RESEARCH ARTICLE

Age Detection by Deep Learning from Dental Panoramic Radiographs

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Abstract

The use of deep learning approaches is growing day by day in the solution of various real-world problems in engineering science. Health sciences problems are also one of the areas in that deep learning is frequently applied. Especially in digital forensics cases and anthropology, when determining the identification of living individuals or corpses, the most important specification is to state the age of the person. At the stage of determining the age, the analysis of bone or tooth development of people is two of the most trustworthy methods. Moreover, there is a distinctive interrelation between the eruption of permanent and primary teeth and the chronological age of the individual. In this study, a deep learning approach is suggested as an alternative to age determination using traditional methods. A total of 627 dental orthopantomographic images gathered from individuals between the ages of 2 and 21 were employed in this study. The data set consists of two different classes, individuals under the age of 13 and individuals aged 13 and over, who have completed the eruption of their permanent number 7 teeth. Firstly, feature extraction was operated on the data by using the Convolutional Neural Network (CNN) architecture, which is one of the deep learning approaches. Afterward the feature extraction phase, the system was completed using four different classifiers. 70% of the dataset is allocated for training while in the rest is reserved for testing. The results achieved using various evaluation metrics are presented in detail with a complexity matrix, tables, and graphs. In this study, 84% accuracy, 85% F-score, and 76% sensitivity values were reached using the Alexnet architecture and k-nearest neighbor (k-NN) algorithm. It is forecasted that the proposed system will ensure age determination in less time and abate the cost compared to traditional age determination methods. Besides, the study will both support dentists in the clinical environment and can be used in education.

Keywords: deep learning, dental age estimation, machine learning

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1. Introduction

In forensic cases, all sorts of information about one person, which having such as gender, age, and ethnic origin, have been used to keep light on the events. In this respect, age estimation is of major importance in terms of shedding light on forensic events as it has provided information about the offender and the victim [1]. Today, one

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of the most common methods used for age estimation on both living persons and corpses is the examination and evaluation of bone and tooth development. In corpse remains, the teeth retain their structure for a long time due to their hard structural features. This provides valuable information to forensic scientists [2]. There has a positive relationship between dental age and chronological age. Therefore, it is widely used in dental and forensic studies to determine the age of infants and children.

Dental age is determined by comparing the developmental stages of temporary and permanent teeth in humans with dental development charts prepared by different researchers. Researchers have determined various scales according to the developmental stages of permanent and temporary teeth in the radiographs. Researchers aimed to determine the tooth age by comparing these scales with the scales they formulated. The age of 14, which is the eruption time of the permanent second molars, is considered the end of the childhood and mixed dentition period and this period is a reliable detection method used in age determination [3]. Atlas method and scoring method are used to determine the age of children's teeth. The Atlas method was first developed by Schour and Massler in 1941 [4- 5]. The scoring method was developed by Demirjian. In this method, the development of seven left lower mandibular teeth was scored in 8 categories (A-H) [6].

In this study, orthopantomography images of individuals under the age of 13 and above, including the age of 13 when the permanent 7th teeth have completed their eruption, were used. With these images, the reliability of the artificial intelligence-based deep learning method has been tested.

In the second part of the study, a literature review was made. İn the third chapter, the material, data set, and algorithms used in the study have been explained. The fourth chapter is reserved for the interpretation of the test results. Finally, in the results chapter, the results of the study and its contribution to the literature are given.

2. Related Works

Computed technologies, which are making more progress every day, also affect the studies made with medical imaging methods. In this section, studies with dental x-ray images for age determination are briefly mentioned.

Panoramic dental x-ray images and deep learning architecture (DLA) were employed in a study that made age estimation. The data utilized in this study consist of dental x-ray of adolescents aged 11-20. The dataset comprises 14.000 panoramic dental x-ray images. As a result, it performed better than the prediction of dental specialists with a 17.52 percent error rate [7].

