The Promise of Self-Supervised Learning for Dental Caries

Tran Quang Vinh, Haewon Byeon*
Department of Digital Anti-Aging Healthcare (BK21), Inje University, Gimhae 50834, South Korea

***Abstract*—Self-supervised learning (SSL) is a type of machine learning that does not require labeled data. Instead, SSL algorithms learn from unlabeled data by predicting the order of image patches, predicting the missing pixels in an image, or predicting the rotation of an image. SSL has been shown to be effective for a variety of tasks, including image classification, object detection, and segmentation. Dental image processing is a rapidly growing field with a wide range of applications, such as caries detection, periodontal disease progression prediction, and oral cancer detection. However, the manual annotation of dental images is time-consuming and expensive, which limits the development of dental image processing algorithms. In recent years, there has been growing interest in using SSL for dental image processing. SSL algorithms have the potential to overcome the challenges of manual annotation and to improve the accuracy of dental image analysis. This paper conducts a comparative examination between studies that have used SSL for dental caries processing and others that use machine learning methods. We also discuss the challenges and opportunities for using SSL in dental image processing. We conclude that SSL is a promising approach for dental image processing. SSL has the potential to improve the accuracy and efficiency of dental image analysis, and it can be used to overcome the challenges of manual annotation. We believe that SSL will play an increasingly important role in dental image processing in the years to come.**

Keywords—Machine learning; dental imaging; dental caries; oral diseases

I. Introduction

Artificial intelligence (AI) represents a domain within computer science that focuses on crafting intelligent entities, these being systems endowed with the capacities of logical deduction, knowledge acquisition, and independent decision-making. The field of AI has witnessed remarkable achievements in formulating potent methodologies to address a diverse spectrum of challenges, spanning from strategic game playing to intricate medical diagnostics [1]. Interest in the medical application of AI has lately surged due to the impact of this technology on the outcome and caliber of clinical practice during and after the 1980s [2]. Precision medicine, population health, and natural language processing are just a few of the areas of healthcare and medical practice where AI has been researched [3].

Machine learning (ML), a type of AI that allows computers to learn without being programmed. ML algorithms are trained on large datasets of data, and they can then be used to make predictions or decisions. ML is being used in a variety of medical applications, including diagnosis, treatment planning, drug discovery, personalized medicine, and healthcare management. ML algorithms have been shown to be effective in a variety of tasks, such as detecting cancer, planning radiation therapy, and identifying potential new treatments for diseases [4].

Annotation in medical imaging is the process of labeling or describing medical images with relevant information. This information can be used to train machine learning algorithms to diagnose diseases, plan treatments, or conduct research. There are a variety of ways to annotate medical images, including: Manual annotation, Semi-automated annotation, and Automated annotation [5]. Nonetheless, the substantial expenses tied to acquiring essential specialized annotations often impede endeavors to employ machine learning algorithms for aiding clinical applications. Even partially automated software tools might fall short of significantly alleviating the financial burden associated with annotations. [5]. Self-supervised representation learning [6] is a type of machine learning that learns to represent data without being explicitly labeled. This is in contrast to supervised learning, where the data is labeled with the desired output. Recently, interest in these techniques has increased [7, 8]. In particular, self-supervised representation learning may enhance label effectiveness and performance in scenarios involving the classification of dental caries. In the area of dental caries, this article reviews self-supervised algorithm and compare it to other learning techniques.

II. Materials and Methods

A. Artificial Intelligence and Machine Learning in Dental Caries

Dental caries, commonly known as tooth decay, is a disease that causes tooth decay by bacteria in the mouth producing lactic acids, which directly harm the tooth surface layer known as the enamel layer. This can progressively lead to a small hole or cavity in the teeth; if not treated, this can cause discomfort, infection, and finally tooth loss [9]. Early detection of carious lesions is necessary for the management of dental caries.

