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Improving Gender Classification With Feature Selection In Forensic Anthropology

Nurul Liyana Hairuddin, Lizawati Mi Yusuf*, Mohd Shahizan Othman, Hairudin Abdul Majid

Faculty of Computing, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia

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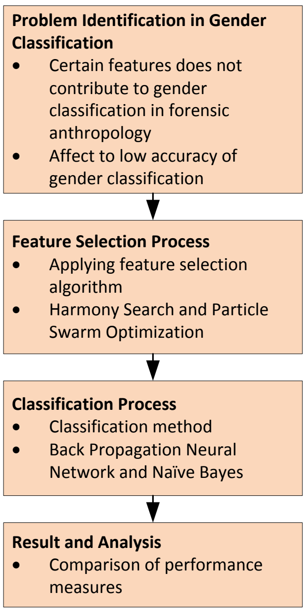
*Corresponding author
lizawati@utm.my

Graphical abstract



Abstract

Gender classification has been one of the most vital tasks in a real world problem especially when it comes to death investigations. Developing a biological profile of an individual is a crucial step in forensic anthropology process as for the identification of gender. Forensic anthropologists employ the principle of skeleton remains to produce a biological profile. Different parts of skeleton contains different features that will contribute to gender classification. However, not all the features could contribute to gender classification and affect to a low accuracy of gender classification. Therefore, feature selection method is applied to identify the most significant features for gender classification. This paper presents the implementation of feature selection approaches which are Particle Swarm Optimization (PSO) and Harmony Search (HS) algorithm using three different dataset from Goldman Osteometric Dataset, Osteological Collection and George Murray Black Collection. All three dataset contains 4081 samples of metrics measurement and have gone through the process of classification by using Back Propagation Neural Network (BPNN) and Naïve Bayes classifier. The main scope of this paper is to identify the effect of feature selection towards gender classification. The result shows that the accuracy of gender classification for every dataset increased when feature selection is applied to the dataset. Among all the skeleton parts in this experiment, clavicle part achieved the highest increment of accuracy rate which is from 89.76% to 96.06% for PSO algorithm and 96.32% for HS.

Keywords: Forensic Anthropology, Gender classification, Feature Selection, Particle Swarm Optimization (PSO), Harmony Search (HS)

1.0 INTRODUCTION

Forensic anthropologist plays an important role in a field of forensic science [1-2]. The anthropologist need to understand variations of various forms of skeletal properties and apply their understanding to their task, so that, a reasonable conclusion can be concluded. In forensic anthropology process, one of the important tasks is developing a biological profile of the decease and classifying gender is one of them. Here, gender classification is the main subject in forensic anthropology for a positive identification and skeletal remains is used as a medium to classify gender in order to develop a biological profile.

Different parts of skeleton contain different features that will contribute to gender classification. However not all features in a dataset could contribute in gender classification. Therefore, feature selection method has been used in this research to determine the most significant features for gender classification. These selected features will lead into an accurate determination of gender of each person and assist mainly in forensic anthropology area. Forensic anthropologists employ the principles of skeletal growth, development and variation of biological profile of an individual which are gender, age, stature and ancestry [1]. Developing a biological profile is one of the most crucial steps in forensic anthropology processes [2]. Gender classification is one of the most important tasks as in the process of producing positive identification, gender is the first main step before other step can be taken [1-3]. Identification of unknown remains is a complicated task and it will be more authentic when the skeleton found is complete for analysis. But it is very rare to have a complete human skeleton in forensic cases as skeletal remains are often incomplete, burned, or in damaged condition [2, 4].

There are some studies already exist on gender classification from skeleton parts such as pelvic bones [2, 5-7], sternum [8-9] mandible [10-11], femur [12-13] and many other parts of the human skeleton show gender difference. Metric information from femur, humerus, radius, tibia and pelvic can be used to develop a biological profile especially gender and age with high degree of accuracy [14]. Although some parts of skeleton can give a high degree of accuracy, there are certain situation where the accuracy of gender classification produced is not good. The problem that can be identified is when the dataset comes in bulk and presented many features but some features cannot contribute to gender classification. Thus, with these unimportant and insignificants features, it will lead to a bad accuracy of gender classification. In order to remove the unimportant features in a dataset, feature selection method can be used to select only the most significant features which can lead into a good classification accuracy.

Based on previous work on feature selection, there are many algorithms which have been used to increase the performance of classification in many areas such as in biomedical, engineering and computer science. Table 1 shows a summary of some previous works which applied feature selection in classification process.

