focused on dental factors. However, this cross-sectional study delved into the prevalence of malocclusion among Inuit (Eskimo) youth, aged 5-22 years, residing in Labrador, Canada. Moreover, 63% of parents appeared to recognize their child's occlusal issues, with 70% expressing a willingness for their children to undergo orthodontic treatment if necessary. The prevalence and awareness of malocclusion demonstrated a positive correlation. The study indicated a clear need for orthodontic intervention and however there was lack of machinery and other requirements. Therefore we make sure the availability of each machinery and required tools. Mircea Paul Muresan et.al,[7] Deep convolutional neural networks (CNNs) have become increasingly popular in medical research as of their remarkable performance in detection, prediction, and classification tasks.. According to this study, we here by proceed towards automatic teeth detection and classification of dental problems using panoramic X-ray images, aiming to support medical staff in making accurate diagnoses. We collected panoramic radiographs from three dental clinics and annotated them, highlighting 14 different dental issues. This model lacks in identification of teeth in the buccal cavity and hence leads to poor visibility. That being the case we try to convert the poor quality image into a good quality by using digital image processing techniques. Atif Emre Yuksel et al,[8] The paper introduces a fresh deep learning framework called "DENTECT," designed to promptly identify five distinct dental treatment modalities and simultaneously assign numbers to teeth based on the FDI notation in panoramic X-ray images. DENTECT represents the first system focusing on the identification of multiple dental treatments, including periapical lesion therapy, fillings, root canal treatment (RCT), surgical extraction, and conventional extraction. The framework achieves an average precision (AP) score of 89.4% for enumeration and 59.0% for treatment identification. Although this model shows a better precision rate we make a severe effort on increasing the rate of teeth identification. Mai Thi Giang Thanh et al,[9] ,The article outlines the development and evaluation various techniques like dep learning and convolution neural networks for classifying orthodontic clinical photos based on their orientations. This classification is a crucial step in dental section and medication planning, especially considering the varied facial and dental situations encountered in different approach. This development of a fully automated orthodontic diagnostic system in the future, potentially help in streamlining and enhancing the efficiency of orthodontic practices. However the model fails to identify the images on different orientation, whereas we recognize each orientation. Jiho Ryu et.al, [10] The study aimed to upright the productiveness of a deep learning system, employing CNNs, for automatically detecting caries on bitewing radiographs. A dataset of 2468 bitewings was annotated by three dentists to establish a reference standard, with 1257 images labelled as having caries and 1211 as sound . The caries detection module achieved impressive results.. The metrics indicate the system's effectiveness in accurately identifying caries lesions on bitewing radiographs, suggesting its potential utility as a tool to assist dental professionals in diagnostic tasks. This model mainly focuses on bitewings with fewer dataset. However we focus on every aspect of the oral with a larger dataset. Tae Seen Kang et.al, [11] The study aimed to scrutinize whether convolutional neural networks (CNNs) could discriminate between optical coherence tomography (OCT) images detects qualitative and quantitative morphological changes of dental hard and soft tissues.Overall, while CNNs showed promising discriminatory ability in distinguishing between right and left OCT images, particularly in horizontal orientation, careful consideration is warranted when preprocessing or manipulating image data to avoid introducing biases that may affect the performance of machine learning models. However, CNNs exhibited lower accuracy in discriminating right horizontal images compared to left horizontal images. Hence we try get accuracy of each dimensions of the image captured. Duc Long Duong et.al, [12] Optical coherence tomography (OCT) is a valuable imaging modality that offers high-resolution cross- sectional and three-dimensional images of living tissue, particularly useful for examining caries. However, fundus images can be influenced by factors like camera lens, flash, and lighting conditions. Since OCT is unaffected by these factors, the study aims to assess the asymmetry between right and left eyes using high-resolution OCT images with CNN models. Therefore before being affect by the external factors we capture the images by highly qualified lens and lighting conditions. Fatemeh Rashidi Ranjbar & Azadeh Zamanifar, [13] This pilot study aimed to utilize deep learning, specifically the YOLOv7 model, for diagnosing damaged teeth and proposing treatment plans based on panoramic dental x-ray images. A dataset comprising 1025 panoramic images of patients over the age 14 were accompanied for training and testing the model. This study highlights the promising practice for deep machine learning in dentistry, particularly in diagnosing dental diseases and planning treatments. The explains only about diagnosing only for age group of 14 and hence the result would not be same for every age group. Hence we try a huge dataset along every orientation of the teeth. Dc Shubhangi et.al [14] The study aimed to develop an automated tooth detection and dental condition categorization system by the use deep learning convolutional neural networks (CNNs) applied to panoramic dental radiographs. An annotated dataset was utilized upskill the CNN and obtain semantic segmentation data. The outcomes of the study demonstrated the superiority of the proposed solution compared to other approaches, showcasing its effectiveness in tasks such as tooth categorization, identification of illnesses, and severe gum diseases like periodontitis. By automizing the identification of tooth and other various dental condition in making more accurate diagnosis decisions. However the model fails give the correct percentage of illnesses in number ,whereas we give accurate percentage. Elias Oeschger et.al,[15] The study you've described investigates the interconnection among tooth agenesis and craniofacial size in modern humans. This paper focuses whether individuals with tooth agenesis exhibit differences in craniofacial size compared to those without. Facial centroid size, a measure of overall facial size, was assessed in participants with different numbers of missing teeth. Overall, this study contributes to our understanding of how inherent detailed both tooth development and facial morphology in modern humans, shedding light on the complex interplay between evolution and development in shaping the human head. Mohamed Estai et.al [16] The study described focuses on evaluating a machine learning system, notable use convolutional neural networks (CNNs), for automatically identifying caries on bitewing radiographs. The Faster region-based CNN was employed to identify regions of interest (ROIs) potentially containing lesions. These results suggest that the deep learning practice, especially using CNNs, holds potential for automating the detection of caries in dental radiographs, which could aid in early diagnosis and treatment planning. The research examines only on bitewing radiographs only with fewer dataset were only 10% of them were used for validation.

