Forensic Science International 367 (2025) 112353

Contents lists available at ScienceDirect

Forensic Science International

journal homepage: www.elsevier.com/locate/forsciint

Do machine learning methods solve the main pitfall of linear regression in dental age estimation?

Andrea Faragalli [a,*], Luigi Ferrante [a], Nikolaos Angelakopoulos [b], Roberto Cameriere [c], Edlira Skrami [a]

[a] Center of Epidemiology, Biostatistics and Medical Information Technology, Department of Biomedical Sciences and Public Health, Università Politecnica delle Marche, Ancona 60126, Italy

[b] Department of Orthodontics and Dentofacial Orthopedics, University of Bern, Freiburgstrasse 7, Bern 3010, Switzerland

[c] AgEstimation Project, Department of Medicine and Health Sciences "Vincenzo Tiberio", University of Molise, Campobasso, Italy

ARTICLE INFO

Keywords:
Age estimation
Machine learning
Dental maturation
Accuracy
Estimation bias

ABSTRACT

Introduction: Age estimation is crucial in forensic and anthropological fields. Teeth, are valued for their resilience to environmental factors and their preservation over time, making them essential for age estimation when other skeletal remains deteriorate. Recently, Machine Learning algorithms have been used in age estimation, demonstrating high levels of accuracy. However, their precision with respect to the trend of age estimation error, typical in some traditional methods like linear regression, has not been thoroughly investigated.

Aim: To evaluate and compare the performance of frequently used Machine Learning-assisted methods against two traditional age estimation methods, linear regression and the Segmented Normal Bayesian Calibration model.

Methods: Overall, 1.949 orthopantomographs from black and white South African children aged 5–14 years, with 49 % males, were evaluated. The performance of Random Forest, Support Vector Regression, K-Nearest Neighbors and the Gradient Boosting Method were compared against traditional linear regression and the Segmented Normal Bayesian Calibration model. The comparison was based on accuracy measures, including Mean Absolute Error and Root Mean Squared Error, and precision measures, including the Inter-Quartile Range of the error distribution and the slope of the estimated age error relative to chronological age.

Results: The Machine Learning methods outperformed linear regression and the Segmented Normal Bayesian Calibration models in terms of accuracy, although the differences were small. Gradient Boosting Method and Support Vector Regression achieved the highest levels of accuracy (Mean Absolute Error: 0.69 years, Root Mean Squared Error: 0.85 years). All Machine Learning methods and linear regression exhibited significant bias in residuals, whereas the Segmented Normal Bayesian Calibration model showed no significant bias. Gender-stratified analyses revealed similar results in terms of the accuracy and precision of all considered models.

Conclusion: Although Machine Learning methods demonstrate high levels of accuracy, they may be prone to trends in error distribution when estimating dental age. Evaluating this error is crucial and should be an integral part of model performance evaluation. Future research should aim to improve accuracy while rigorously addressing systematic biases.

1. Introduction

The age estimation process, used to determine the chronological age of individuals lacking identity documents or to assess the age of human remains, is a critical aspect in both anthropological and forensic fields [1]. Typically, these age assessments rely on radiological analysis of specific body parts, such as hand-wrist bones [2], knee, clavicle and teeth [3–6]). Dental structures are easily assessed through X-rays and are increasingly recognized for their utility in age estimation because they are not affected by external factors such as malnutrition [7], the premature loss of primary teeth, dental crowding, or decay. Furthermore, the development of teeth demonstrates a notable resilience to

* Correspondence to: Centre of Epidemiology, Biostatistics & Medical Information Technology, Faculty of Medicine and Surgery, Università Politecnica delle Marche, Via Tronto 10/A, Ancona 60200, Italy.

E-mail address: a.faragalli@staff.univpm.it (A. Faragalli).

https://doi.org/10.1016/j.forsciint.2024.112353
Received 24 June 2024; Received in revised form 4 October 2024; Accepted 18 December 2024
Available online 20 December 2024

Table 1
Performance of the considered age estimation models in the testing dataset (males and females combined).

Model	MAE	RMSE	IQR_{ERR}	b_{ERR}	
				Coef.	p
GBM	0.69	0.85	1.20	−0.20	< 0.001
K-NN	0.73	0.92	1.24	−0.19	< 0.001
RF	0.74	0.92	1.28	−0.20	< 0.001
SVR	0.69	0.85	1.25	−0.19	< 0.001
Linear regression	0.83	1.00	1.44	−0.31	< 0.001
SNBC	0.76	0.95	1.27	0.03	0.123

MAE: Mean Absolute Error, RMSE: Root Mean Square Error; IQR_{ERR}: Inter-Quartile Range of error distribution; β_{ERR}: regression coefficient of the estimated age error to chronological age.
GBM: Gradient Boosting Model; K-NN: K-Nearest Neighbour; RF: Random Forest; SVR: Support Vector Regression; SNBC: Segmented Normal Bayesian Calibration model.

external environmental factors, making them particularly significant for paleoanthropology and forensic science [8]. Teeth often remain intact and well-preserved even when other skeletal remains have deteriorated, making them essential, and sometimes the only, pieces of evidence available. Within this context, the association between an individual's chronological age and the maturation of their teeth is frequently explored through the application of traditional linear regression models. However, a notable drawback of these models is their inclination to overestimate age in younger subjects and underestimate it in older ones [9,10], as well as their tendency to produce biased estimates [11]. The relationship between chronological age and dental maturation during early life stages is non-linear [12], and may feature one or more breakpoints. More recently, the Segmented Normal Bayesian Calibration (SNBC) model has been introduced, taking into account the non-linear relationship between chronological age and dental maturation while mitigating bias in age estimation [13]. The model was validated using the sum of open apices as dental maturity index [14]. The findings showcased a high level of accuracy, with a Mean Absolute Error (MAE) of 0.77 years in males and 0.72 years in females, alongside the absence of systematic bias in age estimations.

