



Articular Eminence Mandibular Fossa and Artificial Intelligence: A Systematic Review

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ARTICLE INFO	ABSTRACT
Published Online: 15 November 2025	Artificial intelligence has devastated almost every field, including health. Scientific publications concerning the medical field and AI have been increasing steadily in recent years, covering almost all medical specialties. This study aims to systematically synthesize current research and the influence of different artificial intelligence models on the exploration of the other side of the TMJ: the articular eminence-mandibular fossa complex, using medical imaging and/or other types of datasets. Several databases PubMed (PM), Web of Science (WS), Scopus (SC), Science Direct (SD), Springer (SR), Research Gates (RG), and Taylor and Francis on line (TF) were consulted for articles on the subject of « Articular Eminence-Mandibular Fossa and Artificial Intelligence », from 1945 to 2025. One hundred and thirty four (134) studies were identified, of which twenty one (21) were included, totaling more than 3574 patients between controls and patients with TMDs and more than 23000 different types of images. Papers retained used MRI, CBCT, or OPG imaging alone or in combination with other types of features (namely radiomics extracted from this area), without forgetting other categories of datasets in order to explore this part of TMJ. To achieve this goal, various artificial intelligence models were used, including Machine Learning models (Random forest, Decision Tree, XG Boost, KNN, SVM...), and Deep Learning algorithms (ANN, DenseNet-121, U-Net, Seg-Net, MobileNet V2, ResNet-101...). Artificial intelligence method can help in this sense by exploration of temporal cavity, segmentation of its parts, and detection of different pathologies that can affect the joint in general.
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KEYWORDS: Articular Eminence-Mandibular Fossa-Artificial Intelligence-Systematic Review	

I. INTRODUCTION

The temporomandibular joint, which has a complex composition, is made up of the temporal fossa, the mandibular condyle, the articular disc, and the surrounding joint capsule and ligaments [1], of which the temporal cavity (mandibular fossa and articular eminence) constitutes an important part.

Temporomandibular disorders (TMD) is an umbrella term, that refers to disorders associated with the masticatory muscles of the stomatognathic system, temporomandibular joint (TMJ), or both [2]. These pathologies can affect the different parts of this joint and notably the complex articular eminence-mandibular fossa.

Among these disorders, we can mention degenerative disorders (namely osteoarthritis, erosion, osteophyte, flattening...), and disc displacements.

Artificial intelligence is a field of computer science dedicated to the development of computer algorithms to perform tasks traditionally associated with human intelligence such as the ability to learn and solve problems. This includes machine learning (ML), representational learning and deep learning [3].

The AI-supported clinical decision-making in the field of TMD may significantly reduce the percentage of cases that progress to the complicated forms of TMD by allowing early diagnosis [4].

The aim of this study is to determinate the exploration and detection of the temporal cavity, the diagnosis of the different disorders which can affect it, and the contribution of data extracted from this cavity in the training and testing of AI algorithms.

II. MATERIALS AND METHODS

The aim of this literature review is to study the various contribution of artificial intelligence to have an accurate diagnosis for the physicians.

This systematic review of the literature was carried out according to the PRISMA search criteria.

Artificial intelligence (AI) promises to transform many fields, including the medical sector. By combining several techniques such as language processing, data mining, and machine learning, AI helps improve the quality of care, for example by facilitating assisted operations, remote patient monitoring, the design of smart prosthetics, and the personalization of treatments using big data. The text distinguishes two approaches: on the one hand, so-called "strong" AI, which aims to reproduce human thought and potentially create superior intelligence, and on the other hand, the digital approach, which relies on data analysis to detect regularities without a predefined model. In medicine, particularly thanks to language models (LLM), these techniques are used to automatically extract information from large sets of clinical data. However, these models are being tested for various uses, such as the detection of anatomical entities, their segmentation, automatic report entry, or patient analysis.

Finally, the text highlights the importance of studying the TMJ anatomy parts specially the articular eminence-mandibular fossa complex.

A. *Precise Question*

How can artificial intelligence help in the exploration of the articular eminence-mandibular fossa complex?

B. *Research strategy*

A search was carried out on research articles published in the different electronic databases (PubMed, Web of Science, Science Direct, Scopus, Springer, Taylor and Francis on line, and Research Gates). Whatever the year of publication: the search was conducted on August the 25th 2025 in Oujda Morocco.

