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Artificial Intelligence Application and Performance in Forensic Age Estimation with Mandibular Third Molars on Radiographs

SUMMARY

Background/Aim*: Age estimation is of great importance due to legal requirements. Although there are many methods used, most of them are based on age related dental changes. Artificial intelligence based programs, one of the most current and popular topics in recent years, are becoming more and more important in dental studies. This study aims to measure the performance of deep learning in forensic age estimation from mandibular third molars using panoramic radiographs.* ***Material and Methods:*** *In our study, panoramic radiographs of male and female patients between the ages of 16-26 years who applied to our department for various reasons were used. The pixel-based Convolutional Neural Networks (CNN) method, one of the types of artificial neural networks, was applied. The high performance ResNeXt-101 model and Adamax algorithm were selected. The learning rate was set to 0.001. The dataset was labeled with the DentiAssist platform and randomly divided into 80% training and 20% testing. 1296 data under 18 and 1036 data over 18 were used. Dropout method was applied in case of over memorization. In the last step of the hidden layer, a linear two-class prediction was obtained using a structured fully connected layer.* ***Results:*** *The performance metrics for the ResNeXt neural network were 4.36% accuracy, 83.95% precision, 84.56% recall, 84.56% F1-score and 84.14% F1-score (80% confidence interval) when adequate training was provided.* ***Conclusions:*** *Artificial intelligence, which eliminates the subjective margin of error compared to conventional methods and rapidly processes a large amount of data, has achieved promising results in forensic age determination.*

Keywords: Artificial Intelligence, Age Estimation, Mandibular Third Molar, Orthopantomography

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Introduction

Forensic age estimation is of great importance for paleodemographic research and legal needs in forensic cases[1]. In some parts of the world; social and legal problems such as insufficient population registrations, wars, migrations, and natural disasters increase the necessity of forensic age estimation[2]. There are many methods used in forensic age determination. These methods have been developed by considering the physical characteristics of the person, height and weight, signs of puberty, mental and spiritual development, and development of bone and tooth structures[3]. Although various methods exist, most of the methods recorded in the literature for age estimation in adults are related to age-related dental changes. These methods are based on the study of dental tissue and morphology from early fetal life to adulthood[4]. The use of dental radiographs for age estimation includes the evaluation of morphologically different mineralization stages, the degree of formation and eruption of root and crown structures of teeth, and observation of the formation of primary and permanent teeth[5]. The branch of dentistry in which the identity of the individual is determined by examining the dental structures with these methods is called forensic dentistry[6].

According to the United Nations Convention on the Rights of the Child, an individual under the age of 18 is defined as a child. The most commonly used age limit for determining childhood and adulthood is 18 years[7]. The only group of teeth that continue to develop at the age of 18 are the third molars[8]. Radiographic evaluation of teeth is one of the commonly used age determination methods in individuals under the 16 years of age[9]. Since the root apex of the other teeth is closed after the age of 16, the group to be used for age estimation may be the third molars, which is the only tooth group in the developmental stage at the age of 18 years. However, evaluating the apical development of third molars in cases that complete the dental development stages early may not always give accurate results in determining the 18-year age threshold[10].

Artificial intelligence (AI) models are intelligent mathematical technologies that imitate the human brain and can solve problems and make decisions after training[11,12]. AI, which is used in many branches of science and is one of the most popular topics of today, has also taken place in dentistry studies and its position in the literature is increasing day by day[13,14]. When the literature is examined, it is promising that AI applications aim to reproduce the cognitive processes on humans and reach the same results with experts and health professionals in the optimum time[15]. Considering other existing studies, age determination by AI can be used in large human populations by providing faster and more accurate diagnoses compared to traditional methods, and the workload of experts can be alleviated[16]. AI offers an optimum approach with a groundbreaking technology for measurement examinations that take time to interpret and require attention in dentistry. Therefore, it is clearly stated in the literature that applications developed with AI have the ability to improve health data outcomes, reduce health expenditures, and advance medical studies[17].

Based on these ideas, our study aims to measure the performance of deep learning in forensic age estimation from mandibular third molars using panoramic radiographs. As a result of the study, the performance of deep learning technologies, which is an important sub-branch of artificial intelligence, in the field of dentistry is demonstrated with outstanding success.