In the recent years, several Machine Learning (ML) algorithms have been deployed for age estimation. These methods can be classified as either fully automated or ML-assisted. Fully automated approaches are gaining popularity as they allow for the estimation of chronological age from dental maturation without human intervention. Within this framework, a two-step process is employed: initially, models such as Convolutional Neural Networks [15–17] or Multilayer Perceptron [18] are directly applied to images (such as X-rays) to assess dental maturation, which is subsequently utilized in the second step by other ML algorithms (e.g., Decision Tree, Support Vector Machine, Random Forest, K-Nearest Neighbors, Gradient Boosting Method) ([19–24] for estimating chronological age.

The ML-assisted methods exclusively encompass the second step of the aforementioned process, wherein dental maturation indices (such as Demirjian, [5] Cameriere [14,25], Willems [26] methods) are assessed by a medical specialist. The ML methods employed for age estimation have demonstrated high levels of accuracy regardless of the dental maturity index utilized in the analysis, with MAE levels ranging between 0.49 and 0.63 in males and between 0.44 and 0.64 in females [24,27,28]. Furthermore, these studies have reported a slight improvement in accuracy in age estimation compared to traditional methods. However, most comparisons are conducted relative to linear regression models, which are known to produce biased estimates. A systematic review conducted by Niño-Sandoval et al. [29] highlighted the differences in error rates between manual methods and Artificial Intelligence (AI) techniques, with AI methods demonstrating better performance in terms of Root Mean Squared Error (RMSE) and MAE. This review pointed out the advantages of AI in data processing and emphasized the necessity for more comprehensive comparisons between machine learning and deep learning methods to fully comprehend their capabilities and limitations [29]. Similarly, Murray et al. [30] stressed the importance of refining ML models to enhance their accuracy and mitigate biases, particularly in legal contexts where precise age estimation holds paramount importance. These findings highlight the ongoing need for refining and validating ML models across diverse populations to ensure their reliability and fairness. Furthermore, the existing literature on ML methods applied to the chronological age estimation using dental maturation did not investigate the potential presence of systematic bias, which may result in overestimating age in younger subjects and underestimating age in older ones. Addressing this bias is crucial for ensuring the reliability of these methods in practical applications.

In this study we aimed to evaluate the precision level of commonly used ML-assisted methods- Random Forest (RF), K-Nearest Neighbors (K-NN), Gradient Boosting Method (GBM), Support Vector Regression (SVR) for estimating chronological age, investigating the presence of systematic bias and to comparing their performance with that of linear regression and a Segmented Normal Bayesian Calibration model.

2. Methods

2.1. Study sample and data collection

In this cross-sectional study, we used orthopantomographs (OPGs) from healthy living black and white South African children aged 5–14 years. The children's samples were collected from the database of a private orthodontic clinic in Pretoria, South Africa, and they were part of the orthodontic treatment plan. They were registered anonymously and their sex, date of birth, and date that the X-rays were performed were recorded for each panoramic radiograph. None of them were taken exclusively for this research. The chronological age was calculated as decimal age by subtracting the date of birth from the date of taking the orthopantomography.

Subjects who had their seven left permanent mandibular teeth present were included in the study, while those with systemic diseases, congenital disorders, dental irregularities such as tooth fusion, gemination, missing or extra teeth, or individuals undergoing orthodontic treatments at the time of OPG collection were excluded. The projections were used to determine the dental maturation assessed by the sum of open apices of the seven left permanent mandibular teeth, referred to as the dental maturity index, S [14]. The entire dataset utilized in this study had been previously published [31].

Ethical review and approval were waived for this study. It was conducted in conformity with the regulations on data management of the Italian law on privacy (Legislation Decree 196/2003 amended by Legislation Decree 101/2018).