Data were retrieved from the following databases through the Mohamed First University Institutional Access: PubMed (PM), Web of Science (WS), Scopus, Science Direct (SD), Springer, Taylor and Francis on line, and Research Gates (RG).

The keywords and Boolean operators used to search the PubMed, Web of Science, Springer, Scopus, Science Direct, Taylor and Francis on line, and Research Gates were, in the titles and abstracts, indicated as follows: "Articular eminence-mandibular fossa and Artificial Intelligence".

The filters "articles concerning the human species" were applied.

C. *Eligibility criteria*

To be included in this review, articles should focus on the contribution of AI in the study of TMJ's articular eminence and mandibular fossa.

Inclusion criteria were as follows:

- Articles (research article, conference paper, book chapter...) that address the segmentation, detection, and exploration of the articular eminence by using artificial intelligence.
- Articles (research article, conference paper, book chapter...) that address the segmentation, detection, and exploration of the mandibular fossa by using artificial intelligence.
- Articles (research article, conference paper, book chapter...) that address the segmentation, detection, and exploration of the articular eminence-mandibular fossa complex by using artificial intelligence.
- Articles (research article, conference paper, book chapter...) that address the TMJ exploration in its entity or TMD including the exploration of articular eminence and /or mandibular fossa by using artificial intelligence.
- Human articles.
Exclusion criteria were as follows:
- Letters, abstracts of oral or written communication, review, systematic review, editorials.
- Non-human articles.
- Articles that address the segmentation, detection, and exploration of the articular eminence and /or mandibular fossa without using artificial intelligence.
- Articles that address the TMJ in general or any other component of TMJ other of the the articular eminence and/or mandibular fossa.

D. *Selection of articles*

After deleting duplicates, the three reviewers (Oussama Abali, Pr. Aissa El Miad Kerkour, and Pr. Abdelkrim Daoudi) independently checked the titles and abstracts of the articles to ensure that they corresponded to the various inclusion criteria. The full texts of eligible articles available according to the three reviewers were collect-ed and read in their integrity. The final selection of articles for this literature review was made by consensus between the three reviewers.

E. *Correlation of data/information*

All articles have been sorted according to several themes: Country of origin of the article, artificial intelligence algorithms and architecture used, task performed by the AI, type of features used and/or any other features, number of images used, AI reference standard, year of publication.

F. *Risk of bias assessment*

All three reviews strictly applied the inclusion and exclusion criteria to avoid any risk of bias when studying the various articles included using a sensitivity analysis method. For this study, the authors used QUADAS-2 tool to assess the risk of bias for each included article. This tool allows the assessment of risk of bias and applicability judgement by having four assessment domains (patient selection, index test, reference standard, flow and timing).

The results in most studies regarding the four domains varied from low, low to moderate, and moderate.

III. RESULTS

A. Articles selection

A total of 134 references from different databases were obtained by searching and using the previously cited keywords according to the following distribution:

- PubMed (PM): 16 from 2005 to 2025,
- Web of Science (WS): 15 from 2020 to 2025,
- Scopus: 01 from 2025,
- Science Direct (SD): 34 from 1945 to 2025,
- Springer: 55 from 1974 to 2025,
- Taylor and Francis on line: 21 from 2009 to 2024.

Literature systematic reviews, Letters, abstracts of oral or written communication, case report, conferences review, correspondences (n= 34) were removed, giving a total of 100 references analyzed.

After reading the titles and abstracts, 88 references were excluded, as they did not meet the inclusion criteria, not being interested in both articular eminence-mandibular fossa complex and artificial intelligence. The full-text versions of the 12 articles were collected and checked for suitability for inclusion in the study. After reading the full texts, one article were excluded as duplicates.

Ultimately, 11 articles were obtained (from the previous databases). In the addition of ten articles from Research Gates (RG). The FLOW diagram as shown in Fig 1 explains the selection of the retained articles.

In total, we have 21 articles were included in this review by consensus between the three reviewers and studied in detail.

