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치의과학박사 학위논문

Automated human identification system via the construction of a database using convolutional neural networks in dental panoramic radiographs

파노라마방사선영상을 이용한 딥러닝 기반의 데이터베이스 구축 및 개인식별 수행의 자동화

2022년 8월

서울대학교 대학원

치의과학과 영상치의학 전공

최 혜 란

Automated human identification system via the construction of a database using convolutional neural networks in dental panoramic radiographs

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이 논문을 치의과학 박사학위논문으로 제출함

2022년 6월

서울대학교 대학원

치의과학과 영상치의학 전공

최 혜 란

최혜란의 치의과학 박사학위논문을 인준함

2022년 7월

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위 원 ______________________ (인)

Abstract

Purpose: The aim of this study was to construct a database of individuals' dentition automatically with dental panoramic radiographs (DPRs), and to propose a novel method to identify individuals by recognizing their dentition changes using a pretrained object detection network which was a convolutional neural network modified by EfficientDet-D3. The feasibility of this method was evaluated by simulating an automated human identification process.

Materials and Methods: Among adults aged 20 to 49 years who took DPRs more than two times, recent and past images were assumed to be postmortem (PM) and antemortem (AM), respectively. The dataset contained a total of 2,058 paired DPRs per patient. The simulation algorithm was composed of three phases based on the dentition of unknown PMs. When constructing a database of AM dentition in phase 1, information on each individual's teeth state was distinguished in six different states: natural teeth, treated teeth without canal filling, treated teeth with canal filling, missing teeth, pontics, and implants. In phase 2, the degree of similarity was calculated for every pair of 1,029 individuals. In the final phase 3, the scored similarities were sorted in descending order and a matched AM's rank identical to an unknown PM was measured by extracting the top 20.0%, 10.0%, and 5.0% candidate groups. Finally, the percentage of that rank was calculated as the success rate. Additionally, the values of similarity score were compared to analyze whether the similarity scores according to the imaging time interval showed a statistically significant difference.

Results: The similarity showed a statistically significant difference between the two groups based on the period between the date of the most recent DPR and that of the past DPR imaging at 17.7 years.

The matched AM was ranked in the candidate group with a success rate of 83.2%, 72.1%, and 59.4% in the entire imaging time interval for extraction of the top 20.0%, 10.0%, and 5.0% candidate group, respectively. On the other hand, the success rate in a group with less than 6,450 days of imaging time interval was 84.0%, 72.7%, and 59.4% for same order, respectively.

The success rate was dependent upon the sex. The success rate of the top 20.0%, 10.0% and 5.0% candidate groups in the entire imaging time interval was 71.3%, 64.0% and 52.0%, respectively, among the male subjects, while that of the same candidate groups was 97.2%, 81.1% and 66.5%, respectively, among the female subjects. In the imaging time interval of fewer than 6,450 days, the success rate of the top 20.0%, 10.0% and 5.0% candidate groups was 71.3%, 63.6% and 51.8%, respectively, among the male subjects, while that of the same candidate groups was 97.8%, 81.8% and 66.9%, respectively, among the female subjects.

Conclusion: In the forensic human identification process, the developed method was useful for dental professionals, effectively to reduce the size of the AM candidate group to be reviewed. If a large database would be constructed by adding various conditions other than teeth information, the accuracy of human identification would be improved even further.

Keyword: Human identification; disaster victim identification; forensic science; radiography; deep learning; artificial intelligence

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Introduction

The human identification issue becomes more important when catastrophes sometimes cause large-scale death. Among the people who died in the east Japan earthquake and tsunami in 2011, the number of people identified by dental examination was approximately 10% of the total number of victims whose identities were confirmed. In case of the Daegu subway fire disaster in Korea in 2003, a similar pattern was observed. Disaster victim identification by dentists, therefore, has garnered growing attention. Teeth and dental treatment types are useful for human identification because they are resistant to destruction by fire[1]. The use of teeth — one of the hard tissues of the human body — helps narrow down the potential candidates or accurately confirms their identification.

With the increasing age in the society, the identification of individuals using dental restorations is more likely because the number and complexity of dental restorations increase with age[2]. Other previous study stated that individuals who had received several complicated dental treatments were easier to be identified than those who had not received or rarely received such treatments[3]. On the other hand, the dental panoramic radiograph

(DPR) is a reliable tool for human identification because it is regularly taken and updated. As DPR is widely used in clinical practice, it has a high potential for clinical use. The DPR, which contains most of the major dental information, is widely used in clinical practice.

In recent years, artificial intelligence (AI) can play an important role in the types of image processing that are cumbersome or time-consuming for the observer[4]. The object detection, image classification, and pattern recognition using deep learning have developed rapidly and are being applied to medical and dental imaging diagnosis[5, 6]. The convolutional neural network (CNN) is a method that is prominent in the image domain, and is particularly useful for finding patterns for image recognition[7] including radiological applications in general medical fields[7, 8]. In particular, object detection has recently developed remarkably, showing the achievement of establishing an efficient model called end-to-end learning[9-11] beyond transfer learning[12] and active learning[13, 14]. This allows the output to be quickly obtained directly from the input image without the need for a pipeline network[11].

At the present time, there are some existing studies individually identifying natural teeth or dental restorations using deep learning[15−23]. Studies related to human identification that simply compare the DPR images themselves have been predominant[24−30]. To date, few studies have performed a comprehensive simulation of human identification process using detection information by deep neural network.

For the realization of the ultimate comprehensive human identification, an approach through database construction is essential taking one step forward from existing studies of human identification which were mainly simple comparison between images through collection of a certain amount of sample. When the database is constructed, various parameters can be extracted from images, and it is ultimately possible to develop human identification methodology from diverse viewpoints.

The aim of this study was to develop an automated system of human identification that has not yet been investigated as a basis for disaster victim identification in the field of forensic science. This study confirmed the possibility of actual human identification by establishing a dentition database of individuals based on their DPR records and simulating the human identification process considering the dentition changes.

