Application of deep learning in evaluating the anatomical relationship between the mandibular third molar and inferior alveolar nerve: A scoping review.

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Abstract

Background: With advancements in deep learning-based dental imaging analysis, artificial intelligence (AI) models are increasingly being employed to assist in mandibular third molar surgery. However, a comprehensive overview of the clinical utility remains limited. This scoping review aimed to identify and compare deep learning models used in the radiographic evaluation of mandibular third molar surgery, with a focus on AI model types, key performance metrics, imaging modalities, and clinical applicability.

Material and Methods: Following the PRISMA-ScR guidelines, a comprehensive search was conducted in the PubMed and Scopus databases for original research articles published between 2015 and 2024. Systematic reviews, editorial articles, and studies with insufficient datasets were excluded. Studies utilising panoramic radiographs and cone-beam computed tomography (CBCT) images for AI-based mandibular third molar analyses were included. The extracted data were charted according to the AI model types, performance metrics (accuracy, sensitivity, and specificity), dataset size and distribution, validation processes, and clinical applicability. Comparative performance tables and heat maps were utilised for visualisation.

Results: Of the initial 948 articles, 16 met the inclusion criteria. Various convolutional neural network (CNN)-based models have been developed, with U-Net demonstrating the highest accuracy and clinical utility. Most studies employed panoramic and CBCT images, with U-Net outperforming other models in predicting nerve injury and evaluating extraction difficulty. However, substantial variations in dataset size, validation procedures, and performance metrics were noted, highlighting inconsistencies in model generalisability.

Conclusions: Deep learning shows promising potential in the radiographic evaluation of mandibular third molars. To date, most studies have relied on two-dimensional images and focused on detection and segmentation, while predictive modeling and three-dimensional CBCT-based analysis are relatively limited. To enhance clinical utility, larger standardized datasets, transparent multi-expert annotation, task-specific benchmarking, and robust external/multicenter validation are needed. These measures will enable reliable pre-extraction risk prediction and support clinical decision-making.

Keywords: Deep learning, mandibular third molar, inferior alveolar nerve, artificial intelligence, CBCT, panoramic radiograph.

Introduction

Third molar extraction is among the most frequently performed procedures in oral and maxillofacial surgery. Sensory disturbances involving the lower lip and chin, caused by the injury to the inferior alveolar nerve (IAN), are rare complications that may impair the patients' quality of life. Among several contributing factors, such as patient age, surgeon experience, traumatic tissue handling, and postoperative swelling, the proximity of the tooth root to the inferior alveolar nerve canal has been identified as the most significant [1-3].

Artificial intelligence (AI)- and deep learning-based diagnostic and predictive modelling methods have demonstrated utility in addressing complex clinical problems [4-8]. Several recent studies have explored deep learning in clinical dentistry, particularly in analysing panoramic radiographs and cone-beam computed tomography (CBCT) images to predict the risk of inferior alveolar nerve damage or evaluate extraction difficulty based on the positional relationship between the third molar and the mandibular canal [9-24].

However, despite advances in deep-learning-based dental imaging analysis, comprehensive evaluations of the clinical benefits of these models remains limited. This scoping review aimed to systematically map the AI models employed for mandibular third molar image analysis and to evaluate their potential clinical advantages.

Material and Methods

A comprehensive literature search was conducted using the PubMed and Scopus databases to identify relevant studies published between 1 January 2015 and 31 December 2024. The search strategy was formulated to capture studies employing deep learning models for assessing the mandibular third molar and IAN using radiographic imaging. The following search query was employed: ("deep learning" [Title/Abstract] OR "inferior alveolar nerve" [Title/Abstract] OR "artificial intelligence" [Title/Abstract] OR "radiography" [Title/Abstract]) AND ("dental" [All Fields] OR "third molar" [All Fields]) AND ("image" [Title/Abstract] OR "analysis" [All Fields]) AND ("detection" [All Fields] OR "classification" [All Fields] OR "segmentation" [All Fields] OR "prediction" [All Fields]). No restrictions were applied to the study design, provided the studies met the predefined eligibility criteria.