2.2. Statistical analysis

The following machine learning supervised regression algorithms were utilized for age estimation:

- The Random Forest algorithm was applied in this study to analyze dental features across multiple decision trees for prediction purposes. It mitigates the risk of overfitting by averaging the results. Hyperparameters, including the number of trees and the depth of each tree, underwent tuning via grid search to optimize performance. This model adeptly manages complex relationships between dental characteristics and age, yielding robust and precise age estimates;
- Support Vector Regression is a variant of the Support Vector Machine specifically designed for regression tasks. SVR operates by transforming input data into a high-dimensional feature space and subsequently identifying a hyperplane that optimally fits the data within a predefined margin of error;

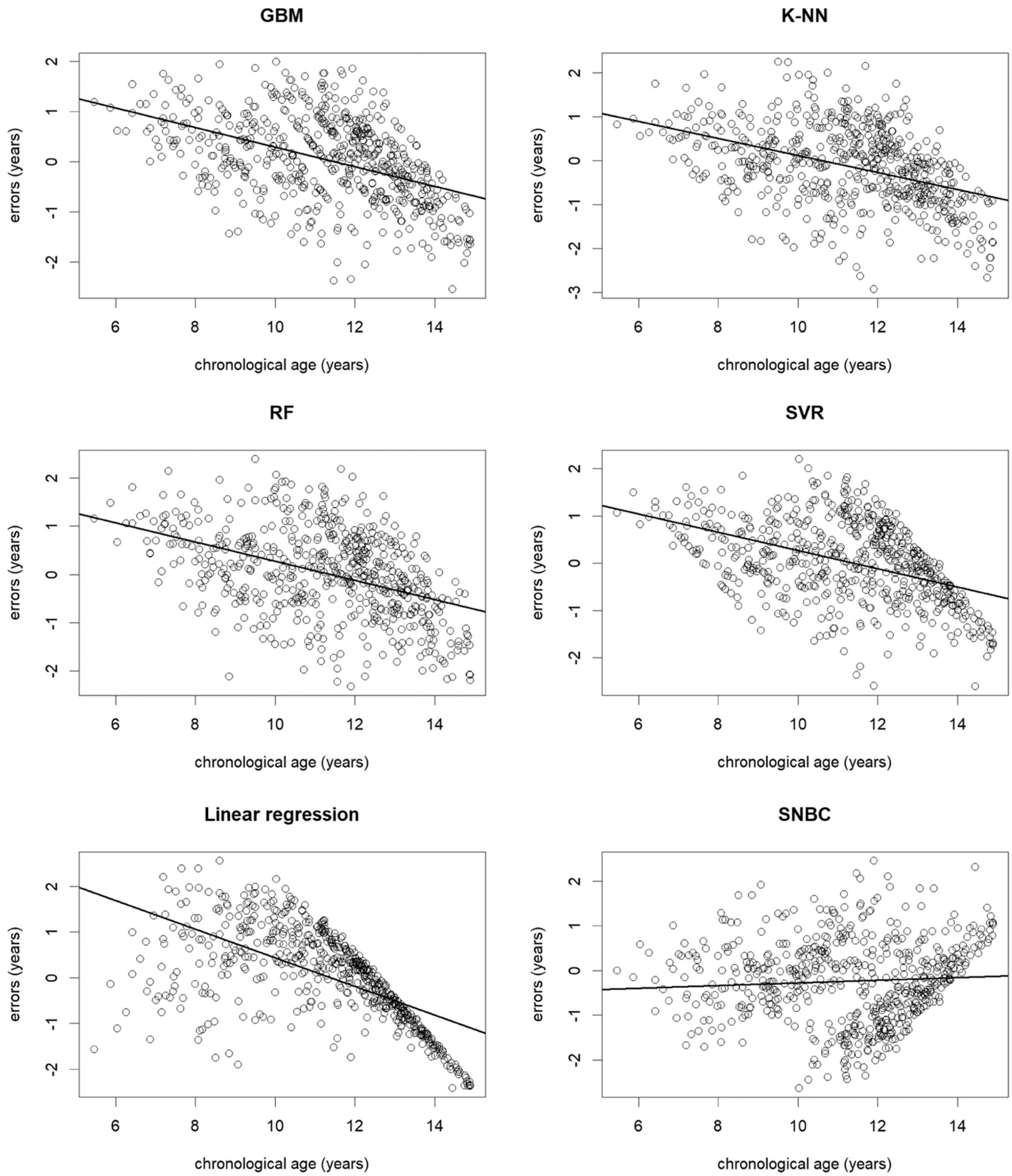

Fig. 1. Regression results of the estimated age error to the chronological age in all considered models in train data (male and female).

- K-Nearest Neighbors model predicts an individual's age by analysing the ages of the 'k' nearest data points in the feature space, typically using Euclidean distance. This method is particularly useful when there's a distinct pattern or clustering of ages within the dataset;
- Gradient Boosting Method builds models sequentially, with each new model correcting errors made by its predecessors. In dental age estimation, GBM iteratively enhances predictions by concentrating on instances that were difficult to estimate in previous rounds, thereby effectively refining its accuracy based on dental features.

In addition, a linear regression model and the Segmented Normal Bayesian Calibration model [13] were used to estimate age. The SNBC model determines a posterior distribution of age based on the dental maturity index. This approach requires both a prior distribution of the model parameters and the age. Due to the lack of pre-existing information, we opted for an uninformative uniform prior distribution.

A stratified 5-fold cross-validation was performed for model evaluation on the entire dataset. In this approach, the data was first stratified by gender to ensure each fold maintained the same proportion of male and female samples as the original dataset. The stratified data was then randomly partitioned into five equal folds. For each fold, the model was trained on 70 % of the data (training set) and evaluated on the remaining 30 % (testing set). This process was repeated five times, ensuring that each data point was used for testing exactly once.

The Kolmogorov-Smirnov test was performed to evaluate differences in the age distribution in both the samples.

