



# Reliability of Artificial Intelligence Using Cone Beam Computed Tomography (CBCT) Images in Maxillofacial Region – A Systematic Review and Meta Analysis

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## KEYWORDS

Artificial  
Intelligence,  
Cone beam  
Computed  
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## ABSTRACT:

**BACKGROUND:** Artificial Intelligence (AI) has the ability to process huge datasets, disclose human essence computationally, and perform like humans as technology advances. The applications of machine learning and artificial intelligence has become popular within the last decade.

**AIM:** The present study aimed to investigate the performance of AI using cone-beam computed tomography (CBCT) images

**MATERIALS AND METHOD:** Studies using application of Cone beam computed tomography to develop or implement AI models were sought by searching electronic databases including PubMed, Google scholar, Scopus in the field of Dental and maxillofacial Radiology. The customized assessment criteria based on PRISMA guidelines and COCHRANE assessment tool were adapted for quality analysis of the studies included.

**RESULT:** All the studies were methodologically acceptable with low risk of bias due to two step selection process. Most studies focused on AI applications for an automated localization of cephalometric landmarks, classification/segmentation of maxillofacial cysts and/or tumors, and identification of periodontitis/periapical disease. The performance of AI models varies among different algorithms.

**CONCLUSION:** The application of AI for detection and segmentation using CBCT images is comparable to services offered by trained dentists and can potentially expedite and enhance the interpretive process. Implementing AI into clinical dentistry can analyse a large number of CBCT studies and flag the ones with significant findings, thus increasing efficiency.

## INTRODUCTION:

Artificial intelligence (AI), first coined by John Mc Carthy, defined as the capability of a machine to imitate

intelligent human behaviour to perform complex tasks, such as problem solving, object and word recognition, and decision-making<sup>(1,2)</sup>. Many AI models are being developed for automatic disease risk prediction,



abnormality/pathology detection, diagnosis of disease and prognosis evaluation in the field of clinical medicine (3,4,5). Recent advances in artificial intelligence (AI) and state of art neural networks have been used for various applications that include speech, vision, robotics, natural language processing, and machine learning to name a few. A popular subset of machine learning in diagnostic imaging is called deep learning. Deep learning artificial intelligence (AI) systems, also referred to as deep neural networks, are capable of learning by extracting features from training data and interpreting test data, without explicit instructions.

Convolutional neural networks are a deep learning architecture used for large and complex images such as cone-beam computed tomography (CBCT) and magnetic resonance imaging (6). Periapical, bitewing, panoramic, and lateral cephalometric conventional radiographs are used in conjunction with CBCT images in the field of Oral and Maxillofacial Radiology (OMR) to detect dental caries, periapical and periodontal disease, root fractures, osteoporosis, cysts, and tumors of the jaws (7). Furthermore, incorporating AI into the process saves a tonne of time and physical labor (8). This study offers a promising contribution in demonstrating that AI systems offer high accuracy and excellent reliability (9). Therefore, this metaanalysis was undertaken to investigate the performance of AI using cone-beam computed tomography (CBCT) images.

## METHODOLOGY:

The current study was conducted according to the preferred reporting items for systematic review and meta-analysis (PRISMA) guidelines.

Data sources and search strategy:

This systematic review employed a comprehensive data search methodology, primarily conducted through electronic searches across reputable databases, including PubMed, Google Scholar, Scopus, and Web of Science. Additionally, manual searches were conducted for articles published between 2000 and 2023. The search utilized Mesh terms such as "Artificial Intelligence," "Machine learning," "Deep learning," "CBCT" (Cone beam computed tomography), "Neural network," and "Dentistry" to identify relevant articles. Boolean

operators (AND, OR) and language filters for English were employed in the electronic database searches.

