REVIEW ARTICLE

Jurnal Radiologi Dentomaksilofasial Indonesia August 2022, Vol. 6, No. 2: 89-94
P-ISSN.2685-0249 | E-ISSN.2686-1321

http://jurnal.pdgi.or.id/index.php/jrdi/index

Artificial intelligence based on Convolutional Neural Network for detecting dental caries on bitewing and periapical radiographs

Amelia Roosanty[1], Rini Widyaningrum[2*], Silviana Farrah Diba[2]

ABSTRACT

Objectives: This narrative review is written to describe the accuracy of caries detection and find out the clinical implications and future prospects of using Convolutional Neural Network (CNN) to determine radio-diagnosis of dental caries in bitewing and periapical radiographs.

Review: The databases used for literature searching in this narrative review were PubMed, Google Scholar, and Science Direct. The inclusion criteria were original article, case report, and textbook written in English and Bahasa Indonesia, published within 2011-2021. The exclusion criteria were articles that the full text could not be accessed, research article that did not provide the methods used, and duplication articles. In this narrative review, a total of 33 literatures consisting of 30 articles and three textbooks reviewed, including four original articles on CNN for caries detection.

Conclusion: Results of the review reveal that GoogLeNet produces the best detection compared to Fully Convolutional Network (FCN) and U-Net for caries detection in bitewing and periapical radiographs. Nonetheless, the positive predictive value (PPV), recall, negative predictive value (NPV), specificity, F1-score, and accuracy values in these architectures indicate good performance. The differences of each CNN's performances to detect caries are determined by the number of trained datasets, the architecture's layers, and the complexity of the CNN architectures. The conclusion of this review is CNN can be used as an alternative to detect caries, increasing the diagnostic accuracy and time efficiency as well as preventing errors due to dentist fatigue. Yet the CNN is not able to substitute the expertise of a radiologist. Therefore, it is need to be revalidated by the radiologist to avoid diagnostic errors.

Keywords: *Dental caries, bitewing radiograph, periapical radiograph, deep learning, convolutional neural network*

Cite this article: Roosanty A, Widyaningrum R, Diba SF. *Artificial intelligence based on Convolutional Neural Network for detecting dental caries on bitewing and periapical radiographs.* Jurnal Radiologi Dentomaksilofasial Indonesia 2022;6(2) 89-94. https://doi.org/10.32793/jrdi.v6i2.867

INTRODUCTION

The evolution of times must be followed by a rapid technological development. The growth of artificial intelligence (AI) is tangible evidence from technological development. Artificial Intelligence is a computerized system which can imitate human's intelligence so they can make their own decisions.[1,2] One of tremendous development in radiology is the discovery of Computer-Aided Diagnosis Systems (CADs).[3] The CADs are an example of AI that can be used to detect diseases and assist practitioners in making diagnoses. One application of CADs is the use of machine learning (ML) systems, which can automatically process and analyze images and produce algorithms from previously trained data.[4]

Convolutional neural network (CNN) is a part of machine learning that consists of some computing network layers that can learn data component and change the image volume to a specific classification.[4] Convolutional neural network is the most recent advancement from artificial neural network that mimics the neurological system of human in responding to stimuli.[1] The CNN layers include convolution layers, pooling layers, fully connected layers, and drop out layers. The functions of CNN's layers are to gradually learn about data characteristics. Convolution layers are used to extract features from input data and then proceed the data convolutionally, providing linear transformation based on the data. The functions of pooling layers are to prevent overfitting due to image reduction. The fully connected layer is a layer that will transform the data so it can be classified linearly using vectors. The dropout layer is a layer that can randomly regularized and eliminate neurons and make the program works and learns the input faster.[5,6] Convolutional neural network is able to classify two-dimensional image as input, and when integrated with a deep learning algorithm, they may be utilized to identify abnormalities and diseases in the human body. In dentistry, CNN can be used to assist practitioners in recognizing anomalies in radiographs, such as bone resorption and dental caries.[7,8,9]

