Gustavo Sacchet

DETECÇÃO DO SEGUNDO CANAL MÉSIO-VESTIBULAR POR MEIO DE REDES NEURAIS CONVOLUCIONAIS

Dissertação apresentada à Universidade de Caxias do Sul, para obtenção do Título de Mestre em Ciências da Saúde.

Caxias do Sul

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Orientador: Prof. Dr. Luciano da Silva Selistre

Co-Orientador: Prof. Dr. Thiago de Oliveira Gamba

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PROFA. DRA. VANDREA CARLA DE SOUZA

DETECÇÃO DO SEGUNDO CANAL MÉSIO-VESTIBULAR POR MEIO DE REDES NEURAIS CONVOLUCIONAIS

Gustavo Sacchet

Dissertação de Mestrado submetida à Banca Examinadora designada pelo Colegiado do Programa de Pós-Graduação em Ciências da Saúde da Universidade de Caxias do Sul, como parte dos requisitos necessários para a obtenção do título de Mestre em Ciências da Saúde.

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Dedicatória

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Sumário

Esta dissertação de Mestrado Acadêmico Stricto Sensu é apresentado no formato exigido pelo Programa de Pós-Graduação em Ciências da Saúde da Universidade de Caxias do Sul. A mesma é constituída da secção de “Introdução com referências bibliográficas”, a inclusão do artigo original submetido/publicado em periódico Qualis A na classificação da Coordenação de Aperfeiçoamento de Pessoas em Nível Superior (CAPES), e as “Considerações Finais e Perspectivas”.

RESUMO

O sucesso do tratamento endodôntico depende, entre outros fatores, da localização e tratamento de todos os canais radiculares, sendo o segundo canal mésio-vestibular (MV2) dos molares superiores um dos principais responsáveis por falhas quando não é identificado. O objetivo deste estudo foi desenvolver e avaliar o desempenho de uma rede neural convolucional para detecção do MV2 em molares superiores, em imagens de tomografia computadorizada de feixe cônico (TCFC). Vinte e dois molares superiores ex vivo foram submetidos à TCFC, e os volumes foram segmentados para gerar máscaras de verdade fundamental do MV2. A partir desses volumes, foram obtidos cortes bidimensionais utilizados para treinamento e teste de um modelo U-Net com backbone DenseNet-121. O desempenho do modelo foi comparado ao de um avaliador humano experiente, utilizando as métricas de acurácia, precisão, recall e F1-score. O observador humano alcançou acurácia de 0,98 e recall de 0,98 no conjunto de teste. O modelo apresentou acurácia de 0,83, precisão de 0,99 e recall de 0,66, com desempenho reduzido nos casos mais complexos, especialmente em canais calcificados ou muito próximos ao canal mésio-vestibular principal. Dentro dessas condições, o modelo proposto demonstrou alta precisão e acurácia global aceitável para a detecção do MV2 em cortes de TCFC, sugerindo potencial uso como ferramenta auxiliar na prática endodôntica e na interpretação de exames por imagem, embora ainda não substitua o julgamento do especialista.

Palavras-chave: Tomografia computadorizada de feixe cônico; Deep learning; Endodontia; Molar superior; Segundo canal mésio-vestibular.

ABSTRACT

The success of endodontic treatment depends, among other factors, on the location and treatment of all root canals, with the second mesiobuccal canal (MB2) of maxillary molars being one of the main causes of failure when not identified. The aim of this study was to develop and evaluate the performance of a convolutional neural network for the detection of MB2 in maxillary molars on cone-beam computed tomography (CBCT) images. Twenty-two ex vivo maxillary molars were scanned with CBCT, and the volumes were segmented to generate ground truth masks of the MB2 canal. From these volumes, two-dimensional slices were obtained and used to train and test a U-Net model with a DenseNet-121 backbone. Model performance was compared with that of an experienced human observer using accuracy, precision, recall and F1-score as evaluation metrics. The human observer achieved an accuracy of 0.98 and a recall of 0.98 on the test set. The model achieved an accuracy of 0.83, a precision of 0.99 and a recall of 0.66, with reduced performance in more complex cases, especially calcified canals or canals located very close to the main mesiobuccal canal. Under these conditions, the proposed model demonstrated high precision and acceptable overall accuracy for MB2 detection on CBCT slices, suggesting its potential as an auxiliary tool in endodontic practice and image interpretation, although it does not yet replace specialist clinical judgment.

