Artificial neural network for gender determination using mandibular morphometric parameters: A comparative retrospective study

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Abstract: Gender determination is of paramount importance in order to identify the diseased in cases of mass disasters and accidents and to resolve all medico-legal issues in cases of violence. Skeletal bones are the strongest bones in the body and they play a crucial role in identifying a person’s gender. ANN is a relatively new technology, is fast emerging as a better prediction model for gender when used with skeletal bones like the femur. Prior studies have extensively used discriminant analysis, logistic regression and other similar statistical tools to understand the role of the mandible and its efficacy in gender determination. This study uses Artificial Neural Networks (ANN) for gender determination and compares results thus obtained with logistic regression and discriminant analysis using mandibular parameters as inputs. Digital panoramic radiographs were used to measure the mandible of 509 individuals. Six linear parameters and one angular parameter of each individual were obtained. Logistic Regression, Discriminant Analysis, and ANN analysis were performed on these parameters. The discriminant analysis had an overall accuracy of 69.1%, logistic regression showed an accuracy of 69.9% and ANN exhibited a higher accuracy of 75%. The results revealed that ANN is a good gender prediction tool for gender determination using mandible parameters.

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PUBLIC INTEREST STATEMENT
Gender determination is of paramount importance in order to resolve all medico-legal issues. Mandibular morphometric parameters measured on panoramic radiographs are good source for gender determination of the unknown. This study uses Artificial Neural Networks (ANN) for gender determination and compares results thus obtained with logistic regression and discriminant analysis using mandibular parameters as inputs. Skeletal bones are the strongest bones in the body and they play a crucial role in identifying a person’s gender. ANN being a relatively new technology, is fast emerging as a better prediction model for gender when used with skeletal bones like the femur. In this study, ANN gave better accuracy in gender prediction than other prediction models like discriminant analysis and logistic regression. The ANN model depicted 75% of accuracy in gender determination for males and females using mandibular morphometric parameters. Therefore, ANN can be a useful tool for gender prediction using mandible parameters.
prediction tool that can be applied in the field of forensic sciences for near accurate results. Its application is promising as it automates and eases the method of identifying unknown gender or age with minimal errors.

Subjects: Neural Networks; Legal Aspects of Medicine; Medical Technology & Engineering; Dentistry; Oral Medicine

Keywords: Artificial intelligence; artificial neural network; mandible; gender classification; panoramic radiographs; forensic; dentistry

1. Introduction

Gender determination is of paramount importance in order to identify the diseased in cases of mass disasters, accidents and to resolve all medico-legal issues in cases of violence. Skeletal bones are the strongest bones in the body and they play a crucial role in identifying a person’s gender. Gender determination is greatly accurate when the whole skeleton is available; about 95% accurate with pelvis; and 90% accurate with skull bones (More, Vijayvargiya, & Saha, 2017). Whereas, in cases of major disasters, when the body is mutilated beyond the scope of visual identification, the skull, mandible, and teeth often prove to be a valuable source of identification. The mandible is a dense compact bone in the orofacial skeletal structure that is durable, can resist post-mortem changes and is the last skeletal bone to cease growth. It shows gender dimorphism as it is sensitive to adolescent growth spurt. It also has different growth rates in both genders and the different masticatory forces for males and females also influence the shape of the mandible (Raj & Ramesh, 2013). Hence, it is an efficient gender determination tool that is frequently chosen in solving forensic cases. Gender determination using the mandible is usually done by evaluating its metric and non-metric parameters either on dry mandible or by using radiographs. The radiological methods are more preferred as they are less complex, non-destructive, and can be applied to both the dead and the living with no loss of any evidence (Patil, Pai, & Naik, 2018).

Forensic gender determination has received great research attention since the 1960s. Most of the studies pertaining to the mandible and its accuracy in gender determination have applied similar statistical tests and have developed models using discriminant analysis (Jambunath, Govindraju, Balaji, Poornima, & Latha, 2016; Kumar et al., 2016; More et al., 2017; Park & Park, 2018; Vahanwala, 2019). Artificial neural network (ANN) is the new technology on the block which is witnessing a remarkable rise in its use in forensic sciences (Kozan & Zelenchuk, 2017). This artificial intelligence technology is based on a mathematical model and is designed to mimic human brains (Kozan & Zelenchuk, 2017; Sikka & Jain, 2016). It is widely used to identify patterns and identify and classify genders in forensic studies (Alunni, Du Jardin, Nogueira, Buchet, & Quatrehomme, 2015; Kozan & Zelenchuk, 2017). Warren McCulloch and Walter Pitts introduced the technique to dentistry in 1943. Since then it has been used in developing the tooth prediction model, clinical decision-making, and identifying the relationship between dental pains and brushing parameters. ANN has also been used in forensic sciences to predict age and gender using skeletal bones (Kozan & Zelenchuk, 2017). However, not much evidence exists on ANN and its application in gender prediction using mandibular radiological parameters. Hence, we conducted this study with an aim to evaluate the reliability of artificial neural networks as a gender prediction tool in comparison to other techniques such as logistic regression and discriminant analysis.

