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ANALYSIS OF MACHINE LEARNING METHODS FOR GENDER AND AGE IDENTIFICATION

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ABSTRACT

An automatic individual identification system is needed to support the forensic odontology process more efficiently and easily because there is still opportunity to be developed. The purpose of this research was to analyze the machine learning method for gender and age identification based on mandibular parameters in panoramic radiography. The machine learning methods used are MLP (Multilayer Perceptron), Decision Tree, Naive Bayes, *k*-NN (Nearest Neighbors), Logistic Linear, and SVM (Support Vector Machine). The data for this research were taken from the Dental and Oral Hospital, Faculty of Dentistry, Universitas Airlangga Surabaya. The data consisted of 120 patients based on the validation results of radiology experts, consisting of 61 males and 59 females, and was divided into 104 training data, and 16 testing data. The mandibular image on panoramic radiography was measured for nine parameters, namely ramus height left (x_1), ramus height right (x_2), ramus length left (x_3), ramus length right (x_4), bigonial width (x_5), bicondylar breadth (x_6), anterior mandibular corpus height left (x_7), anterior mandibular corpus height right (x_8), mandibular corpus length (x_9) using the ImageJ application by radiology experts. The best machine learning method for gender identification is *k*-NN, with evaluation values of accuracy, precision, recall, and f1 score, respectively, of 0.750, 0.764, 0.750, and 0.733. And the best method for age identification is MLP, with values of accuracy, precision, recall, and f1 score, respectively, of 0.625, 0.267, 0.350, and 0.297.

Keywords: *Mandibular Parameters; Machine Learning; Gender Identification; Age Identification.*

1. INTRODUCTION

All dental techniques related to forensic dental identification are used in postmortem investigations. This is useful for establishing the truth and determining the identity of victims and perpetrators for legal purposes in the judicial process. Forensic identification is the process of finding the identity of living or dead victims of crime, natural disasters, accidents, and fires for the benefit of the family and the judiciary [1], [2], [3], [4]. Gender identification in forensic anthropology and dentistry can be done by various methods, including morphological or nonmetric, metric, geometric morphometric, and molecular methods. This identification can be done by using various elements of the human skeleton, namely the pelvis, skull, teeth, and soft tissue [5]. In addition, age identification is very important to identify victims because age is important for every aspect of life, such as education, employment, and health. Age estimation can be done for both living and deceased people. In living people, age estimation can be used to explain civil and criminal matters. In deceased people, age estimation is used to identify deceased victims, such as accident victims [6], [7].

Panoramic radiography is the standard examination used for diagnosis and treatment planning because it allows bilateral views and sufficient information about vertical dimensions. This radiographic project is also useful for

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examining the dental structures as well as the maxillary and mandibular bones, with the ramus, condyle, and corpus of the mandible clearly visible on both sides. This allows identification of gender and age [8], [9], [10]. Gender determination using the mandible is usually done by evaluating its metric and non-metric parameters either on the dry mandible or using radiography. The mandible, or maxilla, is a bone that can provide gender information because it has different dimorphics and morphologies between men and women. Changes in the size of the mandible between men and women can be caused by muscle activity when chewing, race, genetics, and the difference in the size of the mandible, a method of gender identification can be used [11], [12], [13].

In physical and forensic anthropology, bone fragment analysis is used to estimate age and gender. Today, forensic anthropology is used to perform primary and secondary identification, especially in cases of mass disasters. Secondary identification is essential in cases where primary identification is not possible, and gender estimation is essential to expert practice. Dentistry and forensic anthropology use a variety of approaches to determine gender. Dental methods for researching sexual dimorphism can rely on the morphology and measurements of teeth and other structures such as the sinuses, mandible, palate, and lips. In forensic practice, methods such as data mining, machine learning, and big data can be used to determine gender [14], [15], [16]. Some researches that use machine learning for identification include determining gender and age based on teeth by applying neural network computing [6], [7], conducting evaluation and verifying the accuracy of gender identification based on teeth on panoramic radiographs using machine learning methods [14], matching teeth on panoramic radiographs with machine learning for person identification [17], perform forensic identification in the event of a disaster victim using panoramic radiographic tooth matching based on contour feature extraction [18], forensic identification of mass casualties using panoramic radiographic teeth with the CNN method [19], perform identification of unknown bodies based on tooth contours on panoramic radiographs using neural network methods [20], conduct gender and age identification in one model with multitasking learning method [21], evaluate the results of deep learning methods in automatically detecting or segmenting tooth parts, fillings, tooth roots, and implant teeth on panoramic radiographs [22], conducting evaluation of morphometric assessment of tooth chronology or estimation of tooth age using deep learning method [23], create a discriminant function to determine gender based on mandibular morphology. The parameters measured in the mandible were 11, namely two gonial angles, two mandibular ramus heights, two mandibular ramus widths, two mandibular corpus lengths, two nasal line maxilla, and anterior mandibular corpus heights. Of the 11 parameters measured in the mandible, only 9 parameters were significant for determining gender [24], the parameters of the mandibular bone that can be measured include the length of the mandibular body, mandibular angle and minimum ramus breadth, which are dimorphic indicators for distinguishing gender [25], [26]; ramus height can be used for age and gender estimation [27]; mandibular ramus. With the development of technology, the way to identify victims, both living and dead individuals can use medical images. Between lateral cephalograms and orthopantomography (panoramic radiography), images can be significantly used to distinguish gender by measuring mandibular parameters [28]. For example, identifying gender using a skull skeleton modeled in 3D is an effort to make it easier to determine the victim's identity [29]. Several researches have continued to try to find the best method for identifying victims, whether living or dead [30]; [31]. For example: comparing the results of gonial angle measurements on panoramic and lateral cephalometric radiographs, with the aim of assisting in orthodontic treatment and surgery [32]; another aim is to evaluate the relationship between gender identification and age [33]. Related research creates automated computation based on CT scans to assess mandibular geometric parameters from anatomical landmarks [34], create facial reconstruction from mandibular parameters or landmarks. Mandibular landmark points can be used as a reference in performing 3D skull reconstruction [35], [36]; to correlate the relationship between mandibular development in male and female genders with age [37], to assess the variations in mandibular morphology among patients in six age groups and find any associations between these features on cone-beam computed tomography (CBCT) and panoramic radiography (PR) [38].

