ORAL HEALTH OF AGRIBUSINESS WORKERS: CHALLENGES OF THE 2030 AGENDA AND ESG CRITERIA, PROMOTING WELL-BEING AND INCLUSION TO INCREASE PRODUCTIVITY

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ABSTRACT

Contemporary dentistry aims to replace private care with the sanitary model. Agribusiness workers have difficulties accessing dental services. The dental care system has difficulties in acquiring, updating, referring and monitoring patients. Artificial intelligence is a computer system that performs tasks that require human knowledge and skills such as recognizing patterns and images, understanding written and spoken open language, perceiving relationships/nexuses, following decision algorithms, understanding concepts, reasoning through the integration of new experiences by self-improvement. This research aims to demonstrate the importance of a convolutional network of dental data analysis that enables the diagnosis of different pathologies that may be found in agribusiness workers and the respective referral to the oral health recovery and control services of this target population. With the bibliometric review carried out, it was realized that the construction and wide use of convolutional networks in the different dental specialties can contribute to the improvement of primary oral health care, in the private network and especially in the public network, thus benefiting agribusiness workers with an increase in quality of life, oral health indices and indicators, as well as in their productivity.

Keywords: Dentistry. Convolutional Networks. Agribusiness. Diagnosis.

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INTRODUCTION

Rural populations are communities whose ways of life and production are mainly related to land and water (BRASIL, 2013), being a space traditionally with little government action in the implementation of public policies related to the promotion of health and social assistance (SILVA, 2012). When compared to urban populations, they face a series of inequities, which impact their quality of life and must be analyzed in the light of their socioeconomic determinants and the orientation of the State in guaranteeing their rights (PESSOA, 2018). This context impacts their oral health indicators, intensifying more severe health problems that are expressed in the differences in availability and quality of health care offered (RÜCKERT, 2018). Access and accessibility to Primary Oral Health Care services are not ensured, based on the distances between rural communities, oral health services and support points (places that decentralize care, being a reference for other (distant) micro-areas assigned to a territory covered by oral health (CAVALCANTI, 2012). In Brazil, the guidelines of the National Oral Health Policy (PNSB/04) were launched, aiming at access, equidistal confrontation of the predominant epidemiological situation (including rural populations) and greater allocation of financial resources to structure a network of oral health services, with national capillarity, under the coordinating eye of PHC (CHAVES, 2018). However, studies on the performance of oral health teams show a legacy of the persistent biomedical model in professional care performance, little focused on community actions, with a lack of planning and low interaction with other primary health care workers (DOS SANTOS, 2016).

Oral diseases affect productivity (UN/SDG 2.a goal) in agribusiness, facilitate the emergence/evolution of secondary pathologies in those affected. Analyses between geographic space and oral health are gradually increasing (SILVA-JUNIOR et al., 2017), but little is known about the spatial distribution of oral pathologies using intelligent systems in this context. Currently, the oral health system aims to replace biomedical care with the sanitary model (UN objective/SDG 16.6) that coexists in a fragmented way. Dental services need to review their work logic, seeking to get closer to users, becoming humanized and problem-solving, as health surveillance (as a management component) provides methods/technologies/knowledge in view of the needs of a territory covered by oral health (UN/SDG objective 1.3). Studies on dental caries are carried out in urban areas, although invasive dental procedures against this disease frequently occur in patients from rural areas (BRANDÃO et al., 2020), taking into account that knowledge of oral health conditions in this context (UN/SDG goal 1.4) - almost 20% of the country's inhabitants - is still superficial (IBGE, 2016). Inequalities in oral health should lead to the introduction of actions (UN goal/SDG 3.3) that reduce the health deficit of different social groups (MALDONADO, 2021) including in agribusiness workers (UN goal/SDG 3.4) where health promotion, disease prevention, and early intervention actions are low-cost and preserve quality of life (XIAUO et al., 2019) because reducing problems in the oral health of the community is a professional responsibility and, above all, of the State (UN/SDG objective 3.8).

The science of solving clinical problems through image analysis aims to extract information efficiently in the search for improvement in clinical diagnosis (SÁNCHEZ, 2021). Artificial intelligence is a technological advance that captivates researchers around the world. It does not replace the role of a human professional, but will be integrated into a rewarding and successful practice (KALAPPANAVAR, 2018) in the dental field, based on a computer system that performs tasks that require human knowledge and various skills such as recognizing patterns and images, understanding open written and spoken language, perceiving relationships/nexuses, following decision algorithms, understand concepts, reason through the integration of new experiences by self-improvement, solving problems and performing tasks (LOBO, 2018).

