CNN in Periodontology: A Review

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Abstract

Periodontal Disease (PD) may be characterized by gingival inflammation, loss of connective tissue attachment, or the destruction of alveolar bone. It accounts for the sixth most common inflammatory disease known to mankind[1]. The conventional methods in use, today, to diagnose PD include clinical assessment and the analysis of radiographs[2] by subject experts. Increasingly, there is a need for a more standardized method to diagnose PD, owing to various limitations of the conventional diagnosis paradigm — inaccuracy from human error, contradictory assessments by individual examiners, and the dearth of time to parse through large amounts of data to arrive at precise diagnoses. The advent of Artificial Intelligence, with its nascent diagnostic tools, seeks to make crucial inroads into this gap in various fields of research. Breakthroughs in Machine Learning (ML) and its more robust subset, Convolutional Neural Networks (CNN), over the last decade[3] have opened doors to wide-ranging applications — facial and speech recognition, climate mapping, colorization of black and white images, document analysis and preservation, etc. The use of CNN in healthcare has successfully aided medical imaging analysis, cancer screenings, and prediction of neurological conditions. ML may also soon be harnessed to advance dentistry as a discipline. The use of CNN as an unsupervised diagnostic tool in Periodontology, however, has been extremely limited, primarily due to hardware constraints, but also because of the lack of efficient interaction between the exclusive disciplines of AI and dentistry. With the right algorithms and the expertise of examiners trained both in dentistry and neural networks, it is safe to posit that revolutionary leaps can be made in dental diagnostics and prognostics.

Keywords: Artificial Intelligence, CNN, Neural Networks, Periodontitis, Diagnocat, Diagnostic Aid