Keywords: Cone-beam computed tomography; Deep learning; Endodontics; Maxillary molar; Second mesiobuccal canal.

1. INTRODUÇÃO

O tecido conjuntivo, de localização única, entre as paredes duras e mineralizadas de dentina, chama-se polpa dental. Quando se trata do conjunto entre polpa e dentina, se forma o que chamamos de complexo dentino-pulpar, de estreita relação funcional e embriológica [1,2].

A cavidade pulpar, é dividida em duas partes: câmara pulpar e canal radicular, a primeira é localizada na porção coronária e a segunda na raiz do elemento dentário, que por meio de um feixe vásculo-nervoso, tem íntimo contato com os tecidos periapicais e sistema circulatório [2,3,4].

As doenças periapicais e pulpares, têm como agentes principais os microrganismos e seus produtos[5]. Nesse sentido, os canais radiculares, quando submetidos a um tratamento endodôntico, devem receber uma limpeza e modelagem adequada, visando uma descontaminação de qualidade[6].

O principal objetivo da terapia endodôntica é preservar e manter os elementos dentários na cavidade bucal[7]. Para tal, é fundamental a realização de um preparo químico- mecânico satisfatório do complexo câmara pulpar e canais radiculares, visando uma terapia adequada. Para esse propósito, é de suma importância o conhecimento dos detalhes e particularidades do sistema de canais radiculares[8,9].

A complexidade anatômica do sistema de canais radiculares dificilmente é identificada em detalhes nas radiografias periapicais convencionais, dependendo da habilidade do operador, estruturas mais complexas, ou até mesmo canais supranumerários, podem passar despercebidos durante o processo[10]. Levando em conta que os molares superiores são os elementos com maior número de raízes, consequentemente maior número de canais radiculares, pode-se concluir que possuem uma maior variabilidade anatômica no sistema de canais radiculares, sendo assim, os elementos mais difíceis para serem tratados [11,12].

A presença de uma complexidade maior, reflete diretamente no aumento da porcentagem de falhas no tratamento endodôntico[13,14]. Uma alta taxa percentual dessas falhas, é oriunda da não localização do segundo canal mésio-vestibular (MV2), cuja dificuldade de identificação reflete não somente pela dificuldade de ser visto na radiografia periapical convencional, mas também na sua visualização clínica, devido ao excesso de dentina depositada na sua entrada[15,16].

Fernandes *et al.* (2019)[7] realizaram um estudo com 200 pacientes, 100 do sexo masculino e 100 do sexo feminino, todos possuíam 2 primeiros molares superiores e 2 segundos molares superiores, totalizando 800 dentes. O MV2 esteve presente em 92% dos primeiros molares superiores direitos e 87% para os primeiros molares superiores esquerdos, prevalência maior quando comparados com os segundos molares superiores, nos quais a taxa foi de 69% para os do lado direito e 65% para os do lado esquerdo. O que comprova que a grande maioria dos elementos dentários desta classe, possuem a presença do MV2[7].

Al-Saedi et al. (2020)[17] realizaram um estudo retrospectivo em uma amostra de 353 pacientes iraquianos, avaliando 655 primeiros molares superiores por meio de tomografia computadorizada de feixe cônico (TCFC), com o objetivo de determinar a prevalência do segundo canal mésio-vestibular. O MV2 foi identificado em 81,68% dos molares analisados. Esses resultados confirmam que, em grande parte dessa população, há um segundo canal na raiz mésio-vestibular, destacando a necessidade de cuidadosa exploração anatômica e do uso de métodos avançados de imagem para aumentar a taxa de detecção do MV2[17].

A identificação do MV2 se tornou uma das principais buscas quando se realiza um tratamento de canal em um dos elementos citados anteriormente, tendo isso em vista que, diversos métodos podem auxiliar nessa identificação, quando usados, aumentam a taxa de visualização e tratamento deste canal[17]. Dentre eles, tem como principais: as lupas de aumento[18,19], microscópio cirúrgico endodôntico[18] e a tomografia computadorizada de feixe cônico para fim endodôntico (TCFC) [13,15,16,21].