Table 1 Previous Work on Feature Selection

Author	Data	Algorithm	Accuracy (%)
[15]	Gene Expression	KNN	77.16
		KNN + Improved Binary PSO	92.29
[16]	Vote	Naïve Bayes	90.10
		Naïve Bayes + ReliefF algorithm	91.70
[17]	Spam	ANN	91.76
		ANN + ACO	92.55
		ANN + PSO	97.38

As from Table 1, Chung *et al*. [15] used Improved Binary Particle Swarm Optimization (PSO) for feature selection on gene expression dataset together with K-Neural Network (KNN) as a classifier. The result shows classification accuracy increased from 77.16% to 92.29%. Other than that, according to Novakovic [16], when Naïve Bayes is used to the vote dataset, the accuracy of classification is 90.10% while when feature selection of ReliefF algorithm is applied, the accuracy increased to 91.70%. Same goes to the experiment made by Taha *et al*. [17], the accuracy of spam classification increased from 91.76% to 92.55% when Ant Colony Optimization (ACO) is applied and 97.38% when PSO is applied to the dataset.

All these results from previous works show that feature selection did help in increasing the accuracy of classification in certain area and this paper proposed to apply feature selection of PSO and HS to find out the effect of feature selection towards gender classification in forensic anthropology area by using skeleton dataset. The overall process of gender classification and data used in this experiment has been discussed in Section 2.

This paper aims at identifying the effect of feature selections using Particle Swarm Optimization (PSO) and Harmony Search (HS) algorithm to the accuracy or performance of gender classification when applied to different type of dataset contained different parts of skeleton. These two feature selection algorithms will be discussed in detail in Section 2.

This paper is arranged as follows: current section gives an overall overview of this research and describe on the literature review of this research. Section 2 discusses on the methodology of overall experiment. Section 3 focuses on experimental results, followed with Section 4 which is conclusion and future works based on the previous section.

2.0 METHODOLOGY

This section presents the methodology of gender classification process. The framework of this paper is shown in Figure 1.

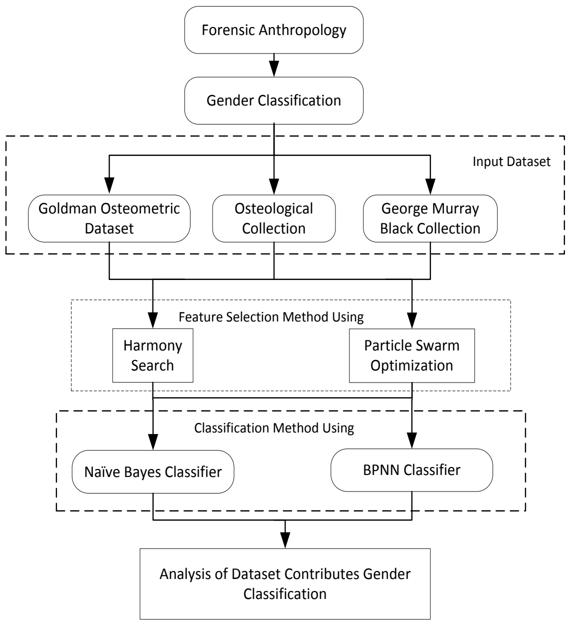


Figure 1 Framework of Paper

Initially, to investigate the effect of feature selection to the performance of gender classification, all the dataset are applied to the classification without any feature selection process. This step is needed to compare the performance of gender classification with full features dataset and selected features dataset.

Next, the experiment continued with the collection of three dataset as the input in feature selection process. Through the process of feature selection (HS and PSO), the most significant features or attributes are formed. All these attributes are then used to form new dataset which will be used to find out the performance of gender classification. The classifiers used in this experiment are Back

Propagation Neural Network (BPNN) and Naïve Bayes (NB).

2.1 Dataset

There are three types of dataset used which are Goldman Osteometric dataset [22], Osteological Collection [23] and George Murray Black Collection [24]. Generally, all three dataset contains metric measurement from different part of skeleton and all of them grouped into two gender classes which are male and female. Table 2 summarized the characteristics of all the dataset used in this research.