The discipline of dentistry saw the emergence of AI, just like other industries. In a dental clinic, it can carry out simple and difficult tasks with higher precision, accuracy, sensitivity, and—most importantly—in less time [10]. In recent years, Machine Learning algorithms have the potential to be used to develop automated caries detection systems that are more accurate and efficient than traditional methods. Adaptive neural network architecture [11], deep learning [12], an artificial multilayer perceptron neural network [13], convolutional neural network [14], backpropagation neural network [15], and

*Corresponding Author.

k-means clustering [16] are some of the different methods used in dentistry, specifically for the detection of caries. A large, difficult assignment has been seen to disappear utilizing these strategies. Therefore, this review aims to provide an overview of the diverse artificial techniques used to identify dental cavities in this systematic review, as follows:

B. *Artificial Neural Networks*

Artificial Neural Networks (ANNs) are computational systems profoundly influenced by the functioning of biological nervous systems, such as the human brain. ANNs consist predominantly of numerous interconnected computational units, commonly known as neurons. These neurons collaboratively operate in a distributed manner to assimilate knowledge from input data, with the objective of refining their ultimate output.

O'Shea [17] represented the fundamental architecture of an ANN as depicted in Fig. 1.

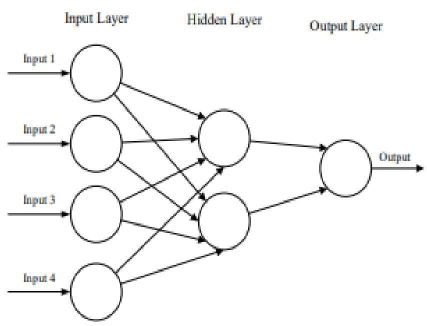

Fig. 1. The basis of a number of common ANN architectures.

The input, often organized as a multidimensional vector, is introduced to the initial layer, known as the input layer. Subsequently, this input is propagated through intermediary layers called hidden layers. In these hidden layers, decisions are made based on the preceding layer's information. The hidden layers then assess how alterations within themselves positively or negatively impact the final output. This iterative process of evaluating and adjusting is termed learning. The stacking of multiple hidden layers, creating a tiered arrangement, is commonly referred to as deep learning.

C. *Adaptive Neural Network Architecture*

An adaptive neural network architecture refers to a type of artificial neural network that can dynamically adjust its structure and parameters based on the characteristics of the input data. In the context of images, an adaptive neural network architecture is designed to intelligently adapt its layers, nodes, or connections to better capture the features present in the input image. This concept aims to enhance the network's performance by tailoring its architecture to the specific complexities and patterns within the image data.

The adaptive nature of such architectures allows the neural network to optimize its internal representation as it learns from the data. Traditional neural network architectures have fixed structures, making them less flexible in handling variations in data characteristics. In contrast, an adaptive neural network architecture has the ability to modify itself during training, potentially leading to improved accuracy, efficiency, and generalization. Haykin [18] presents a conceptual framework outlining a singular stage of neural processing intended for adaptable behavior in Fig. 2.

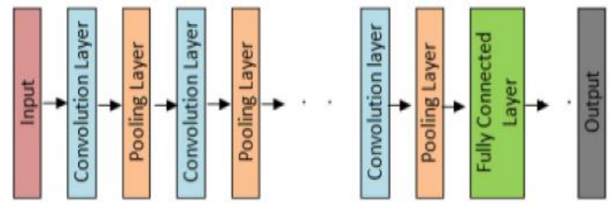

Fig. 2. Schematic diagram of an adaptive system.

The model centers on the retention of past experiences to predict likely future occurrences. Specifically, for a given input vector x(n-1) at time n-1, the model estimates the expected value x*(n) at time n. By comparing this prediction to the actual value x(n), the difference, termed the correction or innovation signal, is computed. A non-zero correction signifies an unfamiliar condition, necessitating model updates to better anticipate similar situations. This dynamic adjustment enables the model to learn and adapt to its environment, as it continually operates in real-world scenarios.

