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ARTIFICIAL INTELLIGENCE FOR DENTAL IMAGE ANALYSIS: SOCIAL ASPECTS AND EXAMPLE USE CASES

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Abstract

Dental imaging is a specific part of biomedical imaging that not only includes many of its particularities but also presents several specificities. Oral public health impacts especially vulnerable populations that face precarious hygiene conditions. In recent years, the use of computational technologies for evaluation, diagnosis, prevention and treatment of oral diseases increased, promoted by the advent of digital radiology and artificial intelligence. However, these solutions in dental imaging are not so popular in all regions, as it is in high-income regions due to several factors such as resistance from specialists to incorporate computational solutions in their clinical routine and the lack of access to health services and available data. Nevertheless, there are efforts to develop technology in this field aiming the identification, classification, segmentation, and prediction of oral issues in digital radiographs, resulting in applications such as orthodontics and aesthetics. Moreover, artificial intelligence techniques have recently emerged showing impressive results in different areas. This article briefly presents three use cases of solutions for oral health, developed in a research center which is part of a public health center in Brazil. We also assess the importance of the development of medical AI-based technologies in low and middle-income regions.

Keywords: Artificial Intelligence, Dental Imaging, Public Health.

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1. INTRODUCTION

Digital image examinations are currently a prevalent technology in medical and dental practice being employed in the diagnosis of several oral diseases. Digital radiography provides high quality images, which facilitate the application of computer methods to process and analyze the examinations. This integration of digital radiography with computer-assisted analysis has revolutionized the field of oral health diagnostics. By harnessing the power of computer algorithms, clinicians can now detect subtle abnormalities, assess bone density, and track changes over time with greater precision than ever before. Furthermore, digital image examinations offer enhanced storage and retrieval capabilities, enabling clinicians to easily access and share patient records. This facilitates interdisciplinary collaboration and ensures that all relevant healthcare providers have access to comprehensive diagnostic information. In addition to their diagnostic utility, digital image examinations also play a crucial role in patient education. Clinicians can use visual aids such as annotated images and 3D reconstructions to explain diagnosis and treatment plans to patients, empowering them to make informed decisions about their oral health.

Computer methods, especially those that include Artificial Intelligence (AI), have the potential to improve the accuracy and consistency of diagnosis (ABDALLA-ASLAN et al., 2020). Several AI solutions for oral radiology have emerged in the last few years, aiming to automate the identification and evaluation of oral diseases, potentially reducing possible errors resulting from experts' subjectivity , showing promising results for this problem (ABDALLA-ASLAN et al., 2020). Medical imaging in general presents an excellent potential for image processing solutions since diagnostic imaging is an essential part of a wide range of medical areas (SCHWENDICKE et al., 2019). Moreover, image evaluation already constitutes an important step in the diagnosis of several issues, including oral diseases being applied in cariology, endodontics, periodontology, orthodontics, and forensic dentistry (SCHWENDICKE et al., 2019). It also lowers costs by eliminating routine tasks and modernizing the diagnostic process. AI-powered algorithms can analyze vast amounts of imaging data quickly and accurately, assisting clinicians in making more informed decisions (SCHWENDICKE; SAMEK; KROIS, 2020).

In the oral radiology field, AI solutions offer several advantages. They can detect subtle abnormalities that may be overlooked by human observers, leading to earlier detection and treatment of oral diseases. Additionally, AI algorithms can provide quantitative assessments of disease severity and progression, allowing for more personalized treatment plans tailored to each patient's unique needs. The integration of AI with digital image examinations holds tremendous promise for the future of oral health diagnostics. As technology continues to advance, AI-powered solutions are likely to play an increasingly important role in improving patient outcomes and reducing healthcare costs.

Despite these promising developments, there are still challenges to overcome before AI solutions can be widely implemented in clinical practice. Even considering the great potential of using AI-based solutions for oral imaging, there are several challenges that must be overcome in this context, such as data privacy, algorithm transparency, lack of a regulatory approval ensuring the safe and ethical use of AI in healthcare, the lack of available data, the subjectivity of oral diseases' diagnosis, the lack of diagnostic standards, the complexity of some oral diseases, and the resistance from specialist to include computational tools in their routine.

The issues for AI-based solutions in this field are aggravated by social and economic inequality, which creates a disparity in access to advanced diagnostic tools between affluent and lower-income regions, exacerbating existing healthcare inequalities. In high-income countries, the number of image exams are substantially superior compared to the number of such exams in other regions, due to the availability of these technologies. A published report informed an average of 3.3 dentists per 100,000 resident population between 2014 and 2019 in the Africa continent (World Health Organization; 2020), while another report exposed an average of 61.06 active dentists per 100,000 resident population in the United States in the same year 2019 (AMERICAN DENTAL ASSOCIATION, 2020). This is reflected by the trends in the dental imaging market. North America dominated the dental imaging market in 2023 with 33.14%, followed by Europe and Asia Pacific, with 28.41%, and 24.20% of the market, respectively (PRECEDENCE RESEARCH, 2024). In contrast, all Latin America, Africa and Middle East together only hold 14.25% of the market (PRECEDENCE RESEARCH, 2024).

