Artificial Intelligence for Cone Beam Evaluation of Lower Third Molars and Possible Postoperative Nerve Injury: A Systematic Review

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AIM: The risk of injuring the inferior alveolar nerve (IAN) is always present during the surgical removal of mandibular third molars. Cone beam computed tomography (CBCT) helps visualize their anatomical relationship, but interpretations vary between operators. Computational models with deep learning can provide constant evaluation of third molar position and canal proximity, to help in improving preoperative assessment, and thus reduce this risk.
METHODS: This systematic review followed Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to evaluate the effectiveness of computational models in predicting IAN injury using CBCT of lower third molars. A PICOS (P, Population; I, Intervention; C, Comparison; O, Outcome; S, Study) framework guided study selection. Several databases, like PubMed, Scopus, etc., were searched for studies published between October 2020 and February 2025. From the 983 records screened, 7 studies met eligibility. Three individual reviewers extracted the data and examined the study quality using the Newcastle-Ottawa Scale to determine bias and methodological rigor.
RESULTS: Seven high-quality studies examined computational models for mandibular canal (MC) segmentation using CBCT and panoramic imaging. Three-dimensional U-shaped Convolutional Neural Network (U-Net) models reached up to 99% accuracy with Dice similarity coefficients (DSC) between 0.76 and 0.782, outperforming two-dimensional models. Classification networks such as DenseNet201 and MobileNet achieved over 98% accuracy and F1-scores up to 0.94. Segmentation was more than 100 times faster than manual tracing. Metrics included DSC values up to 0.9730 and Hausdorff Distance as low as 0.705 mm. Quality of studies scores ranged from 9 to 10 and risk of bias was low in maximum domains.
CONCLUSIONS: Computational models show significant potential to improve preoperative assessment and predict IAN injury during mandibular third molar surgeries by enhancing MC segmentation and diagnostic accuracy.

Keywords: deep learning; convolutional neural networks; automated evaluation; nerve proximity

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Introduction

The assessment of mandibular third molars is an essential step in oral and maxillofacial surgery because of their close anatomical relationship with adjacent neurovascular structures, like the inferior alveolar nerve (IAN). It is important for careful pre-operative examination since nerve injury is one of the major risk factors even while using advanced surgical techniques and modern imaging. Cone beam computed tomography (CBCT) provides three-dimensional (3D) images that clearly show root morphology, bone quality, and the exact course of the IAN thus helping clinicians to accurately assess mandibular third molar relationships and plan the surgery. While CBCT offers detailed information, interpretation relies on clinician expertise, and differences between observers can affect accuracy [1–3].

Convolutional neural networks (CNNs) and generative adversarial networks (GANs) help to improve image clarity, automate mandibular canal segmentation, and predict surgical consequences. These methods evaluate CBCT scans with high precision, identifying high-risk features such as nerve proximity or compression [1,4]. CNNs have been applied to segment the mandibular canal, accurately locating the IAN near impacted third molars [5,6]. They augment the diagnostic dependability, help in preoperative planning, and estimate surgical complexity to guide uneventful extraction procedures [7,8]. Panoramic imaging remains widely used due to its accessibility and low cost, with trained models now capable of detecting impacted third molars, assessing angulation, and predicting nerve injury risk with strong accuracy [9–13].

Predictive models developed from imaging data and patient-specific characteristics help in the accurate estimation of nerve injury risk. These models measure factors like bone density, root shape, and depth of impaction, thus providing information that is not obtained only from conventional imaging [14–16]. Systems designed with transparency also help clinicians to review and validate the results to strengthen confidence and support to be used in daily practice [8,17]. Their application includes clinical diagnosis, surgical planning, and application during the procedure. Models trained on CBCT datasets can identify critical areas like thin cortical bone or proximity of the nerve canal, and they can guide the choice of extraction pathway, thus reducing operative time and risk of complications [7,18,19]. However, certain challenges like the need for large, diverse datasets representing the differences in anatomy and imaging methods to achieve reliable outcomes exist [20,21]. The advancement in technological improvements, combined with rigorous validation and evidence from multiple studies, has led to the elaborate integration of these applications [1,22,23].

