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Segmentation of periapical lesions with automatic deep learning on panoramic radiographs: an artificial intelligence study

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Abstract
Periapical periodontitis may manifest as a radiographic lesion radiographically. Periapical lesions are amongst the most common dental pathologies that present as periapical radiolucencies on panoramic radiographs. The objective of this research is to assess the diagnostic accuracy of an artificial intelligence (AI) model based on U^2-Net architecture in the detection of periapical lesions on dental panoramic radiographs and to determine whether they can be useful in aiding clinicians with diagnosis of periapical lesions and improving their clinical workflow. 400 panoramic radiographs that included at least one periapical radiolucency were selected retrospectively. 780 periapical radiolucencies in these anonymized radiographs were manually labeled by two independent examiners. These radiographs were later used to train the AI model based on U^2-Net architecture trained using a deep supervision algorithm. An AI model based on the U^2-Net architecture was implemented. The model achieved a dice score of 0.8 on the validation set and precision, recall, and F1-score of 0.82, 0.77, and 0.8 respectively on the test set. This study has shown that an AI model based on U^2-Net architecture can accurately diagnose periapical lesions on panoramic radiographs. The research provides evidence that AI-based models have promising applications as adjunct tools for dentists in diagnosing periapical radiolucencies and procedure planning. Further studies with larger data sets would be required to improve the diagnostic accuracy of AI-based detection models.

Keywords Artificial intelligence, Diagnosis, Panoramic radiograph, Deep learning, Periapical lesion

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Introduction

Periapical periodontitis (PP) is caused by a bacterial infection in the root canal, leading to bone resorption around the apex of the tooth [1]. This bone loss is a result of the immune system's response to fight the bacterial infection. Literature shows that the prevalence of PPs varies significantly between studies, however, Tiburcio-Machado et al. [2] carried out a systematic review that concluded the prevalence of PPs at the individual level to be 52%. Since PP can have an impact on general and oral health in a negative manner, its diagnosis and treatment should be addressed with urgency [2]. Untreated infection can spread and progress with swelling, which may require hospitalization. PP is usually diagnosed with careful clinical and radiological examination. PP often manifests as periapical radiolucencies on radiographs, which are usually referred to as periapical lesions (PLs) [3]. Periapical lesions can exhibit a variety of patterns on radiographs, ranging from little enlargement of the periodontal ligament to clearly defined radiolucent lesions [4, 5].

Panoramic radiographs or in other words orthopantomograms (OPG), periapical radiographs, and cone-beam computed tomography (CBCT) are amongst different types of imaging techniques that can be used to identify periapical lesions. OPGs are two-dimensional tomographic images of the whole maxillo-mandibular area. This allows clinicians to assess the mandibular teeth and maxillary teeth at once. In comparison, CBCT has higher diagnostic accuracy than OPGs when diagnosing periapical lesions. However, CBCT is not routinely available in most dental practices, and it is more costly with higher radiation exposure when compared with OPGs [4, 6, 7]. These limits the use of CBCTs when compared to OPGs [4, 6, 7]. Even though OPGs have inferior resolution compared to CBCT imaging, they are routinely utilized as the initial line of imaging tool for clinical examination in dental practices for assessment, diagnosis, and treatment planning purposes of both jaws concurrently [8]. Periapical radiographs are also useful diagnostic investigations when assessing periapical lesions. However, full-mouth periapical radiographs are not routinely used for screening purposes of periapical lesions. Appropriate evaluation of OPGs depends on the knowledge, training, and experience of the clinician examining the images, and inaccurate evaluation of the OPGs may lead to incorrect diagnosis, resulting in wrong treatment of the condition [9]. Whilst dentists are trained to make correct diagnoses of periapical lesions, misdiagnosis can occur. Furthermore, OPGs are also routinely used by emergency departments of district hospitals to assess emergencies with odontogenic causes. If the hospital does not have a maxillofacial surgery department on-site, the assessment of these radiographs may need to be made by the emergency medical practitioners. Errors can occasionally occur in the diagnosis of periapical lesions, leading to incorrect treatment plans. Authors believe that the panoramic-based artificial intelligence (AI) model can support the screening process to minimize misdiagnosis of periapical lesions while providing a secondary validation tool. It will also ultimately help clinicians to save time which will free their time to focus more on treatment of the problem.

