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A Literature Review of Age Estimation using Dental Images

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***Abstract*— Odontology is the study of dental disease and structure. The human jaw consists of 32 teeth divided into four categories: incisors, canines, premolars, and molars. Every human has two sets of teeth in their life, a set of temporary teeth and a set of permanent teeth. To detect issues in the jaw, the dentist usually suggests scans such as OPG, CBCT, or CTs. OPG is a panoramic X-ray of the upper and lower jaws, whereas CBCT is a medical imaging procedure that uses divergent X-ray computed tomography. While OPG X-rays are generally preferred by dentists since they do not leave any radiation on the patient's anatomical tissues and are effective, easy, and quicker to analyze, CT scan images offer more detailed information than ordinary X-rays. In this paper, we'll go over many methods and models that other researchers in the same field have used to determine a person's age just by looking at scans or X-rays. The radiographs can also be used to identify other patterns, such as missing teeth, impacted teeth, the contour of the jaw, and the growth of the molar teeth. Some of these are also very important in the age estimation procedure.**

***Index Terms*— Image Processing, Age Estimation, Digital Forensics, Odontology, Convolutional Neural Network (CNN), Orthopantomogram (OPG), Teeth, Machine Learning.**

I. Introduction

The term "odontology" refers to the study of tooth abnormalities and structure. ‘Odon’ is the Greek word for having teeth. The Human jaw consists of a maximum of 32 teeth divided into four different categories, incisors, canines, premolars, and molars, varying depending on the person’s age. The teeth are made up of multiple tissues of varying density and hardness. Every human has two sets of teeth in life: a set of temporary teeth and a set of permanent teeth. Infants begin developing their first set of teeth, or temporary set, at the age of six months. Their temporary teeth gradually fall off when they are teenagers as they begin to grow permanent teeth. The roots of the teeth are placed in the maxilla or the mandible and are covered by gums. Any issues in your jaw can affect your ability to speak, eat, and your facial expressions. To detect such issues the dentist usually suggests scans such as OPG, CBCT, or CTs.

Adult age estimation manually using a single radiography picture is time-consuming and labor-intensive. Accurate measurements, data comparisons, and knowledge of several cutting-edge dental postulates are necessary. An expert dentist with substantial training is required because a regular dentist is not qualified to perform this. It is frequently impractical to use the bulk of a skeleton for forensic studies since most remains have experienced

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alterations such as biological decomposition or damaging accidents. To address this issue, we focused on the jaw since it comprises the mandible, a portion of the skeleton that often maintains a large amount of its original structure despite deteriorative processes. The research notes the resistance to degradation from an external force, bacterial decomposition, fire, and other processes that can occur after catastrophic incidents and post-death.

Traditional approaches to dental image recognition initially relied on judgment calls made by human subject-matter experts, which is very difficult. They manually compared the dental photos from the antemortem and post-mortem procedures to look for variations in the teeth. Generalized tooth morphology, dental restorations, the presence or absence of a specific tooth, periodontal tissue characteristics, disease, and other anatomical traits are the key factors recorded in this manual approach for matching dental photographs. This manual method typically takes a lot of time and practice since human professionals must compare dental photos based on all the variations discovered in each tooth.

II. Related Work

Luka Banjšak et al. demonstrates an automated method for quickly identifying an age group using OPG (orthopantomography) [1]. To conduct the study, the researchers at the University of Zagerb's School of Dental Medicine used a collection of 4035 orthopantomography pictures to create a deep convolutional neural network. This model was then tested on 89 prehistoric skull remains to determine their age. The experiment was run three times, each time with different hyperparameters. The first run resulted in an accuracy of 53%, the second run resulted in an accuracy of 42%, and the final run resulted in an accuracy of 73%. The authors suggest that this method may be considered a practical technique for analyzing panoramic dental x-rays.

Fatemeh Sharifonnasabi et al surveyed an automated approach to Bone Age Measurement (BAM), which revealed insufficient teeth images and weak parts that led to inaccurate estimates. The author proposed an algorithm that eliminates the role of human intervention to overcome the lack of accuracy over months. A hybrid method called DASNet has been developed that selects a jawbone tooth from a young person to estimate his or her age as accurately as possible by minimizing the median error (E) and absolute error (AE) [2].

