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A Comprehensive Review on Detection of TMJ Osteoarthritis

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Abstract

Temporomandibular joint osteoarthritis (TMJOA) is a degenerative disorder that causes pain, functional impairment, and reduced quality of life. Traditional diagnostic methods, such as manual radiographic assessments, are time consuming and prone to subjectivity. Recent advancements in artificial intelligence (AI), particularly deep learning models, offer promising solutions for automated and accurate TMJOA detection. This review comprehensively examines AI-based approaches, including Convolutional Neural Networks (CNNs), YOLO variants, and hybrid architectures, for diagnosing TMJOA using imaging modalities like panoramic radiographs, cone-beam computed tomography (CBCT), and magnetic resonance imaging (MRI). Key studies demonstrate that AI models achieve high accuracy in condylar segmentation, bone deformation classification, and early OA detection, often outperforming traditional methods. However, challenges such as dataset limitations, model generalizability, and clinical validation remain. The integration of AI with biomechanical and clinical data further enhances diagnostic precision, supporting personalized treatment strategies. This review highlights AI's transformative potential in TMJOA diagnosis while emphasizing the need for standardized protocols and multicenter collaborations to improve clinical adoption.

Keywords: *Tempo-mandibular joint (TMJ), Tempo-mandibular Joint Osteo-Arthrosis (TMJOA), Convolution Neural Network (CNN), medical Imaging.*

1. Introduction

Jaw movement plays a crucial role in our daily life, as it is essential for basic functions such as speaking, chewing, swallowing, and expressing emotions. Proper movement of the jaw ensures smooth coordination between the muscles, bones, and joints. Disruptions in this system, such as temporomandibular joint (TMJ) dysfunction or osteoarthritis, can lead to significant pain, functional impairment, and reduced quality of life.Osteoarthritis (OA) is a common and progressive degenerative joint disorder that leads to structural changes within the joint, causing pain and reduced mobility. Weight-bearing joints such as the knees, hips, spine, and fingers are most frequently affected due to continuous mechanical stress {Citation}[1].While osteoarthritis is commonly seen in joints like the knees, hips, and hands, it's important to note that it can also affect other areas such as the wrists, shoulders, ankles, and even the temporomandibular joint (TMJ), which connects the jaw to the skull. When osteoarthritis affects the TMJ, it can lead to the deterioration of joint cartilage, the underlying bone, the synovial lining, and nearby tissues [2]. Over time, this results in noticeable changes like reshaping of the joint, cartilage wear and tear, reduced joint space, and problems with movement. People with TMJ osteoarthritis may experience symptoms such as jaw pain, stiffness, difficulty opening the mouth fully, clicking or grinding sounds, and trouble chewing or speaking. Globally, osteoarthritis affects around 15% of the population, making it a major contributor to disability across the world [3]. In computer vision, Deep Convolutional Neural Networks (DCNNs) work very well. They are used in many tasks like understanding videos, finding objects in pictures, cutting out parts of images, sorting images into groups, recognizing speech, and understanding human language [4]. One of the hardest and most important jobs in computer vision is object detection, which means finding and recognizing objects in images or videos [5]. This review explores the implementation of a neural network-based AI model for the radiographic detection of TMJ-OA. The study aims to evaluate the effectiveness and reliability of AI assisted diagnosis in improving clinical outcomes and supporting decision-making in dental and medical practice. And to analyse current detection methods and see which one is better. In this paper, we review over 50 research studies on AI-based detection of temporomandibular joint osteoarthritis (TMJOA) to evaluate which models are best suited for this task and how each model performs across different imaging modalities and diagnostic objectives. By consolidating and comparing reported results, we aim to identify performance trends, methodological strengths, and areas where current approaches can be improved. This work does not propose or implement a new AI model; rather, it is a review paper that systematically examines existing studies to compare methodologies, performance, and applicability of AI-based approaches for TMJOA detection. Manual Methods for TMJ Assessment The most commonly used methods to assess vertical condylar asymmetry are those developed by Kjellberg [15] and Habets [16], where the former calculates a symmetry index based on condylar and ramus height ratios, while the latter uses a linear asymmetry index derived from the height difference between the left and right condyles [17]. The Habets method is a widely used technique for evaluating vertical asymmetry of the mandibular condyles using panoramic radiographs. It involves measuring the vertical heights of the condyle and ramus on both sides of the mandible and calculating an asymmetry index (AI) to quantify differences [15]. The asymmetry index is calculated using the formula: AI (%) = $(R - L)$ $(R + L)$ X 100 (1). An AI greater than 6% is considered indicative of significant asymmetry [16]. This method is particularly useful in orthodontics and for diagnosing temporomandibular joint (TMJ) disorders, as it provides a simple and non-invasive means to assess mandibular asymmetry. The Kjellberg method focuses on assessing condylar asymmetry by calculating the ratio of condylar height to the total height of the mandibular ramus using panoramic radiographs. This ratio helps in determining the symmetry between the left and right condyles [18]. The method involves measuring: Condylar Height (CH): Distance from the most superior point of the condyle to the mandibular notch.Ramus Height (RH): Distance from the mandibular notch to the gonion (the most posterior-inferior point on the angle of the