In high-income countries, where resources are more abundant, patients have

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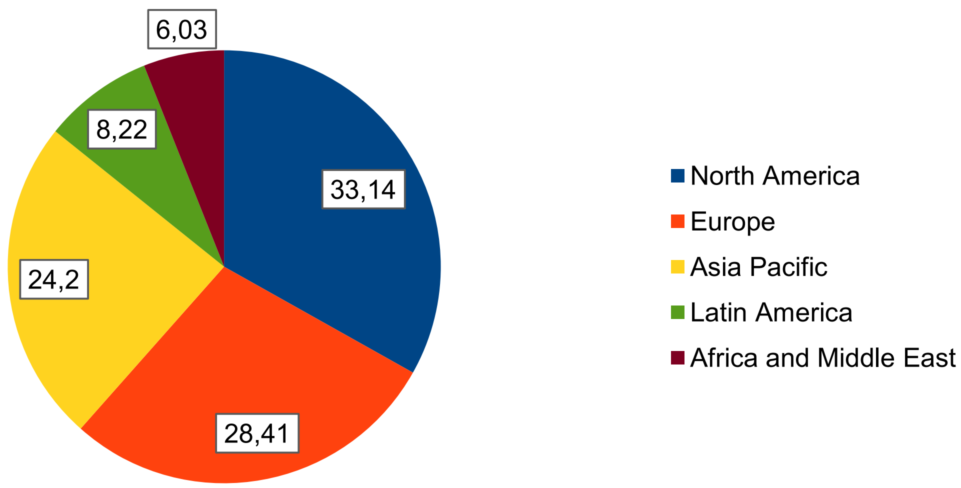
greater access to digital image examinations, leading to earlier detection and treatment of oral diseases (WHITE; PHAROAH, 2009). Conversely, in low and middle-income countries, access to digital radiography and other advanced imaging technologies may be limited due to cost constraints and infrastructure challenges. As a result, patients may experience delays in diagnosis and treatment, leading to poorer health outcomes. Ultimately, overcoming or at least reducing the gap in access to digital image examinations and other advanced diagnostic tools is essential for promoting health equity and ensuring that all individuals have the opportunity to receive timely and appropriate care for oral diseases.

Figure 1 – Dental imaging market share by region in 2023 (in %), according to PRECEDENCE RESEARCH (2024).



Source: The authors (2024).

This work briefly discusses efforts of developing solutions for some of the main problems for AI-based image processing in dentistry. More specifically, in order to demonstrate the feasibility of using the mentioned techniques, three of the applications (arch identification, mandibular canal segmentation, and segmentation of tissue layer) are selected for practical exemplification. Moreover, the challenges resulting from socio-economic inequality are discussed in this article, as well.

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2. ARTIFICIAL INTELLIGENCE IN ORAL HEALTH

Digital images, including medical images (exams) can be modeled as multidimensional matrices, commonly two or three-dimensional structures. There are several techniques in computer science that can be employed to process digital signals that present such structures. Such techniques can be employed to improve, analyze, and extract information from this data. Some acquisition devices can even apply these techniques automatically, after the images' acquisition and before their storage (WHITE; PHAROAH, 2009).

Four main problems are mostly related to medical imaging applications: enhancement, classification, identification, segmentation. Figure 2 illustrates them. The enhancement task consists of processing an image in order to improve its overall quality (Fig. 2 (a)), for example, reducing noise, increasing resolution, improving edges definition, etc. The classification task consists of analyzing the visual patterns of an image in order to associate it to a specific class, normally pre-defined, as the example in Figure 2 (b). In the identification task, the focus is to define the region of the image that encloses an object i.e., its location. For example, tooth detection (Fig. 2 (c)). Finally, the segmentation task aims to identify an object in the image, determining its exact boundaries and isolating it from the rest of the image. Figure 2 (d) shows an example of the desired results of this task.

In the last few years, the use of artificial intelligence (AI) techniques has increased significantly for such problems, driven by results that demonstrate their potential. Specifically for image processing, particularly for medical imaging, AI techniques have shown remarkable promise in improving the accuracy and efficiency of diagnostic processes. In the realm of medical imaging, AI-powered algorithms have been increasingly utilized to assist clinicians in tasks such as image segmentation, feature extraction, and disease classification. One of the key advantages of AI in medical imaging is its ability to handle large volumes of complex data and extract meaningful insights quickly and accurately. AI algorithms can analyze medical images with unprecedented speed and precision, enabling clinicians to make more informed decisions about patient care. Moreover, AI techniques have the potential to enhance the detection and diagnosis of a wide range of medical conditions, including oral diseases. By leveraging machine learning and deep learning algorithms, AI systems

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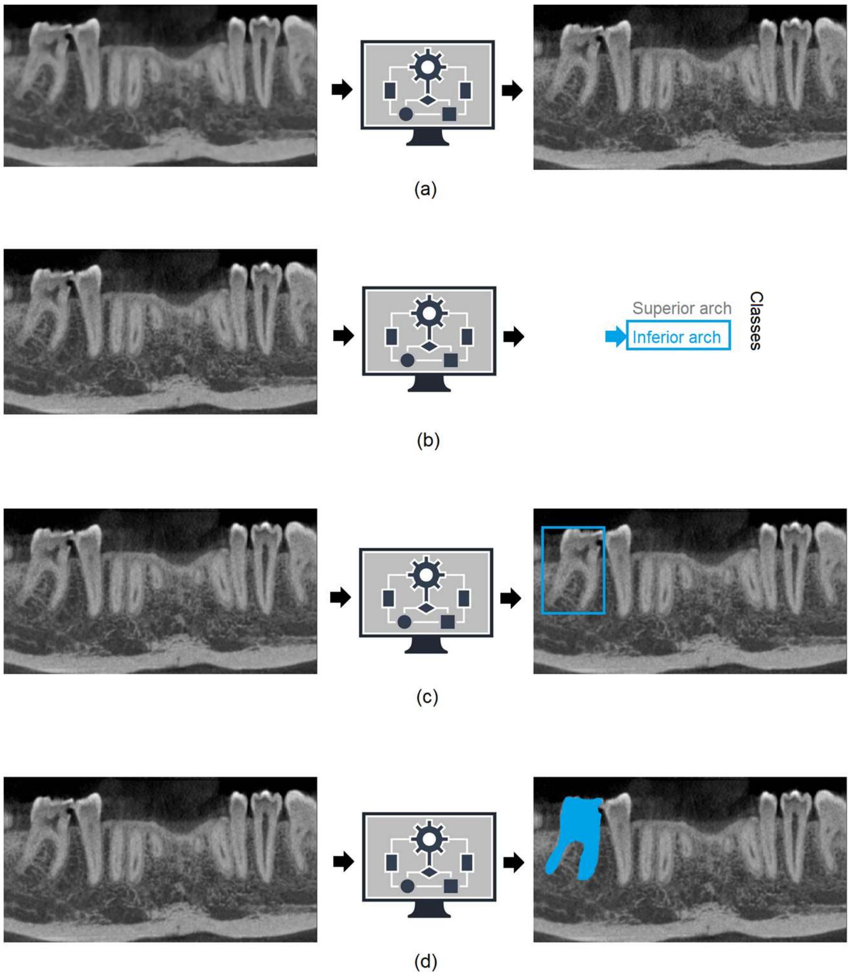
can learn from large datasets of annotated medical images to identify patterns and anomalies that may be indicative of disease. Furthermore, AI solutions can help improve the consistency and reproducibility of diagnoses by reducing the influence of subjective factors such as inter-observer variability. By providing objective and quantitative assessments of imaging findings, AI algorithms can enhance the reliability of diagnostic interpretations and facilitate more consistent treatment decisions. Overall, the increasing use of AI techniques in medical imaging holds great promise for improving the accuracy, efficiency, and accessibility of diagnostic processes for oral diseases and other medical conditions. As AI technology continues to evolve, it is likely to play an increasingly important role in transforming the field of oral radiology and enhancing patient care outcomes.