The process of gender and age identification based on teeth on panoramic radiographs with machine learning has been widely carried out. However, the identification process based on mandibular parameters on panoramic radiographs using machine learning is very small, and some is done semi-automatically (using the discriminant analysis method). This research identified gender and age group based on mandibular parameter measurements on panoramic radiography. This

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research used panoramic radiography data from the Dental and Oral Hospital, Faculty of Dentistry, Universitas Airlangga with ages 19-70 years, as many as 120 patients (61 male, 59 female). Therefore, this research aims to analyze machine learning methods (MLP, Decision Tree, Naive Bayes, *k*-NN, Logistic Linear, and SVM) for gender and age identification based on mandibular parameters on panoramic radiographs. This research analyzes the most appropriate method for gender and age identification. Identification requires precision and accuracy, so the best and most precise method is needed for identification.

2. METHOD

2.1 Dataset

The data of this research were taken from the Dental and Oral Hospital of the Faculty of Dentistry, Universitas Airlangga Surabaya. The data were first selected and validated by radiology experts. The data consisted of 120 patients consisting of 61 male, 59 female, and were divided into 104 training data, and 16 testing data. Table 1 is the division of training and testing data.

Table 1: Data Description

Age	Training		Testing		Total
	M	F	M	F	
19-29	11	11	4	3	29
30-39	10	10	1	1	22
40-49	10	10	2	0	22
50-59	10	10	0	1	21
60-70	11	11	2	2	26
Total	52	52	9	7	120

The data contains gender and age, age data is grouped into five based on Table 1. The age groups consist of 19-29 years (group 1), 30-39 years (group 2), 40-49 years (group 3), 50-59 years (group 4), 60-70 years (group 5).

2.2 Proposed Research

This research conducted gender identification and age groups using machine learning models (MLP (Multilayer Perceptron), Decision Tree, Naive Bayes, *k*-NN (Nearest Neighbors), Logistic Linear, and SVM (Support Vector Machine)). The machine learning models were evaluated to find the most appropriate ones for gender and age group identification. The evaluation used accuracy (Equation 1), precision (Equation 2), recall (Equation 3), and F1 score (Equation 4). Explanation of Equations 1 to 4: $\hat{y}$ is the predicted value of the i sample, y is the actual value, TP is the number of true positives, FN is the number of false negatives, FP is the number of false positives.

$$Accuracy = \frac{\sum_{i=1} \hat{y}_i = y_i}{N} \quad (1)$$

$$\Pr ecision = \frac{TP}{TP+FP} \quad (2)$$

$$\mathrm{Re}\, call = \frac{TP}{TP+FN} \quad (3)$$

$$F1 = \frac{2.TP}{2.(TF+FP+FN)} \quad (4)$$

Figure 1 is the proposal for this research. This research conducted two identifications, namely gender and age. The machine learning models used are Multilayer Perceptron (MLP), Decision Tree, Naive Bayes, *k*-NN (Nearest Neighbors), Logistic Linear, and SVM (Support Vector Machine). The model was tested and evaluated to find the best accuracy.

Panoramic radiographic data of the mandible section was measured using the ImageJ application by a radiology expert and used as training and testing data, with nine mandibular parameters as in Figure 2, namely *ramus height left* (x_1), *ramus height right* (x_2), *ramus length left* (x_3), *ramus length right* (x_4), *bigonial width* (x_5), *bicondylar breadth* (x_6), *anterior mandibular corpus height left* (x_7), *anterior mandibular corpus height right* (x_8), *mandibular corpus length* (x_9).

The Multilayer Perceptron model for gender identification uses the following architecture: 9 neurons input layer, 20 neurons hidden layer, 1 neuron output layer. The Multilayer Perceptron model for age group identification uses the following architecture: 9 neurons input layer, 18 neurons hidden layer, 5 neurons output layer. Figure 3 is an example of the architecture of the neural network layers. In the hidden and output layers there are two processes, namely the entry process for accumulation (Equation 5), and the activation process (Equation 6). In the activation process, this research uses the logistic activation function (Equation 6). Explanation of Equation 5 b is bias, dan w is the weight, x is the input variable, from i .