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mandible) [19]. A symmetry index less than 93% indicates significant asymmetry [20]. This method is valuable in clinical settings for evaluating patients with TMJ disorders, facial asymmetries, and for planning orthodontic or surgical interventions. Both methods provide clinicians and researchers with reliable tools for assessing mandibular asymmetry, aiding in the diagnosis and treatment planning of TMJ disorders and related conditions. Manual measurement methods such as those proposed by Habets et al. and Kjellberg et al. have traditionally been employed for evaluating condylar asymmetry and deformation using panoramic radiographs. While these techniques offer a basic, accessible framework for asymmetry index calculation, they are significantly limited by several factors. One major drawback is the inter- and intra-observer variability, where repeated measurements by the same or different observers may lead to inconsistent results due to subjective landmark identification [21,22]. Moreover, these methods are dependent on 2D panoramic radiographs, which inherently distort the true anatomical structure due to projection errors, magnification, and superimposition of adjacent tissues, leading to reduced diagnostic accuracy [23]. Additionally, head positioning errors during radiograph acquisition can significantly impact measurement reliability, especially when evaluating bilateral condylar morphology [24]. These methods are also time consuming, requiring manual tracing and measurement, which limits scalability and integration into modern digital workflows. The rise of AI and 3D imaging modalities, particularly CBCT, offers more precise and reproducible alternatives, enabling automated detection of condylar deformation with greater accuracy and objectivity [25,26].

2. Methodology

Kim et al. [27] developed an AI model to automatically detect TMJOA using CBCT images. A dataset of 3,514 side-view CBCT images showing bone changes in the jaw joint was used. The authors trained a single-shot detection (SSD) model to classify the region of interest into two categories. The model achieved an accuracy of 86%, with a precision of 85%, recall of 84%, and F1 score of 84%. These results indicate the potential of AI to support early and automated TMJOA diagnosis. The authors suggested incorporating additional data such as clinical signs, demographic information, and medical history to enhance diagnostic performance further. Kim et al. [28] proposed an AI-driven system for detecting TMJ osteoarthritis using panoramic dental X rays. The study utilized convolutional neural networks (CNNs) and Faster R-CNNs for mandibular condyle localization and condition classification. A dataset of 1,000 retrospectively collected panoramic images was annotated into normal, abnormal, and unreadable categories. To enhance model training, data augmentation techniques such as rotation and shifting were applied. The Faster R-CNN model achieved condyle detection precision of 99.4% (right) and 100% (left) at IoU > 0.5. For OA classification, the CNN model attained a sensitivity of 0.54, specificity of 0.94, and accuracy of 0.84. Despite its reliance on panoramic imaging, which lacks 3D detail, the system shows promise as a preliminary diagnostic aid. The study recommends future improvements like integrating CT data, symmetry analysis, and expanded datasets. Eun-hye Choi et al. [29] collected orthopantomogram (OPG) images from patients at the Orofacial Pain Clinic, Seoul National University Dental Hospital, to detect temporomandibular joint osteoarthritis (TMJOA). They employed a two-step model combining Faster R-CNN with Inception V3 for identifying the region of interest (ROI) and Keras' ResNet model for classification. The images were categorized into normal, indeterminate, and OA. The AI model's performance was suboptimal, achieving an accuracy of 78%, sensitivity of 73%, and specificity of 82%. This study demonstrates the potential of AI in assisting diagnosis, particularly in clinical settings lacking access to specialists or advanced imaging like CT. Ribera et al. [30]

