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Application of Deep Learning Algorithms in Segmentation of Mandibular Nerve Canal in Orthopantomogram (Panoramic) Radiographs: A State-Of-Art Systematic Review

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Abstract

Objectives: To assess the current landscape and efficacy of artificial intelligence (AI) and deep learning (DL) algorithms in detecting and segmenting mandibular canals in orthopantomogram (panoramic) radiographs.

Methods: Research on the detection and segmentation of the mandibular canal for developing AI models was conducted by searching five major electronic databases. The PICO

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question was, “Are 2D radiographic images suitable for utilizing deep learning algorithms to identify the infra-alveolar nerve?” The included studies adapted customized assessment criteria based on QUADAS-2 for quality assessments.

Results: 255 records were identified during the initial electronic search. After a thorough evaluation, six studies specifically addressing the detection and segmentation of mandibular canals were selected for inclusion. Various outcome metrics were reported. The dice coefficient varies between 0.78 and 0.97 between models. Also, sensitivity (recall) varies from 0.83 to 0.99, indicating high performance in various DL models.

Conclusion: The AI models discussed in the included studies vary in performance. Additionally, the outcome metrics reported were not consistent, making it difficult to compare all the deep learning (DL) models comprehensively. The impressive performance of these DL models should be evaluated using external datasets to compare their effectiveness and train them to achieve better results.

Keywords: Artificial intelligence, Machine learning, Radiology, Diagnosis, Mandibular canal.

1. INTRODUCTION

The Inferior Alveolar Nerve (IAN) is a crucial sensory nerve in the maxillofacial region, requiring careful attention during surgical procedures to avoid complications. This nerve runs through the Inferior Alveolar Nerve Canal (IAC), providing sensory input to the teeth, surrounding tissues, and associated muscles [1]. Injury to the IAN can cause partial numbness in areas such as the lower lip, tongue, chin, and buccal mucosa, which may result in complete sensory loss. Such damage can also lead to spontaneous or stimulus-induced pain, allodynia, and nerve injuries like neuropraxia, neurotmesis, and axonotmesis, potentially causing hyperalgesia [2, 3].

The panoramic radiograph (orthopantomogram or OPG) is the imaging technique of choice for evaluating impacted third molars (M3s). Preoperative OPG imaging is instrumental in assessing the risk of IAN injury during M3 removal surgeries. It is frequently used in initial evaluations, as it provides insights into root morphology, tooth angulation, and the type of impaction [4–6].

Cone beam computed tomography (CBCT), a more advanced imaging modality, generates three-dimensional images of dental structures and the surrounding anatomy, offering superior detail compared to traditional radiography. Compared to traditional panoramic radiographs, CBCT offers superior accuracy in visualizing nerve proximities, assisting procedures such as wisdom teeth extraction [7–10]. However, OPG radiographs are still the primary modalities used in various dental treatments and diagnostic procedures due to their lower radiation exposure and cost-effectiveness compared to CBCT radiographs [7–10].

Deep learning (DL) has gained interest in recent years as it allows machines to imitate human intelligence independently. AI has made significant advancements in dentistry, including disease diagnosis, localization, and classification [11–15]. Integrating AI solutions into routine dentistry practice face challenges related to the nature of dental data, limited benefits of current AI applications, and insufficient reproducibility and robustness in dental AI research. Tackling these challenges is essential to ensure the successful integration of AI technologies into dental clinical practices on a broader scale [15–18].

The utilization of AI applications can significantly enhance performance and aid in facilitating well-informed decisions, thereby maximizing treatment outcomes and offering patients superior care. Within dentistry, Artificial Intelligence (AI) has predominantly served to bolster the efficiency and precision of diagnoses. This systematic review seeks to ascertain the precision of current Deep Learning (DL) algorithms in identifying IAN by analyzing Orthopantomography (OPG) radiographs. The null hypothesis postulated that DL algorithms would prove unable to identify IAN utilizing 2D radiographic images accurately.