Systematic review was adopted to follow the PICO criteria (Table 1)

Table 1 - Description of the PICO (P = Population, I = Intervention, C = Comparison, O = Outcome) elements

Research question	What will be the diagnostic performance of artificial intelligence using CBCT images?
Population	CBCT images obtained from human subjects in the dental and maxillofacial region
Intervention	Diagnostic model based on AI algorithms
Comparison	Reference standard, such as expert's judgment, clinical/pathological examination, etc;
Outcome	Diagnostic performance of the proposed AI model

## STUDY SELECTION

The electronic database search yielded total of 658 articles. Then, 285 articles retrieved after reading the title and after this, 133 articles were screened by reading abstract. Finally retrieved articles (n=32) were assessed for eligibility criteria (Figure 1)

## SELECTION CRITERIA

The inclusion criteria were:

- (1) Articles within 2000 to 2023 were included
- (2) peer-reviewed full-text articles published in the English language
- (3) articles that evaluated AI systems using CBCT images of the head and neck of adult patients
- (4) articles that explored automatic detection or segmentation of anatomical landmarks or pathological lesions



The exclusion criteria were:

- (1) Animal studies
- (2) Review articles, letter to editors and case reports/ case series involving less than 10 cases
- (3) Full-text is not available or accessible

- (4) Articles that evaluated AI systems such as 2D IMAGES, OPG, CT, MICRO CT, MRI etc..

#### SELECTION PROCESS:

Figure 1 details the process of article review and selection. The Cochrane tool for assessing the risk of bias was used to evaluate the studies that were included in this meta-analysis (Table 2)