Literature Review

In the field of forensic science, a number of studies have been continually exploring the diversity of the dentition and have attempted using DPRs in application for human identification from the early 1990s[2, 31, 32]. Pretty and Sweet[3] stated that individuals who had received several complicated dental treatments were easier to be identified than those who had not received or rarely received such treatments; the discrepancy according to the time is divided into two categories: one explainable and one unexplainable in the identification process. Explainable discrepancies arise from teeth extraction or restoration replacement. Unexplainable discrepancies arise from cases where teeth were present at the time of death but not before it. The unexplainable discrepancies were suggested to be excluded[15].

In addition to research on diversity, several studies have tried to use radiographs to identify individuals. Wenzel and Andersen[31, 33] conducted a study that identified victims based on bitewing radiographs. There were some studies which had shown an identification system that uses image processing to analyze the appearance of teeth on radiographs and match patterns[28]. One of these studies also presented an identification system that used the appearance pattern of teeth for identification. This system matched the database of radiographs taken before death with dental radiographs taken after death.

Despite different characteristics, some studies have assessed the use of radiographs for age analysis and sex confirmation as well as their application in criminal investigations. Tuteja et al.[34] and Saxena et al.[35] have estimated age by evaluating the eruption stage of the third molar based on DPRs and reported that the values of the width and length of the pulp measured on the radiograph correlated with age. Another study found that in addition to DPR, posterior anterior cephalometric radiograph could be used to classify patterns of the frontal sinus and nasal septum for human identification[36].

The deep learning detection technique was newly introduced and added to the aforementioned research trend in about 2012[37]. A deep convolutional neural network (CNN) produced significant results in ImageNet classification work, and as improved networks such as R-CNN, faster R-CNN, and ResNet continued to be developed, there was remarkable progress in object detection tasks [38-40].

Early research, which incorporated deep learning in human identification, mainly consisted of studies that detected teeth and implants individually from various radiographs, including DPR. The detection performance regarding teeth and teeth numbers[18, 21, 22], prostheses, apical lesion[41], dental caries[42, 43], periodontal bone loss[44, 45], mandibular nerves with third molars[46] has recently reached over 90% as the network architecture is being developed at a fast pace. On the other hand, human identification studies based on anatomical structures that go beyond simple detection studies have also been introduced[47]. Such studies used anatomical structures as target identifiers in the DPR to detect antemortem DPR.

Forthcoming research conducted virtual simulations of human identification based on the similarity of DPRs[24, 29, 30]. Studies tested how accurately the deep neural network could identify antemortem DPR among randomly collected DPRs. Such studies proved that deep learning technology could reasonably conduct human identification, and relevant studies have been actively conducted.

Materials and Methods

1. Data

This study was approved by the Institutional Review Board (IRB) of Seoul National University Dental Hospital (SNUDH) with a waiver for informed consent (ERI20032). The data acquisition and all experiments were performed under the relevant research regulations and guidelines. This study was conducted based on the DPRs of 1,029 patients for simulation of postulated human identification process. The dataset contained a total of 2,058 DPRs with paired images of the recent and past DPRs per each patient. These images were randomly selected after removing identifiable information of patients and retrospectively reviewed from the picture archiving and communication system (PACS) at SNUDH. The radiographic images were obtained using panoramic radiographic machines including OP-100 (Imaging Instrumentarium, Tuusula, Finland) and RayScan alpha-P (Ray, Gyeonggi, Korea).

The DPRs were collected with information of age and sex from January 2000 to November 2020 for the purpose of dental treatment or diagnosis. Among adults aged from 20 to 49 years who took the DPRs more than two times, taken at regular intervals, the recent and past DPRs are assumed to be postmortem (PM) and antemortem (AM), respectively. The time points of PM and AM DPRs taken were also collected as 6-digit codes, which consisted of 2-digit of year, 2-digit of month, and 2-digit of day.

2. Detection of natural teeth and dental treatment types using pretrained model

The detection of natural teeth and dental treatment types and the identification of teeth number were performed using the pretrained object detection network.

Dataset

A total of 1,638 DPRs were randomly selected and retrospectively reviewed after de-identifying from the PACS at SNUDH. These DPRs were mutually exclusive with the existing 2,058 DPRs of 1,029 individuals.

The annotation work was performed on all teeth and dental treatment types on the DPRs using bounding box according to 4 annotation categories with 5 colors. The categories and coding colors were as follows: 1) natural teeth and teeth numbering (red when present and yellow when lost), 2) prostheses (lime green), 3) treated root canals (purple) and 4) implants (blue).

Natural teeth labeling included the marks of teeth number simultaneously. The World Dental Federation notation was used to carry out the teeth numbering annotation. If a tooth was lost in any position, annotation was conducted after the likely location of the original tooth was predicted. One oral and maxillofacial radiologist manually conducted annotation task consistently using a fully web-browser based labeling system developed by Digital Dental Hub (DDH Inc., Seoul, Korea). The types of label export for administration were JSON (JavaScript Object Notation). The cross-check was also performed after all annotation work was completed.

The DPRs were randomly separated into a training set (60%), a validation set (20%), and a test set (20%). The training set was used for the learning of the image patterns; the validation set was used for verification of the training task, and the test set was used to evaluate the final trained model.

Network architectures and training strategies

Motivated by the recent progress of object detection using deep learning, it was a CNN-based object detection network named EfficientDet for the teeth and treatment pattern analysis on DPRs. EfficientDet was an object detection model that used EfficientNet as the backbone network, a bi-directional feature pyramid network (Bi-FPN), and a compound scaling rule. EfficientNet was the CNN-based network that did the compound scaling to scale three subjects which were the depth (number of layers), width (number of channels), and image resolution. Bi-FPN incorporated the multi-level feature fusion that enabled information to flow in both the top-down and bottom-up directions while using regular and efficient connections. Compound scaling simply referred to scaling up all dimensions such as the backbone, input image size, network width and depth at the same time to achieve maximum performance during training. In this study, the EfficientDet-D3 was utilized with the backbone EfficientNet-B3.