Deep learning models, such as CNNs, classify the relationship between mandibular third molars and the mandibular canal on panoramic radiographs with high accuracy [24–26]. These models identify the spatial proximity of the IAN more precisely than conventional methods, enhancing preoperative risk assessment. Data augmentation has increased model stability and helped constant detection of risk factors in various clinical cases, while recent advances in CNN-based systems map the anatomical relationships in complex surgeries. The spatial association between third molars and the IAN remains a critical concern, as nerve injury continues to pose a major risk. This review evaluates the predictive value of computational models in assessing nerve injury risk during third molar extraction using CBCT data, providing evidence to guide surgical planning and improve patient outcomes.

Methods

Research Question

"How effective is Artificial intelligence (AI) in the evaluation of lower third molars using CBCT, particularly in predicting and preventing postoperative nerve injury?"

PICOS Question

This review used the PICOS framework.

Population (P): Patients aged 18–90 undergoing mandibular third molar extraction or preoperative evaluation, including dentulous and edentulous individuals, with CBCT or panoramic imaging to assess nerve injury risk.

Intervention (I): Computational models such as CNNs, U-shaped Convolutional Neural Network (U-Net), YOLOv3, and Faster R-CNN applied for mandibular canal segmentation, third molar detection, angulation assessment, and nerve risk prediction.

Comparison (C): Manual evaluations by clinicians or radiologists and comparisons across model types.

Outcome (O): Accuracy, sensitivity, specificity, Area Under the Curve (AUC), Intersection over Union (IoU), precision, recall, and F1-score for preoperative risk assessment.

Study design (S): Retrospective, observational, experimental, and comparative CBCT-based studies.

Search Strategy

Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines were followed to identify relevant studies in the comprehensive search process (Fig. 1). The search strategy used major databases, including PubMed, Scopus, Web of Science, and Google Scholar. Keywords included "*Artificial intelligence*", "*AI*", "*Cone beam computed tomography*", "*CBCT*", "*third molar*", "*mandibular nerve*", "*inferior alveolar nerve*", "*postoperative nerve injury*", "*nerve compression*", "*deep learning*", "*machine learning*", "*neural networks*", "*image segmentation*", and "*dental surgery*". Boolean operators AND, OR, and NOT were applied to combine terms and refine results. The search targeted studies on both preoperative and postoperative evaluations, highlighting nerve-related risks during mandibular third molar extractions.

Eligibility Criteria

This review included studies that applied computational methods like machine learning and deep learning to analyze CBCT images of mandibular third molars. Only studies evaluating or predicting nerve damage, especially with IAN injuries, were considered. Studies demonstrating accurate detection of high-risk features, including nerve proximity, compression, or direct contact, were included. Publications in English from 2020 to 2025 were included. Studies focusing on other anatomical regions, non-human subjects, unrelated topics, or lacking confirmed results for nerve injury were excluded. Case reports and editorials were excluded.