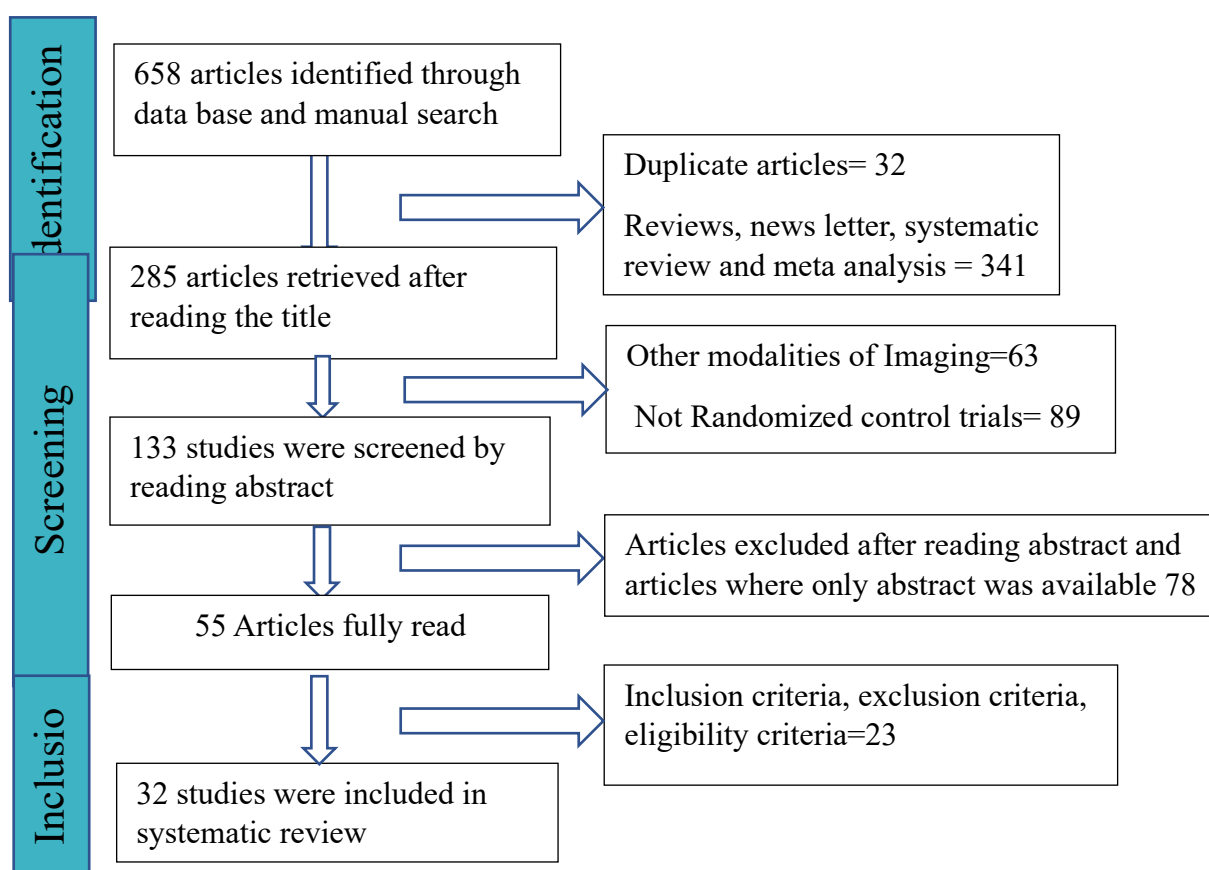


Figure 1: Study selection flowchart

AUTHOR YEAR	SELECTION BIAS	PERFORMANCE BIAS	DETECTION BIAS	REPORTING BIAS	OTHER BIAS
Setzer 2020	-	-	+	+	+
Orhan 2020	-	?	+	+	+



Lee 2020	-	-	+	+	+
Hagneadar 2018	?	-	+	+	+
Shankeeth Vinayagalingam 2018	?	-	+	+	+
Dumast 2018	-	-	+	+	+
Shoukri 2019	?	?	+	+	+
Gozde Eser 2023	-	-	+	+	+
Wang H 2021	-	-	+	+	+
Wang X 2021	-	-	+	+	+
Jaskari 2020	?	-	+	+	+
Leonardi 2020	-	-	+	+	+
Abdolali 2016	-	-	+	+	+
Shaheen 2021	?	?	+	+	+
Orhan 2020	-	?	+	+	+
Yuma Miki 2016	?	-	+	+	+
Benyo 2012	?	-	+	+	+
Arturo flores 2009	-	?	+	+	+
Fatemeh Abdolali 2016	-	-	+	+	+



Fatemeh Abdolali 2017	-	?	+	+	+
Neelapu 2018	-	-	+	+	+
Jesus montufar 2018	-	?	+	+	+
Jesus montufar 2018	-	?	+	+	+
Marina codari 2016	-	-	+	+	+
Abhishek Gupta 2016	-	?	+	+	+
Abhishek Gupta 2015	-	?	+	+	+
Erkang Cheng 2011	?	-	+	+	+
Shialeh Shahidi 2014	-	-	+	+	+

- High risk of bias      + Low risk of bias      ? Unclear risk of bias

Table 2: Cochrane Collaboration's tool for assessing the risk of bias (adapted from Higgins and Altman), omitting attrition bias due to the nature of AI studies

### DATA EXTRACTION (Table 3):

A data extraction tool was used to extract relevant information including total sample size, training sample, validation sample, testing sample, type of AI model, purpose, benchmarking to experts, preparation of images and reported performance measure.

With regard to the applications of these AI models, eight (10-17) reported on localization/measurement of cephalometric landmarks, five (18-22) on classification/segmentation of maxillofacial cysts and/or tumours, two (23,24) on detection of periapical lesions, and six (25-30) on detection, diagnosis, classification,

segmentation and staging of TMD, three on classification and segmentation of jaws and teeth (32-34). Furthermore, single study was found for the age estimation (31), Segmentation of nasal cavity and pharyngeal airway (35), Segmentation of mandibular canal (36,37), Identification of root canals (38), Detection of third molars (39), Detection of odontoid process of epitropheus (40), To quantify 3D asymmetry of maxilla in cleft patients (41)

### STUDY QUALITY ASSESSMENT (Table 2):

A risk of bias assessment tool, specific to diagnostic and prediction models in AI research, does not exist. Assessing the risk of bias in studies that evaluate the



performance of AI is somewhat ambiguous owing to the novelty of these studies. Nevertheless, we used the Cochrane tool to assess the risk of bias and evaluate the studies included in this meta-analysis which revealed moderate certainty of evidence. With regard to the selection of reference standard, most studies were considered as having a “low” risk of concern.

Table 3: Characteristics of the AI models proposed in the studies included

**RESULTS:**

Among 32 studies, 25 studies were included for meta-analysis due to heterogeneity of data in the remaining studies.