As shown in Figure 1, the network architecture was designed properly to ensemble the subset networks for the detection of natural teeth and dental treatment types. Given the input of DPR, each sub-network was trained separately. Each sub-network was trained using the Focal Loss, with learning rate of 0.0001, batch size of 4, and Adaptive Moment Estimation (Adam) optimizer. The training was conducted for 270 iterations. The experiments were simulated on Ubuntu OS (Canonical Ltd., London, UK) with GPUs of Quadro RTX 8000 48GB (Nvidia corporation, Santa Clara, CA, USA) using PyTorch (Facebook, Menlo Park, CA, USA) library[48]. The input images were resized into 896 x 896 pixels and then were applied data augmentation process using Albumentations[49] library to increase the diversity of data training. Data augmentation method includes image flip, image manipulation, and contrast normalization. Specifically, the images were flipped horizontally and vertically, and transformed by manipulation of brightness, sharpness, and blur. During the inference, given a single input of DPR image, each sub-network detects natural teeth with corresponding teeth numbers, prostheses, treated root canals, and implants, respectively. Then, the ensemble network combines all the outputs. In the case of natural teeth, no detection was performed for the area of a missing tooth.

Table 1 presents the overall performance of the model and the composition of the dataset description that ensembles sub-network for each different task in the network architecture. The performances were evaluated using the standard of average precision (AP) and average recall (AR) under the intersection over union (IoU) of 0.5. A true positive is considered only for prediction scores over 50% and an IoU with a threshold value of 0.5.

3. Data postprocessing

A database was developed by generating the dental information using pretrained model from each set of pairs of the PM and AM DPRs of 1,029 patients. Because detectable information which could be extracted from one DPR using deep neural networks was much various, it was simplified to focus on the main dental components. This dental information consisted as follows: 1) natural teeth including teeth number, 2) prostheses, 3) treated root canals and 4) implants.

Based on the individual's teeth change state with direction, the detected natural teeth and dental treatment types were data-postprocessed as objective values. As the condition of the teeth changes in Figure 2, the possible past status of tooth condition in each tooth condition is summarized as follows; 1) past status of the natural teeth: natural teeth, 2) past status of treated teeth (no root canal treatment): treated teeth (no root canal treatment) and natural teeth, 3) past status of treated teeth (root canal treatment): treated teeth (one or more root canal treatments), treated teeth (no root canal treatment), and natural teeth, 4) past status of missing teeth: missing teeth, fixed partial denture, implant prostheses, treated teeth (one or more root canal treatments), treated teeth (no root canal treatment), and natural teeth, 5) past status of fixed partial denture: missing teeth, fixed partial denture, implant prostheses, treated teeth (one or more root canal treatments), treated teeth (no root canal treatment), and natural teeth, 6) past status of implant prosthetic teeth: missing teeth, fixed partial denture, implant prostheses, treated teeth (one or more root canal treatments), treated teeth (no root canal treatment), and natural teeth.

4. Comparison of similarity scores between the groups of imaging time interval

During the collection stage of DPRs in 1,029 patients, the time points at which the most recent and past DPRs were recorded were collected. The imaging time interval was calculated as the number of days by subtracting the first date DPR taken from the most recent date DPR taken.

The cut-off value was determined by using the regression method to analyze whether the similarity score showed a statistical difference according to the interval between the PM and AM examination points. First, the imaging time intervals, a sequence of consecutive numbers, were divided into units of 100 days to set a discrete section, and dummy variables were generated. In other words, the value was set to 0 and 1 in cases when the interval between examination points was lower or higher than the discrete value, respectively. The individual regression model was used to establish the relationship between each of the discrete values of this interval between examination points and the dependent variable which is the similarity scores. Since the minimum value of the examination points variable was 1 and the maximum value was 7,732 days, a total of 77 regression equations were derived as the dummy variables are introduced by dividing by 100 days as follows.

$$Y_{i} = b_{0_j} + b_{1_j} X_{i} + e_j \quad (i = 1 \ldots 1029,\ j = 1 \ldots 77)$$

Y_i: Similarity scores between 1,029 DPRs of PM and AM pairs

X_i: Dummy variables from the division into units of 100 days of the imaging time intervals

The 77 regression coefficients derived were plotted to analyze the trend. The section in which the trend changed most rapidly was set as the cut−off value. Finally, groups were divided based on this cut−off value, and the Student's *t*−test was performed. The SPSS 23.0 for Windows (IBM, Chicago, IL, USA) was used for statistical analyses.

5. Evaluation of human identification process

To simulate the automatic process of human identification, the algorithm of performing human identification was implemented by deriving possible candidates from the AM database assuming the situation when an unknown DPR was given in the PM database. Total three phases were established as shown in Figure 3. In this final phase 3, similarity scores were calculated by 1:1 matching for dentition information of one anonymous DPR and all AM dentitions.

In phase 1, using the pretrained model, all teeth number and therapeutic identifiers of 1,029 AM patients were detected and postprocessed. In the scoring step which is phase 2, the difference score was calculated to estimate the similarity score in PM−AM pairs. This difference score was evaluated by comparing the dental condition of each position. A score of 0 point indicated that the position and state were the same, and a higher score indicated that the distance difference between the tooth conditions increased. During this process, a relatively large score which is a maximum of 10 points indicated teeth whose positions were unavailable in the past to increase the difference. In other words, a penalty of 10 times was imposed in case of the unexplainable discrepancy. Table 2 summarizes the calculation methods of difference and similarity scores. The difference score was subtracted from 1 to finally obtain the similarity score. After sorting the finally derived similarity scores in descending order, the top 20.0%, 10.0%, and 5.0% candidate groups were extracted. The success rate was calculated after the rank was checked how the matched AMs actually exist in this group. Same calculations were conducted within sex groups, respectively. All of the above processes were fully automated based on a deep neural network.

Results

1. Descriptive statistics

The sex distribution of individuals participating in this study was as follows: 465 men and 564 women, with 45.2% and 54.8%, respectively. The mean age of the individuals was 35.5±15.3, the youngest individual was 20 and the oldest individual was 49.

