

Deep Learning for Automated Assessment of Mandibular Alveolar Bone Quality and Quantity on Cone Beam Computed Tomography for Dental Implant Planning: A Narrative Review

Kelsa Angelina Cen¹, Eha Renwi Astuti^{2*}, Ramadhan Hardani Putra²

¹Undergraduate Student, Faculty of Dental Medicine,
Universitas Airlangga, Surabaya, Indonesia

²Department of Dental Radiology, Faculty of Dental Medicine,
Universitas Airlangga, Surabaya, Indonesia

E-mail: kelsa.angelina.cen-2023@fkg.unair.ac.id; eha-r-a@fkg.unair.ac.id

*Corresponding author details: Eha Renwi Astuti; eha-r-a@fkg.unair.ac.id

ABSTRACT

Background: Dental implants have become a preferred option for rehabilitating tooth loss, yet their success depends heavily on the quality and quantity of the alveolar bone at the planned implant site. Cone Beam Computed Tomography (CBCT) is the standard imaging modality for pre-surgical bone assessment, but manual measurement of bone dimensions across numerous cross-sections is time-consuming and operator-dependent, while the grey values of CBCT do not reliably represent bone density. Deep learning has therefore been explored to automate both aspects of bone evaluation. **Purpose:** This narrative review discusses the current application, performance, and limitations of deep learning for automated assessment of mandibular alveolar bone quality and quantity on CBCT to support dental implant planning. **Review:** A literature search was performed through PubMed, ScienceDirect, Web of Science, Scopus, and IEEE Xplore for articles published between 2012 and 2026. For bone quality, convolutional neural network (CNN) classifiers reached 86% accuracy in Lekholm and Zarb classification and outperformed implantologists; Nested U-Net enabled region-wise density grading, and a generative model reduced the error of CBCT-based bone mineral density measurement from 54.29% to 8.32%. For bone quantity, segmentation-based systems using U-Net++ and YOLOv8 delineated the alveolar ridge with Dice coefficients of 0.91–0.98, produced width measurements with a mean absolute error of 1.19 mm, and generated treatment suggestions agreeing with clinicians in 94% of cases. Small single-device datasets, heterogeneous reference standards, and the absence of links to clinical outcomes remain the main limitations. **Conclusion:** Deep learning shows promising performance for automated evaluation of mandibular bone quality and quantity on CBCT, but it should currently serve as a clinician-supervised decision-support tool.

Keywords: artificial intelligence; bone density; cone beam computed tomography; deep learning; dental implant

INTRODUCTION

Edentulism remains a substantial global oral health burden. Based on data from the Global Burden of Disease (GBD) 2021 study, edentulism affected approximately 353 million people globally, corresponding to an age-standardized prevalence of 4.11%, and the number of edentulous individuals is projected to exceed 660 million by 2050 [1]. In Indonesia, the self-reported prevalence of edentulism among adults aged 50 years and older was 7.2% [2]. Partial tooth loss can affect mastication and speech and is associated with several domains of oral health-related quality of life, including physical health, psychological health, and social relationships [3]. Among the available rehabilitation options, implant-supported prostheses provide better stability and masticatory efficiency and have been associated with significant improvements in quality of life [4].

The success of implant therapy depends largely on the condition of the alveolar bone at the planned implant site. Bone quality, which is related to bone density and the characteristics of cortical and trabecular bone, plays an important role in primary implant stability and osseointegration [5,6]. Bone quantity, primarily represented by the available bone height and width, influences the selection of implant length and diameter and may determine the need for bone augmentation [6]. Lower bone density has been associated with reduced implant stability and an increased risk of early implant failure [7]. In the posterior mandible, the available bone height is determined by the distance between the alveolar crest and the mandibular canal, making accurate assessment essential to minimize the risk of inferior alveolar nerve injury [8].