Table 2 Characteristics of Dataset

Dataset	Skeleton Parts	Number of Samples	Number of Features
Goldman Osteometric Dataset [22]	Femur	1241	14
	Humerus	1206	10
	Tibia	1211	8
Osteological Collection [23]	Sacrum	91	6
George Murray Black Collection [24]	Calcanium	96	7
	Clavicle	127	12
	Humerus	109	36

2.1.1 Goldman Dataset

The database used was taken from The Goldman Data Set consists of osteometric measurements taken from 1538 human skeletons origin or state in case of United States [22]. Generally individual aged above 20 years old are used in this study. Measurements were taken bilaterally from three long bones which are humerus, femur, and tibia and all these osteometric measurements are taken in millimeters. Femur consists of 14 features while humerus consists of 10 features and tibia consists of 8 features.

2.1.2 Osteological Collection

The 91 samples used are derived from Osteological Collection of the Anthropology Section, Department of Anatomy, School of Medicine, National Autonomous University of Mexico (UNAM) [23]. 42% females and 58% males ranging in age of 21 to 67 years old of human skeleton are examined. Six metrical parameters of sacrum bones were measured.

2.1.3 George Murray Black Collection

George Murray Black Collection consists of male and female adult of Australian Aboriginies from Murray River Valley, Swanport and South Australia [24]. The skeletons were collected in the course of controlled archeological excavation from University of Melbourne which was reburied in 1984. In this studied, three parts of skeleton are chosen which are calcanium, clavicle and humerus.

In the upcoming subsection, feature selection algorithm which focused on HS algorithm and PSO is briefly explained together with BPNN and Naïve Bayes classifier which are used in classification process.

2.2 Feature Selection

In machine learning tasks, dimensionality is an important characteristic and existing learning methods are facing challenges in high dimensional data [18]. Unimportant and insignificants data available in the dataset need to be removed as it affect the learning process and reduce the classification accuracy. So, feature selection is applied to select the most significant features to give a better model performance. In this paper, PSO and HS are proposed to do feature selection for gender classification in forensic anthropology.

2.2.1 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is one of the optimization techniques and kind of evolutionary computation technique. The technique is derived from research on swarm such as bird flocking and fish schooling [19]. In the PSO algorithm, instead of using evolutionary operators such as mutation and crossover to manipulate algorithms, for a d-variable optimization problem, a flock of particles are put into the d-dimensional search space with randomly chosen velocities and positions knowing their best values [19]. The velocity of each particle, adjusted accordingly to its own flying experience and the other particles flying experience [19]. The i th particle is represented as $x_i = (x_{i,1}, x_{i,2}, \dots\, x_{i,d})$ in the d-dimensional space. The best previous position of the i th particle is recorded as,

$$Pbest_i = (Pbest_{i,1} Pbest_{i,2} \dots\, Pbest_{i,d}) \quad (1)$$

The index of best particle among all of the particles in the group is $gbest_d$. The velocity for particle i th particle is recorded as,

$$v_i = (v_{i,1}, v_{i,2} \dots v_{i,d}) \quad (2)$$

The modified velocity and position of each particle can be calculated using the current velocity and distance from $Pbest_{i,d}$ to $gbest_{i,d}$ as shown in the following formulas:

$$V_{i,m}^{(t+1)} = W.V_{i,m}^{(t)} + c_1 * rand() * (Pbest_{i,m} - x_{i,m}^{(t)} + c_2) * rand() * (gbest_m - x_{i,m}^{(t)}) \quad (3)$$

$$X_{i,m}^{(t+1)} = X_{i,m}^{(t)} + V_{i,m}^{(t+1)} \quad (4)$$

$$i = 1,2, \dots, n$$
$$m = 1,2, \dots, d$$

Where:
$n = Number\ of\ particles\ in\ the\ group$
$d = Dimension$
$t = Pointer\ of\ iterations\ (generations)$
$V_{i,m}^{(1)} = Velocity\ of\ particle\ i\ at\ iteration\ t$
$W = Inertia\ weight\ factor$
$C_1 C_2 = Acceleration\ constant$

2.2.2 Harmony Search (HS)

HS is a natural music-based optimization algorithm which musician's goal is to search for a perfect state of harmony [20]. In music improvisation, in order to produce one harmony vector, every player will produce any pitch at the feasible range [20]. Once all the pitches produce a good solution, each variable's memory will store that experience, and it will add up the possibility to produce a good solution for the next time [20-21]. Parameters used in HS are size of harmony memory (HMS), harmony memory (HM), harmony memory considering rate ($HMCR$), and pitch adjusting rate (PAR).

