四川大学学报（医学版）
Journal of Sichuan University (Medical Sciences)

Available online at http://www.jsu-mse.com

Research Article

颞下颌关节盘与人工智能：系统评价

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Received: 2024-01-23 Reviewed: 2024-09-25
Accepted: 2024-11-27 Publication: 2024-12-29

【摘要】：
背景：人工智能（AI）在医疗保健领域的整合正在迅速扩大， 医学成像领域取得了重大进展。 本综述旨在系统地评估当前关于各种 AI 模型在颞下颌关节关节盘评估中的应用的研究， 颞下颌关节关节盘是关节解剖 和生理学的重要组成部分。 方法： 在多个数据库（包括 PubMed、Web of Science、 Scopus、 ScienceDirect、 Springer 和 Google Scholar） 中进行了全面的文献检索， 查找 1982 年至 2024 年期间发表的以关节盘病理学和 AI 技术交叉为重点的文章。 共确定了 175 项研究，从中选出 18 项进行深入审查。 这些研究涵盖了超过 4,834 名患者， 包括对照组和关节盘移位患者， 并分析了超过 36,000 个成像数据集。 结果： 大多数选定的研究都采用了磁共振成像 (MRI)， 该成像被视为可视化关节盘状况的黄金标准， 无论是单独使用还是与其他成像方式一起使用。 研究确定了多种 AI 方法，包括机器学习技术，例如随机森林、XGBoost、K 最近邻 (KNN) 和支持向量机 (SVM)，以及深度学习架构，例如人工神经网络 (ANN)、卷积神经网络 (CNN)、U-Net、SegNet 和 ResNet 34。 结论：AI 在关节盘移位评估中的应用已显示出在提高诊断准确 性和促进个性化治疗策略方面具有巨大潜力。 这些发现强调了 AI 对传统诊断实践的变革性影响， 表明在临床环境中管理关节盘疾病的未来前景光明。

【关键词】： 颞下颌关节， 关节盘， 人工智能

Temporomandibular Joint Disc and Artificial Intelligence: A Systematic Review

【Abstract】:
Background: The integration of artificial intelligence (AI) in healthcare is rapidly expanding with significant advancements in the field of medical imaging. This review aimed to systematically evaluate the current research on the application of various AI models in the assessment of the articular disc of the temporomandibular joint, a crucial component of the anatomy and physiology of the joint. **Methods**: A comprehensive literature search was conducted across multiple databases, including PubMed, Web of Science, Scopus, ScienceDirect, Springer, and Google Scholar for articles published between 1982 and 2024 that focused on the intersection of articular disc pathologies and AI technologies. A total of 175 studies were identified, of which 18 were selected for in-depth review. These studies encompassed a cohort of over 4,834 patients, including controls and individuals with articular disc displacement, and analyzed more than 36,000 imaging datasets. **Results**: Most of the selected studies employed magnetic resonance imaging (MRI), which is regarded as the gold standard for visualizing articular disc conditions, either in isolation or alongside other imaging modalities. A variety of AI methodologies have been identified, including machine learning techniques such as Random Forest, XGBoost, K-Nearest Neighbors (KNN), and Support Vector Machines (SVM), as well as deep learning architectures such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), U-Net, SegNet, and ResNet 34.

Conclusions: The application of AI in the evaluation of articular disc displacement has demonstrated significant

potential for enhancing diagnostic accuracy and facilitating personalized treatment strategies. These findings underscore the transformative impact of AI on traditional diagnostic practices, suggesting a promising future for the management of articular disc disorders in the clinical setting.
【Keywords】: Temporomandibular joint, articular disc, artificial intelligence

1. Introduction

The temporomandibular joint (TMJ) is the joint between the condyle of the mandible and mandibular fossa of the temporal bone. The jaw joint is the most functional part of the head and allows numerous complex jaw functions, including but not limited to opening and closing the jaw and digestion-related movements [1].