2. METHODS

2.1 Search Strategy and Information Sources

The present systematic review was conducted according to Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standards [19]. The research question was formulated based on the PICO elements: "Are 2D orthopantomogram radiographic images appropriate for deep learning algorithms to identify and detect the infra-alveolar nerve canal?"

Research articles were systematically located and assessed using five databases: MEDLINE via PubMed interface, PMC, Scopus, Embase, and Web of Science up to June 2023. For each database a series of specific keywords for artificial intelligence and deep learning with combination to a series of keywords for the mandibular canal were designed and used. Two reviewers, N.T. and M.A., independently assessed the titles and abstracts, while a third reviewer, M.D., resolved disagreements. All studies meeting the eligibility criteria and with the full text available were included.

2.2 Eligibility Criteria

The systematic review included studies meeting the following criteria:

1. Research employing deep learning techniques to evaluate prediction and diagnostic accuracy.
2. Studies focused on the assessment of OPG radiographic images for detection and prediction purposes.
3. Reporting efficiency and performance metrics as results.

Research that matched the prerequisites above was included. The following exclusion criteria were set:

1. Secondary studies such as scoping review, systematic review, or meta-analysis.

2. Articles using 3D radiographical modalities such as CBCT.
3. Articles without a focus on IAN detection on radiographical images using deep learning algorithms.

2.3 Data Collection and Data Items

Data extracted from scholarly articles, including author name, publication year, image type, dataset size, model architecture, and findings, including studies using multiple test datasets or model variations.

2.4 Risk of Bias Assessment

The quality of the included studies was evaluated using the Assessment Tool for Diagnostic Accuracy Studies 2 (QUADAS-2) [20]. This tool is composed of four key components: patient inclusion, index tests, reference standards, and patient flow throughout the study, including the sequence of index tests and reference standards. Each aspect was independently assessed by two authors (M.A. and N.T.) to determine the risk of bias. Bias levels were categorized as "low," "high," or "unclear." If disagreements arose, a third author (M.D.) was consulted to resolve them.

The findings were analyzed based on three main criteria: "patients' participation," "methodology," and "adequacy of outcomes." Additionally, the heterogeneity of the results across the studies was carefully examined.

2.5 Effect Measures

All the studies included in the review examined the efficacy of deep learning (DL) models for detection and segmentation tasks. The outcomes varied across the studies, including the F1-score, Jaccard Index, sensitivity, and precision. All relevant outcomes were collected and documented for a qualitative data synthesis.

3. RESULTS

3.1 Study Selection

A total of 255 publications were screened. Ultimately, ten full-text articles were evaluated for eligibility, with only six meeting the inclusion criteria. The remaining four articles were excluded for various reasons: Two studies specifically examined the relationship between the mandibular canal and impacted third molars, one did not utilize any AI algorithm, and one analyzed CBCT radiographs. (FIGURE 1)