Now days more 15% of people suffer from abnormal of teeth , due to this predicament it is hard for people to smile openly as they will be in shade of consciousness of abnormal teeth. People also more likely to pay more attention to towards oral health as it is associated with body well being. Due to this, demand for the dental resources have also increased. In dentistry, reinforcement learning procedures are used for automatic identification of tissues and teeth segmentation in a panoramic X-ray. The literature lacks enough supportive information on accuracy of automated tools in detecting malocclusion and assessing treatment needs from photos or other diagnostic images. Therefore our model is designed to over come this problem by using machine learning techniques. Our proposed system detects the malocclusion in teeth from the photos or other diagnostic images with high accuracy and efficiency.

The key contribution of our project focuses on dealing with instantaneous sources. And our project model uprises with collection of various kinds of features. The main difference in this project is that, the angle of rotated teeth, spacing between teeth are measured and display on the teeth which is defected. Our project will identify multiple type of defect in single image if present. We are collection variety kind of datasets and real time images so we can check our models consistency for all kind of images. Our project is also working of high processing time so that the model doesn't take longer time in noticing and gives the accurate result.

## III. Methodology

The convolutional neural network has shown to be very effective in image processing and feature extraction, which makes it an ideal tool for diagnosing abnormalities in teeth. Additionally, it can handle a large amount of data, and the convolution section of the proposed method simplifies the feature extraction process. This study aims to create a model that takes an image as input and determine if there are any defect in the teeth . Figure 1 illustrate the proposed algorithm's flow and operation.