Interpreting images is a preliminary phase to the diagnosis and dental treatment plan. The combination of artificial intelligence and Dental Radiology improves diagnostic accuracy, professional routine, provides data, prioritizes exams according to severity (LIEW, 2018) generates descriptive reports, measures lesions saving clinical time, retrieves previous data or finds similar findings in other images, providing a list of possibilities (YAJI et al., 2018) establish parameters, including improving forensic identification (De TOBEL et al., 2017) as the success of an algorithmic system in relation to tooth detection/numbering approaches the level of experts (LEE et al., 2020). GEETHA et al. (2020) used an artificial neural system to check for caries on radiographs: the accuracy was 97.1%. Neural networks detect/classify dental restorations (ABDALLA-ASLAN, et al., 2020) with an accuracy of 93.6%. In recent years, advances in the area of technology have been developing the large area of health, specifically in the analysis of radiological images (SÍLIO, ET., AL 2023).

Thus, the objective of this research is to demonstrate the importance of developing a convolutional system of analysis of dental radiographic images, capable of identifying individuals and pathologies in individuals living/domiciled in rural areas/agribusiness workers, which speeds up the indication of exams, diagnosis, referral, pointing out the spatial/geographic distribution of these patients, in the support prior to decision making in public/private dental services (UN goal/SDG 16.17).

METHODOLOGY

The research was characterized/modeled as a descriptive research through a bibliometric survey in national and international databases (PUBMED, SCIELO, SCOPUS, BBO) in view of the proposed theme (use of convolutional networks in radiology and other dental specialties) through the use of key terms and previously established Boolean descriptors, namely: "DENTISTRY" *and/or* "CONVOLUTIONAL NETWORKS" *and/or* "AGRIBUSINESS" *and/or* ORAL DIAGNOSIS" respectively (but not necessarily in this order).

To carry out the literary survey, the following parameters were chosen, characterized as filters: 1) the exclusion of publications that did not provide full text; 2) simple abstracts; 3) publications that were outside the 8-year time window; 4) publications that were outside the proposed context, thus obtaining a "base" database of publications.

With the review, these publications were read and consequently the information/content that related/inserted or pointed to convolutional networks as "formative bases" of a forensic dental identification platform on the following aspects: 1) dental identification by differentiating permanent or deciduous dental elements of individuals, as shown in Figure 1:

Figure 1: FDI Scientific Notation for dental identification.