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utilized the ShapeVariation Analyzer deep learning model to classify mandibular condyles based on morphological shape. Mesh-based features, including normal vectors, curvature, distances, shape index, curvedness, position, and heat kernel signatures, were extracted for classification. The model achieved a maximum training accuracy of 92%. This study also emphasized the use of web based platforms for multi-centre data processing and AI model deployment. These approaches provide considerable support in achieving personalized and precise TMJOA diagnosis. Precision (P) = Recall (R) = True Positive True Positive + False Positive True Positive True Positive + False Negative (2) (3) F1 Score (F) = 2X(PrecisionXRecall) (4) Precision+Recall Han et al. [31] introduced a deep learning model using a modified U-Net and CNN to measure mandibular condyle cortical bone thickness from 12,800 CBCT images. The model achieved intersection-over-union (IoU) scores of 0.870 for marrow bone and 0.734 for cortical bone. A 3D color map was also generated, closely resembling ground truth annotations. This approach enables automated monitoring of bone health in the TMJ region. In a study by Jung et al. [32], researchers created a diagnostic tool powered by deep learning to differentiate between normal and osteoarthritic temporomandibular joints (TMJ) using panoramic X-ray images. They worked with a dataset of 858 images from 518 individuals, which they divided into training, validation, and test sets in a 60:20:20 ratio. Two well-known pretrained convolutional neural networks— ResNet-152 and EfficientNet-B7—were used through transfer learning to classify the images. The models' effectiveness was assessed based on metrics such as accuracy, specificity, sensitivity, and area under the curve (AUC), and Grad-CAM was used to visually interpret which image features the models focused on. The results showed high accuracy, with ResNet-152 achieving 87% and EfficientNet-B7 slightly higher at 88%. Interestingly, both models outperformed general dentists and TMD specialists in diagnosing osteoarthritis from these images, highlighting the potential of AI-assisted panoramic imaging as a reliable screening approach for TMJ OA. Kong et al. [33] created an AI-based system for diagnosing TMJ disorders using MRI. The model segmented the TMJ disc, condyle, and temporal bone to assess pathology risk. With a sensitivity of 98.8%, the system effectively identified abnormal cases, though limited dataset size affected generalizability. Authors called for larger multi-center datasets and standardized protocols to improve accuracy and clinical adoption. Chang et al. [34] proposed an AI-based system to detect TMJ disc displacement (TMJDD) using sagittal MRI. Their study involved 52 patients and 32 healthy controls. A U-net architecture was used for segmenting the joint cavity, followed by classification using InceptionResNetV2, InceptionV3, DenseNet169, and VGG16 models. InceptionV3 achieved the highest performance with a recall of 1, precision of 0.81, accuracy of 0.85, and F1 score of 0.9. These results show promise for automated MRI based TMJDD detection. Almasan et al. [35] conducted a systematic review and meta-analysis to assess the role of AI in TMJOA diagnosis using cone-beam computed tomography (CBCT) and panoramic radiography. The review synthesized data from seven selected studies, involving 10,077 TMJ images. Transfer learning, specifically ResNet models, was widely used. The analysis included the application of QUADAS-2 and MI-CLAIM tools to evaluate bias and model reporting quality. A pooled sensitivity of 0.76 and specificity of 0.79 were reported. Furthermore, the study explored the integration of 3D condylar shape analysis, radiomics, clinical, and proteomic data to improve diagnostic accuracy. Model performance improved notably when indeterminate cases were excluded and models were fine-tuned. Eser et al. [36] evaluated the performance of the YOLOv5 architecture for segmenting TMJ and classifying OA conditions in sagittal CBCT images. A dataset comprising 2000 sagittal CBCT sections was used,