The studies were selected based on predefined inclusion and exclusion criteria to ensure relevance and methodological rigor. Two independent reviewers initially screened the articles by evaluating their titles and abstracts. Full-text articles were subsequently assessed for final inclusion according to the eligibility criteria. Disagreements between reviewers were resolved through discussion; and if necessary, a third reviewer was consulted.

Studies were included if they used deep learning models for mandibular third molar and IAN assessment, employed panoramic radiographs or CBCT as imaging modalities, reported quantitative performance metrics such as accuracy, sensitivity, specificity, and area under the curve (AUC); and were published in English within the defined timeframe. Studies were excluded if they applied non-deep learning methodologies, did not directly pertain to mandibular third molar assessment, or were categorised as review articles, case reports, editorials, or conference abstracts.

The study selection process is illustrated in the PRISMA 2020 flow diagram (Figure 1). A total of 948 articles were identified from PubMed (n=825) and Scopus (n=123).
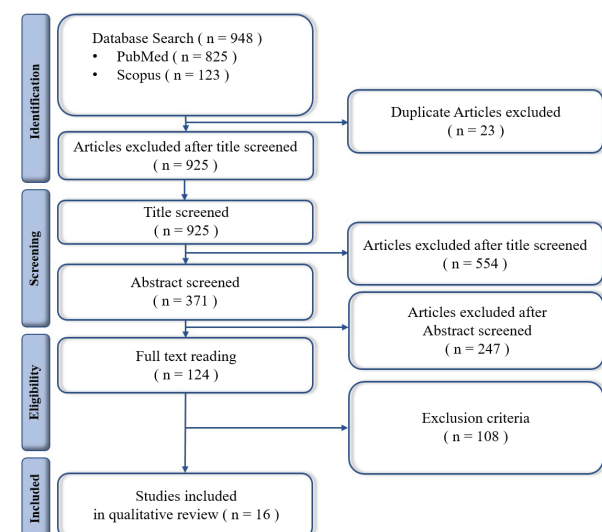

Figure 1: Study selection flow chart.

After the removing 23 duplicate records, 925 unique records were retained for screening. After title and abstract screening, 554 records were excluded for not meeting the eligibility criteria. Subsequently, 371 reports were retrieved in full-text and all were successfully obtained. After full-text assessment, 124 reports were reviewed for eligibility, of which 108 were excluded due to insufficient data (n=68), irrelevance to the study topic (n=25), lack of radiographic imaging (n=10), or unavailability of the full text (n=1). Sixteen studies met the inclusion criteria, and were included in the final systematic review.

Data charting was conducted using a standardised data extraction form calibrated beforehand to ensure consistency and accuracy. The extraction form included predefined categories, such as study characteristics (author, publication year, and country), methodological details (study design, dataset size, and imaging modality), deep learning model information (architecture and training parameters), performance metrics (accuracy, sensitivity, specificity, and AUC), and clinical applicability.

Two independent reviewers charted the data in duplicate to minimise errors and biases. Any discrepancies

were resolved through discussion, and a third reviewer was consulted, if necessary. This approach ensured high reliability of data extraction and reduced subjectivity in data interpretation. In cases of unclear or missing information, the corresponding authors of the included studies were contacted for further clarification.

Results

Among the 16 articles reviewed, a notable increase was observed by 2022 in studies evaluating deep learning models for detecting and classifying the impaction status of the third molar, assessing its positional relationship with the mandibular canal, and predicting the risk of IAN injury (Figure 2).
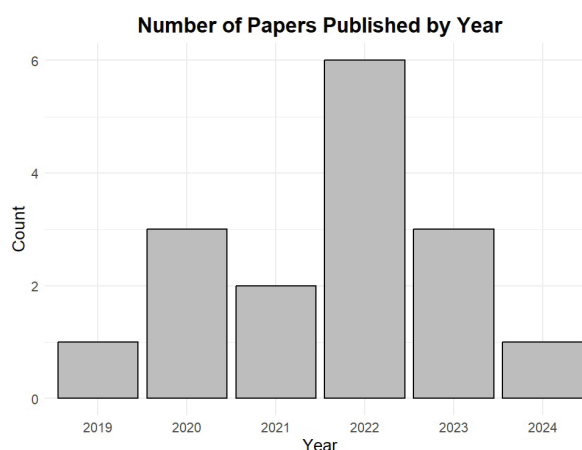

Figure 2: Number of papers published annually.

