Deep Neural Networks for Assessing the Legal Age from Panoramic Dental X-ray Images

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***Abstract*—Forensic anthropologists and odontologists frequently need to establish the age of a living or deceased individual. In particular, a relevant problem consists of determining the legal age for persons not possessing identity documents or for whom it is not possible to have trustworthy information on their date of birth. An accurate technique to perform this measurement involves the analysis of panoramic dental X-ray images (orthopantomography), conducted by experienced forensic scientists. Although studies in the literature on automatic methods for age estimation based on dental images present promising results, none of them specifically focus on establishing the legal age. In this paper, we propose a method based on deep learning for assessing the legal age. Specifically, we consider the legal age as 18 years and propose a method that mimics the analysis performed by human experts by examining the third molars with Deep Neural Networks (DNNs). Our method can assess the legal age from a single or multiple molar images by using a score-level fusion strategy. We assessed the performance of our method using a specifically collected dataset composed of 220 samples from individuals ranging from 15 to 22 years old. The obtained results proved the applicability of our method as a decision support tool for forensic scientists.**

***Index Terms*—Age, dental biometrics, convolutional neural networks, forensics**

I. Introduction

Forensic anthropologists and odontologists are frequently asked to estimate the age of living or deceased individuals. In this context, one of the most relevant problems consists of assessing the legal age for persons not possessing legal documents. This problem is particularly significant since regulations are usually different for underage and adult persons.

Assessing the legal age could be a particularly difficult task for forensic odontologists, especially if the real age of the individual is just slightly lower or higher than the legal age. In this case, even assessments performed by experienced scientists could be erroneous (human error). In this paper, we consider the legal age threshold as 18 years, since this value is used in a wide number of countries [1].

Forensic anthropologists and odontologists frequently perform age assessment by analyzing orthopantomography images. Specifically, scientists evaluate the growth stage of every tooth using well-established approaches in the literature. Relevant approaches are the staging techniques proposed by Demirjian [2] and Moorees [3]. Considering the legal age as equal to 18 years, the most relevant information is represented by the growth stage of the third molars. Many forensic anthropologists and odontologists, therefore, perform the legal age assessment by analyzing only the portions of images representing the third molars. Specifically, they frequently consider only the third molars of the inferior arch since they are more visible compared to the ones of the upper arch. Fig. 1a shows an orthopantomography image acquired from a 16-year-old individual, while Fig. 1b shows an orthopantomography image acquired from a 21-year-old individual. Fig. 1c and Fig. 1d show enhanced regions of Fig. 1a depicting the third molars of the inferior arch. Fig. 1e and Fig. 1f show enhanced regions of Fig. 1b depicting the third molars of the inferior arch. While the size of teeth is different between subjects, the shape of the third molars is different for underage and adult individuals.

In the literature, there are various studies on age estimation

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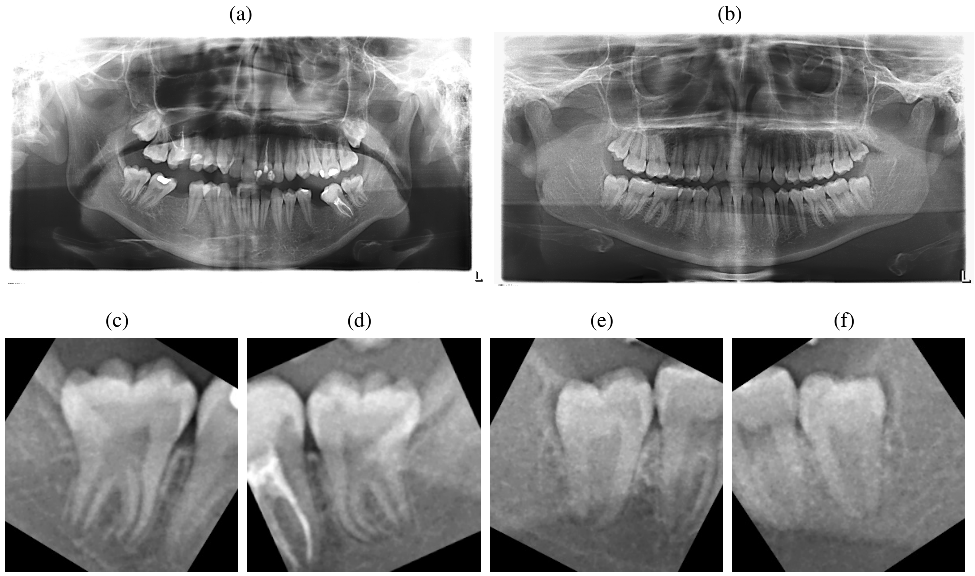