In another study, a method based on deep learning was proposed to state the chronological age of young people. Deep convolutional neural network (DCNN) trained with MRI images of the upper thorax, jaw, and left hand. The proposed method was trained and interpreted on the 3D MRI dataset of 103 male volunteers aged between 13.01 and 24.89 years. It attained a mean absolute error of 1.3±1.13 years with the regression-based solution [8].

A study was conducted to roughly classify adolescent age based on dental x-Ray images. These dental images consist of 456 Malaysian children. Dental x-Ray images have been trained by DCNN. Age categories in this study were classified as 1-4, 5-7, 8-10, 11-13, and 14-17, and on the mean, the accuracy achieved for this five-class problem was approximately 81.83% [9].

In a preliminary study that included 14 men and 16 women, a study was conducted with orthopantomography films whose age range was between 15 and 86 years. In this study, Inception-v3, Xception, VGG16, MobileNet-v2, InceptionResNet-v2, and ResNet50 were used with CNN architecture. An accuracy value of 100.0% was obtained with VGG16 [10].

Another Artificial Intelligence-enhanced study processed ~300 examples taken by cone-beam computed tomography (CBCT) of persons aged from 14 to 60 years. Researchers evaluated the ratio between tooth and pulp. They also compared a neural network model with a linear regression model. The presented results indicate that the linear regression model has an MAE of 8.17 years, and an RMSE of 10.26 years while the neural network model has an MAE of 4.12 years and an RMSE of 4.40 years [11].

Deep convolutional neural networks were used with a dataset consisting of 4035 pantographic images to estimate the age group. The proposed neural network was applied to estimate the age of 89 archaeological skull remains. The accuracy performance of the proposed network architecture is 73% [12].

4035 pantographic radiographs were used in the study to evaluate the accuracy value of dental age estimation from X-rays images. In addition, a learning set consisting of 76.416 dental radiographs of persons aged 19-90 was used. As a result, the mean error value was observed as 2.95 years for the panoramic images. For single tooth images, it was observed as 4.68 years [13].

Zaborowicz et al. proposed a deep neural network model to provide age determination from dental images [14]. The proposed study aimed to validate the ability to construct a more accurate deep neural network model than previously produced models. In the quality parameters of the proposed model, the MAE error was between 2.34 and 4.61, and the RMSE error was between 5.58 and 7.49.

Yeon-Hee Lee et al. managed to accurately predict the age group of people with permanent teeth using five different machine learning algorithms [15]. In this study, 471 digital panoramic dental images collected from patients were used. As a result of the study, AUC values between 0.85 and 0.88 were obtained for five different machine learning models.

In this study, a method is brought forward to estimate age from 627 dental orthopantomographic images for two classes aged 2-13 years and 13-21 years. The study aims to reduce the age estimation error rate.

3. Materials and Methods

3.1. Dataset

The data set used in this study was obtained from Elazig Fırat University Faculty of Dentistry, Department of Oral, Dental, and Maxillofacial Radiology. The dataset labeled by the dentist consists of two classes: under 13 years old and over 13 years old. Orthopantomographic images of a total of 627 people were used in the study. While 325 orthopantomographic images were used for 13 years old and younger, 302 data were used for 13 years old and over. While 30% of the data was used as test data, 70% was used in the training phase. Information about the data set is given in Table 1. In addition, in Figure 1, the dental orthopantomographic image of two age groups from the data set are shown.

Table 1. Numerical information of the classes in the data set used in age estimation

Data Groups	Data Count
2-13 Age	325
13-21 Age	302
Total	**627**

a) 14 Years Teeth Image **b)** 2 Years Teeth Image

Figure 1. Dental orthopantomographic images

3.2. Machine Learning and Deep Learning Architecture

The dental orthopantomographic image can be utilized to determine a person's age since tooth development is one of the long-term processes in the human body's bone structure, Within the scope of the study, a deep learning method has been proposed for automatic age estimation of individuals aged 2-13 and 13-21 years to reduce this estimation error. In this study, the data set was adjusted to have two different classes of orthopantomography images of individuals aged 2-13, including 13 years, and 13-21 years of age. The main reason for this distinction is that it is 13 years old when the eruption of number 7 teeth is completed, and 14 years old, which is considered the end of the mixed dentition period. In this direction, Alexnet architecture, which is based on CNN deep learning, was used for feature extraction. After feature extraction, k-Nearest

Neighbor Algorithm (k-NN), Naive Bayes Algorithm (NBA), Decision Tree (DT), and Linear Discriminant (LR) algorithms were used in the classification phase. The operating scheme of the system is illustrated in Figure 2.

