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Artificial Intelligence and Machine Learning in Orthodontics: A review of literature

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ABSTRACT: The increasing use of Artificial Intelligence (AI) and Machine Learning (ML) has had a significant impact on orthodontics, particularly in improving areas such as clinical imaging analysis, treatment planning, and diagnostics. AI-driven tools, such as Convolutional Neural Networks (CNNs), enhance skeletal maturity assessment and play a major role in the classification of dental conditions. Despite challenges like methodological variability and regulatory approval, AI continues to advance orthodontic research and practice.The objective of this article is to explore the integration of artificial intelligence (AI) and machine learning (ML) in orthodontics, highlighting their impact on clinical imaging, diagnostics, and treatment planning while addressing challenges such as data privacy, methodological variability, and regulatory constraints. By analysing various studies, this review aims to demonstrate the advancements AI has brought to orthodontics and emphasize the need for standardized data practices, transparency, and collaborative research to drive further progress.Relevant articles were selected using the Google Scholar search engine, focusing on peer-reviewed studies published between 2019 and 2024. To ensure unbiased evaluation, two independent reviewers assessed the chosen studies.Artificial intelligence and machine learning have significantly improved diagnostic precision and treatment workflows in orthodontics. However, further advancements are needed in areas like data standardization, privacy protection, and regulatory approval.

KEYWORDS: Artificial Intelligence (AI), Machine Learning (ML), diagnostics, clinical imaging, data standardization.

I. INTRODUCTION

Machine learning (ML) and artificial intelligence (AI) [1] are being rapidly integrated into orthodontics and have significantly enhanced the availability of various applications for the clinical imaging analysis of patients, the planning of treatment, and the advancement of diagnostic algorithms. Constituent technologies, such as deep learning models (DLMs), [2]including Convolutional Neural Networks (CNN) and machine learning (ML) algorithms are utilized in aspects such as skeletal maturity assessment through cervical vertebrae maturation analysis, recognition and classification of dental conditions. Computer-Aided-Design (CAD) [4] supportive software in synergy with modern IOS enables the production of realistic digital representations of dentition, which facilitates the simulation of dental operations. However, there are still some concerns involving methodological variability in AI research, problems with data segmentation, and the relatively low number of AI devices approved by regulations [3]. Moreover, considering AI integration in orthodontic practice, consideration must be given to aspects such as research transparency, the possibility of reproducing results [5], and the validation of AI procedures to make usage safe. However, the current and future use of AI and ML in orthodontics continues to grow towards enhancing the efficiency of sharing data, standardization, and quality of research in orthodontics.

II. MATERIALS AND METHODS

The Google Scholar search engine was employed to choose relevant articles from peer-reviewed scholarly articles; articles in the English language published between the years 2019 to 2024 were considered for this review. In the cases of topics that had little to no recent articles or topics that required comparison of older and new results to show similarity or otherwise, earlier articles were referred. References were also examined to ensure no relevant studies were overlooked. To prevent bias, two reviewers independently evaluated the selected studies.

III. REVIEW OF LITERATURE

Of the reviewed studies, one study mentioned the execution of a comprehensive data extraction procedure by A.C. A.M. and L.T.A.-S. [1], where the extracted data was systematically organized and reviewed by L.T.A.-S. They entered the data into a pretested Excel form where the following characteristics of the study were collected: country of origin, the year of publication, the clinical field, and the details of the data like the input data type (covariates, images, etc.), source and size of the data [1]. For every study, they documented the kind of machine learning model, deep learning architecture (if any), data augmentation, reference tests, comparators, performance metrics, and their corresponding values. This approach helped to avoid the potential assumption that some data may be missing or not fully reported and provided a clear understanding of the materials, methods, and data utilized in various studies. Such a comprehensive extraction method allowed comparison of the use of AI and ML across numerous domains of orthodontics, including image analysis, segmentation, and classification (with a focus on data management), architectures of the models, and measurement of performance.

