Review Article

Limitations of Artificial Intelligence in Orthodontics. Literature Review

Sadia Naureen

ABSTRACT

In the 21st century, advances in computer technology and data science have brought significant innovation to orthodontics, especially through Artificial Intelligence (AI) and Machine Learning (ML). This study, conducted from July 2 to August 15, 2024, in the Orthodontic Department at Rawal Institute of Health Sciences Islamabad, reviews AI's transformative role in dentistry, focusing on its applications, benefits, and challenges. A comprehensive literature search across PubMed and Google Scholar yielded 260 peer-reviewed articles from 2001 to 2024. After applying stringent selection criteria, the review focused on AI's historical development, applications, and limitations in orthodontics. While AI enhances diagnostic imaging and patient care, it cannot replace clinical expertise. Key challenges include patient privacy, data security, and ethical considerations. AI systems rely heavily on high-quality data, necessitating rigorous training. Therefore, AI should be viewed as an adjunct in orthodontics, providing a "second opinion" to support clinical decisions.

Key words: Artificial Intelligence, Hazards, Machine learning, Orthodontics.

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INTRODUCTION:

In the 21st century, we are witnessing unprecedented advancements in computer technologies and data science, which hold significant potential for applications in orthodontics. One such innovation is Artificial Intelligence (AI), defined as the replication of human cognitive abilities within a machine that is designed to simulate human thought processes.[1] Arthur Samuel coined the term "Machine Learning" (ML), a branch of AI focused on developing algorithms and statistical models that enables computer to learn from historical data and predict conclusions, or decisions without requiring explicit human intervention.[2]

A major leap in this domain occurred with the rise of hypercomputers and the shift from central processing units (CPUs) to graphic processing units (GPUs), which facilitated the handling of vast data—commonly named as "Big Data." The concept of Big Data gained prominence in the early 2000s following Laney's publication that introduced volume, velocity, and variety. Since then, the continuous collection of data has resulted in an ever-growing dataset that fuels innovation.[3,4]

In past few years, deep learning has revolutionized machine learning, marking a major advancement in the field.[5] Both AI and deep learning have gained immense traction in dentistry, where they rely extensively on the availability of large-scale data.[6] Until recently, artificial intelligence (AI) primarily operated within the realm of narrow intelligence and supervised learning, such as automated cephalometric point recognition, tooth segmentation from 3D files, and orthodontic treatment staging. The next advancement involves developing neural networks emulating general intelligence akin to human cognition. Utilizing powerful computers and sophisticated algorithms, these networks will learn to diagnose orthodontic issues and plan treatments, ultimately suggesting optimal strategies for enhanced outcomes and greater predictability.[7] AI is mainly based on electronic data,which is not biological in nature.[8] Integrating patient autonomy, informed consent, ethics, and morality into AI remains challenging, as these are inherently human attributes. While AI serves as a tool within electronic systems, it lacks the ability to recognize patient autonomy, personal identity, or well-being. Additionally, the collection and sharing of vast amounts of data raise significant concerns regarding safety, privacy, and ethics.[9] (Medical healthcare data is among at the most sensitive and confidential). Incorporating AI into routine medical and dental care necessitates careful consideration of issues related to the public sector, patient privacy, and the autonomy rights of patients. A thorough understanding of the possible adverse impacts of AI in dentistry could potentially reshape the current trajectory of its adoption. Furthermore, the future of dental healthcare may increasingly prioritize human-centered AI, focusing on patient well-being, ethical transparency, and respect for patient autonomy.[10] Such an approach would encourage responsible AI development, aligning technology more closely with the specific needs and rights of patients within the field of dental care.

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METHODOLOGY:

A comprehensive search was conducted using the PubMed and Google Scholar databases, targeting peer-reviewed articles published between 1st July 2001 and 30th June 2024. The search employed keywords such as “Hazards of Artificial Intelligence,” “Hazards of Artificial Intelligence in Dentistry,” “Artificial Intelligence in Orthodontics: Pros and Cons,” “Application and Challenges of Artificial Intelligence in Orthodontics,” and “Limitations of Artificial Intelligence in Dentistry,” yielding 88, 78, 15, 12, and 67 papers, respectively.