Procedure of harmony search started with initialization of problem and algorithm parameters. Optimization problem is specified as $\min\{f(x)|x \in X\}$ subject to $g \geq 0$ and $h(x) = 0$ where $f(x)$ is the objective function, $g(x)$ is the inequality constraint function and $h(x)$ is the equality constraints function. HM matrix in HM is initialized randomly. A new harmony vector $x^t = (x_1^t, x_2^t, .. x_i^t)$ is generated based on three rules which are memory consideration, pitch adjustment and random selection:

$$x_i^t \begin{bmatrix} x_i^t \in \{x_i^1, x_i^2, .. x_i^{HMS}\} with\ probability\ HMCR \\ x_i \in X_i\ with\ probability\ (1 - HMCR) \end{bmatrix} \quad (5)$$

Pitch adjusting for x_i^t is given as:

$$x_i^t \leftarrow \begin{cases} Yes\ with\ probability\ PAR \\ No\ with\ probability\ (1 - PAR) \end{cases} \quad (6)$$

If pitch adjustment decision for x_i^t is yes, x_i^t is modified as:

$$x_i^t = x_i^t + rand() * bw \quad (7)$$

Where bw is arbitrary distance and $rand()$ is random number between 0 and 1. PAR and bw are adjusted as:

$$PAR(gn) = PAR_{min} + \frac{PAR_{max} - PAR_{min}}{NI} \times gn \quad (8)$$

Where gn= 1,2,..., NI, $PAR(gn)$ is the pitch adjusting rate for generation or improvisation of gn, NI is number of improvisation, PAR_{min} is the minimum pitch adjusting rate and PAR_{max} is the maximum pitch adjusting rate. If the new memory is better than the previous memory in HM, the new harmony memory is included in the HM and the existing worst harmony is excluded from HM.

2.3 Classification

Back Propagation Neural Network and Naïve Bayes classifier have been employed in this experiment to classify gender into female and male.

2.3.1 Back Propagation Neural Network (BPNN)

In NN, there are a set of nodes called neurons and connection between them and there is weight associated with the connections. Most of the neural network architecture contains three layers in its structure [25] which are input layer, hidden layer and output layer. Every node from input layer is attached to a node from hidden layer and every node in hidden layer is attached to one output layer [26]. Figure 2 shows the BPNN architecture for this experiment.

In this experiment, the number of nodes in input layer is the number of features in the dataset. So, the number of neuron in the input layer will be varied according to the number of features for every dataset. According to Saurabh [27], by using rule-of-thumb, the number of hidden layer neurons are 2/3 number of the size of the input layer. The number of hidden layer in this experiment is fixed to one layer after trial and error process is done. From the trial and error process, the result produced is better with one number of hidden layer compared to two and three number of hidden layers. In the output layer, two neurons are used as the output of gender which is male or female.

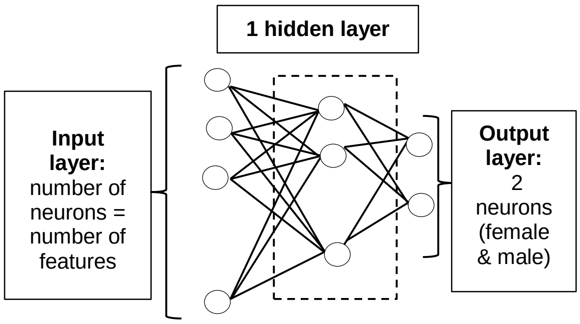


Figure 2 Architecture of BPNN

2.3.2 Naïve Bayes

Naïve Bayes (NB) algorithm is a simple classifier where a set of probabilities are calculated by counting the frequency and combinations of values in a given dataset [28]. It is a practical classifier which has been applied in many applications. Bayes theorem is used and given the value of the class variable, all attributes are assumed to be independent. In a real world application, Naïve Bayes tends to perform well and learn quickly in various supervised classification problems. Thus, it has been used in many different fields for classification and decision making.

Since Naïve Bayes is relatively robust, easy to implement and accurate algorithm, it is used to compare the accuracy of gender classification with BPNN. This phase is to find out which type of classifier would produce a better performance in gender classification.

Section 3 has discussed the experimental result obtained from this experiment which focused on the selected features and accuracy of gender classification.

3.0 RESULTS AND DISCUSSION

Accuracy is used to measure performance in gender classification. The formula used are shown below:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

where:

TP = True Positive
TN = True Negative
FP= False Positive
FN = False Negative

The performances of gender classification have been evaluated on the original dataset and the dataset that have gone through the process of feature section. The purpose of this step is to find out the effect of feature selection towards the performance of gender classification.