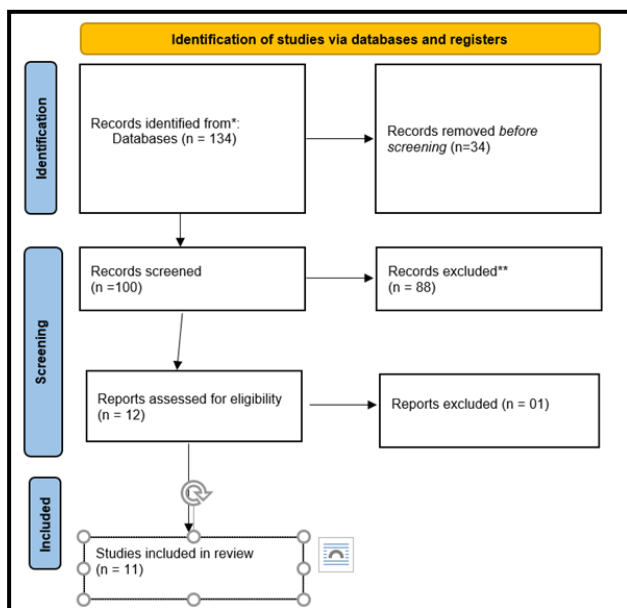


Figure 1. Diagram of FLOW.

B. Classifying articles by theme

After reading and analysis, the articles were classified in a table, according to year of publication, author, country of

origin and artificial intelligence model used, type of data base used, number of features, and reference standard used.

C. Study features

The 22 studies from different databases aforementioned reporting the application of artificial intelligence models covered the period from 2003 to 2025 in the exploration, segmentation of the temporal cavity, the detection of pathologies using data extracted features from the articular eminence-mandibular fossa complex.

The table 1 shows the distribution of items according to country of origin.

The country of origin was determined according to the location of the structure (university or hospital) where the data collection was carried out.

If the location of the structure is not mentioned, we use the country of origin of the structures (hospital or university) to which the authors belong.

If the structures to which the authors of the article belong have a different country of origin, this will be mentioned in the table as "country of mixed origin".

The twenty-one paper were included in this review by consensus between the three reviewers and studied in detail.

Table 1. Number of articles published by country of origin.

Country origin.	Number of the articles
USA	05
China	03
Turkey	03
Canada	02
Russia	02
S. Korea	02
Japan	01
Netherlands	01
New Zealand	01
Poland	01

The different categories of AI algorithms used depending on the years: The table 2 shows the distribution of articles using artificial intelligence (Machine Learning and Deep Learning algorithms) used for the exploration, segmentation of the temporal cavity, and the detection of its pathologies over the years.

Table 2. Breakdown of studies included from 2003 to 2025 according to the AI model used.

Model AI used.	200	201	202	202	202	202	202
	5	5	1	2	3	4	5
Deep Learning	01	00	02	02	03	02	02
Machine	00	00	01	01	02	02	01

Learning							
DL/ML algorithms or AI algorithm model	00	01	00	00	00	01	00

Types of data used and variability in the number of articles analysed: The table 3 shows the different types of dataset used for training and testing the different algorithms by number of articles retained.

Table 3. Number of articles by type of data analysed.

Data types	Number of articles
Radiological data only (MRI images)	07
Radiological data only (CBCT/CT images)	06
Radiological data only (OPG/Radiographic images)	02
Radiological data with other data (clinical, biological, radiomic features....)	05
Other features (ultrasonographic...)	01

Sixteen of selected paper (15) 71,42% of total articles retained used radiological images (MRI, CBCT/CT, OPG...) only as dataset for training and testing of Deep Learning/Machine Learning algorithms.

Five articles adopted the association between radiological images (mostly CBCT scans) and other features (clinical, radiomics, biological...).

The last only paper used measurement of the TMJ space from ultrasonographic as dataset.

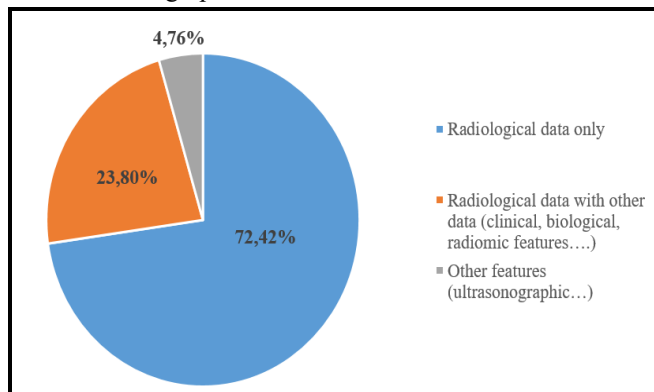


Figure 2. Graph of the distribution of the percentage of features used as dataset in the selected articles.