Dental caries is a tooth disease which induced

[1]Faculty of Dentistry, Universitas Gadjah Mada, Yogyakarta, Indonesia 55281

[2]Department of Dentomaxillofacial Radiology, Faculty of Dentistry, Universitas Gadjah Mada, Yogyakarta Indonesia 55281

[*]Correspondence to:
Rini Widyaningrum
rinihapsara@ugm.ac.id

Received on: April 2022
Revised on: July 2022
Accepted on: July 2022

by the activity of *Streptococcus mutans* and *Streptococcus sorbinus.*[10] The prevalence of dental caries is up to 72.6% which indicates dental caries is one of the most common dental diseases that found in Indonesia.[10] If dental caries is not treated, it will extend to the deeper tooth layer, making the host uncomfortable due to discomfort and, as a result, affecting the quality of life.[11] Given these considerations, early identification of caries is essential in order to avoid future risks and complication.[12] Early detection of dental caries can be done by visual observation with using basic instruments such as probe to detect caries lesion.[13] Another method for detecting caries lesion is observing radiographs, particularly bitewing and periapical radiographs, to detect the caries extension to deeper tooth layers.[14,15]

The development of computerized technology especially AI being used to support diagnosis is growing rapidly. Yet there is lack of information on CNN's applications for caries detection using bitewing and periapical radiographs, so that this review is aimed to provide more information that systematically written about the accuracy of dental caries detection, as well as to describe the clinical implications and future prospects of CNN-based AI for detecting caries using bitewing and periapical radiographs.

REVIEW

This narrative review describes the accuracy of dental caries diagnosis using CNN on periapical and bitewing radiographs as the input for image processing. The literatures in this review were collected from three databases, i.e. ScienceDirect, PubMed, and Google Scholar. The literature searching was done by using some keywords. The keywords were periapical radiography, bitewing radiography, dental caries, convolutional neural network, and deep learning. Boolean formula such as AND, OR, "" and () also used to simplify the literature searching. Indonesian and English original article, case report and textbook which published within 2011-2021 are the inclusion criteria for the literature searching. Meanwhile, articles which their full text could not be accessed, original article which doesn't contain its methods, and article with duplication must be removed because they were the exclusion criteria.

Figure 1 illustrates the flow of the literature searching for the review. Total of 3206 articles were obtained from three databases. Following that, a selection of articles with duplication was performed, resulting in the elimination of 1532 articles and the maintenance of 1674 articles. The criteria for inclusions and exclusions were then