The average imaging time interval of one individual between the most recent and past DPR taken was 2,197.5±1,934.7 days. The minimum value was 1 day and the maximum value was 7,732 days.

2. Comparison of similarity scores between the groups of imaging time interval

The plot of each of the derived regression coefficients is shown in Figure 4. The section or imaging time interval between 6,400 and 6,500 days, in which the trend changed most rapidly was chosen to be the cut-off value. The regression coefficient showed the most rapid change from −0.22 to 0.15. Accordingly, this cut-off value was finally determined to be 6,450 days.

Based on this cut-off value, the variables of imaging time interval were divided into two groups. As shown in Table 3, the similarity score showed a statistically significant difference between the two groups based on the period between the date of the most recent DPR and that of the past DPR imaging at 17.7 years ($p<0.05$)

3. Performance of human identification process

The matched AM was ranked in the candidate group with a success rate of 83.2% for extraction of the top 20.0% candidate group. In other words, target individual was, on average, in the top 20.0% candidate group with an 83.2% probability. The values for the success rate were 72.1% and 59.4% for the extraction of the top 10.0% and 5.0%, respectively. As shown in Table 4, there was a difference in the success rate according to sex. In case of men, the values for the success rate were 71.3%, 64.0% and 52.0% for the extraction of the top 20.0%, 10.0% and 5.0%, respectively. In case of women, on the other side, the values for the success rate were 97.2%, 81.1% and 66.5% in the same order.

Table 5 represented performance of human identification process in a group with less than 6,450 days of imaging time interval.

Table 1. The number of objects in dental panoramic radiographs and detection performance of the network

Category	The number of objects in each stage used in the network				Detection performance[1)]	
	Training	Validation	Test	Total	Average precision	Average recall
Natural teeth	27,302	10,139	8,926	46,367	99.1%	99.6%
Prostheses	7,763	2,824	2,502	13,089	80.6%	84.3%
Treated root canals	2,170	813	684	3,667	81.2%	89.2%
Implants	643	212	157	1,012	96.8%	98.1%

1) Average precision and recall values are calculated under a threshold value of the intersection over union of 0.5 for detection performance of natural teeth and dental treatment types.

Table 2. How to calculate the similarity score[1)]

Teeth status of Postmortem(PM) (index score)	Teeth status of Antemortem(AM) (index score)	Difference score[2)]
Natural teeth (0)	Natural teeth (0)	(PM score – AM score)
Treated teeth without canal filling (1)	Natural teeth (0)	10 (Penalty score)
	Etc.	(PM score – AM score)
Treated teeth with canal filling (2)	Natural teeth (0) Treated teeth without canal filling (1)	10 (Penalty score)
	Etc.	(PM code – AM code)
Missing teeth (3) Pontics (4) Implants (5)[3)]	Natural teeth (0) Treated teeth without canal filling (1) Treated teeth with canal filling (2)	10 (Penalty score)
	Etc.	If AM tooth status was equal to PM tooth status, then score was 0. Otherwise, score was 1.

1) The similarity score = (1 – difference score)

2) Difference scores are summed up for all teeth position and finally divided by 320 which represents for total number of tooth multiplied by penalty score.

3) The state of missing teeth, pontics, implants can shift mutually.

Table 3. Results of Student's *t*−test between the shorter and longer imaging time interval groups

The imaging time intervals	N[1)]	Similarity score[2)]	F	p−value[3)]
< 6,450 days	994	0.948±0.069	7.511	0.006
≥ 6,450 days	35	0.915±0.091		

1) The number of dental panoramic radiographs in each group

2) Standard deviation

3) Statistical significance at $p<0.05$

Table 4. Success rates of human identification process in the entire imaging time interval

The extraction rates of top candidate group	Success rate		
	Total	Men	Women
20.0%	83.2%	71.3%	97.2%
10.0%	72.1%	64.0%	81.1%
5.0%	59.4%	52.0%	66.5%

Table 5. Success rates of human identification process in the imaging time interval of fewer than 6,450 days

The extraction rates of top candidate group	Success rate		
	Total	Men	Women
20.0%	84.0%	71.3%	97.8%
10.0%	72.7%	63.6%	81.8%
5.0%	59.4%	51.8%	66.9%

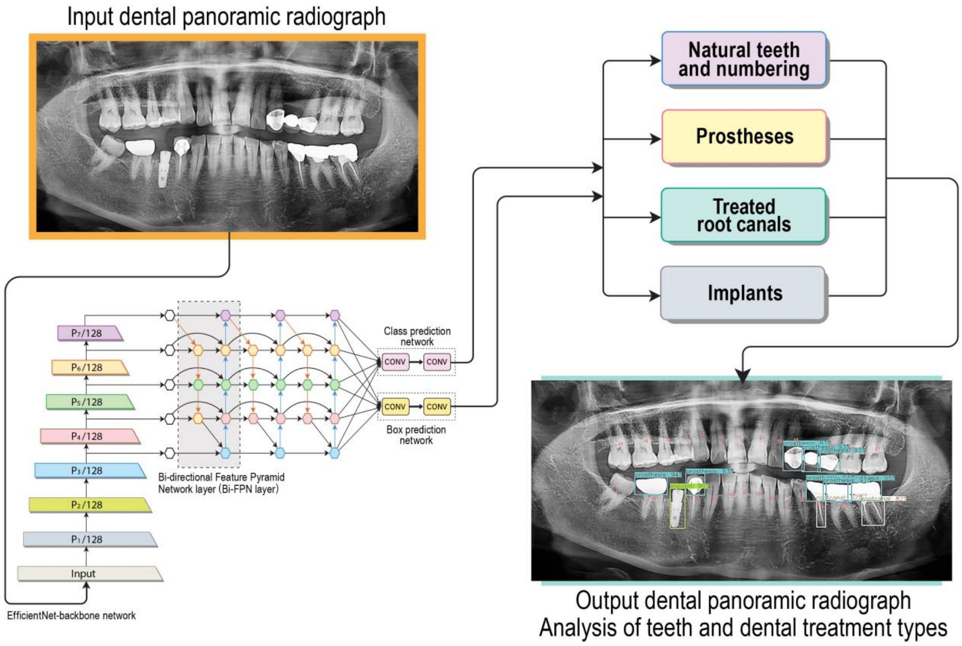

Figure 1. A deep neural network architecture for detection of natural teeth and dental treatment types