Figure 2 - Main computational tasks in oral imaging: (a) image enhancing, (b) classification, (c) object detection, and (d) segmentation.



Source: The authors (2023)

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Section 4 presents three example use cases where AI solutions are applied to solve specific problems in the oral health field. Moreover, the mentioned solutions, were created and developed in a public health center to attend to potentially vulnerable populations, which is an important social aspect discussed in Section 3.

3. SOCIAL ASPECTS OF AI TECHNOLOGIES IN VULNERABLE SETTINGS

Besides the great technical potential, the social impact AI solutions can achieve is huge. The potential of AI-based technologies in the medical field can be especially helpful for vulnerable populations since the lack of resources can be combated with these technologies at certain points, being an alternative to decrease limitations of precarious settings. Health systems generate large volumes of data which also creates opportunities for the application of AI-based solutions, promoting the enhancement of individual and population health. Moreover, the use of health data to generate AI-based systems can enhance healthcare delivery, and improve diagnosis and treatment, resulting in a dramatic improvement of healthcare systems. However, there are several ethical, regulatory and financial factors to be considered. One main factor that affects the prevalence of such solutions is the socio-economics conditions of the region.

High-income countries have been benefiting from the integration of AI into their healthcare ecosystems in different ways (WAHL et al., 2018). Even considering that resource-poor regions were initially neglected in the recent growth of AI-based solutions, it can be observed that there are several recent factors that encourage the development of such solutions in such places, such as a strong mobile phone penetration, developments in cloud computing and substantial investments in health information digitalization. These new settings provide the support needed to create useful applications of AI that have the potential to impact a population and impact other digital health technologies.

The development of AI imaging solutions still face a great limitation due the lack of publicly available data in low-middle income regions. Even considering the recent growth of mobile technologies in low-middle income regions, this is not enough to make AI imaging solutions available for this population. Such data depends on the acquisition of expensive image devices that may not be available in precarious settings. As an example of the mentioned despaired conditions, as previously commented in Section

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1, a recent report showed that the different in the market size for high vs. medium and low income regions is huge. This scenario shows a drastic contrast, with scarce access to technology and poor health conditions in most settings in low/middle income regions.

One alternative to proceed to the development of AI-based imaging solutions in these scenarios is the use of datasets available in the literature. However, datasets available in the literature are often acquired by the authors in their associated institutions. Therefore, it is highly representative of the population treated in this institution. This is especially problematic if we consider that these works tend to originate from high-income countries (e.g., several European countries, such as France, Spain, Sweden, etc.) with a population with very particular socio-economic characteristics due the access to public health systems with greater financial resources, completely different from the conditions faced by vulnerable populations.

The scarcity of data from low and middle-income regions poses a significant challenge to the development and implementation of AI imaging solutions for these populations. Without access to diverse and representative datasets, AI algorithms may not perform optimally when applied to populations with different demographics, disease profiles, and imaging practices. Furthermore, the lack of publicly available data from low and middle-income regions hinders efforts to develop AI solutions that are tailored to the specific needs and challenges faced by these populations. Without access to relevant data, developers may struggle to train AI algorithms that are capable of accurately detecting and diagnosing oral diseases prevalent in these regions. In order to exemplify one of the many issues this represents, we can cite the bias inherent to a particular dataset composed of data acquired in an specific institution since institutions tend to target different populations and consequently the solutions created from this dataset are more trustworthy for that population (SCHWENDICKE et al., 2019; SCHWENDICKE; SAMEK; KROIS, 2020). Let's consider public health systems as the developer and provider of an AI-based system. Public emergency hospitals tend to attend more vulnerable patients with more severe lesions and often more neglected health. Comparatively, private institutions tend to provide more routine check-ups and periodic preventive evaluations, leading to a lot of data of patients with a good health condition. These demographically contrasting representations promote construction of non generic solutions due to sub-representation aspects. If we consider a classification system for example, where we define two classes “healthy” and “ill”, the datasets acquired in the two considered scenarios will drastically differ in the number of cases for each class, which can result in solutions with opposite bias, hardly generalizable (MORAN et al., 2022).