Types of AI applications for the temporal cavity complex study: The AI algorithms carried out several tasks. Whether

in the detection and segmentation of the different components of the temporal cavity (mandibular fossa and articular eminence), the realization of measurements of the different components of the TMJ, notably the temporal cavity complex, or in the contribution in the diagnosis of TMD bone change or TMJOA).

The table 4 shows the distribution of articles using artificial intelligence algorithms (Deep Learning and Machine Learning) according to the different tasks carried out over the years.

Table 4. Breakdown of studies included from 2005 to 2025 according to the Task done by Artificial Intelligence model used.

Task done	2005	2015	2021	2022	2023	2024	2025	Total
Temporal cavity complex segmentation and detection	00	00	02	01	02	03	03	11
Temporal cavity complex measurements	01	00	00	00	00	01	00	02
TMD (bone change or TMJOA) diagnosis	00	01	01	02	03	01	00	08

We can see in the figure 3 that 52.38% of the articles selected addressed the detection and segmentation of the temporal cavity complex (articular eminence and mandibular fossa), while 36.36% were interested of TMD diagnosis (bone changes, TMJOA...).

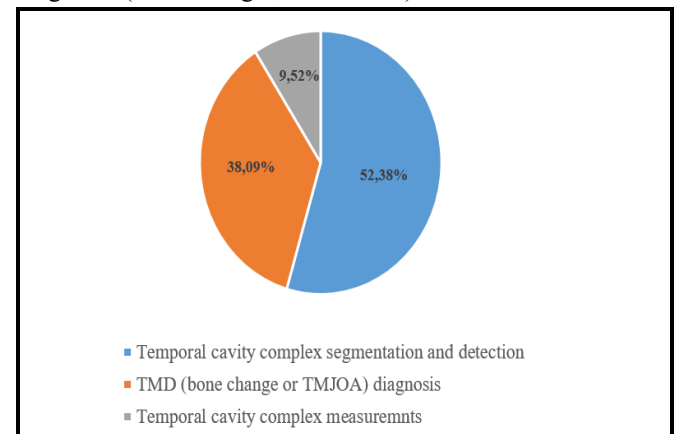


Figure 3. Graph showing the percentage of different tasks performed by AI models concerning the study of the temporal cavity complex in the selected articles.

Reference standard used to evaluate AI performance: The table 5 shows the distribution of articles retained (n=21) by the reference standards used.

Most articles (n=12) used the usual single reference standard (expert judgment, AI algorithms comparison, and methods comparison).

Six articles used the combination between AI algorithms comparison and expert judgment, or between AI algorithms comparison and expert judgement with about three papers for each.

We can see the use of other evaluation standards such as comparison between healthy and TMD group, or anatomic region comparison.

Table 5. Number of articles by reference standard used.

<i>Reference standard</i>	<i>Number of article</i>
Expert judgement	05
AI algorithms comparison	04
Method comparison	03
Combination between AI algorithms comparison and method comparison	03
Combination between expert judgment and AI algorithms comparison	03
Other	03

IV. DISCUSSION

A. Temporal cavity and Machine Learning

Seven studies adopted Machine Learning algorithms for temporal cavity exploration or by the exploitation of data extracted from this cavity in the diagnosis of pathologies affecting the TMJ, in particular the TMJOA.

The aim of this study was to compare the morphometric and morphologic analyses of the bone structures of temporomandibular joint (namely articular tubercle and mandibular fossa) and masticatory muscles on Cone beam computed tomography in healthy and TMD subject by using several Machine Learning classifiers.

For sagittal plan,

- Eleven parameters were assessed; healthy subjects had higher values than TMDs group in nine parameters namely: distance between the most anterior point of the head mandible and mandibular fossa bone surface opposite (AJS), distance between the most superior point of the head mandible and the deepest point of the mandibular fossa bone surface opposite (SJS), and the angle between the line drawn from the inferior point of the articular tubercle to the deepest point of mandibular fossa and the line drawn tangent of the Frankfort horizontal plane (ATI).

- Five parameters were significantly higher in healthy males than healthy females, we can note Distance between the most superior point of the head mandible and the deepest point of the mandibular fossa bone surface opposite (SJS) and Distance between the posterior point of the head mandible and the mandibular fossa bone surface opposite (PJS).