With the emergence of AI in recent years, their use in medical imaging can aid with increased diagnostic accuracy. AI may be defined as 'the capability of computer systems or algorithms to imitate intelligent human behavior' [10]. AI has found applications across various domains within dentistry, aiming to enhance the clinical decision-making process and aid in disease detection and treatment planning stages [11–15]. Machine learning (ML) is a branch of AI where algorithms learn expected outcomes from the data rather than adhering to pre-programmed directions. Neural networks (NN) represent a subclass of machine learning where the algorithm tries to loosely mimic how the human brain operates. Neural networks are great for simple problems but for complex vision tasks such as this, a more complex architecture is needed. Deep neural networks (DNN) solve this problem by utilizing much larger networks. This allows DNNs to utilize much larger datasets and empowers computers with the ability to autonomously learn, reason, and tackle challenges akin to human cognitive processes.

Deep learning is a branch of AI where algorithms acquire knowledge from extensive datasets rather than adhering to pre-programmed directions [16]. Neural networks (NNs) represent a class of artificial intelligence algorithms that, through the mechanism of deep learning utilizing vast datasets, empower computers with the ability to autonomously learn, reason, and tackle challenges akin to human cognitive processes, thereby fostering decision-making and problem-solving capabilities [15, 17].

For the detection of periapical lesions, different NN-based algorithms have been utilized including convolutional NN (CNN) [4, 18–20], CNN using U-Net [21], D-CNN [6] across different radiological imaging modalities which consists of OPGs, periapical radiographs, and CBCT. To the best of the authors' knowledge, there are no currently available studies in the literature, assessing the accuracy of diagnosis of U2-Net-based deep learning algorithm in the detection of periapical lesions. This study wants to determine whether the U2 Net-based model can be beneficial in aiding clinicians with diagnosis and clinical workflow.

Previous research has established some clinical value of AI technology.

Materials and methods

This retrospective study was performed upon approval of the Ethical Review Board of the Cyprus International University (Approval Number EKK23-24/005/10) and was carried out under the Helsinki Declaration standards at the university clinic.

Data preparation and labelling

All OPGs that were taken at the private dental imaging center in Nicosia between January 2024 and April 2024 were included in the study. Informed written consents were taken from the patients for their images to be useful for clinical research. These radiographs were anonymized before collection and were reviewed retrospectively. Any images that were deemed to be low quality with distortion, with significant artifacts, and radiographs that included any primary teeth were excluded from the study. Finally, 400 OPGs were included in the study. All OPGs were taken using a single source, the Newtom GO 3D/2D [Quantitive Radiology s.r.l., Verona, Italy] panoramic imaging system, with scanning parameters 80 kVp, 8 mA, exposure time 14.2 s according to the guidelines of the manufacturer.

Once the panoramic images were obtained in a DICOM format, they were converted into PNG files and uploaded onto the Computer Vision Annotation Tool (CVAT) online database, for the labeling process. Two examiners (M.B. – oral and maxillofacial surgery resident with over 6 years of clinical experience and M.F. – dental and maxillofacial radiologist with over 7 years of clinical experience) independently performed the manual segmentation of periapical lesions on the images whilst the third examiner (K.O), a dental and maxillofacial radiologist with over 20 years of clinical experience, was available to settle any existing disagreements among the two examiners. When there was a disruption in the lamina dura around the apex of the tooth and radiolucency was present, the area was labeled as a periapical lesion. The images were reviewed by the same examiners after a month, to validate the previous annotation. Before the annotation stage, the above-mentioned examiners were calibrated on 15 OPGs to eliminate any disagreements amongst them and then re-calibrated using 30 OPGs. The Kappa coefficient for inter-examiner agreement in detecting periapical lesions of 95% was achieved.

The segmentation of apical lesions utilizing a machine-learning approach based on the U²-Net architecture was performed. This segmentation process was crafted on a dataset that underwent no augmentation, stressing the raw representational capacity of the machine learning model. The dataset was randomly split, with 10% allocated for validation, 5% for testing, and the remaining 85% for training.

Model pipeline

The pipeline adopted in this research involved the following procedures:

- Preprocessing of the medical images.
- Pixel-wise classification within the image as lesion or non-lesion.
- Extraction of the segmented lesion for further volumetric analysis.

Preprocessing

This study undertook minimal preprocessing to maintain the integrity of the original images. The dataset split was determined randomly, with 10% allocated for validation and 5% for testing, with the remaining images used for training.