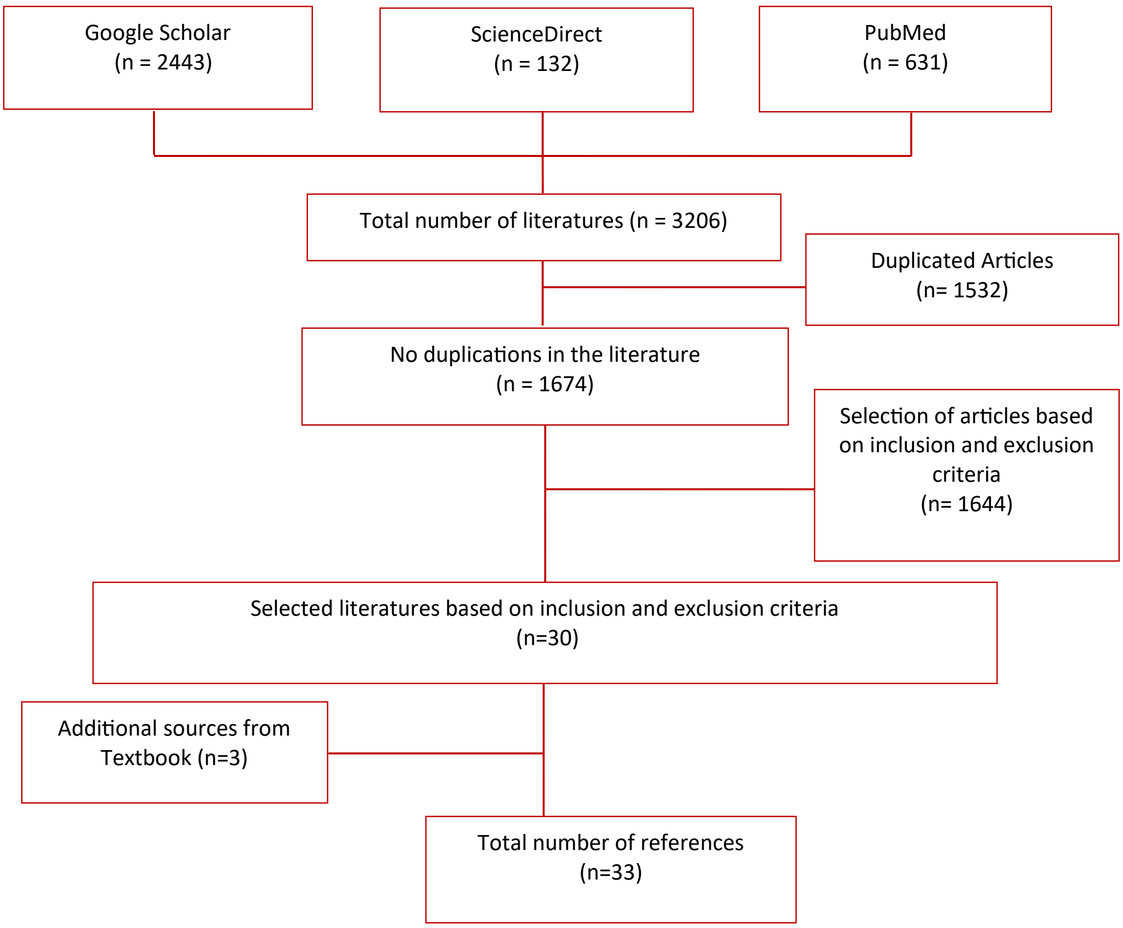

Figure 1. The literature searching and selection for the review

carefully selected, leaving 30 articles. Three textbooks were added as the supplementary literatures which made total of 33 literatures were reviewed in this narrative review. Due to the obvious scarcity of research conducted to develop CNN for caries detection on bitewing and periapical radiographs, only four of 33 articles were identified as the main articles to be discussed in this review. The others were used for supporting the theories and to describe the clinical implementations and future prospect of using CNN for caries detection. The main articles were divided into two divisions, two articles clarified the accuracy of caries detection using CNN with periapical radiograph as the input image, while the other two did the research with bitewing radiograph as the input image.

DISCUSSION

This narrative review comprises four main literatures that demonstrate CNN's ability to detect caries lesions. In this narrative review, two types of indicators are used, one for evaluating its validity and the other for evaluating the algorithm used in detecting caries lesions in bitewing and periapical radiographs. The positive predictive value (PPV), recall, negative predictive value (NPV), and specificity were used for measuring the validity of the system's capability to detect caries. On the other hand, F1-Score and accuracy were used for assess the performance of algorithms that were produced by the system for detecting caries. Only three CNN architectures i.e. FCN, U-Net, and GoogLeNet, were used in the four main studies discussed in this review to develop deep learning for caries detection on periapical and bitewing radiographs.[16,17,18]

The differences of FCN, U-Net and GoogLeNet architectures are the structures and the numbers of layer contain in each architecture used for detecting images as input data. FCN is the most fundamental CNN architecture, with only main layers such as convolution, pooling, and ReLU.[19,20,21] U-Net is a development of FCN architecture that is mostly used for processing biomedical image because it can classify data efficiently and provide accurate output in a short time.[9] U-Net can be recognized by its symmetrical architecture by its three main parts; down-sampling, bottleneck and up-sampling parts.[9] GoogLeNet is an architecture with various pooling layer sizes to process input in various sizes ranging from 1x1 pixel to 7x7 pixel, so it is capable to improve object detection and classification accuracy.[18,22]