Para endodontistas que realizam o tratamento de canal, a TCFC é recomendada quando a radiografia periapical convencional é inconclusiva ou incompatível com os achados clínicos[22,23]. Na endodontia, a TCFC pode ser utilizada em diversas situações[22,24,25], bem como detectar fraturas radiculares[26,27], reabsorções[27], localização de canais não tratados[28,29], e até mesmo realizar o planejamento de acesso a canais calcificados[31,32], a utilização da TCFC, tem sido o padrão ouro para a identificação do MV2, possibilitando uma visualização tridimensional das estruturas anatômicas, com uma dose de radiação menor quando comparada com a tomografia computadorizada tradicional, facilitando um melhor planejamento e consequentemente um melhor prognóstico no tratamento[13,15,21,33].

Aliado ao avanço tecnológico na endodontia, com a implementação da TCFC, os progressos na área da computação dedicada à área da saúde também acompanharam a evolução, com o surgimento de algoritmos aplicados na análise desses exames, que são orientados por inteligência artificial (IA), tendo como exemplo, as redes neurais convolucionais (RNC), que são capazes de executar tarefas que anteriormente exigiam a presença de um humano para serem realizadas[34,35].

O funcionamento das redes neurais convolucionais (RNC) se dá de forma semelhante ao funcionamento dos neurônios de um ser humano, possuindo diversas camadas de conexões neurais e sendo submetidas a treinamentos para aprendizagem de tarefas específicas. Os algoritmos possuem um potencial avançado para analisar imagens digitais, tornando assim o fluxo de trabalho para o profissional muito mais automatizado, facilitando a previsibilidade dos resultados, reduzindo o tempo clínico e contribuindo para um melhor prognóstico. [36,37].

A partir de 2015, com a consolidação do chamado *deep learning*, arquiteturas convolucionais profundas passaram a dominar as tarefas de visão computacional, com marcos importantes como o desenvolvimento da U-Net para segmentação de imagens biomédicas e a introdução das redes residuais (ResNet), que permitiram treinar redes muito mais profundas por meio de conexões de atalho e redução do problema do “desaparecimento” do gradiente[38.]

No contexto da análise de imagens médicas, as RNC rapidamente se tornaram a metodologia de escolha para classificação, detecção e segmentação de estruturas em diferentes modalidades de imagem, frequentemente com desempenho comparável ou superior ao de especialistas em tarefas bem definidas[39.] Nesse cenário, o uso de uma rede neural convolucional se justifica por explorar de forma eficiente a estrutura espacial das imagens de TCFC, oferecer maior precisão na detecção de padrões leves, como a identificação do canal MV2. Além disso, em termos de eficiência, as RNC são capazes de analisar milhares de imagens em poucos segundos, com reprodutibilidade e sem fadiga, o que as torna potencialmente mais eficientes que o observador humano para o rastreio sistemático de grandes volumes de exames, reservando ao clínico a interpretação final e a integração com os achados clínicos[39].

Portanto, este estudo teve como objetivo desenvolver e avaliar uma rede neural convolucional baseada em U-Net, com backbone DenseNet-121, para detecção e segmentação do segundo canal mésio-vestibular em molares superiores em tomografias computadorizadas de feixe cônico, bem como comparar seu desempenho ao de um examinador humano experiente.

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3. ARTIGO

Detection of the Second Mesiobuccal Canal in Maxillary Molars Using Convolutional Neural Networks

Detection of the Second Mesiobuccal Canal

Authors

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Authorship statement

The author declares that he has made substantial contributions to the conception and design of the study, acquisition, analysis and interpretation of data, and to the drafting and critical revision of the manuscript. The author has approved the final version to be published and agrees to be accountable for all aspects of the work, ensuring that questions related to the accuracy or integrity of any part of the study are appropriately investigated and resolved.

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Conflict of interest statement

The author declares that there is no conflict of interest related to the content of this work.

Detection of the Second Mesiobuccal Canal in Maxillary Molars Using Convolutional Neural Networks

ABSTRACT

Objective: To develop and evaluate a convolutional neural network for detection of the second mesiobuccal canal in maxillary molars on cone-beam computed tomography images.

Materials and methods: Twenty-two ex vivo maxillary molars were scanned with cone-beam computed tomography (CBCT). Volumes were segmented to generate ground truth masks of the second mesiobuccal canal (MB2) and converted into two-dimensional slices for training and testing a U-Net with DenseNet-121 backbone. Model performance was compared with an experienced observer using accuracy, precision, recall and F1-score.

