



## Sex Estimation Based on Tooth Measurements on Panoramic Radiographs with Classical and Machine-Learning Classifiers

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Article Info	ABSTRACT
<p><b>Article type:</b> Original Article</p> <hr/> <p><b>Article History:</b> Received: 25 Mar 2024 Accepted: 15 Sep 2024 Published: 12 Apr 2025</p> <hr/> <p><b>*Corresponding author:</b> Center for Healthcare Data Modeling, Department of Biostatistics and Epidemiology, School of Public Health, Shahid Sadoughi University of Medical Sciences, Yazd, Iran  Email: <a href="mailto:fallahzadeh.ho@gmail.com">fallahzadeh.ho@gmail.com</a></p>	<p><b>Objectives:</b> This study assessed sex estimation of Iranians according to maxillary left first molar measurements made on panoramic radiographs using classical and machine-learning classifiers.</p> <p><b>Materials and Methods:</b> In this cross-sectional study, tooth length- and width-related variables were calculated for maxillary left first molars on 131 panoramic radiographs (65 males, 66 females; age range of 18-30 years). A subsample of the radiographs was selected and reevaluated by two examiners after 1 month. The intra-class correlation coefficient (ICC) was calculated to assess reliability. The regularized discriminant analysis (RDA), support vector machine (SVM), and cascade-forward and feed-forward neural network models were used for sex estimation. Comparisons were made with the Mann-Whitney and t tests.</p> <p><b>Results:</b> The intra-observer reliability was 0.9. SVM had the best performance on the test data in both classification schemes. The crown length at the cemento-enamel junction (CEJL) and total crown length (CL) in the classification scheme I (sex estimation based on length and width variables), and CEJL/root length (RL), cemento-enamel junction width (CEJW)/CEJL, and RL/total tooth length (TTL) in the classification scheme II (sex estimation based on the ratio of variables) were important variables for sex estimation determined by the SVM model. The CEJL had the highest discriminative potential with an area under the curve (AUC) of 78.8. The ratio of variables did not substantially improve sex estimation compared with single variables.</p> <p><b>Conclusion:</b> CEJL is a reliable measure for sex estimation in Iranians with values higher than 6.25 indicating the male sex and other values indicating the female sex.</p> <p><b>Keywords:</b> Radiography, Panoramic; Molar; Maxilla; Machine Learning; Sex Characteristics; Support Vector Machine; Forensic Dentistry</p>

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### INTRODUCTION

Accurate sex determination is a key requirement for identification of human remains in conditions such as fires, road accidents, plane crashes, and natural disasters such as floods and earthquakes [1].

Gender, age, and racial background are the main attributes of biological identification determined by forensic anthropologists; among which, sex determination is the first step [2]. Sex estimation is performed according to the metrical and morphological

features of the skeleton; among different bones, the pelvis and skull have marked differences in different individuals, which can be predictive of gender [3-5]. Nonetheless, dentition appears to be a valuable sex indicator, especially in young individuals since most teeth are fully developed before skeletal maturation [2]. Teeth are rich in genetic information; however, DNA isolation is difficult. However, measurement of tooth dimensions is a fast, reliable, non-invasive, and cost-effective method compared to DNA isolation [6].

The remarkable potential of teeth for sex estimation has long been recognized. As a result, several studies have evaluated sexual dimorphism using tooth crown dimensions measured intraorally [2-4], on dental casts [5-15], or on skeletal and dental remains [11,16,17]. The mesiodistal and buccolingual dimensions of permanent tooth crowns, canine index, and intercanine width are commonly measured and used for this purpose. Besides, diagonal measurements such as mesiobuccal-distolingual and distobuccal-mesiolingual measurements [11,18,19], and the mandibular canine index, expressed as the ratio of mesiodistal dimension of canines and the intercanine arch width have also been used for sex determination [20,21]. Previous studies made such measurements on all teeth [7,10,14,15], only on maxillary teeth [9], or only on randomly selected teeth [2-4,6,8,9,14]. It has been reported that canine tooth dimensions provide the highest sexual dimorphism [6,9,12-15,22], followed by premolars [5,8,16], first and second molars [2,5,11,16], and maxillary incisors [8,23].

