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Review Article

Applications of Artificial Intelligence in Orthodontics

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Artificial intelligence (AI) technology is a tool for finding insights in different kind of information in medical field. The purpose of this article was giving a brief introduction to applications of AI in orthodontic treatment. The reviewed literatures were further categorized into (1) extraction or non-extraction therapy in orthodontic treatment, (2) orthognathic surgery, (3) segmentation and landmark identification, (4) growth prediction, (5) cleft related studies, and (6) TMD classification. ***(Taiwanese Journal of Orthodontics. 32(2): 85-92, 2020)***

Keywords: artificial intelligence; machine learning; orthodontic treatment

INTRODUCTION

Human brain is one of the most complicated calculators in the world. The thirst for unveiling its sophisticated yet beautiful structure reflects the process we, as human beings, trying to understand ourselves. Alan Turing brought up the concept of Turing machine in 1936, which can simulate the process of human calculation. The concept of Turing machine as well as theory of computation provided fundamental basis for the development of artificial intelligence (AI). Twenty years later, the term "artificial intelligence" was coined in 1956 in Dartmouth Summer Research Project. AI by definition, is the study of any device that perceives its environment and takes actions that maximize its chance of successfully achieving its goals.[1] Real-world applications of AI include health care, automotive, finance and economics, video games, etc. AI can be further classified as strong AI or weak AI.[2, 3] Weak AI can deal with specific tasks while strong AI which haven't been invented yet can deal with all problems and experience consciousness. AI is the goal, while machine learning is the way we try to accomplish this long-lived dream.

In the beginning, people tried to build hand crafted AI, which means trying to incorporate all the possibilities and its corresponding solutions into computer programs. Under certain circumstances, it works pretty well. Nonetheless, hand crafted AI by no means could really surpass human brain because it literally cannot "learn" anything by itself. As for modern AI, which people tried to endow machine with learning ability, owns the potential of developing abilities beyond its creator. Machine learning, briefly speaking, is the process finding a function from given data. The function can later on

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turn new input data such as sounds, images, into valuable output information such as speech recognition and facial recognition. Machine learning could be divided into training process and testing process (Figure 1). In training process, a set of function, also known as model, was evaluated by training data and computer algorism to come up with the best function. Followed by testing process, the chosen function was evaluated by testing data again to see if it is really workable.

The state-of-the-art machine learning method 'deep learning' is based on artificial neural network (ANN) (Figure 2). ANN was inspired by biological neural network which help us to sense the world and learn from it. The basic unit of ANN is called an artificial neuron.

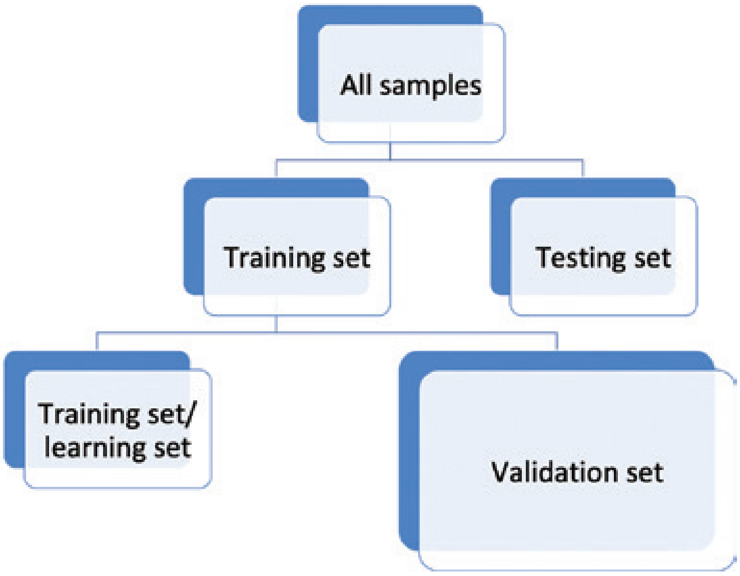

Figure 1. *All samples will be firstly divided into training set and testing set. Training set will be further divided into training set/learning set and validation set for preventing overfitting. Finally, testing set will be used for model evaluation.*

