A Meta-Analysis of the Diagnosis of Condylar and Mandibular Fractures Based on 3-dimensional Imaging and Artificial Intelligence

Fan Wang, MSc,¶ Xuejiao Jia, MSc,† Zhao Meiling, BMed,‡ Fahmi Oscandar, drg, M.Kes, Sp.OF (K-OFK), PhD,§ Hadhrami Ab Ghani, BEng, MEng, PhD,|| Marzuki Omar, BDS, MSc(Clin)OMFS, MFDRCS, MBBS,¶ Su Li, MSc,# Li Sha, MSc,** Junping Zhen, PhD,† Yuan Yuan, MSc,†† Bin Zhao, MSc,‡‡ and Johari Yap Abdullah, BS & IT, GradDip ICT, MSc, PhD¶§§*

From the *Shanxi Medical University School and Hospital of Stomatology; †Department of CT, Faculty of Medicine, Shanxi Medical University Second Affiliated Hospital; ‡Department of Stomatology, Sinochem Second Construction Group Hospital, Taiyuan, China; §Department of Oral and Maxillofacial Radiology-Forensic Odontology, Faculty of Dentistry. Universitas Padjadjaran, Bandung, West Java, Indonesia; ||Faculty of Data Science and Computing, Universiti Malaysia Kelantan; ¶School of Dental Sciences, Health Campus, Universiti Sains Malaysia, Kota Bharu, Kelantan, Malaysia; #Department of Stomatology, Beijing Xuanwu Traditional Chinese Medicine Hospital, Beijing, China; **Department of Community Health, Advanced Medical & Dental Institute, Universiti Sains Malaysia, Pulau Pinang, Malaysia; ††School of Basic Medical Sciences, Shanxi Medical University; ‡‡Shanxi Medical University School and Hospital of Stomatology, Taiyuan, Shanxi, China; and §§Dental Research Unit, Center for Transdisciplinary Research (CFTR), Saveetha Institute of Medical and Technical Sciences, Saveetha Dental College, Saveetha University, Chennai, India.

Received February 12, 2025.
Accepted for publication May 18, 2025.

Address correspondence and reprint requests to Bin Zhao, School and Hospital of Stomatology, Shanxi Medical University, Taiyuan 030001, China; E-mail: sxmu0688@126.com; Johari Yap Abdullah, BS & IT, GradDip ICT, MSc, PhD, School of Dental Sciences, Health Campus, Universiti Sains Malaysia, Kota Bharu 16150, Kelantan, Malaysia and Dental Research Unit, Center for Transdisciplinary Research (CFTR), Saveetha Institute of Medical and Technical Sciences, Saveetha Dental College, Saveetha University, Chennai 602105, India; E-mail: johariyap@usm.my
F.W., X.J., and M.Z. contributed equally to this work.

Ethical approval was not required for this meta-analysis as it utilized publicly available data.

Informed consent was obtained from all individual participants included in the study.

All data generated or analyzed during this study are included in this published article [and its supplementary information files.

F.W.: contributed to conception, design, acquisition, analysis, interpretation, drafted and critically revised manuscript. X.J.: contributed to acquisition and drafted manuscript. M.Z.: contributed to acquisition and drafted manuscript. F.O.: contributed to design and critically revised manuscript. H.A.G. and M.O.: contributed to conception and critically revised manuscript. S.L. and L.S.: contributed to analysis and critically revised manuscript. J.Z. and Y.Y.: contributed to conception, design and critically revised manuscript. B.Z.: contributed to conception, design and critically revised manuscript. J.Y.A.: contributed to conception, design and critically revised manuscript.

The authors report no conflicts of interest.

Supplemental Digital Content is available for this article. Direct URL citations are provided in the HTML and PDF versions of this article on the journal's website, www.jcraniofacialsurgery.com.

Copyright © 2025 by Mutaz B. Habal, MD

ISSN: 1536-3732
DOI: 10.1097/SCS.0000000000011622

Abstract: This article aims to review the literature, study the current situation of using 3D images and artificial intelligence-assisted methods to improve the rapid and accurate classification and diagnosis of condylar fractures and conduct a meta-analysis of mandibular fractures. Mandibular condyle fracture is a common fracture type in maxillofacial surgery. Accurate classification and diagnosis of condylar fractures are critical to developing an effective treatment plan. With the rapid development of 3-dimensional imaging technology and artificial intelligence (AI), traditional x-ray diagnosis is gradually replaced by more accurate technologies such as 3-dimensional computed tomography (CT). These emerging technologies provide more detailed anatomic information and significantly improve the accuracy and efficiency of condylar fracture diagnosis, especially in the evaluation and surgical planning of complex fractures. The application of artificial intelligence in medical imaging is further analyzed, especially the successful cases of fracture detection and classification through deep learning models. Although AI technology has demonstrated great potential in condylar fracture diagnosis, it still faces challenges such as data quality, model interpretability, and clinical validation. This article evaluates the accuracy and practicality of AI in diagnosing mandibular fractures through a systematic review and meta-analysis of the existing literature. The results show that AI-assisted diagnosis has high prediction accuracy in detecting condylar fractures and significantly improves diagnostic efficiency. However, more multicenter studies are still needed to verify the application of AI in different clinical settings to promote its widespread application in maxillofacial surgery.