Semantic segmentation

The semantic segmentation task entails labeling each pixel in an image for comprehensive classification. The U²-Net architecture, an evolution of the U-Net model, was deployed to classify pixels as belonging to either apical lesions or background. U²-Net uses what is called an encoder-decoder architecture. Encoding path also known as down convolution helps the model capture semantic information, and decoding path also known as upsampling helps the model recover spatial information. U²-Net effectively captures high-level semantic information while preserving spatial detail necessary for precise pixel classification. (Figures 1, 2 and 3)

Implementation

A U²-Net model served as the foundation for this study's algorithm, executing an end-to-end training and testing regimen. The present study's algorithm was based on the Python implementation of U²-Net. All training and experiments were done using NVIDIA® GeForce® RTX 2080 Ti GPU. The model architecture was configured to accept input shapes of 512×1024 with a depth of 1 channel, handling the classification task across two possible classes. The optimization process was conducted using an Adam optimizer with a learning rate of 0.0002. A specialized form of the loss function, the weighted sparse categorical cross-entropy, was adopted to manage the imbalance inherent in the segmentation tasks. The model was trained on a batch size of 4, enabling the network to learn from finely tuned gradient updates throughout 500 epochs. The model with the best validation dice score is used for testing.

Results

The study's U²-Net model yielded segmentation performance with a dice coefficient of 0.788 (95% CI: 0.775–0.801) and an Intersection over Union (IoU) of 0.715 (95% CI: 0.700–0.730) on the test dataset and a dice coefficient of 0.83 (95% CI: 0.818–0.842) and an Intersection over Union of 0.73 (95% CI: 0.715–0.745) on the validation dataset. The precision of the segmentation was calculated at 0.776 (95% CI: 0.760–0.792), while recall was 0.854 (95% CI: 0.840–0.868) on the test dataset. The results of the studies indicate a robust detection of apical lesions by the network. Notably, an F1 score of 0.81 (95% CI: 0.796–0.824) on the test dataset further demonstrates the balanced accuracy of the segmentation performance. The proposed architecture is also compared against other popular architectures. UNet architecture had a dice