In this review, the first indicator used to assess the accuracy of CNN for detecting caries lesions is PPV. Positive predictive value indicates the possibility of a disease being revealed after the instrument indicates a positive result for disease detection.[23] As shown in Table 1, the average PPV for all studies are ≥0.600. The recall indicator, which can show the system's ability to detect a disease[24], is also used in these studies. According to Table 1, the recall value is ≥0.650. Lee et al. (2018)[18] obtained the highest performances from these two values, with a PPV index of 0.827 and a recall index of 0.810. After all, all of the studies produce high recall results, with the exception of the experiment using U-Net architecture and bitewing radiographs as input data, which produces a moderate recall,

Table 1. The Performance of CNN-based AI for Detecting Caries Lesion using Bitewing and Periapical Radiographs (PPV, Recall, NPV, Specificity)

CNN ARCHITECTURES	NUMBER OF SAMPLES USED FOR SYSTEM'S TRAINING	NUMBERS OF SAMPLES FOR ACCURACY TESTS	PPV	RECALL (SENSITIVITY)	NPV	SPECIFICITY
FCN (Srivastava et. al., 2017)[16]	2500 bitewing radiographs	500 bitewing radiographs	0.615	0.805	-	-
U-Net (Cantu et. al., 2020)[9]	3293 bitewing radiographs	393 bitewing radiographs	0.700	0.750	0.860	0.830
U-Net (Lee et. al., 2021)[17]	304 bitewing radiographs	50 bitewing radiographs	0.633	0.650	-	-
GoogleNet (Lee et al., 2018)[18]	2400 periapical radiographs	600 periapical radiographs	0.827	0.810	0.820	0.830

Table 2. The Performance of CNN-based AI for Detecting Caries Lesion using Bitewing and Periapical Radiographs (F1-Score and Accuracy)

CNN ARCHITECTURES	NUMBER OF SAMPLES USED FOR SYSTEM'S TRAINING	NUMBER OF SAMPLES FOR TESTING THE PERFORMANCE OF CNN'S ALGORITHM	F1-*SCORE*	ACCURACY
FCN (Srivastava et. al., 2017)[16]	2500 bitewing radiographs	500 bitewing radiographs	0.700	-
U-Net (Cantu et. al., 2020)[9]	3293 bitewing radiographs	393 bitewing radiographs	0.730	0.800
U-Net (Lee et. al., 2021)[17]	304 bitewing radiographs	50 bitewing radiographs	0. 650	-
GoogleNet (Lee et al., 2018)[18]	2400 periapical radiographs	600 periapical radiographs	0.818*	0.820

that indicate moderate sensitivity as well. According to the theory demonstrated by Chan et al. (2017), the recall number that is considered as a high sensitivity is ≥0.700.[25] These indicators demonstrate that periapical radiographs fed into the GoogLeNet architecture produce the best results for detecting caries lesions.

The third indicator used in the review to assess CNN's performance in detecting caries lesions is NPV. Negative predictive value is an indicator indicates the possibility of a disease going undetected after the instrument or system produce a negative result in the detection of a disease.[23] Based on the results of this review in Table 1, the best NPV result was obtained by Cantu et al. (2020) [9], who developed U-Net architecture using datasets of bitewing radiographs, even though the result did not differ significantly from the other studies.

The last indicator to show CNN's validity to detect caries is specificity. Specificity is an indicator that indicates the system's ability to detect caries-free area[(24)]. According to Table 1, the CNN method for detection of caries lesion on using bitewing radiograph that apply the U-Net architecture developed by Cantu et al. (2020)[9] reveals the similar specificity to Lee et al. (2018).[18] Lee et al. (2018)[18] developed a GoogLeNet architecture to empower a CNN to detect caries lesions on periapical radiographs. Both the U-Net and GoogLeNet architectures have a high specificity in detecting caries on radiographs, which means they are accurate in revealing areas that are not affected by caries lesions.