Models' performance was evaluated using the following accuracy and precision measures:

Table 2
Performance of the considered models of age estimation in males in the testing dataset.

Model	MAE	RMSE	IQR_{ERR}	β_{ERR} Coef.	p
GBM	0.65	0.80	1.12	−0.20	< 0.001
K-NN	0.68	0.83	1.24	−0.12	< 0.001
RF	0.71	0.88	1.31	−0.17	< 0.001
SVR	0.64	0.79	1.09	−0.20	< 0.001
Linear regression	0.80	0.98	1.33	−0.28	< 0.001
SNBC	0.67	0.83	1.12	0.01	0.623

MAE: Mean Absolute Error, RMSE: Root Mean Square Error; IQR_{ERR}: Inter-Quartile Range of error distribution; β_{ERR}: regression coefficient of the estimated age error to chronological age.
GBM: Gradient Boosting Model; K-NN: K-Nearest Neighbour; RF: Random Forest; SVR: Support Vector Regression; SNBC: Segmented Normal Bayesian Calibration model.

Table 3
Performance of the considered models of age estimation in females in the testing dataset.

Model	MAE	RMSE	IQR_{ERR}	β_{ERR} Coef.	p
GBM	0.67	0.81	1.08	−0.17	< 0.001
K-NN	0.73	0.89	1.28	−0.26	< 0.001
RF	0.82	0.89	1.24	−0.16	< 0.001
SVR	0.68	0.82	1.24	−0.21	< 0.001
Linear regression	0.86	1.07	1.54	−0.19	< 0.001
SNBC	0.72	0.89	1.32	−0.01	0.834

MAE: Mean Absolute Error, RMSE: Root Mean Square Error; IQR_{ERR}: Inter-Quartile Range of error distribution; β_{ERR}: regression coefficient of the estimated age error to chronological age.
GBM: Gradient Boosting Model; K-NN: K-Nearest Neighbour; RF: Random Forest; SVR: Support Vector Regression; SNBC: Segmented Normal Bayesian Calibration model.

- Mean Absolute Error;
- Root Mean Squared Error;
- Inter-Quartile Range of error distribution (IQR_{ERR});
- the slope (β_{ERR}) of the estimated age error to chronological age. This measure is particularly useful for determining whether the estimated residuals of each method have a significant relationship with chronological age. It helps identify if age is being under- or overestimated by the model.

The age estimation error was calculated by subtracting the predicted age from the observed chronological age in the test sample.

The performance of the aforementioned ML methods was compared with that of the linear regression model and the SNBC model.

The whole analysis was performed using R statistical software, version 4.3.2.The following R packages were used for the ML models: gbm, knn, randomForest, e1071 (a package that provides functions for support vector machines and other machine learning methods). The statistical significance was assessed at a level of probability of 0.05.

3. Results

The whole analysis was performed using a dataset of 1949 OPTs (962 males), with an overall median age of 11.5 years (1st; 3rd quartile: 9.8; 12.7 years), 11.8 years (1st; 3rd quartile: 9.9; 12.9 years) and 11.4 years (1st; 3rd quartile: 9.6; 12.5 years) in males and females, respectively. The dental maturity index, S, ranged between 0.13 and 1.03 in the entire dataset.

No difference in the distribution of age and S between the training and test samples was detected by the Kolmogorov–Smirnov test, which did not reject the null hypothesis of no differences between the two distributions ($p = 0.761$ and $p = 0.915$ respectively). No differences were also reported in each gender stratification.

Table 1 reports the predictive performance of ML, linear regression and SNBC models applied to the test dataset. Although all ML methods outperformed both linear regression and SNBC model in terms of MAE and RMSE, the differences were marginal. Notably, the GBM and SVR models exhibited the lowest error levels, with MAE values of 0.69 and RMSE values of 0.85. Additionally, the GBM model exhibited the lowest level of variability in age estimation errors, with an IQR_{ERR} 1.2, suggesting a tighter error distribution compared to other models. Despite their higher accuracy, all ML models, along with the linear regression model showed significant biases in the residuals of estimated age relative to chronological age, with β_{ERR} ranging between −0.19 in K-NN and SVR to −0.31 in linear regression ($p < 0.001$ for all ML and linear regression model). In contrast, the SNBC model exhibited no significant trend in the age estimation error ($p = 0.123$), with a β_{ERR} of 0.03, highlighting its reliability in minimizing bias. These results are shown in Fig. 1, which illustrates the regression results of the estimated age error relative to chronological age for all models using training data. The figure distinctly shows the significant negative trend in residuals for the linear regression, GBM, K-NN, RF, and SVR models. This trend indicates a systematic overestimation of age in younger subjects, and underestimation in older ones, revealing a potential area for model adjustment.

In the gender-stratified analyses, the GBM and SVR models exhibited slightly better performance compared to the Segmented Bayesian model in terms of MAE, RMSE and $IQR_{ERR,}$ for both males and females (as shown in Tables 2 and 3, respectively). For males (Table 2), the SVR model achieved the lowest MAE (0.64) and RMSE (0.79), with an IQR_{ERR} of 1.09, indicating high accuracy and low variability in error. Similarly, the GBM model displayed a MAE of 0.65 and RMSE of 0.80. Likewise, for females (Table 3), the GBM and SVR models exhibited the best performance in terms of MAE, RMSE and IQR_{ERR}, although both models again displayed a significant negative trend in estimation residuals ($p < 0.001$), consistent across both gender datasets (Figs. 2 and 3).