Currently, utilization of machine learning algorithms is on the rise, and their application in dentistry is no exception. Data mining has its importance in dentistry, especially in oral medicine and radiology [24]. Radiography is useful for sex estimation. It allows different tooth root and crown measurements and can provide valuable information about the maxillary sinuses, which cannot be acquired through other means [25]. On radiographic images, it is common for the measured dimensions to exhibit strong correlations and to

be expressed as linear combinations of one another. In such cases, it becomes crucial to employ analytical methods that can effectively address these relationships. Traditional statistical techniques may struggle with multicollinearity, leading to unreliable estimates and inflated standard errors. Therefore, utilizing advanced methods such as support vector machine (SVM) can provide suitable solutions to classification problems without requiring prior assumptions about the distribution and interdependency of the data [25].

Most studies have chosen statistical methods such as regression, discriminant analysis, and t-test to examine sexual dimorphism [8,26-28]. In studies that used the machine learning techniques, the accuracy of prediction increased to 95% while the accuracy of the discriminant analysis test was above 70% [29]. The majority of such measurements present good to excellent accuracy in the training samples but occasionally unsatisfactory results in cross-population tests [30], highlighting the necessity of population-specific standards. This study aimed to assess the degree of sexual dimorphism by evaluation of the performance of models derived from classical and machine-learning classifiers in maxillary first molar teeth for sex estimation, and in particular, to detect which tooth dimension is most sex-related to improve the accuracy of sex prediction in practice.

## MATERIALS AND METHODS

This cross-sectional study evaluated 131 panoramic radiographs of 65 males and 66 females between 18 and 30 years retrieved from the archives of the Department of Oral and Maxillofacial Radiology, Dental Faculty. The study was approved by the ethics committee of the university (IR.SSU.SPH.REC.1398.049).

The inclusion criteria were optimal quality of radiographs, presence of fully developed permanent teeth, no extracted/missing teeth, no coronal restoration or occlusal wear, visualization of maxillary left first molar, absence of periapical lesions, and no orthodontic treatment. Images with artifacts were excluded. All radiographs had been obtained with a digital

X-ray unit (Proline, Planmeca, Finland) with 90kV tube potential, 12mA tube current, and 18 seconds exposure time.

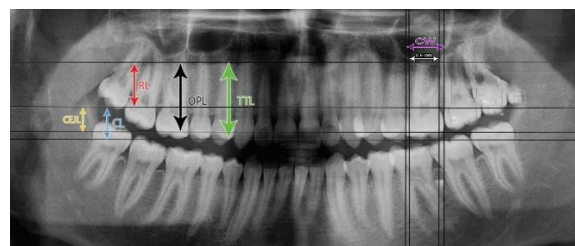
Figure 1 shows the four landmarks identified on each tooth, namely the most occlusal point (O), the root apex (A) [the mesial root apex (MA) was considered for multi-rooted teeth], the mesial cemento enamel junction (MCEJ), and the distal cemento enamel junction (DCEJ). The landmarks were used for dimensional measurements [30].



**Fig 1.** Landmarks identified on a maxillary first molar: most occlusal point (O), mesial root apex (MA) in single-rooted teeth, root apex (A), mesial cemento enamel junction (MCEJ), distal cemento enamel junction (DCEJ). The horizontal line represents the investigated tooth's occlusal plane (OP) and is defined as the line connecting the cusp tips.

The definitions of the length, width, and ratio variables used in this study are presented in Figure 2 and Table 1. A total of 7 length measurements in millimeters were made on each molar tooth, including the total tooth length (TTL), occlusal plane length (OPL), total crown length (CL), crown length to the cemento enamel junction (CEJL), root length (RL), maximal crown width (CW), and cemento enamel junction width (CEJW). Using the length ratios of the same tooth allowed for correction of radiographic deformation. In premolars and molars, due to occasional presence of the buccopalatal inclination, buccal and palatal cusps were not overlapping. To assess the inter-rater

(interobserver) reliability, a subsample of 15% of the radiographs was selected and reevaluated by two examiners (oral radiologists) after 1 month, and the intraclass correlation coefficient (ICC) was calculated to quantify the degree of reliability.



**Fig 2.** Guide placement to perform length and width measurements. The image shows the horizontal guides placed for length measurements on tooth #14: total tooth length (TTL), occlusal plane length (OPL), root length (RL), total crown length (CL), and crown length to the cemento enamel junction (CEJL). The vertical guides placed for width measurements of tooth #14: maximal crown width (CW), cemento enamel junction width (CEJW).

### **Statistical analysis:**

Descriptive statistics including the mean and standard deviation values and 95% confidence intervals (95% CI) were reported for continuous variables. The normality of data distribution was analyzed by the Shapiro-Wilk test. For each variable, males and females were compared using the Mann-Whitney U test or independent samples t-test.