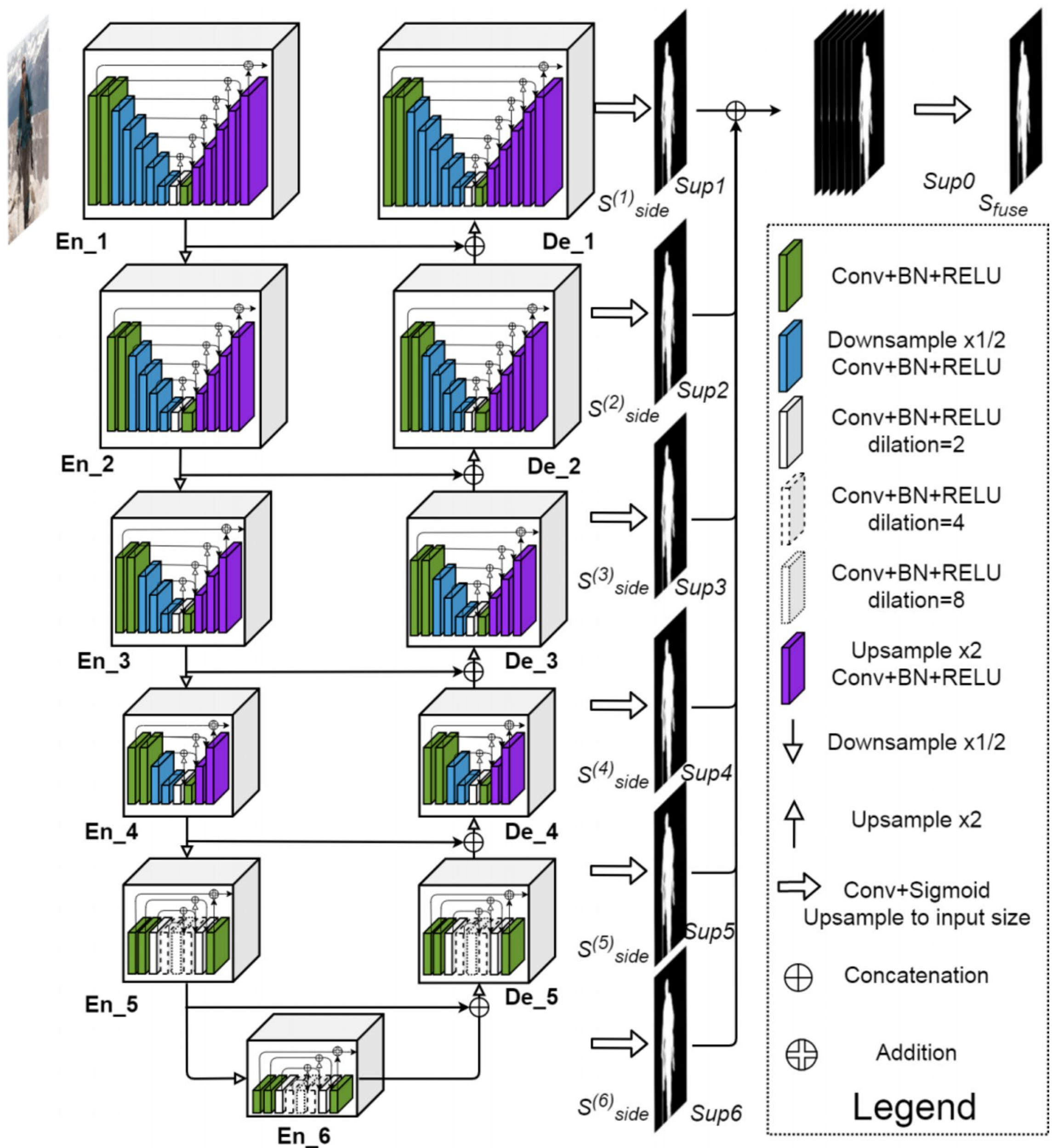

Fig. 1 U²-Net Architecture

coefficient of 0.761 whereas ResUnet had a dice coefficient of 0.772.

Discussion

Advancements in artificial intelligence have led to rapid enhancements in the analysis of medical and dental images, facilitated by the utilization of deep learning algorithms and U [2]-Net [22, 23].

The U [2]-Net benefits from its layered residual U-structured blocks, enabling it to gather extensive local and global details from both shallow and deep layers. By employing the residual U-block, the U [2]-Net effectively extracts intra-stage multi-scale features while preserving feature map resolution. This approach results in diverse receptive fields and enhanced multi-scale contextual characteristics, significantly boosting the segmentation performance of the U [2]-Net, particularly in identifying edge information [22].

OPGs represent a commonly utilized imaging modality in the regular operations of dental clinics and hospitals when dealing with dental emergencies. They offer a wider scan of oral structures and are considered relatively safe [24]. Thus, we utilized state-of-the-art deep learning detection models on panoramic dental radiographs for