Cone Beam Computed Tomography (CBCT) has become widely used for pre-surgical implant assessment because it provides three-dimensional images of the maxillofacial region and allows accurate linear measurement of the alveolar bone [9,10,11]. Nevertheless, two important problems remain in daily practice. First, assessing the available bone across hundreds of CBCT cross-sectional images is time-consuming, demands considerable focus, and is prone to variability and measurement errors [12]. Second, unlike the Hounsfield units (HU) of conventional CT, CBCT grey values may differ depending on the imaging system and scanning conditions, which can limit their use for quantitative bone density assessment [13,14]. Although CBCT grey values may provide information about bone density, their relationship with primary implant stability remains unclear [15].

Deep learning, a subfield of machine learning that uses multilayer neural networks to learn image features directly from data, has been increasingly applied in dentomaxillofacial radiology to automate detection, segmentation, classification, and measurement tasks [16,17,18]. In the field of implant dentistry, several systematic reviews have summarized the use of artificial intelligence (AI) for implant planning in general [19,20]; however, studies specifically addressing automated evaluation of bone quality and bone quantity, the two fundamental bone parameters in implant site assessment, remain limited and vary considerably in terms of architectures, datasets, and evaluation metrics. This narrative review was therefore conducted to discuss the current applications, performance, and limitations of deep learning for automated assessment of mandibular alveolar bone quality and quantity on CBCT to support dental implant planning. The literature was searched in PubMed, ScienceDirect, Web of Science, Scopus, and IEEE Xplore for articles published between 2012 and 2026, using combinations of the keywords “artificial intelligence”, “deep learning”, “convolutional neural network”, “cone beam computed tomography”, and “dental implant” or “implant planning”.

DISCUSSION

Deep learning in CBCT image analysis

Artificial intelligence refers to computational systems that mimic human cognitive abilities such as pattern recognition and decision-making. In conventional machine learning, relevant image features must first be extracted manually before they are used for prediction, whereas deep learning automatically learns hierarchical features directly from raw image data through multiple layers of artificial neurons [16,17]. Convolutional neural networks (CNNs) are widely used deep learning architectures in dental radiography because they can automatically learn relevant image features through multiple hidden layers [17].

In CBCT-based implant planning, deep learning is typically applied through several types of tasks. Classification assigns an image or region to a predefined category, such as a bone quality type;

segmentation delineates structures such as the alveolar ridge or mandibular canal at the pixel or voxel level; measurement algorithms then derive clinically relevant dimensions from the segmented structures [21]. Image-to-image translation models, such as generative adversarial networks, can also convert CBCT images into images with CT-like quantitative properties [22]. As discussed below, bone quality assessment has mainly been approached through classification and image translation, whereas bone quantity assessment has mainly relied on a segmentation-then-measurement strategy.

Radiographic parameters of bone quality and quantity on CBCT

Bone quality is commonly classified using the Lekholm and Zarb (L&Z) classification, which divides bone into four types based on the characteristics of cortical and trabecular bone, ranging from type I, consisting almost entirely of homogeneous compact bone, to type IV, which has a thin cortical layer surrounding low-density trabecular bone [23]. Because this classification relies on visual judgment without quantitative criteria, its reproducibility on CBCT is limited, and the distinction between types II and III is particularly difficult [24,25]. The Misch classification describes bone density from D1 to D5 and associates each category with a range of HU values derived from conventional CT [6]. These HU-based thresholds, however, cannot be directly transferred to CBCT, because although CBCT grey values may correlate with HU, they can be affected by the imaging device, exposure parameters, artefacts, and the position of the region within the field of view [13,14].

Bone quantity is evaluated primarily through the available bone height and width. In the mandible, bone height is measured from the alveolar crest to the superior border of the mandibular canal and determines the appropriate implant length, while buccolingual width determines the appropriate implant diameter [6,8]. Implant planning should also consider the available bone dimensions and maintain a safe distance from the mandibular canal to reduce the risk of complications [8]. Accurate delineation of both the alveolar ridge and the mandibular canal is therefore the foundation of automated bone quantity assessment.

