A Review on Temporomandibular Joint Disorder Recognition using Artificial Intelligence Models

Vijaya Kumar K
Department of Computer Engineering,
Women's Polytechnic College,
Puducherry, India..

Santhi Baskaran
Department of Information Technology,
Puducherry Technological University,
Puducherry, India

Abstract:- Temporomandibular Joint (TMJ) disorder is a set of orofacial ache syndromes that are the most frequent non-dental ache issue in the maxillofacial area. It mostly refers to a group of musculoskeletal problems that can impact the masticatory system. It is believed that 60-70% of the population suffers from the minimum any signs. This condition is quite common in the wide-ranging community, yet women are afflicted at a 4:1 fraction. Over the past decades, advanced Artificial Intelligence (AI) methods including machine and deep learning algorithms have been developed to recognize and categorize the TMJ disorder early from different imaging modalities like panoramic images, X-ray images, etc. Amongst, panoramic radiograph is utilized as a preliminary forecasting technique in association with a complete medicinal evaluation to diagnose TMJ disorder. The findings observed from such methods can help the physicians in decision-making and early diagnosis of TMJ disorder. This paper presents a detailed review of different machine and deep learning algorithms developed to recognize and categorize TMJ disorder from panoramic images. First, different TMJ disorder recognition and categorization models designed by many researchers based on machine and deep learning algorithms are studied in brief. Then, a comparative study is conducted to understand the drawbacks of those algorithms and suggest a new solution to classify the TMJ disorder accurately.

Keywords:- *Temporomandibular disorder, Temporomandibular joint, Artificial intelligence, Machine learning, Deep learning, Panoramic imaging.*

I. INTRODUCTION

Agriculture The most frequent kind of arthritis that affectsthe Temporomandibular Joint (TMJ) is osteoarthritis (OA). OA is a damaging process that distorts the osteoarticular plane of the mandibular condyle and fossa. Excessive mechanical stress on joint tissue is the most prevalent cause of OA. Resorption of the subarticular bone occurs when a weight is used consistently and the chondromalacia softens. Radiological osteoarthritis is caused by a gradual bone alteration that results in the deterioration of the subchondral cortical unit and bone [1-2].

TMJ-OA is diagnosed with therapeutic records, quantifiable diagnostics and scan evaluation. TMJ-OA manifests medically as reduced mobility of the subordinate jaw because of the discomfort, crepitus and neighboring paraspinal soreness in the joint support. Whilst a scan analysis reveals structural bone alteration, OA has been diagnosed [3-5]. Further, with orthopantomography, OA may be used to assess the condylar and Ramal asymmetry of the mandible in individuals with Juvenile Idiopathic Arthritis (JIA). There are various general disorders and diagnoses of TMJ, which are categorized into painful and non-painful conditions [6-7]. Table 1 explains those disorders and their clinical findings.

Conditions	Disorders	Medical Results
Painful Conditions	Myalgia	Ache in the masseter or temporalis while palpating or opening the mouth
	Local myalgia	Ache in the masseter or temporalis that is confined to the point of palpation
	Myofascial pain	Pain in the masseter or temporalis muscle that extends outside the location of probing yet remains inside the muscle's boundaries
	Myofascial pain with referral	Ache in the masseter or temporalis muscle that extends outside the boundaries of the muscle being palpated
	Arthralgia	Ache in the TMJ when palpated or in working
	Head pain contributed to TMJ	Headache in the temples when the temporalis muscle is palpated or during function
Non-painful Conditions	Displacement of the disc with reduction	When performing a function, the TMJ clicks.
	Displacement of disc with reduction and with intermittent locking	TMJ clicking with reported instances of restricted mouth opening
	Displacement of disc without reduction and with limited opening	The limited mouth opening has an impact on working, by means of a most aided opening of <40mm.
	Displacement of disc without reduction and without limited opening	The limited mouth opening has an impact on working, by means of a most aided opening of ≥40mm.
	Degenerative joint disorder	TMJ crepitus during function
	Subluxation	Jaw locking in an open mouth pose, unable to close devoid of a self-maneuver