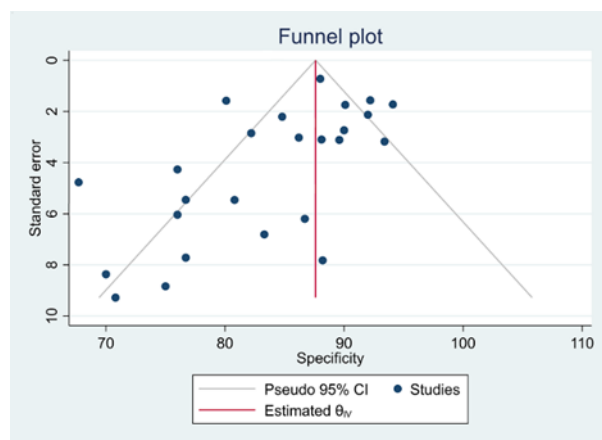


Figure 2: Funnel plot of sensitivity of the studies included for meta-analysis

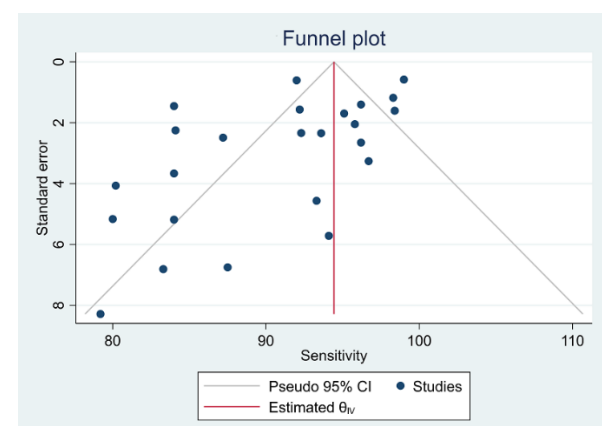


Figure 3: Funnel plot of specificity of the studies included for meta-analysis

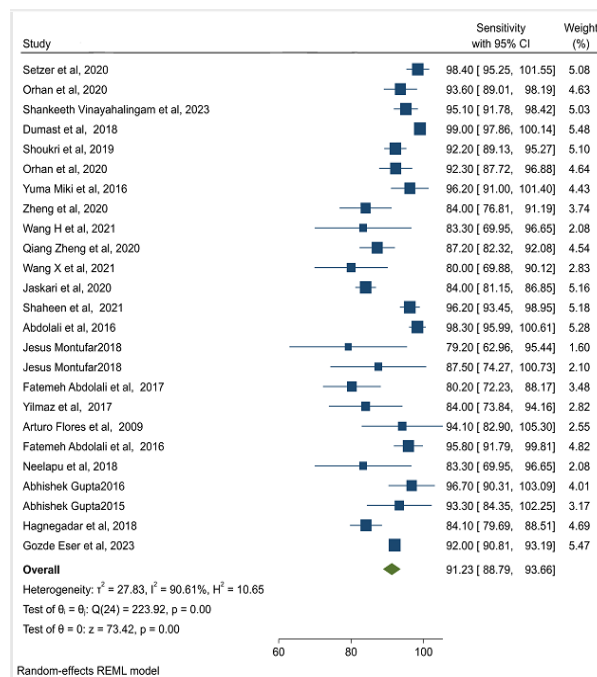


Figure 4: Forest plot of sensitivity of the studies included for meta-analysis

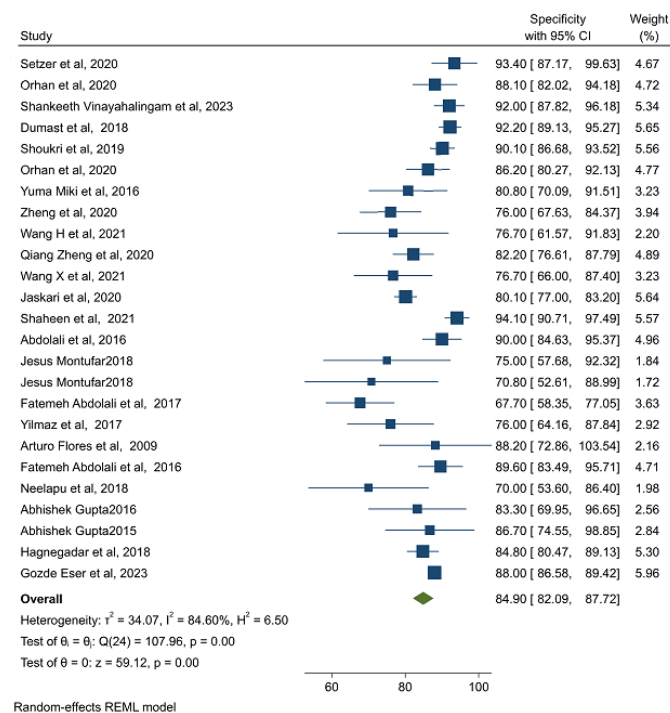


Figure 5: Forest plot of specificity of the studies included for meta-analysis



Forest plot demonstrates sensitivity and specificity of AI using CBCT was found to be 91% and 84%

## DISCUSSION:

The objective of this systematic review was to evaluate the performance of AI using CBCT images, which are 3D images commonly used for diagnostic purposes of the head and neck. The study aimed to pinpoint specific areas of interest where AI applications could be beneficial, employing DMFR methods and devices. The findings revealed a noteworthy rise in the quantity of studies utilizing clinical images within the dental and maxillofacial realm to construct AI models, particularly since the year 2006.

As the imaging techniques employed in Dental and Maxillofacial Radiology (DMFR) predominantly rely on X-rays, primarily utilized for assessing the condition of hard tissues, the majority of AI models proposed in related studies have focused on addressing clinical issues related to teeth and jaws. Initially, computer-aided programs for clinical diagnosis heavily relied on 2D images such as periapical, panoramic, and cephalometric radiographs. However, there has been a growing trend in recent studies to develop AI models based on Cone Beam Computed Tomography (CBCT) images, aiming to address a broader spectrum of clinical challenges.

As outlined in this review, there has been a consistent growth in the documentation of artificial intelligence (AI) techniques applied to various aspects of Dental and Maxillofacial Radiology (DMFR) for over a decade. The majority of these studies concentrate on four primary applications: the automatic localization of cephalometric landmarks, classification/segmentation of Temporomandibular Disorders (TMD), classification/segmentation of maxillofacial cysts and/or tumors, and the identification of periodontitis/periapical disease. Moreover, these studies failed to compare AI against an objective gold standard. The segmentation tasks included segmentation of pulp, teeth, jaws, maxillae in cleft patients, mandibular canal, sinonasal cavity, and pharyngeal airway.