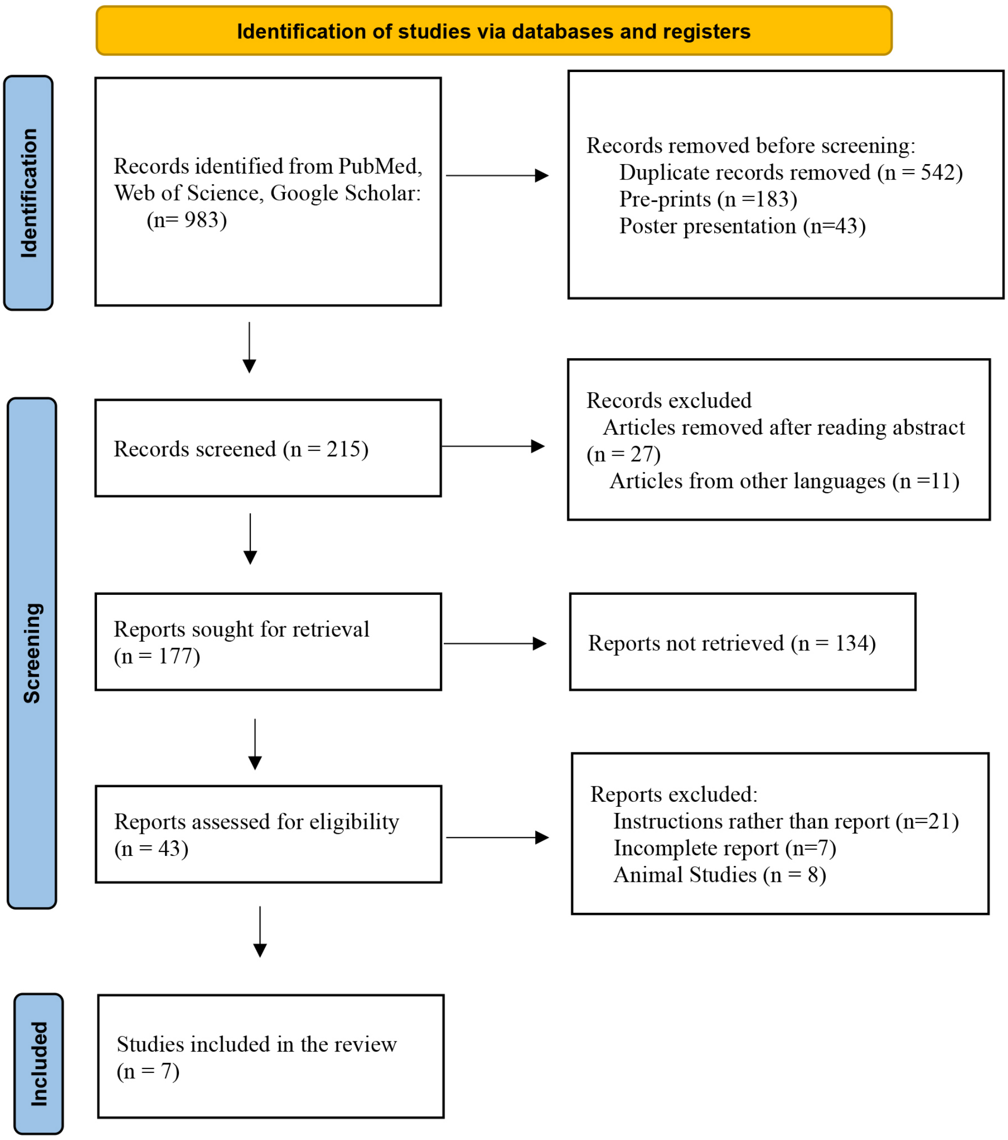

Fig. 1. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 flowchart for the review.

Data Extraction and Quality Assessment

Out of 983 records, only 7 studies were included in the review (Fig. 1). Three reviewers (VPV, MMM, HU) extracted data on study design, patient demographics, computational methods (deep learning, machine learning), CBCT imaging, and outcomes related to nerve injury. They assessed model accuracy in predicting the mandibular canal's proximity to the IAN and identified potential biases or limitations. Findings were synthesized narratively for studies with comparable outcomes, and quality was evaluated using the modified Newcastle-Ottawa Scale (NOS) [27]. Quality was assessed across selection, comparability, and outcome domains using the modified NOS. The modified NOS used in this study comprises three domains — Selection (S1–S4), Comparability (C1), and Outcome (O1–O2) — with criteria scored as one star (* = 1 point) or two stars (** = 2 points), yielding a maximum achievable score of 10 points (4 for Selection, 2 for Comparability, and 4 for Outcome).

Risk of Bias Assessment

The three reviewers (VPV, MMM, HU) applied the NOS to assess the risk of bias in the selected studies and assessed the outcome measures, comparability between groups [27]. Reviewer VR focused on outcome assessment and follow-up adequacy, GC evaluated group comparability, and GM assessed selection criteria. Studies were categorised as "good" or "moderate quality" based on their NOS total score. No studies with a high risk of bias were included in the final meta-analysis. This structured process ensured inclusion of studies with strong methodology. The PRISMA 2020 checklist is in the **Supplementary Material**.