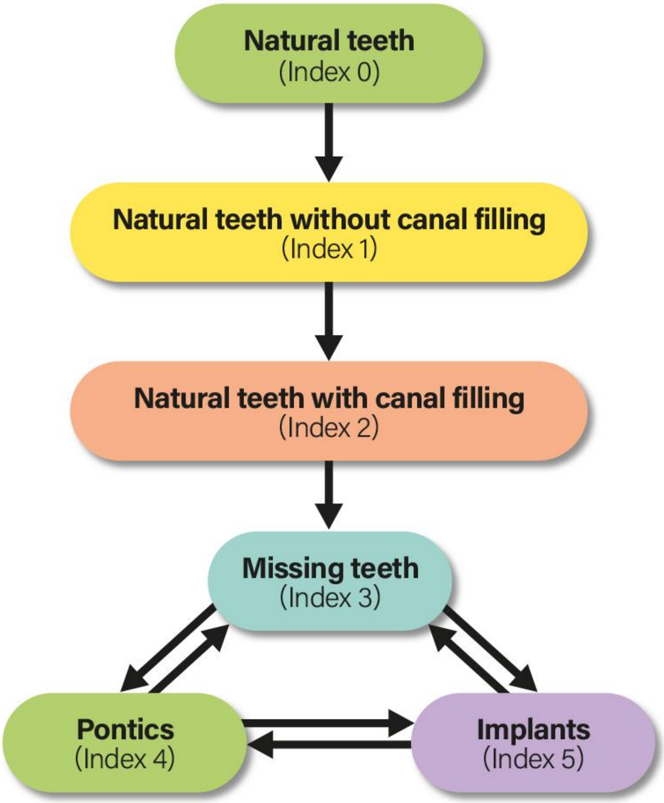

Figure 2. Index system based on the degree of dental treatment. Tooth status can be changed only in the direction of the arrow. In particular, tooth status can be converted to each other in case of missing teeth, pontics, and implants.

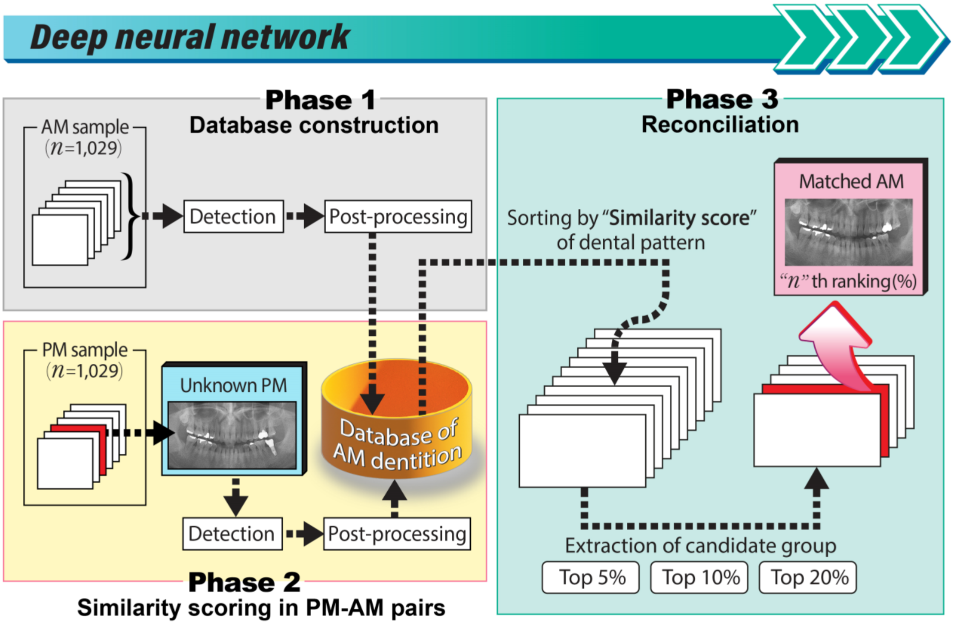

Figure 3. A scheme of simulation of human identification for automated human identification process based on the dentition of unknown postmortem (PM). In phase 1, a database of antemortem (AM) dentition was constructed. In phase 2, the similarity scores were calculated for every pairs of PM-AM dental panoramic radiographs. In phase 3, the scored similarities were sorted in descending order and extracted for top 20.0%, 10.0%, and 5.0%. The matched rank was calculated as the success rate for percentage.