This review article is organized following a meticulous analysis and examination of the pertinent literature available in the English language. Duplicates, studies involving animals, in vitro experiments, case reports, pilot studies, and redundant or irrelevant data were excluded. The remaining material was carefully reviewed and incorporated into this article. The final selection of articles included those covering the historical development, applications, challenges, and limitations of AI, with a focus on systematic reviews, meta-analyses, and original research articles.

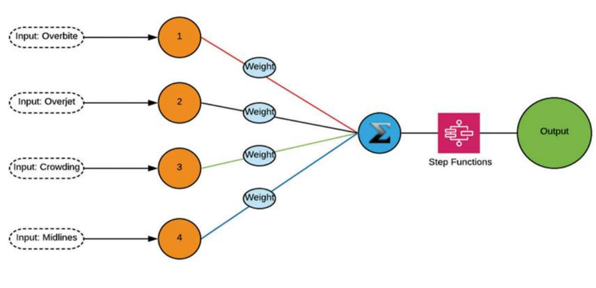
DISCUSSION:

Functioning of Artificial Neural Networks

An Artificial Neural Network (ANN) is a machine learning technique inspired by biological neurons, processing input data through multiple layers to produce output. Variants include Deep Neural Networks (DNNs), which have many hidden layers for complex feature extraction, and Convolutional Neural Networks (CNNs), which use filters to capture spatial information. Generative Adversarial Networks (GANs) generate new data that closely resembles the input data.[10]

Neural networks consist of nodes, or neurons, connected by links that represent the "weights," indicating their influence (figure 1). Each node corresponds to a variable, mirroring the columns in a data table. Inputs such as overbite, overjet, and crowding start with random weights (0 to 1%) and are linked to input nodes that compute correlations.To improve learning, extra "hidden layers" are added, forming deep learning neural networks that enhance prediction accuracy. These networks detect patterns and calculate the probability of correct outcomes, with the final diagnosis determined by input data volume and assigned weights.For neural networks to function effectively, large datasets must be properly labeled and weighted.[11]

Figure 1: Simple neural network showing the input layer, the hidden layer, and the output layer.[11]



Data safety

AI relies heavily on comprehensive computer knowledge, with data protection, extraction quality, and reliability being pivotal concerns. Storing such vast amounts of data necessitates significant investment in large-scale solutions such as cloud storage or data-sharing systems. To ensure consistency and improve accuracy, data collection formats must be standardized from the outset. Unfortunately, existing healthcare databases are not yet sufficiently advanced. Due to the limited availability of high-quality digital data, less than 20% of global medical data has been accessible for use in AI machine learning algorithms.[12] For instance, common limitations in databank analysis, such as unverified diagnosis codes, incomplete information on disease severity, lifestyle factors, habits, and unmeasured confounders, are notable challenges when utilizing Taiwan’s National Health Insurance Research Database.[13]

Patient handling:

Orthodontic treatment typically extends over 3-4 years, making patient management a critical concern. While AI models present impressive potential, they still require ongoing human oversight, as errors can occur during patient care.In orthodontics, the adoption of AI has led to the creation of various AI-based programs, such as WeDoCeph (Audax, Ljubljana, Slovenia), WebCeph (Assemble Circle, Seoul, Republic of Korea), and CephX (ORCA Dental AI, Las Vegas, NV, USA). These systems can automatically identify cephalometric landmarks, compute angles and distances, and generate cephalometric reports with significant findings.However, this accessibility has also sparked concerns about patient safety, especially when AI is used for diagnosis and treatment.[14]Being inherently machine- and software-based, AI lacks the capacity for interpersonal relationships, such as empathy and compassion toward patients. This introduces ethical and security risks, as patient confidentiality becomes more challenging to uphold when sensitive information is stored within systems.[15]

AI models without robust quality control are prone to data errors, outliers, and sudden trend shifts. Additionally, poor integration with clinical workflows limits their ability to adapt to changing data. Concerns also arise over AI reinforcing racial or socioeconomic disparities in healthcare. To address these challenges, AI systems must be built for continuous learning and adaptation.[16] As with any medical technology, the establishment of a robust AI governance framework is essential to maintain result accuracy and ensure patient safety.[17] Continuous evaluation of algorithm performance is crucial to prevent degradation and to enable timely intervention when necessary.One of the most troubling facets of the unpredictable behavior exhibited by AI-driven diagnostic algorithms within clinical settings is their failure to identify and address issues as they occur. In the absence of robust internal monitoring systems, these algorithms may yield inaccurate outputs alongside valid ones. This unpredictability poses a significant risk of patient harm, often occurring without the awareness of the clinical staff, local system administrators, or the manufacturers involved.[18]