Table 1: General Diagnoses of TMJ and Their Clinical Findings

Once bone changes in the TMJ are detected, panoramic scans are commonly employed premature phases of prognosis. Nevertheless, since the TMJ contains tiny bone patterns at the joint point and the joint is hidden with the large cranium, basic imaging is hard to detect bone changes [8]. Also, structural alterations or lesions in the TMJ are frequently missed in basic scans due to inadequately demineralized bone tissue in the early stages of OA [9]. Hence, analyzing panoramic radiographs requires trained professionals with significant clinical expertise, and more radiography must be prescribed whenever needed. Regrettably, transmitting panoramic scans to an expert and waiting for the results is inconvenient if hospital professionals who are able to properly treat OA depending on the panoramic scans are not accessible. Further, since it is impossible for a physician to identify the therapeutic condition of osteoarthritis rapidly, the process of forwarding panoramic scans and receiving diagnostic findings should definitely be repeated. To solve such challenges, many AI including machine and deep learning classification models have been developed to recognize and categorize TMJ-OA using different radiographs [10].

The main goal of this manuscript is to give a complete survey of various recognition and categorization models for TMJ disorders from various imaging modalities. Also, a comparative study is presented to address the advantages and disadvantages of those models to suggest future scope. The rest of the sections are prepared as follows: Section II discusses various models designed to recognize and categorize TMJ disorders. Section III provides the comparative analysis of those models. Section IV summarizes the entire study and suggests the upcoming scope.

The rest of the sections are prepared as follows: Section II discusses various methods designed different methods to detect and classify TMJ-OAs. Section III provides the comparative analysis of those methods. Section IV summarizes the entire survey and recommends the upcoming scope.

II. SURVEY ON DIFFERENT ALGORITHMS FOR TMJ-OA DETECTION AND CLASSIFICATION

Ariji et al. [11] developed a deep learner model using the DetectNet structure executed with the DIGITS to identify and categorize radiolucent tumors in the mandible on panoramic radiographic. First, panoramic imaging of patients with mandibular radiolucent tumors was collected. Then, lesion tags and ROI coordinates were generated. Moreover, the training samples with related tags were fed to the DetectNet to recognize and categorize radiolucent lesions of the mandible.

Choi et al. [12] designed a novel AI framework for diagnostic choice. At first, the data about the surgical and non-surgical treatment cases were collected. Then, such data was fed to the 2-layer Neural Network (NN) with a single hidden unit. Also, the training has been conducted in three phases and four optimum structures have been considered to determine the hit choice hit percentages of diagnostics. The absolute prognosis hit percentage has been determined via evaluating the original prognosis with the prognosis predicted using the NN.

Shoukri et al. [13] developed a minimally invasive method for diagnosing TMJ-OA. The aim was to analyze associations amid a set of biomarkers, which were related to condylar structure and to employ AI to analyze texture characteristics in a NN. In this method, serum and salivary stages of inflammatory biomarkers have been measured by the protein microarrays. Also, the NN has been learned by another condyles to recognize and categorize the TMJ-OA.

Li et al. [14] suggested the multilayer perceptron artificial NN to estimate OA diagnosis strategies, like the computation of mining/non-mining, extraction motifs and anchorage motifs. First, the data regarding OA diagnosis cases were collected and the K-nearest neighbor algorithm was applied to handle the discrete input characteristics with absent details. Also, the most relevant features were extracted and fed to the multilayer perceptron to estimate OA diagnosis strategies.