Another study used 80 digitized X-ray images [2]of lateral cephalometric films from the American Association of Orthodontists Foundation's Craniofacial Growth Legacy Collections to define CVM stages. These images were later independently reviewed and manually grouped into six stages (CS1–CS6) by an orthodontist and clinician scientist. The dataset included 1012 images of both male and female patients; the aim was to compare the size and shape of cervical vertebrae. [2]The issues arising from morphological differences in the vertebrae posed a problem in identifying differences between them; therefore, the study used deep learning techniques through a developed AggregateNet model. They split the dataset into a 4:1 ratio to obtain the training and testing sets for male and female subjects. Images were subject to initial processing and a data augmentation process that involved rotating, translating, and varying the contrast of the images to avoid overfitting. The model was equipped with three sub-networks and directional edge filters to allow for enhanced differentiation of the stages of CVM; modifications made to the AggregateNet model allowed it to categorize cervical vertebrae of similar shapes and sizes. Lastly, they cropped the dataset and grouped it to obtain the relevant vertebral features, and the final images were resized to 77 x 35 pixels to train the model.

One study employed 3D intra-oral scans [4]from 900 patients randomly selected from France and Belgium concerning the European General Data Protection Regulations (GDPR). Qualified orthodontists and dental surgeons conducted the scanning. Each patient underwent intraoral scanning in the upper and lower jaw. The team used three kinds of intraoral scanners, all of them of high accuracy (from 10 to 90 micrometers and point resolution (from 30 to 80 points per square millimeter), including Primescan by Dentsply, Trios3 by 3Shape, and iTero Element 2 Plus [4]. A gendered balance was achieved within the set, at 50% of males and 50% of females, along with a balanced age distribution, the majority being below 16 years of age. The data was obtained primarily from patients looking for orthodontic and prosthetic treatment. The steps involved in the annotation process for this dataset included preprocessing, alignment, and segmentation of the 3D scans. In the first step, redundant and degenerated mesh faces were removed for refining purposes, after which they aligned the scans with the occlusal plane. From the 3D scan, each tooth was individually and manually cropped, followed by UV mapping to flatten the mesh for easier annotation. Based on the UV maps, they made annotations manually and transferred them back to the 3D models. The teeth were then labelled using the FDI numbering system. In the last step, clinical experts conducted thorough checks to verify the accuracy of the annotations. The dataset, which now had 1800 3D scans for 900 patients [4], was split into training and test sets for a segmentation and labelling challenge and archived on Figshare.

Data sharing [5] is encouraged in the field of research for verifying results and addressing complex questions by creating large multi-center datasets. Numerous funding agencies such as the NIH, the European Commission, and NSF have implemented policies promoting data sharing. However, research reveals that, despite these efforts, actual data sharing remains infrequent. A clinical trial participants survey [5]showed that 82% believed sharing de-identified data was beneficial, and 93% expressed readiness to share data with researchers. However, privacy concerns and competitive behaviour manifest data withholding, which hinders training, slows scientific progress and negatively impacts the growth of knowledge in research fields. Although many journals nowadays mandate data sharing, investigators often refuse to provide raw data when requested, citing concerns over patient privacy. Secure access networks, differential privacy, and de-identification are some examples of approaches that have been emerging to address these concerns while enabling safe data sharing. [5]The European Union's General Data Protection Regulation (GDPR), effective in 2018, was designed to bring about data protection and privacy along with public access, imposing penalties for breaches. Irrespective of the many challenges surrounding data sharing, researchers have found ways to do so by providing code for data reproduction or repositories, solidifying the belief that data sharing is possible regardless of privacy concerns.

Despite code posing fewer privacy risks than data [5], potential information leakage concerns remain, for example, patient details in word embeddings.

Whilst sharing code offers benefits compared to sharing data, it remains less preferred due to a wide range of reasons like the risk of finding bugs, code quality concerns, and the supporting user's workloads. However, code sharing is still integral as it can offer valuable insights into a study. Journals like PLOS ONE encourage code sharing and require code to be well documented, open, and archived with an identifier. A downside is that practical constraints limit peer review of code alongside papers. However, an alternative way to assess shared code is via post-publication review.