$$y\_in = b + \sum x_i w_i \quad (5)$$

$$y\_out = \frac{1}{1+\exp(-y\_in)} \quad (6)$$

$$y(x) = w^T x + b \quad (7)$$

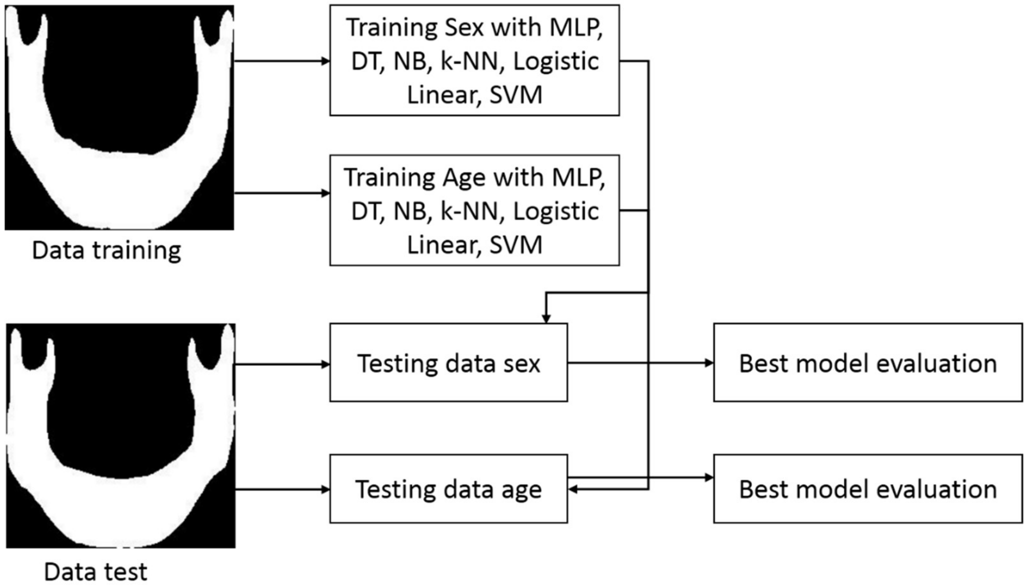

Figure 1: Research Proposal

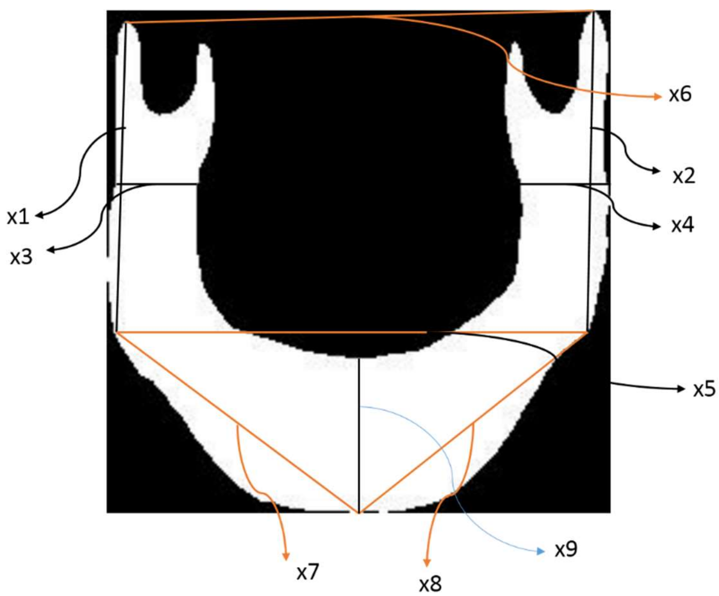

Figure 2: Mandibular Parameters

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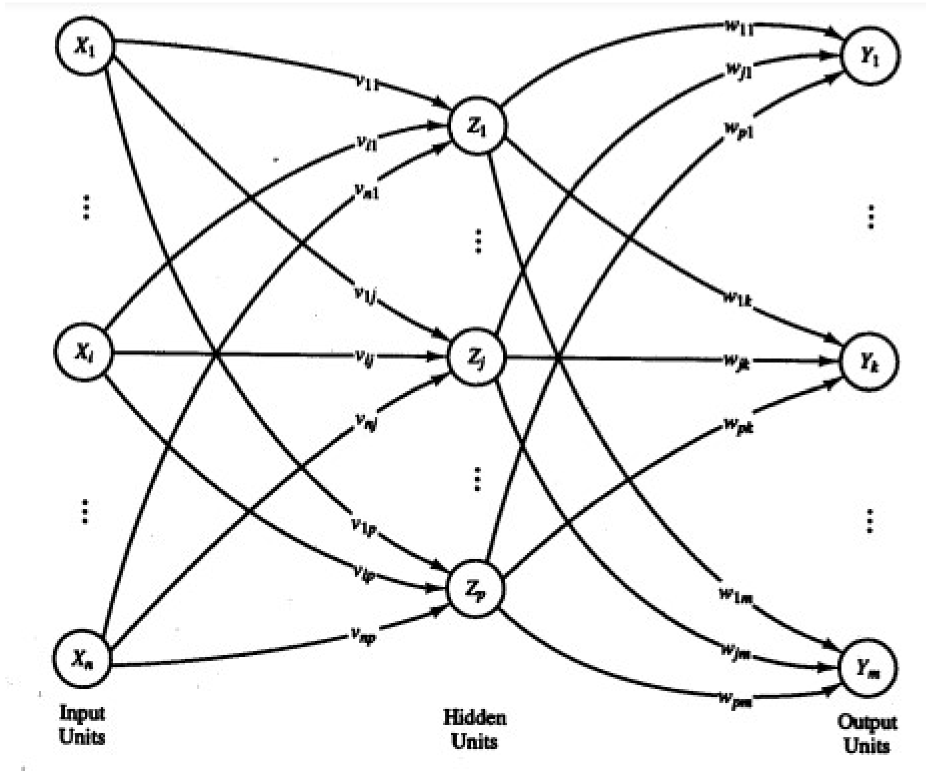
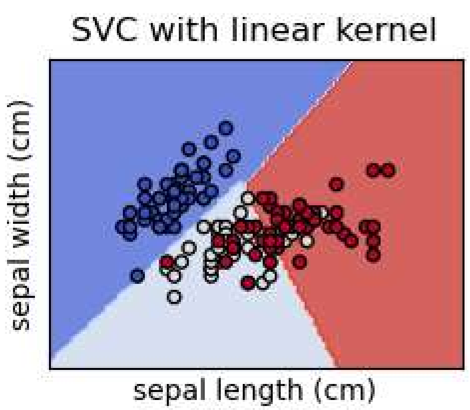
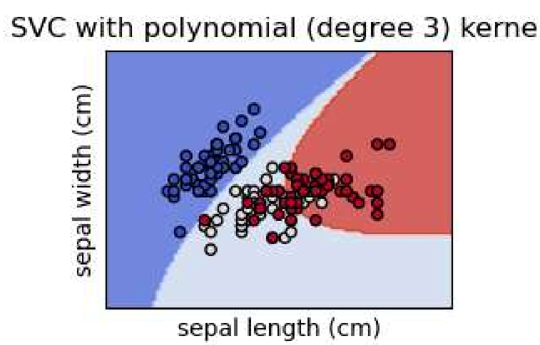