Table 3 shows the number of original features and the number of selected features after the process of feature selection is done. Figure 3, 4 and 5 shows the graph of features reduction for every dataset respectively.

Table 3 Performance of Feature Selection

Dataset	Skeleton Parts	Algorithm	Number of Features
Goldman Osteometric Dataset	Femur	NONE	14
		PSO	8
		HS	8
	Humerus	NONE	10
		PSO	7
		HS	7
	Tibia	NONE	8
		PSO	7
		HS	7
Osteological Collection	Sacrum	NONE	6
		PSO	4
		HS	5
George Murray Black Collection	Calcanium	NONE	7
		PSO	3
		HS	3
	Clavicle	NONE	12
		PSO	7
		HS	7
	Humerus	NONE	36
		PSO	11
		HS	14

Table 3 shows the performance of feature selection for every dataset. NONE is considered as the original dataset with complete features. Every dataset shows a reduction of features after feature selection is applied to the dataset. Certain dataset only reduced one features from original dataset and certain dataset reduced more than half of original dataset. This result is because of the algorithm and type of dataset used.

Based on Figure 3, it can be seen that among femur, humerus and tibia, femur reduced the highest number of features which are 42.86% for both PSO and HS. Figure 4 shows PSO has reduced around 33.33% of features and HS reduced 16.67% of features. Figure 5 shows the highest percentage of reduction where calcanium reduced 57.14% for both PSO and HS while clavicle reduced 41.67% for both PSO and HS. The highest reduction of features in George Murray Black Collection is humerus where it reduced to 69.44% for PSO and 61.11% for HS.

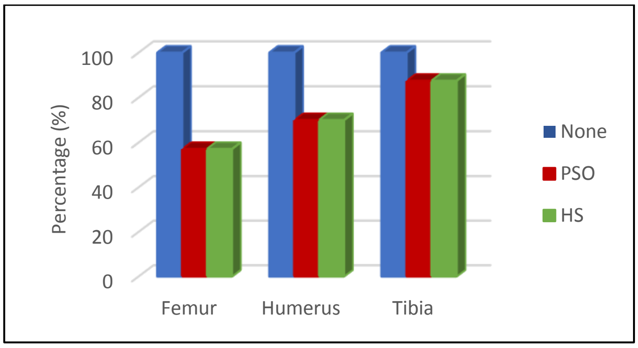


Figure 3 Features Selection for Goldman Osteometric Dataset

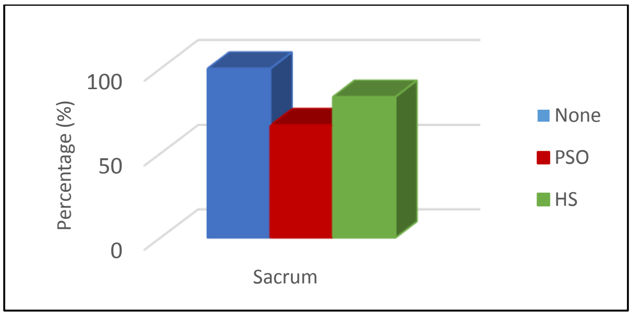


Figure 4 Features Selection for Osteological Dataset

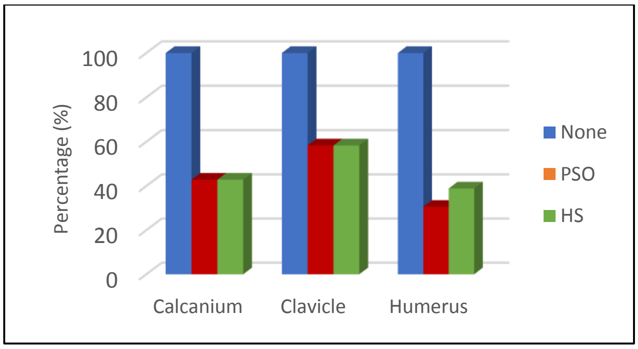


Figure 5 Features Selection for George Murray Black Collection

Based on three figures shown above, it can be concluded that feature selection helps in reducing the number of features and it reduced the dimensionality of dataset. Once the dimensionality of the dataset has reduced, it can help to improve the performance of machine learning.

Table 4 presents the results for three dataset with two different classification algorithms which are BPNN and Naïve Bayes. Feature selection algorithm did affect the performance of gender classification. It can be seen that, the accuracy for both type of classifiers increase after feature selection is done for every parts of skeleton and dataset.