Table 1. Characteristics of included studies.

Year & Author	Aim	Sample & Population	Study design	Imaging tool	Model/Method	Comparison/Key Findings
Kwak GH *et al.*, 2020 [11]	Evaluate 2D and 3D networks for MC segmentation	102 patients (18–90 years) undergoing CBCT for TMJ	Retrospective	PaX-Zenith 3D (VATECH)	2D U-Net, SegNet, 3D U-Net	3D U-Net outperformed 2D networks; SegNet highest among 2D models
Orhan K *et al.*, 2021 [13]	Detect impacted M3 and assess relation to anatomical structures	130 M3 from 65 patients	Retrospective	CBCT	CNN with U-Net-like architecture	Compared with a single radiologist, high agreement (Kappa analysis)
Lahoud P *et al.*, 2022 [19]	Develop fast, accurate MC segmentation for surgical planning	235 CBCT scans (training 166, testing 39, validation 30)	Retrospective observational	3D Accuitomo, ProMax 3D MAX, Scanora 3Dx, NewTom VGI EVO	3D U-Net CNN, voxel-wise segmentation	Compared with expert manual tracing, high accuracy, IoU, DSC, and improved efficiency
Liu MQ *et al.*, 2022 [28]	Automatic detection and evaluation of M3 and MC	254 CBCT scans (116 M, 138 F, mean 29.2 years)	Retrospective	CBCT (single facility)	U-Net for segmentation, ResNet-34 for classification	Compared with two radiology residents, the high detection and classification performance
Kempers S *et al.*, 2023 [4]	Assess M3–MC relation to predict IAN injury	863 panoramic radiographs	Retrospective, annotated analysis	Cranex Novus e	U-Net segmentation, nerve skeletonization, rule-based classification	Compared with clinician annotations; weighted F1 score 0.94
Yağmur ÜS & Namdar PF, 2024 [29]	Evaluate MC segmentation on CBCT using deep learning	300 patients	Experimental	Planmeca ProMax 3D Mid (0.4 mm^3)	nnU-Net v2	Compared predicted vs ground truth using Dice coefficient and confusion matrix metrics
Yasin ET *et al.*, 2025 [30]	Classify M3–MC spatial relationship for preoperative risk	305 CBCT scans	Experimental	CBCT	CNNs: MobileNet, Xception, DenseNet201	Compared CNN models; evaluated accuracy, precision, recall, F1-score

Footnote: DSC (Dice similarity coefficient) is a statistical measure used to evaluate the accuracy of image segmentation models. CBCT, Cone beam computed tomography; CNN, Convolutional neural network; MC, mandibular canal; M3, mandibular third molar; TMJ, Temporomandibular Joint; U-Net, U-shaped Convolutional neural network; nnU-Net, No-New-Net; IoU, Intersection over Union; 3D, three-dimensional; IAN, inferior alveolar nerve; 2D, two-dimensional; MC, mandibular canal; MAX, maximum; M, male; F, female.

Table 2. Outcomes and key findings.