Figure 3: Multilayer Neural Network Architecture

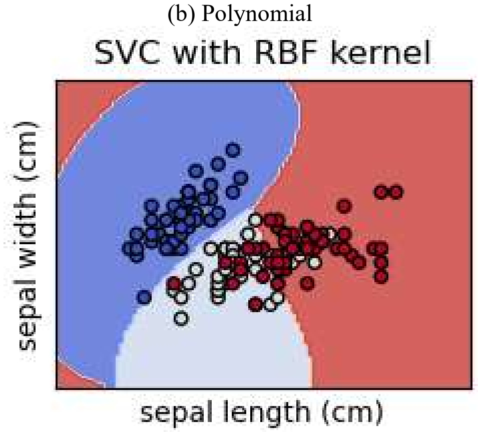
Multilayer Perceptron and SVM are methods in neural networks. The SVM training process to obtain a hyperplane using Equation 7. Explanation of Equation 7, is the weight and bias, is the input variable, and is the kernel. The kernel in SVM contains linear, polynomial, and RBF as in Figure 4.



(a) Linear



(b) Polynomial



(c) RBF

Figure 4: Kernel in SVM

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Method k-NN carry out the classification process based on the closest distance or neighborhood, with k number of nearest neighbors (smallest order). Equation 8 is the process of finding the closest distance. Explanation of Equation 8 x are the input variables of each i test and training data. In this research, a test was used k (1, 2, 3) to get k the best. The Naive Bayes method performs classification by finding the highest probability of the output class (Equation 9). Explanation of Equation 9, $P(Y \mid X)$ probability of output variable class against input variable, $P(X)$ the probability of the input variables, and $P(Y)$ the probability of each class of output variables.

$$D = \sqrt{\sum (x_{train\_i} - x_{test\_i})^2} \quad (8)$$

$$P(Y \mid X) = \frac{P(X \mid Y) P(Y)}{P(X)} \quad (9)$$

3. RESULT

This research conducted gender and age identification based on panoramic radiographic images. The mandibular image on panoramic radiography was measured using nine parameters as in Figure 2, namely ramus height left (x_1), ramus height right (x_2), ramus length left (x_3), ramus length right (x_4), bigonial width (x_5), bicondylar breadth (x_6), anterior mandibular corpus height left (x_7), anterior mandibular corpus height right (x_8), mandibular corpus length (x_9) using ImageJ application by radiology experts. The measurement results of nine parameters are used as input for the machine learning model. The statistical values of the training data are as in Table 2, and the testing data are as in Table 3.

Figure 5 is a representation of the boxplot diagram of the training data. Figure 6 is a representation of the boxplot diagram of the testing data. Figure 7 is the correlation between mandibular parameters to gender and age. The brighter the color of the diagram, the higher the correlation of the parameters to gender and age.

Table 2: Training Data Statistics

Parameters	Min	Max	STD	Mean	Var	Median
x_1	105.97	158.20	10.08	134.22	101.59	134.27
x_2	102.35	164.75	11.21	132.83	125.58	133.50
x_3	23.50	40.00	3.55	32.51	12.57	32.00
x_4	22.50	42.00	3.61	32.25	13.04	32.00
x_5	190.02	221.23	7.60	209.49	57.82	210.46
x_6	196.73	220.77	5.00	211.29	25.00	212.25
x_7	106.89	158.76	8.67	134.77	75.22	134.62
x_8	108.98	151.77	8.27	132.46	68.32	133.08
x_9	34.00	95.00	7.95	74.29	63.25	73.75

Table 3: Testing Data Statistics

Parameters	Min	Max	STD	Mean	Var	Median
x_1	112.66	151.60	9.92	136.54	98.36	139.38
x_2	118.15	146.56	8.34	132.47	69.51	132.88
x_3	28.50	37.50	3.23	33.63	10.42	34.00
x_4	29.00	39.50	3.76	33.47	14.15	33.75
x_5	194.54	218.58	5.96	213.07	35.47	215.10
x_6	201.21	218.51	4.50	210.50	20.21	210.68
x_7	127.36	152.40	7.31	134.51	53.40	132.78
x_8	119.38	145.00	6.94	133.01	48.14	133.20
x_9	59.50	81.00	6.84	70.16	46.72	72.25