Key Words: Artificial intelligence, diagnosis, fracture, mandibular condyle, precision medicine

Mandibular condylar fractures account for a large proportion of maxillofacial fractures. The latest research shows that the proportion of condylar fractures in mandibular fractures ranges from 16.5% to 56%.[1] The incidence of single unilateral and bilateral condylar fractures is about 17%, whereas the proportion of condylar fractures in multiple mandibular fractures is as high as 63%. The "Expert Consensus on the Diagnosis and Treatment of Condylar Fractures in Adults" released by China in 2023 pointed out that condylar fractures account for about 24.2% to 29.7% of mandibular fractures, and the ratio of unilateral to bilateral occurrence is about 2.6 to 3.1:1.[2] The high incidence and prevalence of condylar fractures highlight their importance in maxillofacial surgery.

The accurate classification and diagnosis of condylar fractures is challenging, mainly because of the special anatomy of the mandibular condyle, the maxillary artery, parotid nerve, auriculotemporal nerve, and facial nerve, as well as the temporomandibular joint, and the characteristics of different types of fractures.[1] The specific location, displacement, degree, number and type of condylar fractures are affected by the direction, magnitude and location of the external force and the traction of the muscles around the condyle.[3] This makes diagnosis and classification more complicated.[3]

Different types and locations of condylar fractures may require different treatment strategies,[4] ranging from nonsurgical management to complex surgical interventions. Because of the difficulty of surgery and the potential risk of complications, choosing the appropriate treatment method is crucial to opti-

Copyright © 2025 Mutaz B. Habal, MD. Unauthorized reproduction of this article is prohibited.

mize the patient's treatment and recovery.[5] Studies have shown that some patients with condylar head fracture (CHF) do not receive open surgery in their treatment options, which may miss the best time.[6] Experts and surgeons participating in the study unanimously recognized its effectiveness. The pathogenesis after fracture, including bone resorption, bone deformity, and scar formation, also requires accurate diagnosis to formulate a reasonable treatment plan.[6]

There is still a lack of unified standards for the classification and terminology of mandibular condylar fractures. Since MacLennan first proposed the 4-type classification system in 1952,[7] the classification of condylar fractures has been evolving. New classification methods have been proposed by Spiessl,[8] Lindahl, the Groningen International Consensus Conference in the Netherlands,[9] and the Strasbourg Osteosynthesis Research Group (SORG).[10] In particular, the 1999, 2005 and 2014 classifications are widely used[11] (Figure 1). Although these classifications are widely used, they are subjective and have limitations. Therefore, there is an urgent need for a more accurate and objective classification system in the field of maxillofacial surgery to achieve more precise diagnosis and treatment.

Since the birth of computed tomography CT technology in 1971, maxillofacial diagnosis, especially the imaging diagnosis of mandibular condylar fractures, has undergone significant changes. Traditional x-rays can only provide 2-dimensional views, which can easily miss diagnosis when complex fractures or condylar areas overlap. However, 3-dimensional CT and CBCT technology can provide more detailed 3-dimensional images, significantly improving diagnostic accuracy, especially in complex fractures. plays an important role in assessment[12] and surgical planning.[13] These technologies can not only accurately display the location[14] and morphology of fractures,[14] but also capture information about surrounding soft tissues such as muscles, ligaments, and nerves, which helps to assess healing and predict complications.[15] Although 3-dimensional imaging technology has significant advantages in maxillofacial diagnosis, in practical applications, doctors may encounter difficulties in unclear fracture boundaries.[16] In addition, the limited availability of 3D CT in certain regions has hampered its widespread use as a routine diagnostic tool.[17]

Deep learning is an advanced machine learning algorithm.[18] From the early decision tree, support vector machine, naive Bayes algorithm to artificial neural network, it has important significance in the field of medical image processing and analysis.[19,20] Convolutional Neural Network (CNN) is one of the most widely used deep learning models and is good at processing 2-dimensional or 3-dimensional images. CNN reduces spatial dimensions through pooling layers, has strong generalization ability, and can extract features from large-scale data, but has limitations in identifying image spatial relationships and rotating objects.[21,22] U-Net is an improved CNN model designed for medical image segmentation[19]and can accurately identify image boundaries. Multiscale learning models (such as MS-D CNN) can provide accurate segmentation results even in small sample cases.[22] In addition, the "look once" (YOLO)-based method significantly improves the diagnostic efficiency and accuracy of condylar fractures.[23]