Deep learning for bone quality assessment

Pornvoranant et al. [25] addressed the subjectivity of the L&Z classification by evaluating five pre-trained CNNs using transfer learning on 1,100 cross-sectional CBCT images of edentulous ridges from 163 patients, with the ground truth established by consensus of two experienced oral and maxillofacial radiologists. Inception-ResNet-v2 achieved the highest testing accuracy of 86%, with areas under the curve above 0.90 for all bone types, and showed stronger agreement with the ground truth ($\kappa = 0.813$) than residency students and implantologists, whose accuracies ranged from 64% to 75%. Notably, human assessors had the greatest difficulty distinguishing bone types II and III, whereas the model found types III and IV the most challenging,

because these two types differ only in trabecular bone density rather than cortical bone width.

Instead of assigning a single category to a whole cross-section, Xiao et al. [26] developed a Nested U-Net-based system that segments regions of different bone density within the mandibular implant site. Using CBCT data from 70 patients with mandibular dentition defects, the jawbone was divided into five density types based on HU ranges, from type 1 (1000–2000) to type 5 (–200–100), and labelled by four implant clinicians with confirmation by a senior clinician. After training on 605 image sets, the model reached a maximum average Dice coefficient of 0.75 on the test set, and the mean HU of each predicted category was close to that labelled by the clinicians, for example 1520 versus 1519 for type 1 and 352 versus 351 for type 4. Such region-wise grading may help clinicians anticipate local variations in density that could cause drill deviation during osteotomy. However, the authors acknowledged that prospective clinical studies are still required to confirm the practical feasibility of the proposed classification system.

The problem of unreliable CBCT grey values was directly addressed by Park et al. [22], who applied QCBCT-NET, a model combining a Cycle-GAN and a multi-channel U-Net, to convert CBCT images into quantitative CBCT images for bone mineral density (BMD) measurement. The model was trained using 7,500 pairs of CT and CBCT slices from 30 patients, and BMD was measured in 36 volumes of interest at potential implant sites in each patient, with quantitative CT serving as the ground truth. Compared with conventionally calibrated CBCT, the deep learning-based images reduced the mean absolute percentage error from 54.29% to 8.32% and increased the coefficient of determination from 0.24 to 0.85, with a mean absolute percentage error of 7.89% in the mandible. Importantly, the accuracy of conventional CBCT decreased as the site of interest moved away from the centre of the field of view, whereas the deep learning-based measurements remained uniform across all sites.

Taken together, these studies illustrate three complementary approaches to deep learning-based bone quality assessment: reproducing an established qualitative classification more consistently than clinicians [25], producing a finer region-wise density map [26], and improving the quantitative reliability of CBCT for bone density measurement [22]. The first two approaches rely on reference labels established by clinicians, whereas the third directly addresses the limitations of CBCT grey values in quantitative bone density assessment.

Deep learning for bone quantity assessment

Kurt Bayrakdar et al. [27] evaluated a commercially available deep CNN-based system for implant planning on 75 CBCT images comprising 508 implant regions. The system detected missing teeth and relevant anatomical structures and automatically measured bone height and thickness.

Bone height measurements were comparable to manual measurements in some regions, whereas significant differences were found for bone thickness in all regions. The detection rates for the mandibular canal (72.2%) and maxillary sinus (66.4%) were also considerably lower than for missing teeth (95.3%) [27]. These findings indicated that bone thickness measurement and the detection of anatomical structures remained important areas for improvement.