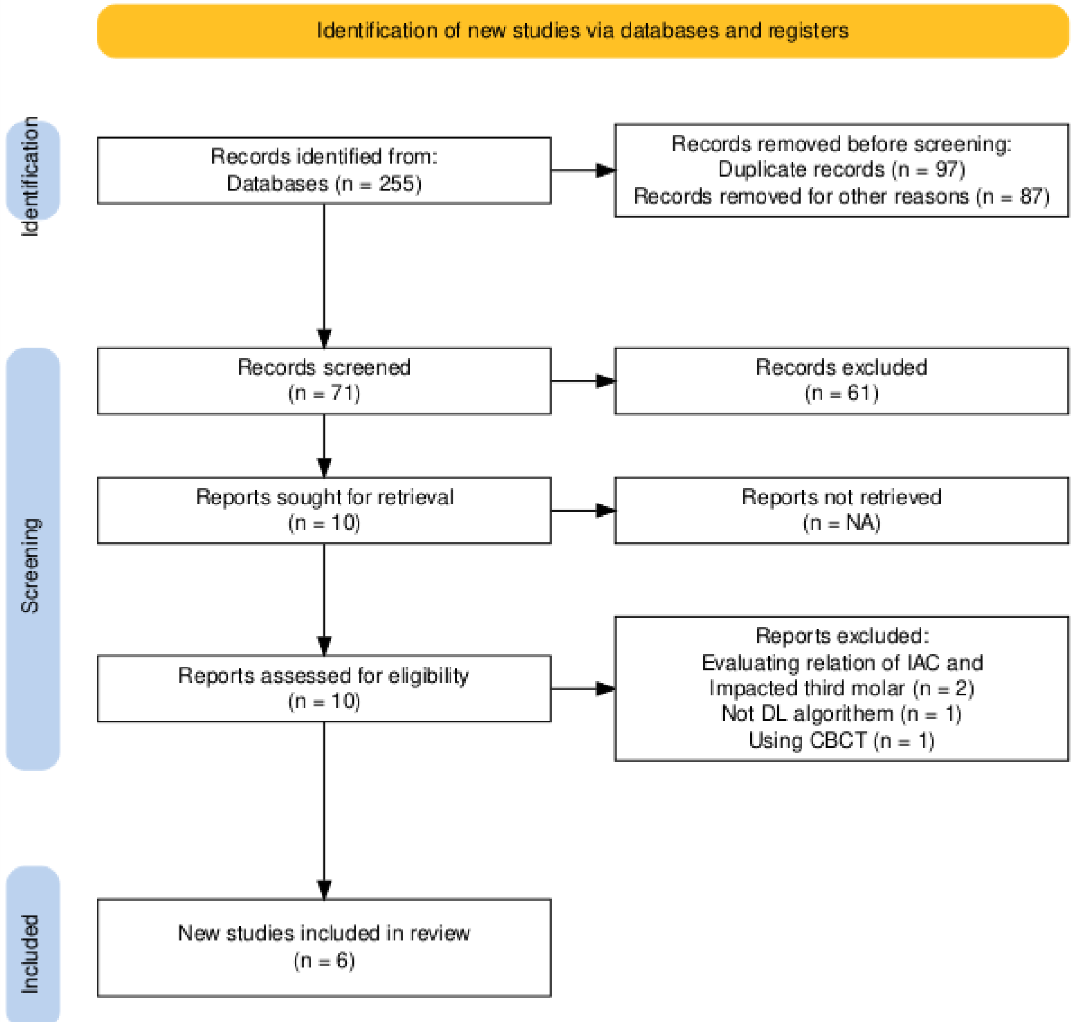

Figure 1: The PRISMA flow diagram for screening and selection of articles.

3.2 Study Characteristics

TABLE 1 demonstrates the key characteristics of the included studies. Each study implemented various DL models. All studies used dental panoramic for the data set except one that used CBCT-reconstructed panoramic radiographs (which did not interfere with the results obtained and current review aims).

3.3 Risk of Bias in Studies

There were also no concerns regarding the applicability of the studies to the research question. The patient populations, interventions, and outcomes were consistent with the aims of this meta-

Table 1: The characteristics of the included studies.

Study	Deep learning model	Data set	Annotation	Number of classes	Task of learning	Results for IAC
Cha, et al., (2021)	Panoptic DeepLab	90 dental OPGs (51 included)	Dental practitioner and radiologist	Eight classes, including background	Semantic segmentation	PQ = 65.97 SQ = 65.97 RQ = 100 IoU = 0.639
Mahesvari, et al., (2022)	MELMANN	220 dental OPGs	Not mentioned	IAC	Segmentation, Classification	DEavg = 0.43 DEstd = 0.60 Time = 1.526 ± 0.4 Dice coefficient = 0.854 ± 013
Pandyan, et al., (2022)	BRISK	45 CBCT-reconstructed panoramic dental radiographs	Not mentioned	IAC	Detection	MAE = 7.95 DEavg = 0.67 DEstd = 0.80 Time = 1.963 ± 0.4 Dice coefficient = 0.829 ± 013
Vinayahalingam, et al., (2019)	U-net	81 dental OPGs	Two separate observers	IAC, Teeth in total, Mandibular third molars	Detection	Sensitivity = 84.7 Specificity = 96.7 Dice coefficient = 80.5 Jaccard index = 68.7
Zhao, et al., (2023)	Mask rcNN	280 dental OPGs (40 for IAC)	Not mentioned. Applying Labelme software.	All teeth separately, IAC	Object detection, Semantic Segmentation	Precision = 76.05 Recall = 83.7 F1-score = 78.1
Bag et al. (2023)	YOLO-v5	981	Pediatric dentist and radiologist using CranioCatch software.	Nine anatomic landmarks	Detection, Segmentation	Precision = 0.94 Sensitivity = 0.99 F1-score = 0.97