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categorized into four groups: healthy, erosion, osteophyte, and flattening. The YOLOv5 model achieved a sensitivity of 1, precision of 0.7678, F1 score of 0.8686, and overall classification accuracy of 76.78%. Prediction accuracy for healthy joints was 88%, flattened joints 70%, erosion 95%, and osteophyte 86%. The study validated the potential of YOLOv5 as a clinical decision-support tool for early TMJOA diagnosis. James et al. [37] systematically reviewed how clinical variables, diagnostic parameters, and image acquisition techniques influence deep learning applications for TMJ diagnosis. Using PRISMA guidelines, they evaluated 20 studies from multiple medical databases and assessed their quality using MI-CLAIM and GRADE frameworks. Key inputs for deep learning models included radiographic metrics like bone volume and trabecular patterns, as well as MRI features such as joint space narrowing and disc morphology. Their review showed that AI performed comparably to clinicians for detecting OA from radiographs but had lower performance on disc disorders using MRI. Data quality, inconsistent standards, and imaging bias were cited as limitations. Ozsarı et al. [38] reviewed the application of AI in TMJ diagnostics by analyzing 66 studies across multiple categories including segmentation (11 studies), Juvenile Idiopathic Arthritis (3), TMJOA (10), Temporomandibular Joint Disorders (21), decision support systems (6), reviews (10), and sound analysis (5). The review emphasized the increasing adoption of AI for TMJ research and the diverse range of applications across clinical and research domains. Esra et al. [39] reviewed deep learning approaches for detecting dental diseases using a corpus of 101 eligible articles from 2019 to May 2023. The majority of studies focused on classification (51 studies) using panoramic radiographs (55 studies). Pretrained networks such as Faster R-CNN, YOLO, and U-Net were commonly used. However, explainability and human-AI comparison were limited. The authors emphasized the need for reproducibility and clinical safety to support practical implementation. Figure. 2 showcases two analytical views relevant to the application of AI in temporomandibular joint (TMJ) diagnostics. The waterfall chart on the left quantifies the cumulative accuracy contributed by each AI model, revealing that models like ResNet, DenseNet169, and InceptionV3 significantly boost overall performance. YOLOv5 and R-CNN also contribute substantially, emphasizing their utility in clinical image interpretation. On the right, the pie chart visualizes the proportional usage of AI techniques across reviewed studies. CNN dominates with 25% representation, followed by YOLO (20%) and ResNet (15%), highlighting current research preferences. This dual representation aids in understanding not only model effectiveness but also the popularity of techniques employed in TMJ analysis. Sunaina et al. [40] investigated the potential of artificial intelligence (AI) to enhance the diagnosis of temporomandibular joint (TMJ) osteoarthritis using cone-beam computed tomography (CBCT) images. Recognizing the limitations of subjective human interpretation, the study aimed to develop and validate an AI model for accurate TMJ osteoarthritis detection. A total of 2,737 CBCT images from 943 patients were used to train and validate a convolutional neural network, with object detection integrated through a single-stage regression model. Diagnostic performance was evaluated using a test set of 350 images, assessed independently by two expert evaluators following the Diagnostic Criteria for Temporomandibular Disorders (DC/TMD). Compared to an experienced oral radiologist, the AI model demonstrated significantly better agreement with the gold standard. Notably, Cohen's kappa showed statistically significant improvements in diagnosing all TMJ osteoarthritis signs collectively ($P = 0.0079$) and subcortical cysts ($P = 0.0214$). This highlights AI's potential to reduce interpretation subjectivity and speed up TMJ OA diagnostics. Xiang et al. [41] developed a cephalogram-based nomogram model to screen for