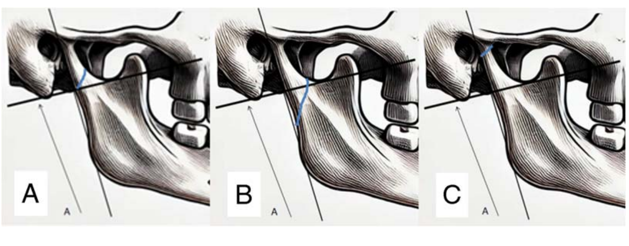

FIGURE 1. (A) Condylar neck fracture, (B) condylar base fracture, (C) capitellum fracture (through the condylar head).

Artificial intelligence has made significant progress in the detection and classification of fractures. Through deep learning models such as convolutional neural networks (CNN),[24] AI can automatically locate and classify fractures in whole-body CT images with an accuracy comparable to clinical experts[25] Studies have shown that DenseNet-169 and Faster R-CNN perform well in maxillofacial fracture classification and detection.[26]

Although deep learning has great potential in image analysis, it still faces some limitations. Deep learning relies on a large amount of high-quality data, and the diagnosis of complex or rare cases is challenging. The interpretability and transparency of the model are also key issues.[27]

Deep learning, as the core of AI, has been widely used in fields such as organ segmentation, cancer diagnosis,[28] retinal lesion detection, and maxillofacial surgery fractures.[29] In particular, the high sensitivity[30] and accuracy of the CNN model[28] in the detection of mandibular condylar fractures shortens CT interpretation time and reduces missed diagnoses.[31] Although widespread clinical application has not yet been achieved, the value of AI in automatic lesion detection has been recognized[27] In recent years, the application of artificial intelligence (AI) in the diagnosis of maxillofacial fractures has made significant progress.[32] The 3-dimensional algorithm accurately measures the condylar fracture volume and combines 3-dimensional CT and DICOM data for semi-automatic image segmentation,[27] which helps to evaluate the relationship between fracture reconstruction, function and pain.[33]

In this review, we attempted to review the literature on the application of AI algorithms in mandibular condylar fractures, but almost no one has published relevant literature, and condylar fractures are part of mandibular fractures. Therefore, we expanded the search scope and reviewed the relevant literature on the application of AI algorithms to CT images in mandibular fractures, aiming to evaluate the accuracy and practicality of AI in imaging for mandibular fractures.

MATERIALS AND METHODS

Search Strategy and Study Selection

A systematic review of all relevant studies published from the inception of the databases to April 17, 2024 was performed using PubMed, Web of Science, Embase, and the Cochrane Library. The Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) 2020 reporting guideline was used to design the review.[34] The inclusion criteria and analysis plan were decided a priori registered on PROSPERO. In each database, the following keyword combinations were searched and manually screened to identify relevant articles: (1) condylar fracture AND machine learning OR ML OR deep learning OR artificial intelligence OR AI OR convolutional neural network OR CNN OR Neural Networks OR you only look one OR YOLO OR computer. (2) Mandibular fractures AND machine learning OR ML OR deep learning OR artificial intelligence OR AI OR convolutional neural network OR CNN OR Neural Networks OR you only look one OR YOLO OR computer.

Copyright © 2025 by Mutaz B. Habal, MD

Copyright © 2025 Mutaz B. Habal, MD. Unauthorized reproduction of this article is prohibited.

Eligibility Criteria and Data Extraction

Research on fracture diagnosis in mandibular imaging using artificial intelligence methods. The authors screened out imaging films of CT images. Original articles. If unpublished articles were retrieved, we would contact the authors.

The research data were independently extracted using a template data extraction form, including the source journal name (country), study design, publication year, sample size, output image, image quality, fracture type and location, AI name, diagnostic accuracy, and sensitivity.

Case reports, abstracts, and literature reviews were excluded.

Doctor Junping Zhen and Xuejiao Jia Physician were independent reviewers who screened and verified the literature retrieved by the authors based on the article topic and the inclusion and exclusion criteria of the article, and negotiated with Doctor Bin Zhao, the third reviewer, to resolve the conflict of whether the literature was adopted or not, and extracted relevant data at the same time. Figure 2 shows a flow chart of the experimental research process.

Literature Search

Supplemental Fig. 1 Flow diagram of the search and inclusion process, Supplemental Digital Content 1, http://links.lww.com/SCS/I30.