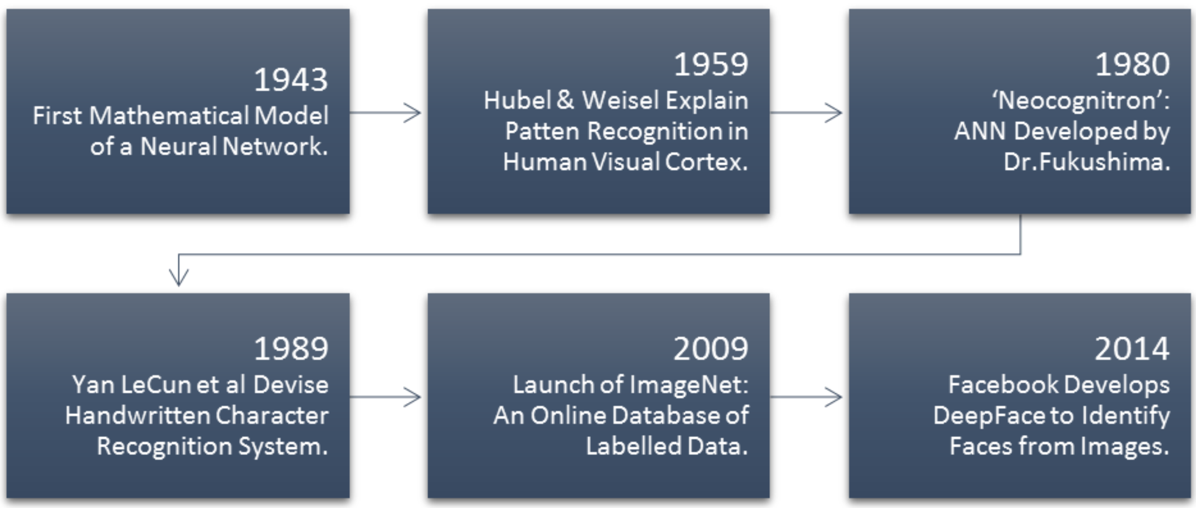
1. Conventional Methods of Diagnosis

Periodontal Disease (PD) is characterized by loss of connective tissue attachment (CAL), probing pocket depth (PPD), tooth mobility and bleeding on probing (BoP)[4]. In the conventional methods to identify and diagnose Periodontally Compromised Teeth (PCT), the periodontal status of a patient's teeth and gums is studied by probing for pocket depth (PPD), identifying the clinical attachment level (CAL), and recording other measurements such as tooth mobility and an array of screening indices. Furthermore, Periodontal Bone Loss (PBL) is identified using bite-wing or peri-apical radiographs, and if necessary, panoramic scans[5]. Clinical assessment, while effective in identifying PCT, has limitations that affect the accuracy of and the time taken for diagnosis. It is heavily dependent on the expertise of each individual examiner, and may be vulnerable to contradictory measurements or conclusions drawn by different examiners at various stages of the diagnosis[6]. The time taken to identify, assess, and diagnose periodontal diseases, too, is impacted by inconsistencies in the process, and is limited by the relative pace of each examiner's analysis. Lastly, the accuracy of a diagnosis is correlated to the amount of information each examiner has access to, and meaningfully processes, in their assessment. Large amounts of data, while necessary to improve accuracy, may slow down or overwhelm individual examiners — a demerit Neural Networks eliminate at the outset.The aforementioned limitations, on the whole, demand a more standardized, feasible, and consistent method to diagnose PCT.

2. CNN as a Potential Solution

Convolutional Neural Network (CNN) is a class of artificial neural networks commonly applied to image recognition, classification, and analysis, that is expressly designed to process large amounts of pixel data and draw insights from it. It's a multi-layered subset of Machine learning (ML) — the application of artificial intelligence (AI) to perform a specific task without using explicit instructions, relying on patterns and inference instead.

3. History of CNN



4. Applications of CNN

Over the last decade, Neural Networks havebeen used to varying degrees of success in a range of fields. They help identify unique features of human or animal faces from images, correcting for specified metrics such as light, angle, posture, etc. They play a major role in understanding gradual climatic changes and in modelling courses of action for control and mitigation. CNNs have also been used in document analysis — in handwriting detection, comparison, analysis, and digitization, with an error rate of 0.4% in some cases. Studies based on collections of natural history, biodiversity, evolution, habitat loss, etc., too are increasingly looking towards AI reinforcements.

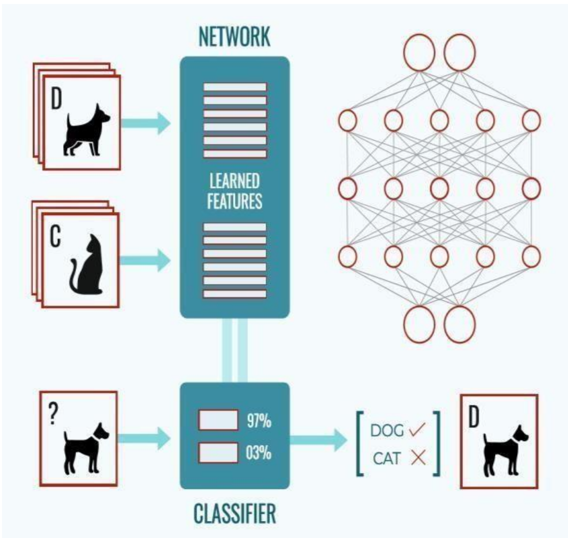
In the field of medicine, besides the promise of application in the prediction of ailments[7], CNNs are already being used to:

- Detect Eye Diseases: Applying deep learning algorithms on OCT (Optical Coherence Tomography) scans can help detect over 50 types of eye diseases.
- Identify Cancer Early: Detect cancerous patterns in mammograms of breast tissue that are too subtle for the human eye, outperforming most traditional models of risk prediction.
- Diagnose Neurological Disorders: Detect acute neurologic events through image analysis, and diagnose Alzheimer's, ADHD, and other autism spectrum disorders through connectome mapping.
- Assess Embryo Quality: Through time lapse images, a CNN can discriminate between poor and good embryo quality

with up to 97% accuracy, and improve IVF.

Dentistry has seen fewer, but deeper attempts to wield CNN to improve diagnostic accuracy[8].