Results: The human observer achieved accuracy 0.98 and recall 0.98. The model achieved accuracy 0.83, precision 0.99 and recall 0.66, with reduced performance in calcified canals and canals close to the main mesiobuccal canal.

Conclusions: The proposed model showed high precision and acceptable overall accuracy, suggesting potential as an adjunctive tool, but not as a replacement for specialist interpretation.

Keywords: Cone-beam computed tomography; Deep learning; Endodontics; Maxillary molar; Second mesiobuccal canal.

INTRODUCTION

The connective tissue located between mineralized dentin walls is called dental pulp, together, pulp and dentin form the dentin-pulp complex, which has a close functional and embryological relationship. [1,2] Pulpal and periapical diseases are mainly caused by microorganisms and their by-products,[5] and successful endodontic treatment depends on adequate chemomechanical preparation of the root canal system and detailed anatomical knowledge. [6,7,8,9]

The anatomy of maxillary molars is particularly complex, with frequent additional canals and considerable morphological variability, [10,11,12] which are not always visible on conventional periapical radiographs.[10] Missed canals are an important cause of endodontic failure, [13,14] especially when the second mesiobuccal canal (MB2) is not identified and treated. [15,16] CBCT studies have shown that MB2 is highly prevalent in different populations,[7,17] reinforcing the need for careful exploration of the mesiobuccal root during treatment.

Several resources can aid in the detection of MB2, including magnifying loupes, operating microscopes and CBCT dedicated to endodontic applications.[13,15,18,19,21] CBCT is indicated when conventional radiography is inconclusive or inconsistent with clinical findings[22,23] and can be used to detect root fractures,[22,24,25] resorptive defects, untreated canals and to plan access to calcified canals.[26,27,28,29,30,31,32] Owing to its three-dimensional visualization with lower radiation doses than medical CT, CBCT has been considered a reference standard for MB2 identification. [13,15,21,33]

In parallel, computing applied to health care has advanced with the development of artificial intelligence (AI) algorithms for imaging analysis, such as convolutional neural networks (CNNs).[34,35] CNNs use multiple layers of artificial neurons to learn task-specific features and have shown high potential for digital image analysis, automation of workflow and reduction of clinical time.[36,37] From 2015 onwards, deep learning architectures such as U-Net and residual networks (ResNet) became dominant in computer vision tasks, enabling highly accurate classification, detection and segmentation in medical images.[38,39] In endodontics, CNN-based tools have already been used for automatic segmentation of teeth and maxillary structures in CBCT, with encouraging results.[34,35,36,37]

In this context, CNNs may efficiently exploit the spatial structure of CBCT images, improve the detection of subtle patterns such as MB2 and assist in systematic screening of large exam volumes, while leaving final interpretation to the clinician.[39] Therefore, this study aimed to develop and evaluate a U-Net CNN with a DenseNet-121 backbone for detecting and segmenting MB2 in maxillary molars on CBCT and to compare its performance with that of an experienced human examiner.

METHODS

Study design and setting

This experimental laboratory study was based on CBCT images of ex vivo teeth. The protocol was approved by the Research Ethics Committee of the Universidade de Caxias do Sul (UCS), Brazil (CAAE 79615224.6.0000.5341). CBCT scans were obtained at the Radiology Clinic of UCS (Block S), and image processing and neural network training were performed at Block 71 (Information Technology sector, UCS).

Sample, image acquisition and eligibility criteria

The dataset consisted of 22 CBCT examinations of extracted maxillary molars obtained by convenience sampling from a pre-existing collection of teeth, some of which had already undergone endodontic treatment. All scans were acquired ex vivo using an Orthopantomograph OP300 MAXIO unit (Instrumentarium Dental, Tuusula, Finland), with a field of view of 50 × 50 mm or 60 × 80 mm, voxel sizes of 0.085, 0.125, 0.200 or 0.280 mm and exposure conditions of 90 kVp and 3.2, 6.3, 8 or 10 mA.