Year & Author	Outcome measures	Accuracy (%)	Key findings	Clinical implications
Kwak GH *et al*., 2020 [11]	Canal pixel accuracy, global & class accuracy, IoU	2D U-Net: GA 82–84%, CA 63–68%; SegNet: GA 96%, CA 90%; 3D U-Net: GA 99%, CA 96%	3D U-Net outperformed all 2D networks; 2D networks showed good results, limited by unclear cortical layers	3D segmentation improves diagnosis and planning, though 3D networks require high GPU memory
Orhan K *et al*., 2021 [13]	Detection of impacted teeth, root/canal numbers, and anatomical relationships	Impacted tooth: 86.2%; Root: 78.6%; Canal: 68.1%	High agreement with expert evaluation (kappa 0.424–0.860); teeth numbering accuracy 96.9%	Improves detection of impacted molars, supports preoperative planning, and reduces surgical risks
Lahoud P *et al*., 2022 [19]	IoU, DSC, Precision, Recall, Accuracy, HD, Time	Accuracy 99.9%; IoU 63.6%; DSC 78.2%; HD 0.705 mm	High segmentation accuracy, 107× faster than manual	Enables precise MC location detection, reduces risk in extractions, implants, and grafting
Liu MQ *et al*., 2022 [28]	Segmentation (DSC, IoU, pixel accuracy) & classification	Classification 93.3%; M3 DSC 0.9730, IoU 0.9606; MC DSC 0.9248, IoU 0.9003	The model outperformed radiology residents; high segmentation and classification performance	Faster, more accurate preoperative M3–MC assessment; improves risk evaluation and planning
Kempers S *et al*., 2023 [4]	Positional relationship classification M3–MC	F1-score: 0.94	High segmentation and classification; lower M3 F1 0.91, IAN F1 0.88	Helps assess IAN injury risk, reduces variability, and supports preoperative planning
Yağmur ÜS & Namdar PF, 2024 [29]	Accuracy, Sensitivity, Precision, DSC	Accuracy 99%; DSC 0.76; Sensitivity 75%; Precision 78%	Effective MC segmentation	Supports preoperative planning; minimizes IAN injury risk
Yasin ET *et al*., 2025 [30]	Accuracy, Precision, Recall, F1-score	MobileNet 99.44%; Xception 98.74%; DenseNet201 98.73%	MobileNet achieved the highest classification accuracy	Enhances preoperative risk assessment, reduces nerve injury, and improves surgical planning efficiency

GPU, Graphics Processing Unit; CA, class accuracy; GA, global accuracy; HD, Hausdorff Distance.

Table 3. Quality assessment was performed for cross-sectional and retrospective studies using the modified Newcastle-Ottawa Scale (NOS).

No	Author & year of study	Selection (S1)	S2	S3	S4	Comparability (C1)	Outcome (O1)	O2	Total Score (Quality)
1.	Kwak GH *et al.* (2020) [11]	*	*	*	*	**	**	*	9 (Very Good)
2.	Orhan K *et al.* (2021) [13]	*	*	*	**	*	**	*	9 (Very Good)
3.	Lahoud P *et al.* (2022) [19]	*	*	*	**	**	**	*	10 (Very Good)
4.	Liu MQ *et al.* (2022) [28]	*	*	*	**	**	**	*	10 (Very Good)
5.	Kempers S *et al.* (2023) [4]	*	*	*	**	**	**	*	10 (Very Good)
6.	Yağmur ÜS and Namdar PF. (2024) [29]	*	*	*	**	*	**	*	9 (Very Good)
7.	Yasin ET *et al.* (2025) [30]	*	*	*	**	**	*	*	9 (Very Good)

In the modified Newcastle-Ottawa Scale (NOS) used in this study, each domain component was scored, where * represents one point and ** represents two points. The maximum achievable score was 10 points, with higher scores indicating superior methodological quality. All included studies achieved "Very Good" quality ratings, scoring between 9–10 points, indicating low risk of bias and robust study design.

Results

Table 1 (Ref. [4,11,13,19,28–30]) summarizes seven studies evaluating computational models for mandibular canal detection and segmentation using CBCT and panoramic imaging. One study applied two-dimensional (2D) U-Net, SegNet, and 3D U-Net to 102 CBCT scans, with 3D U-Net performing best across all metrics [11]. A study analyzed 130 impacted molars using a U-Net-based CNN, showing strong agreement with expert evaluations [13]. A third study tested a 3D U-Net on 235 scans, reporting high Dice similarity coefficient (DSC), IoU, precision, and recall [19]. U-Net and ResNet-34, combined with morphological dilation, were applied to 254 scans to detect and evaluate third molars and the mandibular canal [28]. An explainable system using 863 panoramic radiographs achieved a weighted F1-score of 0.94 for assessing the spatial relationship between third molars and the canal [4]. Another study applied No-New-Net (nnU-Net) v2 to 300 CBCT images, yielding high DSC scores [29]. CNN models, including MobileNet, Xception, and DenseNet201, were compared using 305 CBCT scans, with DenseNet201 showing the highest classification performance [30].