F1-score is a metric that measures CNN's ability to create an algorithm for stating a diagnosis on a scale of 0 to 1.[26] Table 2 shows that the F1-score values from all studies that developed CNN for caries detection are ≥0.650. Table 2 also indicates that three different CNN architectures developed in four studies in the review have a high potential to be developed in detecting caries lesions. However, the studies must be improved further in order to produce a higher F1-score and a more reliable result to support the radio-diagnosis of caries lesion on intraoral radiographs.

Despite the fact that two studies conducted by Cantu et.al. (2020)[9] and Lee et.al. (2021)[17] establish the identical CNN architecture (U-Net), the recall and F1-score values in those studies varied, as shown in Tables 1 and 2.[9,17] The amount of radiograph datasets utilized in the studies may have influenced the discrepancies. Deep learning processes datasets based on its prior experience. The accuracy and complexity of the outcomes will improve when more datasets are used as input data.[27,28]

The accuracy of CNN's algorithm performance is an indicator to show the system's ability to classify the input data proceed in the system.[29] From Table 2, it shows that only two experiments show the accuracy and both are above 0.800 which means they have a great ability in classifying input data which will be proceed by the system.

Overall, GoogLeNet with periapical radiograph as input data produces the best performance of those indicators. This may be happened because GoogLeNet outperforms CNN in terms of accuracy because it has multiple convolution layers of varying sizes on the same level. These layers can help to reduce overfitting incidences, which will help to increase accuracy and shorten the time it takes to detect the object. As the result, GoogLeNet is way more accurate than FCN and its derivate by 0,6% in making classification and detecting an object.[30] In addition, periapical radiographs also have better geometrical accuracy than bitewing radiographs due to the lower magnification, which prevents radiograph distortion so it may help the system to recognize caries lesions better.[31] Furthermore, periapical radiographs provide a better view for tooth coronal than bitewing radiographs, allowing them to identify caries lesions more accurately.[30,31]

The indicators that used to measure the capability of machine's ability to detect disease and making diagnosis are mainly depend on sensitivity and specificity. The greater sensitivity shows the machine's ability to detect the disease and greater specificity used for showing the disease-free area. For this case, there are still limited publication that compare the dentist's and CNN's decision for making a caries diagnosis. From the publication that have been released, CNN has been proven to have a significantly better specificity but has a lower specificity compared to the dentists.[9] Moreover, the accuracy of using CNN to detect objects in radiographs is remarkably similar to an experienced dentist's decision, so it can be considered as a helpful tool for analyzing radiographs for diagnosis.[9] Therefore, CNN can be regarded as a useful tool for analyzing radiographs for diagnosis, and it will reduce the dentist's workload, particularly when detecting initial caries lesions, and the time required to interpret radiographs.[7,18] Even though CNN supposes promising, the dentist must revalidate its results because it has a tendency to over-detect the dental caries on radiographs. Furthermore, the lack of specificity in CNN detection can be balanced with dentist diagnostic skills. This can be taken into consideration that CNN cannot replace the dentist's role in making diagnosis so that the patients will be given a propriate treatment not an overtreatment due to possibility of CNN's error. Dentist also play roles in the initial training process of CNN. They have to choose a proper radiograph that will be used as an input to create an ideal algorithm. As a results of this consideration, it is clear that artificial intelligence systems will not change the role of a dentist. Nevertheless, CNN can be used to assist dentists in making a diagnosis in order to reduce radiographic interpretation workload and time consumption.

CONCLUSION

Based on the review, it is possible to conclude that the use of CNN produces a good performance for detecting caries lesion. However, it cannot yet replace the role of a dentist or radiologist in diagnosing a caries lesion due to lack of specificity and bigger chance for having an overdiagnosis from detecting caries so there might be some errors while the CNN is trying to detect caries lesions. The recent use of a convolutional neural network only assists the dentist in reducing the number of misinterpreted caries lesions in radiographs due to fatigue from a heavy workload, as well as reducing interpretation time so that the work is completed efficiently.