Of the 22 CBCT scans, 10 were acquired with the teeth positioned in the sockets of a dry maxilla and covered with a 5-mm layer of wax to simulate soft tissue, whereas 12 were obtained with the teeth embedded in acrylic resin blocks to reproduce the radiographic conditions of previously obturated canals. In these 10 examinations, the canals had already been obturated before inclusion in the study, and no endodontic procedures were performed as part of this research protocol. Considering the condition of the root canals, 10 examinations corresponded to molars with previously obturated canals and 12 to molars without obturation. The sample comprised 17 maxillary first molars and 5 maxillary second molars.

Examinations were included if they presented permanent maxillary first or second molars with complete root formation, full coverage of crown and root anatomy within the scanned volume and sufficient image quality to assess root canal morphology, regardless of the presence of MB2. Examinations were excluded if the region of interest was not fully included in the field of view, if image quality was inadequate for reliable evaluation or if the teeth did not belong to adult individuals.

Image preprocessing and mask creation

For training and evaluation, input images and corresponding segmentation masks were defined. DICOM files from the CBCT scans were first manually cropped by an experienced dentist so that only one tooth was included in each volume. A specialist endodontist with experience in AI then generated the MB2 masks using 3D Slicer software. For each tooth, two files were created: one with the original CBCT volume and another with the corresponding MB2 mask, which served as ground truth labels. Figure 1 illustrates an example of a CBCT image and its corresponding mask.

The CBCT volumes and masks were randomly divided into training and test sets in an 80:20 ratio. The 3D images were processed using the MONAI library, an open-source framework for AI in medical imaging. From each 3D image, a stack of 2D slices in PNG format was extracted at the level of the MB2 canal, together with the corresponding masks. This procedure generated 2,895 images for training and 725 for testing. Images were resized to 224 × 224 pixels, converted to grayscale and subjected to data augmentation with random 90° rotations and horizontal/vertical flips to increase diversity.[40]

Neural network architecture and training

MB2 detection and segmentation were performed using a U-Net CNN with a DenseNet-121 backbone. U-Net consists of convolutional layers arranged in symmetric encoding and decoding paths.[41] The encoder reduces spatial dimensions and extracts feature maps at different scales, while the decoder reconstructs the segmented image by combining these multiscale features via skip connections.[42] DenseNet-121 was chosen as encoder because of its reported performance in medical and dental image analysis.[43,44,45] Batch normalization layers were used in the decoding stage to stabilise activations and facilitate training.[45,46] The model was implemented in Python, and Figure 2 presents a schematic view of the architecture.

The network was trained to optimise segmentation quality by minimising the difference between predictions and reference masks. The Dice–Sørensen coefficient (Dice) was used as the main loss/metric for segmentation quality, as it quantifies the overlap between predicted and reference regions on a scale from 0 (no overlap) to 1 (perfect overlap).[47]

Performance evaluation and statistical analysis

For model evaluation, predictions were visually analysed by an examiner experienced in CBCT interpretation. For each slice, MB2 presence and location were classified as true positive (TP), true negative (TN), false positive (FP) or false negative (FN). Accuracy was calculated as the proportion of correctly classified slices. Recall (sensitivity) represented the proportion of slices with MB2 correctly identified among all MB2-positive slices, and precision represented the proportion of correct positive predictions among all slices classified as positive. The F1-score, the harmonic mean of precision and recall, was used because the dataset was imbalanced, with more slices without MB2 than with MB2.[47]

The model was trained using the Google Colaboratory online platform, which provides a cloud environment with access to the required Python libraries. A paid plan was used to access an Nvidia L4 graphics processing unit (GPU) with 20 GB of memory and 240 cores, allowing faster matrix computations.

RESULTS

An experienced evaluator selected the axial slices with the best visualization of the mesiobuccal canals in the cervical third of the roots. The human examiner achieved accuracy 0.98 and recall 0.98 on the test dataset. The U-Net + DenseNet-121 model achieved accuracy 0.83, precision 0.99 and recall 0.66. Figure 3 shows an example of a result obtained by the model in a single slice of the scan.

When tested on 725 images, the model produced 228 TP, 378 TN, 117 FP and 2 FN (Table 1). During manual classification, the examiner failed to identify MB2 in only 2 slices, both corresponding to calcified canals. The model showed specific difficulty in detecting MB2 canals very close to the main mesiobuccal canal.