Fig. 1. Examples of orthopantomography images and images of third molars of the inferior arch: a) orthopantomography image acquired from a 16 years old individual; b) orthopantomography image acquired from a 21 years old individual; c) and d) enhanced regions of a) depicting the third molars of the inferior arch; e) and f) enhanced regions of b) depicting the third molars of the inferior arch. While the size of teeth is different between subjects, the shape of the third molars is different for underage and adult individuals.

from orthopantomography images [4]. However, to the best of our knowledge, none of them presents methods specifically designed to assess the legal age.

We propose a decision support system for forensic odontologists aimed at assessing the legal age from orthopantomography images. Specifically, we propose a method based on DNNs designed to replicate the age assessment performed by forensic scientists. Furthermore, our method is designed to require limited computational resources, making it portable on edge devices such as tablets and smartphones used by forensic scientists. Our method takes as input a single or multiple images of the third molars and applies a score level feature strategy to return a Boolean representing adulthood reaching. To search for the best configuration of our method for data collected in real application conditions, we investigated different neural models and fusion strategies.

To the best of our knowledge, there are no publicly available datasets of orthopantomography images. Therefore, we collected a dataset of orthopantomography images simulating cases for which forensic odontologists are asked to assess the legal age in real life. Specifically, we cooperated with Italian hospitals in collecting a dataset of dental radiographs from 237 individuals, ranging from 15 to 22 years old. The performed tests showed that our method obtains satisfactory results, with a classification accuracy of 0.841, thus proving the utility of our method as a decision support tool for forensic scientists.

The contribution of this paper is twofold. First, we present a novel automatic method for legal age assessment designed to evaluate multiple regions of orthopantomography images. Our method represents a valid decision support tool for forensic science, since in our tests, it obtained accuracy comparable to that of a forensic odontologist. Second, we collected a dataset of labeled samples, simulating real conditions for which forensic odontologists are asked to assess the reachment of the legal age.

This paper is organized as follows. Section II describes the state of the art on age estimation from dental radiographs. Section III presents our method. Section IV describes the collected dataset, performed tests, and obtained results. Section V concludes the work.

II. Related Work

Biometric recognition systems are designed to protect access to data and software applications [5] or physical places [6]. Anyway, biometric technologies are also frequently used in forensics. Specifically, biometric technologies are applied to verify the identity of living or deceased individuals [7], or to infer soft biometric characteristics (e.g., age, biological sex, and ethnicity) [8], [9]. In this context, frequently evaluated physiological characteristics include the face, DNA, fingerprints, and dental anatomy.

In the literature, there are studies on automatic methods for the analysis of dental anatomy. Most of these studies use orthopantomography images for identity recognition [10] or for estimating age and biological sex [4].

Considering orthopantomography images, which are the most commonly available data for forensic scientists, there are studies on automatic methods for identity verification [11], tooth segmentation [12], age estimation [13], and biological sex evaluation [14].

Various methods for age estimation can be categorized based on statistical approaches [15], machine learning techniques utilizing handcrafted features [16], or deep neural networks. Generally, methods employing deep neural networks tend to achieve higher accuracy compared to other approaches

[17]. Some studies rely on pre-trained Convolutional Neural Networks (CNNs) [18], while other approaches are based on ad-hoc CNNs [19], [20].

Age estimation methods are usually implemented as multiple-class classifiers, where each class represents a group of ages [20], [21] or as regressors [16], [19], [22]. There is also a study on the classification of children under and over 13 years old [18]. Furthermore, there is an automatic approach to estimate the development stage of single tooths [23].