The documentation in the academic literature on AI applications for health in resource-poor settings is scarce. However, this does not represent a low activity in this field. Many examples of promising technologies were publicized in the media. The growth of the ‘AI for Development’ (AI4D) field, and its community demonstrate the popularization of such solutions in resource-poor settings, exposing several examples how AI has been implemented in such scenarios (MANN; HILBERT, 2018). AI4D refers to the use of AI to promote the socioeconomic development and enhance the quality of life of disadvantaged populations, including people living within developing countries (EAGLE; HORVITZ, 2010). The experience of developing AI-based solutions in resource-poor settings showed that the solutions must add intelligence into existing settings instead of starting new efforts from scratch or trying to replace existing inefficient systems (WAHL et al, 2018). The success of implementing AI applications for a population demands clear specification of the scenario’s usability requirements and access to adequate training data (WEBER; TOYAMA, 2010). Initiatives aiming at collecting and sharing anonymized medical imaging data from low and middle-income regions could help reduce the data gap and facilitate the development of AI imaging solutions that are accessible and effective for these populations. Additionally, efforts to increase access to affordable imaging devices in precarious settings could help expand the availability of data for AI research and development (MHLANGA, 2023).

This work presents a few examples of AI-solutions currently being deployed in the considered settings. We highlight that such solutions are still being validated and have not yet been robustly evaluated, but they do provide insight into how AI solutions can be implemented in such scenarios and their potential beyond them.

4. USE CASES FOR AI-BASED TECHNOLOGIES IN A PUBLIC HEALTH UNIT

This section describes a set of new solutions based on AI techniques and the corresponding experiments to evaluate them. Such solutions were developed in a public health environment aiming to serve the population that attends to this unit.

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This health unit treats patients who are part of the group of people who have an illness or clinical situation that require differentiated dental care, such as patients with autism, schizophrenia, mental or physical disabilities, cerebral palsy, affected communication skills, among other syndromes and disorders. The local has a main dental office, including additional resources, such as oral and inhalation sedation with nitrous oxide; or in some cases, it can be performed under general anesthesia. Moreover, the unit also has devices for radiographic image acquisition, which provide the data required to construct datasets for AI-solutions.

Dentistry for patients with special needs has increased over the years, and involves the dentist's knowledge not only of dental care in general, but also of psychosocial problems that may interfere with the patient's treatment process. These patients constitute a group that can be considered at high risk for the development of oral diseases according to the type of systemic pathogenesis, salivary alteration, cariogenic diet, muscular alteration and ineffective cleaning. Finally, it is important to highlight that this is a public health unit so these patients frequently face socio-economic difficulties along with the mentioned health conditions. This health unit is part of Policlínica Piquet Carneiro (Figure 3), an institute associated with the State University of Rio de Janeiro, Brazil, providing health and medical services for vulnerable populations in the city of Rio de Janeiro.

The solutions presented in this section aim to solve oral health problems, focusing on different case studies, in order to be employed by specialists as supporting tools for those problems. Three different studies have been performed, each one focusing on different imaging tasks.

4.1. Dental arch identification

The dental arch constitutes an important anatomical feature in oral anatomy. It is intrinsically related to the configuration of the oral structures, such as supporting bones, teeth, and oral musculature (ZHU; FANG; ZHANG, 2021). The identification of the dental arch is crucial in order to delineate the patient’s anatomy, define proper treatments, and obtain additional images, such as panoramic views, when an extra radiographic device is not available.

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Figure 3 - Policlínica Piquet Carneiro: public health unit that includes the center where this work was developed, also providing the datasets used in the experiments

Source: http://www.ppc.uerj.br/

The dental arch identification is a task that is commonly performed visually by specialists. They inspect image exams, especially computational tomographs (CTs), in order to denote the dental arch. Computed tomography is a widely used image examination in medical imaging, including oral imaging. It provides detailed images that allow the identification of several oral structures and features. This manual approach performed by specialists to define the dental arch requires time and effort. In this scenario, computational solutions to automate this process, or at least part of it, can be helpful to support specialists during diagnosis and treatment planning. In this sense, for this use case, we propose a new method for arch identification in CTs.

Dataset. In order to develop and test our method, a dataset of CTs were acquired at the health unit mentioned previously. The data were anonymized, in order to preserve patients' privacy. These CT exams cover different regions of the face, always including the mandible. The heterogeneity of the exams is caused by the lack of available data. On the one hand, this heterogeneity can be considered a limitation. On the other hand, using data with such different features promotes a more robust

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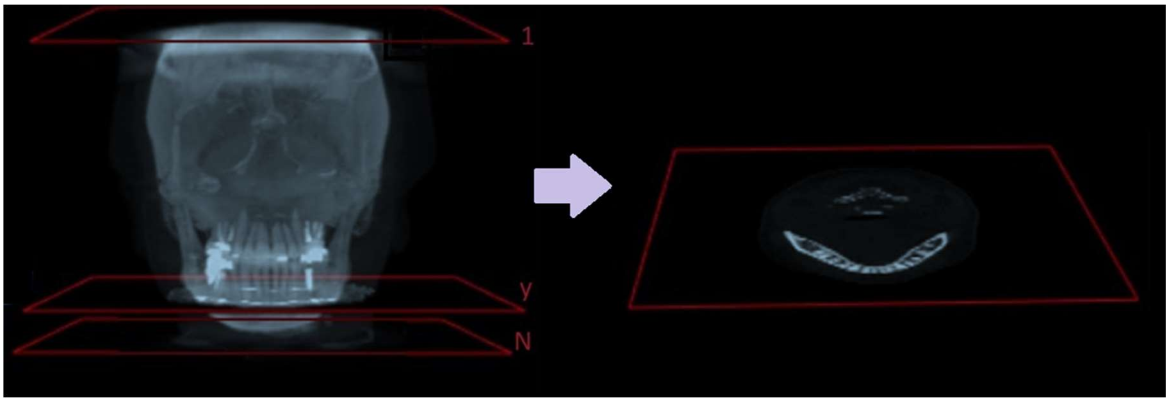
evaluation since the proposed methods are tested considering different scenarios.