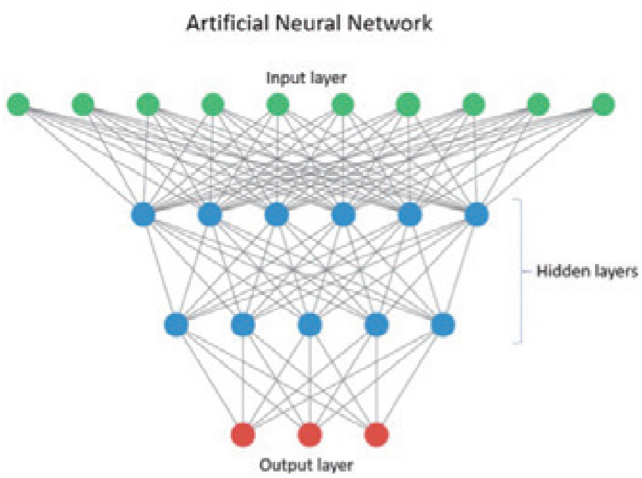

Figure 2. *Artificial neural network (ANN) consist of input layer, output layer and hidden layers in between. Artificial neurons in different layers were connected. Each connection was assigned with a weight representing its relative importance.*

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ANN can be described as a function with both input and output value as a vector. The first layer of ANN is called input layer, it is constituted by the features of the sample as a vector. Between input layer and output layer we can design different number of layers called hidden layers. Within each hidden layer, different numbers of artificial neurons are designed. Within the artificial neuron, input values can be transformed either linear or non-linear through different weights and activation function and its output propagates to the input of the next layer of ANN. Deep learning neural network consists of at least 3 hidden layers.

Convolutional neural network (CNN) is a kind of deep learning neural network. It showed outstanding performance in image recognition and classification.[4] Within convolutional layer, multiple filters extract different patterns in the image and come up with multiple feature maps. Followed by pooling process which streamline the size of the image and reducing the computation. After iterative convolutional and pooling process, the output was connected with fully connected layers to classify the image. Medical field such as dermatology and radiology have shown good result applying CNN as assisting diagnostic tool,[5, 6] yet in orthodontic filed, it has started to get attention gradually.

This article aims to provide an insight into applications of AI related to orthodontic diagnosis and treatment planning.

Extraction or non-extraction therapy in orthodontic treatment

Xie et al. constructed a decision-making expert system for orthodontic treatment of patients aged between 11 to 15 years old to decide whether tooth extraction is needed by using back propagation ANN model.[7] ANN model simulates human neural system, with neural networks which can process nonlinear relationships and exhibit learning ability. 200 subjects were chosen, 120 receiving extraction therapy and 80 receiving non-extraction therapy. 23 indices were selected as input data for each patient, and extraction or non-extraction were calculated as output data. Among 200 subjects, 180 were used as training data and 20 were used as testing data. The constructed ANN in this study showed 80% accuracy in testing set. Moreover, lip incompetence and IMPA(L1-MP) were the two indices that give the biggest contribution to the output data.

Jung et al. also constructed neural network model combined with back propagation algorism.[8] The purpose of the study was to construct an AI expert system for decision of extraction therapy and extraction pattern. There were 156 patients that included in the study. Twelve cephalometric variables and 6 indexes were selected as input data. Extraction or non-extraction and extraction pattern were set as output data. The treatment plans were determined by one orthodontic specialist. Different from Xie's study,[7] it further divided training data into training data and validation data. Iterative learning was stopped at the minimum error point of the validation set to prevent overfitting. The success rate of the models was 93% for the diagnosis of extraction or non-extraction therapy and 84% for the selection of extraction pattern.

Orthognathic surgery

Great investment has been made in research and development of digital orthodontics and 3D simulation of orthognathic surgery.[9] Besides, automated treatment planning and customized surgical set up planning lead to improved diagnostic precision especially among inexperienced doctors.[10, 11] Knoops et al. developed a machine learning framework for automated diagnosis and computer-assisted planning in plastic and reconstructive surgery.[12] They presented the large-scale clinical 3D morphable model (3DMM), a machine-learning framework including supervised learning constructed with surface 3D scan. The model was trained with 4261 faces of healthy volunteers and orthognathic surgery patients. Through automated image processing, it provides binary outcome whether someone should be referred to a specialist with 95.5% sensitivity and 95.2% specificity.

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Then, a specialist can automatically produce 3D simulation of post-surgical outcome with mean accuracy of 1.1±0.3 mm, without the need for conventional time-consuming computer assisted surgical simulation. However, only surface scan was used in this study, so the underline bone movement needed to be calculated according to soft tissue movement which still remain a big task nowadays.