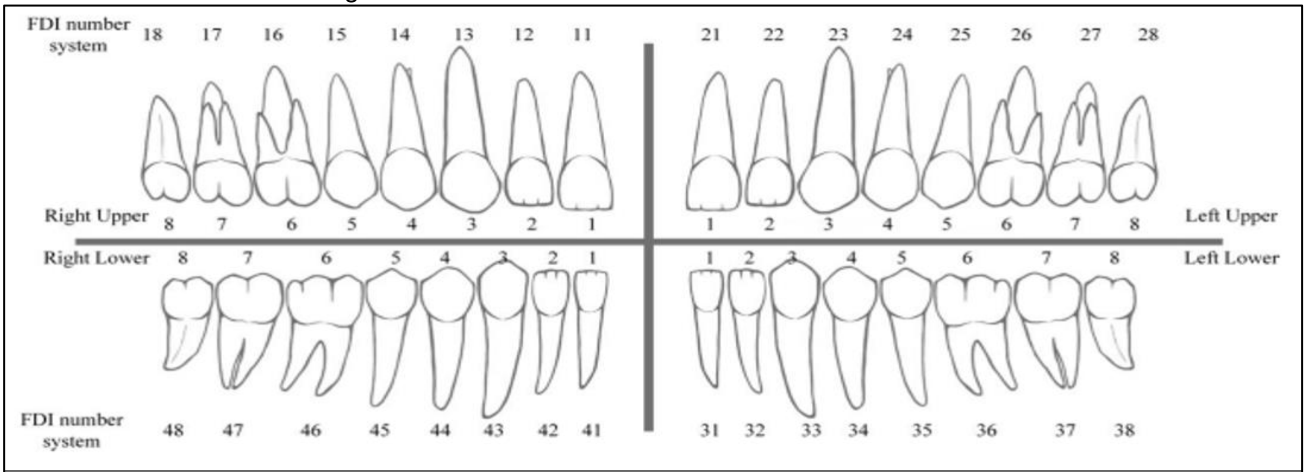


Figura 1:Sistema de numeração dos dentes FDI: 11–18=superior direito 1–8, 21–28=superior esquerdo 1–8, 31–38=inferior esquerdo1–8, 41–48=inferior direito 1–8; 1. Incisivo central, 2. Incisivo lateral, 3. Canino, 4. Primeiro pré-molar, 5. Segundo pré-molar, 6. Primeiro molar, 7. Segundo molar, 8. Terceiro molar.

Source: Adapted from Hu Chen, 2018.

Another aspect considered in the analysis of the publications was the concern with the use of artificial intelligence in the identification of the presence and identification of existing dental treatments, as shown in Figure 2:

Figure 2: Artificial Intelligence performance in the interpretation of intraoral images.