ACKNOWLEDGMENTS

This review is part of the first author's undergraduate thesis, which was supervised by other authors. The authors acknowledge the Faculty of Dentistry Universitas Gadjah Mada for providing support in this work.

FOOTNOTES

All authors have no potential conflict of interest to declare for this article.

REFERENCES

1. Schwendicke F, Singh T, Lee JH, Gaudin R, Chaurasia A, Wiegand T, Uribe S, Krois J; IADR e-oral health network and the ITU WHO focus group AI for Health. Artificial intelligence in dental research: Checklist for authors, reviewers, readers. J Dent. 2021 Apr;107:103610.
2. Azwary F, Indriani F, Nugrahadi DT. Question Answering System Berbasis Artificial Intelligence Markup Language. Kumpul J Ilmu Komput. 2016;04(01):48–60.
3. Bui TH, Hamamoto K, Paing MP. Deep Fusion Feature Extraction for Caries Detection on Dental Panoramic Radiographs. Appl Sci. 2021;11(5):2005.
4. Indolia S, Goswami AK, Mishra SP, Asopa P. Conceptual Understanding of Convolutional Neural Network- A Deep Learning Approach. Procedia Comput Sci [Internet]. 2018;132:679–88.
5. Putra WSE. Klasifikasi Citra Menggunakan Convolutional Neural Network (Cnn) Pada Caltech 101. J Tek ITS [Internet]. 2016;5(1):76.
6. Peryanto A, Yudhana A, Umar R. Klasifikasi Citra Menggunakan Convolutional Neural Network dan K Fold Cross Validation. J Appl Informatics Comput. 2020;4(1):45–51.
7. Ariji Y, Yanashita Y, Kutsuna S, Muramatsu C, Fukuda M, Kise Y, Nozawa M, Kuwada C, Fujita H, Katsumata A, Ariji E. Automatic detection and classification of radiolucent lesions in the mandible on panoramic radiographs using a deep learning object detection technique. Oral Surg Oral Med Oral Pathol Oral Radiol. 2019 Oct;128(4):424-30.
8. Kim D, Choi E, Jeong HG, Chang J, Youm S. Expert system for mandibular condyle detection and osteoarthritis classification in panoramic imaging using r-cnn and cnn. Appl Sci. 2020;10 (21):1–10.
9. Cantu AG, Gehrung S, Krois J, Chaurasia A, Rossi JG, Gaudin R, et al. Detecting caries lesions of different radiographic extension on bitewings using deep learning. J Dent [Internet]. 2020;100(July):103425.
10. Dianawati N, Setyarini W, Widjiastuti I, Ridwan RD, Kuntaman K. The distribution of Streptococcus mutans and Streptococcus sobrinus in children with dental caries severity level. Dent J (Majalah Kedokt Gigi). 2020;53(1):36.
11. Bukhari OM. Dental Caries Experience and Oral Health Related Quality of Life in Working Adults. Saudi Dent J [Internet]. 2020;32(8):382–9.
12. Manton DJ. Diagnosis of the early carious lesion. Aust Dent J. 2013;58(SUPPL.1):35–9.
13. Abdinian M, Razavi SM, Faghihian R, Samety AA, Faghihian E. Accuracy of Digital Bitewing Radiography versus Different Views of Digital Panoramic Radiography for Detection of Proximal Caries. J Dent (Tehran) [Internet]. 2015;12(4):290–7.
14. Takahashi N, Lee C, Da Silva JD, Ohyama H, Roppongi M, Kihara H, Hatakeyama W, Ishikawa-Nagai S, Izumisawa M. A comparison of diagnosis of early stage interproximal caries with bitewing radiographs and periapical images using consensus reference. Dentomaxillofac Radiol. 2019 Feb;48 (2):20170450.
15. White SC, Pharoah MJ. Oral radiography: Principles and