analysis. Therefore, all six studies were deemed eligible and were included in the final analysis without reservations.

3.4 Results of Individual Studies

Cha et al. conducted a study focused on panoptic segmentation, a method that combines instance segmentation and semantic segmentation, applied to panoramic radiographs. The researchers developed a deep neural network model specifically for panoptic segmentation and trained it to identify and segment various anatomical structures, including the mandibular canal, within panoramic images. Evaluation metrics included panoptic quality, segmentation quality, recognition quality, and intersection over union (IoU), which were calculated to assess the model's performance. Considering the previous work of the group, which defined variables related to panoptic segmentations, the definition variables Recognition quality, segmentation quality, and panoptic quality are defined as follows [21]:

$$\text{Recognition quality} = \text{F1-Score (As described earlier)}$$
$$\text{Segmentation quality} = \frac{\sum(p, g) \in TP\ IoU(p,\ g)}{|TP|}$$
$$\text{Panoptic quality} = \text{SQ} \times \text{RQ}$$

Following the calculation of PQ for canal detection, which yielded a score of 65.97, an IoU score of 0.639 was reported. As a result of the extensive evaluation and visualization outcomes, it was determined that the DL-based AI model is capable of efficiently performing panoptic segmentation of images in panoramic radiographs. This innovative machine-learning technique has the potential to greatly aid dental professionals in creating precise treatment plans and accurately diagnosing oral and maxillofacial ailments [21].

P. Uma Maheswari took novel steps for IAN canal segmentations in two separate studies, which are included in the current review [22, 23]. They developed a neural network model that leverages local features to detect the Inferior Alveolar Nerve (IAN) in dental OPG images. Their method involves three distinct stages: novel edge enhancement, candidate classification, and candidate pixel clustering. Initially, the edges of dental panoramic radiographs are enhanced using a specialized structural filter to improve the visibility of the IAN.

The results of this approach are promising, achieving a Dice coefficient of 0.854 ± 0.05 and demonstrating a 96% accuracy rate. The Average and Standard Deviation Euclidean Distance Error (DE) were reported as 0.43 and 0.60, respectively. This innovative methodology not only enhances the visualization of the Inferior Alveolar Canal (IAC), thereby reducing the risk of neurological sensory disorders during oral and maxillofacial surgeries or implantology, but it also provides a highly effective pre-diagnostic tool for surgeons [22].

In their later research, P. Uma Maheswari and colleagues [23], applied advanced image enhancement techniques combining intensity mapping and contrast-limited adaptive histogram equalization. These methods improved image quality, enabling further analysis. The enhanced images were divided into the upper and lower jaws using the B-spline method. The lower jaw was then further segmented into two sections using the vertical integral projection technique.

To delineate the edge regions of the tooth and canal areas, the local phase congruency system was employed. The identified edge points were classified as Binary Robust Invariant Scalable Key (BRISK) points, serving as feature descriptors for segmenting the Inferior Alveolar Canal (IAC). A curve-fitting approach was used to link the feature points within specific coordinates, effectively distinguishing the IAC.