DISCUSSION

The use of AI in dentistry has expanded rapidly, and in endodontics it has been applied to detection of periapical lesions, differentiation between cysts and granulomas, identification of vertical root fractures (VRF), determination of working length and assessment of root canal morphology.[48] In this study, the U-Net + DenseNet-121 model showed lower performance than the human examiner in terms of accuracy, recall and F1-score, although both achieved the same precision (0.99). The architecture was chosen for its theoretical capacity to represent a wide variety of anatomical patterns, combining information at different scales and efficiently reusing feature maps through dense connections.[42,43]

The lower performance of the model likely reflects limitations of the training dataset, which included a relatively small number of teeth and did not adequately represent highly complex cases, such as severely calcified MB2 canals or canals very close to the main mesiobuccal canal. Furthermore, all scans were acquired on a single CBCT unit under a limited set of acquisition protocols, which may have conditioned the model to this specific device and restricted its ability to generalise. More diverse datasets and alternative architectures, such as 3D U-Net variants or models incorporating attention mechanisms, may help capture subtle patterns more effectively.

Despite these limitations, the accuracy obtained (0.83) is comparable to that reported in other deep learning applications in endodontics. Yang et al.[49], using ResNet-based models for VRF detection in CBCT images, reported an accuracy of 84% with ResNet50,[50] using 5,306 slices from 88 teeth. Fukuda et al.[51], using a DetectNet-based model[52] to identify VRF on panoramic radiographs, found an accuracy of 80%. Hiraiwa et al.[53], applying AlexNet[54] and GoogleNet[55] architectures to evaluate root morphology of mandibular first molars on CBCT and panoramic images, reported a diagnostic accuracy of 86.9%. Although these studies differ in objectives, imaging modalities and sample size, they collectively suggest that CNN-based models can achieve performance in the range of 80 - 87% in complex endodontic tasks.

More directly related to MB2 detection, Albitar et al.[56] used a 3D U-Net[57] to automatically detect and segment unobturated MB2 canals in previously treated maxillary molars on CBCT, reporting 90% accuracy, 80% sensitivity and 100% specificity. Their model benefited from a 3D architecture that exploits volumetric continuity and from a more homogeneous set of cases, whereas the present study worked with a larger number of slices and greater anatomical variability, approximating clinical reality. Additionally, studies by Orhan et al. [57] and Setzer et al. [58] reported accuracies above 90% for periapical lesion detection using U-Net CNNs trained on CBCT images, and Hu et al. [59] achieved 97.8% precision for in vivo VRF diagnosis using a ResNet50-based model. [50] These high values may partly reflect the relatively greater conspicuity of VRF and periapical lesions compared with small accessory canals such as MB2, which are more susceptible to the effects of artefacts and calcifications.

Overall, current evidence shows that deep learning models trained on CBCT data can perform very well in a range of endodontic applications. Even so, detecting small structures with high anatomical variability, such as the MB2 canal, remains one of the most challenging tasks. In this context, the present study offers a consistent initial demonstration that a U-Net CNN with a DenseNet-121 backbone is capable of segmenting and detecting the MB2 canal on *ex vivo* CBCT scans with high precision and an overall accuracy that can be considered acceptable when compared with the performance of an experienced examiner.

These findings reinforce the idea that convolutional neural networks can act as allies to the endodontist, assisting in the localisation of MB2 canals and contributing to greater standardisation in image interpretation, without replacing the specialist’s clinical judgement. Building on this foundation, future studies with larger and more diverse samples, images acquired on different CBCT devices and more advanced architectures, such as 3D versions of U-Net or models incorporating attention mechanisms, have the potential to improve model sensitivity while maintaining high precision, bringing the use of AI increasingly closer to everyday clinical practice.

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TABLES

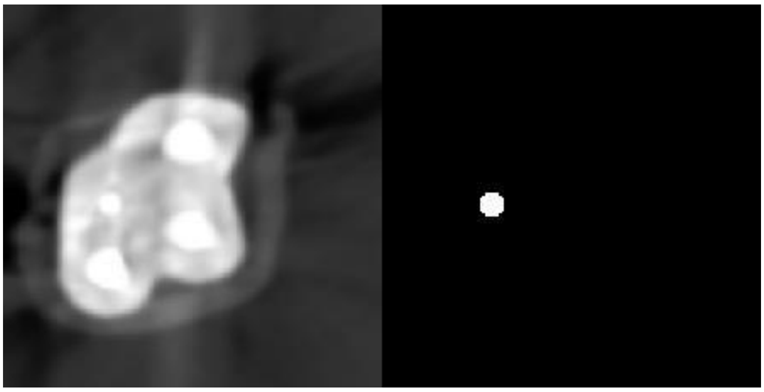
TABLE 1: Results obtained in the study

Classifier	Accuracy	Recall	Precision	F1-Score
Human	0,98	0,98	0,99	0,98
U-NET + DenseNet-121	0,83	0,66	0,99	0,79

SOURCE: The author.