Weichel et al. developed a computer-assisted planning system based on CT, cephalometric and plaster model.[13] The system referred to a knowledge base built in semantic web standard Resource Description Framework Schema, which transferred human knowledge into machine readable data. Gradient descent algorism was used to find local minimum of the loss function. Loss function described how good the current regression we applied. The bigger the calculated result deviate from optimal result, the bigger the loss function become. Good general agreement between the automatically generated planning proposal and planning result of a maxillofacial expert was found. But it is a preliminary study with only 5 cases was evaluated.

Comparing to Knoops's study who used 3DMM to come up with diagnosis, Choi et al. applied ANN obtained from 12 measurement values of the lateral cephalogram and 6 additional indexed.[11] The machine learning model consisted of 2-layer neural network with one hidden layer. The sample included 316 patients with 160 were planned with surgical treatment and 156 were planned with non-surgical treatment. The success rate of the model showed 96% for whether the patient need surgical treatment, and 91% for the detailed diagnosis of surgery type and extraction decision. The success rate is comparable between these two studies.

Niño-Sandoval et al. tried to predict mandible bone morphology based on maxilla morphology using ANN.[14] 299 lateral cephalograms was obtained from Colombian patients with 19 landmarks on X and Y coordinates. The result showed high predictability of the selected mandibular variables which might be quite helpful for craniofacial reconstruction.

Patcas et al. conducted an interesting study assessing the impact of orthognathic treatments on facial attractiveness and estimated age by AI technologies.[15] For age estimation, the convolutional neural network (CNN) model was trained with > 0.5 million facial images with age labels acquired from the Internet Movie Database and Wikipedia. For attractiveness prediction, the CNN model was trained on data from a dating site with > 13000 face images and >17 million ratings for attractiveness. Presurgical and postsurgical photos of 146 consecutive orthognathic patients were collected for this single-center study. According to the algorism, 66.4% of the patients improved with the treatment resulting in younger appearance of nearly 1 year. The study showed that AI might be an objective way evaluating treatment outcome in terms of aesthetic improvement.

Segmentation and landmark identification

Image segmentation is the process we isolate the pixels of target organs or lesion from medical images such as X-rays, CT, or MRI.[16] Image segmentation plays an important role in automated or semi-automated computer-aided diagnosis systems, and it is also important in volumetric medical image analysis. Landmark identification in lateral cephalometric X-ray have been of paramount importance in terms of diagnosis and treatment planning in orthodontic treatment for decades.[17] In this session we reviewed studies applied machine learning to perform segmentation and landmark identification.

Wang et al. developed a method for automated segmentation of maxilla and mandible through CBCT.[18] They applied a learning-based framework to simultaneously segment both maxilla and mandible from CBCT based on random forest.[19] Dice ratio is a popular way evaluating volumetric segmentation of medical images. The definition is the sum of intersection voxels of the learned and ground truth sets times two divided by the sum of the respective voxels. When Dice ratio equals

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to 1 means perfect match between learned and ground truth set, and zero indicates no similarity. In this study, 30 CBCT were validated base on manually labeled ground truth. The average Dice ratio of mandible and maxilla were 0.94 and 0.91 respectively.

Chen et al. used a machine learning algorism based on Wang's technique[18] to assess maxillary structure variation in unilateral canine impaction.[20] Subjects included 30 study group patients with unilateral maxillary canine impaction and 30 healthy control group subjects. Maxillary structure was auto-segmented and no significant difference in bone volume was found between impacted side and non-impacted side in study group. Study group had significant smaller maxillae volume than control group. The segmentation efficiency has been greatly improved by the automatic algorism.

Several studies looked into automated landmark identification of lateral cephalometric.[21-25] Arik[22] first applied CNNs for automated lateral cephalometric landmark identification. Park and Hwang[23, 25] used deep-learning method You-Only-Look-Once version 3 to train on 1028 cephalograms. The mean detection error of a total of 80 landmarks between AI and human was 1.46±2.97 mm. Kunz[24] used open source CNN deep learning algorism (Keras & Google Tensorflow) for 12 commonly used orthodontic parameters automatic identification. A set of 50 cephalometric X-rays were analyzed. Mean difference between AI and humans' gold standard were less than 0.37° for angular parameters and less tvhan 0.20 mm for metric parameters and less than 0.25% for the proportional parameter facial height. Nishimoto[21] used CNNs with personal computer and lateral cephalometric X-rays gathered through the internet and still get the result without significant difference between AI and hand traced cephalometric landmarks.