Deep learning models play a crucial role in evaluating the positional relationship between the mandibular third molar and the IAN, as well as in assessing the risk of nerve injury. To systematically analyse, this study categorised AI models according to their imaging analysis approaches and objectives.

The AI models were applied to four principal domains of image analysis. Some models focused on determining the presence and impaction status of the third molar, whereas others were designed to identify its spatial relationship with the IAN. Additionally, segmentation techniques were employed to delineate anatomical structures at the pixel level, thereby offering more detailed spatial information. Predictive models were used to assess extraction difficulty and estimate the risk of nerve injury, thereby supporting clinical decision-making. The distribution of model backbones across the included studies is summarized in Figure 3.

Table 1-4 summarise the characteristics and training methodologies of various AI models, thereby facilitating a comparative analysis of their applications in assessing mandibular third molar. These tables offer a comprehensive overview of the utilisation of different AI techniques in radiographic image analysis, aiding in the identification of key patterns across different studies.
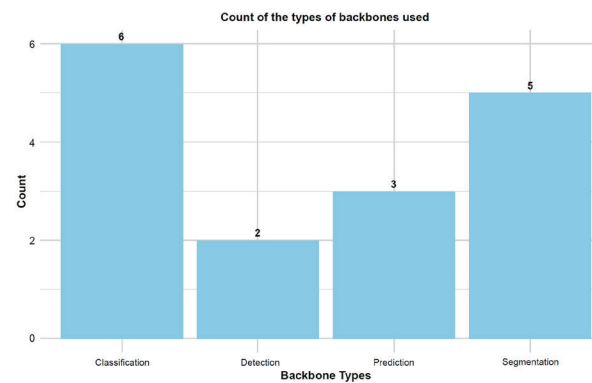
Figure 3: Types of backbones used for data analysis in the included papers.

Table 1 provides an overview of the classification models employed to detect the presence and impaction status of mandibular third molars. The most frequently utilised architectures comprised MobileNet-V2, VGG-16, and ResNet-50 with dataset sizes ranging from 500 to 1,330 images. Multiple data augmentation techniques, such as image rotation, flipping, and resizing, were applied to enhance model generalisability. Classification models were frequently integrated with detection and segmentation models to strengthen multitask learning frameworks.

Table 2 summarises object detection models used to automatically localise mandibular third molars and analyse their spatial relationships with the IAN. Commonly employed architectures include YOLOv3, ResNet-50, and VGG-16, with dataset sizes ranging from 440 to 579 panoramic images. Data augmentation techniques, such as image rotation and flipping, were frequently applied to improve model robustness. Detection models are essential for preoperative risk assessment, as they accurately delineate third molar boundaries and estimate proximity to the IAN.

Table 3 outlines segmentation models employed to delineate anatomical structures such as the mandibular canal and third molars, at the pixel level. The U-Net architecture was most frequently used, featuring in five studies due to its up-sampling and skip connection mechanisms, which facilitate precise segmentation despite limited datasets. Other architectures, such as SegNet and 3D U-Net, were applied in selected cases. Dataset sizes varied considerably, ranging from 81 to 3,200 images, with data augmentation techniques, such as image rotation, scaling, and elastic deformation, enhancing model generalisation. Segmentation models demonstrated high accuracy in outlining the mandibular canal and third molars, with Dice coefficients ranging from 0.80 to 0.94. These findings suggest that AI-based segmentation may significantly enhance diagnostic precision during third molar extractions.

Table 4 summarises predictive models developed to assess extraction complexity and risk of IAN injury.

Table 1: Characteristics of AI models used in the included studies according to the object detection method: Classification.