Material and Methods

Ethical Approval

This study obtained ethical approval from the Ethics Committee of Necmettin Erbakan University, Faculty of Dentistry, under date 27.04.2023, decision number: 2023/278. The study was carried out in accordance with the International WHO Declaration of Helsinki.

The study was conducted using panoramic radiographic images, which have optimal diagnostic adequacy and were taken under ideal conditions, of male and female patients with mandibular third molars aged 16-26 years who applied to Necmettin Erbakan University, Faculty of Dentistry, Department of Oral and Maxillofacial Radiology between January 2021 and February 2023 for various reasons. Panoramic radiographs were taken by the same technicians under ideal conditions on a Morita Veraviewepocs 2D device (J Morita MFG Corp., Kyoto, Japan) at 70 kVp, 10 mA, 10 s and on a Newtom GiANO HR 2D device (NewTom GiANO HR, Italy) at 77 kVp, 6 mA, 12.7 s in accordance with the manufacturer's recommended protocols. The study was conducted with PyTorch library, one of the most commonly used deep learning libraries in Python programming language. Thanks to the artificial neural networks it contains in deep learning algorithms, it offers learning and perception abilities as well as the ability of people to learn. For neural networks, the activation function has certain parameters along with the optimization functions used. Convolutional Neural Networks (CNN), one of the types of artificial neural networks, apply a pixel-based method by applying filters on image data. Therefore, it was decided that the most suitable neural network for this study was CNN by filtering the images with various kernels and giving them to the pooling layer. Thanks to the state-of-the-art transfer learning, working with pre-trained ImageNet[18] weights is supported without the need for retraining the neural network weights. Among the many artificial neural network algorithms in the literature, the ResNeXt model, which is a frequently used and high-performance network, has been selected. For the ResNeXt model, a multi-layer neural network has been chosen and the ResNeXt-101 model has been chosen, and a high performance is expected due to the high number of hidden layers it contains (Figure 1).

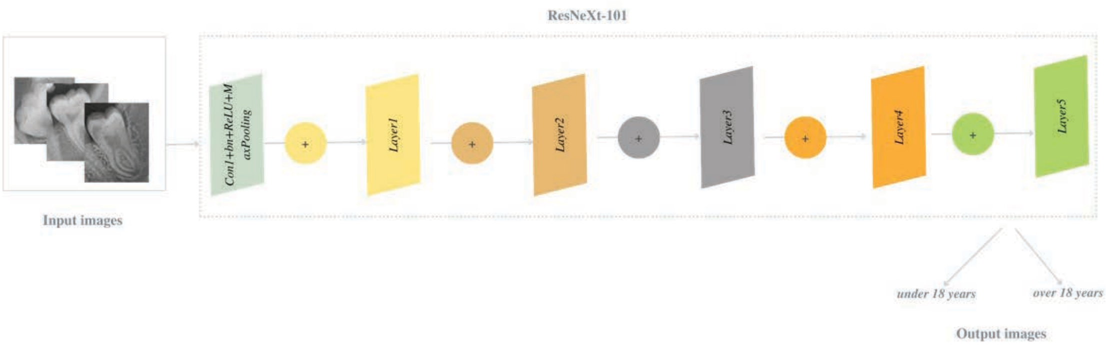

Figure 1. The ResNeXt neural network architecture created for the classification task

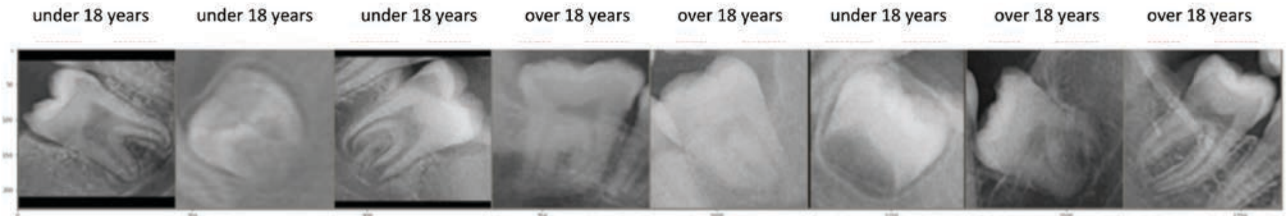

Figure 2. The following figure belongs to the samples in the dataset (Accordingly, it is concluded that different examples suitable for real world data are used for the dataset)