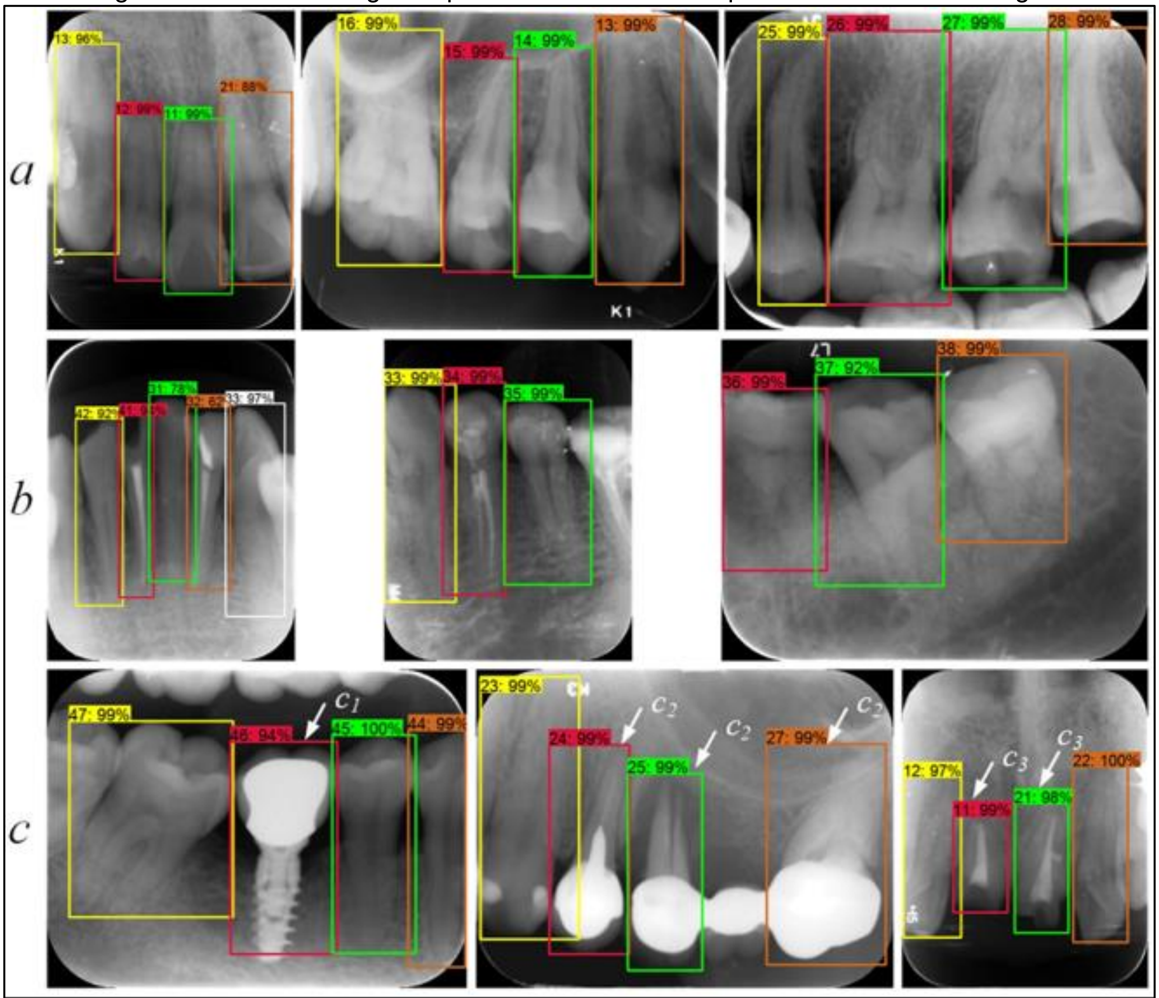


Figura 2 - Imagens de amostra anotadas corretamente por redes neurais no conjunto de dados de teste: (a) dentes superiores e (b) dentes inferiores, incluindo incisivos, caninos, pré-molares e molares; (c) alguns casos complicados, incluindo (c1) restauração de implante, (c2) coroa e ponte, (c3) dentes defeituosos.

Source: Adapted from Hu Chen, 2018.

Regarding the use of these convolutional networks in Dental Science, the focus of this research remained on their use in different dental specialties (regardless of whether this specialty is present and performed daily in the public and/or private dental care network) with filters of this collection of information/content in these publications: 1) the clinical analysis of new cases and those under treatment (in view of the addition of clinical information of these patients); 2) the identification and diagnosis of lesions in hard tissues (dental elements and respective bone bases – maxilla/mandible) such as dental caries, periodontal disease, oral cancer, presence and indication of endodontic treatment, orthodontics, use and need for prostheses, use and need for osseointegrated dental implants; 3) convolutional networks, which have an auxiliary character in decision-making regarding treatment possibilities; 4) the use of intra/extraoral radiographs (mainly panoramic radiographic shots) of dental patients in the training of these convolutional networks and the use of these types of images so that they can assist in decision-making to help the dental surgeon.

RESULTS

Artificial intelligence has recently attracted significant public interest and is impacting many industries worldwide. Especially in health care, it promises to be truly transformative (RODRIGUES, et al., 2021) and the (clinical/routine) use of this type of information technology in the dental profession has increased substantially in recent years.

Employing technology, especially artificial intelligence technology, in the medical and dental field reduces costs, time, improves the quality of care, reduces human intervention and subjective errors to it, in addition to characterizing the era in which we currently live: "the Fourth Industrial Revolution" (KHANNA, 2016) because it is a fact that the combination of artificial intelligence with professionals in the radiological area (Radiologists) results in the formation of a form of hybrid intelligence, which promises to achieve even higher levels of diagnostic accuracy (LIEW, 2018).

The impact of artificial intelligence on the radiologist's routine should be gradual, providing data that the professional cannot extract from the images, prioritizing exams according to severity (PAIVA, 2017).

In certain areas of Radiology, artificial intelligence is capable of generating radiological reports with a preliminary description of the imaging findings and measurement of some lesions, and can even detect small changes in the images, saving time and helping in the recovery of previous patient data or finding similar findings in other images, providing a list of possibilities, improving the diagnosis and consequently the treatment plan offered to the clinical case in question.

That said, after the search in the databases, with the application of the key terms and established Boolean descriptors, a bibliometric review was carried out, in view of the assembly of a database/publications of interest and, after the extraction of the information/contents of these publications, a descriptive overview was obtained about the importance and practical functionality of a convolutional platform for the acquisition and classification of clinical data and photographic and radiographic images Intra/extraoral, emphasizing the importance that, allied to it, there must be a specialist system with a motor algorithm that allows inferring diagnoses suggestive of detection, capable of issuing opinions with decision support elements for referral to public/private dental services, facilitating the access of agribusiness workers to preventive/curative dental services. A total of 43 national and international articles were found, and after applying the respective filters, 20 of them were excluded.