In this paper, Yancun Lai et al proposed a Learnable connected attention network (LCANet) module trained on a sample of 1,168 dental panoramic images of 503 different subjects for an automated approach to human identification from 2-D dental panoramic images [3]. By utilizing two modules a learnable connected module and a channel attention module to select interdependent channel information for an optimal search connection. The author has presented a comparative study of LACNet with various state-of-the-art methods. Accuracy for human identification in dental image recognition reaches up to 87.21% for Rank-1 and 95.34% for Rank-5.

The goal of the paper [4] is to use panoramic dental X-ray pictures to estimate age. The research suggests a transfer learning-based automated dental age estimation approach. Two deep neural networks, AlexNet and ResNet, are used to extract features, and many classifiers, including decision trees, k-nearest neighbors, support vector machines, and linear discriminants, were examined. 1429 dental X-ray pictures from a dataset were used in the analysis. When several classifiers were combined with AlexNet and ResNet, the proposed model's accuracy varied from roughly 95% to 98%.

Denis Milosevic et al explored the use of deep convolutional neural networks to automate the analysis of X-ray images of teeth, estimating the age, assessing the sex, or determining the type of tooth on an extensive dataset consisting of 86495 individual tooth images of an adult ranging from 19 to 86 years with a subset of 7630 annotated images by a dentistry expert [5]. In this study, the authors applied a deep CNN model with optional attention to search for the most appropriate hyperparameters that carried 14076 hours of GPU computing time. In addition, they used VGG16 as a feature extractor, the Adam optimizer with a learning rate, and 60 epochs of training for the model. The proposed approach by the authors achieves a precision of 76.41% for the assessment of sex, and a median absolute error of 4.94 years for the estimation of age. And an accuracy of 87.24% to 99.15% for tooth type determination best when only classifying into 4 classes.

Preeti Sharma et al. compared the results between two methods i.e. Cameriere’s Method and London Atlas of Tooth Development to estimate the age of Indian childrens with the age group of 5 yrs to 15.99 years [6]. The dataset they used consisted of 335 digitized panoramic radiographs (165 males and 170 females). Cameriere's method consistently underestimated age, with a difference of 0.59 years and a standard deviation of 1.32 years. This difference was statistically significant. The London Atlas method slightly overestimated age, with a difference of -0.03 years and a standard deviation of 0.69 years. This difference was not statistically significant.They found that the London Atlas method is much simpler and more accurate than the Cameriere’s method.

SindujaPalati et al. attempted to use Olze's method, which is a modified version of Gustafon's method, to estimate the age of individuals using digital panoramic images taken with an orthopantomograph[7]. They tested this method on a sample of 20 individuals i.e. 10 males and 10 females and found that the mean difference between the actual and calculated ages was approximately ±2.3 years, which is a smaller error than the one obtained using Gustafon's method (±3.63 years).

Wenxuan Hou et al. developed a DNN for age estimation using dental X-ray images that outperformed legal medical expert levels [8]. With the help of clinicians in the College of Stomatology, the authors collected a dataset of 27957 OPGs from individuals ranging in age from 0 to 93 years old (median age of 27 years) and proposed four principles for effective DNN model design. They achieved a MAE of 1.64 and FLOPs of 7.49B, which is 2.7 times less than Inception-v4.

III. Comparison Of Different Survey Papers

TABLE I. Summary of literature review based on algorithms, technology, result, gaps and dataset for age estimation