Orthodontic treatment need

The need for orthodontic treatment is determined using standardized indices that assess various diagnostic factors, mainly focusing on the positioning of teeth. Recently, a new multicentric benchmarking dataset was created to compare AI-based tooth segmentation and labeling models, following the "3DTeethSeg'22 challenge." This dataset includes 1,800 labeled intraoral scans from three different commercially available scanners to improve generalization. The leading model achieved an impressive segmentation accuracy of 0.99. However, even with these advancements in automated tooth evaluation, deciding on the necessity for orthodontic treatment is still challenging, particularly in borderline cases. This complexity is exacerbated by significant interexaminer variability, with kappa values ranging from 0.16 to 0.37 for remote evaluations and 0.22 to 0.38 for on-site assessments. Such variability creates challenges for training models and affects the integration of AI into orthodontic evaluations.[19]

Growth analysis

A crucial aspect of designing an orthodontic treatment plan involves analyzing growth patterns and estimating biological age. Several methods can be employed to determine a patient's developmental stage, with one of the most widely used being the evaluation of cervical vertebrae stages (CVS) through lateral cephalometric radiographs.[20] In a study by Kök et al.[21] seven AI algorithms commonly used for classification were compared: k-nearest neighbors (k-NN), Naive Bayes (NB), decision tree (Tree), artificial neural networks (ANN), support vector machine (SVM), random forest (RF), and logistic regression (Log.Regr.). Logistic regression performed the worst in identifying stages CVS1, CVS4, CVS5, and CVS6, often misclassifying CVS4 as CVS3 and CVS5 as CVS4. All algorithms, except for ANN, had difficulties consistently and accurately classifying the stages. However, ANN struggled specifically with correctly identifying CVS5. The confusion matrices revealed ANN's classification accuracy for each stage as follows: CVS1 (93%), CVS2 (89.7%), CVS6 (78%), CVS3 (68.8%), CVS4 (55.6%), and CVS5 (47.4%).

Cephalometric analysis

AI tools have the capability to analyze images obtained from a wide range of imaging modalities, including X-rays and MRIs. Cephalometric analysis and pretreatment imaging are vital in orthodontics, making the field ideal for AI integration. Various AI programs, like WeDoCeph, WebCeph, and CephX, can automatically identify cephalometric landmarks, calculate angles and distances, and produce detailed reports. Additionally, these AI tools are now available on mobile platforms, enhancing accessibility and ensuring global users have equal access.However, it is essential to acknowledge the limitations of AI in cephalometric analysis. Currently, these systems still fall within the scope of supervised machine learning. Common errors in AI-assisted cephalometric analysis include tracing inaccuracies, errors in landmark identification, and miscalculations in measurements.[22] With respect to automated landmark identification, challenges persist, such as variations in individual skeletal structures, image blurring caused by device-specific projection magnifications, and image complexity due to overlapping contralateral structures.[23] Even minor errors in these processes can lead to misclassification, ultimately resulting in potential misdiagnoses.

Radiographic errors are significantly high for several hard tissue landmarks, such as the posterior nasal spine, lower incisor, articular, pterygomaxillary fissure, and upper incisor, even with advanced techniques.[24] Identifying these points is difficult due to the complexities caused by varying X-ray projections on the left and right sides of the craniofacial structure. In cases of malocclusion, the presence of open root apices and dental crowding further reduces the accuracy of AI detection for both upper and lower incisors.[25]

Research conducted by Duran et al. using automatic cephalometric analysis software, including OrthoDx™ and WebCeph, supports these observations.[26] Landmarks such as the basion and orbitale are typically regarded as challenging to identify and are often considered unreliable in cephalometric assessments. Additionally, finding the porion is difficult due to various radiolucencies in the area that can mimic the internal auditory meatus.[27] Regarding soft tissue landmarks, points such as pronasale, subnasale, and pogonion exhibit lower accuracy, often due to increased darkness or reduced brightness in these areas compared to others.[28]