### A. Proposed System

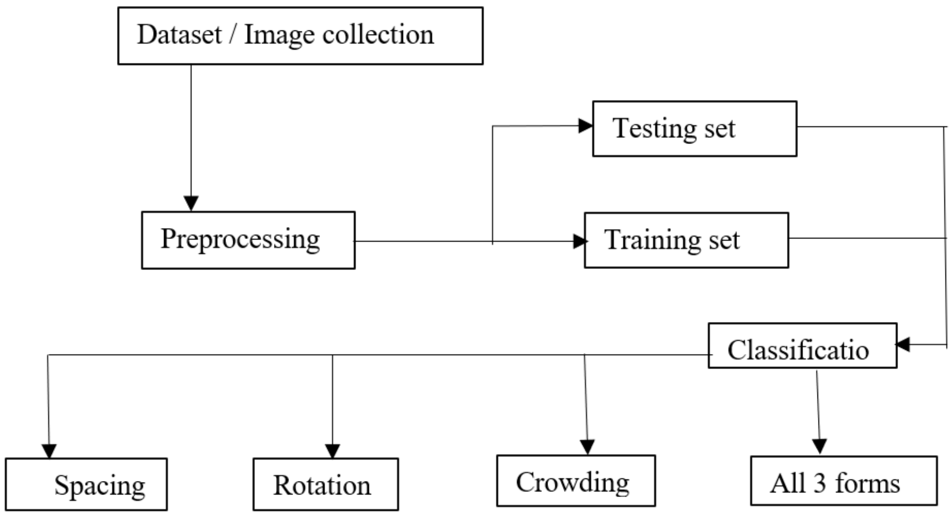



Figure 1 Architecture of Proposed system

Figure 1, Initially images or datasets will be collected. Datasets can be from real world from clinical images or image acquired from Kaggle. These images or datasets is sent to next step that preprocessing, which contains image resizing, augmentation, feature extraction, image loading. Predicted output after applying algorithm to the dataset will be as shows in above picture. Machine is capable to identify crowding ,rotation, spacing and all 3 forms. It also able to give the angle of rotation, length of spacing and crowding percentage. Model contains algorithms to process the data. CNN are more effective than other techniques at handling enormous datasets and challenging tasks. Due to their resistance to changes in object positions, CNNs are very good at tasks like object localization and detection. CNN is end to end learning, where the model gains knowledge directly from the input data. CNN can recognize complicated patterns and connections.

### B. Data Preprocessing

1) **Data Resizing:** The input images are normalized in various ways before feeding it to convolution neural networks. Data resizing is recommended stage of pre-processing. The technique equalizes all of the images in the datasets and transforms the image size of the fit the model developed. The data resizing would minimize the memory to be used when the images are loaded into the training stage.
2) **Data Augmentation:** Image augmentation is the method to expand the training dataset by implementing various transformations to the existing images. This strategy aids in the model's performance enhancement capability and reduces overfitting issues. Image augmentation aims to introduce variability and diversity in a training datasets, which helps to improve the model's generalization ability. Some of the popular augmentation techniques includes random rotations, flips, translations, and alteration in the brightness or contrast. Augmentation helps in preventing overfitting and improves the model's.
3) **Feature Extraction:** Extract meaningful features from the images using techniques such as edge detection, colour histogram, or deep learning-based feature extraction methods. This step is crucial for capturing relevant information and reducing the dimensionality of the data.