Consistent with the results of the entire dataset, only the SNBC model showed a non- significant relationship between residuals and chronological age, both for males and females ($p = 0.623$ and $p = 0.834$, respectively). This finding underlines the potential of the SNBC model as a reliable tool for age estimation where bias minimization is critical.

4. Discussion

In recent decades, the international research community has intensified efforts to estimate the chronological age of individuals using machine learning methods, largely focusing on dental maturity indices. These methodologies have demonstrated promising outcomes, surpassing the estimation accuracy achievable with traditional methods [24,27,28]. Despite their potential, many of these studies have not adequately addressed the precision levels of these ML methods, particularly in terms of systematic bias, a well-known concern in the age estimation process. In this study, we employed widely used ML algorithms such as Random Forest, Support Vector Regression, K-Nearest Neighbors, and Gradient Boosting, to estimate chronological age. Their performances were compared to traditional non-ML methods such as linear regression and a fully Bayesian calibration method which can easily capture the non-linear relationship between chronological age and dental maturation process. The latter has been shown to remove the systematic bias in age estimation in juveniles.

The study findings highlight the nuanced capabilities and limitations inherent in the application of some of widely used machine learning algorithms for age estimation purposes. All the considered ML algorithms showed a slightly higher accuracy (in terms of Mean Absolute Error and Root Mean Squared Error) compared to traditional models. For instance, MAE ranged between 0.64 and 0.71 in males and between 0.68 and 0.82 in females. However, the differences between ML and

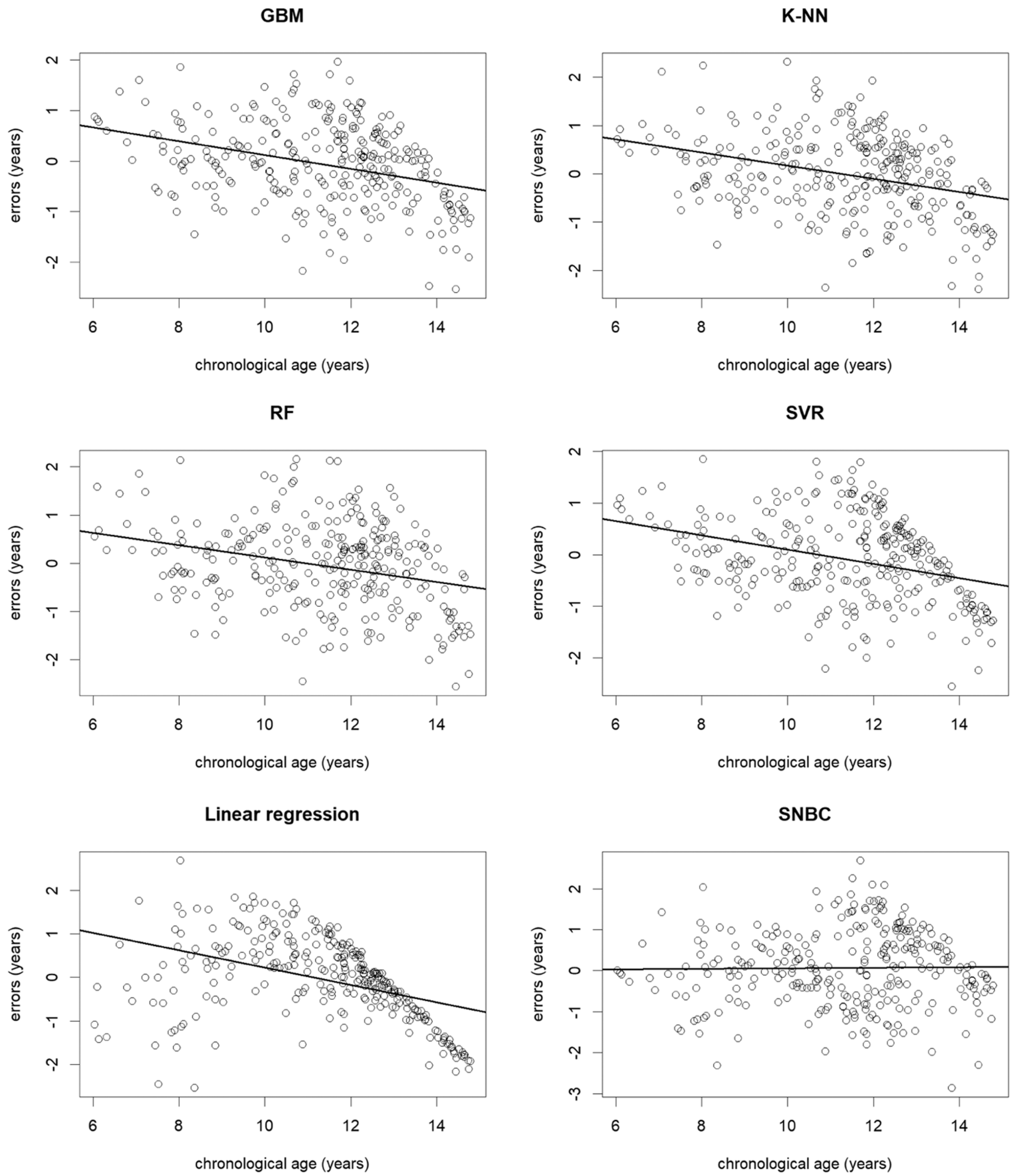

Fig. 2. Regression results of the estimated age error relative to chronological age in all the considered models for males.