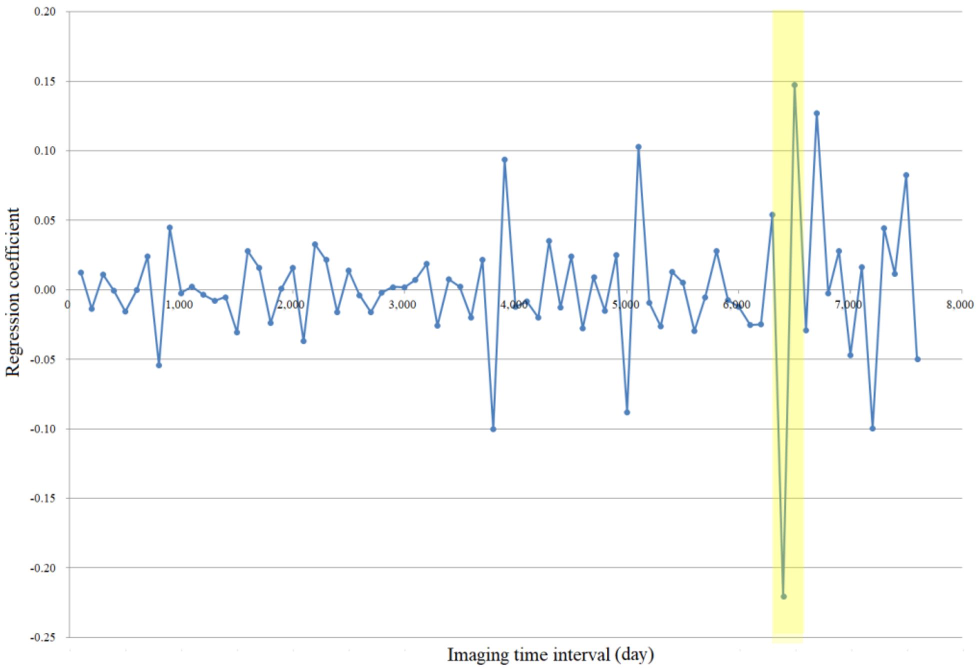

Figure 4. Determination of the cut−off value of the imaging time intervals from the trend analysis of regression coefficients

Discussion

Diagnostic imaging is one of the medical imaging areas to which AI has been introduced most actively. The application of AI technologies is carried out in various domains, including the detection of diseases, classification of lesions or segmentation of organs, measurement of volume or length, and image transformation or reconstruction[50, 51]. Particularly in the field of human identification, DPRs or periapical radiographs are often used to detect and classify dental information, and the relevant research outcome obtained by deep learning is comparable to the outcome by radiologist[21–23].

The research on human identification based on DPRs splits between before and after the application of deep learning. The research on human identification conducted by using deep neural network began with the detection of teeth and dental prostheses from DPRs[16–23, 50, 52]. Many of the recently conducted studies include the studies on the detection of natural teeth and teeth numbers using Faster Region–based Convolutional Neural Network (Faster R–CNN). In one of these studies where the natural teeth and teeth numbers were detected on the periapical radiographs, a filtering algorithm was employed to improve the AI performance[21]. A filtering algorithm was constructed to delete overlapping boxes detected by Faster R-CNN associated with the same tooth. The objective metrics for both precision and recall exceeded 90%. In another study, Faster R-CNN was used to detect the natural teeth and teeth numbers on DPRs[22]. The network in this study utilized the classical Visual Geometry Group 16 (VGG-16) CNN together with the heuristic algorithm to improve results according to the rules for spatial arrangement of teeth. Another study was conducted by combining Faster R-CNN and transfer learning[23], wherein a pretrained model was employed to detect the teeth and teeth numbers on the periapical radiographs, and transfer learning techniques were applied for dataset training. The results of this study showed that the values for the F1 score, precision and sensitivity were 0.8720, 0.7812 and 0.9867, respectively.

Going further from the excellent research results on detection, the research trend of deep learning in the field of human identification is gradually shifting to other areas. Based on the outstanding detection performance of AI described above, the comprehensive establishment and automation of human identification processes are drawing attention. Especially, among the studies conducted on human identification by employing CNN as one of the deep neural networks, the mainstream research trend has been the comparison of the images themselves before and after the DPR. There was a report on human identification performed by detecting the teeth together with the maxillomandibular morphological features[29]. The visualization of CNN showed that the teeth, maxilla, and mandible all contributed to human identification. The proposed model achieved Rank-1 accuracy of 85.16% and Rank-5 accuracy of 97.74% for human identification. In addition, the latest report on human identification based on DPRs[30] showed that the method proposed in the study achieved 88.72% rank-1 accuracy and 95.79% rank-5 accuracy due to end-to-end deep learning using a convolutional neural network. A modified VGG-16 model with two fully connected layers was applied for human identification via the gradient-weighted class activation mapping (Grad-CAM) technique in the most recent study[24].

All of the above studies have introduced a methodology to search out how similar the before and after images were. The mainstream themes of existing studies had been to find possible candidates based on the similarity of the image itself or to measure similarities based on various identifiers by extracting certain features or patterns from DPRs. Extracting features or performing comparisons on the images could be intuitive and fast, but it might also be affected by several endogenous variables such as the distortion, contrast, and resolution of DPRs[47]. In some cases, data collections might not be carried out with a unified principle of imaging by institutions and medical staff, and the quality of DPR images might vary depending on imaging conditions such as the type of imaging device.

Nowadays, different models for human identification, however, have been proposed. The database searching based on the basic assumption of tooth movement and sorting by similarity calculation is useful for human identification, and previous study have confirmed the decisive role that the sorting method, while taking similarity into consideration, plays in human identification[53]. All processes, including database construction and sorting by similarity calculation, were manually performed in this study. In addition, the superiority of the model for automatically detecting natural teeth and dental treatment types has already been acknowledged through the preliminary study[20].

The significance of this study is that, rather than comparing the images themselves, the dental information from DPR images was converted into objective information, to prevent in advance errors that could be generated from the analysis performed by simple image comparison. In addition, the network architecture of this study increased the efficiency by implementing both detection and classification through a single path in a structure similar to the end–to–end deep learning. End–to–end deep learning refers to the network in which the architecture allows all the parameters of a model to be trained simultaneously with respect to a single loss function[9, 11]. Hence, the weight of network might be optimized by directly considering the input and output of the neural network. In the presence of sufficiently labeled data, the training could be carried out by the neural model, and there is less need for directly design a pipeline[10]. This means that extraction of features by humans is unnecessary[11]. The drawback is that when there are nodes of too many layers or when the memory is insufficient, end–to–end learning might not be carried out. As the complexity of a problem is increased, the efficiency could be increased when the entire network is divided into pipeline networks.

There is other significance in that this study considerably contributed to the whole process for human identification accounting for PM and AM similarities were automated through deep learning including advanced automatic detection of natural teeth and dental treatment types, construction of an individual database based on this information. During the entire identification process, 32 teeth were classified into 6 states to increase the diversity of teeth arrangement, and a step for compressing and deriving a high probability group from possible candidates into a group was added. We believe that assigning directionality to tooth change increased the probability of identification.