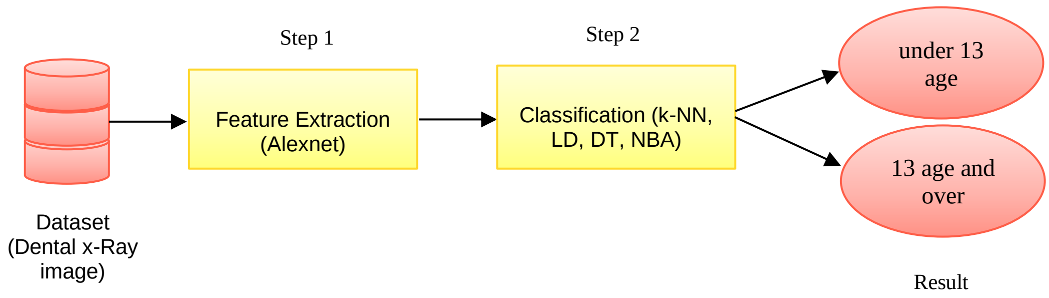


Figure 2. Operating scheme of the system

3.3. Evaluation Criteria

After feature extraction with deep learning architectures, complexity matrix and Receiver Operating Characteristic (ROC) curve were applied to assess the accuracy of the system that performs classification with machine learning algorithms. The complexity matrix determines the accuracy, sensitivity, specificity, and F1-score performance values, while the ROC curve shows the sensitivity and specificity. The complexity matrix is given in Table 2. In addition, according to Table 2, the accuracy, sensitivity, and F1-score performance values were calculated between Equation 1 and Equation 3, respectively [16].

Table 2. Confusion Matrix

Confusion Matrix		**Actual Values**	
		Positive States	Negative States
Prediction	Positive	TP (True Positive)	FP (False Positive)
	Negative	FN (False Negative)	TN (True Negative)

$$Accuracy = \left(\frac{(TP + TN)}{(TP + FP + FN + TN)}\right) \quad (1)$$

$$Sensitivity = \left(\frac{(TP)}{(FP + FN)}\right) \quad (2)$$

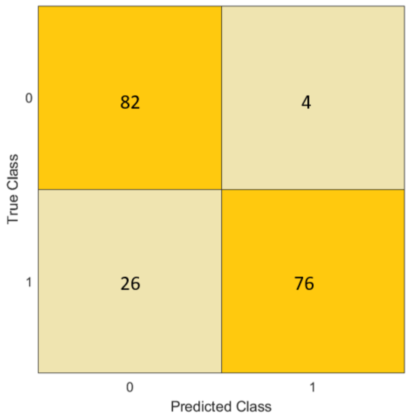
$$F1\ Score = \left(\frac{(2TP)}{(2TP + FP + FN)}\right) \quad (3)$$

4. Experimental Study

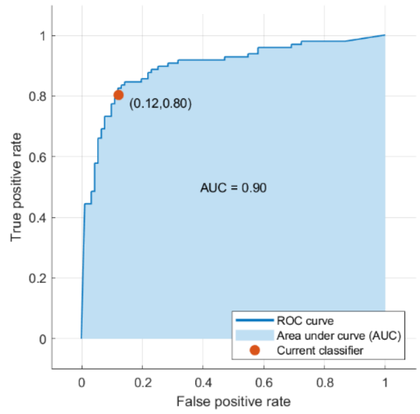
In this study, a system that aims to determine the age of an individual with a dental orthopantomographic image is proposed. First, feature extraction was applied with Alexnet architecture, which is based on deep learning. Then, The four classification algorithms with the best results are given in Table 3. The highest accuracy rate, 84% accuracy value was obtained in the k-NN algorithm after feature extraction with Alexnet architecture.