Temporomandibular joint (TMJ) disorders are the second most common chronic musculoskeletal disorders in the world after lower back pain, affecting 1,8%-33,4% of the global population and are estimated to cost healthcare at approximately $4 billion per year. TMJ disorders include joint disorders (disc displacement and mobility), joint diseases (most commonly arthritis, condylysis, osteonecrosis, synovial chondromatosis), joint fractures, developmental disorders, and masticatory muscle disorders (muscle pain, contracture, hypertrophy, and impaired movement) [2].

2. Methodology

This literature review aimed to study the various contributions of artificial intelligence to the accurate diagnosis of maxillofacial surgery.

2.1. Precise Question

How can artificial intelligence help explore TMJ discs?

2.2. Research Strategy

Articles published in different electronic databases (PubMed, Web of Science, Science Direct, Scopus, Springer, Google Scholar). Whatever the year of publication, the search was conducted on February 10, 2024, in Oujda.

The keywords and Boolean operators used to search PubMed, Web of Science, Springler, Scopus, Science Direct, and Google Scholar are indicated in the titles and abstracts as follows:

“Temporomandibular Disc and Artificial Intelligence”

Filters “articles concerning human species” were applied.

2.3 Inclusion and Exclusion Criteria

For inclusion in this review, articles should focus on the contribution of AI to the exploration of the TMJ.

The inclusion criteria were as follows.

Articles in the AI field of artificial intelligence

- Articles concerning TMJ disk segmentation, exploration, detection, localization

- Articles on TMJ disk displacement, perforation, and

Articles using medical radiologic images and/or any other medical features of the TMJ disc.

The exclusion criteria were as follows.

letters, abstracts of oral or written communication.

- systematic literature review
- non-human articles,

Articles dealing with any other component of the TMJ.

2.4 Selection of Articles

After removing duplicates, three reviewers (Pr. Abdelkrim DAOUDI, Pr. Aissa El Miad KERKOUR and Oussama Abali independently checked the titles and abstracts of articles to ensure that they met the inclusion criteria. The full texts of the eligible articles available from the three reviewers were collected and read to ensure their integrity. The final selection of articles for this literature review was based on consensus among the three reviewers.

2.5 Correlation of Data and Information

Articles were sorted according to the following themes:

Country of origin of the article.

AI model and architecture

- Task performed by AI

Types of radiological images and/or other features.

Number of images and/or radiographs used

- AI reference standard
- Year of publication.

3. Results

3.1. Article Selection

A total of 175 references from different databases were obtained by searching for previously cited keywords according to the following distribution:

PubMed (PM) 20

Web of Science (WS):10

-Scopus :13,

Science Direct (SD):112

-Springer :20.

The literature reviews (n= 23) were removed, and 152 references were analyzed.

After reading the titles and abstracts, 116 studies were excluded because they did not meet the inclusion criteria and were not interested in either TMJ discs or artificial intelligence. Full-text versions of the 36 articles were collected and checked for suitability for inclusion in the study. After reading the full text, 22 articles were excluded as duplicates.

Ultimately, 14 articles were obtained in this review (from the previous databases) in addition to four articles from Google Scholar (GS).

In total, 18 articles were included in this review by consensus among the three reviewers and were studied in detail.

3.2 Classification of articles by theme

After reading and analysis, the articles were classified according to the year of publication, author, country of origin, artificial intelligence model used, type of images, number of images, and reference standard used (Table 1).

表 1

Table 1 Summary of the different articles selected by tear of publication, country origin, dataset, AI model, and reference standard