Aliaga et al. [15] developed a novel automated technique to identify particular points and lines in dental panoramic radiographic. The main tasks involved in this technique were: (1) detection of artificial patterns using Fuzzy K-means categorization, (2) modifying a tangent line to the minor boundary of the minor jawbone depending on shape investigation, grey-level dilation, Binarization and tagging, (3) detection of the mental foramen area and its center depending on multi-thresholding, Binarization, morphological functions and tagging, (4) creating a perpendicular line to the tangent across the center of the intellectual foramen area, as well as 2 parallel lines to the tangent via boundaries on the intellectual foramen crossed via the perpendicular, (5) Once dynamic filtering to the perpendicular line was applied, a scan was conducted traveling along the tangent to identify aggregation of binary points and (6) recognition of the subordinate mandible alveolar crest line depending on the inter-teeth gap recognition using saliency and desired characteristic representation.

Abdalla-Aslan et al. [16] designed an automated computer vision scheme depending on AI to identify and categorize the different dental restitutions in panoramic radiographic. First, panoramic photos were collected and cropped automatically to get the ROI having maxillary and mandibular alveolar ridges. Then, restitutions have been split via the neighboring dynamic threshold and different features have been obtained by the structure and distribution of gray level ranges. Further, such features were used to train the cubic Support Vector Machine (SVM) with Error-Correcting Output Code (ECOC) for categorizing the restorations into various classes.

Lee et al. [17] developed a diagnostic system to automatically identify TMJ-OA from Cone Beam Computed Tomography (CBCT) images with AI. In this system, the CBCT images of patients treated with TMJ-OA were considered for image collection. Then, a single-shot recognition was trained to obtain the ROIs, which were further categorized into indeterminate OA and OA based on the image analysis criteria for diagnosing TMJ-OA.

Ismael & Khidhir [18] presented a method to categorize jaw cancers using X-ray panoramic images. First, the X-ray panoramic images were collected and augmented by the horizontal flipping and rotation. Then, such images were fed to the pre-trained VGG16 and VGG19 to distinguish oral and maxillofacial disorders.

Zhang et al. [19] suggested a new end-to-end deep learning partition model using 3D U-Net for the TMJ partition in CBCT images. First, the CBCT images were acquired and preprocessed to solve the overfitting problem. Then, those images were given to the 3D U-net, which uses the Binary Cross Entropy (BCE) to train the model and split the TMJ region from the CBCT volumes.

Suhail et al. [20] created an AI decision-making framework for the prognosis of orthodontic mining by an ensemble random forest classifier. The main intentions were: (i) to create a decision-making framework, which simulates the expert's decision of whether a tooth requests to be mined or not depending on normalized orthodontic pre-diagnosis files and (ii) to compute the data components needed in modeling orthodontic mining/non-mining diagnosis decision.

Lee et al. [21] analyzed the discriminating efficiency of Convolutional NN (CNN), employed with the different transfer learning mechanisms, on the categorization of particular characteristics of OA in panoramic images. First, a panoramic image database was collected from multiple participants who experienced both skeletal bone mineral mass and panoramic scan analyses at the Korea University Ansan Hospital. Then, a standard CNN with 3 convolutional layers, VGG16, transfer learning model from VGG16 and fine-tuned VGG16 with transfer learning model were applied to detect OA in the collected panoramic images.

Kim et al. [22] developed a technique, which obtains the condylar area and estimates its irregularity based on the CNN and faster Region-based CNN (R-CNN). First, the panoramic scans were gathered and 2 different techniques were applied: (i) one was used to recognize the TMJ-OA and nearby anatomical patterns and (ii) another was used to estimate whether the recognized anatomical area contains any irregularity depending on the shape of the TMJ. At last, a scheme was applied to determine the existence or nonexistence of TMJ-OA.

Choi et al. [23] designed an AI framework to identify TMJ-OA from Orthopantomogram (OPG). Initially, an object recognition scheme was applied to capture ROI along with the mandibular condyle and nearby patterns from all OPG images. For all ROIs, feature vectors were obtained by the Inception ResNetV2 model. After that, the SVM was utilized to estimate the label related to the attribute map. Also, bounding-box regression has been conducted to calculate the position of the TMJ-OA pixels. Further, Karas' ResNet structure was trained using the extracted ROI images to categorize them into healthy, indeterminate OA and OA.