2. Materials and methods

A retrospective study was conducted after gaining approval from the institutional ethics committee for a period of 6 months from Jan 2018 to June 2018. One thousand digital panoramic radiographs, which were taken using Kodak 8000C Digital Panoramic and Cephalometric system with exposure parameters of 66kVp, 12mA, and 14s were selected from the existing database. Radiographs of individuals with ages ranging from 18 years to 70 years, and with no distortion or
superimposition were included in the study. Radiographs of completely edentulous arches, with previous trauma, lesions, syndromes or developmental disorders affecting jaws were excluded. After exclusion, a total of 509 radiographs were available for linear and angular measurements of the mandible.

The below mentioned morphometric parameters were evaluated. The parameters were selected based on previous studies (Kumar et al., 2016; More et al., 2017; Raj & Ramesh, 2013).

(a) **Maximum Ramus Breadth (MRB)**—Measurement of the smallest anterior-posterior diameter of the ramus

(b) **Bi-condylar width (BiCW)**—Distance between the most lateral points on the two condyles

(c) **Condylar Height (CoH)**—Distance of the line drawn perpendicular from the top-most point of the condyle (condylion) to the horizontal line measuring the maximum ramus breadth

(d) **Coronoid height (CorH)**—Distance of the line drawn perpendicular from the top-most point on coronoid to the horizontal line measuring the maximum ramus breadth

(e) **Bigonial Width (BiGW)**—Distance between both Gonia points

(f) **Bimental Width (BiMW)**—Distance between both mental foramen

(g) **Gonial angle (GoA)**—Assessed by tracing a line tangent to the lower border of the mandible and another line tangent to the distal border of the ramus on each side. The intersection of these lines formed the gonial angle

2.1. Measurement of variables

The morphometric measurements were done using Digimizer Image analysis software by single trained oral and maxillofacial radiologist who has experience of more than 5 years in seeing and reporting panoramic radiographs and other extraoral radiographs (Figure 1).

2.2. Intraobserver variability

To assess the reliability in measuring the parameters on digital radiography by the trained radiologist, each measurement was repeated twice on two different occasions. Intra-class correlation coefficient value ranging from 0.84 to 1 was observed, suggestive of good to excellent intraobserver agreement as shown in Table 1.
2.3. Computational techniques—artificial neural network

ANN consists of neurons that are connected by links, each of which has a numerical weight associated with it. Each neuron computes the weighted sum of their input links and compares the result with the threshold value. The output of each neuron depends on the activation function used.

A feed-forward neural network with backpropagation learning algorithm is a useful technique (Illustrated in Figure 2). The feed-forward neuron network consists of one input layer, one output layer, and a number of hidden layers. Each neuron in a layer is connected to the other neurons in the adjacent layers. The sigmoid and linear functions are usually adopted as the activation functions on the hidden and output layers for this kind of network, respectively. In order to train the network, the input data are received via the input layer and distributed to the hidden layers. Neurons in the hidden layers detect the information via their weights, perform the calculation according to the corresponding activation function and then propagate the output signal to the next layers.

2.4. Network architecture

In this study, the feed-forward neural network with backpropagation technique is used and eight models were created for each group of data. Each model represented the prediction of success using each performance measure. The model architecture (Figure 3) was composed of one input layer, one or two hidden layers, and one output layer. The input layer had two nodes per the number of success factors from the survey. The output layer had 1 node per each performance measure.

Table 1. Correlation co-efficient showing intra-observer agreement

| Parameters         | MRB | BiCW | CoH | CorH | BiGW | BiMW | GoA |
|--------------------|-----|------|-----|------|------|------|-----|
| Intra class        | 0.84| 0.99 | 0.99| 0.83 | 1    | 0.99 | 0.99|
| correlation values |     |      |     |      |      |      |     |
2.5. Network training and validation
The software Matlab R2019a with neural network toolbox is used for neural network operation. Both success factors and performance measures of training and validation set data were passed through the network for training. This research uses the TRAINLM network, the fastest back proposition algorithm as a training function that updates weight and bias values according to Levenberg-Marquardt optimization. However, though TRAINLM requires more memory than other algorithms it is the most preferred and recommended algorithm.