Table 3. Accuracy, precision, and F1-Score values of machine learning algorithms

		Accuracy	Sensitivity	F1-Score
Alexnet	k-NN	**0.8404**	0.7593	0.8454
	LD	0.8245	0.7692	0.8092
	DT	0.7713	0.7363	0.7571
	NBA	0.8032	0.8462	0.8063



a) Complexity Matrix



b) ROC Curve

Figure 3. Complexity Matrix and ROC curve

In Figure 3, the complexity matrix and ROC curve of the k-NN algorithm, which has the highest accuracy value, are shown. Finally, the performance comparison of the algorithms applied in the proposed system is listed in Figure 4. The highest accuracy and F1-score values were achieved by the k-NN algorithm. In addition, the highest sensitivity value was obtained by the NBA.

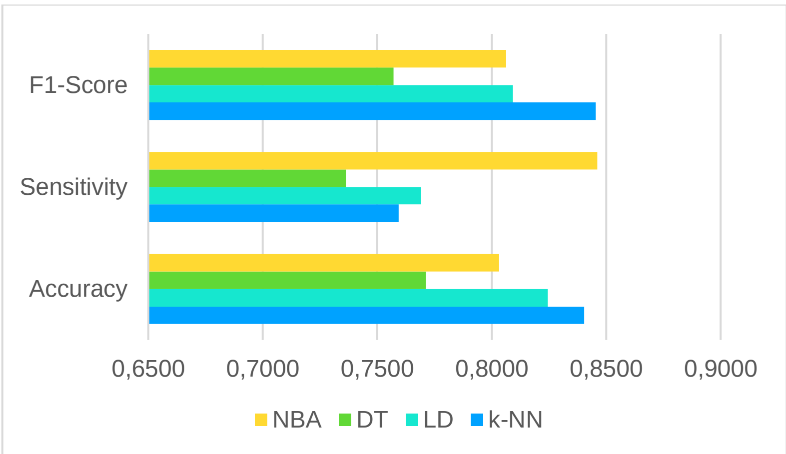


Figure 4. Performance comparison of algorithms

In the literature, many studies have been carried out for the estimation of tooth age, and the architecture, the number of data sets, and the accuracy values they used are presented in Table 4. The data set used in the proposed study is different from the other studies presented in the table. However, all of the studies in the table are similar in that they are based on artificial intelligence.

In Table 4, the architecture, the number of data sets, and the accuracy rates of the studies carried out for the determination of age from the teeth in the literature are represented. On the other hand, more data is collected in the proposed system. In addition, the data set used in the study has a balanced distribution. This situation positively affects the success of the system.

Table 4. Comparison of studies on tooth age determination

Architecture Used	Data Size	Accuracy
Fuzzy Segmentation, DCNN [9]	456	%81.83
CNN,VGG16 [10]	30	%100
Suggested Study	**627**	**%84**

5. Conclusion

The timing of teething, the period of tooth exchange, or the degree of tooth corrosion is a substantial diagnostic agent in assessing an individual's age of development. In many areas, a system based on deep learning architecture has been proposed that makes age estimation from dental data obtained from living individuals. In this study, a system based on deep learning architecture has been proposed that makes age estimation from dental data obtained from living individuals in many fields such as forensics, anthropology, and international adoption. It is aimed to increase performance by applying different machine learning methods to the obtained data. In the study, 84% accuracy, 85% F-score, and 76% sensitivity values were reached using the Alexnet architecture and k-NN. In future studies, different feature extraction deep learning architectures will be developed. In addition, it is planned to increase the number of data and the number of classes. Finally, an age determination system will be developed using different state-of-the-art classifiers and their hybrid versions.

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