Bormane & Kakkeri [24] adopted various supervised machine learning classification systems to identify TMJ disease from Surface Electromyography (SEMG). Initially, the SEMG data was recorded and collected as a database. Then, the different common features were obtained from the given database. Also, the most significant features were selected and provided to the different machine learning classifiers to categorize them into healthy and TMJ.

Ito et al. [25] developed an entirely computerized articular disc identification and partition model to assist in the treatment of TMJ-OA on MRI. In this model, some MRI images were collected and analyzed by the different deep learning-based semantic partition schemes such as Detection for Displaced articular DISC based on CNN (3DiscNet), U-Net and SegNet-fundamental to split TMJ articular discs.

III. COMPARATIVE STUDY

In this section, a comparative scrutiny of the above studied ML and DL algorithms for FDD and classification according to their merits and demerits in Table 2.

Ref. No.	Algorithms	Merits	Demerits	Performance
[11]	DetectNet	Better sensitivity to identify radiolucent lesions of the mandible.	More training data was required for precisely identifying small lesions.	210 panoramic images for training, 50 for testing 1 and 25 for testing 2 datasets
[12]	2-layer NN	High success rate.	The drawback was exclusion of skeletal asymmetry cases.	Dataset containing 316 cases of Korean patients
[13]	NN	The maximum score of consistency in sorting condyles depending on the severity of OA.	It needs idea quantitative radiomic characteristics of subchondral bone pattern while large-scale dataset was used.	17 TMJ-OA patients data
[14]	Multilayer perceptron NN	High sensitivity and it can offer better guidance for orthodontic diagnosis.	It has a high complexity for large-scale dataset.	302 patients who accepted orthodontic diagnosis at the Department of Orthodontics, West China Hospital of Stomatology in Chengdu, China
[15]	Fuzzy K-means, texture analysis, grey-level dilation, multi-thresholding, Binarization, morphological functions and tagging	Better robust and reliability for early OA identification.	It needs additional features because mandible alveolar crest line was complex to identify.	A total of 370 images dental panoramic images
[16]	SVM with ECOC	Better accuracy to identify and categorize dental restorations.	It needs more training images. The restorations that were not properly recognized did not undergo the categorization task.	738 dental restitutions in 83 unknown panoramic scans
[17]	Single-shot training	It can help physicians with diagnosis and decision making for diagnosis of TMJ-OA.	It needs more training images with other data like signs, patient's details and clinical files.	3,514 training sagittal CBCT images of the TMJ, 2 sets of 300 images for testing
[18]	Pretrained VGG16 & VGG19	Less complexity and better accuracy.	It needs a large-scale dataset to enhance accuracy.	116 panoramic images
[19]	3D U-Net	High efficiency to partition the TMJ area from CBCT images.	Few edge details were missed, which affects the partition efficiency.	45 TMJs CBCT images obtained from the Peking University School and Hospital of Stomatology
[20]	Ensemble random forest classifier	Better reliability and generalizability.	It does not consider atypical extraction patterns and the diagnosis results were restricted to non-surgical orthodontic measures.	Dataset comprising 300 pre-diagnosis patient files acquired from a personal exercise in Norwalk, Ohio, USA
[21]	CNN with 3 convolutional layers, VGG16,	It can be helpful and consistent in the programmed	It needs more qualified labeled image dataset to increase the accuracy.	680 panoramic images

ISSN No:-2456-2165

	transfer learning model from VGG16 and fine-tuned VGG16 with transfer learning model	monitoring of osteoporosis patients.		
[22]	CNN and faster R-CNN	It supports physicians to decide proper prognosis, which reduces the redundant scanning and prognosis measures.	Sensitivity was less since the dataset was limited.	5503 panoramic images
[23]	Inception ResNetV2 and SVM	It can useful to diagnose TMJ-OA efficiently.	The quantity of training images was low.	1189 OPG images
[24]	AdaBoost, decision trees, gradient boosting, Xtreme gradient boosting and Cat boost classifier	High accuracy.	It needs deep learning to train and categorize more images accurately.	-
[25]	3DiscNet, U-Net and SegNet-Basic	Completely automated strategy and achieved promising outcomes.	Robustness was not effective and the ground truth images were generated by a limited number of experts.	A total of 217 MRI images