In the sample selection process, we first searched the database using the search terms “mandibular fracture” and “mandibular condyle fracture”. A total of 1186 documents were found, and 0 documents were found in other libraries, for a total of 1186 documents. 1070 irrelevant documents were excluded. The full texts of the remaining 14 documents were more suitable, but 5 of them were excluded because they did not contain content about mandibular fracture or mandibular condyle fracture. When extracting data later, 2 documents were excluded because no relevant data was found, leaving 7 documents that met the requirements (Supplemental Table 1).[23,26,30,35–38]

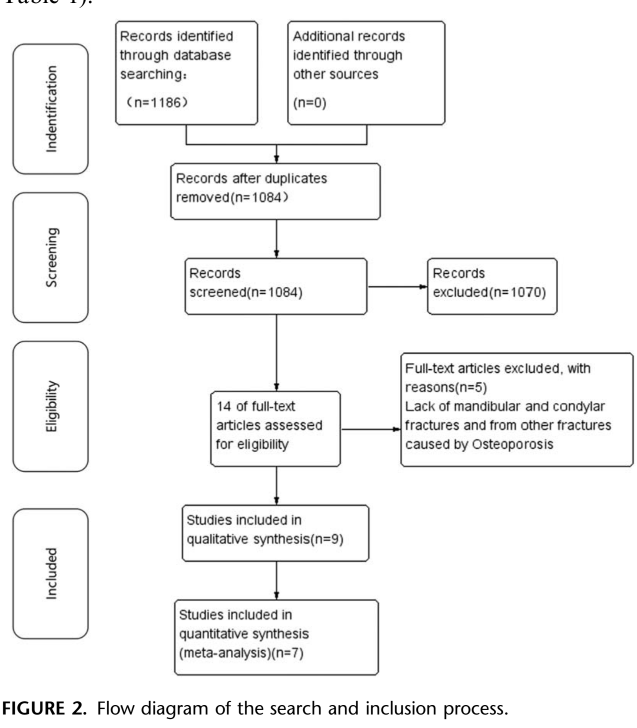

FIGURE 2. Flow diagram of the search and inclusion process.

Data Extraction

Supplemental Table 1. Included studies on the application of artificial intelligence in CT images for the diagnosis of mandibular fractures and condylar fractures, Supplemental Digital Content 5, http://links.lww.com/SCS/I34.

Meta-Combined Effect Size

The data used in this article are a single-arm experiment with a ratio as the indicator.

A single-arm trial refers to a clinical trial in which all subjects are in the same observation group and no other experimental group or control group is set up. Single-arm trial meta-analysis is a quantitative comprehensive analysis of all single-arm trials with the same purpose.

Number of studies: $k = 7$
Number of observations: $O = 5161$
Number of events: $e = 4299$

	proportion	95%−CI
Common effect model	0.8115	[0.7998; 0.8227]
Random effects model	0.9271	[0.8682; 0.9608]

Quantifying heterogeneity:

$tau^2 = 0.6240$ [0.1955; 3.7144]; $tau = 0.7899$ [0.4421; 1.9273]

$I^2 = 96.5\%$ [94.6%; 97.7%]; $H = 5.34$ [4.30; 6.63]

In the above results, the last one is the heterogeneity test. The *P*-value is <5%, indicating that there is heterogeneity. The random effects model should be used, and I^2 is relatively large.

The combined prediction accuracy is 0.9271, the confidence interval is [0.8682, 0.9608], and the combined effect size is the proportion in the first column (Supplemental Table 2, Supplemental Digital Content 6, http://links.lww.com/SCS/I35).

Supplemental Table 2. The proportions after the meta-heterogeneity test are as follows: Supplemental Digital Content 6, http://links.lww.com/SCS/I35.

Supplemental Fig. 2 Heterogeneity forest plot of mandibular fracture and condylar fracture deep learning detection reports, Supplemental Digital Content 2, http://links.lww.com/SCS/I31.

Supplemental Fig. 2, Supplemental Digital Content 2, http://links.lww.com/SCS/I31 In the forest plot, studies 1 to 7 represent the 7 selected studies, events represent the correctly predicted fracture images, and total represents the total number of images. Proportion represents the proportion of correctly predicted fractures in the total number of images. Weight represents the method of merging the effects of the random effects model.

Publication Bias Detection

The *P*-value of Egger test[39] was 0.0213, which was <5%, indicating that there was publication bias.

Funnel Chart

Supplemental Fig. 3 Funnel plot for detecting publication bias in mandibular fractures and condylar fractures using artificial intelligence, Supplemental Digital Content 3, http://links.lww.com/SCS/I32.