N° of Biblio	Author's Name	Year of Publication	Country of origin	Dataset	Image Number	AI Model and Architecture	Reference Standard
3	Yeon, Hee Lee, et al.	2022	S. KOREA	MRI	2519	VGG16	Expert judgment /Comparison Alg AI
5	Bolun Lin et al.	2022	CHINA	MRI	9009	ResNet 34	Comparison Algorithm AI
6	Shota Ito et al.	2022	JAPAN	MRI	217	U-Net, 3Disc Net, Seg-Net	Comparison Algorithm AI
7	Michihito Nozawa et al.	2022	JAPAN	MRI	1200	U-Net modified	Comparison Algorithm AI
8	Burcu Bas et al.	2012	TURKEY	Clinical data	-	ANN	Clinical diagnosis
9	Chena Lee et al.	2022	S. KOREA	MRI	5710	GAN model (U-Net)	T2-W1-based diagnosis
10	Kyubaek Yoon et al.	2023	S. KOREA	MRI	2390	Multi-Imput Convolutional Neural Network	Expert judgment
11	Mengxun Li et al.	2022	CANADA	MRI	2614	++U-Net/nn U-Net	Expert judgment
12	Yuki Yoshimi et al.	2023	JAPAN	MRI	536	ED-CNN	CLAHE image/Original image
13	Zih-Kai Kao et al.	2023	TAIWAN	MRI	100	U-Net, Inception ResNet V2, Inception V3, DenseNet 169, VGG16,	Comparison Algorithm AI
14	Brenda de Souza Moura et al	2022	BRAZIL	MRI+Clinical data	459	Deep learning algorithm (1000/50000 step)	Expert judgment
15	SIFA OZSARI et al.	2023	TURKEY	MRI	2576	CNN, Xception, Rest-Net 101, Mobile Net V2, Inception V3, Dense Net-121,	Comparison Algorithm AI
16	Guo Bai et al.	2023	CHINA	MRI	9512	ConvNext MSA Net	Expert judgment
17	John C. Radke et al.	2003	USA	Clinical data	-	ANN	-
18	Jae-Young Kim et al.	2021	S. KOREA	MRI	-	Random forest/MPL/Disc Shape Alone	Comparison Algorithm AI
19	Kaan Orhan et al.	2021	-	MRI+Radiomic features	-	XG Boost/random forest, SVM, KNN, and LR	Comparison Algorithm AI
20	H Iwasaki	2015	JAPAN	MRI+Clinical data	-	BBN/ANN/MRA	Comparison Algorithm AI
21	Kug Jin Jeon et al.	2022	S. KOREA	MRA+Graph path types	-	Automated movement-tracing algorithm	Expert judgment

3.3. Study Features

The 18 studies reporting the application of artificial intelligence models covered the period from 1982 to 2024 (Tables 2 and 3).

•Scopus: 2018–2024
•Web of Science: 2022–2023.
•Science Direct: 1999–2024.
•Springer: 1982–2024.
PubMed: 2003–2023.

表 2

Table 2 Number of articles published by country of origin

Country of origin	Number of articles
USA	01
China	02
S. Korea	05
Turkey	02
Japan	04
Canada	01
Taiwan	01
Brazil	01
Commun	01

表 3

Table 3 Breakdown of studies included from 2003 to 2023, according to the AI model used

Year / **Model AI Used**	2003	2012	2015	2021	2022	2023
Machine Learning	00	00	01	02	00	00
Deep Learning	01	01	00	00	07	05

3.4 Types of AI Applications for TMJ Disc Exploration

3.4.1 Types of Data Used and Variability in the Number of Articles Analyzed

表 4

Table 4 Number of articles by types of data analyzed

Data types	Number of articles
MRI images only	11
MRI images with other data (clinical, radiomic, graphs…)	05
Clinical data	02

表 5

Table 5. Distribution of the included studies from 2003 to 2023 by data form

Year / Data forms	2003	2012	2015	2021	2022	2023
MRI images only	00	00	00	00	06	05
MRI images with other data (clinical, radiomic, graphs…)	00	00	01	02	02	00
Clinical data	01	01	00	00	00	00

3.4.2 Reference Standard Used to Evaluate AI Performance

表 **6**
Table 6 Number of articles by reference standard

Reference standard	Number of articles
Expert judgment	05
Comparison with other software packages	08
Expert judgment / Comparison with other software packages	01
Additional examinations	03
Not available	01

4. Discussion

This study aimed to present the potential uses of AI in the exploration of the temporomandibular disc (TMJ Disc).

4.1. Standard Reference

In most cases, the reference standard used was a comparison with other software applications (eight articles) [5]-[7], [13], [15], [18]-[20]. On the other hand, some articles adopted a comparison with expert judgment (five articles) [10]-[11], [14], [16], [21].