D. *Convolutional Neural Network*

A convolutional neural network (CNN) represents an evolved variant of artificial neural networks, meticulously designed to handle the intricate analysis of visual data like images and videos. Fig. 3 shows the concept model of convolutional neural network. Drawing inspiration from the intricate visual processing mechanism observed in the human brain, CNNs demonstrate exceptional proficiency in tasks that encompass image recognition, classification, and the domain of computer vision. The quintessential prowess of CNNs originates from their innate ability to independently glean intricate features from visual content, thereby accentuating their utility in intricate data interpretation. This is achieved through several distinctive architectural components:

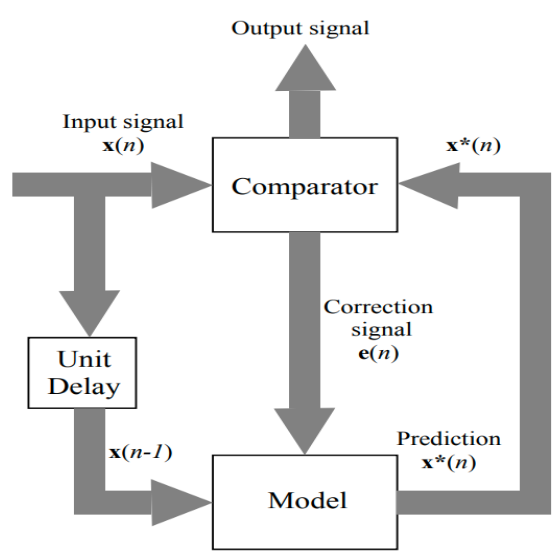

Fig. 3. The concept model of convolutional neural network [19].

- Convolutional Layers: These layers employ adaptable filters for performing convolution operations on input images. This hierarchical feature extraction encompasses both rudimentary features, such as edges, and more intricate features, like object contours.

- Pooling Layers: Subsequent to convolution, pooling layers downsize the spatial dimensions of features while retaining vital information. Employing methods like max-pooling, these layers preserve the maximum value within localized regions, distilling key features. This pooling process bolsters resilience against minor input variations and concurrently reduces computational requirements.

- Fully Connected Layers: Features extracted from prior layers are flattened and channeled through fully connected layers. These layers mirror conventional neural network structures and undertake roles as classifiers or regressors, relying on the features they have learned.

E. *Backpropagation Neural Network*

The backpropagation algorithm, integral to neural network training [20], operates as a pivotal mechanism in optimizing model parameters for improved performance in tasks such as classification, regression, and pattern recognition. This process empowers neural networks to glean insights from labeled training data, effectuating adjustments in weights and biases to minimize the disparity between projected outputs and actual target values. Backpropagation fosters neural networks to refine parameters, facilitating an enhanced fit to training data. By iteratively adjusting weights and biases using gradients, networks learn to identify pertinent features and relationships within data. This systematic learning process enables neural networks, encompassing deep learning architectures like CNNs and Recurrent Neural Networks (RNNs), to achieve elevated levels of performance across various tasks.

F. *K-Means Clustering*

K-means clustering is a widely utilized unsupervised machine learning technique employed to partition a dataset into distinct groups, or clusters, based on inherent patterns in the data. This technique is particularly effective in uncovering underlying structures and relationships within unlabeled datasets. The K in K-means represents the user-defined number of clusters. The choice of K significantly impacts the quality of the clustering results.

G. *Studies of Predicting Depression based on Self-Supervised Learning Method*

Self-Supervised Learning is an emerging machine learning paradigm that leverages unlabeled data to train models in a semi-supervised manner [21]. A two-phase learning scheme in self-supervised learning is illustrated by Taleb et al. [22]. Fig. 4 shows the flowchart of self -supervised learning stages.

Unlike traditional supervised learning, where labeled data is used to directly predict specific targets, self-supervised learning formulates tasks that allow the model to learn meaningful representations from the data itself. In self-supervised learning, the learning signal comes from the data itself, generating surrogate tasks that help the model capture underlying patterns and structures. For a more comprehensive perspective on self-supervised learning, we shall conduct a comparative examination juxtaposed against alternative machine learning techniques. Several studies are illustrated in Table I.

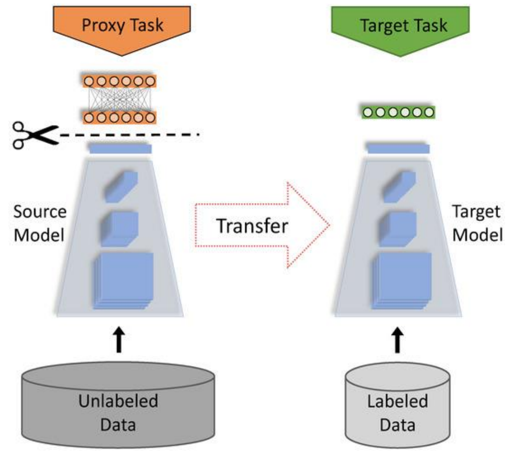

Fig. 4. Flowchart of self-supervised learning stages.