As can be seen from the Supplemental Fig. 3, Supplemental Digital Content 3, http://links.lww.com/SCS/I32, most of the points are concentrated on the right side, which is not symmetrical. If it is a funnel plot without publication bias, it should be a symmetrical funnel-shaped scattered point distribution on both sides. Combined with the Egger test, it can be known that there is indeed a publication bias.

Copyright © 2025 by Mutaz B. Habal, MD

Copyright © 2025 Mutaz B. Habal, MD. Unauthorized reproduction of this article is prohibited.

Sensitivity Analysis

Supplemental Table 3 Sensitivity analysis for artificial intelligence detection of imaging images, Supplemental Digital Content 7, http://links.lww.com/SCS/I36.

Through sensitivity analysis, we can know that excluding one sample will not improve heterogeneity and publication bias (Supplemental Table 3, Supplemental Digital Content 7, http://links.lww.com/SCS/I36).

Cut and patch method
Number of studies: k = 11 (with 4 added studies)
proportion 95% CI
Random effects model 0.8273 [0.6392; 0.9283]
Quantifying heterogeneity:
$tau^2 = 2.5591$ [1.1306; 9.3632]; tau = 1.5997 [1.0633; 3.0599]
$I^2 = 96.3\%$ [94.7%; 97.3%]; H = 5.17 [4.35; 6.13]
Test of heterogeneity:
Q d.f. *P*-value
266.84 10 < 0.0001

In the above results, $I^2 = 96.5\%$ is relatively large, $tau^2 = 0.62$, and the variance between studies is relatively small. The last is the heterogenity test, and the *P*-value is <5%, indicating that there is heterogeneity and the random effects model should be used. The combined ratio of the random effects model is 0.9271, and the confidence interval is [0.8682, 0.9608].

Supplemental Table 4. Summary of publication bias correction using trim and fill method, Supplemental Digital Content 4, http://links.lww.com/SCS/I33.

Supplemental Fig. 4, Draw a forest map using the cut and fill method Supplemental Digital Content 8, http://links.lww.com/SCS/I37.

Perform the Egger test again after using the trim-and-fill method (Supplemental Table 4, Supplemental Digital Content 8, http://links.lww.com/SCS/I37, Supplemental Fig. 4, Supplemental Digital Content 4, http://links.lww.com/SCS/I33).

Linear regression test of funnel plot asymmetry
Test result: $t = 0.62$, df = 9, *P*-value = 0.5481
Bias estimate: 1.2673 (SE = 2.0308)

The *P*-value is greater than 5%, indicating that the publication bias has been corrected. Overall, the prediction accuracy of deep learning models in recent years for mandibular fractures and condylar fractures is ~82.73%.

RESULTS

In the meta-analysis of this review, we evaluated the diagnostic accuracy and practicality of artificial intelligence (AI) algorithms for mandibular fractures and condylar fractures in CT images through a comprehensive analysis of 7 studies that met the inclusion criteria. Here are the key findings from the study results:

Combined Prediction Accuracy

When using the random effects model, the combined prediction accuracy is 0.9271, and the confidence interval is [0.8682, 0.9608], indicating that the AI algorithm is highly effective in the diagnosis of mandibular fractures and condylar fractures. accuracy.

Heterogeneity Analysis

The heterogeneity test results showed that $tau^2 = 0.6240$, $I^2 = 96.5\%$, H = 5.34, indicating significant heterogeneity between studies. This shows that the results of each study are quite different, and a random effects model needs to be used for combined analysis.

Publication Bias Detection

Through Egger linear regression test, the bias estimate was 5.4196, and the *P*-value was 0.0213 (< 0.05), indicating the existence of publication bias. Further funnel plot analysis also supports this conclusion, showing that most research results are concentrated on the right side of the funnel plot and do not show symmetry.

Sensitivity Analysis

Sensitivity analysis showed that excluding any single study would not significantly improve heterogeneity and publication bias, indicating that the study results are robust.

The Trimming and Patching Method Corrected Publication Bias

After adding 4 studies through the trimming and patching method, the prediction accuracy under the random effects model was adjusted to 0.8273, and the confidence interval was [0.6392, 0.9283]. The Egger test was performed again, and the *P*-value was 0.5481 (> 0.05), indicating that publication bias had been corrected.

The results of this meta-analysis show that the deep learning model in recent years has a high accuracy in predicting mandibular fractures and condylar fractures, with a prediction accuracy of ~82.73%. Despite the problems of heterogeneity and publication bias, after correction, the application of AI algorithms in maxillofacial surgery diagnosis still shows great potential.