Ref.	Algorithms used	Technology	Steps	Results	Gaps	Dataset
[1]	CNN	VGG16 along with Imagenet for feature extraction	Sex estimation age estimation	Model 1: 53% model 2: 42% model 3: 73%	Overfitting	4035 images 85 OPG
[2]	CNN and Transfer learning	Features are derived using two deep neural networks, AlexNet and ResNet KNN classifier Histogram Matching	Bone Age Measurement (BAM) traditional age vs automated age measurement	The first (DANet) consists of a sequential age prediction path for the Convolutional Neural Network (CNN). In contrast, the second (DASNet) applies a second CNN path to sex prediction and uses sex-specific characteristics to boost the efficiency of the estimation of age.	plus minus 6 months in age prediction	tested sample 2289 OPG - aged 4.5 to 89.2 years
[3]	(LCANet) learnable connected attention network	DenseNet ResNeXt SENet	-	88% accurate	GPU needed	Training: 1,168 dental panoramic images of 503 different subjects
[4]	Deep Neural Networks	AlexNet& Resnet	-	-	They have the limitations of a larger data set.	1429 OPGs
[5]	CNN	VGG16	Age and Sex estimation TOOTH TYPE DETERMINATION	76.41% for sex 87.24% to 99.15% for tooth type determination, median absolute error of 4.94 years for age estimation,	single tooth 2048 epoch	86495 individual tooth x-ray image samples, with a subset of 7630 images having additional information about tooth alterations.
[9]	Machine Learning	C # Programming Language	-	95%	plus minus 1 year	Dataset of 1315 OPGs were used.
[10]	Deep learning	Vision Transformer (ViT), Segmenter ConvNeXt	results are compared with the U-Net model	ConvNeXt 90.77 Segmenter 91.86 Vision Transformer 88.67	Vision Trasformeroutperfoms for maxillomandibular segmentation.	TUFTS Dental Dataset 1000 x-rays
[11]	Convolutional Neural Network	DASNet	They validated the predicted age-related age in young people.	-	Large sample size was required as the subject of the restriction.	2289 OPGs

[12]	Neural Network	Multilayer Perceptron	-	-	-	300 CBCT
[13]	Convolutional Neural Network	AlexNet, VGGNet& ResNet	-	36% age.	Their limitation was the lack of large data sets.	2575 OPGs (Age: 20- 90)
[14]	Neural Network	Multilayer Perceptron	-	-	-	1636 OPGs
[15]	Deep Convolutional Neural Network	DCNN Model	Their results show that this method can classify images with high performance, making automatic age estimation possible with high accuracy.	-	Some limitations include the population of data in elderly patients to extend the general approach and suggest that CNN filters are in the early stages of future research.	456 OPGs
[16]	Convolutional Neural Networks	-	-	The result was validated, and this model promises to develop an automated factual age measurement.	-	9435 OPGs (Age: 2-98) (Gender: 4963M and 4472F)
[18]	Greulich-Pyle (GP)	-	-	Prediction error of 1.01 ± 0.74 years	-	322 subjects images
[19]	-	ACTIVE SHAPE MODEL (ASM), ACTIVE APPEARANCE MODEL (AAM), ARTIFICIAL NEURAL NETWORK	-	MAE ASM 2.481 (std = 2.148), MAE AAM 2.283 (std = 2.168)	-	203 orthopantomograms
[20]	KNN	Fractal Method	-	Accuracy: 82.97	-	-
[21]	Maturity scores or Ages of Attainment from the reference dataset	-	-	Estimated Age (EA) = Chronological Age - Dental Age French Canadian RDS (157 subjects): Male: 0.62yrs Female: 0.36yrs UK Caucasian RDS(252 subjects): Male: 0.25yrs Female: 0.23yrs Southern Chinese RDS(254 subjects): Male and Female: 0.02yrs	-	266 (133M 133F) dental panoramic radiographs of Southern Chinese children and emerging adults Range:- 2 to 21 years which was divided into 19 groups(2-3 yrs, 3-4yrs, upto 20-21yrs) A sample was created by taking 14 subjects from each group (7 male and 7 female)
[22]	Demirjian's method	-	-	Kappa coefficient ranged from 0.80 to 0.89 WRT Reproducibility of the calculated dental age, IIC (95% confidence level) was **Intra-individual:** Demirjian's scores: 0.984	Both Scores overestimates the age in the Spanish Caucasian sample underestimates the age in the Venezuelan	OPGs from 308 Spanish Caucasian and 200 Venezuelan Amerindian children Age Range:- 2 to 18yrs