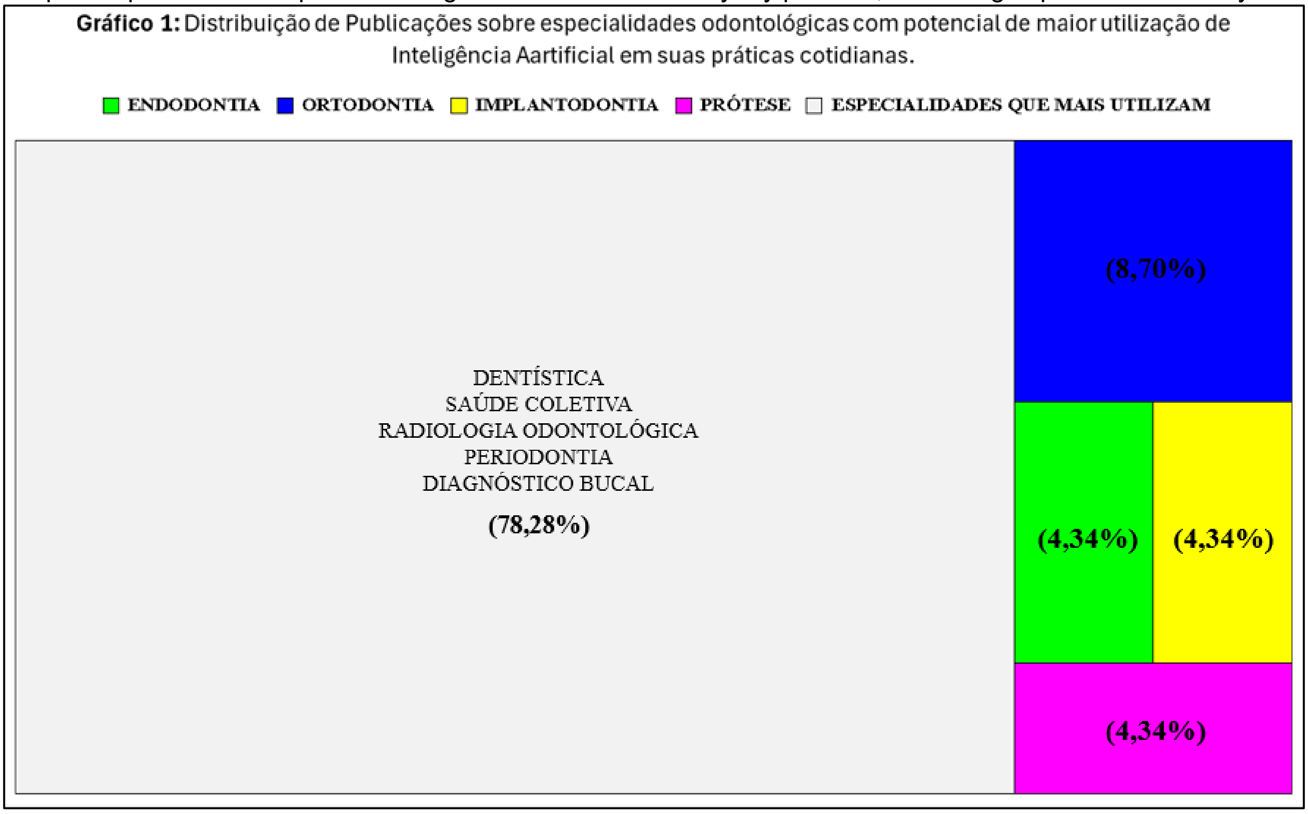
From the remaining publications (N=23) it was possible to prepare Table 1 (which represents the main specialties that use artificial intelligence in daily clinical practice) and Graph 1, which shows the specialties that make little use of this information technology (according to the bibliometric survey carried out), but which certainly has pointed out in its conclusions the positive potential for improvement in the quality of dental care provided.

Table 1: Distribution of publications on dental specialties that most use convolutional networks in daily clinical practice.

DENTAL SPECIALTIES	PUBLICATIONS (N)	PUBLICATIONS (%)
DENTISTRY	5	21,74%
COLLECTIVE HEALTH	3	13,05%
DENTAL RADIOLOGY	3	13,05%
PERIODONTICS	4	17,39%
ORAL DIAGNOSIS	3	13,05%
TOTAL	18	78,28%

Image Source: The authors.

Graph 1: Specialties with potential for greater use of AI in everyday practice, according to publications analyzed.



Source: The authors.