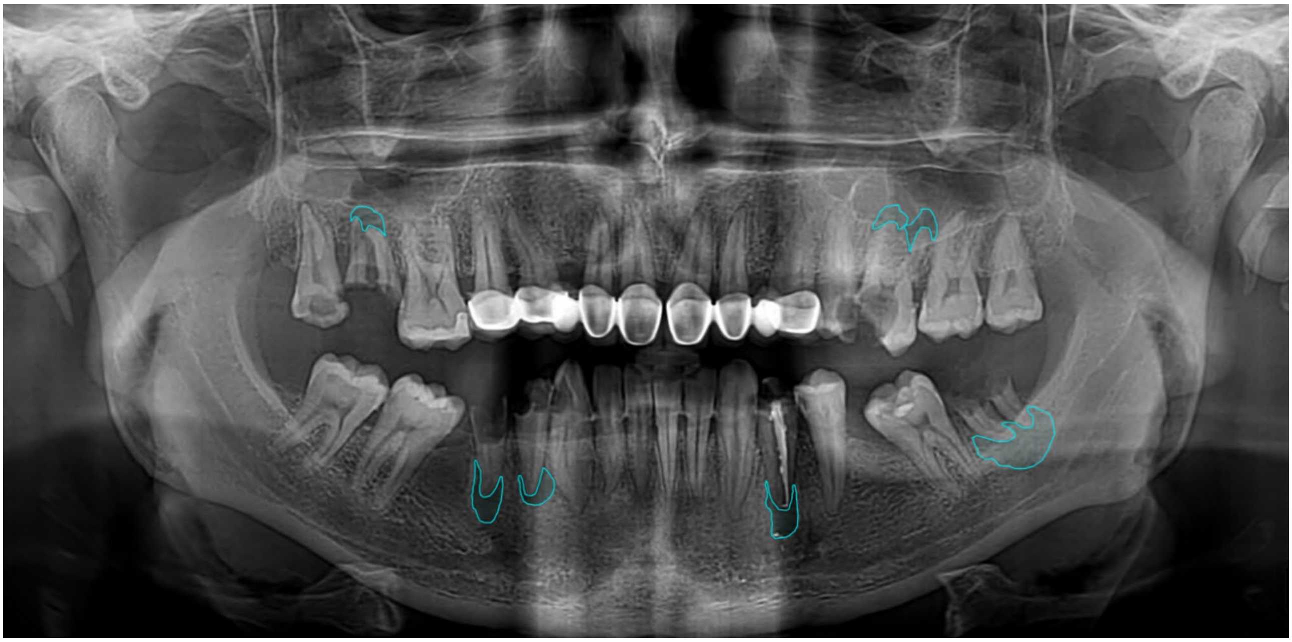

Fig. 2 Segmentation of the apical lesion using the U²-Net

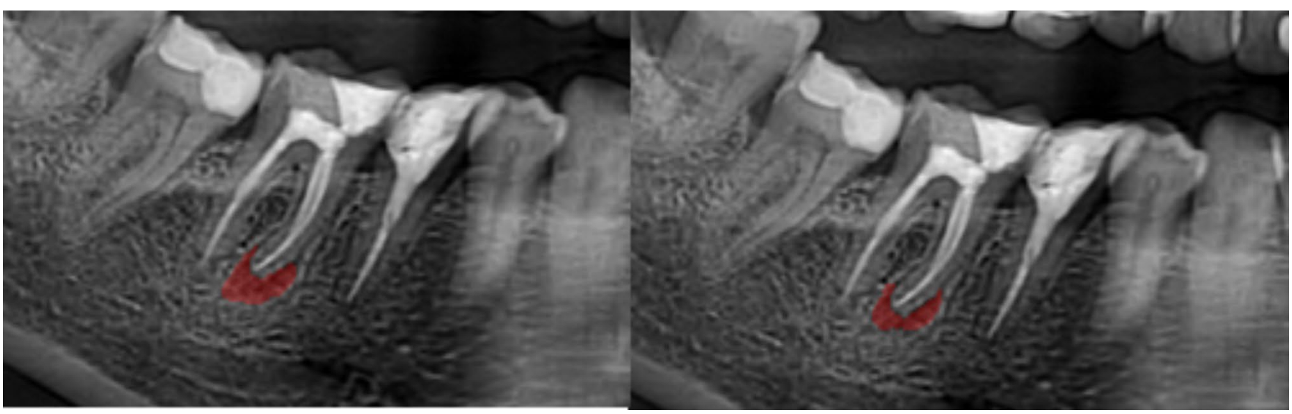

Fig. 3 On the left is the ground truth on the right is the segmentation from our model

detecting periapical lesions. Due to its inherent network architecture, the U [2]-Net accurately segmented periapical lesions around teeth on panoramic radiographs.

Bayrakdar et al. [6] conducted a U-Net model trained on 470 OPGs for segmenting periapical lesions. The model's performance was evaluated on a limited dataset comprising 63 periapical lesions from 47 OPGs. The U-Net achieved sensitivity, precision, and F1-score values of 0.92, 0.84, and 0.88, respectively. Endres et al. [25] introduced a deep-learning model trained on 2902 anonymized OPGs. To verify the algorithm, 24 oral and maxillofacial surgeons independently evaluated the presence or appearance of periapical radiolucencies on a distinct set of OPGs. The results indicated that the developed model surpassed the performance of 14 out of 24 surgeons. Their model attained a precision of 67% and a sensitivity of 51% when tested on 102 radiographs. Song et al. [21] evaluated the effectiveness of a deep convolutional neural network (CNN) algorithm in segmenting apical lesions from panoramic radiographs. They used 1000 OPGs and in the test group of 180 apical lesions, 147 lesions were segmented from OPGs. The F1-score values, as a measure of performance, were 0.828, 0.815, and 0.742, respectively, with IoU thresholds of 0.3, 0.4, and 0.5. Ekert et al. [4] conducted deep convolutional neural networks (CNNs) to detect apical lesions on panoramic dental radiographs. They used a data set of 2001 tooth segments from OPGs. Sensitivity was 0.65 (0.12) and specificity was 0.87 (0.04).