Growth prediction

Timing is one of the key points needed to be considered during treatment planning, especially among growing patients. Several methods have been proposed for growth prediction such as chronological age, menarche, change in voice and body height, and bone age. The gold standard for assessing bone age was obtained by hand-wrist radiographs, however, Lamparski reported that by reading cervical vertebrae stages, similar accuracy could be attained and preventing additional radiation at the same time.[26, 27] Spampinato used deep learning approaches to assess bone age through hand-wrist radiographs.[28] The dataset contained 1391 X-ray left-hand scans of children of age up to 18 years old with bone age values provided by two expert radiologists. The result showed an average discrepancy between manual and automatic evaluation of about 0.8 years. Kok et al. compared different AI algorisms for determination of growth by cervical vertebrae stages.[29] K-nearest neighbors, Naive Bayes, decision tree, artificial neural networks, support vector machine, random forest, and logistic regression algorithms were tested for accuracy. ANN showed most stable result and was suggested the preferred method for determining cervical vertebrae stage.

Cleft related studies

Zhang collected blood samples from healthy control and non-syndromic cleft lip and palate infants (NSCL/P) in Han and Uyghur Chinese population to validate the diagnostic effectiveness of 43 single nucleotide polymorphisms (SNPs) previously detected using genome-wide association studies.[30] Different machine learning algorisms was used to build predictive models with those SNPs and evaluated their prediction performance. The result showed logistic regression had the best performance for risk assessment. Defective variants in MTHFR and RBP4, two genes involved in folic acid and vitamin A biosynthesis, were found to have high contributions to NSCL/P incidence based on feature importance evaluation with logistic regression. This is in consistence with the impression that folic acid and vitamin A are essential for reducing the risk of conceiving an NSCL/P baby.

Patcas et al. used a CNN model previously trained on a dataset of dating site with >13000 face images and

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> 17000 ratings for attractiveness to compare facial attractiveness between treated cleft patients and controls.[31] Human rated significantly higher than AI for the score of attractiveness of controls. Attractiveness scores were comparable in treated cleft patients rated by AI and human. The result suggested that AI still need to improve its interpretation of cleft features impacting on facial attractiveness, to become a better tool evaluating aesthetics.

TMD classification

Shoukri et al. applied neural network to stage condylar morphology in temporomandibular joint osteoarthritis (TMJOA).[32] The neural network was trained on 259 condyles to detect and classify the stage of TMJOA and compare to clinical expert's classification. Condylar morphology was classified into 6 groups by CBCT image. Predictive analytics of the AI's staging of TMJOA compared to the repeated clinicians' consensus showed 73.5 and 91.2% accuracy. The results suggest that TMJOA condylar morphology can be comprehensively classified by AI.

AI have been applied to robotic surgeries in neurological, gynecological, cardiothoracic and numerous general surgical procedures.[2] It is quite promising in the near future that AI robotic technologies could be applied to orthognathic surgery as well. It can reduce infection rate because only robotics have contact with the patient. Higher precision of jaw movement can be expected at the same time. Last but not least, thanks to the power of technology, diagnostic and therapeutic philosophy are going through a paradigm shift from the traditional 'signs and symptoms' approach to 'precision medicine' approach.[33, 34] Starting with patients deep phenotyping, which gathered not only clinical data but genetic and biomarkers information, even lifestyle and environmental condition as well. Then data cleaning, exploratory data analysis, and feature engineering will be conducted by data scientists. Applying AI technology, we can build a diagnostic/prognostic model based on the 'big data' and predicting treatment results. It is not only a one-way process, taking the goodness of the predictive result as a feedback, we can further fine-tune the previous model and feature engineering process to get a positive feedback loop. In orthodontic field, the concept of precision medicine means a more complex diagnostic process, a more personalized treatment planning and a more sophisticated treatment process and those might lead to a more efficient treatment with less side effects and treatment duration. Hopefully, the medical quality could be raised while decreasing the medical costs through the application and development of AI technology.

CONCLUSION

AI technologies have been increasingly applied to the field of orthodontic treatment. It is proved to be a reliable and time saving tool in many aspects. Future effort could be made on creating cloud-based platforms for data integration and sharing. Given that data is the foundation of well-constructed models, with high quality and quantity of data, higher accuracy of predictive result and image interpretation could be achieved through machine learning process. In terms of orthodontic research, a well-trained AI model can help not only landmark identification, but all kinds of linear and angular measurements and volumetric measurements as well. It can save tremendous time by fully automated AI measurements so researchers will have more energy finding new insights within clinical examinations.

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