DISCUSSION

It is possible to say that through past data and through statistical algorithms, the machine will be able to learn how an association should be made. This process, according to Hurwitz and Kirsch (2019) occurs through training, which, also according to the authors, is informed of previous data of entries, which can be historical data, purchases, geographic locations, characteristics of customers/patients, and how this data was classified. It should be noted that without any association rule being defined, the algorithm itself, through statistical tests, will learn and define the rules that define how the input data are related to its classifications (LIN et al., 2021; UTHOFF et al., 2018; WELIKALA et al., 2020). The authors emphasize the fact that due to this process (of learning by oneself) the relationship of the input data with the data of their classifications, *Machine Learning (ML)* began to be used in the health area.

Through this "reasoning" model, whenever a new patient emerges, the algorithm can be used to predict who this patient is, or whether or not a patient has a disease, if the model has already been trained to recognize these signs (through images already analyzed) or symptoms with the disease coming from pre-inserted clinical information and new insertions (Al-RAWI et al., 2022; AUBREVILLE et al., 2017; MAHMOOD et al., 2020; SONG et al., 2021; UTHOFF et al., 2018; WELIKALA et al., 2020; KAYA, 2022).

Figure 2: Artificial Intelligence performance in the interpretation of intraoral images.

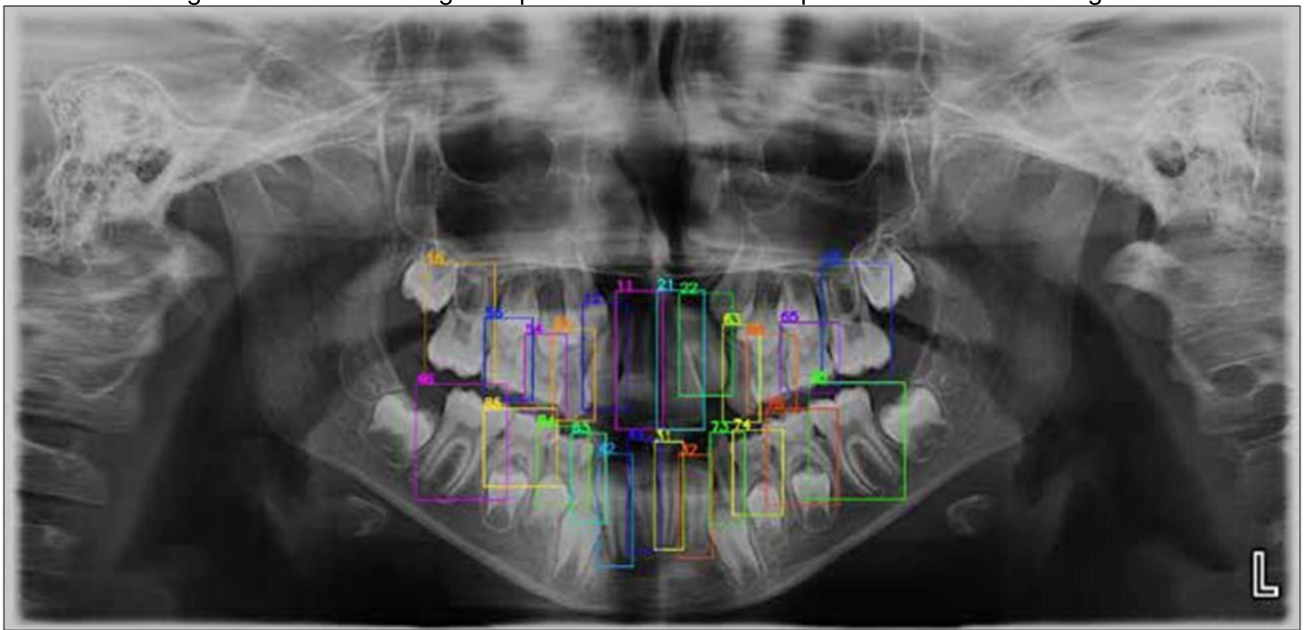


Figura 3 - Resultados da detecção e numeração de dentes permanentes e primários no YOLO V4. As saídas de numeração são escritas com base na notação científica FDI.

Fonte: Adapted from Kaya, 2022.

According to Erickson et al (2017), when using *Machine Learning (ML)* for image-based diagnosis, X-ray images or images of the region where the sign and symptom stand out are routinely used, both in new patients and in patients already undergoing previous treatments (such as training input data) as well as information on which of these patients had or did not have the disease to be analyzed. In this way, the algorithm extracts information on color tones, textures, and formats from the contents of the images that can be converted into numbers to be used in training, generating the rules that will be used to predict images in future new patients.