Focusing specifically on bone width, Hanna et al. [28] developed a U-Net++-based framework using 300 CBCT scans of posterior mandibular edentulous sites. After comparing U-Net, Double U-Net, U-Net++, and DeepLab architectures, U-Net++ was selected and achieved a Dice coefficient of 0.98 for alveolar ridge segmentation, but only 0.56 for mandibular canal segmentation. Buccolingual width was then computed automatically at 2-mm intervals from the alveolar crest to 2 mm above the canal, yielding a mean absolute error of 1.19 mm, a root mean square error of 1.40 mm, and a coefficient of determination of 0.53 against manual measurements. Although the mean difference of 0.75 mm was statistically significant, the authors considered it clinically acceptable for width assessment.

Rashid and Gaghori [12] extended automated quantity assessment into a complete planning workflow. Using 1,072 cross-sectional images from 189 mandibular edentulous cases acquired with two different CBCT machines, a YOLOv8-seg model segmented the alveolar bone and inferior alveolar canal with an overall Dice coefficient of 0.911 (0.993 for bone and 0.927 for the canal). Bone height and width were calculated from the segmentation masks, and the system completed segmentation approximately 2,001 times faster than manual delineation. Width measurements did not differ significantly from those of two operators, whereas height measurements showed statistically significant but very small mean differences of 0.05–0.17 mm, and height measurements also differed significantly between the two human operators themselves. Based on the measured dimensions, the system classified each case into one of 25 categories with corresponding treatment suggestions, such as recommended implant dimensions or the need for augmentation, which matched the assessments of dental specialists in 94% of cases ($\kappa = 0.89$). Earlier work similarly demonstrated that a modified YOLO-based model could detect the alveolar bone and mandibular canal on CBCT and estimate the available bone height and width for posterior mandibular implant planning [29].

Across these studies, the accuracy of bone quantity assessment appears closely linked to the accuracy of mandibular canal segmentation, since the canal defines the lower limit of bone height and the reference level for width measurements. The contrast between the moderate canal segmentation reported by Hanna et al. [28] and the higher performance reported by Rashid and Gaghori [12]

could partly be influenced by differences in annotation approaches, as the latter included the cortical border of the canal in its labels. Width measurement, which is sensitive to the irregular morphology of the resorbed crest, remained the more challenging parameter in two of the three studies [27,28].

Limitations and challenges

Despite these promising results, several limitations restrict the generalizability of the current evidence. Most studies used relatively small datasets, some involving only 30 to 70 patients [26,22], and most were developed using images from a single CBCT device [25,26,22,28]. Because image characteristics differ between scanners and acquisition protocols, a model that performs well on data from one institution may not perform equally well elsewhere [30,31]. This issue is particularly relevant for bone quality assessment, since grey values and apparent density are strongly device-dependent [13,22].

The reference standards also varied considerably, ranging from expert consensus labels [25,26] and quantitative CT [22] to measurements by one or two operators [28,12]. Labels derived from subjective classification may carry the same variability that deep learning is intended to overcome, and measurements by a single operator may introduce observer-dependent bias. In addition, some studies excluded images with artefacts or pathology [25,28], even though artefacts from metallic restorations and patient movement may occur in routine CBCT and can affect image quality and model performance [25,28].

Another important gap is that bone quality and bone quantity have so far been evaluated separately. Hanna et al. [28] explicitly noted that bone density and bone quality were not included in their system, while Rashid and Gaghor [12] focused on bone quantity assessment based on bone height and width. Conversely, the quality-oriented studies did not provide dimensional measurements. Furthermore, none of the reviewed studies correlated the automated outputs with clinical outcomes such as insertion torque, implant stability quotient, or long-term implant survival, so the clinical benefit of automated bone assessment has not yet been demonstrated directly. Finally, the development of such systems depends on sufficiently large and high-quality datasets, whose availability may be limited by ethical issues and patient data protection policies [17].

Clinical implications and future directions

From a clinical perspective, deep learning-based bone assessment may substantially shorten the pre-surgical evaluation process. Instead of manually measuring height and width on numerous cross-sections, clinicians could receive automated bone measurements and suggested treatment options in substantially less time, which they can then review and adjust [12,19]. Such standardized outputs may be especially valuable for less experienced clinicians, who showed lower agreement in bone quality classification [25].