Author		Neural network architecture	Backbone	Data set used to develop the AI model (Number of datasets)	Testing data set	Training and validation datasets	Data augmentation
				Classification			
2021	Vinayahalingam *et al.*	CNN	MobileNet -V2	500 cropped panoramic radiographs (PR) were used to classify carious lesions in mandibular and maxillary third molars	100 images	400 images	Image rotation Flipping Resizing
2022	Sukegawa al.	CNN	VGG-16	1,330 images of mandibular third molars obtained from digital radiographs taken at the Department of Oral and Maxillofacial Surgery at a general hospital between 2014 to 2021.	Not specified	Not specified	Not specified
2022	Choi *et al.*	CNN	ResNet-50	571 panoramic images of mandibular third molars	428 images	143 images	Image rotation Horizontal flipping Brightness adjustment
2022	Sukegawa *et al.*	CNN	ResNet-50 and ResNet50V2	1,279 images of mandibular third molars obtained from patients who visited the Department of Oral and Maxillofacial Surgery at a general hospital between 2014 and 2021	128 images (10% of 1279 images)	1151 images (90% of 1279 images)	Random rotation within the 18 to 18 degrees ranges Random horizontal and vertical flipping Random translation within a range of 30 pixels
2023	Kempers *et al.*	CNN	MobileNet-V2	863 preoperative panoramic radiographs of patients who underwent third molar extraction surgery between 2019 and 2020	130 panoramic radiographs including 217 Images of mandibular third molars	773 panoramic radiographs	Not specified
2023	Youn Kim *et al.*	CNN	WideResNet and LaPlaceNet	1000 panoramic images	Winter's classification: 200 radiographs All impacted teeth detection: 240 radiographs	Winter's classification: 1800 radiographs All Impacted Teeth Detection: 2154 radiographs	Random rotation Horizontal and vertical flipping Random scaling Translation

Table 2: Characteristics of the AI models used in the included studies according to the object detection method: Detection.

Author		Neural network architecture	Backbone	Data set used to develop the AI model (Number of datasets)	Testing data set	Training and validation datasets	Data augmentation
Detection							
2022	**Takebe** *et al.*	CNN	YOLOv3	579 panoramic images	96 images	483 images	Image rotation Flipping
2022	**Celik**	CNN	RCNN, ResNet-50, VGG16 and YOLOv3	440 panoramic images	Not specified	Not specified	Rotation by 5 degrees Horizontal flipping

Table 3: Characteristics of the AI models used in the included studies according to the object detection method: Segmentation.

Author		Neural network architecture	Backbone	Dataset used to develop the AI model	Testing dataset	Training and validation datasets	Data augmentation
Segmentation							
2019	**Vinayahalingam** *et al.*	CNN	U-net	81 dental panoramic images	30 images	70 images	Image rotation Scaling and cropping Color transformation
2020	**Jaskari** *et al.*	CNN	U-net	637 cone beam CT volumes	128 cone beam CT volumes	509 cone beam CT volumes	Random rotation Horizontal and vertical flipping Random scaling Elastic deformation
2020	**Orhan** *et al.*	CNN	U-net	130 cone beam CT volumes	Not specified	Not specified	Not specified
2020	**Kwak** *et al.*	CNN	U-net	100 cone beam CT volumes	20 cone beam CT volumes	80 cone beam CT volumes	Not specified
2022	**Ariji** *et al.*	CNN	U-net	3200 dental panoramic images	1380 images	881 images	Not specified

Table 4: Characteristics of the AI models used in the included studies according to the object detection methods: Prediction.

Author		Neural network architecture	Backbone	Dataset used to develop the AI model	Testing data set	Training and validation datasets	Data augmentation
Prediction							
2021	**Yoo** *et al.*	CNN	ResNet-34	600 preoperative panoramic radiographs including 1053 images of third molars	Not specified	Not specified	Perform image flipping with a probability of 0.5 Randomly adjust the image scale within the range of (0.8, 1.0) Randomly select brightness and contrast adjustment factors within the range of (0.8, 1.2) Edit ROI within the scale range of (0.9, 1.0)
2023	**Jeon** *et al.*	CNN	RetinaNet YOLOv3 EfficientDet-D4	901 panoramic images	178 images	723 images	Image Rotation Horizontal Flip Random scaling Adjust Brightness
2024	**Zirek** *et al.*	CNN	YOLOv8	For Winter's classification: 2000 radiographs For All Impacted Teeth Detection: 2394 radiographs	For each dataset, 10% of the total data	For each dataset, 90% of the total data	Image Rotation Horizontal Flip Random scaling Translation

Frequently utilised architectures included ResNet-34, EfficientDet-D4, YOLOv3, and YOLOv8, with dataset sizes ranging from 600 to 2,394 panoramic radiographs. To optimise prediction accuracy, various data augmentation strategies, including brightness and contrast adjustments, image scaling, and region-of-interest modifications, were employed.