Interpretation. 7th ed. St.Louis: Elsevier; 2014.
16. Srivastava MM, Kumar P, Pradhan L, Varadarajan S. Detection of Tooth caries in Bitewing Radiographs using Deep Learning. 2017 Nov 20;
17. Lee S, Oh S il, Jo J, Kang S, Shin Y, Park J won. Deep learning for early dental caries detection in bitewing radiographs. Sci Rep. 2021;11(1).
18. Lee JH, Kim DH, Jeong SN, Choi SH. Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm. J Dent. 2018 Oct 1;77:106–11.
19. Long J, Shelhamer E., Darrell T. Fully Convolutional Networks for Semantic Segmentation. In IEEE Transactions on Patttern Analysis and Machine Intelligence. 2017:39(4);640-651.
20. Gadosey PK, Li Y, Adjei Agyekum E, Zhang T, Liu Z, Yamak PT, Essaf F. SD-UNet: Stripping Down U-Net for Segmentation of Biomedical Images on Platforms with Low Computational Budgets. Diagnostics (Basel). 2020 Feb 18;10(2):110.
21. Suta IBLM, Sudarma M, Satya Kumara IN. Segmentasi Tumor Otak Berdasarkan Citra Magnetic Resonance Imaging Dengan Menggunakan Metode U-NET. Maj Ilm Teknol Elektro. 2020;19(2):151.
22. Jahandad, Sam SM, Kamardin K, Amir Sjarif NN, Mohamed N. Offline signature verification using deep learning convolutional Neural network (CNN) architectures GoogLeNet inception-v1 and inception-v3. Procedia Comput Sci [Internet]. 2019;161:475–83.
23. Loh TP, Lord SJ, Bell K, Bohn MK, Lim CY, Markus C, Fares Taie H, Adeli K, Lippi G, Sandberg S, Horvath A. Setting minimum clinical performance specifications for tests based on disease prevalence and minimum acceptable positive and negative predictive values: Practical considerations applied to COVID-19 testing. Clin Biochem. 2021 Feb;88:18-22.
24. El-Ela WHA, Farid MM, El-Din Mostafa MS. Intraoral versus extraoral bitewing radiography in detection of enamel proximal caries: An ex vivo study. Dentomaxillofacial Radiol. 2016;45(4):20150326.
25. Chan M, Dadul T, Langlais R, Russell D, Ahmad M. Accuracy of extraoral bite-wing radiography in detecting proximal caries and crestal bone loss. J Am Dent Assoc [Internet]. 2018;149 (1):51–8.
26. DeVries Z, Locke E, Hoda M, Moravek D, Phan K, Stratton A, et al. Using a national surgical database to predict complications following posterior lumbar surgery and comparing the area under the curve and F1-score for the assessment of prognostic capability. Spine J [Internet]. 2021;21(7):1135–42.
27. Hulten G. Building Intelligent Systems. Building Intelligent Systems. New York: Apress; 2018.
28. Singh J, Dhiman G. A survey on machine-learning approaches: Theory and their concepts. Mater Today Proc [Internet]. 2021;(xxxx):1-7.
29. Fadlia N, Kosasih R. Klasifikasi Jenis Kendaraan Menggunakan Metode Convolutional Neural Network (Cnn). J Ilm Teknol dan Rekayasa. 2019;24(3):207–15.
30. Whaites E, Drage N. Essentials of Dental Radiography and Radiology E-Book. 5th ed. Churcill Livingstone: Elsevier Health Sciences; 2013.
31. Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, et al. Going deeper with convolutions. Proc IEEE Comput Soc Conf Comput Vis Pattern Recognit. 2015;07-12-June(June):1–9.
32. Zheng W, Zhang X, Kim JJ, Zhu X, Ye G, Ye B, et al. High Accuracy of Convolutional Neural Network for Evaluation of Helicobacter pylori Infection Based on Endoscopic Images: Preliminary Experience. Clin Transl Gastroenterol. 2019;10 (12):e00109.
33. Müller A, Mertens SM, Göstemeyer G, Krois J, Schwendicke F. Barriers and Enablers for Artificial Intelligence in Dental Diagnostics: A Qualitative Study. J Clin Med. 2021 Apr 10;10 (8):1612.