Nevertheless, deep learning outputs should be positioned as decision-support tools under clinician supervision rather than as autonomous replacements for clinical judgment [17,18]. Future studies should develop integrated systems that assess bone quality and quantity simultaneously, validate them using multicentre datasets acquired with different CBCT devices and protocols, adopt standardized reporting of performance metrics, and evaluate their relationship with clinical parameters such as primary stability and implant success.

CONCLUSIONS

Deep learning has shown promising performance in the automated assessment of mandibular alveolar bone on CBCT for dental implant planning. For bone quality, CNN-based classifiers can reproduce the Lekholm and Zarb classification more consistently than clinicians, segmentation models can map regional density variations, and generative models can markedly improve the accuracy of CBCT-based bone density measurement. For bone quantity, segmentation-based systems can delineate the alveolar ridge with high accuracy, measure bone height and width with small errors, and provide treatment suggestions that largely agree with specialists while greatly reducing analysis time. However, reliance on small single-device datasets, heterogeneous reference standards, less reliable mandibular canal segmentation in some models, the separate evaluation of quality and quantity, and the absence of clinical outcome validation still limit routine application. Deep learning should therefore currently be regarded as a clinician-supervised decision-support tool, and future multicentre studies integrating both bone parameters are needed before its wider adoption in implant planning.

ACKNOWLEDGMENT

The authors would like to thank the Faculty of Dental Medicine, Universitas Airlangga, for the support provided during the preparation of this article.

REFERENCES

- [1] Nascimento, G.G., Alves-Costa, S. and Romandini, M. (2024). Burden of severe periodontitis and edentulism in 2021, with projections up to 2050: The Global Burden of Disease 2021 study. *Journal of Periodontal Research*, 59(5), 823–867.
- [2] Pengpid, S. and Peltzer, K. (2018). The prevalence of edentulism and their related factors in Indonesia, 2014/15. *BMC Oral Health*, 18(1), 44.
<https://doi.org/10.1186/s12903-018-0582-7>
- [3] Berniyanti, T., Palupi, R., Abdulraoof Alkadasi, B., Putri Sari, K., Putri R, I., Salma, N., Prasita, S. and Junior, S.A. (2023). Oral Health-Related Quality of Life (OHRQoL) Analysis in Partially Edentulous Patients with and without Denture Therapy. *Clinical, Cosmetic and Investigational Dentistry*, 15, 89–98.
<https://doi.org/10.2147/ccide.s407136>