Key predictive performance metrics-including accuracy, sensitivity, specificity, precision and F1 score-are consolidated in Figure 4, which serves as a critical reference for assessing clinical applicability.

Studies employing predictive models demonstrated relatively high performance, with certain models achieving >80% accuracy in predicting extraction difficulty

and the risk of IAN injury. Such models offer clinically meaningful insights that support preoperative decision-making and risk stratification.

Deep-learning models have exhibited high reliability in predicting extraction difficulty and the potential for mandibular nerve injury in multiple studies. For example, in a study conducted by Yoo *et al.* [22], the models predicted the depth, ramal relationship, and angulation of the mandibular third molar with accuracies of 78.91%, 82.03%, and 90.23%, respectively, and Cohen's kappa values ranging from 65.23 to 85.54. These findings suggest that a predictive model integrating depth, angulation, and ramal relationship can serve as a reliable tool in clinical settings (Figure 4). Jeon *et al.* [23] evaluated the predic-
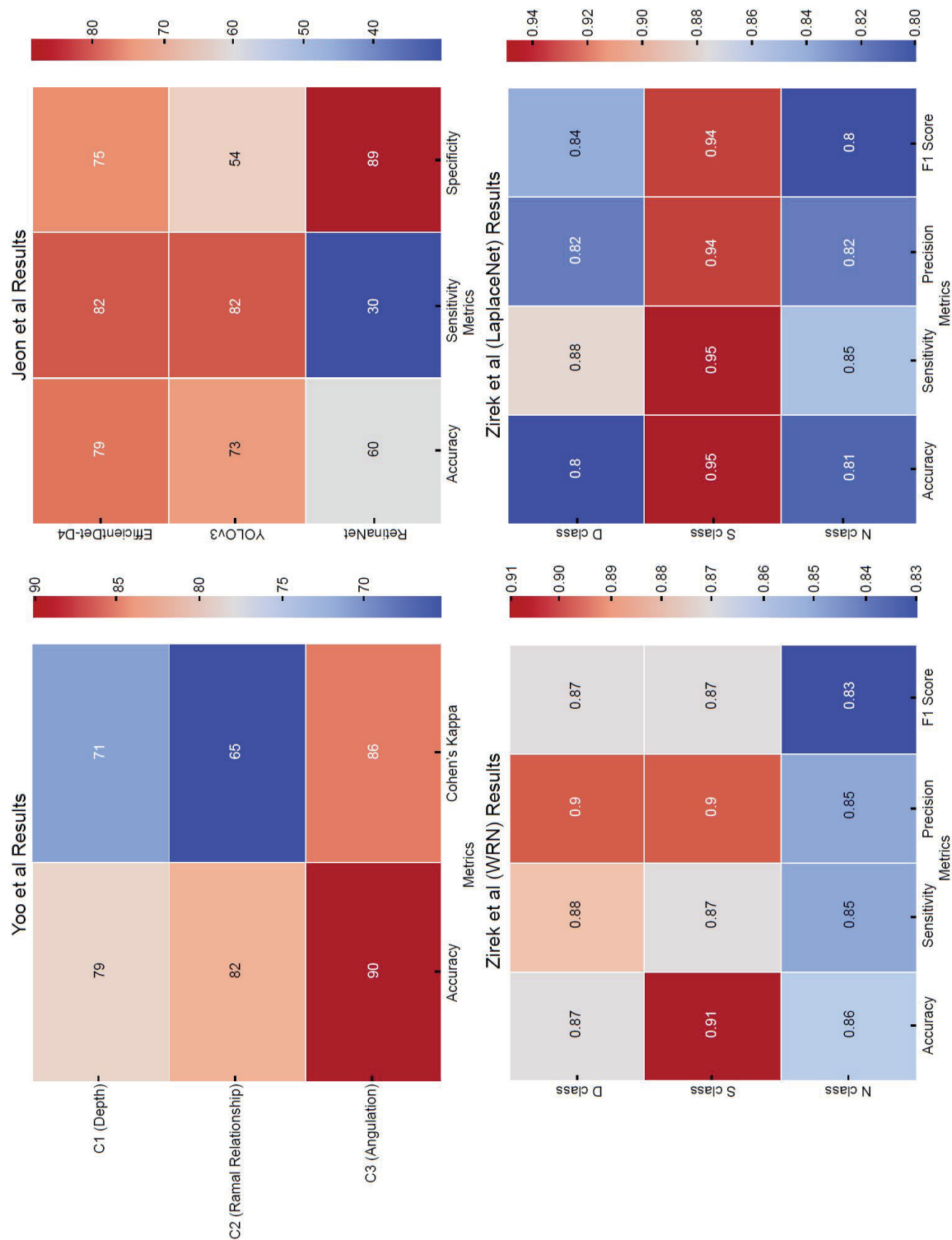
Figure 4: Heatmaps of deep learning model performance regarding prediction.