For coronal plan, 8 parameters were evaluated for both healthy and TMDs group: distance between the most medial point of head of the mandible and the mandibular fossa bone surface opposite (MJS), distance between the most lateral point of head of the mandible and the mandibular fossa bone surface opposite (LJS), distance between the most superior point of head of the mandible and the mandibular fossa bone surface opposite (HM-MF) were higher in healthy subjects [1].

In this paper, they tried to investigate the inclusion of articular fossa data to improve the performance of ML algorithms to detect TMJOA stages by using 10 clinical features, 14 proteins levels from serum and saliva, and 23 imaging biomarkers extracted from 184 hr-CBCT images.

There is no significant difference in the articular biomarkers between TMJOA and control group. We can see also the superior condyle to fossa distance was significantly smaller in diseased patients.

The interaction effects of the articular fossa's radiomics enhanced the performance of ML models to detect TMJOA status.

The best performance was scored by Light GBM model: Accuracy=0,804, Precision=0,804, Recall=0,804, F1Score=0,804 and AUC=0,842 [5].

Celia Le and al aimed to diagnose patients suffering from disease before advanced degradation of the bone caused by TMJOA. For that, five different algorithm were trained and tested by using 2 demographic values, 13 proteins levels, 05 clinical features, and 20 imaging features.

By adding mandibular fossa features, we observed that a substantial number of these features had a overall higher AUC than other features. The fossa features improved the performances of the final model, specially the AUC bu 0,5 and F1 Score by 0,25 ; The Histogram Matched imaging model (HM+Fossa) showed the highest scores : Accuracy=0,794, Recall=0,7935, AUC=0,882, Precision=0,795, and F1 Score=0,787 [6].

The authors proposed a ML model using privileged information (LUPI) and normalized mutual information features selection method (NMFS) to build a performant framework to diagnose TMJOA by adopting as dataset three clinical features, 13 proteins from serum and saliva, and 23 textures features from CBCT images.

LUPI model (trained with KRVFL+biological data) showed better results for articular eminence and joint space measurement than non-LUPI model (trained with RVFL and normal features); although for both models, the results were average.

By comparing different feature integration methods, Clinical and Condyle and 3D Joint Space measurements (NMIFS+ method integration) showed the best scores : AUC=80,9%, F1Score=66,1%, Accuracy=70,9%, Sensitivity=62,7%, Specificity=79,1%, and Precision=77,4% [7].

The main target of this paper was to propose ML and features selection to identify a combination of features, for TMJOA progression. By using 05 clinical symptoms, 14 proteins levels, and 21 radiomics (extracted from the articular fossa and joint space), for the training of the three ML models learning using concave and convex kernels (LUCK), Support Vector Machine (SVM) and Random Forest (RF).

Baseline levels of this mixed data, headaches, lower back pain, restless sleep, muscle soreness, articular fossa bone surface/bone volume and trabecular separation, condylar High Gray Level Run Emphasis and Short Run High Gray Level Emphasis, saliva levels of 6Ckine, Osteoprotegerin (OPG)/Angiogenin, and serum levels of 6ckine and Brain Derived Neurotrophic Factor (BDNF), were the most frequently occurring features to predict more severe TMJ osteoarthritis prognosis.

SVM algorithm using LASSO achieves had the best results: AUC=0,92+/-0,08, Sensitivity=0,85+/-0,19, and Precision=0,76+/-0,18 [8].

In this study, we used six clinical symptoms, 12 radiomics from hr-CBCT images to develop a tool for TMJOA progression prediction and to identify factors contributing to OA progression over 2 to 3 years.

The TMJOA participants presented decrease in the trabecular thickness as well as bone surface/bone volume ratio.

Seven articular fossa-imaging features varied significantly between the baseline and follow up visits of the control group. The clinical features had the highest AUC values followed by the structural parameters of the articular fossa's radiomics.

We developed an open-source tool based on a robust method called Ensemble via Hierarchical Predictions through Nested cross validation (EHPN), which surpassed the performance of the 48 models tested: Accuracy=0,909, AUC=0,835, F1Score=0,843, Precision=0,876, and Recall=0,843 [9].