The findings of this study agree with the results of numerous studies that examine the capabilities of AI for detection and segmentation. Hung et al. <sup>(42)</sup> investigated 50 studies that used AI for numerous clinical applications

in dental and maxillofacial radiology. From their analysis of photographs, 2D and 3D radiography, they concluded that the diagnostic performance of the AI models varies among different algorithms, although the authors were unable to conduct a meta-analysis due to the heterogeneity of the studies. In the current study, we pooled the results because our research question was more focused, and we demonstrated that AI performance was excellent across different algorithms for detection and segmentation.

A meta-analysis conducted in 2022 by FF Badr et al. <sup>(43)</sup> includes thirteen studies for review and analysis. The DICE index/DSC, precision, recall, and accuracy percentage are measured by the pooled performance, which is 0.85, 0.88, 0.93 and 0.83 for the included AI models. On the other hand, our analysis of 25 studies revealed that the sensitivity and specificity of AI models were, respectively, 91% and 84%.

## CONCLUSION:

With the potential to improve and expedite the interpretative process, the use of AI with CBCT images is similar to that of proficient dentists. AI can analyse a large number of studies and flag ones with significant findings, increasing clinical efficiency. Future studies can focus on the ability of AI to recognize connections between imaging and clinical findings that may be oblivious to us humans thus improving patient care. Although human brain is trained to perform to more complicated functions than a developed software, this AI is used for more accurate diagnosis, ease to clinician, reduces working time and early diagnosis and treatment planning for the patient.

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Conflicts of interest: There are no conflicts of interest

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