Ground truth definition. In order to perform an evaluation of the proposed method, a ground truth was established. For that, the image exams were annotated by an expert who is an experienced dentist specialized in oral radiology. The tool the expert used for this annotation task was developed by our research group. The expert observes the axial slice located 10mm above the base of the mandible is selected (Figure 4), which is also used as the input of the proposed method. Using the visual interface of our annotation tool, the expert clicks on a sequence of points to define a dental arch in the selected axial slice. The arches manually defined by the expert for an exam are considered the ground truth for the considered task.

Proposed method. The first part of the proposed method consists of defining the axial slice located 10mm above the base of the mandible as input (Figure 4).

Figure 4 - Selection of input slice



Source: The authors (2023).

For that the scale of the image is considered for calculating the correct arch. Once the input slice is established, a binary image is generated through a thresholding procedure, wherein pixels with values exceeding 1300 are designated as foreground. Consequently, the foreground in this slice encompasses denser tissues such as enamel and mandible borders. In essence, the foreground represents the entire mandibular region, alongside other areas (Figure 5(a)). In the next step, a sequence of morphological operations are applied (Figure 5(b)): a dilation, using a square of side 10 as the structural element, a morphological flood-fill, and an opening (structural

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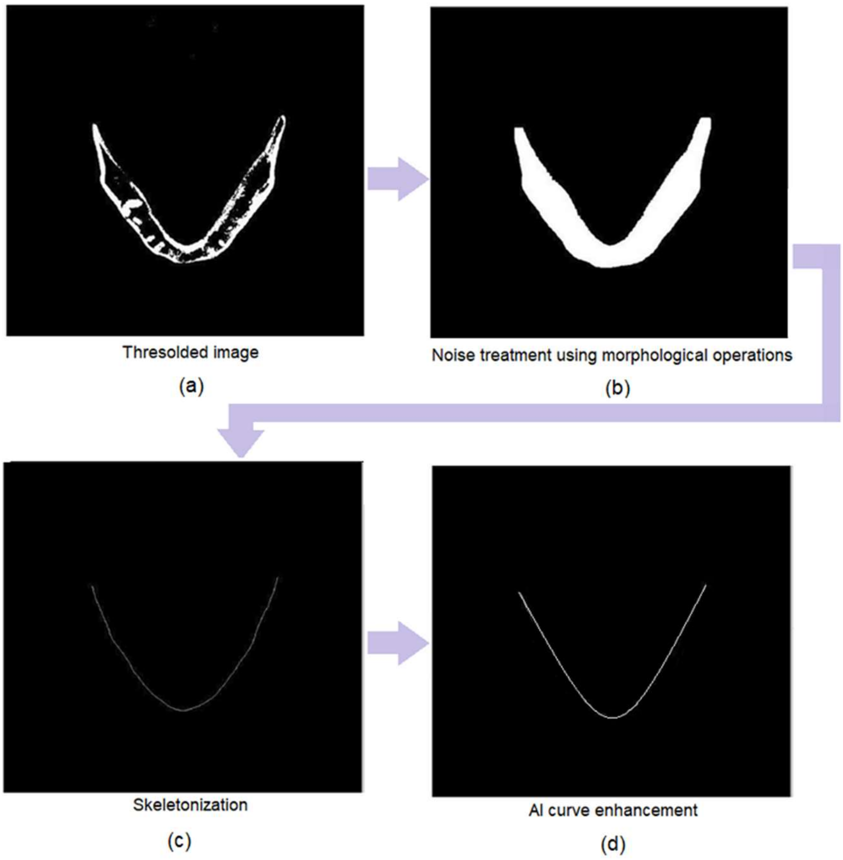
element is a square of size 20). In order to obtain a curve that defines the arch, skeletonization is applied to this image in order to define the arch (Figure 5(c)) (LEE; KASHYAP; CHU, 1994). This arch is then treated using the BézierGAN, a deep learning solution to smooth curves to generate the final curve (Figure 5(d)) (CHEN; FUGE, 2018). This curve is the arch provided by our method. All image processing operations were performed using the scikit image library for Python, which provides implementations for all morphological operations.

Figure 5 - Steps of the proposed arch localization method.



Source: The authors (2023).

Evaluation procedure and results. In order to provide a measure to compare and evaluate the arches defined by the proposed methods, the Intersection over Union (IoU) (Jaccard index), is used in this analysis (EELBODE et al., 2020). The similarity analysis provided by IoU focuses on a geometric perspective in the sense that it compares the areas of the polygons whose vertices are denoted by the sequence of points that compose the arch (example in Figure 6). The optimal and maximal value for IoU is 1, which denotes that the area