2.6. Model prediction
Mean Square Error (MSE) is used to indicate the ability of network performance. Mean Square Error (MSE) is also computed from the actual predicted value and its target. The R-value, which is the coefficient of correlation, is used to measure the correlation between the actual and predicted value. It measures the direction and strength of the linear relationship between the actual and predicted value. In order to find network performance, regression all is preferred, i.e., testing is done on large data. Normally, to decide the network performance, Mean Square Error (MSE), Mean Absolute Error (MAE) and Coefficient of determination ($R^2$) are measured as performance metrics of ANN models and not just regression $R$. $R$ is a coefficient of correlation and $R^2$ is the coefficient of determination. The closer the R-value to 1 the better the correlation.

The following research is conducted on the gender prediction of patients based on their dental records and measurement of morphometric parameters. The output desired from the neural network prediction is gender (Male or Female). The sample target specified for the neural network for training, validation, and testing is Gender (Male or Female).

3. Results
Descriptive statistics of all mandibular parameters of the sample are presented in Table 2. A total of 509 patients (256 males and 253 females) were analyzed. As BiGW and GoA followed normal distribution, Student-t-test was applied for statistical analysis and the remaining parameters were assessed with Mann-Whitney U test for differences between males and females. Except for the gonial angle, all parameters showed a significantly higher value in males compared to females.

| Parameter | Median (Q1-Q3) | Mean (Standard Deviation) |
|-----------|----------------|--------------------------|
| MRB       | 3.393 (3.175, 3.6265) | 19.508 (18.7, 20.167) |
| BiCW      | 1.735 (1.529, 1.926) | 0.932 (0.79, 1.088) |
| CoH       | 5.647 (5.1035, 6.113) | 16.8456 (1.10028) |
| CorH      | 129.5972 (6.82514) |
| BiMW      | 16.8456 (1.10028) | 129.5972 (6.82514) |
| BiGW      | 17.7157 (1.14465) | 127.1005 (7.27757) |
| GoA       | 127.1005 (7.27757) |

P value $<0.001^{**}$ $<0.001^{**}$ $<0.001^{**}$ $<0.001^{**}$ $<0.001^{**}$ $<0.001^{**}$ $<0.001^{**}$
3.1. Logistic regression analysis

Logistic regression (Backward Wald) was applied to identify the variables contributing significantly to gender prediction. BiMW and MRB were removed and other parameters were considered as final variables (Table 3).

Equation: \[ \frac{1}{\exp(10.542 - 0.481 \times \text{BiCW} + 0.971 \times \text{CoH} + 1.402 \times \text{CorH} + 0.270 \times \text{BiGW} - 0.052 \times \text{GoA})} \] (1)

3.2. Discriminant analysis

Discriminant function with all data was computed. An overall 69.1% of the original grouped cases were correctly classified (Table 4).

3.3. Artificial neural network analysis

Table 5 depicts values showing the best performance of the neural network model through the Least Mean squared error (LMSE) and the Error percentage with the various combinations of morphometric parameters. The simulation was carried out with the hidden layer 1 neurons as 50 and Hidden layer 2 neurons as 100.

The error percentage of the neural network model considering all the morphometric parameters. The simulation was carried out with variation in the neurons in the hidden layers. It is observed that the performance of the neural model is best with 70% training, 15% testing and 15% validation data. And with hidden layer 1, it is best with 50 neurons, and with hidden layer 2, it is best with 100 neurons (Table 6).

Confusion Matrix is useful in representing the performance measurement of a machine learning classification. Confusion matrix (Figure 4) shows the four combinations of predicted and actual values.

The commonly used diagnostic evaluation tool is the receiver operating characteristic (ROC) curve. The true positive rate (sensitivity) is plotted in function of the false-positive rate (100-specificity) at various threshold settings. ROC curves for Set 1, Set 2 and Set 3 for gender prediction considering all morphometric parameters (Figure 5).