Mathematical models for sex determination were developed using classical regularized discriminant analysis (RDA) and machine-learning methods such as the support vector machine (SVM) and feedforward and cascade forward neural networks. The multivariate data set contained highly correlated predictors; therefore, RDA was used [31]. The SVM is a supervised machine learning model that uses classification algorithms for two-group classification problems [32].

Different combinations of several internal parameters, i.e., number of hidden layers, number of neurons in each hidden layer, and transfer function, were attempted in the

cascade forward and feedforward artificial intelligence models [33].

Finally, the goodness of fit of the provisional and cross-validated models and the testing sample was evaluated through calculation of accuracy (a measure of total agreement between the real and the projected sex), sensitivity (the proportion of properly classified males), and specificity (the proportion of correctly classified females). All statistical analyses were performed by R 3.6.2 programming language and MATLAB.

## RESULTS

The ICC was above 0.90 for all measurements and the mean inter-observer ICC was 0.83. Table 2 shows descriptive data for all parameters. The mean values of OPL, CL, and CEJL were found to be significantly higher in males than females ( $P<0.05$ ). CL, CEJL, CEJL/RL, RL/TTL, OPL/TTL, CEJW/CEJL, and CEJW/RL did not have a

normal distribution ( $P<0.05$ ). As shown in Table 2, there was a significant difference in the mean values of CEJL/RL, RL/TTL, OPL/TTL, and CEJW/CEJL between males and females ( $P<0.05$ ).

The classification experiments were conducted on the dataset of length and width variables and ratios. The dataset contained 131 data; 105 were used for training, and 26 were used for testing. Table 3 presents the mean goodness of fit indexes for all models, which were calculated with 100 replications for bootstrapping. The SVM with radial basis kernel had the best discriminative ability for the test data in the classification scheme I (sex estimation based on length and width variables) and scheme II (sex estimation based on the ratio of variables). The area under the receiver operating characteristic (ROC) curve (AUC) values for SVM were equal to 75.27% and 70.08% for the schemes I and II, respectively.

**Table 1.** Description of dimensions measured on panoramic radiographs and ratios

Variable	Abbreviation	Description
<b>Tooth length</b>	TTL	The length between O and A or MA
	OPL	The length between OP and A, perpendicular to OP
	CL	The length between O and the cemento-enamel junction (CEJ)
	CEJL	The length between OP and CEJ
	RL	The length between CEJ and A or MA
<b>Tooth width</b>	CW	Maximal crown width
	CEJW	Width between MCEJ and DCEJ
<b>Ratios</b>	CEJL/TTL	Crown length/total tooth length
	CEJL/RL	Crown length/root length
	RL/TTL	Root length/total tooth length
	OPL/TTL	Occlusal plane length/total tooth length
	CEJW/CEJL	Crown width/crown length
	CEJW/TTL	Crown width/total tooth length
	CEJW/RL	Crown width/root length

O: most occlusal tooth point, A: root apex, MA: mesial root apex, CEJ: cemento-enamel junction, MCEJ: mesial cemento-enamel junction, DCEJ: distal cement-enamel junction, OP: occlusal plane

**Table 2.** Comparison of maxillary first molar dimensions according to sex

Variable	Female				Male				P-value
	Minimum	Maximum	Mean	SD	Minimum	Maximum	Mean	SD	
TTL	16.3	23.7	19.74	1.56	14.1	24.6	20.19	1.76	0.128
OPL	14.8	21.4	17.58	1.43	12.9	21.8	18.31	1.69	0.008*
RL	9.2	15.1	11.62	1.24	6.7	15.2	11.48	1.49	0.556
CW	8.4	12.1	10.41	0.76	8.7	12.7	10.65	1.76	0.102
CEJW	7.6	9.2	7.58	0.63	6.5	9.1	7.37	0.67	0.171
CL <sup>a</sup>	6.7	9.5	8.06	0.61	7.1	9.7	8.57	0.67	<0.001*
CEJL <sup>a</sup>	4.5	7.4	11.62	1.24	4.4	7.9	11.48	1.49	<0.001*
CEJW/RL <sup>a</sup>	0.5	0.87	0.66	0.08	0.47	1.13	0.69	0.11	0.11
CEJL/RL <sup>a</sup>	0.39	0.66	0.52	0.07	0.35	0.9	0.59	0.1	<0.001*
CEJW/CEJL <sup>a</sup>	1.01	1.63	1.27	0.14	0.85	1.68	1.16	0.15	<0.001*
OPL/TTL <sup>a</sup>	0.81	0.95	0.89	0.03	0.8	0.94	0.91	0.03	<0.001*
RL/TTL <sup>a</sup>	0.51	0.66	0.59	0.03	0.48	0.64	0.57	0.03	<0.001*
CEJW/TTL	0.32	0.49	0.66	0.08	0.28	0.54	0.69	0.11	0.987
CEJL/TTL	0.32	0.49	0.66	0.08	0.28	0.54	0.69	0.11	0.987
age	18	30	23.82	3.47	18	30	24.69	3.65	0.157