Three articles used additional examinations as references to evaluate their algorithms: T2-weighted imaging-based diagnosis, CLAHE image/original image, and clinical diagnosis [8]-[9], [12].

Conversely, one study used a combination of expert judgment and comparison with other software [3], and another article did not have a clearly established reference standard allowing their software to be evaluated [17].

4.2. Databases

Two articles used clinical features, including clicks, maximum mouth opening, lateral movements, deviation of the mandible [8], medical history, clinical examination, joint vibration analyses, and electromyographic results [17]) to train the algorithms.

Other studies mostly used MRI images.

•MRI images were adopted to train algorithms in 12 (12) articles [3], [5]-[7], [9]-[13], [15]-[16], [18].

•MRI images associated with clinical data [14], [20], radiomic features [19], or graph path types [21].

4.3. AI Model and Architecture

4.3.1 Deep Learning

Fourteen (14) studies adopted deep learning algorithms for TMJ disc exploration based on MRI images only or MRI images with clinical data, and they mostly used expert judgment or comparisons with other algorithms as references.

A VGG16 deep learning model (trained by 2519 MRI images) was used in [3] to detect anterior disc displacement (ADD), using the following three strategies:

• Fine-tuned model (AUC = 0.8755, precision = 77%)

•From the abrasion model, AUC = 0.83, and precision = 75%

•Freez model (AUC = 0–59).

It can be observed that the “Fine tuning model” shows the heaviest AUC, with accuracy = 0.7692, sensitivity = 0.6536, specificity = 0.9415, and compared to the ensemble model, Experts 1 and 2.

The ensemble model demonstrated the best performance: accuracy = 0.8312, sensitivity = 0.8214, and specificity = 0.8457[3].

In [5], an attempt was made to develop a deep learning model to assist clinicians in evaluating ADD “the ResNet 34 model,” which was trained using 9009 MRI images.

Three models were developed in this study.

•The maximum open-mouth position model showed the best performance: accuracy = 0.970, AUC = 0.990, sensibility = 0.975, and specificity = 0.961.

• Close-mouth position Model 1 occupied the second place, accuracy = 0.863, AUC = 0.92, sensibility = 0.735, specificity = 0.926.

•And in the last place, the close mouth position model 2 with accuracy = 0.839, AUC = 0.885, sensitivity = 0.665, and specificity = 0.909 [5].

Another attempt was made in [6] to detect and segment articular TMJ discs on MRI (217 sagittal images) using three deep learning models: 3DiscNet, U-Net, and Seg-Net Basic.

For this purpose, they were tested in three positions (normal position, ADD position, and a combination of the previous positions). 3DiscNet achieved faster convergence than Seg-Net Basic, and U-Net, 3DiscNet, and Seg-Net Basic demonstrated concordance with manual segmentation and demonstrated the best performance for the three positions:

•Normal position: 3DiscNet reached Dice = 0.76, sensitivity = 0.73,

•ADD position: 3DiscNet scored Dice = 0.70, sensitivity = 0.72.

•Combination position: Seg-Net showed Dice = 0.74, sensitivity = 0.70.

The U-Net model demonstrated the lowest results, with a large number of false positives and false negatives on all datasets [6].

The aim of this study was to construct a deep learning model (U-Net) for the automatic segmentation of TMJ discs on MRI images (1200 images).

The model demonstrated excellent results at both positions.

•Normal position disc, recall = 91.6%, precision = 90.2%, measure F = 90.8%

•ADD position: recall = 92.9%, precision = 82.6%, and F = 87.5% [7].

A deep learning algorithm (ANN) was developed in [8] based on the clinical data (clicks, maximum mouth opening, lateral movements, deviation of the mandible) of 219 patients (161 for training and 58 for testing) divided into several categories (ADDWR unilateral, ADDWoR unilateral, ADDWR bilateral, ADDWoR bilateral, ADDWR on one side, and ADDWoR on the other side).