TABLE I. SUMMARY OF DENTAL CARIES DETECTING STUDIES

Article	Data	Models /Algorithms	Results
Patil et al. (2019)[11]	Small size of dataset (45 dental images)	K-nearest neighbor, ANN	Accuracy=95%, Precision=90%,
Casalegno et al. (2019)[12]	217 X-dental images	Convolutional Neural Network (CNN) algorithm	Accuracy of 85.6% and 83.6%
Devito et al. (2008)[14]	160 radiographic images	Backpropagation algorithm	Accuracy= 88.4%
Zanella-Calzada et al. (2018)[23]	9812 subjects were in an age range of 0 to 80 years old; 4830 belonged to the masculine gender and 4982 to the feminine gender	ANN by classifying subjects	Accuracy= 88%
Lee et al. (2018)[24]	2417 images (853 healthy tooth surfaces/1,086 non-cavitated carious lesions/431 cavitations/47 automatically excluded images during preprocessing).	Convolutional Neural Networks	Accuracy= 93%
Taleb et al. (2022)[22]	38,094 bitewing radiographs	Self-Supervised Learning Algorithms	ROC-AUC= 71.50 Sensitivity=51.80 Specificity of 91.30

III. Results and Discussion

Patil et al. (2019) [11] embarked on a comprehensive exploration to discern the optimal algorithm for diagnosing tooth caries. This endeavor entailed a thorough assessment of multiple algorithms, including support vector machines (SVM), k-nearest neighbors (KNN), Naïve Bayes (NB), and the adaptive dragonfly algorithm (ADA-NN). Their dataset encompassed 120 dental images, forming the foundation for a series of three distinct tests, each centered around 40 dental images. Notably, the ADA-neural network emerged as a consistent frontrunner across these evaluations, showcasing superior performance vis-à-vis the aforementioned algorithms. Impressively, the ADA-neural network surpassed its counterparts by margins of 5.5%, 11.76%, and 6.5%, respectively. However, it's crucial to acknowledge that Patil and collaborators operated within a notably constrained dataset, comprising a mere 45 images, thereby raising legitimate queries regarding the reliability of their findings. The utilization of such a limited dataset, consisting of merely 45 images, inevitably instills doubts concerning the robustness of their outcomes. Within this subset, 30 images were earmarked for training, while the remaining 16 were allocated for testing.

In parallel, the studies orchestrated by Devito et al. [14] harnessed the potent backpropagation algorithm within deep learning for dental caries prognosis. In the realm of Devito et al.'s investigation, the training dataset encompassed 80 dental images, with the remaining 80 images partitioned into two distinct subsets: 40 images for validation purposes and an additional 40 images designated for comprehensive testing [14]. Expanding the scope of inquiry, Devito and associates directed their efforts toward forecasting the proximal category of dental caries through the prism of X-ray dental radiographs, culminating in a commendable accuracy level of 88.4%.

Likewise, Casalegno et al. (2019) [12] pursued a separate avenue of exploration, deploying a dataset brimming with 217 X-ray dental images. Embracing the CNN algorithm, their study undertook the ambitious task of caries prediction, encompassing the nuanced realms of proximal and occlusal caries. Impressively, the outcomes bore witness to a level of accuracy amounting to 85.6% for proximal caries and 83.6% for occlusal caries.

The expedition orchestrated by Lee et al. (2018) [24] unfolded within the realm of CNNs, their dataset comprising 2,417 images. This comprehensive assemblage featured 853 images depicting healthy tooth surfaces, 1,086 images of non-cavitated carious lesions, 431 images capturing cavitations, and a subset of 47 images that underwent automatic exclusion during the preprocessing phase. It's noteworthy; however, Lee and co-authors deviated from the conventional dataset division percentages of 25%, 50%, 75%, and 100% for training. Rather, their dataset was bifurcated into a training set (comprising 1,891/673/870/348 images for each respective category) and a test set (consisting of 479/180/216/83 images for the corresponding categories). This unconventional distribution, though divergent, did not deter them from achieving an impressive diagnostic precision through CNNs, boasting an accuracy rate approximating 93.3%.