\* Significant (P<0.05) using student t-test and <sup>a</sup> Mann-Whitney U test, SD: Standard deviation

**Table 3.** Performance of SVM, RDA, feed-forward and cascade-forward neural network models for the classification schemes I and II with 100 replications for bootstrapping

Model		Data set	Sensitivity	Specificity	Accuracy	Precision	AUC
SVM	Classification Scheme I	Training	72.53	65.94	76.92	74.40	76.07
		Test	66.44	70.95	73.68	71.22	75.27
	Classification Scheme II	Training	73.92	71.06	74.33	70.24	75.81
		Test	70.33	69.18	69.88	71.05	70.08
RDA	Classification Scheme I	Training	64.08	73.66	67.81	69.31	72.51
		Test	69.34	67.97	74.52	70.71	74.77
	Classification Scheme II	Training	71.67	65.96	76.58	74.30	75.07
		Test	68.04	64.34	67.24	66.92	66.42
3 layers, feed-forward	Classification Scheme I	Training	80.05	66.38	73.2	79.89	73.21
		Test	73.67	58.59	66.35	69.8	66.13
2 layers, feed-forward	Classification Scheme II	Training	80.94	75.33	78.22	81.06	78.13
		Test	68.81	62.16	64.73	67.34	65.13
A single layer, cascade-forward	Classification Scheme I	Training	83.51	75.89	79.78	81.50	79.70
		Test	68.31	64.34	65.99	67.23	66.32
2 layers, cascade-forward	Classification Scheme II	Training	78.31	77.32	77.64	77.91	77.82
		Test	68.90	69.96	69.03	69.84	69.43

Figure 3 indicates the share of each variable in sex prediction with SVM. In the classification scheme I, two variables of CL and CEJL, and in the classification scheme II,

three ratios of CEJL/RL, CEJW/CEJL, and RL/TTL had the best performance. The cut-off points of these variables are shown in Table 4.

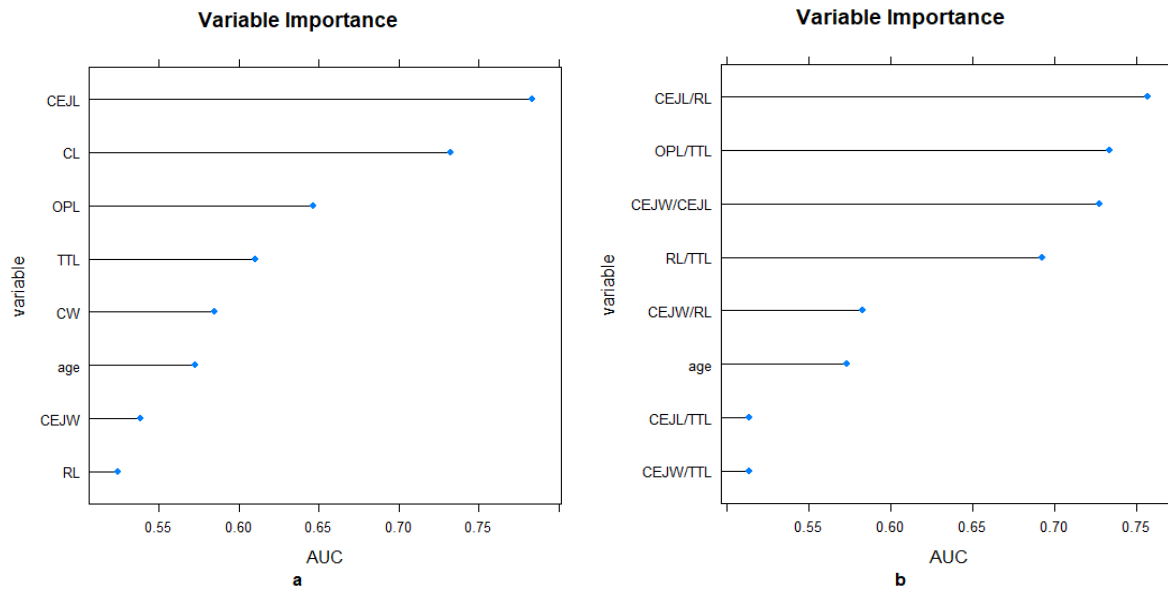


Fig. 3. Variable importance based on the SVM for (a) Classification scheme I (sex prediction based on length and width variables), and (b) Classification scheme II (sex prediction based on the ratios of variables)