To the best of our knowledge, there are no previous reports that segmented apical lesions utilizing a machine-learning approach based on the U²-Net architecture. Our study was conducted on a significantly larger sample size of 780 periapical lesions on 400 OPGs with U [2]-Net, and the model was able to achieve a dice score of 0.788 on the validation set and precision, recall, and F1-score of 0.776, 0.854, 0.81 respectively on the test set.

Apart from OPGs, alternative radiographic methods have been evaluated for automated diagnosis of periapical lesions. One CBCT study was conducted with 1000 sagittal and coronal sections of CBCT scans to classify teeth as healthy or with endodontic lesions with CNN. They have found 70% accuracy[19]. Also, another study aimed to develop and validate a deep convolutional neuronal network for the automated detection of osteolytic periapical lesions in CBCT scans with modified U-net architecture. They used a total of 144 CBCT scans and concluded sensitivity and specificity values of lesion detection as 97.1% and 88.0%, respectively [26].

Identifying and recording pathologies in dental X-rays requires a significant amount of time, and despite the thorough training received by both general and specialized dentists, they remain susceptible to human error. Misdiagnosis, particularly the failure to detect periapical lesions, accounts for a considerable number of complications in dental practice. In this context, the suggested technology has the potential to assist clinicians in completing dental charts and reducing diagnostic errors in identifying periapical lesions [25, 27, 28]. Our panoramic-based AI model has taken on average 1.2 s to evaluate a radiograph. The proposed model can be used as an adjunct to minimize errors in the diagnosis of periapical lesions whilst ensuring effective time management of the clinical workflow. Moreover, the model has an easy-to-use interface which can be comfortably utilised by non-experts in the field. Clinicians can incorporate this AI system into their daily clinical practice by either initially using the system and then verifying it themselves or upon reporting on the radiograph, via using the system for confirmation purposes. However, the authors recognize that these possible benefits or implementation strategies should be further explored by clinical studies and cost-benefit analysis to obtain reliable data.

Despite the significant advancements deep learning has brought to detection applications, numerous challenges and constraints must be addressed before AI applications can be seamlessly integrated into clinical settings. Ideally, studies should utilize extensive, well-balanced, and high-quality image datasets sourced from various multicenter devices. However, there is a noticeable absence of reliable, large, publicly available, and independent datasets for comparison purposes. A significant matter is the lack of standardization and comparability between different research. The metrics utilized to assess model performance and accuracy vary considerably among studies, encompassing precision, recall, accuracy, F1 score, AUC, and others. While each metric has its strengths and appropriateness in specific contexts, the inconsistent application across studies hinders direct result comparison. The absence of a unified standard for evaluation and presentation complicates the comparison of model effectiveness and the derivation of conclusions regarding optimal practices and superior strategies [24, 29].

Detailed error analysis revealed that false positives were primarily associated with regions containing radiolucencies caused by overlapping anatomical structures or artifacts in the panoramic images. These were misinterpreted as periapical lesions by the AI model. Conversely, false negatives predominantly occurred with smaller, less distinct lesions, where the model had difficulty differentiating them from healthy tissue.

To address these limitations, future work will involve incorporating additional preprocessing steps aimed at filtering out noise and artifacts. Furthermore, expanding the training dataset, particularly with more diverse and subtle lesion cases, could help the model better generalize to smaller lesions, ultimately reducing both false positive and false negative rates. These enhancements will contribute to improving the overall robustness and accuracy of the segmentation model in clinical settings.

Besides, the study utilized OPGs that were obtained from a single source limited to patients based in Cyprus. Even though the model has achieved successful diagnostic accuracy, further studies with data collection from multiple resources based in different countries would be useful to test the robustness of the model and increase its generalizability across different locations. Additionally, we used OPGs of patients with permanent dentition exclusively. Mixed dentition cases were excluded, necessitating further research to develop an optimized algorithm applicable to both permanent and mixed dentition. Furthermore, a limitation lies in the fact that the OPGs used for training were solely diagnosed visually through radiograph inspection. Achieving more precise diagnoses would entail incorporating clinical data such as percussion, thermal, and electric pulp tests, which were not considered in this study. Therefore, future investigations could enhance algorithm performance by training them on images diagnosed through a broader array of diagnostic techniques. Finally, this study has tested an AI model based on U [2]-Net architecture exclusively. Whilst the model was deemed successful in achieving diagnostic accuracy, further studies evaluating its diagnostic accuracy against AI models utilizing different architectures may be beneficial in establishing the most successful architecture to assess periapical lesions.