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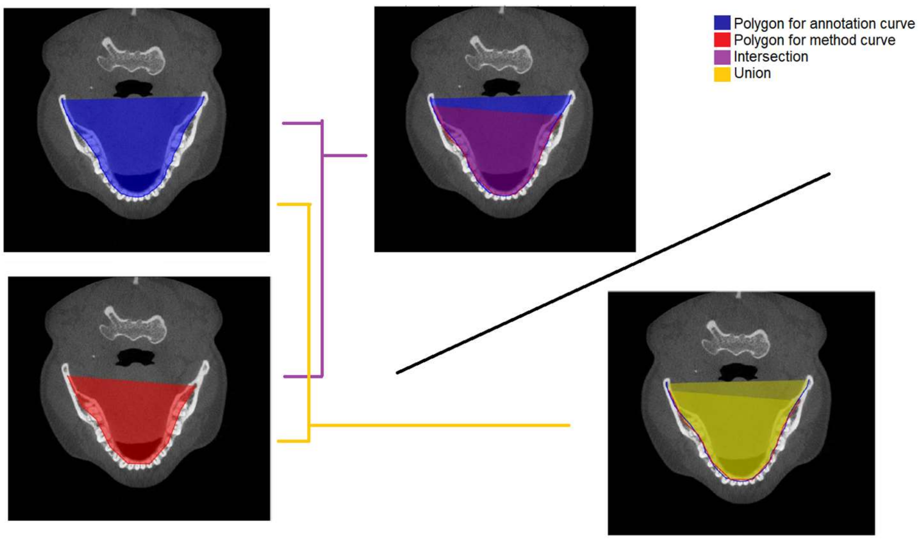
of the intersection of the two polygons is identical to the area defined by their union, i.e. the polygons are equal. The mean IoU value per case (similarity of the polygon with limits provided by ground truth arches and the polygon defined by the arch achieved by the method for a case) is 0.851 with standard deviation of 0.128.

The inclusion of the AI final step to enhance the arch shape substantially improved the quality of the arch compared with a previous version of the method (OLIVEIRA et al., 2022). The average performance of the proposed method can be considered high, even considering that, in some cases, it presents poor results. The promising results presented here suggest that these methods can be used as auxiliary tools for the proposed task.

Figure 6 - Example of polygons obtained considering the ground truth curve and the method's curve, and their resultant intersection and union áreas.



Source: The authors (2023).

4.2. Mandibular canal localization

Surgical and restorative interventions constitute routine tasks for dentists. Notably, a key concern during these procedures is the potential risk of injuring the inferior alveolar nerve (IAN), which regulates the sensory function of the mandibular area (NGUYEN; GRUBOR; CHANDU, 2014; IWANAGA et al., 2022). The mandibular canal (MC) is a significant anatomical feature situated within the mandible, serving as a conduit for the IAN bundle.

Cone beam computed tomography (CBCT) serves as the primary imaging modality for identifying the patient's mandibular canal. While numerous segmentation methods for the mandibular canal have been documented in the literature, many of them are characterized by their time-intensive nature and lack of precision. Given the limited contrast of the mandibular canal in comparison to surrounding tissues, its visualization is inherently challenging, rendering automatic segmentation a difficult task (WHITE; PHAROAH, 2009). The proposed method for the considered task aims to provide a precise and fast mandibular canal segmentation for computed tomography.

Dataset. The CBCT scans utilized in this study were obtained using a Cone Beam iCat® computed tomography scanner. The dataset comprises 20 CBCT scans obtained from various patients, including 17 women and 3 men, aged between 11 and 71 years, with a standard deviation of 19.05 years. The exams were acquired in the same health unit described in the previous section. For the quantitative numerical evaluation of the proposed method, an expert used the InVesalius software to visualize the axial, sagittal and coronal slices of all exams in the dataset, and delimites the corresponding mandibular canal area in these slices (AMORIM et al., 2015). The regions annotated by the expert are used as the ground truth for comparison with the regions pointed as the mandibular canal by the proposed method.

Proposed method. The initial step of the proposed method involves delineating an arch that outlines the shape of the mandible, applying the method presented in the last section. Subsequently, transverse planes are generated based on this arch. Within these transverse planes, which are perpendicular to the arch, the mandibular canal is readily identifiable visually as a circular structure (Figure 7). In the proposed method, the transverse planes are used as input of the end-to-end convolutional neural network (CNN) to detect circle areas for objects proposed in a previous work (ERCAN et al., 2020). For each transverse plane, the CNN model finds circular structures automatically.

The three-dimensional structure of the canal is defined by selecting for each transverse projection the circle closest to the circle of the canal of its immediate neighbor. In other words, the closest subsequent circles obtained are aggregated to create a three-dimensional structure (Figure 8) and the points that belong to this structure are highlighted in the three-dimensional view of the exam.