5. The Process



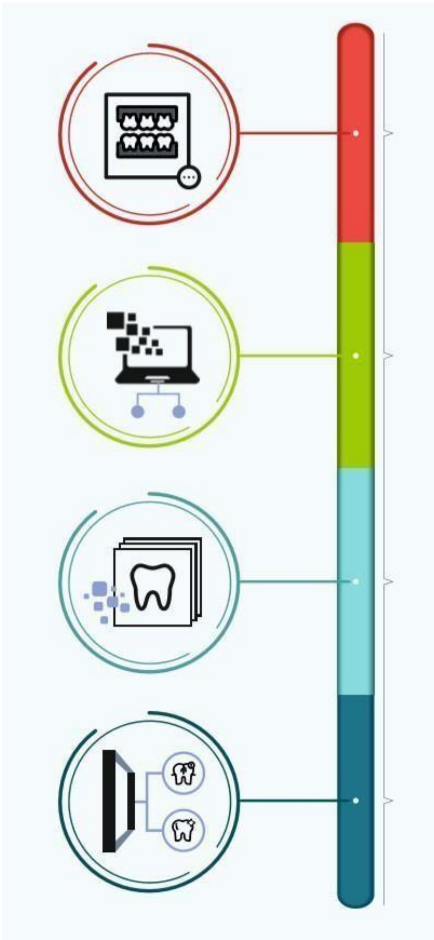
The functional mechanism of CNN involves multiple layers of neural networks, including disparate input and output layers of pooled modular data at either end. Input data involves several image datasets, fed to the network layers along with a predetermined set of weights — making CNN a more robust structure for detection than traditional shallow learning algorithms[9]. For the purpose of diagnosing PCT, the input dataset would be multiple radiographs of teeth with and without Periodontal Bone Loss (PBL).

CNNs could be wielded to process high resolution 2D or 3D radiograph images to locate, identify, and diagnose PCT — overcoming, if not eliminating the previously mentioned limitations with clinical diagnoses.

A simplified case of the functioning of a CNN:

- The CNN is fed labelled data of cat and dog images.
- It learns the features of each category, and develops a model to classify unlabeled data.
- When an unlabeled image is fed into the network, it identifies category-based features and classifies the new data as either cat or dog.

The stacked network layers in the CNN then learn from the continuous stream of input data, as the mathematical algorithms of the CNN extract minute characteristics, called features, from the pooled image datasets. These features could be shapes, edges, corners, spots and patterns in each image from the dataset. Following the weighted recognition of features from the input datasets, a model is developed to classify new data into one of two categories based on the learnt features. Thus, when unseen data is fed into the CNN, the output is the successful classification of the data with a binary vote — in this case, the presenceor absence of PBL.



Pre-Processing:

Radiograph images are cropped, resized, transformed to grayscale, and normalized by pixel, for processing.

Data Input:

Image data is split into training and validation sets, and passed through layers of the network

Training:

Chained functions extract CNN features from different aspects of the image: edges, shapes, structures, etc.

Classification:

Final layers of the network use this learning to translate feature-filtered images into votes: PCT or not.

6. Key Studies That Have Used CNN to Identify Periodontal Diseases

While various studies have attempted to wield CNN to improve diagnostic accuracy in other fields of medicine[10,11,12], few have successfully achieved it in dentistry.

I. Joachim Krois et al, 2019 (TensorFlow and Keras)[13]: Compared the diagnostic performance of a CNN in detecting PBL from segmented panoramic radiographs with the diagnosis of six experienced dentists.

- CNN did not prove to be significantly superior compared to examiners. Hypothesis that it would be, was rejected.
- However, limited agreement between dentists was evidenced.

II. Jae-Hong Lee et al, 2018 (Keras framework in Python)[14]: Diagnosis and prediction of periodontally compromised teeth using a deep learning based convolutional neural network algorithm. Based on another research by the same team using CNN to identify dental caries[15].

- Supervised deep learning using CNN algorithm was performed using a prelabeled periapical radiographic dataset.
- The results showed similar diagnostic accuracy to those obtained by board-certified periodontists.