- [4] Duong, H.Y., Rocuzzo, A., Stähli, A., Salvi, G.E., Lang, N.P. and Sculean, A. (2022). Oral health-related quality of life of patients rehabilitated with fixed and removable implant-supported dental prostheses. *Periodontology* 2000, 88(1), 201–237.
- [5] Yusa, K., Ishikawa, S., Suzuki, N. et al. (2024). Clinical evaluation of bone quality of particulate cancellous bone and marrow, and implant prosthetic rehabilitation. *Journal of Stomatology, Oral and Maxillofacial Surgery*, 125(12 Suppl 2), 101862.
- [6] Resnik, R.R. (ed.) (2021). *Misch's Contemporary Implant Dentistry*. 4th edn. St. Louis, Missouri: Elsevier.
- [7] Gong, T., Wang, L.Q., Tong, X., Zhang, Y. and Shu, L.J. (2025). Impact of age-related bone density variations on dental implant stability and success rates: A retrospective analysis. *International Dental Journal*, 75(6), 103942.
- [8] White, S.C. and Pharoah, M.J. (2014). *Oral Radiology: Principles and Interpretation*. 7th edn. St. Louis: Elsevier.
- [9] Jacobs, R., Salmon, B., Codari, M., Hassan, B. and Bornstein, M.M. (2018). Cone Beam Computed Tomography in implant dentistry: recommendations for clinical use. *BMC Oral Health*, 18(1), 88. <https://doi.org/10.1186/s12903-018-0523-5>
- [10] Fokas, G., Vaughn, V.M., Scarfe, W.C. and Bornstein, M.M. (2018). Accuracy of linear measurements on CBCT images related to presurgical implant treatment planning: A systematic review. *Clinical Oral Implants Research*, 29(Suppl 16), 393–415.
- [11] Carneiro, A.L.E., Reis, I.N.R., Bitencourt, F.V., Salgado, D.M.R.A., Costa, C. and Spin-Neto, R. (2024). Accuracy of linear measurements for implant planning based on low-dose cone beam CT protocols: a systematic review and meta-analysis. *Dentomaxillofacial Radiology*, 53(4), 207–221. <https://doi.org/10.1093/dmfr/twae007>
- [12] Rashid, M.O. and Gaghori, S. (2025). Clinical application of a deep learning system for automatic mandibular alveolar bone quantity assessment and suggested treatment options using CBCT cross-sections. *Medicine*, 104(30), e43257. <https://doi.org/10.1097/MD.00000000000043257>
- [13] Pauwels, R., Jacobs, R., Singer, S.R. and Mupparapu, M. (2015). CBCT-based bone quality assessment: are Hounsfield units applicable? *Dentomaxillofacial Radiology*, 44(1), 20140238. <https://doi.org/10.1259/dmfr.20140238>
- [14] Razi, T., Emamverdzadeh, P., Nilavar, N. and Razi, S. (2019). Comparison of the Hounsfield unit in CT scan with the gray level in cone-beam CT. *Journal of Dental Research, Dental Clinics, Dental Prospects*, 13(3), 177–182.
- [15] Lee, S.H., Yun, P.Y., Yi, Y.J. et al. (2023). Low bone density predictability of CBCT and its relation to primary stability of tapered implant design: A pilot study. *Journal of Oral Implantology*, 49(5), 556–563.
- [16] Janiesch, C., Zschech, P. and Heinrich, K. (2021). Machine learning and deep learning. *Electronic Markets*, 31, 685–695. <https://doi.org/10.1007/s12525-021-00475-2>
- [17] Putra, R.H., Doi, C., Yoda, N., Astuti, E.R. and Sasaki, K. (2022). Current applications and development of artificial intelligence for digital dental radiography. *Dentomaxillofacial Radiology*, 51(1), 20210197. <https://doi.org/10.1259/dmfr.20210197>
- [18] Schwendicke, F., Samek, W. and Krois, J. (2020). Artificial Intelligence in Dentistry: Chances and Challenges. *Journal of Dental Research*, 99(7), 769–774. <https://doi.org/10.1177/0022034520915714>
- [19] Alqutaibi, A.Y., Algabri, R., Ibrahim, W.I., Alhaji, M.N. and Elawady, D. (2025). Dental implant planning using artificial intelligence: A systematic review and meta-analysis. *The Journal of Prosthetic Dentistry*, 134(5), 1619–1629. <https://doi.org/10.1016/j.prosdent.2024.03.032>
- [20] Zaww, K., Abbas, H., Vanegas Sáenz, J.R. and Hong, G. (2026). AI-driven innovations for dental implant treatment planning: A systematic review. *Journal of Prosthodontic Research*, 70(2), 192–205. https://doi.org/10.2186/jpr.JPR_D_24_00338
- [21] Urban, R., Haluzová, S., Strunga, M., Surovková, J., Lifková, M., Tomášik, J. and Thurzo, A. (2023). AI-assisted CBCT data management in modern dental practice: Benefits, limitations and innovations. *Electronics*, 12(7), 1710. <https://doi.org/10.3390/electronics12071710>
- [22] Park, C.-S., Kang, S.-R., Kim, J.-E., Huh, K.-H., Lee, S.-S., Heo, M.-S., Han, J.-J. and Yi, W.-J. (2023). Validation of bone mineral density measurement using quantitative CBCT image based on deep learning. *Scientific Reports*, 13(1), 11921. <https://doi.org/10.1038/s41598-023-38943-8>
- [23] Al-Ekrish, A.A., Widmann, G. and Alfadda, S.A. (2018). Revised, Computed Tomography-Based Lekholm and Zarb Jawbone Quality Classification. *International Journal of Prosthodontics*, 31(4), 342–345. <https://doi.org/10.11607/ijp.5714>