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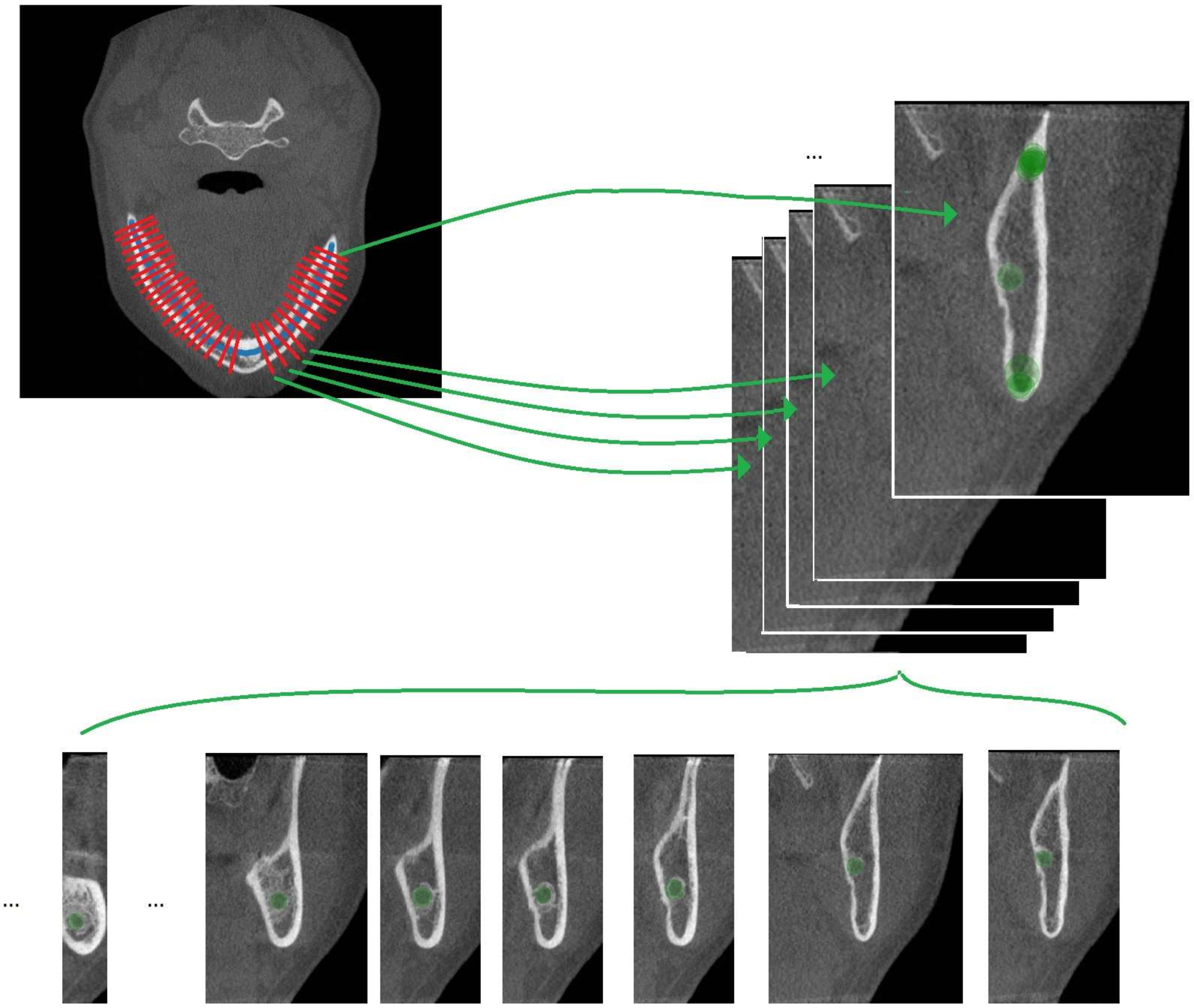
Figure 7 - Graphical representation of the steps composing the canal segmentation method



Source: The authors (2023).

Evaluation procedure and results. The initial assessment of the canals obtained through the method involved a qualitative visual examination conducted by a human expert. In this evaluation, the specialist visually inspected the volumes generated and assessed whether they closely resembled the actual canals observed in the examinations. Based on this visual inspection, it was noted that the visual quality of the volumes can be deemed satisfactory, indicating that the obtained volumes closely approximate the real structure.

The quantitative analysis in our evaluation consists of a comparison, performed using the Intersection over Union (IoU). In this case, the IoU compares the volumes defined manually by the expert (ground truth) and the volumes obtained through the

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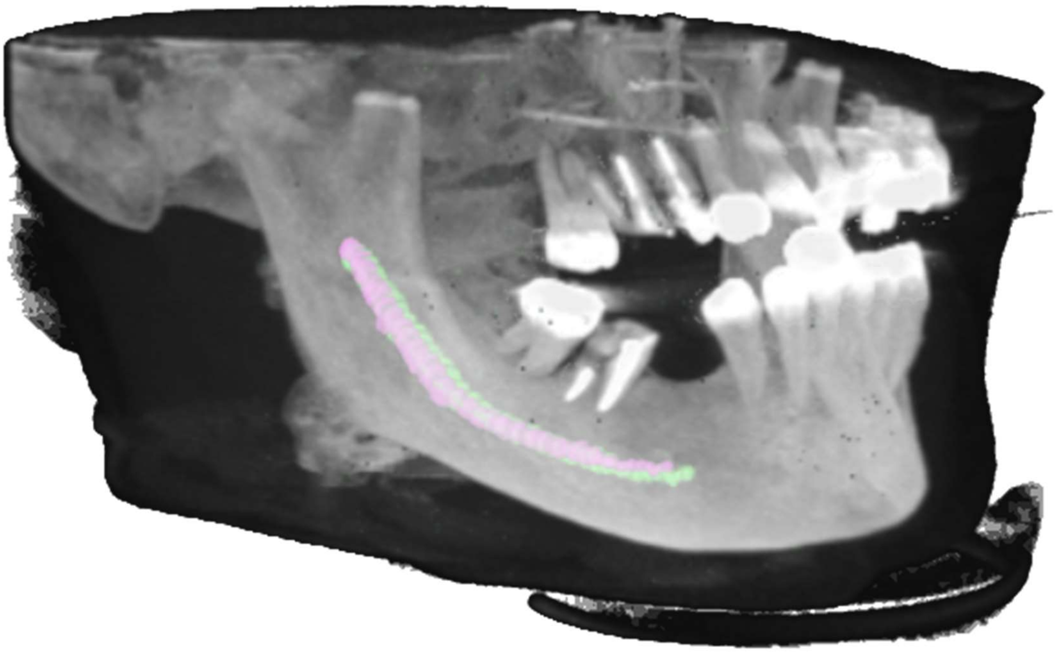
method. The mean IoU value is 0.940 with a standard deviation of 0.125. The results suggest that the proposed method is promising and has the potential to be used as an auxiliary tool for segmentation of the mandibular canal. Moreover, our work aims to encourage the scientific community to deepen solutions for mandibular canal segmentation tasks.

Figure 8 - Three-dimensional plot of the gold standard (in pink) and the result of the proposed method (in green) in the CT exam.