Table.2 Comparison of Different Fruit Disease Detection and Classification Algorithms using Fruit Images

IV. CONCLUSION

In this paper, a detailed comparative study on various TMJ-OA recognition and categorization models depending on AI algorithms using different imaging modalities was presented. From this study, it is obvious that identification of TMJ-OA before surgery is the most essential. Nonetheless, relying solely on clinical indicators or panoramic images to make a treatment plan has restrictions. Different studies have compared the existence or lack of bone alteration among the mandibular condyles in panoramic images. According to this survey, it is addressed that the faster R-CNN model accomplishes a better mean precision, accuracy and sensitivity compared to the other models for TMJ-OA recognition and categorization. On the other hand, this model has less sensitivity because of using a limited dataset. Also, its design was limited to the condylar area, whereas other areas or disorders were needed to increase the model efficiency.

REFERENCES

[1.] Dygas, S., Szarmach, I., & Radej, I. (2022). Assessment of the morphology and degenerative changes in the temporomandibular joint using CBCT according to the orthodontic approach: a scoping review. BioMed Research International, 2022, 1-28

[2.] Monasterio, G., Castillo, F., Betancur, D., Hernández, A., Flores, G., Díaz, W., ... & Vernal, R. (2018). Osteoarthritis of the temporomandibular joint: clinical and imagenological diagnosis, pathogenic role of the immuno-inflammatory response, and immunotherapeutic strategies based on T regulatory lymphocytes. In Temporomandibular Joint Pathology-Current Approaches and Understanding. IntechOpen, pp. 69-97.

[3.] Wright, E. F., & North, S. L. (2009). Management and treatment of temporomandibular disorders: a clinical perspective. Journal of Manual & Manipulative Therapy, 17(4), 247-254.

[4.] Gauer, R., & Semidey, M. J. (2015). Diagnosis and treatment of temporomandibular disorders. American Family Physician, 91(6), 378-386.

[5.] Li, D. T. S., & Leung, Y. Y. (2021). Temporomandibular disorders: current concepts and controversies in diagnosis and management. Diagnostics, 11(3), 1-15.

[6.] Schiffman, E., Ohrbach, R., Truelove, E., Look, J., Anderson, G., Goulet, J. P., ... & Svensson, P. (2014). Diagnostic criteria for temporomandibular disorders (DC/TMD) for clinical and research applications: recommendations of the International RDC/TMD Consortium Network and Orofacial Pain Special Interest Group. Journal of Oral & Facial Pain and Headache, 28(1), 6-27.

[7.] Peck, C. C., Goulet, J. P., Lobbezoo, F., Schiffman, E. L., Alstergren, P., Anderson, G. C., ... & List, T. (2014). Expanding the taxonomy of the diagnostic criteria for temporomandibular disorders. Journal of Oral Rehabilitation, 41(1), 2-23.

[8.] Talmaceanu, D., Lenghel, L. M., Bolog, N., Hedesiu, M., Buduru, S., Rotar, H., ... & Baciut, G. (2018). Imaging modalities for temporomandibular joint disorders: an update. Clujul Medical, 91(3), 280-287.

[9.] Bag, A. K., Gaddikeri, S., Singhal, A., Hardin, S., Tran, B. D., Medina, J. A., & Curé, J. K. (2014). Imaging of the temporomandibular joint: an update. World Journal of Radiology, 6(8), 567-582.

[10.] Bichu, Y. M., Hansa, I., Bichu, A. Y., Premjani, P., Flores-Mir, C., & Vaid, N. R. (2021). Applications of artificial intelligence and machine learning in orthodontics: a scoping review. Progress in Orthodontics, 22(1), 1-11.