Diagnosis and Treatment Planning

Extraction Decision Making

One of the most intricate challenges in orthodontic treatment is deciding whether extractions are needed for a particular case. This decision is influenced by several factors, including the specific orthodontic issue, patient preferences, expected results, sociocultural factors, and the orthodontist's professional viewpoint. These elements all play a role in shaping the patient's perspective on the recommended extraction therapy.[29,30] Additionally, the orthodontist's decision-making is influenced by their experience, training, and clinical philosophy.[31]These variables make the extraction decision particularly difficult, even for seasoned practitioners. Moreover, treatment recommendations can significantly differ among experts, particularly in borderline cases, further complicating the extraction decision process.[32]

In recent years, various AI tools have emerged to aid in orthodontic treatment decisions.[33,34] Initial research on AI-assisted extraction decision-making has shown promising results, with AI systems aligning with expert evaluations over 80% of the time.[35] For example, a study by Xie et al.[36] found an 80% agreement between AI predictions and expert opinions on extraction decisions, although it was based on just 20 cases. Similarly, Jung and King[37] assessed an artificial neural network (ANN) that achieved 93% accuracy in distinguishing between extraction and non-extraction cases using 12 cephalometric variables, along with an 84% success rate in identifying specific extraction patterns.Semerci et al.[38] reported comparable outcomes, with 94% accuracy in differentiating extraction scenarios, 84.2% for extraction patterns, and 92.8% for anchorage patterns. These studies emphasized key factors for predicting treatment outcomes, including upper arch crowding, positioning of anterior teeth, lower incisor inclination, overjet, overbite, and lip closure ability.

However, it's important to recognize significant limitations in these studies that could introduce bias. For example, the AI systems were trained on data from a small group of experts, which may only represent their individual treatment philosophies without proper validation. Additionally, critical dental factors like extensive fillings, periapical lesions, periodontal issues, previous root canal treatments, and tooth loss were not considered.

Given these limitations, reaching a conclusive decision on orthodontic extractions can be difficult, particularly in borderline cases. Various factors, such as systemic diseases, ongoing growth, and patients' primary concerns, can influence the extraction decision. Therefore, the Arch Length Discrepancy (ALD) value should not be the sole criterion for determining extractions but rather one of several considerations when addressing overcrowding.[39,40] In cases of bimaxillary protrusion, midline discrepancies, profile improvements, orthognathic surgery, and other aesthetic factors, extraction may be necessary despite the normal ALD value.[41] Orthodontists develop treatment plans not only based on clinical data but also on their accumulated experiences, which may include biases from past outcomes. This indicates that treatment strategies can be shaped by a clinician's personal experiences, background, philosophy, aesthetic preferences, and educational influences.[43] Considering these limitations, it's crucial to recognize that reaching a conclusive decision about orthodontic extraction therapy can be complex, particularly in borderline situations. Numerous factors influence the extraction decision in orthodontic treatment planning, including systemic health conditions, ongoing growth, and patients' primary concerns. As such, the Arch Length Discrepancy value alone cannot serve as the sole criterion for extraction but should be considered a primary factor when addressing crowding issues[39,40] Even with a normal ALD value, tooth extraction may be required for cases like bimaxillary protrusion, correcting midline discrepancies, improving facial profiles, orthognathic surgery, or other aesthetic factors. Orthodontists create treatment plans that consider clinical data as well as their own experiences and possible biases from prior cases. As a result, these plans can be shaped by the clinician's personal history, educational background, treatment philosophy, aesthetic preferences, and the institutions they are associated with.[41]To effectively address specific malocclusions with numerous variables, software must gather and learn from extensive data. This is necessary for determining and implementing the most suitable treatment approach. Typical AI models, developed using narrow and specific datasets, often struggle to perform adequately across a broad spectrum of information.[42] Currently, the entire dental field, encompassing orthodontics, is deficient in curated "benchmarking" datasets that facilitate the testing of AI software on standardized, representative data, thereby enabling meaningful comparisons among various applications. Additionally, the absence of uniform reporting metrics further complicates the evaluation and comparison of orthodontic AI technologies.[43] Validation of the AI models for orthodontic treatment planning remains crucial and is currently lacking. Data sets are constructed using unicentric data; in some studies, only 1 expert provided the treatment decisions.[30,35] Moreover, the excessive use of AI in orthodontic diagnosis and treatment planning may hinder the development of critical thinking and learning skills in young, inexperienced practitioners. Another concern is the lack of transparency and accountability. The decision-making processes of AI systems can be opaque, making it challenging to provide explanations or hold them responsible for their outcomes.[44-46]