The aim of this manuscript was to evaluate and develop a predictive model for bilateral posterior condylar displacement by using 166 CBCT images. Three ML models were adopted:

- For the LASSO modelling, the predictor variables included Articular eminence inclination (AEI), ANB angle, S-Go/N-Me, and age,
- For the Random Forest modelling, the predictor variables were Articular eminence inclination (AEI), S-Go/N-Me, and age,

- For the XGBoost modelling, the predictor variables were S-Ar-Go', Articular eminence inclination (AEI), age, and Y-axis.

Articular eminence inclination and age were identified as significant risk factors for bilateral post condylar displacement. The LASSO model was identified as the best risk evaluation model with AUC of 0,723 and Root Mean Square Error (RMSE) of 0,516 [10].

B. Temporal cavity and Deep Learning

Shankeeth Vinayahalingam and al proposed an automated segmentation tool based on a DL algorithm (3DU-Net) for accurate 3D reconstruction of the TMJ by using 162 CBCT images.

The first and second 3D U-Net used for condyle and glenoid fossa as one entity, the third one was used to distinguish between previous segmented entities.

The model showed excellent scores for the glenoid fossa segmentation: Accuracy=0,989, Precision=0,961, Recall=0,974, Dice=0,966, and IoU=0,936 [11].

The authors tried to train and test a Neural Network with one hidden layer by using radiographics images of 14 TMJ from 12 cadavers.

The measurements between the true lateral transcranial radiographs (TLTC) and the TMJ specimens and between the oblique lateral transcranial radiographs (OLTC) and the TMJ specimens by using multiple variables fossa length (ab), anterior joint space (cd), posterior joint space (ef), and fossa height (jk).

It was shown that the more clinically important larger measurements from the OLTC radiographs, length and height of the fossa, can be predicted using the NN model with a maximum error of only ± 1.24 mm [12].

The main goal of this recent study was to develop and validate an AI driven method for the automatic and reproducible measurement of glenoid fossa and joint space with 142 TMJ ultrasonographic images.

To identify the most effective segmentation architecture, we evaluated multiple Deep Learning models, including Residual U-Net, U-Net++, SegResNet, V-Net, Attention U-Net, and DeepLabV3. The segmentation model achieved high performance for the joint space : Dice=0,86+/-0,09, Precision=0,90+/-0,09, Recall=0,84+/-0,15, and VS=0,90+/-0,08 ; On the other hand, for the glenoid fossa, we can see lower performance : Dice=0,60+/-0,24, Precision=0,60+/-0,27, Recall=0,63+/-0,25, and VS=0,86+/-0,10 [13].

The principal aim if this study was to investigate a method for the automated segmentation of the temporal bone by using ensemble DL methodologies especially multiclass segmentation. For that, 3693 MRI images was adopted as dataset.

Concerning the internal test, Seg-Former had the best performances (Dice=0,868, Sensitivity=0,912, and Specificity=0,925) close to the scores obtained by ensemble model.

Concerning the external test, Seg-Former showed average results: Dice=0,733, Sensitivity=0,711, and Specificity=0,834 [14].

About 840 MRI scans were used to train and test four DL models based on ResNet101 framework.

The average recognition rates for articular tubercle fossa was 96,01%, the segmentation-based model outperforming the non-segmentation model : Precision=96,93%, Recall=96,98%, F1Score=96,94%, and Accuracy=96,98% [15].

Sifa Ozsari and al proposed a Deep Learning approaches (Xception, ResNet-101, MobileNetV2, InceptionV3, DenseNet-121 and ConvNeXt) to interpret TMJ disorders on 2576 MRI images from 200 patients.

The best performances of networks for joint cavity effusion was shown by DensNet-121 model: Accuracy=0,81, Precision=0,82, Sensitivity=0,81, F1Score=0,81, AUC=0,82, and Specificity=0,82 [16].

In this paper, they proposed a generative adversarial network (GAN) model for T2-weighted images (WI) synthesis from proton density in a TMJ MRI protocol. For that, they used 7004 images from 314 patients to train and test Deep Learning model based on the pix2pix GAN algorithm.

The PT2WI protocol was evaluated and the k coefficient was 0,88 (almost perfect agreement for effusion) :

- The joint effusion presence, 2% of agreement and 98% of disagreement,
- The joint effusion absence, 10% of agreement and 90% of disagreement [17].

The authors assessed the success and reliability of the detection of maxillary and mandibular anatomic structures on 981 OPG images of pediatric patients by using 2 CNN architectures (YOLOv5) for segmentation.