DISCUSSION

The application of artificial intelligence (AI) and machine learning (ML) technologies in the field of maxillofacial fracture diagnosis has shown significant potential. The application of AI technology, including deep learning and neural networks, to 3-dimensional model construction, precise image segmentation and fracture line identification not only reduces human errors, but also improves the consistency of the diagnostic process. The goal of using AI technology to treat condylar fractures is to help doctors through accurate diagnostic support so that patients can (1) restore the height and protrusion of the mandibular ramus, perform accurate anatomic reduction, and rebuild a good occlusion relationship, (2) minimally invasive surgery to reduce damage, (3) prevent further displacement and heal in the correct position, (4) restore good functional movement of the mandible[40] These details provide important reference and guidance for doctors in dealing with such cases clinically.

However, the application of these technologies also faces challenges and limitations, such as data quality and quantity, interpretability and transparency issues, and comparison with traditional methods. Despite these challenges, the advantages of AI in dealing with complex and ambiguous fractures cannot be ignored.

The application of artificial intelligence technology in the diagnosis of maxillofacial fractures improves the accuracy and efficiency of diagnosis. When dealing with complex and ambiguous fractures, deep learning models can provide more accurate identification of fracture lines and fracture types. The application of artificial intelligence technology in image segmentation reduces human errors and improves diagnostic consistency. By comparing the 3-dimensional position analysis of healthy and affected condyles, artificial intelligence technology can also reveal the impact of physiological changes after fracture on functional recovery.[33]

Copyright © 2025 by Mutaz B. Habal, MD
Copyright © 2025 Mutaz B. Habal, MD. Unauthorized reproduction of this article is prohibited.

Despite the advancement of artificial intelligence technology in the diagnosis of maxillofacial fractures, the coverage and depth of existing research remain limited. The application in multicenter clinical studies is very limited, which limits the overall understanding of the effectiveness of artificial intelligence technology in different types of fractures and in different clinical settings.

Implications for Research

Although artificial intelligence has shown great potential in the diagnosis of maxillofacial fractures, a literature search as of January 2024 showed that there is still limited research on the use of deep learning, especially YOLO technology, for intelligent diagnosis of condylar fracture imaging slices. This indicates that more multicenter studies are urgently needed in this field to verify and optimize the effectiveness of artificial intelligence technology in different clinical settings.

The application of artificial intelligence in maxillofacial surgery is not limited to precise segmentation and image analysis, but also involves clinical decision support.[41] To maximize the clinical value of artificial intelligence, it is crucial to conduct validation studies in different clinical settings. This includes testing and evaluating AI models in different patient populations and different medical institutions. Such studies can reveal how AI models perform in real-world settings, including their effectiveness in different types of fractures, different stages of disease, and different medical conditions. In addition, validation studies can also help identify and address specific challenges that AI models may encounter in actual clinical applications, thereby promoting a wider and more effective application of AI in maxillofacial surgery.

Although this review focuses on the application of artificial intelligence (AI) and machine learning (ML) in the diagnosis of condylar fractures, AI technology also shows great potential in surgical treatment planning and decision support. Traditionally, treatment decisions for condylar fractures rely on the evaluation of variables that affect surgical indications, including primary variables such as the degree of fracture displacement, location, and position relative to the glenoid fossa, as well as secondary variables such as preinjury occlusal relationship and vertical height of the mandibular ramus.[2] With the widespread application of CT enhancement technology, combined with AI technology, preoperative evaluation can be completed more accurately, thus guiding the formulation of surgical treatment plans.

AI and ML technologies can help doctors more accurately identify the specific type and degree of condylar fractures by analyzing large amounts of imaging data, and then choose the most appropriate surgical approach and fixation method.[42] For example, using deep learning algorithms to analyze CT images can accurately assess the fracture line, the location of bone fragments, and the direction of fracture fragments, which is of great significance for selecting surgical approaches, such as the transparotid approach, preauricular approach, and retromandibular approach.[43]

In the future, with the continuous advancement of AI technology, we can expect it to play a more important role in improving the accuracy and efficiency of condylar fracture treatment decisions. AI can not only provide support in the diagnosis stage but also play a key role in surgical planning and subsequent treatment management, providing patients with personalized treatment plans.

CONCLUSIONS

In this literature review, AI has a variety of applications in the diagnosis of maxillofacial fractures, such as 3-dimensional model construction, accurate image segmentation, and fracture line identification. These applications will improve the accuracy and efficiency of diagnosis in the future. AI technology has obvious advantages in dealing with complex fractures and improving image consistency.

Taking all factors into consideration, AI technology has great potential and value in the application of maxillofacial fracture diagnosis. AI technology will first improve the accuracy and efficiency of diagnosis, and secondly, it has special advantages in dealing with complex fractures and improving image consistency. The current difficulty is that AI technology needs to conduct more experiments in a variety of clinical environments to solve the problems of data quality, diversity, and transparency. The direction of future research is the further verification and optimization of AI technology, as well as its wide application in clinical practice. In short, the application prospects of AI technology in the diagnosis and treatment of maxillofacial fractures are clear, and it is expected to provide patients with higher-quality medical services.