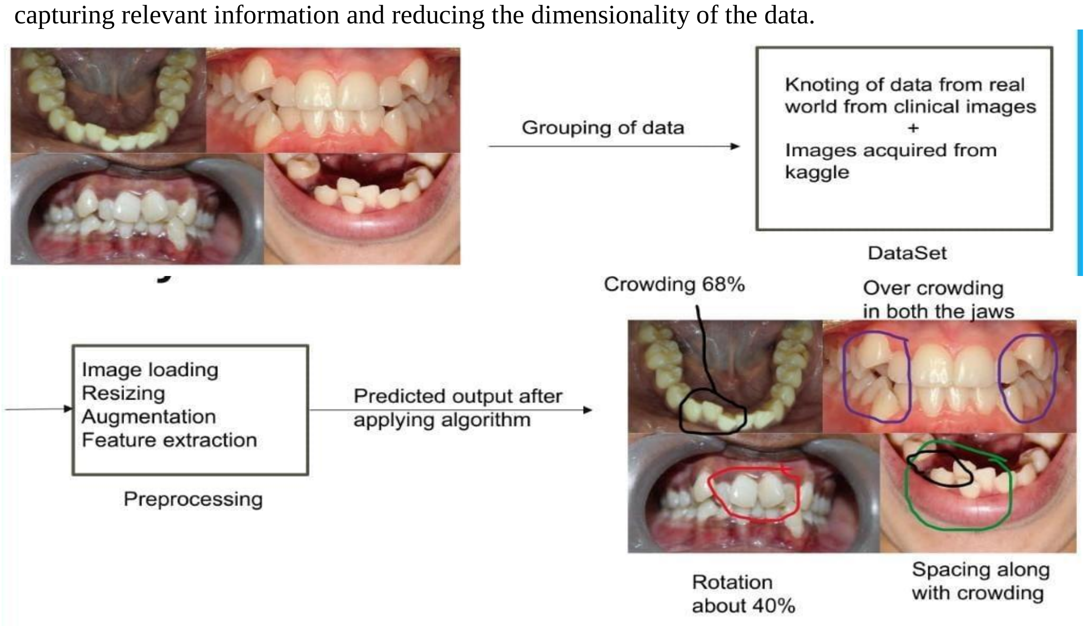



Figure 2: Steps used in our model

Figure 2 shows the steps used in our model. The initial step is the collection of dataset and grouping them. Next the images are sent to the pre-processing steps, which contain resizing, augmentation, and feature extraction . Once the pre-processing step is done, algorithm is applied to get the required output.

### C. YOLO Architecture

The model that was selected to be used for this research study was the "You Only Look Once" model figure 3. This model can identify and localize multiple objects or multiple instances of the same object within an each image. This object detector uses features learned by a deep convolutional neural network to detect objects. It is an entirely convolutional deep neural network, 24 convolutional layers followed by 2 fully connected layers. Alternating 1 x 1 convolutional layers decreases the features of space from preceding layers.

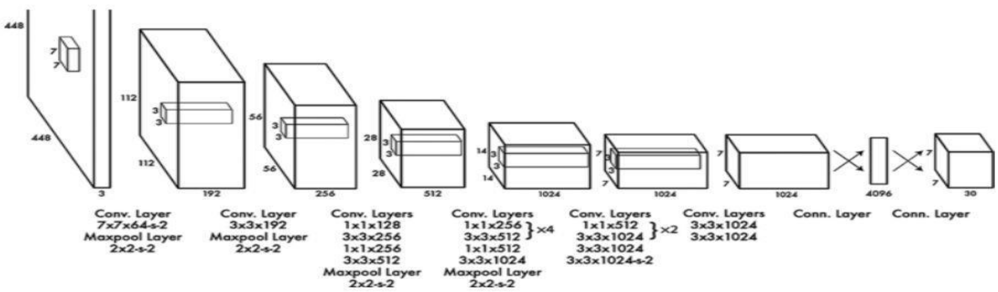



Figure 3: YOLO Architecture

YOLO algorithm takes input as image and it employs a deep convolution neural network to detect the objects in the image. The object detection and localization model divides each of the images into an S x S grid. If the center of an object falls into a grid cell, that grid cell is responsible for discovering that object. Each grid cell detects multiple bonding boxes around the object of interest, each box with its relative confidence number. YOLO forecasts multiple bounding boxes pre grid cell.

## IV. Results and Discussions

### A. Data Set Collection

The main datasets contains 800 intraoral images for each norms of images from patients taken from different angles including Occlusion of left, Occlusion of right, Occlusion of font, Occlusal of upper part, and Occlusal of lower part. These images are clinical patient images. These will be provided by 'The Oxford Dental College" The dataset is at the heart of deep learning research. In this research, we used the real time clinical images for training and validation of the proposed model. Teeth dataset is obtained mainly obtained from clinics and obtained publicly available 'Kaggle' dataset. Some glimpse of dataset images is shown in figure 4.


Normal teeth Rotation Spacing Crowding

Figure 4: Sample teeth images from dataset

### B. Evaluation Parameter

Machine learning performance requires assessment using various evaluation metrics. These metrics gauge the model's predictions across legitimate and phishing classes, encompassing carious machine learning parameters like accuracy of our model , precision of our model, rate of our model, recall of our model, specificity of our model , and F1-score of our model. Accuracy quantifies the model's correctness in making predictions, as indicated by Equation.

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

Precision, a critical evaluation metric, assesses a classifier's accuracy in predicting the positive class. It quantifies how quickly classifier correctly identifies positive instances, particularly relevant in distinguishing phishing URLs. The productivity of various classifiers is notable by determining precision.

$$Precision = \frac{TP}{(TP+FP)}$$

The metrices for different classification models measures how accurately the model identifies positive labels. It assesses the classifier's ability to correctly identify both phishing and legitimate URLs.