IV. DISCUSSION

Artificial Intelligence and Machine Learning have revolutionized the field of orthodontics by allowing for more innovative approaches to tasks like analysing complex data. One study demonstrated how systemic data extraction serves as the cornerstone for AI-driven research [1]; it involved the collection of necessary details such as study origin, data type, and machine learning models to serve as a basis for evaluating the application of AI and ML across orthodontic domains. The study facilitated the evaluation of image analysis, segmentation, and model performance metrics by reviewing and organizing data, ensuring consistency and clarity in comprehending how AI can enhance research in orthodontics.

The use of AI by deep learning models to analyse cervical vertebral maturation (CVM) stages [2]was showcased in another study. Challenges such as differentiating morphological variations in cervical vertebrae were tackled by researchers using digitized X-ray images and implementing the AggregateNet model. To address issues of overfitting, complex data augmentation techniques were employed in the study to aid the model in classifying different shaped and sized vertebrae and to do so with good precision. This study exemplified how AI-based models can enhance diagnostic performance in orthodontic cases to better treatment plans and practices from an organizational perspective.

Likewise, the use of 3D intraoral scans [4]in another study highlighted the role of AI in changing the perception of orthodontics. Using datasets that adhered to privacy regulations such as the GDPR, the study employed preprocessing and segmentation to refine and label dental models. The integration of AI in orthodontics led to teeth labelling and segmentation scans of the highest accuracy and precision utilized in training machine learning models for orthodontic applications. Combined, studies indicate that artificial intelligence and machine learning have improved the scientific corpus of orthodontic studies by optimizing data handling, diagnostics, and scientific methods.

V. CONCLUSION

In conclusion, AI and Machine Learning have been steadily earning their place in orthodontics by providing new and innovative pathways in clinical practice. These tools have since significantly enhanced diagnostic precision and by doing so also improved data management and treatment planning.In studies where AI-driven models have been applied to tasks such as cervical vertebral maturation analysis and 3D intraoral scanning, clear reductions to errors, improvement of workflow, and provision of more personalized treatment for patients have been demonstrated.

Despite all the promise AI and ML can bring, some areas require more advancement — such as standardized data, increased privacy, and broader regulatory approval of AI-based devices. Collaborative efforts are imperative as they are necessary to increase research data; allow for transparency and reproducibility and improve code sharing. The quality of care and overall results will only enhance as the role AI is set to play as it develops in the field of orthodontics is quintessential.

CONFLICTS OF INTEREST
The authors declare no conflicts of interest.

REFERENCES

[1]. Arsiwala-Scheppach, Lubaina T., et al. "Machine learning in dentistry: a scoping review." Journal of Clinical Medicine 12.3 (2023): 937.

[2]. Atici, Salih Furkan, et al. "AggregateNet: A deep learning model for automated classification of cervical vertebrae maturation stages." Orthodontics & Craniofacial Research 26 (2023): 111-117.

[3]. Nordblom, N. F., M. Büttner, and F. Schwendicke. "Artificial Intelligence in Orthodontics: Critical Review." Journal of Dental Research 103.6 (2024): 577-584.

[4]. Ben-Hamadou, Achraf, et al. "3DTeethSeg'22: 3D Teeth Scan Segmentation and Labeling Challenge." arXiv preprint arXiv:2305.18277 (2023).

[5]. Celi, Leo A., et al. "The PLOS ONE collection on machine learning in health and biomedicine: Towards open code and open data." PloS one 14.1 (2019): e0210232.

[6]. Sun, M.-L.; Liu, Y.; Liu, G.-M.; Cui, D.; Heidari, A.A.; Jia, W.-Y.; Ji, X.; Chen, H.-L.; Luo, Y.-G. Application of Machine Learning to Stomatology: A Comprehensive Review. IEEE Access **2020**, 8, 184360–184374.