Taleb et al. (2022) [22] utilized a Self-Supervised Learning Algorithms on dental caries detection. The dataset was obtained by three specialized dental clinics in Brazil, focusing on radiographic and tomographic examinations [22] and consisted of 38,094 BWRs taken between 2018 and 2021. The study's strengths included its pioneering demonstration of self-supervised techniques in dentistry, with the potential to address the immense volume of X-ray images generated globally. Additionally, it employed a dataset of over 30,000 Bitewing Radiographs (BWRs) with EHR-based labels, overcoming the challenge of diagnostic inconsistency by incorporating a refined ground truth. Nonetheless, limitations included the use of EHR-based labels, which may be biased and incomplete, and the focus on tooth-level classification rather than finer assessments. This discrepancy might account for the relatively minor decrement in study results compared to those reported by Lee et al. [24].

In summary, the amalgamation of Self-Supervised Learning Algorithms has shown effectiveness in enhance performance and optimize label utilization in scenarios involving dental caries classification. Nevertheless, the predictive efficacy of machine learning approaches differs between studies due to disparities in data distribution, the characteristics of features integrated into the model, and the manner in which the outcome variable is gauged. Consequently, while certain investigations have indicated proficient performance of ML algorithms, a persistent requirement remains for further research to authenticate the predictive capabilities of each algorithm. This necessity arises from the inability to universally extend the results to encompass all forms of data.

IV. Conclusion

In conclusion, the potential of self-supervised learning for advancing dental caries detection is substantial. By pretraining models on large datasets derived from routine care, self-supervised learning provides a practical solution for scenarios where labeled data is limited. The presented studies underscore the positive impact of self-supervised learning algorithms on the predictive performance of dental caries classification models. However, it's important to acknowledge that the success of self-supervised learning is not uniform across all scenarios. Variability in data distribution, feature characteristics, and outcome measurement can lead to differing predictive performances. While some studies have demonstrated impressive results, the applicability of these findings to all types of data requires careful consideration.

Despite these challenges, the prospect of self-supervised learning remains promising. It offers a pathway to leverage the vast amounts of unannotated data generated in routine clinical practice, potentially revolutionizing dental diagnostics. As this field continues to evolve, further research is imperative to refine methodologies, validate findings, and establish the generalizability of self-supervised learning techniques in dental caries detection. The integration of self-supervised learning into clinical practice could mark a significant advancement in early caries diagnosis, ultimately leading to improved patient care and oral health outcomes.

ACKNOWLEDGMENT

This research Supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF- RS-2023-00237287, NRF-2021S1A5A8062526) and local government-university cooperation-based regional innovation projects (2021RIS-003).

REFERENCES

[1] Isabella Castiglioni, Leonardo Rundo, Marina Codari, Giovanni Di Leo, Christian Salvatore, Matteo Interlenghi, Francesca Gallivanone, Andrea Cozzi, Natascha Claudia D'Amico, Francesco Sardanelli, AI applications to medical images: From machine learning to deep learning. Physica Medica, vol. 83, pp. 9-24, 2021

[2] Alexandra T. Greenhill, Bethany R. Edmunds, A primer of artificial intelligence in medicine. Techniques and Innovations in Gastrointestinal Endoscopy, vol 22, issue 2, pp. 85-89, 2020.

[3] A. Rajkomar, J. Dean, I. Kohane, Machine Learning in Medicine. Adv Exp Med Biol, N Engl J Med, pp. 1347-1358, 2019.

[4] Stefano A. Bini, Artificial Intelligence, Machine Learning, Deep Learning, and Cognitive Computing: What Do These Terms Mean and How Will They Impact Health Care? The Journal of Arthroplasty, vol. 33, issue 8, pp. 2358-2361, 2018.

[5] Grünberg, K., Jimenez-del-Toro, O., Jakab, A., Langs, G., Salas Fernandez, T., Winterstein, M., ... & Krenn, M. (2017). Annotating medical image data. *Cloud-Based Benchmarking of Medical Image Analysis*, pp45-67.