To sum up, the target individual was identified in the candidate group with a probability of 83.2%, 72.1%, and 59.4% when 20.0%, 10.0%, and 5.0% were extracted after calculating and sorting similarity scores, respectively. The success rate was different between the male and female subjects. The success rate of the top 20.0%, 10.0% and 5.0% candidate groups was 71.3%, 64.0% and 52.0%, respectively, among the male subjects, while that of the same candidate groups was 97.2%, 81.1% and 66.5%, respectively, among the female subjects. One of the possible reasons why the overall success rate was higher among the female subjects is that the dental information was extracted more accurately from the female subjects than from the male subjects by deep learning. There could be other possible reasons, including bias of the data. Deep learning has limitations such that it is compared to a black-box model, because the internal process could hardly be inspected at the time of extracting the dental information[54]. Therefore, an additional analysis of the heatmap might be necessary to identify the parts that allowed the pretrained model to extract the dental information more accurately from the female subjects.

Furthermore, the difference in similarity scores between the groups was statistically significant when the interval between examination points was 17.7 years. To elaborate, if the interval between the imaging times was less than 18 years, it could be interpreted that the similarity between the two DPRs is high. In other words, as dental treatment becomes more common, it is very unlikely that a person would go to the dental clinic for the first time in 18 years and take a DPR, thus serving as an objective basis supporting the effectiveness of the human identification algorithm based on similarity of the present study. In conclusion, it is imperative to have an appropriate interval of <18 years between the examination points for human identification using the individual database.

On the other hand, a limitation of this model is that the similarity decreases when it is applied to AM cases with no restorations. For example, the case with the worst outcome was an AM case with 32 natural teeth with no restorations, including 4 third molars. Subsequent extraction of a third molar and treatments on several teeth might have led to poor results due to lowered DPR similarity.

In cases where the similarity score is too low or a discrepancy occurs, completely removing the candidate group could also be considered. However, in this study, candidate groups were not removed, but penalties were given; a penalty of 10 points was given during a step for deriving possible candidate group to greatly increase the difference of tooth change. Furthermore, human identification was performed only using dental information detected via deep learning without considering the individual's estimated date of birth. Adding an individual's estimated date of birth would further improve the performance of narrowing down the candidate group. Moreover, the addition of invariable anatomical structures such as mental foramen, maxillary sinus, and anterior nasal spine, and conditions other than teeth arrangement would further increase the success rate of human identification.

In addition, calculating the rank when 5.0% of candidate groups were extracted revealed that the performance was lower than when 10.0% were extracted. This was attributable to the fact that both had the same similarity score and contained many individuals with the same final rank. In this study, equally ranked individuals were assigned the same rank, and the next individual was ranked by adding the number of individual in the preceding rank. To improve the performance of this model, further consideration for treatment of equal score processing was necessary.

Finally, in the DPR using the pretrained model, several unclear cases occurred during the detection stage of dental treatment types. For example, a restoration treatment such as gold inlay through indirect restoration could be damaged or lost over time, and if the individual receives a direct restoration in the following treatment, the shape of the restoration would appear differently on DPR, often resulting in errors when read by the network. The reason is that direct restoration, such as resin filling, has similar contrast with teeth, and thus could be examined like natural teeth that have not undergone restoration treatments. Even when studied by specialists, many ambiguous cases were often difficult to distinguish whether the tooth was natural or had received a restoration treatment using a resin. Therefore, teeth restored with radiolucent materials without root canal treatment are likely to be classified as natural teeth, but it was assumed that they could be completely distinguished in this study. Additional research is warranted and a follow-up study should divide the prostheses part into indirect and direct restoration, use a large number of samples for learning so that the neural network might distinguish between these two cases, and evaluate the improved performance of the neural network.

In this study, an individual database was established by using DPRs, but ultimately, a system might need to be developed to perform human identification by analyzing a wide range of images. DPR is difficult to obtain with the patients who are unable to take the standing position due to a systemic health condition or with those with trismus[1]. In these cases, the periapical radiographs should be included in the database in preparation of missing information. Since periapical radiographs clearly include partial dental information, several images of periapical radiographs could be taken at a patient’s visit to gather all dental information. Later, deep learning could be applied to identify the teeth numbers and merge the status of all dentition through postprocessing in order to establish the same level of information as the images of DPRs.

Moreover, each hospital currently uses its own radiograph database but building a database that comprehensively manages the radiograph can be useful in various ways, not just for human identification. Although only the information associated with dentition was extracted in this study, the proposed method can be applied to various clinical fields according to the diagnostic purposes, including the detection of many anatomical structures, such as the maxillary sinus, salivary glands and temporomandibular joint, the measurement of the height of alveolar bone, and the detection of dental caries or periapical lesion.

The establishment of individual database using DPRs has various advantages in addition to the application to the dental and medical field. AI can integrate heterogeneous data domains, such as demographic and clinical data, image data, biomolecular data and social network data[55, 56]. Therefore, AI can help to understand the causal relationships and complicated interactions between the data sets, which used to be impossible to recognize in the past, in pursuit of the prediction or early diagnosis of diseases.

When the basis of relevant responsibilities and ethics is clearly prepared and the legislation is performed sufficiently, a highly reliable database could be established in a national scale. Then, the information included in the database could be widely applied to other related fields, including the development of healthcare products and medical applications.

Ultimately, when a big database is constructed by using DPRs under thoroughly examined ethical and institutional consensus at a national level, the DPR images would play the role of an identifier that could represent individuals as much as fingerprints, and the database would be able to function as a library source.

Conclusion

In the human identification process, the developed method could help the interested parties including dental professionals effectively to reduce the size of the AM candidate group to be reviewed while minimizing the need to conduct a full investigation and providing economic advantages. If a larger database is constructed by adding various conditions other than teeth information, the accuracy of human identification could be improved even further.