Conclusion

The research has successfully established the efficacy of a U^2-Net-based algorithm for segmenting apical lesions within medical images. The established model took 1.2 s to evaluate a radiograph and was deemed successful at identifying periapical lesions. This provides evidence that AI-based models have promising applications for clinicians, to assist them in diagnosing periapical radiolucencies and treatment planning of procedures, improving the efficiency of the clinical workflow. For these purposes, further research assessing the extent of usefulness of the U2-Net-based models in assisting clinicians may be undertaken via controlled studies. Moreover, further studies with larger data sets would be required to improve the diagnostic accuracy of AI-based detection models.

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Author contributions
K.O. and N.A designed and directed the study and M.F. and M.B. have made a significant contribution to the execution and writing of the reported study.

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Data availability
The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethical approval
All procedures performed in studies involving human participants were following the ethical standards of the institutional and/or national research committee (EKK23-24/005/10) and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Human ethics and consent to participate
Informed consent was obtained from all individual participants included in the study.

Consent for publication
Patients or their legal delegates gave their informed written consent before radiography and the consent forms were reviewed and approved by the institutional review board of the faculty.

Competing interests
The authors declare no competing interests.

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References

1. Gazivoda D, Dzopalic T, Bozic B, Tatomirovic Z, Brkic Z, Colic M. Production of proinflammatory and immunoregulatory cytokines by inflammatory cells from periapical lesions in culture. J oral Pathol Med. 2009;38(7):605–11.
2. Tibúrcio-Machado CS, Michelon C, Zanatta FB, Gomes MS, Marin JA, Bier CA. The global prevalence of apical periodontitis: a systematic review and meta-analysis. Int Endod J. 2021;54(5):712–35.
3. Patel S, Durack C. Radiology of apical periodontitis. Essential endodontology: Prevention and treatment of apical periodontitis. Dec. 2019;9:179–210.
4. Ekert T, Krois J, Meinhold L, Elhennawy K, Emara R, Golla T, Schwendicke F. Deep learning for the radiographic detection of apical lesions. J Endod. 2019;45(7):917–22.
5. Kanagasingam S, Hussaini HM, Soo I, Baharin S, Ashar A, Patel S. Accuracy of single and parallax film and digital periapical radiographs in diagnosing apical periodontitis–a cadaver study. Int Endod J. 2017;50(5):427–36.
6. Bayrakdar IS, Orhan K, Çelik Ö, Bilgir E, Sağlam H, Kaplan FA, Görür SA, Odabaş A, Aslan AF, Różyło-Kalinowska I. A U-net approach to apical lesion segmentation on panoramic radiographs. BioMed Research International. 2022;2022.
7. Patel S, Brown J, Semper M, Abella F, Mannocci F. European Society of Endodontology position statement: use of cone beam computed tomography in endodontics: European Society of Endodontology (ESE) developed by. Int Endod J. 2019;52(12):1675–8.
8. Prados-Privado M, Villalón JG, Martínez-Martínez CH, Ivorra C. Dental image recognition technology and applications: a literature review. Appl Sci. 2020;10(8):2856.
9. Fitzgerald R. Error in radiology. Clin Radiol. 2001;56(12):938 – 46. https://doi.org/10.1053/crad.2001.0858. PMID: 11795921.
10. Merriam-Webster (2018) Artificial intelligence. https://www.merriam-webster.com/dictionary/artificial%20intelligence. Accessed 20/03/2024.
11. Lee J-H, Kim D-H, Jeong S-N, Choi S-H. Detection and diagnosis of dental caries using a deep learning-based Convolutional neural network algorithm. J Dent. 2018;77:106–11. https://doi.org/10.1016/j.jdent.2018.07.015.
12. Krois J, Ekert T, Meinhold L, Golla T, Kharbot B, Wittemeier A, et al. Deep learning for the radiographic detection of Periodontal bone loss. Sci Rep. 2019;9:8495. https://doi.org/10.1038/s41598-019-44839-3.