4. Discussion

Human mandible displays significant gender dimorphism in both morphological and morphometric parameters. Morphometric parameters are considered to be more accurate than morphological

| Table 3. Gender Classification table showing Logistic regression result for the mandibular parameters |
|---------------------------------------------------|---------------------------------------------------|----------------------|
| Predicted Gender                                  | Female                                            | Male                |
| Female                                            | 161                                               | 78                  |
| Male                                              | 75                                                | 195                 |
| Overall percentage                                |                                                   | 69.9                |

| Table 4. Gender Classification table showing results of the Discriminant analysis |
|-----------------------------------------------|-------------------------------------------------|----------------------|
| Gender                                       | Predicted group membership                      | Percentage accuracy  |
| Females                                      | 160                                             | 66.9%                |
| Males                                        | 78                                              | 71.01%               |
| Overall Percentage                            |                                                  | 69.1%                |
parameters because of the latter exhibit subjective bias (Mağat & Özcan, 2018). Panoramic radiographs were chosen as these are routinely advised screening radiographs with low radiation exposure and short acquisition time. Also, previous studies have stated panoramic radiographs

| Parameter Combination | Sample Type | Sample Size (Nos.) | Least Mean squared error (LMSE) | Coefficient of Correlation (R) | Error Percentage (%) |
|-----------------------|-------------|--------------------|---------------------------------|-------------------------------|----------------------|
| BICW+ BIGW            | Training    | 444                | 0.22071                         | 0.65686                       | 56.31%               |
|                       | Testing     | 95                 |                                 | 0.35598                       |                      |
|                       | Validation  | 95                 |                                 | 0.39376                       |                      |
| BICW+ BIGW+ BIMW      | Training    | 444                | 0.25529                         | 0.50156                       | 54.06%               |
|                       | Testing     | 95                 |                                 | 0.27512                       |                      |
|                       | Validation  | 95                 |                                 | 0.51121                       |                      |
| GoA+ BIGW             | Training    | 444                | 0.22215                         | 0.43966                       | 56.8%                |
|                       | Testing     | 95                 |                                 | 0.32287                       |                      |
|                       | Validation  | 95                 |                                 | 0.49430                       |                      |
| BICW+ BIGW+ BIMW+MRB  | Training    | 444                | 0.20939                         | 0.45878                       | 55.14%               |
|                       | Testing     | 95                 |                                 | 0.40753                       |                      |
|                       | Validation  | 95                 |                                 | 0.65917                       |                      |
| CoH+CoRH              | Training    | 444                | 0.23169                         | 0.36132                       | 67.59%               |
|                       | Testing     | 95                 |                                 | 0.27103                       |                      |
|                       | Validation  | 95                 |                                 | 0.17346                       |                      |
| MRB+BIMW              | Training    | 444                | 0.31346                         | 0.25926                       | 73.06%               |
|                       | Testing     | 95                 |                                 | 0.19835                       |                      |
|                       | Validation  | 95                 |                                 | 0.39452                       |                      |
| MRB+BICW+ BIGW+ GoA   | Training    | 444                | 0.18314                         | 0.41909                       | 57.95%               |
|                       | Testing     | 95                 |                                 | 0.51849                       |                      |
|                       | Validation  | 95                 |                                 | 0.32005                       |                      |
| BIGW+ GoA+ BICW+ BIMW | Training    | 444                | 0.17925                         | 0.56864                       | 46.13%               |
|                       | Testing     | 95                 |                                 | 0.53842                       |                      |
|                       | Validation  | 95                 |                                 | 0.4011                        |                      |

| SET                  | Sample Type | Sample Size (Nos.) | Variation of neurons in hidden layer | Error Percentage (%) |
|----------------------|-------------|--------------------|--------------------------------------|----------------------|
| Set 1                | Training    | 444                | Layer 1: 50 Layer 2: 100             | 23.7%                |
|                       | Testing     | 95                 |                                      |                      |
|                       | Validation  | 95                 |                                      |                      |
| Set 2                | Training    | 444                | Layer 1: 100 Layer 2: 100           | 26.1%                |
|                       | Testing     | 95                 |                                      |                      |
|                       | Validation  | 95                 |                                      |                      |
| Set 3                | Training    | 508                | Layer 1: 100 Layer 2: 150           | 25.5%                |
|                       | Testing     | 63                 |                                      |                      |
|                       | Validation  | 63                 |                                      |                      |
to show reliable and identical linear and angular measurements in comparison with dry mandible (Kim, Lim, & Rhee, 2009; Jambunath et al., 2016; Kambylafkas, Murdock, Gilda, Tallents, & Kyranides, 2006). This study is unique as it adapts a newer technology, ANN applied as a prediction tool in gender determination which has not been much applied to mandibular parameters.