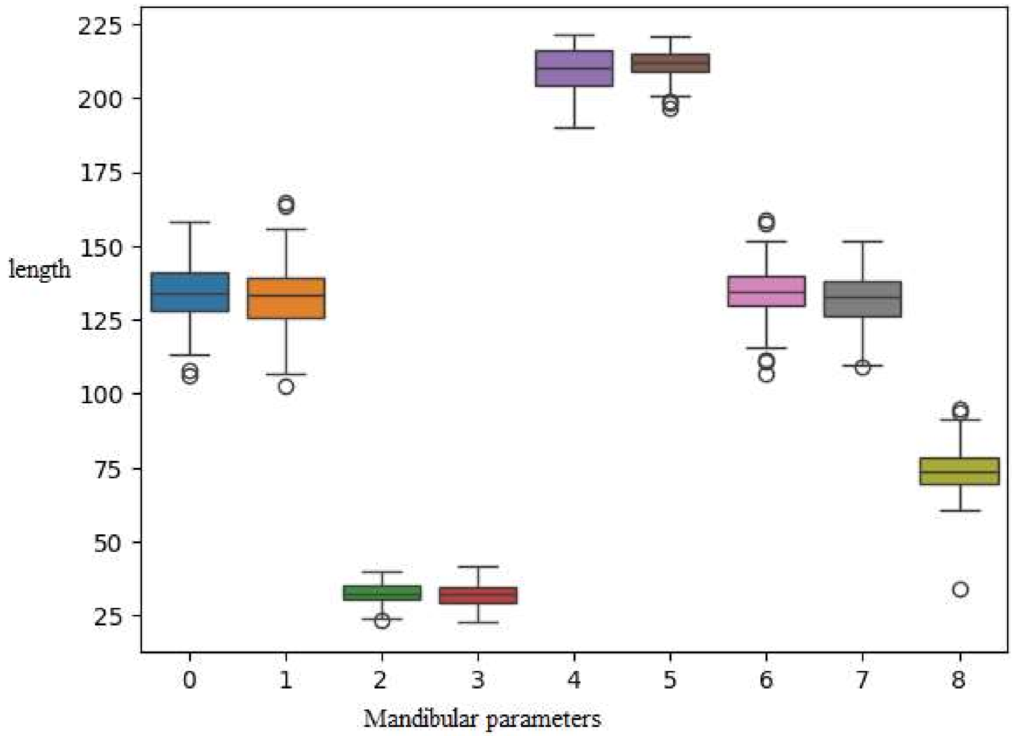

Figure 5: Diagram Boxplot Data Training

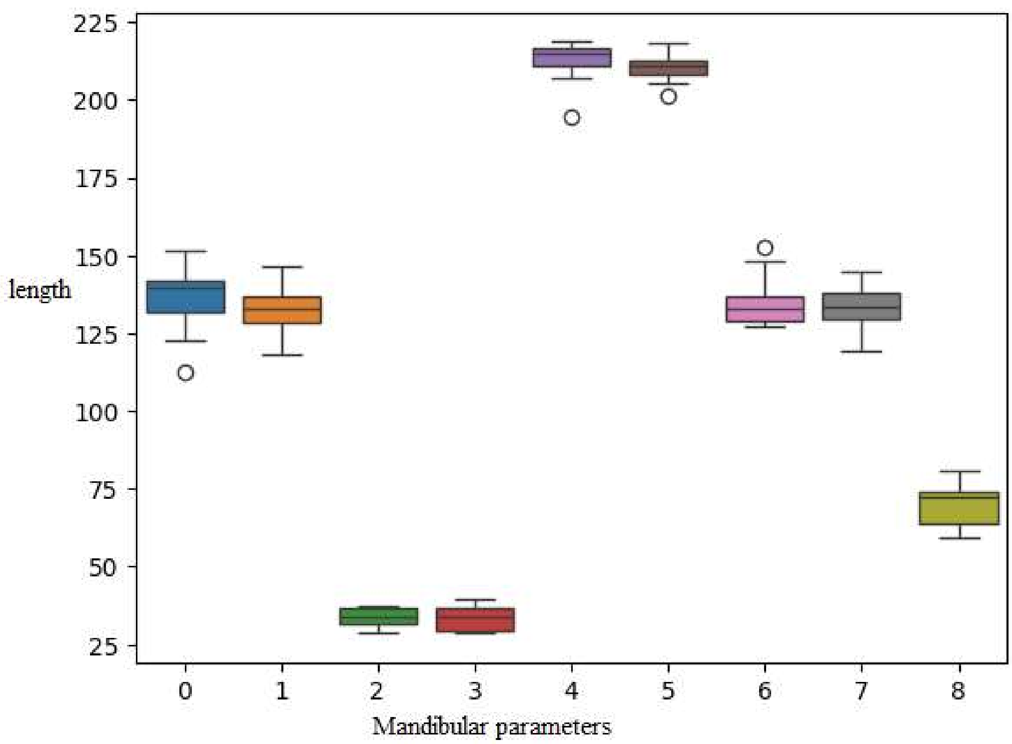

Figure 6: Diagram Boxplot Data Testing

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