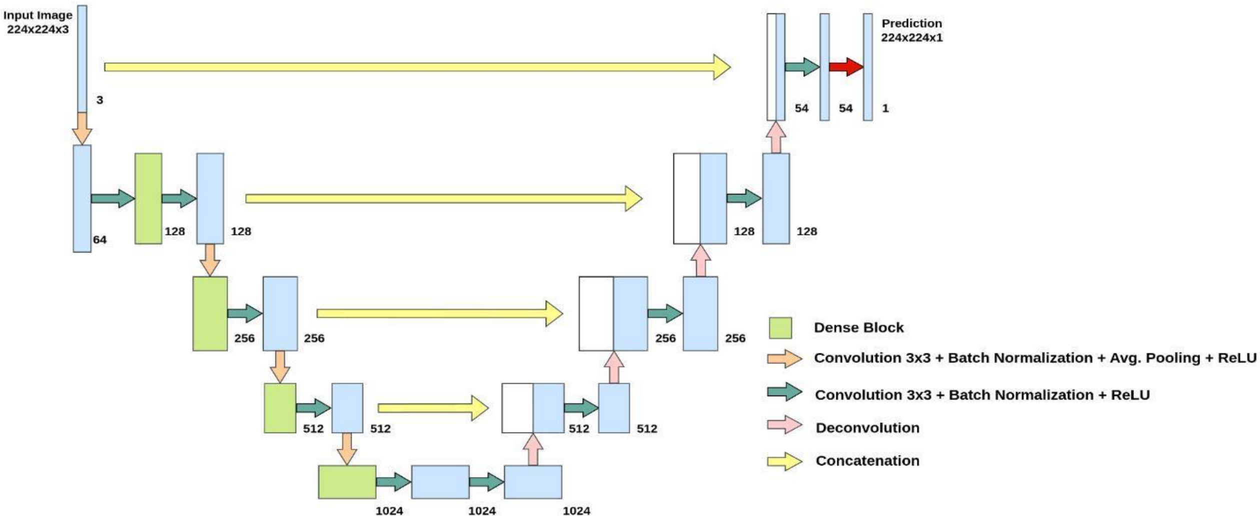
FIGURES

FIGURE 1: Axial CBCT slice at the cervical coronal/root third showing optimal visualization of the mesiobuccal canal.



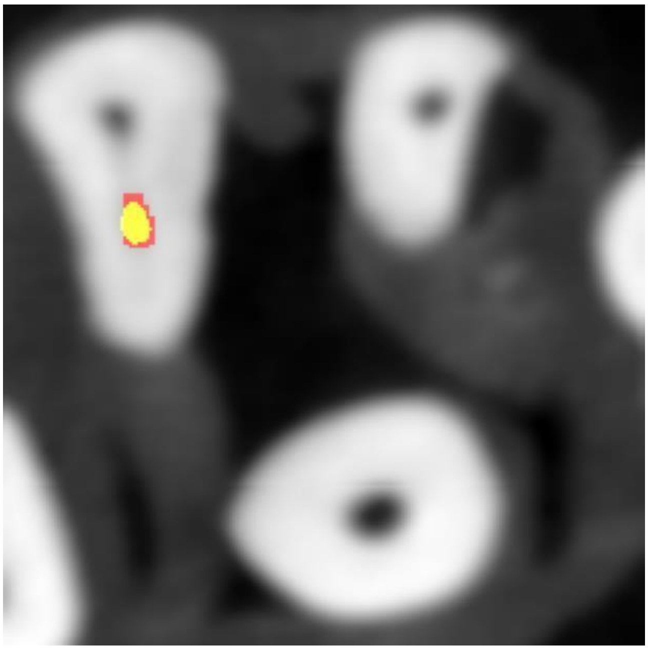
SOURCE: The author

FIGURE 2: U-Net model with DenseNet-121 backbone.