The ResNeXt[19] model in the figure is an enhanced version of the ResNet model that applies batch residual transformations for deep neural networks. The ResNeXt algorithm is a building block iterative neural network structure that collects a set of transforms with the same topology as the ResNet algorithm[19]. The Adamax[20] algorithm, which is an improved gradient descent algorithm, was chosen as the optimization algorithm. The chosen optimizer algorithm is a kind of Adam optimization structure based on the infinity norm[21]. Furthermore, the learning rate for the backward learning algorithm from hidden layers in the neural network was determined as 0.001. Dataset in the study were labeled with the DentiAssist[16] platform and automatically cropped per class using X, Y, width and height positions. The dataset is randomly divided into 80% training and 20% testing. In order for the study to make an unbiased estimation, the data under the age of 18 were rotated 270 degrees and the data was increased. Thus, while the total number of data in the data set was 648 under the age of 18, it reached 1296 with the data increase and the number of data over the age of 18 reached 1036 (Figure 2). In addition, the dropout method was applied against the possibility of excessive memorization in artificial neural networks and some neural networks in the last layer were disconnected by 40%. In the last step of the hidden layer, a linear two-class prediction is obtained using a structured fully connected layer.

Results

Performance metrics were recorded for the last iteration when adequate training was provided for the ResNeXt neural network. The experimental results obtained for the binary classification task are successful and sufficient when the data is considered to be random and difficult. While the batch loss for 16 batch sizes reached 6.328538622779076e-07, the accuracy reached 84.3683083511% for a total of 467 test data during the testing phase.

Performance Metrics

Precision, recall, f1 score and accuracy metrics, which are frequently used in the literature, were used for experimental results (Table 1). Equations 1, 2, 3 and 4 show the calculation of the respective values. There is no single metric suitable for calculating performance for a classification task. For this reason, calculations were made using true positive, true negative, false positive and false negative values. These values are obtained from the figure (Figure 3). It proves how well the learning neural network learns during the test phase.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Table 1. Performance Metrics

Class	Accuracy	Precision	Recall	F1-score
Mandibular Third Molars	84.368308351	83.952384470	84.56006768	84.140253915

