Determination of Gender from Pelvic Bones and Patella in Forensic Anthropology: A Comparison of Classification Techniques

Iis Afrianty*, Dewi Nasien*, Mohammed R. A. Kadir+, Habibollah Haron*
*Faculty of Computing, +Faculty of BioScience and Medical Engineering,
Universiti Teknologi Malaysia, 81310 UTM Skudai
Johor, Malaysia

***Abstract*—the determination of gender is an important part of forensic anthropology because as the first essential step for positive identification process. Besides empirical methods for gender determination such as Discriminant Function Analysis (DFA), Artificial Intelligence methods such as Artificial Neural Network (ANN) should be considered to obtain more accurate determination result. This paper proposes Back propagation Neural Network (BPNN) model of ANN methods. By using data and DFA result of pelvic bones and patella from previous work, this paper compares accuracy of result obtained from the BPNN models. A total sample data of 136 pelvic bones and 133 patellae have been collected. For pelvic bones, BPNN gave average accuracy as much as 98.5% for training and 98.3 for testing. While on left pelvic bones, average accuracy that is obtained are 98.49% for training and 86.6% for testing. For patella bones, all average accuracy (males and females) are obtained by BPNN is 94.09%. If compared with previous study that using DFA obtained accuracy as much as 92.9%. It is concluded that in gender determination, BPNN gives high accuracy of classification for both bones compared with DFA.**

Keywords- Back Propagation Neural Network; Forensic Anthropology; Gender Determination; Patella; Pelvic Bones

I. INTRODUCTION

Forensic anthropology is one of first important steps that have a major goal for identifying of skeletal remains includes an assessment specific to the cause and the manner of death [1-3]. The identity of skeletal remains is an essential part of post-mortem to recognize of biological profile of unknown remains. In previous work, for identification of skeletal remains, forensic anthropologists used DNA (Deoxyribose Nucleic Acid) analysis in the laboratory [4]. DNA is largely widespread that DNA could lead to identification. But, it has disadvantage that cannot be extracted if skeleton in burned or damaged condition, thus cannot give data on some of the essential parameters of the biological profile [4]. With the lack of DNA analysis, forensic anthropology present with give contributes in identification, particular in gender determination.

The determination of gender is one of main goal of forensic anthropology in identification process [5]. Gender determination is more reliable if the complete skeleton is available for analysis. But in forensic cases, human skeletal remains are often with conditions like incomplete, not intact, burned, or damaged [6]. Knowledge of the gender of an unknown set of remains is essential to make a more accurate estimation of age [7].

From previous work, numerous studies already exist on gender determination from primary anatomical parts such as the pelvis [8], skull bone [9], mandible [10, 11], clavicle [12, 13], femur [14-17] and many other parts of the human skeleton show gender difference. The pelvic bones are a part of the best skeletal parts to accomplish a reliable sexual diagnosis [18] because it has long been recognized as the most dimorphic bone, particularly in adult individuals [19]. One of the skeletal parts more attention recently is patella [20].

Gender determination is the classification of an individual as either male or female. In gender determination process, many of anthropologists use Discriminant Function Analysis (DFA) [8, 21-23]. DFA is one of include of linear approach and be the most popular technique. DFA is an economic, robust, easy-to-use modeling method compared to a neural network, which is quite complicated and time consuming to implement [14]. But, DFA has lack that gave to slightly better results of classification [24] and also quite constraining. This paper will propose Back Propagation Neural Network (BPNN) for gender determination from pelvic bones and patella, and then compare result of average accuracy that produces by BPNN and DFA for both bones.

II. MATERIALS AND METHODS

Generally, in gender determination process has two methods for measurement of data collection namely morphologic and metric method [22, 25]. The morphologic method is the observation of sexual traits on bones and the metric method is based on measurements and statistical techniques. This method has advantage namely the ability to obtain results quickly with high classification accuracy if the bone is available and the observer has enough experience. On the other hand, the metric method is based on measurements and statistical techniques [20]. Metric measurements were preferred due to their easy repeatability, high accuracy, and no requirement for special skill [12]. The metric method should be used in combination with the morphological method that is called morphometric.

The pelvic bones are considered to get more accurate determination result. They are structurally related to organ support and are functionally articulated to facilitate the erect position, as well as permitting the bipedal locomotion of the human body [23]. On pelvic bones are composed of three bones, namely the pubic, ischial, and iliac. Morphologically, the male pelvic is longer, robust, and displays more rugged

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features with marked muscle insertions whereas the female pelvic shows a wider sciatic notch with an obtuse angle [23].