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파노라마방사선영상을 이용한 딥러닝 기반의 데이터베이스 구축 및 개인식별 수행의 자동화

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최 혜 란

1. 목 적

2003년 2월에 발생한 대한민국 대구지하철 화재 참사 및 2011년 3월에 발생한 동일본 대지진 등 대형 참사가 발생하였을 때 희생자 개인식별은 법치의학적으로 매우 중요한 주제이다. 인체에서 강도가 높은 조직 중 하나인 치아를 개인식별에 사용하는 것은 잠재적인 후보자를 압축하고 개인식별의 정확도를 높이는데 도움이 된다. 치과 진료가 보편화되면서 한 개인이 평생 동안 한 장 이상의 파노라마방사선영상 기록을 남길 가능성이 매우 높아졌고, 평균 수명과 함께 구강위생수준이 증가함에 따라 잔존 치아수도 증가했다. 이로 인해 개인이 가지는 치과 치료 패턴은 더욱 다양해지고 개별화되어 한 개인을 나타내는 유일무이한 특징점이 될 수 있다. 본 연구에서는 파노라마방사선영상을 이용하여 딥러닝으

로 사전 훈련된 객체인식 모델을 이용하여 치아의 변화를 인식 후 개인의 치열에 대한 데이터베이스를 자동으로 구축하고, 개인식별을 자동화하는 새로운 방법을 제안하고자 한다.

2. 방 법

2000년 1월 1일부터 2020년 11월 30일까지 서울대학교치과병원에 진료목적으로 내원하여 최소 2장 이상의 파노라마 방사선사진을 촬영한 20-49세 환자 1,029명의 방사선사진 중 최근 및 과거 사진을 각각 사후(postmortem) 및 사전(antemortem) 영상으로 가정하여 쌍을 이루어 영상을 수집하였다. 상기 영상과 중복되지 않는 1,638장의 파노라마 방사선영상으로 사전 훈련된 딥러닝 모델을 사용하여 총 2,058장의 영상에서 치아 번호 및 자연치, 보철물, 근관치료가 수행된 근관, 임플란트 정보를 자동으로 탐지하였다. 탐지된 정보는 최종적으로 6가지의 치아 상태를 결정할 수 있도록 수치화되었다. 6개의 상태는 자연치, 처치치(근관치료가 수행되지 않음), 처치치(근관치료가 수행됨), 발치, 가공치, 임플란트이다.

1,029명의 가장 최근 영상과 과거 영상이 각각 촬영된 시점 간 시간 기간을 일수로 계산하여 이 시간 간격에 따른 유사도 점수가 통계학적으로 유의한 차이를 보이는지 Student's *t*-test을 시행하였다.

개인식별 시뮬레이션 과정은 미지의 사후 영상이 제시되었다고 가정하고 이 사후 영상의 치열을 기준으로 총 세 단계로 구성하였다. 첫번째 단계에서는 모든 개인의 사전 치열 정보를 상기 6가지 상태에 근거하여

데이터베이스로 구축하였다. 두번째 단계에서는 미지의 사후 영상과 기존 1,029명의 사전 영상과의 유사도 점수(similarity score)를 계산하였다. 최종 단계에서는 점수화된 유사도를 내림차순으로 정렬하여 상위 20.0%, 10.0%, 5.0% 후보군을 추출하여 미지의 사후 영상과 매칭되는 사전 영상의 순위를 측정한 뒤, 해당 순위의 백분율을 성공률(success rate)로 변환하였다. 또한, 성별군 안에서 각각 동일한 방식으로 성공률을 추가적으로 계산하였다. 한편, 유사도 점수가 통계학적으로 유의미한 차이를 보이는 cut-off value보다 촬영시점 간 기간이 적은 구간을 한정하여 상기 성공률을 동일한 방식으로 도출하였다.

3. 결 과

본 연구에 참가한 개인의 성별 분포는 남성 465명(45.19%), 여성 564명(54.81%)이었고 평균 연령은 35.49±15.27세였다. 또한 최근 및 과거 파노라마 방사선사진 촬영시점 간 기간의 평균값은 2,197.5±1,934.7일이었다.

사전 훈련된 객체인식 딥러닝 모델의 성능은 자연치, 보철물, 근관치료가 시행된 근관, 임플란트에 대하여 평균 정밀도(average precision)가 각각 99.1%, 80.6%, 81.2%, 96.8%로 나타났다. 한편 평균 재현율(average recall)은 동일한 항목에 대하여 각각 99.6%, 84.3%, 89.2%, 98.1%로 나타났다.

촬영시점 간 기간에 따른 유사도 점수의 Student's *t*-test 시행 결과 약 17.7년을 기점으로 통계학적으로 유의미한 차이를 나타내었다.

미지의 사후 영상에 대해 매칭된 사전 영상은 상위 20.0% 후보군을 추출하였을 때 83.2%의 성공률을 나타내었으며, 상위 10.0%, 5.0% 후보군을 추출하였을 경우에는 각각 72.1%, 59.4%의 성공률을 보였다. 성공률은 성별 간 차이를 나타내었는데, 남성의 경우 상위 20.0%, 10.0%, 5.0% 후보군 추출시 71.3%, 64.0%, 52.0%의 성공률을 보였고, 여성의 경우 같은 경우에 97.2%, 81.1%, 66.5%의 성공률을 보였다.

한편, 촬영시점 간 기간이 17.7년보다 짧은 구간에 한정하여 동일한 방식으로 성공률을 도출하였다. 상위 20.0% 후보군을 추출하였을 때 84.0%의 성공률을 나타내었으며, 상위 10.0%, 5.0% 후보군을 추출하였을 경우에는 각각 72.7%, 59.4%의 성공률을 보였다. 남성의 경우 상위 20.0%, 10.0%, 5.0% 후보군 추출시 71.3%, 63.6%, 51.8%의 성공률을 보였고, 여성의 경우 같은 경우에 97.8%, 81.8%, 66.9%의 성공률을 보였다.

4. 결 론

본 연구에서는 개인의 치열 변화 가능성을 고려한 데이터베이스 검색 알고리즘이 개인식별을 수행하는데 있어서 효과적이며 딥러닝을 통한 자동화가 가능함을 확인하였다.

주요어 : 법치의학, 개인식별, 파노라마 방사선사진, 데이터베이스, 치열, 딥러닝, 인공지능

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