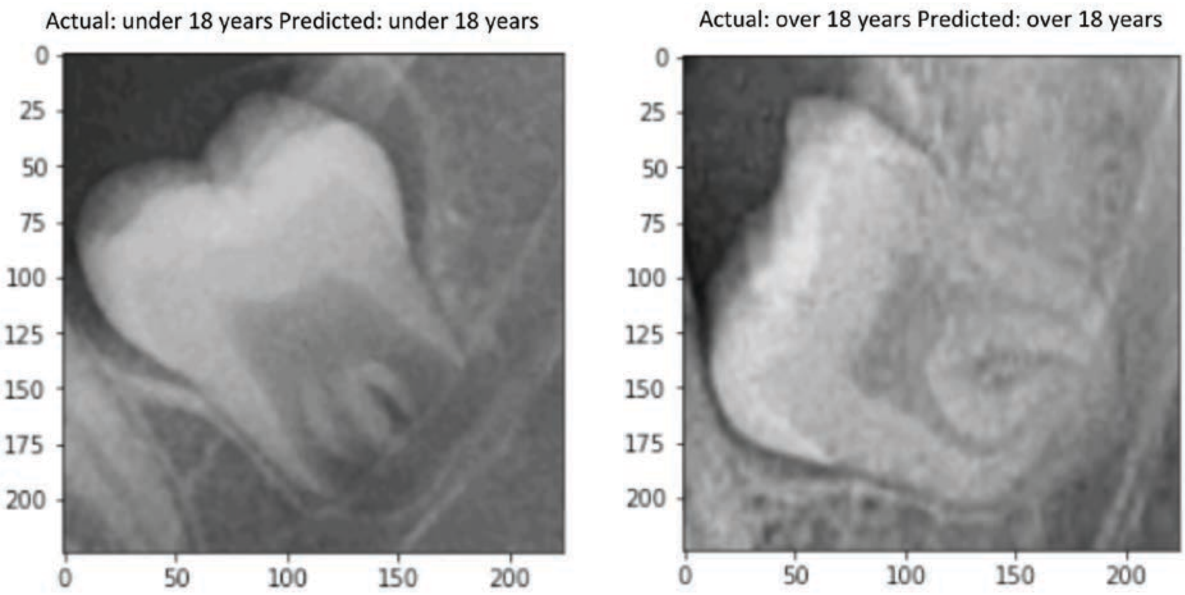

Figure 3. Retroalveolar X-ray used for the Performance Metrics recording

Matrix

When the matrix is examined in detail, the values located diagonally represent the True Positive (TP) values. In this case, the relevant TP, True Negative (TN), False Positive (FP), and False Negative (FN) values for the performance metrics included in the equations were calculated from this matrix (Figure 4). For the confusion matrix, the horizontal axis shows the predicted labels, while the vertical axis contains the actual labels, that is, expert information. When the matrix is examined, the vertical axis represents the true label class, while the horizontal axis represents the predicted label class. Accordingly, in the test data, while 225 correct predictions were made for the under-18 class, 45 misclassifications were made with over-18 predictions. While there are 169 correct predictions for the over 18 class, there are 28 incorrect predictions. Since third molars can be found in the jaws as fully impacted or semi-impacted teeth, the presence of different data in the cluster also reveals a challenging estimation task.

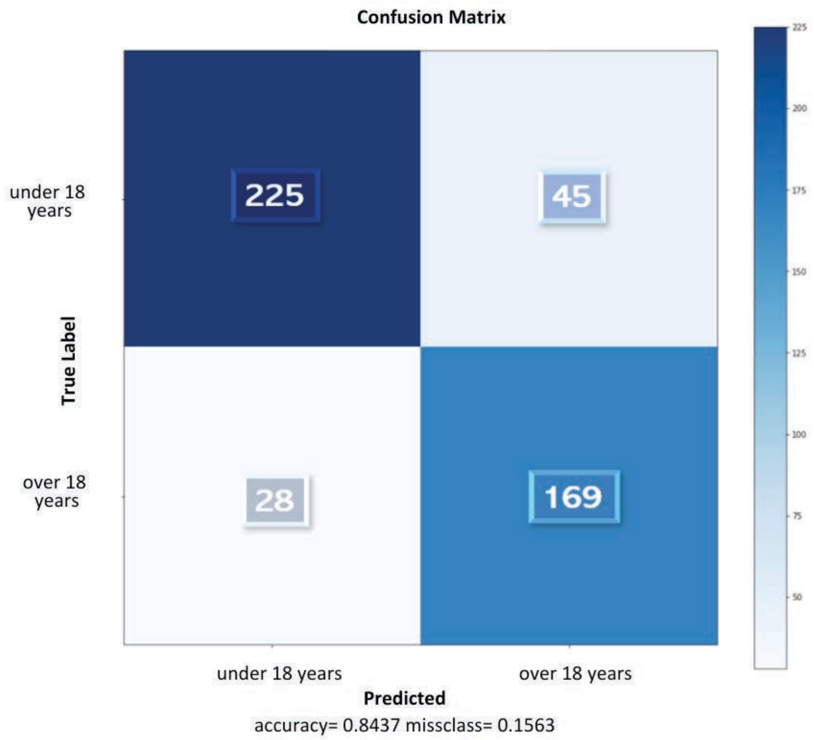

Figure 4. Performance metrics calculated from the matrix

Discussion

Among the different biomarkers used for age estimation in forensic medicine, dental structures are among the important indicators of aging[21]. There are many studies on this topic in the literature and most of these methods are based on X-rays. Age is estimated by evaluating tooth mineralization, crown formation, root development, apex maturation, and tooth eruption[22, 23]. Despite many developments and extensive studies in this field of research, a consensus on a precise and effective method for age determination for all age groups within conventional methods has not yet been achieved[24]. The main difference between conventional methods, first described by Demirjian[25] in 1973 and since then many methods have been developed, and AI is that AI extracts a set of features from raw data without the need for human intervention after learning[16]. Limitations of conventional methods include the increased error rate due to subjective judgments between observers and the time-consuming implementation. Although limited confirmatory studies, it has been noted that the use of AI in forensics goes beyond traditional practice[11].