III. Shannah Therese A. Aberin et al, 2017 (TensorFlow and Keras)[16]: To Find another criterion to detect periodontal disease.

- Deep CNN showed it could classify healthy images 98% of the time.
- An accuracy of 75.5% was achieved on its overall performance, in correctly classifying images of healthy and unhealthy teeth.

IV. Asghar Tabatabaei Balaei et al, 2017[17]: Used intra-oral images of before and after periodontitis treatments to investigate the application of computer vision algorithms in the detection and diagnosis of periodontitis.

- Resulted in 66.7% accuracy.
- By quantifying the distinction between the "before" and "after" periodontitis treatment, the classification system could provide non-dental health professionals with an effective treatment method.

7. Common Limitations of Key Studies

The few applications of CNN in identifying PCT appear to have a set of common shortcomings that kept them from achieving a level of accuracy in diagnosis significantly greater than the clinical attempts of trained examiners. These limitations primarily concern the input data. The data sets fed into the CNNs are often insufficient for effective learning of vital features that distinguish compromised teeth from healthy ones. Also, these images often need to be cropped into segments or minimized in resolution to save computing time, power, and storage space, which erases valuable composite information and severely affects accuracy.

Another limitation is that it is impossible to make a complete diagnosis of PCT using only 2-dimensional periapical radiographs. For accurate diagnosis and prediction of PD, it is necessary to comprehensively review radiographic and clinical data, such as the patient's history, clinical probing depth, CAL, bleeding on probing, mobility, percussion, and electric pulp test, above and beyond the binary output from the CNN. Using 3-dimensional deep CNN algorithms, with CT and MRI data may further improve accuracy, which was beyond the scope of the aforementioned studies.

8. Diagnocat

Diagnocat is an artificial intelligence tool for the interpretation of dental computed tomography images. It includes a range of AI-based applications for various dental practices, such as Radiological Study, Implantology Report, Endodontic Study, Third Molar Study, and Stereo Lithography.

While it uses complex CNN algorithms in its functioning, the front-end of Diagnocat is simplified to ease the process of diagnosis for practitioners untrained in computing or machine learning. Its diagnostic process is as follows:

- CBCT (cone beam computed tomography) images are uploaded in DICOM format.
- The tool's CNN analyses patient's maxillofacial anatomy and periodontal conditions in a few minutes.
- The tool displays panoramic and cross-sectional images with relevant insights.
- A report is generated with visual and textual descriptions of teeth of interest.

As a diagnostic tool that achieves clinical levels of accuracy with pace, consistency, and meaningful insight, Diagnocat overcomes the limitations of clinical diagnosis for tangible reasons. It consists of a large pre-trained dataset, using of 20,000 dental computed tomography images to compare the features of unseen datato. In contrast to prior attempts in the field of AI aided diagnostics, the tool is based on 3D convolutional neural network models. Most importantly, however, it was developed in collaboration with experts in maxillofacial radiology and dentistry, on meticulously established principles and with deep subject insight.

9. Conclusion

Clinical diagnosis of PCT is limited by various factors that could be overcome with the

Application of CNN. Present day CNN algorithms that use 2-D radiographs match the accuracy of individual examiners, in detection and diagnosis of Periodontal Diseases. This accuracy, however, could be improved significantly by reviewing clinical data comprehensively[18], such as the patient's history, clinical probing depth, CAL, bleeding on probing, mobility, percussion, etc. The role of CNN in the identification and treatment of PCT, too, is likely to improve manifold with the advance of 3D algorithms and computing power. While algorithms may be re- written and strengthened repeatedly to improve the accuracy of diagnoses, technological advancements in the resolutions of radiography, 3D capturing, and minimizing size and maximizing image quality, all need to improve at a comparative pace.

There is, still —and perhaps always will be— a need for human judgement and expertise in calibrating and designing the algorithms, and in extracting meaningful insights from AI-generated reports. Having subject experts study the diagnostic reports of ever-improving AI tools to arrive at the best suited modes of treatment, appears to be the ideal way forward in the constant pursuit of quick, accurate, and effective diagnosis.

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