Beside those pelvic bones, patella bones are also researched to know of identification. The patella is small compact bone that articulates with the distal anterior end of the femur [2]. In the gender determination literature using patella, most researchers use Discriminant Function Analysis (DFA). In previous studies, there are a few studies about determination of gender from patella and one of studies is research of [20], which results from their research that the average accuracy of classification techniques, DFA.

In this paper use sample data of 136 pelvic bones and 133 patellae which have been collected and grouped by ages and measured use metric method.

The framework of this paper is shown in Figure 1.

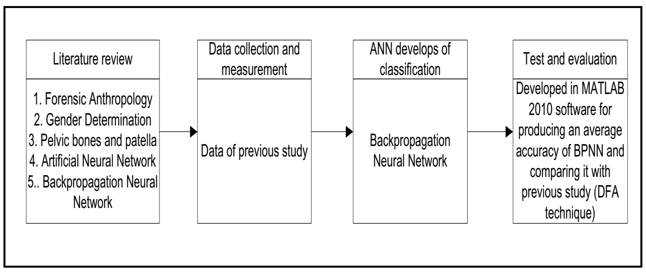

Figure 1. Framework of this paper.

Explanations of the Figure 1 are:

1. **Literature review**
   Literature review was done to learn about forensic anthropology, gender determination of skeletal remains, learn a part of skeletal remains such as the pelvic bones and patella, techniques used for classification such as ANN, and learn one of method of ANN, namely Back Propagation Neural Network.

2. **Data collection and measurement**
   The data are generated based on statistics values of previous study [23] and [20]. Data is used in gender determination are sample data of pelvic bones and patella. There are136 sample data for pelvic bones (55 females pelvic and 81 males pelvic) in age groups from 21 to >67 years old while for patella bones, there are 113 patellae (57 males, 56 females) in three groups. The variables for measurement of pelvic bones consist of 9 variables, namely total pelvic height, total iliac width, minimum pubic width, spino sciatic length, acetabular diameter, transverse acetabular diameter, pubis length, ilium length, and ischium length. The patella consists of three variables in measurement, namely height, width, and thickness.

3. **Artificial Neural Network (ANN) develops of classification: Back Propagation Neural Network**
   Artificial neural network (ANN) models are inspired by the models of the brain that are built on networks of processing units called neurons that are arranged in layers and are connected to one another by restricted links and links between neurons have associated weights [26]. ANN is well known by its ability for generalization, its massive parallel processing power and its high nonlinearity [2], making it perfect for gender determination. The three fundamental classes of ANN architectures, namely single layer feedforward, multilayer feedforward, and recurrent networks. Back Propagation Neural Network (BPNN) is a systematic method of training multilayer artificial neural networks technique to classify or predict [27].

4. **Test and evaluation**
   Test and evaluation is developed MATLAB 2012a software. The result is obtained from BPNN will be compared with previous technique, namely DFA.

The neural network methodology is well known by its ability for generalization, its massive parallel processing power and its high nonlinearity, making it perfect for gender estimation [2]. Back-propagation (BP) is a systematic method of training multilayer artificial neural networks. BP consists of (1) an input layer with nodes representing input variables to the problem, (2) an output layer with nodes representing the dependent variables, and (3) one or more hidden layers containing nodes to help capture the nonlinearity in the data [27]. The neurons between layers can be fully or partially interconnected between layers with weight (w).

III. RESULT

As the patella is very resistant to postmortem changes, the present study aims to estimate the gender on the basis of metric methods of patella bones. There are three age groups of that cases, namely group A (young), group B (middle aged), and group C (old age). Group A had an age range of 19 to 39 years, group B had age range of 40 to 64 years, and group C had an age range over 65 years. The while, pelvic bones consists of a pair of hipbones, pubic, and behind by the sacrum. The pelvic girdle is another element of the skeleton that exhibits sexual dimorphism [28]. For the sample data of pelvic bones, we use 136 data (55 females and 81 males).

The gender determination is obtained using back propagation neural network and developed in MATLAB 2012a. In determination of average accuracy of male and female can be visualized as a confusion matrix, where each column represents the predicted instances of a character, while each row represents the actual instances of an output. A confusion matrix is a visualization tool typically used in supervised learning. The data are generated based on statistics values of previous study [20] and [23] which provide information about mean, standard deviation (SD), minimum, and maximum.

The gender determination process in MATLAB2012a, using 50000 epochs, activation function is used the tan-sigmoid or tansig, and learning rate is 0.1. The BPNN architecture for patella consists of 3 neurons for input layer which adjusted on parameters, 4 neurons for hidden layer, and 2 neurons for output layer in achieving the target is desired, namely female and male. The comparison between training and testing in processing are 70% and 30%, respectively. The BPNN architecture of patella can be seen in Figure 2.