tion of extraction difficulty and mandibular nerve damage by comparing the EfficientDet-D4, YOLOv3, and RetinaNet models and reported that the EfficientDet-D4 model exhibited the highest performance (accuracy, 78.65%; sensitivity, 82.02%) (Figure 4), indicating its clinical potential for precise preoperative evaluation. To ensure comparability across studies, specific as-

sumptions were applied when necessary. Studies reporting multiple performance metrics for various models or configurations were standardised by selecting the most clinically pertinent metrics (accuracy for overall classification and AUC for risk prediction tasks). In cases where the sensitivity and specificity values were not explicitly reported, these values were calculated based on

the available confusion matrix data, wherever possible. An essential task in developing a predictive model is to minimise both false-positive and false-negative results by maintaining a balance between sensitivity and specificity. Zirek *et al.* [24] reported promising performance metrics for models such as WideResNet and LaplaceNet, with accuracies ranging from 80-91%, depending on the specific task (Figure 4). However, the reported precision and recall values varied, suggesting that further optimisation is necessary for the clinical application of these models.

A structured critical appraisal was conducted using a modified Joanna Briggs Institute (JBI) checklist for diagnostic and prognostic studies. This evaluation focused on study design, methodological rigour, dataset quality, model performance evaluation, and risk of bias. Each study was scored according to these criteria and those with significant methodological limitations were interpreted cautiously during data synthesis. The appraisal findings were discussed to highlight the strengths and limitations of the existing literature.

Excluding five studies, the remainder employed data augmentation techniques, such as image flipping, rotation, and scaling, to enhance model generalisability and reduce overfitting. Experts conducted annotations for labelling standards, region-of-interest identification, and segmentation tasks, applying various deep-learning algorithms depending on the specific task. More than 50% of these studies provided detailed information regarding the annotators (clinical experts and radiologists) and the annotation protocols employed. Several studies demonstrated annotation robustness by involving multiple annotators and incorporating consensus or correction steps to ensure accuracy. Despite high performance on controlled datasets, real-world clinical application remains challenging due to anatomical variability and inconsistencies in image quality.

The extracted data were synthesised using descriptive and visual analyses. Descriptive statistics, including means and standard deviations, were utilised to summarise performance metrics across various AI models. The key findings for predictive tasks are presented as a comparative heat map to facilitate pattern recognition and trends in performance (Figure 4).

Furthermore, the reported limitations of the included studies, particularly dataset heterogeneity and external validation constraints, were analysed to inform recommendations for future research. These findings were incorporated into the Discussion section to suggest future directions, such as the need for multicentre validation studies and standardised evaluation frameworks.

Discussion

Attempts to utilise imaging techniques for predicting postoperative outcomes based on the anatomical relationship between the mandibular third molar and the inferior alveolar canal have been ongoing since the 1960s [25]. In 1990, Rood and Shehab reported that features such as curvature of the mandibular canal and tooth root darkening were significantly associated with damage to the IAN [25]. A systematic review published in 2017 concluded that, although predicting the absence of nerve damage using panoramic radiographs alone remains challenging, radiographic indicators such as canal curvature and root darkening are valuable for assessing the risk of postoperative nerve injury [26].