The effectiveness of this methodology was evaluated against other contemporary techniques. The results demonstrated an average accuracy of 91.003% and a Dice coefficient of 0.829 ± 0.13, outperforming many deep learning-based methods in terms of precision. The authors further reported an MAE of 7.95%, with DEavg and DEstd values of 0.67 and 0.80 mm, respectively. In conclusion, the method delivers enhanced results and empowers dentists to successfully locate the IAN canal during preoperative diagnostic procedures while minimizing complications associated with oral surgery and implantology.

Vinayahalingam et al. [24], have created and tested an automated method using deep-learning to accurately identify and separate the IAN on panoramic radiographs. To do so, they first manually segmented the IAN on 81 panoramic radiographs as a reference. Next, they implemented a U-net deep-learning approach to train the convolutional neural network (CNN) on the reference data for detecting and segmenting the IAN. Finally, they used the trained U-net to automatically identify and separate structures on the original panoramic radiographs. Dice coefficients were employed to assess the similarity between manually and automatically segmented Inferior Alveolar Nerve (IAN) structures. The results showed a mean Dice coefficient of 0.768±0.119 for the training data and 0.805±0.108 for the validation data. Intersection over Union (IoU) values were also calculated, with the training data scoring 0.638±0.145 and the validation data achieving 0.687±0.14. In addition to these metrics, optical inspection revealed promising sensitivity levels of 0.838±0.132 for the training set and 0.847±0.099 for the validation set. Specificity values were also high, recorded at 0.96±0.02 for the training data and 0.967±0.025 for the validation data. These results suggest that the automated segmentations performed using the U-net model were largely satisfactory. The authors concluded that machine learning holds great promise for accurately segmenting anatomical structures and supporting clinical decision-making processes. However, they emphasized the need for further refinement of the algorithm to improve its accuracy.

In a study by Zhao et al. [25], a novel approach was introduced for identifying and segmenting 32 teeth and two mandibular nerve canals in panoramic dental X-rays. The method leveraged the Mask RCNN instance segmentation algorithm, which demonstrated several improvements over the Faster RCNN algorithm. Notably, the inclusion of a semantic segmentation branch in Mask RCNN allowed for the direct identification of teeth and mandibular nerve canal positions. Another key feature of this algorithm was the incorporation of ROI Align, which significantly enhanced segmentation accuracy. The study utilized 120 training sets, 40 validation sets, and 120 test sets. Of the test sets, 40 were allocated to full-tooth panoramic X-rays, 40 to edentulous panoramic X-rays, and 40 to mandibular canals. Results showed that the algorithm achieved average precision, recall, and F1-score values of 76.05%, 83.70%, and 78.10%, respectively, for detecting the Inferior Alveolar Nerve (IAN) canal. The authors concluded that this algorithm effectively identified each tooth, including missing teeth, as well as the mandibular nerve canals in panoramic dental X-rays. Furthermore, it addressed the complexities of evaluating the oral state, which is often hindered by the dense anatomical structures visible in panoramic dental images.

Bag et al. [26], conducted a pioneering study to evaluate the accuracy and effectiveness of artificial intelligence in detecting anatomical structures in the maxillary and mandibular regions of pediatric panoramic radiographs. The study analyzed 981 labeled panoramic radiographs of pediatric patients, utilizing 2D CNN architectures for model training over 500 epochs. The researchers developed YOLO-v5 models implemented in PyTorch, which were subsequently tested on a 10% subset of the data. The results were remarkable, achieving an F1 score of 0.97, a precision of 0.94, and a sensitivity of 0.99, highlighting the AI model's strong predictive capabilities and reliability.

4. DISCUSSION

Artificial intelligence (AI) is revitalizing the traditional dental science. AI-based solutions are commonly utilized to develop automated software applications that simplify dental diagnostics [27]. Most of these are clinical decision support systems, which help and guide experts in making better decisions. As the substantial rising demand since their efficacy [28], these systems are used to enhance diagnosis, treatment planning, and prognosis prediction [29]. Artificial Intelligence has revolutionized dentistry and made it easier. The main goal of AI-powered clinical decision support systems is to give medical practitioners competent assistance [30]. Computer programs known as clinical decision support systems are designed to help diagnostic clinical decisions [31].