$$Recall = \frac{TP}{(TP+FN)}$$

Using the algorithm and the Convolutional Neural Network Model we would be able to build a system that gives a correct output based on the image that is given to the system and classify the image on correct norm that may be crowded, spacing and rotation. The technique used , that is deep convolutional neural networks is used to identify and accurately target dental malocclusion from locally sourced clinical images . The engine will be capable of detecting and localizing malocclusion from locally sourced clinical images accurately. Our prior domain knowledge ,especially regarding teeth malocclusion detection rules and guidelines played an important role in promoting the teeth accuracies, with an increase in the precision and recall. Finally, the performances of our proposed system will be very convenient for all the dentist who use clinical images to detect Orthodontic malocclusion. Upon analysing various datasets and many other clinical observation we able to identified the defect in the teeth and an accurate, Fig 5 results can be given from the doctors and best treatment can be given to the defected people. This consumes less time comparatively and helps the dentist to make time for other clinical procedures.

### C. Result Comparison

Table 1: Comparison of other methods

| Sl No. | Method | Accuracy | Precision | Recall |
|---|---|---|---|---|
| 1. | YOLO v3 | 57.82% | 58.32% | 56.78% |
| 2. | CNN | 61.56% | 62.22% | 60.77% |
| 3. | Deep Learning and image processing | 49.74% | 50.58% | 49.83% |
| 4. | YOLO v5 (our) | 62.74% | 61.27% | 61.78% |

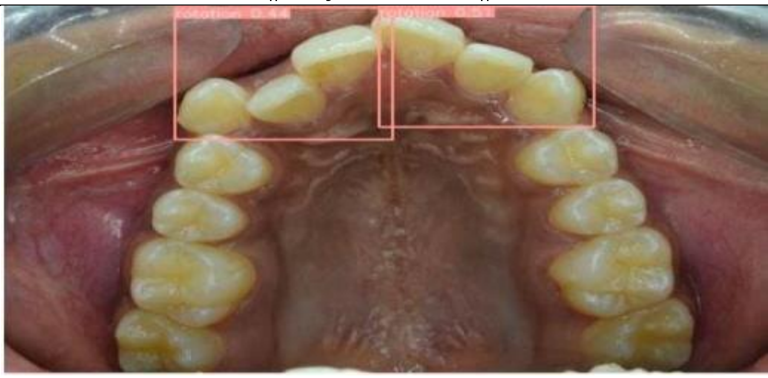
Table 1 shows the comparison of accuracy and other parameters with other different methods. The first method uses YOLO v3 for there model, It shows that its getting accuracy 57.82% because YOLO v3 struggle to detect smaller objects due to its anchor box designed and high memory is required. In second method CNN method is used , we can see the accuracy is more than the first method because CNN is good at recognizing small objects clearly. Third method uses Deep learning technique, it shows low accuracy as it can't give correct result if image quality is low or not clear. The fourth method is our method , we use YOLO v5 which has better performance than other methods. YOLO v5 is best at object detection network in the literature, considering both inference time and detection accuracy. It shows 62.74% accuracy as shows in the above table.

Table 2: Result of our method

| Sl No | Input | Output | Classification |
|---|---|---|---|
| **1** |  |  | Multiple Rotation(0.39 and 0.37) |
| **2** |  |  | Crowding (0.57 and 0.42) and rotation (0.47 and 0.47) |
| **3** |  |  | Crowding (0.65) |

The table 2 shows the results obtained from our method. It shows the input given and output obtained images. In output, the malocclusion of teeth region is detected and classifies the defect of the teeth with the value.


**(a)**



**(b)**


**(c)**

Figure 5: Result of the proposed model

Figure 5 shows the result of our project a) displays the teeth having multiple spacing problem in single teeth b) shows the teeth having multiple rotation defect c) image shows single crowding problem in the teeth. We can observe that our model can identify same and different categories of multiple defect in single teeth.

## V. Conclusion

A critical aspect has been taking time to analyse the teeth and then take the right action to correct the malocclusions that are present. We built a model that will detect the spacing, crowding and rotations in the teeth so that it will help the doctors to directly analyse the required action to be taken for the malocclusion. This model helps to reduce the time spent on the patients to check for the malocclusion and helps to take further treatment that is needed. This model has overall accuracy of 62.74%.This model is very convenient in terms of time. the model is consistently good in quality and performance and be surely trusted. It is capable of identifying and pin out the alignment of the teeth .and is able to detect and categorize the clinical images based on different types like spacing, crowding, and rotation.

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