[7]. Schwendicke, F.; Chaurasia, A.; Arsiwala, L.; Lee, J.-H.; Elhennawy, K.; Jost-Brinkmann, P.-G.; Demarco, F.; Krois, J. Deep learning for cephalometric landmark detection: Systematic review and meta-analysis. Clin. Oral Investig. **2021**, 25, 4299–4309.

[8]. Farhadian, M.; Shokouhi, P.; Torkzaban, P. A decision support system based on support vector machine for diagnosis of periodontal disease. BMC Res. Notes **2020**, 13, 337.

[9]. Abdalla-Aslan, R.; Yeshua, T.; Kabla, D.; Leichter, I.; Nadler, C. An artificial intelligence system using machine-learning for automatic detection and classification of dental restorations in panoramic radiography. Oral Surg. Oral Med. Oral Pathol. Oral Radiol. **2020**, 130, 593–602.

[10]. Hägg U, Taranger J. Maturation indicators and the pubertal growth spurt. Am J Orthod. 1982; **82**(4): 299-309.

[11]. Hunter CJ. The correlation of facial growth with body height and skeletal maturation at adolescence. Angle Orthod. 1966; **36**(1): 44-54.

[12]. Tofani MI. Mandibular growth at puberty. Am J Orthod. 1972; **62**(2): 176-195.

[13]. Lewis AB, Garn SM. The relationship between tooth formation and other maturational factors. Angle Orthod. 1960; **30**(2): 70-77.

[14]. Acosta JN, Falcone GJ, Rajpurkar P, Topol EJ. 2022. Multimodal biomedical AI. Nat Med. 28(9):1773–1784.

[15]. Ajayi EO. 2005. Cephalometric norms of Nigerian children. Am J Orthod Dentofacial Orthop. 128(5):653–656.

[16]. Arsiwala-Scheppach LT, Chaurasia A, Müller A, Krois J, Schwendicke F. 2023. Machine learning in dentistry: a scoping review. J Clin Med. 12(3):937.

[17]. Atici SF, Ansari R, Allareddy V, Suhaym O, Cetin AE, Elnagar MH. 2023. AggregateNet: a deep learning model for automated classification of cervical vertebrae maturation stages. Orthod Craniofac Res. 26(Suppl 1):111–117.

[18]. Cui, Z., Li, C., Chen, N., Wei, G., Chen, R., Zhou, Y., & Wang, W. (2020). Tsegnet: an efficient and accurate tooth segmentation network on 3d dental model. Medical Image Analysis, 69, 101949.

[19]. Cui, Z., Li, C., & Wang, W. (2019). Toothnet: Automatic tooth instance segmentation and identification from cone beam ct images. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 6368–6377).

[20]. Eck, M., DeRose, T., Duchamp, T., Hoppe, H., Lounsbery, M., & Stuetzle, W. (1995). Multiresolution analysis of arbitrary meshes. In ACM Conference on Computer graphics and interactive techniques (SIGGRAPH '95) (pp. 173–182).

[21]. Tang, L., Zhan, Y., Chen, Z., Yu, B., & Tao, D. (2022). Contrastive boundary learning for point cloud segmentation. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 8489–8499).

[22]. National Institutes of Health (NIH). NIH releases strategic plan for data science. Retrieved November 1, 2018, from

https://www.nih.gov/news-events/news-releases/nih-releases-strategic-plan-data-science.

[23]. Kucur ȘS, Hollo´ G, Sznitman R (2018) A deep learning approach to automatic detection of early glaucoma from visual fields. PLOS ONE 13(11): e0206081. https://doi.org/10.1371/journal.pone.0206081 PMID: 30485270

[24]. Ioannidis J. P., Greenland S., Hlatky M. A., Khoury M. J., Macleod M. R., Moher D., et al. (2014). Increasing value and reducing waste in research design, conduct, and analysis. Lancet, 383(9912), 166–75. http://dx.doi.org/10.1016/S0140-6736(13)62227-8 PMID: 24411645

[25]. Savage CJ, Vickers AJ (2009) Empirical study of data sharing by authors publishing in PLOS journals. PLOS One 4: e7078. https://doi.org/10.1371/journal.pone.0007078 PMID: 19763261