[11.] Ariji, Y., Yanashita, Y., Kutsuna, S., Muramatsu, C., Fukuda, M., Kise, Y., ... & Ariji, E. (2019). Automatic detection and classification of radiolucent lesions in the mandible on panoramic radiographs using a deep learning object detection technique. Oral Surgery, Oral Medicine, Oral Pathology and Oral Radiology, 128(4), 424-430.

[12.] Choi, H. I., Jung, S. K., Baek, S. H., Lim, W. H., Ahn, S. J., Yang, I. H., & Kim, T. W. (2019). Artificial intelligent model with neural network machine learning for the diagnosis of orthognathic surgery. Journal of Craniofacial Surgery, 30(7), 1986-1989.

[13.] Shoukri, B., Prieto, J. C., Ruellas, A., Yatabe, M., Sugai, J., Styner, M., ... & Cevidanes, L. (2019). Minimally invasive approach for diagnosing TMJ osteoarthritis. Journal of Dental Research, 98(10), 1103-1111.

[14.] Li, P., Kong, D., Tang, T., Su, D., Yang, P., Wang, H., ... & Liu, Y. (2019). Orthodontic treatment planning based on artificial neural networks. Scientific Reports, 9(1), 1-9.

[15.] Aliaga, I., Vera, V., Vera, M., García, E., Pedrera, M., & Pajares, G. (2020). Automatic computation of mandibular indices in dental panoramic radiographs for early osteoporosis detection. Artificial Intelligence in Medicine, 103, 1-38.

[16.] Abdalla-Aslan, R., Yeshua, T., Kabla, D., Leichter, I., & Nadler, C. (2020). An artificial intelligence system using machine-learning for automatic detection and classification of dental restorations in panoramic radiography. Oral Surgery, Oral Medicine, Oral Pathology and Oral Radiology, 130(5), 593-602.

[17.] Lee, K. S., Kwak, H. J., Oh, J. M., Jha, N., Kim, Y. J., Kim, W., ... & Ryu, J. J. (2020). Automated detection of TMJ osteoarthritis based on artificial intelligence. Journal of Dental Research, 99(12), 1363-1367.

[18.] Ismael, A. K., & Khidhir, A. M. (2020). Evaluation of transfer learning with CNN to classify the jaw tumors. In IOP Conference Series: Materials Science and Engineering, IOP Publishing, 928(3), 1-7.

[19.] Zhang, K., Li, J., Ma, R., & Li, G. (2020). An end-to-end segmentation network for the temporomandibular joints CBCT image based on 3D U-Net. In IEEE 13th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics, pp. 664-668.

[20.] Suhail, Y., Upadhyay, M., & Chhibber, A. (2020). Machine learning for the diagnosis of orthodontic extractions: a computational analysis using ensemble learning. Bioengineering, 7(2), 1-13.

[21.] Lee, K. S., Jung, S. K., Ryu, J. J., Shin, S. W., & Choi, J. (2020). Evaluation of transfer learning with deep convolutional neural networks for screening osteoporosis in dental panoramic radiographs. Journal of Clinical Medicine, 9(2), 1-15.

[22.] Kim, D., Choi, E., Jeong, H. G., Chang, J., & Youm, S. (2020). Expert system for mandibular condyle detection and osteoarthritis classification in panoramic imaging using R-CNN and CNN. Applied Sciences, 10(21), 1-10.

[23.] Choi, E., Kim, D., Lee, J. Y., & Park, H. K. (2021). Artificial intelligence in detecting temporomandibular joint osteoarthritis on orthopantomogram. Scientific Reports, 11(1), 1-7.

[24.] Bormane, D. S., & Kakkeri, R. B. (2021). Detection of temporomandibular joint disorder using surface electromypgraphy by supervised classification models. Materials Today: Proceedings, 1-4.

[25.] Ito, S., Mine, Y., Yoshimi, Y., Takeda, S., Tanaka, A., Onishi, A., ... & Tanimoto, K. (2022). Automated segmentation of articular disc of the temporomandibular joint on magnetic resonance images using deep learning. Scientific Reports, 12(1), 1-10