linear regression or SNBC methods, for example in MAE when considering both genders, were small, lower than 0.2 years and 0.1 years, respectively. Other studies [18,19,32] have reported similar differences in MAE between conventional age estimation methods and ML methods, less than 0.21 years in Korean juveniles and young adults, using Lee's method [19] and 0.38 years in French population using Demirjian's and Willems' methods [18].

Despite the high levels of accuracy demonstrated by ML methods in age estimation, our analysis reveals a critical issue: the tendency of the considered models to introduce systematic bias. Specifically, the selected ML models exhibited a pattern of overestimating age in younger subjects and underestimating it in older subjects. This systematic bias underscores the complexity of accurately modelling the nonlinear relationship between dental maturity and chronological age, a challenge that is not fully mitigated by the advanced computational techniques employed by ML algorithms. Such biases are not merely statistical concerns; they can have significant legal and ethical implications. Moreover, the direction of this bias-overestimating younger people and underestimating older people-is exactly what is intolerable in the legal context. his issue carries severe legal implications regarding the rights of individuals, especially when determining the legal age of unaccompanied minors in immigration, in criminal proceedings, sexual offense cases, or marriage-related matters.

In addition, as reported by a recent systematic review on age estimation methods using artificial intelligence in panoramic radiographs [29], the performance indicators used by authors in these studies primarily include Mean Absolute Error, Mean Error and Root Mean Squared Error, without considering measures related to the behavior of errors. This oversight hampers a comprehensive understanding of the distribution of these errors, which is crucial for assessing the true

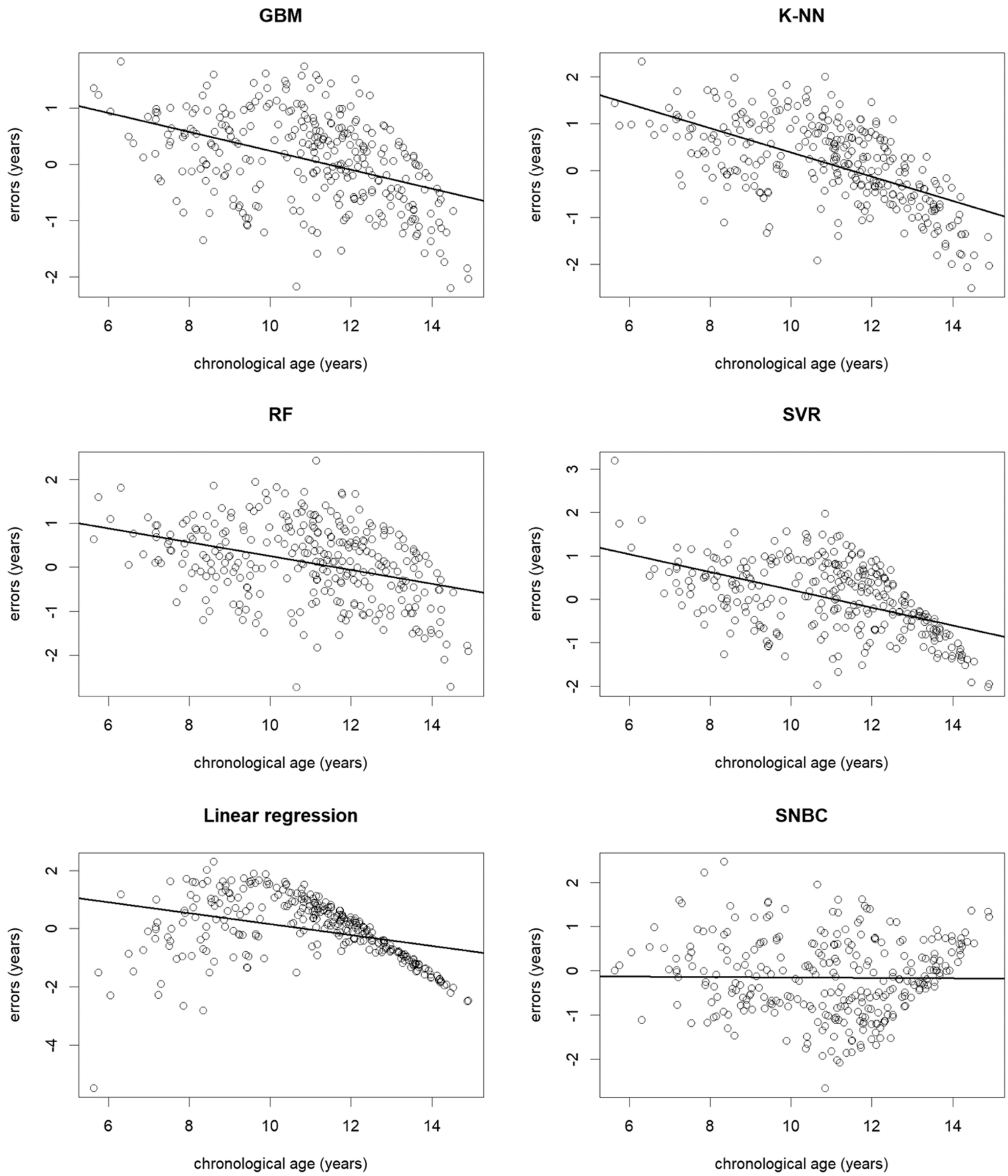

Fig. 3. Regression results of the estimated age error relative to chronological age in all the considered models for females.