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DJDs. Using data from 502 patients and 36 cephalometric features, a logistic regression-based model was created. The final score integrated 22 significant variables and clinical features. The model achieved an AUC of 0.893 and showed good calibration, indicating strong predictive utility for early DJD detection in clinical dentistry. Fontana et al. [42] introduced the EHPN (Ensemble via Hierarchical Predictions through Nested cross validation) model to forecast TMJ OA progression. In a longitudinal study of 106 subjects, the model incorporated 18 machine learning and statistical techniques. EHPN achieved 0.87 accuracy, 0.72 AUC, and 0.82 F1-score. SHAP analysis highlighted key biomarkers (e.g., VEGF, ENA-78) and patient variables (e.g., headache, sleep quality). The study emphasizes personalized diagnostics and precision medicine for TMJ OA. Table 1 presents a consolidated benchmark of AI-based temporomandibular joint osteoarthritis (TMJOA) detection studies reviewed in this paper. It compares key aspects such as imaging modality, model architecture, dataset size, performance metrics, and unique features. This comparative analysis highlights trends, strengths, and research gaps, providing a structured view of the current state of the art. Duman et al. [43] examined the potential of YOLOv5 for early TMJOA detection from CBCT sagittal images. Using 2000 images from 290 patients, the model was trained to segment the TMJ and classify it into healthy, erosion, osteophyte, and flattening categories. The segmentation task yielded high scores (sensitivity: 1, precision: 0.9953, F1: 0.9976, AUC: 0.9723), while classification accuracy was 76.78%. The results highlight the suitability of YOLOv5 for rapid, automated TMJ diagnostics. Ibrahim et al. [44] investigated variability in mandibular condyle morphology by developing a deep learning-based detection method using YOLOv8 for ROI localization and MobileViT for feature extraction. They also implemented a modified Mountaineering Team-Based Optimization (MTBO) algorithm for feature selection. Using a dataset of 3000 panoramic images categorized into round, pointed, angled, and flat condyle shapes, their model achieved 81.5% accuracy in binary and 83.5% in multi-class classification tasks. The study demonstrates how advanced DL architectures and optimization algorithms can enhance morphological characterization of the TMJ. Zhu et al. [45] developed a deep learning-based diagnostic system to assess anterior disc displacement (ADD) in the TMJ using MRI. Leveraging the ResNet101_vd architecture, the model was trained to detect regions of interest, segment anatomical structures, and classify ADD conditions. A total of 1,458 MRI scans were used, with data split across two hospitals. Four models were implemented: ROI detection, segmentation, and two classification models (with and without segmentation). The segmentation-based classification model achieved precision rates above 92%, outperforming the non-segmentation approach. Grad-CAM heatmaps and annotated segmentations improved clinical interpretability. Despite minor external testing performance drops, the system showed robust diagnostic capabilities for TMJ ADD. The reviewed studies collectively demonstrate an evolving landscape of deep learning approaches for TMJOA detection. Figure 1 systematically compares the frequency and application of architectures across these studies. YOLO (You Only Look Once) and CNN-based frameworks (e.g., ResNet, InceptionV3) are most prevalent due to their efficacy in object detection and image classification tasks. U-Net dominates segmentation workflows (e.g., condyle localization), while hybrid models (e.g., Faster R-CNN + ResNet) address multi-stage challenges like ROI detection followed by classification. Recent works increasingly adopt optimized architectures (e.g., YOLOv5/YOLOv8, MobileViT) and feature-engineering techniques (e.g., radiomics, shape analysis), indicating a shift toward computational efficiency and multimodal integration. Elizabeth et al. [46] introduced a hybrid framework combining 3D explainable deep learning with multiscale

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biomechanical modeling to analyze TMJ disorder etiology. A 3D-CNN was used to identify morphological risk features across condyle, ramus, and chin regions. These AI-derived insights guided biomechanical simulations, which revealed that flatter condylar shapes and smaller mandibles increase joint loading, reduce nutrient diffusion, and elevate disc strain energy. This integrative method enhances the mechanistic understanding of TMJ pathologies and expands AI's applicability even in smaller datasets. Across the reviewed studies, dataset usage varied considerably between models. For instance, YOLOv5 was commonly applied to CBCT datasets, with sample sizes ranging from 2,000 sagittal sections to over 12,000 images in certain segmentation studies. InceptionV3 appeared in MRI-based TMJ disc displacement detection, typically on smaller datasets of fewer than 100 subjects, while ResNet variants (e.g., ResNet-152, ResNet-101) were trained primarily on panoramic radiographs or MRI scans, with dataset sizes spanning from under 1,000 to more than 1,400 images. EfficientNet-B7 was evaluated on panoramic radiographs in datasets of around 850 images. In several cases, the exact dataset size, acquisition parameters, and metric computation procedures (e.g., whether accuracy was calculated on validation or independent test sets) were not reported, limiting the ability to directly compare performance across models. This heterogeneity should be considered when interpreting Figures 2–4, as differences in sample size, modality, and metric definitions may influence reported performance as much as, or more than, the model architecture itself. Figure. 3 provides a dual-chart comparison to analyse the prevalence and performance of various AI models applied in temporomandibular joint (TMJ) research. The left panel illustrates the number of times each model appears in the literature, with CNN and YOLO emerging as the most frequently utilized architectures. This indicates their dominance and reliability in image-based diagnostics. The right panel presents the sum of accuracy and error values for the key models, showcasing that models like ResNet, DenseNet169, and InceptionV3 consistently demonstrate high accuracy with relatively low error rates. These insights highlight the evolving preference for more accurate and computationally efficient models in TMJ osteoarthritis diagnosis.