To the best of our knowledge, there is only one study in the literature reporting results on the legal age estimation [22]. However, this study considers only a single tooth and has been tested for a dataset of samples collected from a wider set of ages compared to real forensic applications. In contrast, we propose a method capable of using multiple images of teeth to assess the legal age, which has been evaluated for a dataset simulating data analyzed by forensic odontologists in real scenarios.

III. Proposed Method

We propose a novel automatic method to assess the legal age using one or more images representing the third molars of the lower arch in orthopantomography images. Each available image of the third molar is processed using a DNN-based classifier. Since one of the third molars might not be present in orthopantomography images, our method employs an ad-hoc score-level fusion strategy to classify the attainment of age of maturity. Fig. 2 illustrates the schema of our method.

A. DNN-based Classifier

The DNN-based classifier takes a single image of the third molar as input. To achieve state-of-the-art accuracy, we utilize three DNNs trained on extensive datasets of images. Each selected network has an input layer designed for images sized 224×224 pixels, thus normalizing the size of the cropped face image accordingly. The fine-tuning process involves a two-class classification, where the positive class represents an age greater than or equal to 18 years old, while the negative class represents less than 18 years old.

The chosen DNNs are Shufflenet V2 [24], ResNet-18 [25], and ResNet-34 [25]. These networks have been trained using the image datasets ImageNet [26] (composed of $14,197,122$ images).

- **Shufflenet V2** is a lightweight network presented in [24]. It achieves accurate results with limited computational complexity by using pointwise group convolutions and bottleneck-like structures. Additionally, it employs a channel shuffle operation to facilitate information communication between different groups of channels, thereby improving accuracy.
- **MobileNetV3** is the latest generation of MobileNets. The implementation of automated search algorithms combined whith a better network design allowd MobileNetV3 to improve the accuracy and latency compared to MobileNetV2 on ImageNet. Two model architectures are available, MobileNetV3-Large and MobileNetV3-Small which are targeted for high and low resource use cases [27]. This makes it a more suitable option than deeper architectures like ResNets for real environment implementations even though ResNet presents better results.
- **ResNet-18** is a DNN based on the architecture described in [25]. This network has been trained for classification using the softmax loss function for MSCeleb-1M and fine-tuned for VGGFace2. The architecture consists of 18 blocks, each comprising a linear operator followed by one or more non-linear operators such as ReLU and max pooling. The first 15 blocks are convolutional, while the last 3 blocks are fully connected.
- **ResNet-34** and **ResNet-50** are a deeper versions of ResNet-18, with a total of 34 and 50 layers respectively.

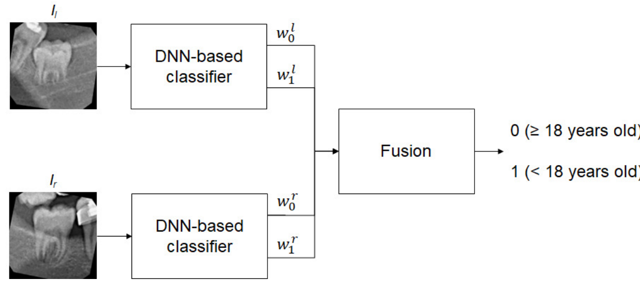

Fig. 2. Schema of our method for assessing the legal age.

Once trained, the output layer of the network is removed. Therefore, the output consists of the weights $[w_0, w_1]$, representing the values assigned to the two output classes before performing the maximum argument operation to select the final classification result.

B. Score-level Fusion Strategy

Since one of the third molars might not be present in orthopantomography images, we use an ad-hoc score-level feature strategy.

The inputs of the fusion strategy are the sets of weights $[w_0^l, w_1^l]$ and $[w_0^r, w_1^r]$, obtained by applying the DNN-based classifier to the left third molar image I_l and to right third molar image I_r, respectively. The output of the fusion strategy is the class value c. Images from subjects presenting only one third molar of the inferior arch are mirrored to simulate the other teeth.

The fusion strategy can compute new weights $[\hat{w}_0, \hat{w}_1]$ in six modes.