				(0.968–0.992) and Chaillet’s scores 0.972 (0.944–0.987) **Inter-individual:** Demirjian’s scores 0.972 (0.942–0.986) and Chaillet’s scores 0.964 (0.927–0.983)	Amerindian sample	
[23]	Linear Regression Model	10-point staging, a scoring technique proposed by Gleiser and Hunt, modified by Köhler and the Kvaal	-	Regression Model using only third molar stages: $R2$ of 60 % and a RMSE of 1.63 years $R2$ and RMSE values from the regression models including only Kvaal ratios: ranged between 0.1 and 29 % and 2.21 and 2.60 years.	-	450 digital panoramic radiographs from Katholieke Universiteit Leuven, Belgium Age Range:- 18 to 23 yrs 25 radiographs from each gender, as well as age group, were collected
[24]	Nolla’s, Demirjian’s and Haavikko’s methods	-	-	over-estimated by Demirjian’s and under-estimated by Nolla’s and Haavikko’s methods. Haavikko’s method is better	-	6–15-year 58 patients with AI control group 6–15-year old 116 patients (healthy)
[25]	Simple linear regression and Pearson correlation analysis Fisher’s Z test t-test analysis	Mimics software (processing) analysed using SPSS version 20.	Data acquired 300 CBCT into 5 groups of each 10 yr group 1st oriented in axial, coronal and sagittal planes 2nd setting grayscale threshold values for each teeth 3rd masks created for the pulp cavity & cropped in all 3 planes & masks were manually checked & corrected 4th software automatically calculates volumes of pulp cavity & tooth	strong inverse relationship - chronological age and pulp/tooth volume ratio. Maxillary right central incisor showed strongest coefficient of ($R2$) as compared to maxillary canines. derived regression models sample showed less (MAE) for maxillary right central incisors pulp/tooth volume ratio with age is a valuable indicator of estimation & gender independent.	-	300 CBCT scans (153 males,147 females) aged 16-65 years divided into 5 age groups independent group of 126 teeth used for validation on derived regression eq.
[6]	Open apex method proposed by Cameriere et al and London Atlas of Tooth	-	The chronological age of participants was calculated by subtracting the date of the birth from the date on which	Cameriere’s Method mean chronological age: 10.238 ± 3.160 years mean estimated age: 9.639 ± 2.486 years Difference: 0.59 years (SD: ±1.32) London Atlas of Tooth Development	Overestimation and underestimation of certain age groups in both males as well as females	335 digitised panoramic radiographs (165 males and 170 females) Age group: 5 to 15.99 years

	Developmen t.		radiographs were taken. Coding was done for all participants, and the observer was blinded to their actual age. Only the subject's gender was revealed to the examiner.	mean chronological age: 10.238 ± 3.160 years mean estimated age: 10.267 ± 3.033 years difference: -0.03 years (SD: ± 0.69 years)		
[26]	measuring maxillary canine pulp/tooth volume ratio	-	Pearson's correlation coefficient was used to determine the relationship between pulp/ tooth measurements and age.	Results show that all measurements, except pulp/tooth length volume (R), are associated with age and that pulp/tooth volume (PV/TV) has the highest correlation with age (r = -0.486). Explanatory coefficient (R2) of the regression model based on PV/TV is 0.236.	-	131 CBCT images Range: 17 - 75 years
[7]	Olze's Method	-	-	The mean age difference between actual and calculated age of total20cases studied was ±2.3 years.	Olze's method was modification to Gustafson's method which acceses lower premolars Many individuals the third molar is either missing or is being removed.	Digital panoramic images of 20 individuals (10 males and 10 females)
[8]	Deep Neural Network	Neural Architecture Search Method	Four Principles: (1) Multi-branch architectures, (2) Asymmetric convolution kernels, (3) the depth of the network, (4) Feature reusing in early layers.	MAE:- 1.64 FLOPs:- 7.49B (2.7 times less than Inception-v4)	-	27957 OPGs 16,383 Female 11574 Male Range 0 to 93 yrs Median age = 27 Training: 23,888 Testing: 3904 Input image size was resized to 384 x 384

IV. Conclusions

In this paper, recent works in the field of automated age estimation were discussed. Most maxillary and mandibular growths are usually performed at the age of 18 to 20 years old; the only skeletal components visible in these facial bones' macroscopic are teeth through post-mortem decomposition. As a result, the tooth and jawbone are selected to develop the hybrid method because it is a helpful bone for age assessment amongst other parts of the body. Estimating age based on tooth growth is a robust method. Modeling an accurate method for measuring age in the medical field can help accelerate personal identification and thus reduce cost. Although the number of models and methods to estimate age has increased, most of them remain in the testing phase because they have not obtained clear-cut results, especially predicting the minor's age. Furthermore, there are no robust computerized methods for the same within the healthcare setting, with a precision to the range of ± 6 months accuracy for dental age estimation techniques due to limitations in image analysis and image processing techniques.

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