performance and reliability of these models. Addressing this gap, our study also explored the presence of systematic bias, revealing that while ML models can achieve slightly better or comparable accuracy, they may still exhibit significant trends in residuals relative to chronological age, thereby impacting their reliability in practical applications.

In contrast, the Segmented Bayesian Normal Calibration model emerges as a robust approach that effectively addresses the non-linearity of the relationship between chronological age and dental maturation process. By not exhibiting the same systematic bias as its ML counterparts, the SNBC model provides a more reliable and unbiased estimation of chronological age. The performance of this model underscores the crucial role of integrating a deep understanding of biological growth patterns and dental development into the modeling process, a facet often overshadowed by the emphasis on computational methodologies within ML-based studies. The SNBC model's unbiased performance suggests it may be better suited than frequently used ML models in scenarios where precision and fairness are paramount. Moreover, the gender-stratified analyses indicated that while some ML models performed comparably or even slightly better than the SNBC model in terms of MAE, RMSE, and IQR_{ERR}, they still exhibited a significant bias in estimated residuals. This finding is particularly relevant for forensic and anthropological applications, where precision and unbiased estimations are critical for ethical and legal considerations.

5. Limitations and strengths

Some limitations of this study should be acknowledged. While we employed a variety of widely used ML models, our study was confined to this specific subset, potentially overlooking other ML approaches that could offer better performance or reduced bias. Exploring additional ML algorithms could provide further insights into optimizing age estimation methods. Furthermore, our study did not consider fully automated models that directly interpret radiographic images. These models, often based on deep learning, such as Convolutional Neural Networks, have shown considerable promise in various medical image analysis tasks [15–17].

The study has several strengths. To our knowledge, it represents the first investigation into the error patterns in age estimation when ML methods are employed in this context, thus contributing significant insights into the precision and overall performance of these methodologies. Additionally, the study encompasses a range of widely utilized ML models with varying levels of complexity, spanning from simpler algorithms to more intricate ones. This approach facilitates comparisons across a spectrum of methodologies. Moreover, the study benefits from a large sample size, comprising approximately 1900 orthopantomographs, which furnishes a robust dataset for model training and testing, thereby enabling the evaluation and comparison of several age estimation models. Among the traditional methods for age estimation, this study uses, alongside linear regression, the Segmented Normal Bayesian Calibration model-a flexible tool that can be easily adapted to other populations or characteristics through changes in the distribution of priors, allowing a more in-depth comparison of performance with ML methods.

6. Conclusion

Our study contributes to the field of forensic anthropology and dental age estimation by conducting a comprehensive comparison of the performance between traditional methods and frequently utilized ML techniques. The advancement in dental age estimation techniques reflects a broader trend towards the integration of sophisticated computational methods in forensic science. While these developments offer promising avenues, particularly in terms of accuracy in age estimation, the persistence of systematic bias remains a significant challenge. The study highlights the importance of employing appropriate measures to meticulously assess both the accuracy and precision of the model utilized for age estimation. Evaluating the performance of ML models alongside traditional methods necessitates considering their behavior in error patterns. Neglecting this aspect may lead to misleading conclusions, impacting the applicability of these models in forensic contexts.

Future research endeavors should not solely prioritize enhancing the accuracy of age estimation models but also diligently scrutinize and mitigate systematic biases. A broader diffusion of machine learning algorithms integrated with Bayesian methods could potentially offer more balanced solutions, reducing biases while maintaining high accuracy.

CRediT authorship contribution statement

Edlira Skrami: Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Roberto Cameriere:** Conceptualization. **Nikolaos Angelakopoulos:** Resources, Data curation. **Luigi Ferrante:** Writing – review & editing, Methodology, Conceptualization. **Andrea Faragalli:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Formal analysis.