- **Maximum**: this fusion strategy computes a set of new weights $[\hat{w}_0, \hat{w}_1]$ before calculating c, as follows:

$$\hat{w}_0 = \max(w_0^l, w_0^r), \quad \hat{w}_1 = \max(w_1^r, w_0^r), \tag{1}$$

$$c = \operatorname{argmax}(\hat{w}_0, \hat{w}_1). \tag{2}$$

- **Minimum**: this fusion strategy is similar to Maximum, but computes $[\hat{w}_0, \hat{w}_1]$ as follows:

$$\hat{w}_0 = \min(w_0^l, w_0^r), \quad \hat{w}_1 = \min(w_1^r, w_0^r). \tag{3}$$

TABLE I
DATASET COMPOSITION

Years	Number of subjects
15	17
16	31
17	36
18	33
19	27
20	32
21	40
22	4

- **Mean**: this fusion strategy is similar to Maximum, but computes $[\hat{w}_0, \hat{w}_1]$ as follows:

$$\hat{w}_0 = \text{mean}\,(w_0^l, w_0^r), \quad \hat{w}_1 = \text{mean}\,(w_1^r, w_0^r). \qquad (4)$$

- **kNN**: A classifier based k-nearest neighbors [28] analyzes the feature set $[w_0^l, w_1^l, w_0^r, w_1^r]$ to estimate the class c.
- **Linear**: this fusion strategy is similar to kNN, but is based on a linear classifier [28].
- **FFNN**: this fusion strategy is similar to kNN, but is based on a feedforward neural network classifier trained using the backpropagation algorithm [29]. The topology of the neural network is designed as follows: a single hidden layer composed of log-sigmoidal nodes and an output layer composed of a linear node.

The classifiers based on machine learning techniques (configurations kNN, Linear, and FFN) are trained using the same data employed to train the DNN-based classifier.

IV. EXPERIMENTAL RESULTS

This section describes the used dataset, training and testing process, tuning of the DNN-based classifier, accuracy evaluation, and a comparison with results obtained by an expert forensic odontologist.

A. Dataset

To the best of our knowledge, there are no publicly available datasets of orthopantomography images. Therefore, we collected an image dataset simulating cases for which forensic odontologists are asked to assess the legal age in real life. Specifically, we collaborated with Italian hospitals to gather a dataset of 474 orthopantomography images from 237 individuals, ranging from 15 to 22 years old.

Due to the fact that some of the subjects of the dataset presented none of the two third molars, these subjects were deleted from the data. Images from subjects with only one tooth were mirrored to simulate the other tooth. The final dataset is composed of 220 samples. Table I summarizes the age distribution of the dataset.

Our method takes as input one or more images representing the third molars in orthopantomography images. Therefore, we created enhanced images of the third molars of the inferior arch created by forensic odontologists.

The images of the third molars are obtained by cropping a fixed-size region of 290×290 pixels, centered at coordinates selected by a human operator. The third molar image is then rotated to align its major axis with the y axis.

To simplify the segmentation and rotation processes, we developed a graphical user interface. This software also allows for the insertion of additional annotations to the images.

TABLE II
ACCURACY FOR SINGLE IMAGES

DNN	Learning rate	Batch size	Classification accuracy	Std accuracy
Shufflenet V2	0.001	32	0.759	0.060
MobileNet V3 Large	0.001	64	0.716	0.049
ResNet-18	0.001	64	0.755	0.065
ResNet-34	0.0001	64	**0.773**	0.069
ResNet-50	0.0001	64	0.748	0.064

B. Training and Testing

The DNNs are trained using the Adam optimizer, with learning rates and batch sizes selected by a grid search. The classifiers are trained for 30 epochs, and the learning rate is reduced by a factor of 0.1 every 7 epochs.

The classifiers are tested using a modified 10-fold cross-validation approach. Given that images of the left and right third molars acquired from the same individual often exhibit significant similarities, we ensured that for each fold, samples were drawn from randomly selected individuals. Specifically, we allocated all available samples from 90% of the individuals to compose the training set, while the remaining 10% of individuals' samples formed the validation set. Our experimental findings demonstrate that the conventional 10-fold cross-validation method, which selects random images, yields overly optimistic results. This is attributed to the capability of DNNs to learn information from one of the two samples belonging to the same individuals.