Due to its autonomous learning of data features, AI has the ability to be widely used and performs strongly with large amounts of data. Thus, it can alleviate the workload of experts by providing fast and accurate results[16]. Tobel *et al.*[26] applied an AI-based model for staging lower third molar development using panoramic radiographs. After 5-fold cross-validation using different validation metrics such as performance, accuracy, Rank-N recognition rate, mean absolute difference, and linear kappa coefficient, they found that the convolutional neural networks (CNN) approach outperformed all other tested approaches. The model exhibited equivalent accuracy compared to trained inspectors. Blanco *et al.*[27] used two fully automatic methods to estimate the chronological age of a person from panoramic radiographs. The first one (DANet) consists of a sequential conventional neural path for age estimation, while the second one (DASNet) is a second CNN path for gender estimation. Thus, the study also utilized gender-specific features to improve the performance of age estimation. As a result, DASNet outperformed DANet in all aspects. DASNet can automatically estimate chronological age accurately and quickly for young individuals with incomplete tooth development.

Wu *et al.*[28] in their study, panoramic dental x-rays were used to train an AI model for establishing a population-based standard for dental age. The model was then used to assess the dental age of healthy children and those with growth delay using both conventional methods and AI-assisted standards. The results were compared using paired sample t-tests. The AI-assisted standards provided more accurate predictions of chronological age with errors of less than 0.05 years, while the traditional methods overestimated results in both genders. The CNN revealed delayed dental age in growth delay children of both genders, while the machine learning models only did so in growth delay boys.

In our study, an 84.3% success rate was achieved, similar to the studies in the literature. AI methods, which are capable of processing a large number of data, are expected to be useful in age determination in various legal and anthropological issues such as migration, disaster, and war. In addition, by reducing subjective errors, it can facilitate the work of experts and provide accurate diagnoses in a short time. The high success rate of our study is promising in this respect.

Conclusions

Artificial intelligence, one of the most popular topics of today, is increasingly being used in the field of dentistry. In our study, deep learning achieved fast and successful results in forensic age determination from mandibular third molar teeth using panoramic radiographs of an individual with an unknown date of birth. Although our study contains promising results, comprehensive studies in larger groups are needed.

References

1. Göl E. Usability of dental pulp visibility in digital panoramic radiographs in age estimation in the forensic medicine. 2013.
2. Gunacar DN, Bayrak S, Sinanoglu EA. Three-dimensional verification of the radiographic visibility of the root pulp used for forensic age estimation in mandibular third molars. Dentomaxillofac Radiol, 2022;51:20210368.
3. Yılmazer Ö. Evaluation of the method used in age determination in terms of efficiency. Istanbul: Turkish Ministry of Justice Forensic Medicine Institute, 2006.
4. Limdiwala PG, Shah JS. Age estimation by using dental radiographs. J Forensic Dent Sci, 2013;5:118-122.
5. Avon SL. Forensic odontology: the roles and responsibilities of the dentist. J Can Dent Assoc, 2004;70:453-458.
6. Johnson A, Gandhi B, Joseph SE, Inves C. A morphological study of tongue and its role in forensics odontology. J Forensic Sci Criminal Inves, 2018;7:1-5.
7. Jayaraman J, Roberts GJ, Wong HM, McDonald F, King NM. Ages of legal importance: implications in relation to birth registration and age assessment practices. Med Sci Law, 2016;56:77-82.
8. Mincer HH, Harris EF, Berryman HE. The ABFO study of third molar development and its use as an estimator of chronological age. J Forensic Sci, 1993;38:379-390.
9. Cunha E, Baccino E, Martrille L, Ramsthaler F, Prieto J, Schuliar Y, et al. The problem of aging human remains and living individuals: a review. Forensic Sci Int, 2009;193:1-13.