Table 4. Cut-off points for the important variables based on the SVM model

Variable	Cut-off point		Sensitivity	Specificity	AUC (95% CI)
	Male	Female			
CEJL	>6.25	<6.25	70.8	66.7	78.8(70.8,85.5)
CL	>8.35	<8.35	70.8	69.7	71.9(63.4,79.4)
CEJL/RL	>0.564	<0.564	72.3	77.3	74.7(66.4,81.9)
CEJW/CEJL	<1.18	>1.18	74.2	64.6	72.9(64.6,80.4)
RL/TTL	<0.57	>0.57	74.2	58.5	69.8(60.6,77)

**DISCUSSION**

Generally, different methods have been proposed for sex estimation using radiography. Panoramic radiographs were used for data collection in the present study since they allow recording the principal metric sex-related tooth features described in the literature [30]. Panoramic radiographs are routinely requested for dental examinations, and enable evaluation of both upper and lower teeth in one single radiograph. Furthermore, radiographic dimensions are highly accurate and do not have the problems of direct intraoral measurement of tooth dimensions. On the other hand, the admissibility of intraoral radiographs is significantly associated with the technique used and the professional training of the personnel. In panoramic radiography, there is a clear distinction between the enamel, dentin, pulp,

and the surrounding structures, enabling the measurement of TTL, CL, RL, and mesiodistal tooth width. In measurement of tooth dimensions intraorally or on dental casts, only the visible dimensions can be measured; while panoramic radiography enables measurement of the root length and mesiodistal root width in different sections.

Only young people (18-30 years) were evaluated in the present study to ensure the maturity of roots and minimal wear of the teeth [6,8]. Tooth development and specific pathologies can affect the tooth length, which was one of the variables evaluated in this study. For example, tooth wear increases with age [34]. Most previous studies selected a similar age group for sex estimation [30,35]. According to the existing literature [36], first molar tooth has a key role in gender determination and has been recommended as an



indicator of sex prediction. In forensic dentistry, an accuracy of at least 80% is required for each variable to be used for sex prediction [37].

In forensic anthropology, the accuracy of sex estimation by machine learning methods was between 75% and 95% for the mandible [33], and maxillary tooth plaster images [38]. The accuracy increased to nearly 100% for dental X-rays using multiplayer perceptron neural networks and image processing techniques [39]. In the current study, the highest mean AUC (79.7%) in the training data for sex determination using the length and width variables based on one single layer belonged to the cascade-forward neural network, and the highest mean AUC (78.13%) in the training data for sex determination using ratios of variables based on two layers belonged to the feed-forward neural network; but SVM had the best performance compared with other models in the test data in both classification schemes. The SVM technique may have a superior performance compared to other statistical methods, especially when there are multivariate risk factors with a small sample size and limited knowledge about the underlying biological correlations among the risk factors. It is particularly true in common complex diseases with involvement of several risk factors [29].

Variable importance analysis [40] based on the SVM model and the measured data revealed that CEJL and CL in the classification scheme I and CEJL/RL, CEJW/CEJL and RL/TTL in the classification scheme II had a greater share in sex prediction. Among all, CEJL with an AUC close to 80% may be considered as a useful indicator of sex estimation in the Iranian population. Therefore, values higher than 6.25 for CEJL indicate the male sex while other values indicate the female sex.

Comparison of accuracy values between the present study and previous investigations was difficult, taking into consideration the variability of methods, populations, and sample size, and also the age range. The present results must be interpreted in the young population. The results obtained on panoramic radiographs for all age groups

should be verified on bitewing and periapical radiographs in future studies.

## CONCLUSION

The present results revealed that crown length (CEJL) of the maxillary left first molar may be used for sex estimation in young Iranians. Furthermore, most users of predictive models are often interested in using models that can interpret variables. In SVM, instead of examining the significance and interpretation of individual variables, the effects and significance of a set of variables are analyzed.

## CONFLICT OF INTEREST STATEMENT

None declared.

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