Tooth decay is the most common dental disease and that is why its early stage disclosure is crucial. For the screening and diagnosis of tooth decay, dentists often use dental probes and, through observation of texture and discoloration, can determine whether the tooth is healthy or not. This method is very subjective and is based on the dentist's experience. In particular, proximal surfaces can be problematic on dental examination (BELTRÁN-AGUILAR, et al., 2005). Within this context, Devito et al. (2008) used an artificial neural network to classify proximal dental caries in order to predict whether an orthodontic treatment would require extraction. Moghimi et al. (2012) used artificial neural networks to predict the size of unerupted canines and premolars, within the context of human identification.

In this sense, within the context of the use of artificial intelligence in human identification, in the detection of pre-existing dental treatments and in the identification of new lesions in hard and soft tissues of the oral cavity, aiming at adequate referral of patients to primary, secondary and tertiary oral health services (when necessary), and according to the results of this work, it is noted: 1) that dental caries is a major concern, with 21.74% of the total articles analyzed in the sample due to the fact that it is the most prevalent oral disease, according to the dental literature analyzed; 2) according to the data collected, within the "Collective Health" specialty, the concern with caries diagnosis procedures (including analysis of intra and extra-oral radiographic shots) is present in 26.10% of the studies analyzed (13.05% of studies in the area of Collective Oral Health and 13.05% in Dental Radiology associated with Collective Health); 3) the specialty of Dental Radiology (and Imaging), although being by definition the most interested in the use of this promising information technology, is still timid, in comparison to other specialties, being alone the holder of 13.05% of the publications analyzed.

The detection of dental caries, for example, in intraoral radiological images, can undoubtedly be aided by neural networks, which makes the examination faster and more accurate, but the use of neural networks in conservative dentistry, even though it develops rapidly, is not yet widespread (SUWADEE, 2006). Regarding the main techniques used by the authors (in the analyzed publications), the following are: 1) the periapical intraoral radiographic technique; 2) the interproximal intraoral radiographic technique; 3) the panoramic extraoral radiographic technique, due to the gain in the examination area, using the same dose of radiation, among other intrinsic advantages. Geetha et al., (2020) used an artificial neural network to determine whether or not there were cavities in the 105 X-ray images. They extracted sixteen feature vectors from the segmented image and these were the input nodes. There were two exit nodes that consisted of cavities or healthy teeth. The accuracy of caries detection was 97.1%, and the false positive rate was 2.8%. This study indicates that neural networks can be much more accurate in detecting tooth decay than traditional dental examination. CBCT (computed tomography) is used less frequently in the detection of dental caries (PRADOS-PRIVADO, 2020), being used more in cases of soft tissue lesions because algorithms can be used to locate the edges of anatomical and pathological structures, which can be very similar to each other due to image noise and low contrast (GRAVEL, 2004).

It is also important to highlight in this work the fact that periodontal problems can also be diagnosed through analyses from convolutional networks. According to 31.4% of the studies analyzed, their contents associate the discipline/specialty "Diagnosis in oral health" and "Periodontics". In other words, 31.4% of the studies point to the use of neural networks in the identification of dental support tissue problems as secondary (intrinsic) parameters to the specialty "Oral Diagnosis" based on the most prevalent periodontal diseases and their most suggestive images). By definition and conceptualization, preventive orthodontics is characterized by studies and diagnostic protocols/standards based on minimal clinical interventions in cases of disorders of the stomatognathic system. The use of convolutional networks in this context can be expressed in 8.70% of the studies analyzed. The specialties Endodontics, Implantology and Prosthesis accounted for 4.34% of the percentage of publications each.

CONCLUSION

Through this brief bibliometric review, it is clear that the construction and, above all, the wide use of convolutional networks in different dental specialties can undoubtedly contribute to the improvement of primary oral health care, in the private care network and, above all, in the public network. And yet: agribusiness workers (who do not access, or partially access, such services) would have a significant increase in quality of life, oral health indices and indicators, and especially in their productivity, as convolutional networks would speed up diagnoses of dental caries, periodontal disease, endodontic treatments, bone lesions, neoplasms, use/need for prostheses and implants, in addition to serving as a bridge of access/referral to primary care services (health care units). municipal health and/or private offices), secondary care (specialty centers) and complex oral health care (specialized hospitals).

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