ACKNOWLEDGMENTS

I would like to thank all the supervisors for their hard work and valuable suggestions on this paper. It is their hard work and professional suggestions that have made this paper further improved in terms of academic and normativeness. Special thanks to Dr Xia Yijing for providing important guidance and suggestions throughout the writing process of the paper, which made a key contribution to the completion of this paper. At the same time, I would like to thank all the institutions and personnel who directly or indirectly supported this research for their hard work in experiments, data analysis and discussions. The completion of this paper is inseparable from everyone's joint efforts, and I would like to express my deep gratitude again.

REFERENCES

1. Kozakiewicz M, Walczyk A. Current frequency of mandibular condylar process fractures. *J Clin Med* 2023;12:1–15.
2. Expert consensus on the diagnosis and treatment of condylar fractures in adults [M]. *Chinese Journal of Stomatology* 2023; T_CHSA 011-2023:1–18; .
3. Neff A, Cornelius CP, Rasse M, et al. The comprehensive AOCMF classification system: condylar process fractures—level 3 tutorial. *Craniomaxillofac Trauma Reconstruct* 2014;7(Suppl 1):S044–S058
4. Vidhya V, Dominic S, Mohan S, et al. Outcome of management of mandibular sub condylar fractures based on classification system using cone-beam computed tomography. *J Maxillofac Oral Surg* 2023;22:453–459
5. He D, Yang C, Chen M, et al. Intracapsular condylar fracture of the mandible: our classification and open treatment experience. *J Oral Maxillofac Surg* 2009;67:1672–1679
6. Luo X, Bi R, Jiang N, et al. Clinical outcomes of open treatment of old condylar head fractures in adults. *J Craniomaxillofac Surg* 2021; 49:480–487
7. Mac LW. Consideration of 180 cases of typical fractures of the mandibular condylar process. *Br J Plast Surg* 1952;5:122–128
8. McLeod NM, Keenan M. Towards a consensus for classification of mandibular condyle fractures. *J Craniomaxillofac Surg* 2021;49: 251–255
9. Bos RR, Ward Booth RP, de Bont LG. Mandibular condyle fractures: a consensus. *Br J Oral Maxillofac Surg* 1999;37:87–89
10. Loukota RA, Eckelt U, De Bont L, et al. Subclassification of fractures of the condylar process of the mandible. *Br J Oral Maxillofac Surg* 2005;43:72–73

Copyright © 2025 by Mutaz B. Habal, MD

Copyright © 2025 Mutaz B. Habal, MD. Unauthorized reproduction of this article is prohibited.