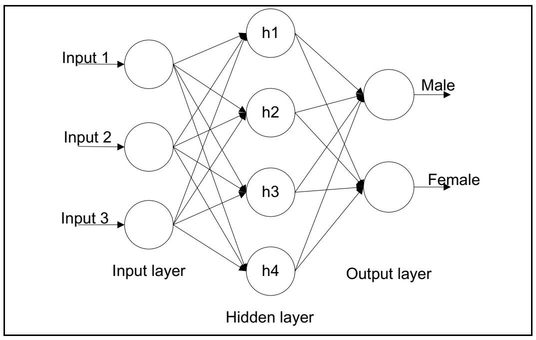

Figure 2. The BPNN architecture of patella's cases

For the parameters of patella are shown in Table 1 and Table 2.

TABLE I. THE DESCRIPTIVE STATISTICAL ANALYSIS OF PATELLA (CM) [20]

Patella Parameters	Statistical Analysis	Age group (years)					
		19-39		40-64		≥ 65	
		Male	Female	Male	Female	Male	Female
Height	Mean	4.504	3.82	4.42	3.94	4.49	3.78
	Min.	4.1	3.5	3.88	3.5	3.98	3.42
	Max.	4.89	4.16	5.13	4.53	5	4.28
Width	Mean	4.61	3.96	4.59	4.1	4.47	3.99
	Min.	4.3	3.55	4.1	3.82	4.1	3.68
	Max.	5.04	4.25	5.1	4.5	4.9	4.42
Thickness	Mean	2.2.7	2.1	2.23	2.04	2.11	1.97
	Min.	2.08	1.7	1.76	1.6	1.82	1.78
	Max.	2.6	2.36	2.6	2.38	2.24	2.1

From descriptive statistical analysis of patella measurements of Table 1, data are generated as input values for BPNN. Data that has been generated, then it is calculated by MATLAB. The result of average accuracy with 10 running time that is obtained by BPNN is shown in Table 2.

TABLE II. THE AVERAGE ACCURACY OF PATELLA USING BPNN

GROUP	NO.	TRAINING (%)		TESTING (%)	
		M	F	M	F
A	1	100	100	100	100
	2	100	100	100	100
	3	100	100	100	100
	4	64	100	75	33
	5	100	100	100	100
	6	100	100	100	100
	7	100	100	77.8	100
	8	100	100	100	75
	9	91	100	87.5	100
	10	55.6	62.5	100	100
	Average	**91.06**	**96.25**	**94.03**	**90.8**
B	1	100	100	80	100
	2	92.3	88.9	80	100
	3	100	100	75	83.3
	4	100	100	100	85.7
	5	100	100	75	83.3
	6	100	90	100	75
	7	100	90	100	75
	8	100	90	100	85.7
	9	100	100	100	100
	10	100	100	100	75
	Average	**99.23**	**95.89**	**91**	**86.3**
C	1	93.3	100	100	100
	2	93.3	100	100	100
	3	93.3	100	100	100
	4	100	94.7	100	100
	5	100	94.7	100	66.7
	6	93.3	100	100	85.7
	7	100	90	100	75
	8	100	94.7	88.9	100
	9	92.9	94.4	100	100
	10	100	94.7	100	100
	Average	**96.61**	**96.32**	**98.89**	**92.7**

From the Table 2, M is male and F is female. For all average accuracy (males and female) is obtained by BPNN is 94.09%. If compared with previous study that using DFA, is obtained 92.9% [20]. This confirms that the use of neural network will improve the accuracy in determination of gender for forensic anthropology. The work by [20], result of DFA can be improved by applying artificial intelligence techniques.

While for pelvic bones, the architecture of BPNN in this case is shown in Figure 3.

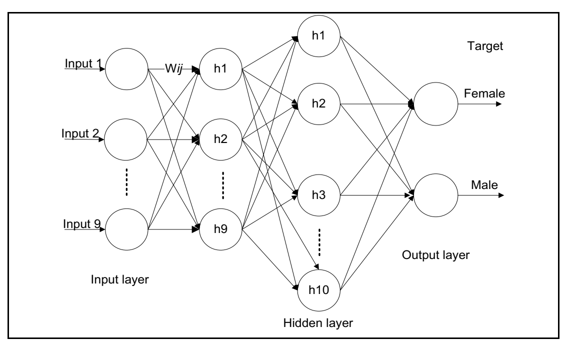

Figure 3. The BPNN architecture of pelvic bones

From the Figure 3 can be seen that architecture of BPNN that is used of this case consist of nine inputs (total pelvic height, total iliac width, minimum pubic width, spino sciatic length, acetabular diameter, transverse acetabular diameter, pubis length, ilium length, and ischium length), three architectures for hidden layer, namely 9, 10, respectively with achievement of target are 1 for female and -1 for male, thus there are two output neurons (male and female). This study using 50000 epochs, activation transfer function using tan-sigmoid, and learning rate is 0.1. For the comparison between training and testing in processing are 70% and 30%, respectively

In Table 3 show the variables of data is used for gender determination on previous study [23], which provide information about mean, standard deviation (SD), minimum, and maximum from number of data on 55 females and 81 males.