Recent studies have shown that AI models, particularly DL approaches such as CNNs, are highly accurate at detecting mandibular canals. A study demonstrated that DL models achieved an accuracy of 93% in identifying mandibular canals on panoramic (OPG) images [32]. Some studies show accuracy rates comparable to or even higher than those of expert radiologists [14]. However, human detection is heavily dependent on the clinician's knowledge and expertise. Experienced radiologists and dental experts often attain good accuracy, but there is considerable variation across practitioners. A study by Kamburoğlu et al. [33], found that experienced radiologists' accuracy in detecting mandibular canals ranged from 85% to 90%. Human interpretation can be subjective, leading to variability in accuracy. Factors like fatigue, experience level, and imaging quality can affect performance [32].

AI models have shown high sensitivity in detecting mandibular canals, with CNNs demonstrating a sensitivity of 92% on panoramic radiographs [34]. These systems can continuously improve their sensitivity through diverse dataset training, enhancing their accuracy in complex cases. However, sensitivity varies among clinicians; a study indicated that manual detection sensitivity ranged from 80% to 87%, influenced by clinician experience and imaging modality. Less experienced practitioners may miss mandibular canals that more seasoned professionals would detect [34].

It can be concluded that AI models have achieved high specificity, effectively reducing false positives, as evidenced by a report of 94% specificity in an AI model detecting mandibular canals on CBCT images [35]. AI models consistently deliver high specificity across different datasets and imaging modalities, reducing the likelihood of false positive results. Specificity in human detection also varies. In a study, the experienced radiologists' specificity in detecting mandibular canals ranged from 82% to 88% [36]. Specificity can be influenced by human error and subjective judgment, leading to variability in identifying true negatives.

This systematic review explored the use of AI technology in dentistry, specifically evaluating its effectiveness in detecting and segmenting the mandibular canal in orthopantomogram (panoramic) images. Key advantages of deep learning include its wide application range and ability to diagnose without altering existing infrastructure. The promising findings of the current study regarding the segmentation IAN have encouraged the successful incorporation of deep learning into routine clinical practice. AI's impact on dentistry often lacks immediate utility. Most current dental AI applications offer only isolated pieces of information, failing to adequately support the complex clinical decisions needed. Furthermore, concerns about transparency and accountability persist [15, 19, 37]. Accurately determining the shape and position of third molar roots relative to the mandibular canal is essential, making studies in this area vital for improving diagnostics. The nature of this systematic review, which analyzes multicenter studies with varying quality of OPG, may pose a significant limitation to the research. Nevertheless, deep learning holds the promise of automatically improving dental radiographs by removing redundant artifacts, as well as providing clinicians with additional data to enhance treatment planning and risk assessment.

AI models and current standard practices have strengths and limitations in detecting mandibular canals. In summary, AI models offer high precision, efficiency, and reproducibility, which can significantly enhance diagnostic capabilities and standardize practices. However, they require substantial initial training and ongoing maintenance and raise regulatory and ethical concerns. Current standard practices benefit from the nuanced understanding and expertise of experienced professionals, but they are time-consuming, subject to variability, and prone to human error. Incorporating AI into standard practices could combine the strengths of both approaches, leading to more accurate, efficient, and reproducible results in mandibular canal detection. There is a need for more structured AI education for dental students and dentist, so they can be more familiar with these technologies.

5. CONCLUSIONS

In dental and maxillofacial surgery and implantology, this novel approach dramatically improves the visualization of the mandibular canal to prevent neurological sensory abnormalities. Considering the advantages of using deep learning, it may enable worldwide uniformity of the dental report and help dentists in their endeavors, saving them time while maintaining the quality for better results. This review could be an initial report to support researchers' AI study in getting precise results and adequately assessing the provided algorithm [38].

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