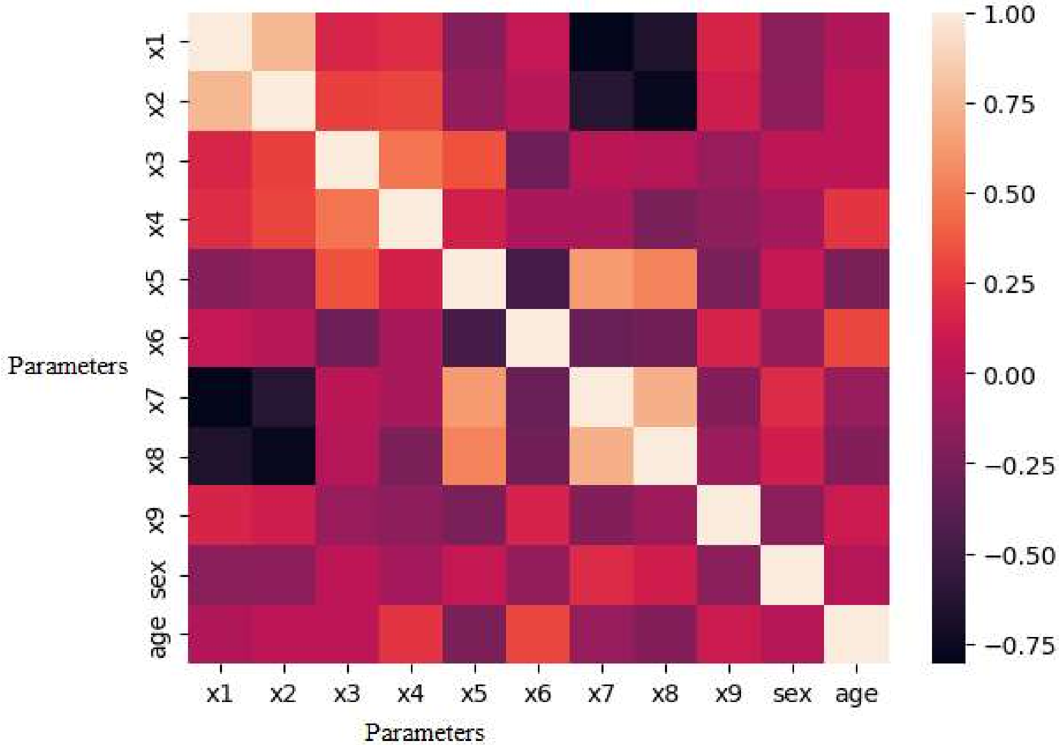
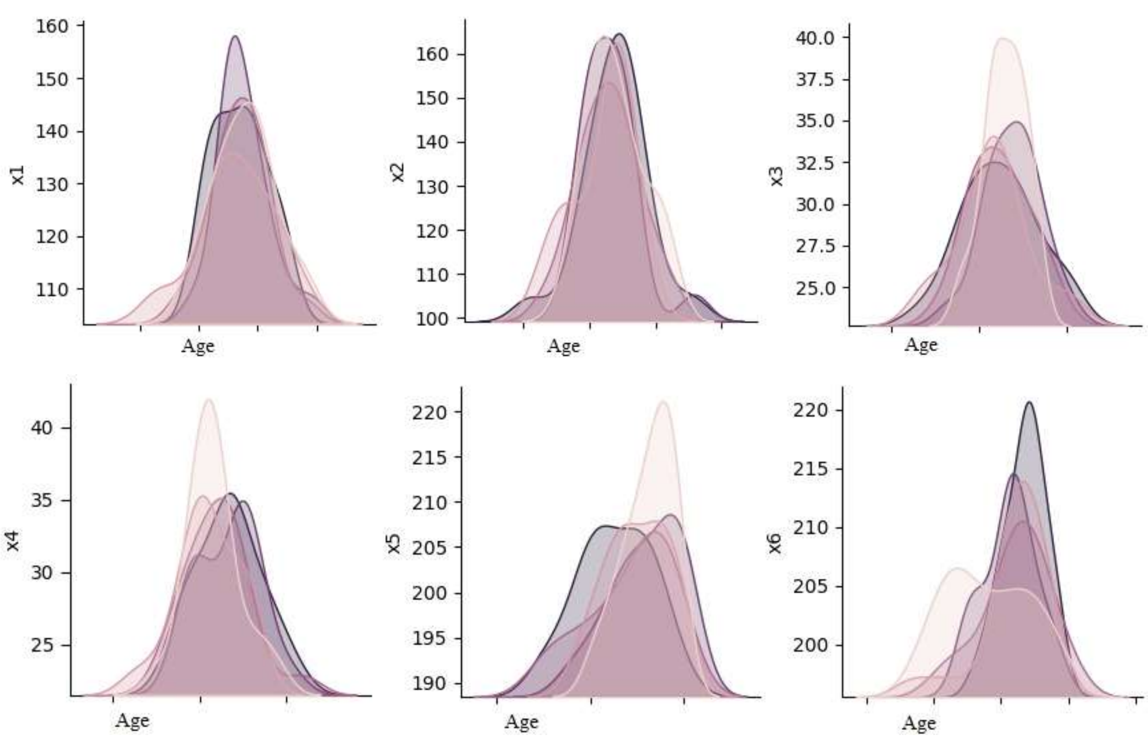


Figure 7: Parameter Correlation to Gender and Age



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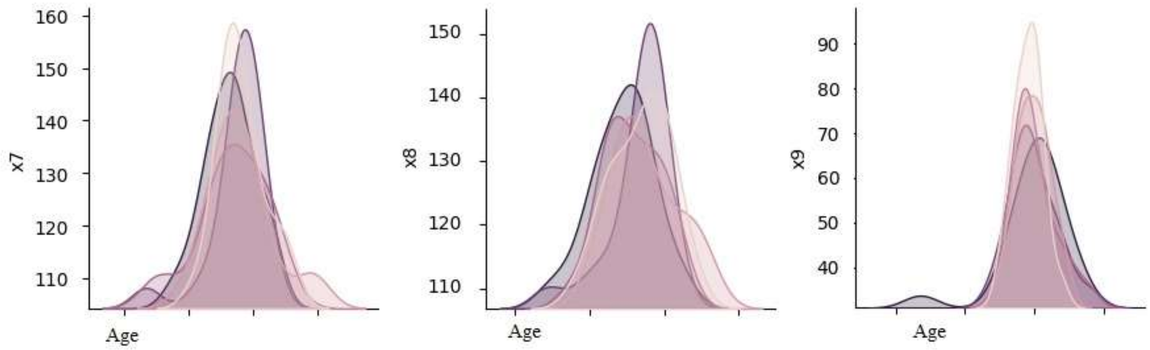