Table 2 (Ref. [4,11,13,19,28–30]) summarizes the main outcomes and clinical relevance of studies on mandibular canal assessment using computational models. One study reported that the 3D U-Net achieved 99% global and 96% class accuracy, outperforming 2D models in segmentation [11]. Another study showed 96.9% accuracy in detecting impacted molars, with substantial agreement with expert evaluations (kappa = 0.424–0.860) [13]. A 3D U-Net study achieved 99.9% segmentation accuracy, a DSC of 78.2%, and a minimal Hausdorff Distance of 0.705 mm, completing segmentation 107 times faster than manual methods [19]. Classification accuracy of 93.3% with DSC up to 0.9730 demonstrated reliable evaluation of third molar–mandibular canal relationships [28]. An explainable system reached an F1-score of 0.94, supporting accurate assessment of nerve injury risk [4]. nnU-Net achieved 99% accuracy and a DSC of 0.76 [29]. MobileNet, Xception, and DenseNet201 exceeded 98% classification accuracy, with MobileNet performing best for predicting the spatial relationship between third molars and the canal [30].

Table 3 (Ref. [4,11,13,19,28–30]) presents the quality assessment of cross-sectional and retrospective studies using the modified version of NOS, evaluating selection (S1–S4), comparability (C1), and outcome (O1–O2). Kwak GH *et al.* (2020) [11] scored 9, showing very good quality with strong selection and comparability. In 2021 [13], a study scored 9, excelling in outcome and comparability. In 2022 [19,28] and 2023 [4], studies achieved 10 points, reflecting optimal methodological rigor, while in 2024 [29] and 2025 [30], studies scored 9, demonstrating notable strengths in outcome and comparability domains.

Overall, all studies exhibited high methodological quality, low risk of bias, and reliable results, providing strong evidence for accurate mandibular canal segmentation, precise third molar localization, and effective risk evaluation in preoperative planning for lower third molar procedures.

Discussion

Models based on computer simulations like the use of convolutional neural networks and U-net improve the preoperative evaluation of third molars of the mandible through enhanced accuracy in practice. They reduce the need for human judgment, minimize errors made by humans, and provide consistent risk stratification, showing high effectiveness in the segmentation of mandibular canals [4,31,32]. Studies involving CNN-based architecture, such as 3D U-Net and nnU-Net, proved excellent performance in segmentation with a high DSC of between 0.76 and 0.97 [11,19,28,29], as well as greater than 98% accuracy [5]. It was proven that such models are able to reduce interobserver variability and increase the reliability of diagnoses. Other studies have confirmed reliable segmentation performance, thus making surgical planning safer and minimizing the possibility of IAN injuries when extracting wisdom teeth [19,32].

Computational models enhance preoperative evaluation of third molars and their relationship to the mandibular canal, improving the prediction of IAN injury. CNN-based models, including ResNet-34, MobileNet, and DenseNet201, achieved classification accuracies above 93%, with MobileNet showing the highest performance in assessing spatial relationships [28,30]. Analysis of 305 CBCT scans using DenseNet201 confirmed consistent high accuracy, supporting real-time clinical decision-making [30]. These models precisely detect tooth positions, analyze mandibular morphology, and evaluate canal proximity, enabling accurate nerve injury risk assessment [1,9,26]. A study reported superior mandibular canal segmentation and lower error rates compared with traditional methods [33]. They provide a detailed assessment of root morphology and identify sinus and periapical pathologies, expanding their value in comprehensive preoperative diagnostics [34–36].