- [24] Rosas-Díaz, J.C., Córdova-Limaylla, N.E., Palomino-Zorrilla, J.J., Guerrero, M.E., Carreteros, R., Cervantes-Ganoza, L.A. and Cayo-Rojas, C.F. (2022). Repeatability and reproducibility of a modified Lekholm and Zarb bone quality classification based on cone beam computed tomography. *Journal of International Society of Preventive and Community Dentistry*, 12(4), 397–405. https://doi.org/10.4103/jispcd.jispcd_291_21
- [25] Pornvoranant, T., Panyarak, W., Wantanajittikul, K., Charuakkra, A., Rungsiyakull, P. and Chaijareenont, P. (2025). A Comparison of Deep Learning vs. Dental Implantologists in Cone-Beam Computed Tomography-Based Bone Quality Classification. *Journal of Imaging Informatics in Medicine*, 38(4), 2462–2471. <https://doi.org/10.1007/s10278-024-01317-1>
- [26] Xiao, Y., Liang, Q., Zhou, L., He, X., Lv, L., Chen, J., Endian, S., Jianbin, G., Wu, D. and Lin, L. (2022). Construction of a new automatic grading system for jaw bone mineral density level based on deep learning using cone beam computed tomography. *Scientific Reports*, 12(1), 12841. <https://doi.org/10.1038/s41598-022-16074-w>
- [27] Kurt Bayrakdar, S., Orhan, K., Bayrakdar, I.S., Bilgir, E., Ezhov, M., Gusarev, M. and Shumilov, E. (2021). A deep learning approach for dental implant planning in cone-beam computed tomography images. *BMC Medical Imaging*, 21(1), 86. <https://doi.org/10.1186/s12880-021-00618-z>
- [28] Hanna, N., Ahmed, J., Sujir, N., Verma, T., Vakharia, K., Rajan, J. and Shenoy, N. (2026). Comparison of artificial intelligence methods with manual measurements for mandibular bucco-lingual bone width assessment using cone-beam computed tomography images. *Oral Radiology*, 42, 774–783. <https://doi.org/10.1007/s11282-026-00916-8>
- [29] Widiastri, M., Arifin, A.Z., Suciati, N., Fatichah, C., Astuti, E.R., Indraswari, R., Putra, R.H. and Za'in, C. (2022). Dental-YOLO: Alveolar Bone and Mandibular Canal Detection on Cone Beam Computed Tomography Images for Dental Implant Planning. *IEEE Access*, 10, 101483–101494. <https://doi.org/10.1109/ACCESS.2022.3208350>
- [30] Iacob, A.M., Verdecchia, A., García-Mesa, Y., Spinas, E. and Cobo, T. (2026). Effectiveness of automated segmentation of maxillofacial structures in cone-beam computed tomography images using artificial intelligence: A systematic review. *International Orthodontics*, 24(1), 101081. <https://doi.org/10.1016/j.ortho.2025.101081>
- [31] Arı, T., Bayrakdar, I.S., Çelik, Ö., Bilgir, E., Kuran, A. and Orhan, K. (2026). Evaluation of cone-beam computed tomography images with artificial intelligence. *Journal of Imaging Informatics in Medicine*, 39(2), 1734–1743. <https://doi.org/10.1007/s10278-025-01595-3>