Figure 8: Representation of Parameters against Age

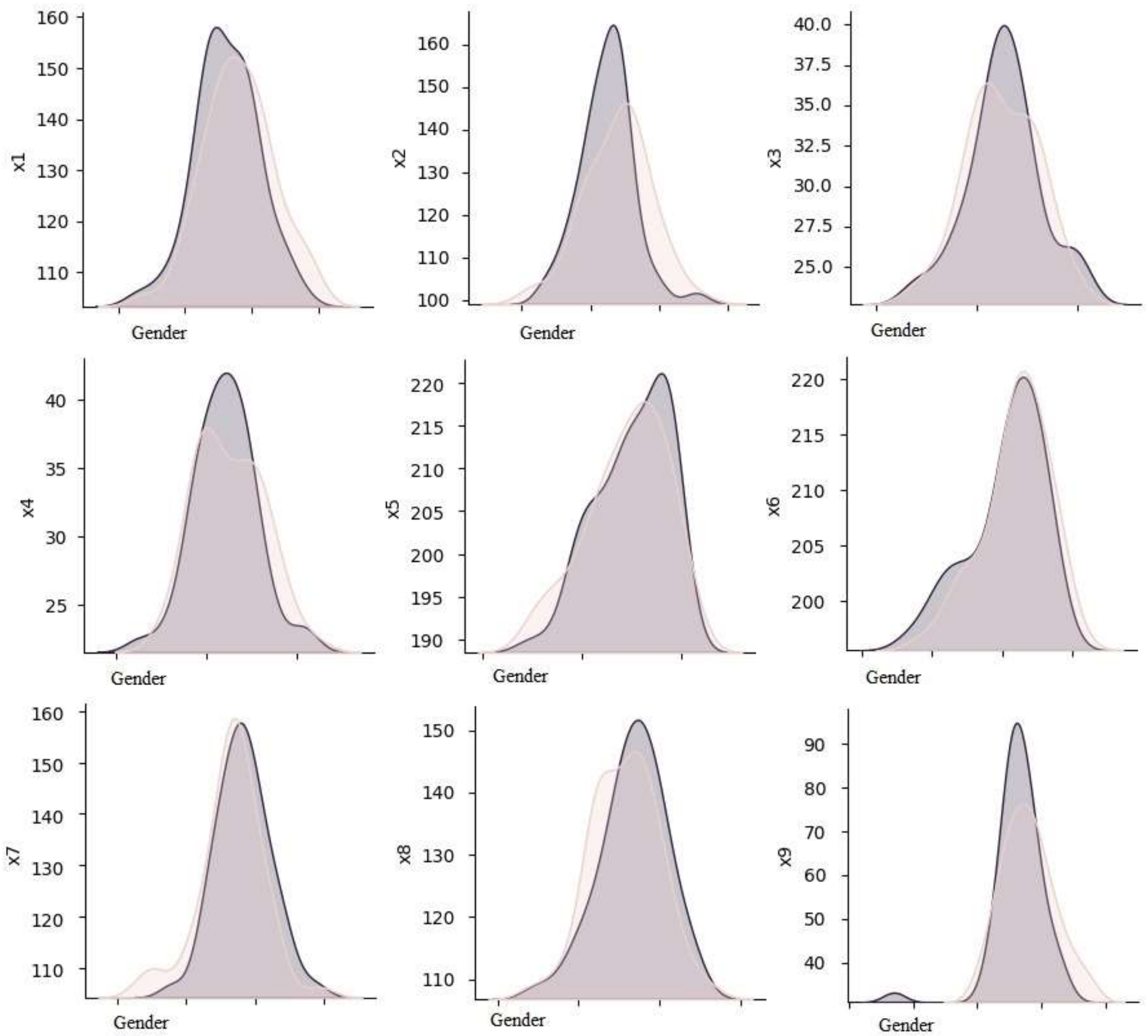

Figure 9: Representation of Parameters against Gender

Figure 8 represents the relationship of each mandibular parameter to age. Figure 9 is a diagram of the relationship of each mandibular parameter to gender. Table 4 is the correlation of each mandibular parameter to gender and age. Based on Figure 8, Figure 9 and Table 4, each parameter has a very small correlation to gender and age. Figure 8 is seen in almost every mandibular parameter $(x_1 - x_9)$ not separate age groups (groups one to five). Figure 9 that all mandibular parameters $(x_1 - x_9)$ does not separate gender (male and female).

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Table 4: Correlation of Training Data to Gender and Age

Parameters	Gender	Age
x_1	-0.18	-0.02
x_2	-0.17	0.03
x_3	0.03	0.03
x_4	-0.07	0.23
x_5	0.07	-0.24
x_6	-0.13	0.30
x_7	0.19	-0.12
x_8	0.12	-0.20
x_9	-0.18	0.09

Table 5: Testing Gender with MLP

Accuracy	Precision	Recall	F1 Score
0.688	**0.688**	**0.690**	**0.686**
0.438	0.219	0.500	0.304
0.688	**0.0688**	**0.690**	**0.686**
0.563	0.550	0.548	0.547
0.563	0.583	0.579	0.561

Table 5 is the result of the evaluation of gender identification of data testing with the MLP method. The MLP test was carried out five times with the aim of finding the highest evaluation value. Table 6 is the result of the evaluation of gender identification of data testing with the SVM method. The SVM test was carried out three times by changing the kernel of the SVM (linear, polynomial, RBF). Table 7 is the result of the evaluation of gender identification of data testing with the *k*-NN. Test *k*-NN was performed three times by changing the neighborhood. (*k*=1, *k*=2, *k*=3).