Jong Huyn et al. [47] evaluated CNNs for detecting TMJ effusion from MRI, also testing the benefit of integrating clinical data. Using 2,948 MRI scans from 1,474 patients, three CNN training strategies were compared: from scratch, fine-tuning, and freezing. The fine-tuned model on proton density (PD) images yielded the best AUC (0.7895), outperforming human experts in specificity (87.25% vs. 58.17%) though trailing in sensitivity (57.43% vs. 80.00%). Grad-CAM confirmed the model's clinical relevance. An ensemble DNN incorporating clinical features improved AUC to 0.8258, particularly for patients aged 41–60. These findings demonstrate the diagnostic enhancement possible through multimodal AI integration. Gwan et al. [48] proposed a deep learning approach for 3D segmentation of the mandibular condyle using CBCT. From 99 patients, 2D sagittal, coronal, and axial slices were extracted and reconstructed into 3D volumes via a U-Net model. Coronal and axial slices yielded Dice scores of 0.92, higher than sagittal (0.82). Errors due to non-uniform image quality were partly corrected via post-processing. This method provides accurate 3D reconstructions for TMJ evaluation, especially useful in anatomical abnormalities. Figure. 4 chronologically maps architectural trends in TMJOA detection research, revealing distinct evolutionary phases. Early studies (2020-2021) predominantly utilized Single-Shot Detectors (SSD) and foundational CNNs like ResNet, prioritizing basic localization capabilities. Subsequent years (2022-2025) witnessed rapid adoption of advanced architectures YOLO variants (v5/v8) emerged as dominant frameworks, offering improved speed-accuracy balance for condylar pathology detection, Transformer-based models (Swin-Transformer) gained traction for capturing

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long-range dependencies in 3D CBCT volumes [31] Hybrid architectures proliferated, combining CNNs with ViT or optimization algorithms for enhanced feature extraction. Yukiko et al. [49] evaluated DL models (GoogLeNet and VGG-16) for condylar OA detection using panoramic TMJ projection images in patients with dentofacial deformities. Three image types—Con-Pa, Open-TMJ, Closed-TMJ—were analyzed. Open-TMJ images provided the highest AUC (0.89 for both models), significantly outperforming the performance of novice residents. This suggests that DL models can aid inexperienced clinicians, particularly when optimal image views are available. Yiwei et al. [50] conducted a comprehensive literature review to summarize machine learning applications in diagnosing and classifying temporomandibular disorders (TMDs). The authors screened databases including PubMed, Google Scholar, and Web of Science for articles published until October 2024. The review emphasized challenges such as dataset limitations, diagnostic inconsistencies, and the need for large-scale multicentre validations. It concluded that while ML models are clinically promising, further longitudinal studies are essential for generalization and clinical adoption. Mahobiya et al. [51] explored ML-based detection of bone deformation using X-rays, CT scans, and MRIs. The study stressed the potential of ML in enhancing diagnostic accuracy while acknowledging challenges like privacy and interdisciplinary collaboration. It highlighted the need for collaboration between medical professionals and AI developers to build reliable diagnostic systems. Kader et al. [52] employed various deep learning architectures on panoramic X-rays to identify TMJ bone deformities. GoogleNet outperformed other models, achieving a classification accuracy of 95.23%. The authors emphasized expanding datasets and including multimodal inputs for improving future model robustness.Lucia et al. [53] analyzed pre- and post-operative CBCT scans of 17 Class III malocclusion patients undergoing orthognathic surgery. Using deep learning, they assessed condylar changes and observed minor variations (less than 1 mm), including bone loss in the superior region and formation on the lateral side. This study underscores the importance of accurate surgical planning and postoperative assessment. Angela et al. [54] compared the surgery-first approach (SFA) and traditional surgery-late approach (SLA) using CBCT scans of 77 patients. AI-assisted analysis showed no significant differences in post-surgical condylar changes (0.41 mm for SFA vs. 0.36 mm for SLA), demonstrating AI's utility in surgical outcome tracking. Seong et al., [55] built an AI model for screening degenerative joint disease (DJD) by combining TMJ panoramic radiographs with joint noise data. Of 3,908 final images (2,127 normal, 1,781 DJD), multiple models were tested using combinations of crepitus, patient-reported noise, and images. The best model, which integrated all joint noise data with imaging, achieved an F1-score of 0.72 and outperformed orofacial pain specialists. This highlights the diagnostic value of combining objective imaging with subjective patient inputs in AI models. Ivanov et al., [56] focused on AI-based segmentation of the TMJ articular disc using MRI, addressing the gap in soft tissue analysis by existing AI tools. A novel dataset of 94 annotated images was augmented, and models including U-Net, YOLOv8n, YOLOv11n, and Roboflow were trained. Roboflow outperformed others in Dice Score, Sensitivity, and Mean Average Precision. Future plans include integrating disc position and jaw distance measurement algorithms to enhance TMJ pathology diagnostics.