11. Loukota RA, Neff A, Rasse M. Nomenclature/classification of fractures of the mandibular condylar head. *Br J Oral Maxillofac Surg* 2010;48:477–478
12. Zhou HH, Liu Q, Cheng G, et al. Aetiology, pattern and treatment of mandibular condylar fractures in 549 patients: a 22-year retrospective study. *J Craniomaxillofac Surg* 2013;41:34–41
13. Cornelius CP, Audigé L, Kunz C, et al. The comprehensive AOCMF classification system: mandible fractures—level 3 tutorial. *Craniomaxillofac Trauma Reconstruct* 2014;7(Suppl 1):S031–S043
14. Du C, Xu B, Zhu Y, et al. Radiographic evaluation in three dimensions of condylar fractures with closed treatment in children and adolescents. *J Craniomaxillofac Surg* 2021;49:830–836
15. Kolk A, Scheunemann LM, Grill F, et al. Prognostic factors for long-term results after condylar head fractures: a comparative study of non-surgical treatment versus open reduction and osteosynthesis. *J Craniomaxillofac Surg* 2020;48:1138–1145
16. Skroch L, Fischer I, Meisgeier A, et al. Condylar remodeling after osteosynthesis of fractures of the condylar head or close to the temporomandibular joint. *J Craniomaxillofac Surg* 2020;48:413–420
17. Li J, Zhai J, Yin Y, et al. Three-dimensional mapping study of pure transverse acetabular fractures. *J Orthop Surg Res* 2022;17:264
18. Hinton GE, Osindero S, Teh YW. A fast learning algorithm for deep belief nets. *Neural Comput* 2006;18:1527–1554
19. Cho H, Lee JS, Kim JS, et al. Empowering vision transformer by network hyper-parameter selection for whole pelvis prostate planning target volume auto-segmentation. *Cancers* 2023;15:1–15.
20. Tian CW, Chen XX, Zhu HY. Application and prospect of machine learning in traumatic orthopedics. *Chinese J Reparat Reconstruct Surg* 2023;37(12):1562–1568.
21. Huang DYThe application value of Convotional Neural Network for accurate diagnosis of skull base fracture [D], *Guangzhou: Guangzhou Medical University* 2022;1–50.
22. Elizar E, Zulkifley MA, Muharar R, et al. A review on multiscale-deep-learning applications. *Sensors* 2022;22:1–28.
23. Son DM, Yoon YA, Kwon HJ, et al. Automatic detection of mandibular fractures in panoramic radiographs using deep learning. *Diagnostics (Basel)* 2021;11:1–19.
24. Inoue T, Maki S, Furuya T, et al. Automated fracture screening using an object detection algorithm on whole-body trauma computed tomography. *Sci Rep* 2022;12:16549
25. Cha Y, Kim JT, Park CH, et al. Artificial intelligence and machine learning on diagnosis and classification of hip fracture: systematic review. *J Orthop Surg Res* 2022;17:520
26. Warin K, Limprasert W, Suebnukarn S, et al. Maxillofacial fracture detection and classification in computed tomography images using convolutional neural network-based models. *Sci Rep* 2023;13:3434
27. Halidanmu A, Feng K, Shi YQ. A review of the applications of deep learning in fracture diagnosis [J]. *Computer Eng Appl* 2024;60 (5) :47–61.
28. Hickman SE, Woitek R, Le EPV, et al. Machine learning for workflow applications in screening mammography: systematic review and meta-analysis. *Radiology* 2022;302:88–104
29. Kim KC, Cho HC, Jang TJ, et al. Automatic detection and segmentation of lumbar vertebrae from X-ray images for compression fracture evaluation. *Comput Methods Programs Biomed* 2021;200:105833
30. Wang X, Xu Z, Tong Y, et al. Detection and classification of mandibular fracture on CT scan using deep convolutional neural network. *Clin Oral Investig* 2022;26:4593–4601
31. Kim D, Chung J, Choi J, et al. Accurate auto-labeling of chest X-ray images based on quantitative similarity to an explainable AI model. *Nat Commun* 2022;13:1867
32. Neuhaus MT, Gellrich NC, Sander AK, et al. No significant bone resorption after open treatment of mandibular condylar head fractures in the medium-term. *J Clin Med* 2022;11:1–10.
33. Buitenhuis MB, Weinberg FM, Bielevelt F, et al. Anatomical position of the mandibular condyle after open versus closed treatment of unilateral fractures: a three-dimensional analysis [J]. *J Craniomaxillofac Surg* 2023;51:682–691
34. Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ (Clin Res ed)* 2021;372:n71
35. Zhou T, Wang H, Du Y, et al. M(3)YOLOv5: Feature enhanced YOLOv5 model for mandibular fracture detection. *Comput Biol Med* 2024;173:108291
36. Zhou T, Du Y, Mao J, et al. Parallel attention multi-scale mandibular fracture detection network based on CenterNet. *Biomed Signal Process Control* 2024;95:106338
37. Son DM, Yoon YA, Kwon HJ, et al. Combined deep learning techniques for mandibular fracture diagnosis assistance. *Life (Basel, Switzerland)* 2022;12:1–20.
38. Seeley-Hacker BL, Holmgren EP, Harper CW, et al. An anatomic predisposition to mandibular angle fractures. *J Oral Maxillofac Surg* 2020;78:2279.e1–.e12
39. Lu V, Tennyson M, Zhou A, et al. Retrograde tibiotalocalcaneal nailing for the treatment of acute ankle fractures in the elderly: a systematic review and meta-analysis. *EFORT Open Rev* 2022;7: 628–643
40. He DM, Yang C. Diagnosis and treatment protocol of mandibular condylar fracture: experience from the TMJ Center of Shanghai Ninth People's Hospital, Shanghai Jiao Tong University School of Medicine. *J Shanghai Jiao Tong Univ* 2022;42: 695–701
41. Rasteau S, Ernenwein D, Savoldelli C, et al. Artificial intelligence for oral and maxillo-facial surgery: a narrative review [J]. *J Stomatol Oral Maxillofac Surg* 2022;123:276–282
42. Emam HA, Jatana CA, Ness GM. Matching surgical approach to condylar fracture type. *Atlas Oral Maxillofac Surg Clin North Am* 2017;25:55–61
43. Al-Moraissi EA, Louvrier A, Colletti G, et al. Does the surgical approach for treating mandibular condylar fractures affect the rate of seventh cranial nerve injuries? A systematic review and meta-analysis based on a new classification for surgical approaches. *J Craniomaxillofac Surg* 2018;46:398–412

Copyright © 2025 by Mutaz B. Habal, MD
Copyright © 2025 Mutaz B. Habal, MD. Unauthorized reproduction of this article is prohibited.