Table 8 is the overall evaluation result of MLP, Decision Tree, Naive Bayes, *k*-NN, Logistic Linear, and SVM methods in gender identification of testing data. The MLP method was tested five times and the highest was taken. The SVM method was tested three times, and the best kernel was polynomial. Method *k*-NN tested three times with *k* the best is *k*=2. Based on Table 8, the best machine learning method for gender identification is *k*-NN with the highest evaluation values of accuracy, precision, recall, f1 score respectively 0.750, 0.764, 0.750, 0.733.

Table 6: Testing Gender with SVM

Kernel	Accuracy	Precision	Recall	F1 Score
Linear	0.500	0.473	0.500	0.467
Poly	**0.625**	**0.619**	**0.625**	**0.619**
RBF	0.563	0.583	0.563	0.561

Table 7: Testing Gender with *k*-NN

k-NN	Accuracy	Precision	Recall	F1 Score
1	0.625	0.635	0.625	0.625
2	**0.75**	**0.764**	**0.75**	**0.733**
3	0.563	0.563	0.563	0.561

Table 8: Testing Gender with ML

Method	Accuracy	Precision	Recall	F1 Score
MLP	0.688	0.688	0.690	0.686
Decision Tree	0.625	0.619	0.625	0.619
Naive Bayes	0.625	0.635	0.625	0.625
***k*-NN**	**0.750**	**0.764**	**0.750**	**0.733**
Logistic Linear	0.688	0.688	0.688	0.686
SVM	0.625	0.619	0.625	0.619

Table 9 is the evaluation result of age data testing identification using the MLP method. The MLP test was conducted five times with the aim of finding the highest evaluation value. Table 10 is the evaluation result of age data testing identification using the SVM method. The SVM test was conducted three times by changing the kernel of the SVM (linear, polynomial, RBF). Table 11 is the evaluation result of age data testing identification using the *k*-NN.

Table 12 is the overall evaluation result of MLP, Decision Tree, Naive Bayes, *k*-NN, Logistic Linear, and SVM methods in identifying age data testing. The SVM method was tested three times, and the best kernel was RBF. Method *k*-NN tested three times with *k* the best is *k*=1. Based on Table 12, the best machine learning method in age identification is MLP with the highest evaluation values of accuracy, precision, recall, f1 score respectively 0.625, 0.267, 0.350, 0.297.

Table 9: Testing Age with MLP

Accuracy	Precision	Recall	F1 Score
0.438	0.191	0.243	0.214
0.563	0.247	0.343	0.268
0.500	0.240	0.314	0.248
0.625	**0.267**	**0.350**	**0.297**
0.500	0.200	0.293	0.238

Table 10: Testing Age with SVM

Kernel	Accuracy	Precision	Recall	F1 Score
Linear	0.438	0.367	0.438	0.347
Poly	0.375	0.343	0.375	0.223
RBF	**0.563**	**0.217**	**0.563**	**0.247**

Table 11: Testing Age with *k*-NN

k-NN	Accuracy	Precision	Recall	F1 Score
1	**0.500**	**0.427**	**0.500**	**0.408**
2	0.438	0.233	0.438	0.267
3	0.500	0.347	0.500	0.352

Table 12: Testing Age with ML

Method	Accuracy	Precision	Recall	F1 Score
MLP	**0.625**	**0.267**	**0.350**	**0.297**
Decision Tree	0.188	0.150	0.188	0.109
Naive Bayes	0.438	0.389	0.438	0.317
k-NN	0.500	0.427	0.500	0.408
Logistic Linear	0.438	0.433	0.438	0.369
SVM	0.563	0.217	0.563	0.247

The following researches conducted identification using mandibular parameters: 1) panoramic radiographic images measured mandibular parameters, the measurement results were used to create a machine learning model (*k*-NN, Naive Bayes, Neural Network, Logistic Regression) for gender identification with 95% accuracy [14]; 2) the panoramic radiographic image measured the mandibular parameters, the measurement results were used for identification search by calculating the similarity distance, the matching results had a correctness of 85% [17].

4. CONCLUSION

This research identified gender and age using MLP, Decision Tree, Naive Bayes, *k*-NN, Logistic Linear, and SVM methods. Input data is in the form of panoramic radiographic images of the mandible. The mandibular image in panoramic radiography is measured by nine parameters, namely ramus height left (x_1), ramus height right (x_2), ramus length left (x_3), ramus length right (x_4), bigonial width (x_5), bicondylar breadth (x_6), anterior mandibular corpus height left (x_7), anterior mandibular corpus height right (x_8), mandibular corpus length (x_9) using the ImageJ application by radiology experts. The results of the data testing evaluation show that the method that has accuracy in gender identification is *k*-NN with *k*=2, and the values of accuracy, precision, recall, and f1 score are sequentially 0.750, 0.764, 0.750, and 0.733. And the method that has accuracy in age identification is MLP, with values of accuracy, precision, recall, and f1 score of sequentially 0.625, 0.267, 0.350, and 0.297. The best machine learning method in gender identification is k-NN. The best method in identifying age is MLP.

Suggestions for further research are to add data so that it can be more varied and represent a large sample.

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