Figure 1. **An OPG image showing the tempo**

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mandibular joint and condylar bone.

Study	Model	Dataset Size	Accuracy
Kim[27]	SSD	3,514 images	Accuracy 86%
Kim[28]	CNN + Faster R-CNN	1,000 images	Accuracy 84%
Eun-hye[29]	Faster R-CNN + ResNet	Unknown	Accuracy 78%
Ribera[30]	ShapeVariationAnalyzer	Unknown	Accuracy 92%
Han[31]	U-Net + CNN	12,800 images	IoU marrow 0.87
Jung [32]	ResNet-152, EfficientNet-B7	858 images	Accuracy 87–88%
Kong [33]	Segmentation + classification	-	Sensitivity 98.8%
Chang[34]	U-Net + InceptionV3	84 subjects	Accuracy 85%
Eser [36]	YOLOv5	2000 sections	Accuracy 76.78%
Sunaina[40]	CNN + SSD	2,737 images	-
Duman [43]	YOLOv5	2000 images	Accuracy 76.78%
Ibrahim [44]	YOLOv8 + MobileViT	3000 images	Accuracy 81.5–83.5%
Zhu [45]	ResNet101_vd	1,458 scans	Precision >92%

Table 1. Key Studies on AI-based TMJOA Diagnosis

Results and Discussion

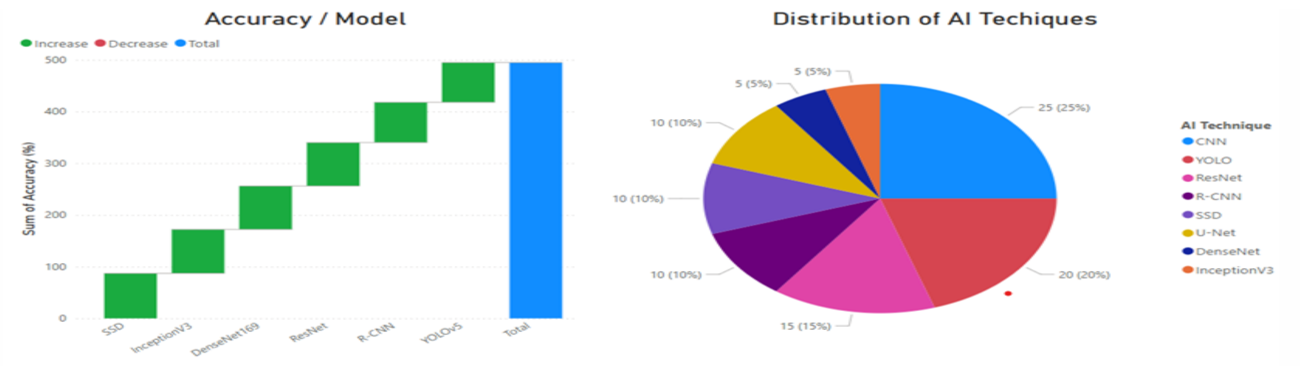

Figure 2 Performance Aggregation and Methodological distribution of AI Models in TMJ Research.

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3. Results

The results obtained from the comparative analysis of various AI models for TMJ osteoarthritis detection indicate clear performance trends across architectures. From *Figure 2 (left)*, the cumulative accuracy contribution shows that models such as ResNet, DenseNet169, InceptionV3, and CNN significantly increase overall accuracy, while SSD contributes comparatively less. The total aggregated accuracy reflects that deep learning models consistently provide strong performance in TMJ diagnosis. From *Figure 2 (right)*, the distribution of AI techniques shows that CNN-based models dominate with approximately 25% usage, followed by YOLO (20%) and ResNet (15%). Other models such as R-CNN, U-Net, DenseNet, and InceptionV3 contribute smaller proportions, indicating that CNN and YOLO architectures are the most widely adopted techniques.In *Figure 3 (left)*, the number of models studied shows that CNN appears most frequently, followed by YOLO and ResNet, confirming their popularity in research. *Figure 3 (right)* shows that ResNet, DenseNet169, and InceptionV3 achieve higher accuracy with lower error rates compared to other models like R-CNN and YOLOv5, which show slightly higher error margins. From *Figure 4*, the chronological trend indicates that earlier studies (2020–2021) mainly used SSD and basic CNN models, while recent studies (2022–2025) have shifted towards advanced architectures such as YOLOv5, YOLOv8, and hybrid models. This shows a clear evolution towards more efficient and accurate models.Additionally, as summarized in Table 1, most models achieve accuracy between 76% and 88%, with some models exceeding 90% in specific tasks such as shape analysis and segmentation.