14804 labels from 981 OPG mixed images of which 1645 for articular eminence. The measurement value for the articular eminence were as follow: F1 Score=0,92, Precision=0,93, and Sensitivity=0,92 [18].

Kristina Belikova and al aimed to develop an end-to-end pipeline that comprises a V-Net for bone segmentation, to extract deep negative volumes from the CT scans.

V-Net also outperform 3D U-Net and 3D U-Net with attention in terms of HD and it is not inferior in other metrics. The temporal bone segmentation results obtained by the five algorithms were close and average, the most efficient of which was V-Net D : Dice=76,9%, CE=0,396, and HD=28,3 mm [19].

In this publication, the aim was to employ two DL approaches (U-Net and nn U-Net) to delineate the articular eminence by using 2614 MRI images from 140 patients.

The models reached near expert for articular eminence segmentation and surpassed non-expert in the same task.

The results were as follows:

- 2D evaluation/nn U-Net : HD=0,843 mm, RMSD=0,022 mm and U-Net : HD=0,880 mm, RMSD=0,020 mm,

- 3D evaluation/nn U-Net: HD=2,212 mm, RMSD=0,013 mm and U-Net: HD=2,665 mm, RMSD=0,014 mm [20].

The objective of this study was to evaluate the performance of an automated two-step model by using 4601 MRI images from 235 children. U-Net++ was used to segment the three anatomical structures namely the articular eminence performing the segmentation slice by slice with 2D sagittal images and the results for the two evaluations were as follows :

- 2D evaluation: HD=0,966 mm, RSD=0,022 mm,
- 3D evaluation: HD=2,842 mm, RSD=0,011 mm [21].

Yi Liu and al aimed to achieve automatic segmentation of the glenoid fossa by using 206 CT scans for training and testing. There are two types of U-Net network 2D and 3D. In our study, a 2D U-Net network was selected, while a 3-class U-Net network was trained for distinguishing between the glenoid fossa and condyle structures in the segmentation target.

The proposed method showed a Dice of 0,90+/-0,04, MSD of 0,19+/- 0,08 mm, and HD=5,09 +/-8,77 mm [22].

C. Temporal cavity and artificial intelligence

Two papers were retained for this part; the first was about a comparison between Deep and Machine Learning models. The authors tried to compare a Bayesian belief network (BBN), Multiple Regression (MR), and an Artificial Neural Network (ANN) to diagnose TMDs by using MRI images. Multiple Regression using resubstitution validation was very accurate in comparison with BBN and ANN.

Artificial Neural Network was very accurate too concerning bone changes namely the articular fossa:

- Resubstitution validation accuracy=99,49%,
- 10-fold cross validation accuracy=97,62% [23].

The first author and al aimed to compare the accuracy of TMJ's components segmentation (articular fossa) and the assessment of the suitability of the data obtained to diagnose TMJ disorders. For that, they used 60 CT images from 240 objects as dataset.

For the first group, the results of CT processing by AI diagnostics algorithms were collected, for the second, the results of CT processing based on the semi-automatic segmentation method.

When segmentation is carried out using AI, the difference between segmented objects is close to zero values. The average time spent on TMJ segmentation was as follows:

- Group 1 : 10,2 s+/-1,23,
- Group 2 : 12,6 s+/-1,87,
- Group 3 : 0,46 s+/-0,12,
- Group 4: 0,46 s+/-0,13 [24].

D. Limitations

Several constraints and limitations have confronted the realization of a systematic review about the study of the temporal cavity using artificial intelligence.

There are not many studies that address the study and the detection of the temporal bone, temporal cavity, or any component of the mandibular fossa articular eminence complex.

Most of papers mention the study, segmentation, or detection of the articular eminence, temporal bone/cavity, or the mandibular fossa in the global study of the TMJ, or during the study and diagnosis of pathologies affecting this joint.

A single article only talked about the comparison between Machine Learning and Deep Learning models in the detection of bone changes (articular fossa) in TMDs.

V. CONCLUSIONS

The main objective of this paper was to provide an update on the study of the mandibular fossa-articular eminence complex, which constitutes the temporal portion of the temporomandibular joint, using artificial intelligence models.

The results obtained were generally promising, even excellent, regarding the detection and segmentation of this important part.

The focus on the study of this complex will be important, and can undoubtedly contribute in the detection and diagnosis of pathologies that can affect the TMJ.

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