10. Streckbein P, Reichert I, Verhoff MA, Bödeker R-H, Kähling C, Wilbrand JF, et al. Estimation of legal age using calcification stages of third molars in living individuals. Sci Justice, 2014;54:447-450.
11. Kozan NM, Zelenchuk GM. Using the artificial neural networks for identification unknown person. IOSR-JDMS, 2017;16:107-113.
12. Katne T, Kanaparthi A, Gotoor S, Muppirala S, Devaraju R, Gantala R. Artificial intelligence: demystifying dentistry–the future and beyond. Int J Contemp Med Surg Radiol, 2019;4:D6-D9.
13. Brickley MR, Shepherd JP, Armstrong RA. Neural networks: a new technique for development of decision support systems in dentistry. J Dent, 1998;26:305-309.
14. Park WJ, Park JB. History and application of artificial neural networks in dentistry. Eur J Dent, 2018;12:594-601.
15. Schwendicke FA, Samek W, Krois J. Artificial intelligence in dentistry: chances and challenges. J Dent Res, 2020;99:769-774.
16. Merdietio Boedi R, Banar N, De Tobel J, Bertels J, Vandermeulen D, Thevissen PW. Effect of lower third molar segmentations on automated tooth development staging using a convolutional neural network. J Forensic Sci, 2020;65:481-486.
17. Tekin BY, Ozcan C, Pekince A, Yasa Y. An enhanced tooth segmentation and numbering according to FDI notation in bitewing radiographs. Comput Biol Med, 2022;146:105547.
18. You Y, Zhang Z, Hsieh CJ, Demmel J, Keutzer K. Imagenet training in minutes. Proceedings of the 47th International Conference on Parallel Processing, 2018;1-10.
19. Xie S, Girshick R, Dollár P, Tu Z, He K. Aggregated residual transformations for deep neural networks. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR),* Honolulu, HI, USA, 2017:5987-5995.
20. Kingma DP, Ba J. Adam: A method for stochastic optimization. ICLR, 2015:1-15.
21. Kazangirler CB, Özcan C, Tekin BY. Ön Eğitimli Evrişimli Sinir Ağları ile UI Öğelerinin Tespiti ve Sınıflandırılması. 5th International Conference on Data Science and Applications, 2022;100-107.
22. Jia L, Zhang W, Chen X. Common methods of biological age estimation. Clin Interv Aging, 2017;12:759-772.
23. Mohammed RB, Koganti R, Kalyan SV, Tircouveluri S, Singh JR, Srinivasulu E. Digital radiographic evaluation of mandibular third molar for age estimation in young adults and adolescents of South Indian population using modified Demirjian's method. J Forensic Dent Sci, 2014;6:191-196.
24. Ilayaraja V, Ganapathy N, Jisha G, Keerthipriyadharshini T, Maheswaran T, Yoithapprabhunath TR. Digitized morphometric analysis using maxillary canine and mandibular first molar for age estimation in South Indian population. Open Dent J, 2018;12:762-769.
25. Mughal AM, Hassan N, Ahmed A. Bone age assessment methods: a critical review. Pak J Med Sci, 2014;30:211-215.
26. Demirjian A, Goldstein H, Tanner JM. A new system of dental age assessment. Hum Biol, 1973;45:211-227.
27. De Tobel J, Radesh P, Vandermeulen D, Thevissen PW. An automated technique to stage lower third molar development on panoramic radiographs for age estimation: a pilot study. J Forensic Odontostomatol, 2017;35:42-54.
28. Vila-Blanco N, Carreira MJ, Varas-Quintana P, Balsa-Castro C, Tomas I. Deep neural networks for chronological age estimation from OPG images. IEEE Trans Med Imaging, 2020;39:2374-2384.
29. Wu TJ, Tsai CL, Gao QZ, Chen YP, Kuo CF, Huang YH. The Application of Artificial-Intelligence-Assisted Dental Age Assessment in Children with Growth Delay. J Pers Med, 2022;12:1158.

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