A study reported a system that achieved a weighted F1-score of 0.94 in evaluating third molar–IAN relationships, producing interpretable results that help clinicians assess nerve injury risk [4]. Another study found strong agreement between model predictions and expert evaluations on panoramic images, which is particularly useful in settings with limited CBCT access [13]. Several studies confirmed that these models reliably analyze root morphology, tooth position, and mandibular canal proximity to predict nerve injury [1,25]. Additional evidence showed that precise evaluation of these features improves risk assessment and enables safer surgical procedures [9,32,37]. One study received a “Very Good” rating with a NOS score of 9 for a cross-sectional and retrospective design [29]. It performed well in participant selection and comparability, though data collection methods carried moderate risk, demonstrating methodological rigor and reducing bias.

These methods assess risk parameters like impaction depth, molar inclination, and distance from the mandibular canal, and correlate them with IAN injury [4,15]. These techniques yield personalized risk prediction for each patient, thus aiding clinicians in conducting surgical operations more safely. Decision support systems suggest surgical procedures using CBCT data to show how computational techniques can be used in clinical practice [17]. CNN-based classifiers accurately categorize positional relations between third molars and the mandibular canal [10,24]. Furthermore, CNN-based classifiers detect complicated positional relationships that are difficult to recognize manually. These findings indicate that computational models can detect subtle anatomical features clinicians may miss, thereby supporting personalized treatment planning, reducing surgical risks, and preventing IAN injury [38].

From this review, it is evident that the involvement of computational tools in surgery leads to improved surgical results and enhanced safety of patients. Incorporation of these tools into the work of clinicians helps standardize risk assessment, minimize interpretation variability, and proactively address the risks of IAN injury, hence promoting accurate diagnosis and informed decision making [4,24,39]. Progress in the field is linked to improved radiographic examination and accuracy in preoperative assessment of third molar extraction cases [40,41]. Improved risk prediction is essential for safer operation processes and personalized treatment plans, as proven by several studies on mandibular canal visibility and implant stability [40–42]. Differences in dataset size (102–1430 scans), imaging type (CBCT versus panoramic), and model architecture (U-Net, nnU-Net, ResNet, YOLOv3) create heterogeneity and limit direct comparisons. Performance metrics such as DSC, IoU, accuracy, and F1-score varied with training, validation, and preprocessing differences, highlighting the need for standardized imaging protocols, shared datasets, and uniform evaluation criteria. Incorporating clinical parameters and NOS scores of 9–10 confirmed strong methodological quality [43].

Strengths and Limitations

This systematic review includes a systematic literature search, objective quality assessment using the NOS. High NOS scores indicate strong methodology and consistent results. Variations in model architectures, imaging types, and performance measures create heterogeneity, while differences in annotation and training reduce reproducibility. The NOS does not fully capture the complexities of advanced computational methods. The review thus demonstrates constant improvements in diagnostic accuracy, reduced observer variability, and better surgical planning for third molar extractions.

Conclusions

The review thus indicates the function of computational models in enhancing the preoperative evaluation and predicting IAN injury during mandibular third molar surgery. High accuracy in mandibular canal segmentation, molar localization, and risk assessment has been achieved using deep learning and CNN-based models, leading to more precise clinical decisions. Generalizability remains limited by narrow demographic representation, the absence of external validation, and variability in model design. Future multi-center studies should apply standardized methodologies and develop interpretable systems to improve reliability and clinical applicability.

Availability of Data and Materials

The data are available on reasonable request from the corresponding authors.

Author Contributions

Conceptualization: VPV and GM; Methodology: VR and VPV; Formal analysis: MMM and HU; Investigation: VPV, VR and GM; GC jointly participated in the conception, design and acquisition of data; Writing—original draft: MMM, HU and VR; Writing—review & editing:

GC; Supervision: GC and GM. All authors contributed to critical revision of the manuscript for important intellectual content. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

Not applicable.

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Conflict of Interest

Giuseppe Minervini was serving as one of the Editorial Board Members and Guest Editors of this journal. We declare that Giuseppe Minervini had no involvement in the peer review of this article and has no access to information regarding its peer review. Other authors declare no conflict of interest.

Supplementary Material

Supplementary material associated with this article can be found, in the online version, at https://doi.org/10.62713/aic.3995.

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