13. Çelik B, Çelik ME. Automated detection of dental restorations using deep learning on panoramic radiographs. Dentomaxillofac Radiol. 2022;51(8):20220244. https://doi.org/10.1259/dmfr.
14. Chen H, Zhang K, Lyu P, Li H, Zhang L, Wu J, et al. A deep learning approach to automatic teeth detection and numbering based on object detection in dental periapical films. Sci Rep. 2019;9:1–11. https://doi.org/10.1038/s41598-019-40414-y.
15. Khanagar SB, Al-Ehaideb A, Maganur PC, Vishwanathaiah S, Patil S, Baeshen HA, et al. Developments, application, and performance of artificial intelligence in dentistry–A systematic review. J Dent Sci. 2021;16:508–22. https://doi.org/10.1016/j.jds.2020.06.019.
16. Mazurowski MA, Buda M, Saha A, Bashir MR. Deep learning in radiology: an overview of the concepts and a survey of the state of the art with a focus on MRI. J Magn Reson Imaging. 2019;49:939–54. https://doi.org/10.1002/jmri.26534.
17. Schwendicke F, Samek W, Krois J. Artificial Intelligence in Dentistry: chances and challenges. J Dent Res. 2020;99:769–74.
18. Ngoc VTN, Viet DH, Anh LK, Minh DQ, Nghia LL, Loan HK, et al. Periapical lesion diagnosis support system based on x-ray images using machine learning technique. World J Dentistry. 2021;12(3):189–93. 12.
19. Calazans MAA, Ferreira FABS, Alcoforado M, de LMG, Santos A, dos. Pontual A Dos A, Madeiro F. Automatic classification system for Periapical Lesions in Cone-Beam Computed Tomography. Sensors. 2022;22(17):13.
20. Li CW, Lin SY, Chou HS, Chen TY, Chen YA, Liu SY, et al. Detection of dental apical lesions using cnns on periapical radiograph. Sensors. 2021;21:21.
21. Song IS, Shin HK, Kang JH, Kim JE, Huh KH, Yi WJ et al. Deep learning-based apical lesion segmentation from panoramic radiographs. Imaging Sci Dent. 2022;52.
22. Kim SH, Kim J, Yang S, Oh SH, Lee SP, Yang HJ, Kim TI, Yi WJ. Automatic and quantitative measurement of alveolar bone level in OCT images using deep learning. Biomed Opt Express. 2022;13(10):5468–82. PMID: 36425614; PMCID: PMC9664875.
23. Liang S, Yin X, Huang L, Huang J, Yang J, Wang X, Peng L, Zhang Y, Li Z, Nie B, Tao J. Automatic brain extraction for rat magnetic resonance imaging data using U^2-Net. Phys Med Biol. 2023;68(20). https://doi.org/10.1088/1361-6560/acf641. PMID: 37659398.
24. Çelik B, Savaştaer EF, Kaya HI, Çelik ME. The role of deep learning for periapical lesion detection on panoramic radiographs. Dentomaxillofac Radiol. 2023;52(8):20230118. https://doi.org/10.1259/dmfr.20230118. Epub 2023 Oct 18. PMID: 37641964.
25. Endres MG, Hillen F, Salloumis M, Sedaghat AR, Niehues SM, Quatela O, Hanken H, Smeets R, Beck-Broichsitter B, Rendenbach C, Lakhani K, Heiland M, Gaudin RA. Development of a deep learning algorithm for Periapical Disease Detection in Dental radiographs. Diagnostics (Basel). 2020;10(6):430. https://doi.org/10.3390/diagnostics10060430. PMID: 32599942; PMCID: PMC7344682.
26. Kirnbauer B, Hadzic A, Jakse N, Bischof H, Stern D. Automatic Detection of Periapical Osteolytic Lesions on Cone-Beam Computed Tomography using deep convolutional neuronal networks. J Endod. 2022;48(11):1434–40. Epub 2022 Aug 8. PMID: 35952897.
27. Ba-Hattab R, Barhom N, Osman SAA, Naceur I, Odeh A, Asad A, Al-Najdi SARN, Ameri E, Daer A, Silva RLBD, et al. Detection of Periapical Lesions on

panoramic radiographs using deep learning. Appl Sci. 2023;13(3):1516. https://doi.org/10.3390/app13031516.

28. Almufleh B, Ducret M, Malixi J, Myers J, Nader SA, Franco Echevarria M, Adamczyk J, Chisholm A, Pollock N, Emami E, Tamimi F. Development of a Checklist to prevent reconstructive errors made by Undergraduate Dental Students. J Prosthodont. 2020;29(7):573–8. https://doi.org/10.1111/jopr.13177. Epub 2020 Apr 27. PMID: 32282105.
29. Schwendicke F, Singh T, Lee JH, Gaudin R, Chaurasia A, Wiegand T, Uribe S, Krois J. Artificial intelligence in dental research: Checklist for authors, reviewers, readers. J Dent. 2021;107:103610.

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