Subsequently, several studies have been undertaken to more accurately evaluate the relationship between the mandibular canal and third molars through advanced imaging modalities, such as CT. However, a recent review indicated that, while CBCT aids in bone removal and surgical planning it does not significantly reduce the incidence of IAN injury following third molar extraction [27]. In general, close proximity to the IAN and curvature of the mandibular canal are key anatomical factors that elevate the risk of postoperative nerve injury. Recently, AI has been employed to automate such assessments, particularly for predicting the position of the mandibular third molar and the associated risk of nerve injury.

This review presents an analysis of studies employing deep learning techniques. The earliest study, published in 2019, primarily focused on segmentation tasks using the U-Net (Table 3) [17]. The U-Net model, initially developed for biomedical applications, demonstrated excellent performance in pixel-wise segmentation tasks. This architecture is well-suited for medical image analysis applications, such as third molar extraction planning, enabling faster and more accurate segmentation than conventional CNN models [28].

Furthermore, the analysed studies predominantly employed classification methods (Table 1) [9-14]. Classification, the simplest form of image analysis, assigns a single label to an entire image, whereas segmentation is employed to detect abnormalities such as tumours on magnetic resonance imaging or CT, through pixel-level classification. Although classification is used more frequently, segmentation remains useful for complex assessments, including evaluation of nerve proximity and extraction difficulty.

A key advantage of AI lies in its capacity to streamline and enhance surgical planning. AI assists clinicians in making informed decisions on extraction strategies, thereby potentially reducing intraoperative complications. Moreover, AI-driven risk assessment tools support patient counselling by offering objective, data-driven predictions of nerve injury risk, thereby enhancing patient understanding and the consent process. Our analysis highlighted certain issues in the published studies. Many studies have used relatively small datasets and implemented data augmentation techniques to prevent overfitting; however, the diversity in dataset

sizes and the absence of standardised evaluation protocols hinder meaningful comparisons. Additionally, due to anatomical variability among patients and differences in image quality, models demonstrating high accuracy in controlled environments may perform sub optimally in actual clinical settings.

To address these limitations and ensure clinical applicability of AI models, future studies should prioritise several key areas. First, multicentre data collection is essential for increasing dataset diversity and improve model generalisability. Institutional collaboration will facilitate the aggregation of heterogeneous imaging datasets and the representation of diverse anatomical variations and clinical contexts. Second, standardised evaluation metrics must be established to ensure consistent benchmarking across studies and enable meaningful comparisons of AI model performances. Third, prospective clinical trials should be conducted to validate AI models in real-world clinical settings. These trials should assess the diagnostic accuracy and the impact of AI-assisted decision making on surgical outcomes and patient safety. Finally, the development of clinically integrated AI tools should be prioritised. Future models should incorporate user-friendly interfaces and real-time processing capabilities to support intraoperative decision making.

Conclusion

Overall, the included studies confirmed that AI and deep learning have been actively used to evaluate the anatomical relationship between mandibular third molars and the IAN. The high values of performance indicators reported in these studies suggested that AI could accurately predict potential complications and support surgical decision-making. However, further research is necessary before clinical implementation becomes feasible.

Future studies should focus on enhancing the generalisability and reliability of AI models by incorporating more diverse datasets, establishing standardised evaluation protocols, and conducting clinical trials to validate AI-based decision support systems in real-world surgical settings. These steps are essential to ensure the seamless and effective integration of AI into clinical workflows, thereby improving patient safety and surgical outcomes.

Author contributions
Suji Ahn and Min-Ji Kim contributed equally to this work (co-first authors).
SA: Conceptualization, literature search, data curation, formal analysis, visualization, writing-original draft, writing-review & editing.
MJK: Conceptualization, literature search, data curation, investigation, writing-review & editing.
JYK: Methodology, validation, supervision, writing-review & editing.
WP: Supervision, project administration, writing-review & editing.

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