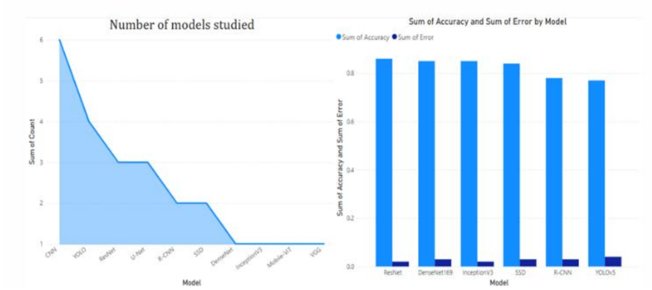

Figure 3 Comparative Visualization of AI Models Studied and Their Performance Metrics in TMJ Analysis

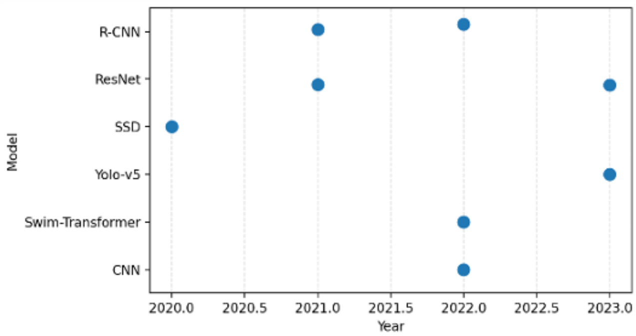

Figure 4 Chronological adoption of deep learning architectures in TMJOA detection research (2020 2025).

Discussion

The results clearly show that deep learning models have become the preferred approach for TMJ osteoarthritis detection due to their ability to automatically extract complex features from medical images. CNN-based architectures dominate both in usage and performance, making them the backbone of most diagnostic systems.
Although YOLO-based models provide slightly lower accuracy compared to models like ResNet or DenseNet, they offer significant advantages in terms of speed and real-time detection, making them highly suitable for clinical applications. Similarly, hybrid models combining detection and classification improve overall performance by addressing multiple tasks efficiently.

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The graphs also highlight that model performance is strongly influenced by dataset size and quality. Models trained on larger datasets tend to achieve better accuracy and generalization, while smaller datasets often lead to variability in results. This explains why some studies report lower performance despite using advanced architectures.
Another important observation is the shift toward advanced and optimized models over time, as seen in Figure 4. The adoption of YOLOv5, YOLOv8, and transformer-based approaches reflects the need for faster and more scalable solutions in medical imaging. However, despite high accuracy, several limitations remain. Lack of standardized datasets and evaluation metrics makes it difficult to directly compare models. Additionally, most models focus on hard tissue analysis and may not perform equally well on soft tissue imaging like MRI. Clinical validation and real-world testing are still limited. Overall, the discussion confirms that AI models—especially CNN, ResNet, and YOLO-based architectures—are effective for TMJ diagnosis, but further improvements in data standardization, multimodal integration, and clinical validation are required for reliable deployment.

Conclusion

This review highlights the growing role of artificial intelligence in detecting temporomandibular joint osteoarthritis. AI models, especially deep learning techniques, have shown encouraging results in analyzing medical images and identifying early signs of TMJOA. These approaches offer faster, more consistent, and often more accurate diagnoses compared to traditional manual methods. However, challenges such as limited datasets, lack of standard protocols, and the need for clinical validation still exist. With continued research, larger data collections, and improved collaboration between medical and technical experts, AI has the potential to become a reliable and widely used tool in TMJ diagnostics, ultimately helping to improve patient care. Most current models are tested on limited data and are not compared under the same conditions, making it hard to know which works best. Future work should compare different models using the same datasets and evaluation methods.

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