Source: The authors (2023)

4.3. Tissue segmentation using AI algorithms

In the planning stages of surgical procedures, precise knowledge of tissue layer locations is crucial to minimize complications and enhance the likelihood of successful outcomes. One approach to achieving this is through the utilization of imaging examinations to assess the patient's anatomy, particularly the positioning of tissue layers. However, due to the small size and interconnected nature of anatomical structures and tissue layers, their identification can present challenges. In essence, differentiating structures for disease assessment, monitoring, and guided procedures using medical imaging can be demanding, particularly for less experienced professionals. Furthermore, the high radiation exposure associated with many imaging

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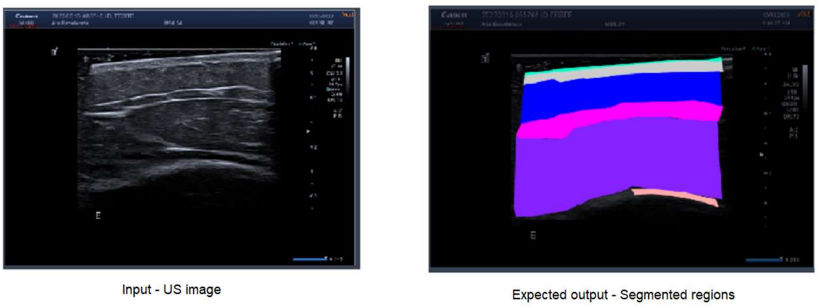
examinations limits their widespread use in the pre-surgical phase.

In recent years, the utilization of ultrasonography (US) has seen a notable rise, emerging as a compelling alternative for the detection, characterization, and monitoring of various diseases. Utilizing high-frequency probes, ultrasonography enables the visualization and characterization of anatomical layers, including tissues, serving as a valuable adjunctive tool in numerous procedures, such as surgeries. Notably, US also stands out as a radiation-free imaging modality, offering numerous advantages in comparison to other imaging modalities (BARCAUI et al., 2015).

The visual identification of tissues in US images is still a challenge for some professionals. In order to provide a supporting tool for this task, the proposed method implements a deep learning (DL) segmentation algorithm for the tissue segmentation task in the US.

Dataset. A total of 100 high-frequency ultrasonography (US) images were acquired from examinations conducted on the aforementioned 91 healthy individuals. These images encompassed the areas of the forearms and thighs. The exclusion criteria considered for the study were as follows: patients who had undergone plastic surgery, received injections of materials such as botulinum neurotoxin, or had any prosthetic devices or non-biological materials present. The imaging device utilized for data acquisition was the Aplio 500 (Canon Medical Systems, Tochigi, Japan). The dataset split defined for this experiment adhered to a ratio of 70:15:15 for training, validation, and test data, respectively. Five classes were considered: epidermis, dermis, hipodermis, muscle components, and cortical bone (Figure 9). The ground truth/gold standard is defined by annotations made by one expert who is a dentist specialized in cosmetic dentistry.

Figure 9 - Example of input and expected output for the considered task.



Source: The authors (2023).

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Proposed method. In this solution, we propose the use of a segmentation neural network, employing one of the most prevalent algorithms in the literature: You Only Look Once (YOLO) (MORERA et al., 2020). The input US images were pre-processed to be used as input for YOLO. After that, a YOLO model was trained for 60 epochs using the following parameters: batch size: 16; learning rate: 0.01; momentum: 0.937; and weight decay: 0.0005.

Evaluation procedure and results. In order to easily depict the performance of the model, the considered metric for results analysis is the Dice coefficient (EELBODE et al., 2020). The Dice coefficient yields a value between 0 and 1, where 0 indicates no overlap between the sets and 1 indicates perfect agreement. In other words, a higher Dice coefficient indicates greater similarity or overlap between the two sets of data.

In medical imaging applications, the Dice coefficient is commonly used to evaluate the performance of segmentation algorithms by comparing the agreement between automated segmentations and manually annotated ground truth segmentations. A high Dice coefficient suggests that the automated segmentation closely matches the ground truth, while a lower coefficient indicates discrepancies or inaccuracies. The results (Dice coefficient values) achieved by the trained model can be observed per class in Table 1.

Table 1 - Results achieved by YOLO algorithm per class.

Class	**Dice coefficient**
Epidermis	0.873
Dermis	0.868
Hipodermis	0.899
Muscle components	0.864
Cortical bone	0.859
Mean	0.873

Source: The authors (2023).

The experiments showed that the YOLO algorithm had promising results,

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suggesting that this kind of solution can be employed for tissue segmentation.

5. FINAL CONSIDERATIONS

Oral health is a critical public health issue, disproportionately affecting vulnerable populations grappling with inadequate hygiene conditions. Over recent years, the adoption of computational technologies for oral disease assessment, diagnosis, prevention, and treatment has emerged, propelled by advancements in digital radiology and artificial intelligence. Nonetheless, widespread adoption of these solutions in dental imaging remains uneven across regions, particularly in low-income areas, due to various factors such as limited access to healthcare services, sparse data availability, and practitioner reluctance to integrate computational solutions into clinical practice. This article provided a brief discussion of the challenges faced in this scenario, along with a concise overview of three innovative use cases for oral health solutions, developed at a research center affiliated with a public health institution in Brazil. The dental arch definition solution not only aids the dentists to better personalize the procedures to the patients' anatomy, but also can be used to generate new images (emulating the panoramic view, e.g.) when other acquisition devices are not available. The accurate identification of the MC, performed by one the proposed methods, provides support during the intervention planning, avoiding the most common complications. The tissue segmentation solution with promising results, also contributes to better preoperative procedures and cost reductions by minimizing the risk of complications. Overall, all solutions provide, in different ways, some enhancement in the health procedures considered, promoting well-being for both patients and professional of the health unit. These examples highlight the development of AI-driven medical technologies tailored for low and middle-income regions. The promising results of the proposed solutions in their preliminary evaluations suggest their potential to be included in the considered setting.

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