The ANN showed the best performance in the unilateral ADDWR (sensitivity = 80%, specificity = 95%) and bilateral ADDWR (sensitivity = 100%, specificity = 89%) [8].

This study proposes a generative adversarial network (GAN) model for T2-weighted image (WI) synthesis from proton density (PD)-WI using a temporomandibular joint (TMJ) magnetic resonance imaging (MRI) protocol. Based on 3417 MRI images (closed mouth) and 2293 MRI images (open mouth) from 314 patients.

The model showed the highest agreement of 85% for ADDWoR with the predicted T2-weighted images in terms of disc displacement, normal position = 83%, and ADDWR position = 77% [9].

An ADD classification model (a multi-input convolutional neural network) was approved for diagnosing TMJ ADD using MRI images divided into two datasets (dataset E: 1790 images, dataset Y: 600 images) and to provide heat maps [10].

For the internal test, the average performances for different categories (Normal, ADD with Reduction “ADcR,” ADD without Reduction “ADsR”):

•AUROC = 0.985,
•Sensibility = 0.950,
•Specificity = 0.919,
• Youden index = 0.869.

For the external test, the average performance for the different categories was as follows:

•AUROC = 0.959,
•Sensibility = 0.926,
•Specificity = 0.892,
• Youden index = 0.806.

The model surpassed all clinicians in measuring the Youden index for the normal and ADcR tests and achieved comparable performance for the ADsR test [10].

This study used 2614 MRI images (1898 images for training and 716 images for testing) to develop two CNN algorithms to delineate the mandibular condyle, articular eminence, and TMJ discs. For this purpose, the ++U-Net algorithm (improved version of U-Net) was used for slice-by-slice segmentation, and the U-Net algorithm was used for 3Dn structure segmentation. The results are as follows.

表 7

Table 7 Performance results of in U-Net/++U-Net models according Coeff **to evaluation type**

Type of evaluation \ Model		nn U-Net	++U-Net
2D evaluation	Dice	0.709	0.701
	Sensitivity	0.703	0.657
	Specificity	1.000	1.000
3D evaluation	Dice Coeff	0.700	0.682
	Sensitivity	0.693	0.629
	Specificity	1.000	1.000

Their performance was compared with manual segmentation by experts [11].

According to [12], AI trained a deep learning algorithm (ED-CNN) based on MRI images (539 images from 49 patients distributed in two datasets, A=437 and B=99) to assess the capacity of the model for segmenting TMJ discs.

Average results of different performances for Experiment 1 between the original image and CLAHE image “contrast limited adaptive histogram equalization

•Original image: Dice = 0.69, sensitivity = 0.77, PPV = 0.66.

•CLAHE images: Dice = 0.71, sensitivity = 0.76, PPV = 0.69.

Average results of different performances for Experiment 2 between the original image and CLAHE image “contrast limited adaptive histogram equalization

•Original image: Dice = 0.34, sensitivity = 0.33, PPV = 0.38.

•CLAHE image: Dice = 0.63, sensitivity = 0.60, PPV = 0.70 [12].

This study also used MRI images (100 images from 84 patients) to develop four CNN algorithms (Inception ResNet V2, Inception V3, DenseNet 169, and VGG16) intended to detect TMJ disc displacement.

The models with the highest performance are as follows:

•Inception V3: Recall=1, Precision=0,81, Accuracy=0,85, Score F1=0,9.

DenseNet 169: recall = 0.92, precision = 0.86, accuracy = 0.85, score F1 = 0.89 [13].

An attempt to establish a deep learning algorithm was made in [14] to determine the position of the TMJ disc using MRI images (459 images from 67 patients).

Deep learning tests were performed with 1,000 and 50,000 steps. Deep learning algorithms were built using Python, a programming language, and implemented using the TensorFlow framework for deep learning, as follows:

•Deep learning algorithm (1000-step tests): sensitivity = 86.2%, specificity = 76.9%

•Deep learning algorithm (50000-step tests): sensitivity = 87.7%, specificity = 76.9% [14].