Declaration of Competing Interest

None

References

[1] E. Cunha, et al., The problem of aging human remains and living individuals: a review, Forensic Sci. Int 193 (1-3) (2009) 1–13.
[2] R. Cameriere, et al., Age estimation using carpals: study of a Slovenian sample to test Cameriere's method, Forensic Sci. Int 174 (2-3) (2008) 178–181.
[3] R. Cameriere, et al., Radiographic analysis of epiphyseal fusion at knee joint to assess likelihood of having attained 18 years of age, Int. J. Leg. Med. 126 (6) (2012) 889–899.
[4] R. Cameriere, et al., Accuracy of three age estimation methods in children by measurements of developing teeth and carpals and epiphyses of the ulna and radius, J. Forensic Sci. 57 (5) (2012) 1263–1270.
[5] A. Demirjian, H. Goldstein, J.M. Tanner, A new system of dental age assessment, Hum. Biol. 45 (2) (1973) 211–227.
[6] R. Schulz, et al., Radiographic staging of ossification of the medial clavicular epiphysis, Int. J. Leg. Med. 122 (1) (2008) 55–58.
[7] R. Cameriere, et al., Effects of nutrition on timing of mineralization in teeth in a Peruvian sample by the Cameriere and Demirjian methods, Ann. Hum. Biol. 34 (5) (2007) 547–556.
[8] B. Pelsmaekers, et al., The genetic contribution to dental maturation, J. Dent. Res 76 (7) (1997) 1337–1340.
[9] R.G. Aykroyd, et al., Technical note: regression analysis in adult age estimation, Am. J. Phys. Anthr. 104 (2) (1997) 259–265.
[10] D. Lucy, Introduction to Statistics for Forensic Scientists, Wiley, 2005.
[11] D. Lucy, A.M. Pollard, Further comments on the estimation of error associated with the Gustafson dental age estimation method, J. Forensic Sci. 40 (2) (1995) 222–227.
[12] L. Ferrante, et al., Bayesian calibration for forensic age estimation, Stat. Med. 34 (10) (2015) 1779–1790.
[13] A. Bucci, et al., Segmented Bayesian calibration approach for estimating age in forensic science, Biom. J. 61 (6) (2019) 1575–1594.
[14] R. Cameriere, L. Ferrante, M. Cingolani, Age estimation in children by measurement of open apices in teeth, Int. J. Leg. Med. 120 (1) (2006) 49–52.
[15] Y.C. Guo, et al., Accurate age classification using manual method and deep convolutional neural network based on orthopantomogram images, Int. J. Leg. Med. 135 (4) (2021) 1589–1597.
[16] M. Han, et al., With or without human interference for precise age estimation based on machine learning? Int. J. Leg. Med. 136 (3) (2022) 821–831.
[17] R. Merdietio Boedi, et al., Effect of lower third molar segmentations on automated tooth development staging using a convolutional neural network, J. Forensic Sci. 65 (2) (2020) 481–486.
[18] A. Galibourg, et al., Comparison of different machine learning approaches to predict dental age using Demirjian's staging approach, Int. J. Leg. Med. 135 (2) (2021) 665–675.
[19] A. Kumagai, et al., Validation of data mining models by comparing with conventional methods for dental age estimation in Korean juveniles and young adults, Sci. Rep. 13 (1) (2023) 726.
[20] D. Pereira de Sousa, et al., Age determination on panoramic radiographs using the Kvaal method with the aid of artificial intelligence, Dentomaxillofac Radiol. 52 (4) (2023) 20220363.
[21] S. Shen, et al., Machine learning assisted Cameriere method for dental age estimation, BMC Oral Health 21 (1) (2021) 641.
[22] S. Shen, et al., Evaluation of a machine learning algorithms for predicting the dental age of adolescent based on different preprocessing methods, Front. Public Health 10 (2022) 1068253.
[23] S. Shen, et al., Using machine learning to determine age over 16 based on development of third molar and periodontal ligament of second molar, BMC Oral Health 23 (1) (2023) 680.
[24] T.J. Wu, et al., Efficacy of machine learning assisted dental age assessment in local population, Leg. Med. (Tokyo) 59 (2022) 102148.
[25] R. Cameriere, et al., The comparison between measurement of open apices of third molars and Demirjian stages to test chronological age of over 18 year olds in living subjects, Int. J. Leg. Med. 122 (6) (2008) 493–497.
[26] G. Willems, et al., Dental age estimation in Belgian children: Demirjian's technique revisited, J. Forensic Sci. 46 (4) (2001) 893–895.
[27] M. Stepanovsky, et al., Novel age estimation model based on development of permanent teeth compared with classical approach and other modern data mining methods, Forensic Sci. Int. 279 (2017) 72–82.
[28] W. Shan, et al., Boosting algorithm improves the accuracy of juvenile forensic dental age estimation in southern China population, Sci. Rep. 12 (1) (2022) 15649.
[29] T.C. Nino-Sandoval, et al., Efficacy of the methods of age determination using artificial intelligence in panoramic radiographs - a systematic review, Int. J. Leg. Med. (2024).
[30] J. Murray, D. Heng, A. Lygate, L. Porto, A. Abade, S. Manica, A. Franco, Applying artificial intelligence to determination of legal age of majority from radiographic data, Morphologie, Volume 108, Issue 360, 2024, 100723, ISSN 1286-0115, https://doi.org/10.1016/j.morpho.2023.100723.
[31] N. Angelakopoulos, et al., Age estimation by measuring open apices in teeth: a new formula for two samples of South African black and white children, Int. J. Leg. Med. 133 (5) (2019) 1529–1536.
[32] J.W., Jian Tao, Andrew Wang, Zhangqian Xie, Ziheng Wang, Shaozhi Wu, Aboul Ella Hassanien, Kai Xiao, Dental age estimation: a machine learning perspective, in: J. Kacprzyk (Ed.), Advances in Intelligent Systems and Computing, Springer, 2020.