Orthognathic surgery

Research on AI in orthognathic surgery treatment planning is limited but promising.[47] Knoops et al.[48] utilized a 3D morphable model (3DMM) to automatically diagnose patients, evaluate their risk levels, and generate simulations for treatment plans, achieving 95.5% sensitivity and 95.2% specificity, with an average accuracy of 1.1 ± 0.3 mm. Meanwhile, Chung et al.[49] developed a method using a DeepPose regression neural network to align CBCT images with optically scanned models, improving accuracy by 33.09% over previous leading techniques. Additionally, Choi et al.[35] demonstrated a model that effectively predicted the need for surgery and outlined extraction plans for surgical patients, with accuracy rates between 88% and 97%.

A systematic review conducted by Salazar et al.[50] highlights that current research findings are challenging to generalize because of considerable heterogeneity. For example, profile preferences vary among different ethnic groups, including Asians, Europeans, and Black individuals. The authors noted that although AI has the potential to be a useful tool in orthognathic surgery planning, human judgment remains essential for making final decisions.

Miscellanious Hazards

Artificial intelligence (AI) presents ethical challenges, particularly in healthcare, where concerns arise about autonomy and decision-making, exemplified by the use of autonomous surgical robots.[51,52] The automation of tasks like image analysis and patient data processing by AI can result in job losses and unemployment.[53]

A major challenge in current orthodontic AI research is its limited generalizability. Due to significant variations in outcomes, metrics, and the lack of standardized datasets, comparing AI across different studies and tasks is extremely difficult. Only a few AI applications in orthodontics have reached full clinical maturity and received regulatory approval.[54] Pianykh[55] highlights several key unresolved issues, starting with reproducibility; AI models are often trained on specific, narrow datasets, limiting their effectiveness across diverse data. Additionally, there are concerns about privacy, safety, and health disparities, particularly regarding AI algorithms that may exacerbate racial or income inequalities. Furthermore, these models can perpetuate biases from their training data, leading to inaccurate diagnoses or treatment for certain demographic groups.[56]

The lack of transparency and accountability in AI systems makes it challenging to understand their decision-making processes, complicating efforts to explain or hold them accountable.[57]There is also a risk of over-reliance on technology, where healthcare professionals may become too dependent on AI, potentially losing the ability to complete tasks without its assistance.[58] Furthermore, AI systems may struggle to grasp context and have difficulty understanding the nuances and subtleties of human health and disease.

Future Implications

Unsupervised learning is a more complex approach where the data lacks labels or classifications. In this method, algorithms are trained to recognize patterns and suggest possible outcomes from the data provided. In orthodontics, unsupervised learning is being increasingly applied to analyze large datasets of malocclusion cases, enabling computers to predict the most effective treatment options.[59] In today's digital era, the phrase "data is power" highlights the importance of ensuring that orthodontic data is protected with the same rigor as medical information, which cannot be shared without prior consent regarding its use. When shared responsibly, the extensive data collected in orthodontic practices, combined with deep neural networks, has great potential to advance the field.Moreover, robotic systems have emerged as invaluable assets, assisting clinicians during surgeries and intricate procedures. Driven by artificial intelligence, these robotic technologies can perform delicate tasks with remarkable precision, leading to improved patient outcomes. The integration of AI with robotics significantly reduces the risk of human error in dentistry, enhancing the accuracy of procedures beyond what traditional methods can achieve.[60]

CONCLUSION:

Undoubtedly, AI has the potential to revolutionize medicine, particularly in the field of diagnostic imaging, including orthodontics. However, AI cannot replace clinical acumen or input of a dentist or radiologist. It is an aid and will always be. Also, every AI tool in dentistry is trained based on annotations by calibrated dental professionals (especially in the deep learning space). If we can trust the reading from electronic sphygmomanometer then there is no reason why similar tools if created in dentistry should not be trusted and accepted to be accurate especially if it has gone through rigorous reliability and validity checks. Errors and Bias in prediction from AI is often introduced by humans during the training process. It still follows the idea of "garbage in , garbage out". If it is fed with faulty data, the output is going to be faulty. Finally, it is important not to be over reliant on AI as a diagnostic tool. It should only be used as

Authors Contribution:
Sadia Naureen: Conception, design, Introduction and discussion

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