Seven deep learning algorithms were assessed in [15] to interpret TMJ disc disorders using MRI images (2576 images from 200 patients) for closed and open mouth positions.

The two models showed the best performance for the closed-mouth position.

•ResNet101: Accuracy = 0.91, precision = 0.91, sensitivity = 0.91, F1 Score = 0.91, AUC = 0.90, specificity = 0.90

•MobileNetV2: Accuracy = 0.97, precision = 0.97, sensitivity = 0.97, F1 Score = 0.97, AUC = 0.95, and specificity = 0.94.

On the other hand, InceptionV3 had the best performance in the open mouth position:

•Accuracy = 0.84, precision = 0.87, sensitivity = 0.84

•F1 Score = 0.85, AUC = 0.86, Specificity = 0.87 [15].

An automatic detection capability was created by training an ANN algorithm to recognize non-reducing displaced disks from frontal chewing data [17]. For this purpose, they only used clinical data from 68 patients (clinical examination, medical history, joint vibration analyses, and electromyographic results).

The ANN algorithm results were as follows: specificity, 100%; sensitivity, 91.8%; and accuracy, 86.8% [17].

4.3.2 Machine Learning

Three studies adopted deep learning algorithms for

TMJ disc exploration based only on MRI images or MRI images with clinical data or radiomic features, and they used a comparison with other algorithms as the reference standard.

According to [18], the MRI images of 443 patients associated with clinical features (changes in condyle and fossa, joint space, disc shapes, and signal intensity of the bone marrow) were used to train a machine learning algorithm (Random Forest) to predict TMJ disc perforation.

The results obtained were compared to those of two other models (multilayer perceptron and disc shape alone):

• Random forest: sensitivity, 96.3%; specificity, 75.8%; AUC, 0.918

•MPL (class of ANN): sensitivity = 85.2%, specificity = 84.8%, AUC = 0.940

•Disc shape alone: sensitivity = 80.8%, specificity = 63.0%, AUC = 0.791 [18].

In the second article, we attempted to classify TMJ pathologies, notably TMJ disc deficits, using MRI images from 107 patients and radiomic features (gray-level co-occurrence matrix GLCM, gray-level run length matrix GLRLM, and gray-level size zone matrix GLSZM) [19].

Six classifiers, logistic regression (LR), random forest (RF), decision tree (DT), k-nearest neighbors (KNN), XGBoost, and support vector machine (SVM), were used for model building to predict TMJ pathologies.

The Random Forest model showed the highest AUC of 0999 for the normal and ADD tests (training set) and 0.742 for the normal and ADD tests (validation set).

The same model shows the best performance in terms of the normal test and ADD test of the training set and the normal test of the test set:

•Normal test of the training set: precision = 0.999, recall = 0.999, and F1 Score = 0.999.

•ADD test of the training set: Precision = 1,00, Recall = 1,00, F1 Score = 1,00.

•Normal test of the test set: Precision = 0.79, Recall = 1,00, F1 Score = 0.88 [19].

The third article described the training of a machine learning model called the Bayesian belief network (BBN) using MRI images of 295 patients and clinical data (bone changes) [20].

5. Conclusions

The articular disc constitutes an integral part of the TMJ anatomy. Disc displacement is the main pathology affecting this structure.

Early diagnosis based on MRI (reference radiological examination) is essential to help clinicians and radiologists perform the study and radiological exploration of the articular disc.

Artificial intelligence can help in this sense by determining the condition of the disc to avoid not only the serious stages of disc displacement (ADD without reduction) but also disc perforations.

Declarations

Author Contributions

Abdlekrim Daoudi contributed to the research conceptualization, methodology, data curation, and investigation. **Oussama Abali** contributed to data curation and visualization of the research findings. **Aissa Kerkour Elmiad** contributed to the validation and statistical analysis of the data, original draft preparation, and overall supervision.

Ethical Approval and Consent to participate

The Research Ethics Committee of Mohammed First University Oujda granted all necessary clearances and ethical approval.

Conflict of interest

The authors declare that they have no conflicts of interest.

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