TABLE III. DATA MEASUREMENT OF PREVIOUS WORK [23]

Measurements		n= 55	Females			n=81	Males		
Right	**Variables**	***mean***	**SD**	**Min**	**Max**	***mean***	**SD**	**Min**	**Max**
1	Total Pelvic height	190.3	10.1	165	209	206.1	9.8	185	239
2	Total iliac width	146.8	9.5	125	166	151.4	8.5	129	179
3	Minimum pubic width	55.6	4	47	65	61.4	4.5	52	74
4	Spino sciatic length	66.1	4.8	57	78	71.8	5.3	58	85
5	Acetabular diameter	48.8	3.1	42	59	54.6	2.9	48	61
6	Transverse acetabular diameter	46.4	2.7	40	55	52.4	2.9	45	59
7	Pubis length	79.2	5.6	69	94	75.2	5.2	60	91
8	Ilium length	121.7	6.9	107	137	130.2	6.6	115	148
9	Ischium length	81	5.1	69	92	89.2	5.7	71	105
Left	**Variables**	***mean***	**SD**	**Min**	**Max**	***mean***	**SD**	**Min**	**Max**
1	Total Pelvic height	190.4	10.2	165	213	206.9	9.7	187	242
2	Total iliac width	147.3	8.9	125	166	151.6	8.7	128	180
3	Minimum pubic width	55.8	4	47	66	61.9	4.6	52	76
4	Spino sciatic length	66.3	4	56	76	72.5	5.6	59	88
5	Acetabular diameter	48.8	2.8	43	58	54.5	2.8	48	61
6	Transverse acetabular diameter	46.3	2.6	41	56	52.2	3	43	59
7	Pubis length	79.8	5.4	67	93	76.5	5.5	63	95
8	Ilium length	122.1	6.8	106	137	130.2	6.6	115	145
9	Ischium length	80.7	4.5	69	90	88.9	5.1	79	106

For next sample of data measurement for left and right pelvic bones then is parsed into some data that according to the information in Table 3. After the data is parsed, then next step are analyzed and calculated by BPNN using MATLAB 2012a. The result of average accuracy of pelvic bones in 10 running times is shown in Table 4.

TABLE IV. THE COMPARISON OF AVERAGE ACCURACY OF BPNN AND DFA

Right	**95 data**	**41 data**	**Left**	**95 data**	**41 data**
No.	**Training (%)**	**Testing-validation (%)**	No.	**Training (%)**	**Testing-validation (%)**
1	97.9	95.1	1	100	97.6
2	97.9	95.1	2	97.6	92.7
3	100	100	3	97.9	97.6
4	100	100	4	100	97.6
5	98.9	97.6	5	97.9	100
6	98.9	100	6	98.9	36.6
7	96.8	100	7	97.9	90.2
8	98.9	100	8	97.9	97.6
9	96.8	97.6	9	97.9	100
10	98.9	97.6	10	98.9	56.1
Average	**98.5**	**98.3**	**Average**	**98.49**	**86.6**

From Table 4, we can be seen that the average accuracy of classification rate obtained using BPNN on right pelvic bones are 98.5% for training and 98.3 for testing. While on left pelvic bones, average accuracy that is obtained are 98.49% for training and 86.6% for testing. If compared with DFA gave 98.5% accuracy [20].

IV. CONCLUSION

From the result of Table 2 and Table 4, it can be concluded that for patella, BPNN technique produces total of average accuracy of classification rate of 96.1% in the sex determination of the patella, compared to 92.9% found in the literature. For pelvic bones, BPNN technique produces total of average accuracy up to 99.05% compared the results of the DFA technique which only reached 98.5%.

This concluded that BPNN produces more accurate result in gender determination compared to DFA. A part of skeleton that is used as an object of gender determination can affect to the accuracy improvement, such as pelvic bone has higher accuracy rate than other parts of the skeleton. Thus, the combination of the pelvic bone with BPNN technique can achieve accuracy is close to 100%. The results of this study confirm that BPNN gives high accuracy for both bones while it gives better accuracy for pelvic bones.

V. FUTURE WORK

From the application of technique in gender determination from patella and pelvic bones can be improved with applying the new hybrid techniques, specific in improve the accuracy. Thus, can obtain the accuracy is the best of the other techniques. And in future work, in this research can also be improved with calculate timing of the process using new hybrid techniques, such as PCA-BPNN.

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