SOURCE: The author.

FIGURE 3: Segmentation result of the model. The yellow region represents the ground-truth mask overlaid on the area predicted by the model.



SOURCE: The author.

CONSIDERAÇÕES FINAIS E PERSPECTIVAS

Este trabalho buscou aproximar a Endodontia da inteligência artificial aplicada à interpretação de imagens, ao desenvolver e testar uma rede neural convolucional baseada em U-Net com backbone DenseNet-121 para a detecção do segundo canal mésio-vestibular (MV2) em molares superiores em cortes de TCFC.

Dentro das limitações já discutidas, o modelo apresentou boa acurácia e alta precisão, mas ainda com sensibilidade inferior à do avaliador humano, principalmente nos casos mais desafiadores, como canais calcificados ou muito próximos ao canal mésio-vestibular principal. Esses resultados reforçam que, no momento, as redes neurais convolucionais têm papel de apoio e não de substituição do especialista, que continua sendo a referência para o diagnóstico e o planejamento endodôntico.

Por outro lado, os achados deste estudo mostram que, mesmo com uma base de dados relativamente pequena, o modelo foi capaz de localizar o MV2 com desempenho consistente. Isso sugere um potencial importante de aplicação futura em ambientes clínicos, especialmente como ferramenta auxiliar para aumentar a taxa de identificação de canais acessórios, reduzir o risco de insucesso relacionado à não localização do MV2, otimizar o tempo de análise de exames e contribuir para maior padronização na interpretação de imagens em serviços de radiologia e na prática endodôntica. Dessa forma, este trabalho sinaliza que a integração entre TCFC e IA é viável e pode, gradualmente, ser incorporada ao fluxo de trabalho, desde que acompanhada de validação rigorosa e uso criterioso.

O estudo encontrou também alguns desafios, como a obtenção de um número maior de primeiros e segundos molares superiores, com diferentes morfologias, mesmo que o número de cortes tenha sido satisfatório, a variedade anatômica ficou aquém do ideal. O uso de apenas um tomógrafo limita a generalização das imagens, tendo em vista que o modelo pode estar condicionado a este aparelho e de dentes posicionados em maxila seca ou em blocos, o que não reproduz totalmente todas as situações clínicas. A presença de artefatos, materiais obturadores ou calcificações também interfere diretamente na qualidade da segmentação, ajudando a explicar parte das limitações observadas no desempenho do modelo.

As perspectivas futuras deste trabalho são inúmeras. O primeiro deles é a ampliação e diversificação da base de dados, com inclusão de um número maior de molares superiores, contemplando diferentes variações anatômicas, graus de calcificação e condições clínicas distintas, como dentes tratados e não tratados. A construção de um banco de imagens estruturado e continuamente atualizado tende a tornar o modelo mais robusto, com maior capacidade de generalização para a realidade do consultório e dos serviços de diagnóstico.

A utilização de tomografias obtidas em diferentes aparelhos, de fabricantes diversos e com protocolos e tamanhos de *voxel* variados, é um passo essencial para reduzir a dependência de um único tomógrafo e aproximar o desempenho do modelo das condições encontradas na prática clínica em diferentes contextos.

Em relação a inteligência artificial, pode-se explorar outras arquiteturas de redes neurais, como versões 3D de U-Net, modelos baseados em ResNet, DenseNet, mecanismos de atenção ou abordagens combinadas, que possam melhorar, a sensibilidade, sem perda importante de precisão. Estudos futuros também podem comparar, de forma mais sistemática, o desempenho do modelo com o de diferentes grupos de observadores (endodontistas, radiologistas, clínicos gerais), em delineamentos prospectivos e com cenários mais próximos da rotina.

Por fim, em uma perspectiva de médio e longo prazo, é possível imaginar a incorporação de ferramentas de IA em *softwares* de visualização de TCFC já utilizados no dia a dia, oferecendo ao profissional um suporte adicional na localização do MV2 e de outras estruturas relevantes. Para que isso se concretize, serão fundamentais a continuidade da pesquisa, a colaboração entre Endodontia, Radiologia e Engenharia, e um compromisso em utilizar a inteligência artificial como parceira da prática clínica, agregando segurança e qualidade ao atendimento, sem substituir o julgamento do especialista.