Data augmentation techniques were applied to the training set to increase the number of samples. Specifically, we applied random horizontal flipping and random rotation to the images. The rotation angle is randomly selected from a range of $[-30, 30]$ degrees.

The selected figures of merit include the classification accuracy and the standard deviation of the classification accuracy obtained across different folds during the validation process.

C. Tuning of the DNN-based Classifier

To select the best configuration of the DNN-based classifier, we evaluated the accuracy obtained by the considered DNN models (described in Section III-A) in their training configuration, considering the classification outcome for each individual image. We also evaluated different learning rates and batch sizes for each model. Table III-A summarizes the best results obtained for the dataset using the modified 10-fold cross-validation approach described in Section IV-B.

Table III-A shows that ResNet-34 obtained the best result, with a classification accuracy equal to 0.773.

We compared the obtained results with those obtained using the conventional 10-fold cross-validation approach, where

TABLE III
ACCURACY OF OUR METHOD WITH DIFFERENT CONFIGURATIONS OF THE FUSION STRATEGY

Image Set	**Fusion strategy**	**Classification accuracy**
Left images	No	0.755
Right images	No	0.791
Complete set	No	0.773
Complete set	Min	0.800
Complete set	Max	0.786
Complete set	Mean	0.791
Complete set	kNN	0.786
Complete set	Linear	0.795
Complete set	FFNN	0.841

samples for the training and validation sets are randomly selected. In this case, the best configuration of ResNet-34 achieved a classification accuracy of 0.811. This outcome demonstrates that the conventional 10-fold cross-validation approach obtains overly optimistic estimations when one of the third molar images of an individual is used for training the DNN, and the other one is used for validating the model.

D. Accuracy evaluation

We evaluated the accuracy of our method by using the proposed fusion strategy and the best performing DNN classifier (ResNet-34 with learning rate equal to 0.0001 and batch size equal to 64). Table III summarizes the results obtained using different configurations of the fusion strategy.

Table III shows that every configuration of the fusion strategy improves the classification accuracy of our method. In particular, the configuration FFNN obtained the best result, with a classification accuracy equal to 0.841. Considering the algorithmic configurations, which do not need any training process, the configuration Mim obtained the best performance, obtaining a classification accuracy equal to 0.800. Table IV reports the confusion matrix obtained using the configuration FFNN.

The results reported in Table III and Table IV can be considered positive, as forensic anthropologists may encounter classification errors when observing this type of data. Moreover, the obtained results are comparable to the state-of-the-art. The only study reporting results on individuals reaching 18 years old is [22], which reported a classification accuracy of 0.923. However, it should be noted that this result pertains to a dataset collected from individuals ranging from 5 to 24 years old, introducing more heterogeneity compared to the datasets used to evaluate the performance of our method. Indeed, the collected dataset is specifically designed to resemble more challenging conditions, typical of real cases in which forensic scientists are asked to assess the attainment of the legal age.

V. CONCLUSION

This paper presented a novel automatic method for assessing legal age using dental radiographs. Specifically, the method employs deep neural networks and a custom fusion strategy to classify regions representing the third molars of the inferior

TABLE IV
CONFUSION MATRIX FOR THE BEST CONFIGURATION OF OUR METHOD

		Actual values	
		Positive	Negative
Predicted values	Positive	0.5636	0.0545
	Negative	0.1045	0.2773

arch. To evaluate the performance of our method, we collaborated with Italian hospitals to collect a labeled dataset of samples reflecting typical conditions encountered by forensic odontologists when assessing the attainment of the legal age. We evaluated the performance of our method under various configurations, achieving a classification accuracy equal to 0.841. Increasing the number of dataset samples would allow a future study to try deeper neural network architectures. This demonstrates the applicability of our method as a decision support tool for forensic scientists. Future studies will focus on collecting larger image datasets to enhance the robustness of our method across heterogeneous conditions.

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