[6] Ericsson, L., Gouk, H., Loy, C. C., & Hospedales, T. M. Self-supervised representation learning: Introduction, advances, and challenges. *IEEE Signal Processing Magazine*, vol *39*(3), pp. 42-62, 2022.

[7] Nima Tajbakhsh, Laura Jeyaseelan, Qian Li, Jeffrey N. Chiang, Zhihao Wu, Xiaowei Ding. Embracing imperfect datasets: A review of deep learning solutions for medical image segmentation. Medical Image Analysis, vol 63, pp. 101693, 2023

[8] Xu, J. A Review of Self-supervised Learning Methods in the Field of Medical Image Analysis. Int. J. Image Graph. Signal Process. vol 13, pp. 33–46, 2021 .

[9] Selwitz, R. H., Ismail, A. I., & Pitts, N. B. Dental caries. The Lancet, issue 9555, vol 369(9555), pp. 51-59, 2007.

[10] N. Ahmed, M. S. Abbasi, F. Zuberi et al., Artificial intelligence techniques: analysis, application, and outcome in dentistry-A systematic review. BioMed Research International, vol. 2021, pp. 1–15, 2021.

[11] S. Patil, V. Kulkarni, and A. Bhise. Algorithmic analysis for dental caries detection using an adaptive neural network architecture. Heliyon, vol. 5, no. 5, 2019.

[12] F. Casalegno et al. Caries detection with near-infrared transillumination using deep learning, Journal of Dental Research, vol. 98, no. 11, pp. 1227–1233, 2019.

[13] C. S. Mackenzie, W. L. Gekoski, and V. J. Knox. Age, gender, and the underutilization of mental health services: the influence of help-seeking attitudes. Aging Ment Health, vol. 10, no. 6, pp. 574-582, 2006.

[14] K. L. Devito, F. de Souza Barbosa, and W. N. F. Filho. An artificial multilayer perceptron neural network for diagnosis of proximal dental caries, Oral Surgery, Oral Medicine, Oral Pathology, Oral Radiology & Endodontics, vol. 106, no. 6, pp. 879–884, 2008.

[15] F. Schwendicke, T. Golla, M. Dreher, and J. Krois. Convolutional neural networks for dental image diagnostics: a scoping review, Journal of Dentistry, vol. 91, p. 103226, 2019.

[16] V. Geetha, K. S. Aprameya, and D. M. Hinduja. Dental caries diagnosis in digital radiographs using back-propagation neural network, Health Information Science and Systems, vol. 8, no. 1, p. 8, 2020.

[17] O'Shea, K., & Nash, R. An introduction to convolutional neural networks. arXiv preprint arXiv:1511.08458 , 2015..

[18] Haykin, Simon. Neural Networks A Comprehensive Foundation. New York: Macmillan College Publishing Company, 1994.

[19] F. Sultana, A. Sufian, and P. Dutta. Advancements in image classification using convolutional neural network. In 2018 Fourth International Conference on Research in Computational Intelligence and Communication Networks (ICRCICN), pp. 122–129, Nov 2018.

[20] Zajmi, L., Ahmed, F. Y., & Jaharadak, A. A. Concepts, methods, and performances of particle swarm optimization, backpropagation, and neural networks. Applied Computational Intelligence and Soft Computing, 2018

[21] L. Jing and Y. Tian. Self-supervised visual feature learning with deep neural networks: A survey. IEEE TPAMI, 2020.

[22] Taleb A, Rohrer C, Bergner B, De Leon G, Rodrigues JA, Schwendicke F, Lippert C, Krois J. Self-Supervised Learning Methods for Label-Efficient Dental Caries Classification. *Diagnostics*. 2022;

[23] L. Zanella-Calzada, C. Galván-Tejada, N. Chávez-Lamas et al., "Deep artificial neural networks for the diagnostic of caries using socioeconomic and nutritional features as determinants: data from NHANES 2013-2014," *Bioengineering*, vol. 5, no. 2, pp. 47, 2018.

[24] J.-H. Lee, D.-H. Kim, S.-N. Jeong, and S.-H. Choi, "Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm," *Journal of Dentistry*, vol. 77, pp. 106–111, 2018.