The artificial neural network is an upcoming technology in forensic dentistry, which streamlines and automates the method of identification of unknown patterns by minimizing errors (Sikka & Jain, 2016). It employs the use of machine learning to diagnose and make predictions through large collected data. Although not many confirmative studies are available, it can be stated that its use in forensic science is progressing beyond conventional practice (Kozan & Zelenchuk, 2017). The use of this technology has been explored for age estimation, gender prediction using skeletal bones – femur, reading facial images, etc. In general dentistry, ANN is applied in building a toothache prediction model to explore the relation between dental pain and influencing factors like tooth brushing frequency and toothbrush replacement time and analyze the factors which influence clinical approach to impacted canines (Xie, Wang, & Wang, 2010). It has also been used to model and understand the need for extraction before orthodontic treatment; evaluate the relation between the property of restorative material and its life span as restoration; and analyze the indirect cause of extraction (Deepti, Jyothi, & Vinay, 2014; Käkilehto, Salo, & Larmas, 2009).
The technique of artificial neural network depends upon a large number of data accumulated; hence, a larger sample of 1000 radiographs was analyzed initially out of which 509 appropriate radiographs were finalized and selected. This sample size is comparable to the previous studies by Tanvi et al., Deeepthi Bharadwaj et al., Naveen et al., and Usha Jambunath et al., (Satish, Moolrajani, Basnaker, & Kumar, 2017; Vahanwala, 2019). All readings were done by a single trained observer (experienced Oral and Maxillofacial Radiologist) at two different times and good intra-observer agreements ranging from 0.83 to 1, for all the metric parameters were observed. A comparable consistency was observed by Tanvi et al.’s study (Vahanwala, 2019).

Humphrey et al. stated that as mandible remodels during its growth process the greatest morphological changes are seen with mandibular condyle and ramus compared to other regions (Vikas, 2018). Hence, in our study, six linear parameters and one angular parameter were considered for gender prediction analysis.

A significant difference was noticed with respect to means of all morphometric parameters measured, out of which BiGW, BiCW, and CoH exhibited pronounced gender difference compared to others. Similar results have been observed in the previous study by Naveen et al. (Kumar et al., 2016). In contrast to linear parameters, which exhibited higher values in male in comparison to female mandibles, the angular parameter, i.e., the GoA showed a differing result. The GoA was higher in females compared to males. This result was very similar to the previous studies done by Sairam et al., Jeong et al., and Usha Jambunath et al. (Jambunath et al., 2016; Joo, Lim, Kwon, & Ahn, 2013; Raj & Ramesh, 2013).
In this study, two standard gender determination methods (discriminant analysis and logistic regression) were analyzed along with artificial neural networks. Discriminant analysis is a robust method that often yields good results for sex discrimination and has been previously applied by researchers. In our study, this technique had an accuracy of 69.1% in identifying males and females. About 79% of females and 66.9% of males were correctly identified using all the six morphometric parameters. A lower accuracy level was seen for males, which has been seen in a previous study (Kumar et al., 2016). Model accuracy using logistic regression also revealed an overall accuracy of 69.9% wherein 67.4% of females and 72.2% of males were correctly identified and classified into their gender category.

The artificial neural network using a combination of all six parameters gave the best result in comparison to previous two techniques. It displayed only 25.5% of error with 75% of samples being correctly classified gender-wise. As the same mandibular parameters have not been applied to artificial neural networks in any of the previous studies, a direct comparison of our study results with the previous study results is not appropriate. But the outcome of this study substantiates gender prediction using ANN to be better than other models like discriminant analysis and logistic regression (Alunni et al., 2015; Park & Park, 2018).

The three gender determination models have shown acceptable results in this study, yet a model showing more than 75% accuracy is more acceptable in our opinion. The results also need to be extrapolated to a larger population considering the fact that skeletal changes in gender are also influenced by various other confounding factors like age, genetic origin, race, living conditions, attachment and use of masticatory muscles, osteoporotic changes (Alunni et al., 2015; Vikas, 2018).

5. Conclusions
Forensic anthropologists are always in an endeavor to improve and develop newer technologies for gender and age estimation using various skeletal bones. Artificial neural network in our study has shown to be a good gender prediction tool in comparison to previously used models – discriminant analysis and logistic regression. Hence, application of this technique in the field of forensic sciences is promising as it automates and eases the method of identifying unknown with minimal errors.

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Declaration of interests
The authors declare that they have no conflict of interest.

Ethical Committee Standards
This research was conducted with permission from Institutional Ethics Committee (Registration Number: ECR/146/Inst/Ka/2013/RR-16) with IEC: 362/2018.

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