Table 4 Performance of Feature Selection
(a) Goldman Osteometric Dataset

Skeleton Part	Algorithm	BPNN Accuracy (%)	Naïve Bayes Accuracy (%)
Femur	NONE	88.72	85.74
	PSO	90.65	87.35
	HS	90.65	87.35
Humerus	NONE	87.64	85.16
	PSO	88.64	86.24
	HS	88.64	86.24
Tibia	NONE	87.52	85.87
	PSO	87.77	86.03
	HS	87.77	86.03

(b)George Murray Black Collection

Skeleton Part	Algorithm	BPNN Accuracy (%)	Naïve Bayes Accuracy (%)
Calcanium	NONE	95.83	93.75
	PSO	97.92	94.79
	HS	97.92	94.79
Clavicle	NONE	89.76	86.61
	PSO	96.06	88.19
	HS	96.32	89.11
Humerus	NONE	97.25	92.66
	PSO	97.82	93.58
	HS	98.17	95.21

(c)Osteological Collection

Skeleton Part	Algorithm	BPNN Accuracy (%)	Naïve Bayes Accuracy (%)
Sacrum	NONE	91.21	84.62
	PSO	92.38	86.81
	HS	95.60	87.91

For Goldman dataset, gender classification for femur part increases from 88.72% (BPNN) and 85.74% (NB) to 90.65% (BPNN) and 87.35% (NB). The increment of accuracy is because of the PSO and HS algorithm where it only selects the most significant features which end up helped to increase the performance of both classifiers. The accuracy for clavicle part in George Murray Black Collection has the highest increment compared to other part of skeleton. The accuracy of BPNN classifier increased from 89.76% to 96.06% when PSO is applied and 89.76% to 96.32% when HS is applied to the dataset. Gender classification for Osteological Collection using BPNN has increased the classification accuracy from 91.21% to 92.38% when PSO is applied and HS algorithm increased the accuracy from 91.21% to 95.60%. From Table 4, it can be concluded that the performance of gender classification is better when only the most significant features involved in the process of classification for every dataset.

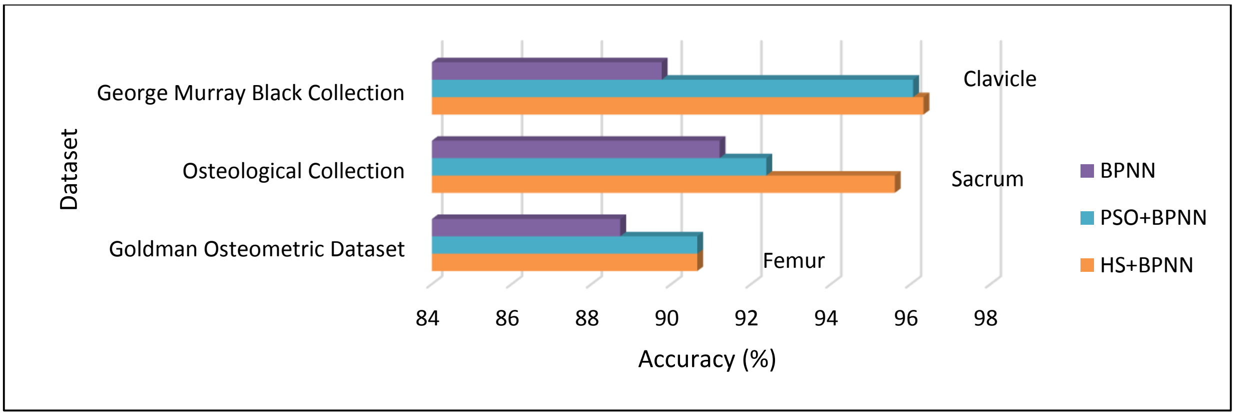


Figure 6 Performance of Gender Classification Based on Three Different Dataset

Based on Figure 6, since BPNN gave a higher accuracy compared to Naïve Bayes classifier for overall dataset, BPNN performance is visualized respectively to show the difference of accuracy based on different algorithm. In this part, comparison on feature selection technique and classification are explored. For Goldman Osteometric Dataset, Femur presented the highest increment of accuracy compared to other parts which is 1.93%. The accuracy before feature selection is applied is 88.72% while after feature selection is applied, accuracy increase to 90.65% for both algorithm. Next, for Osteological Collection, the performance of BPNN classifier for Sacrum part increase by 1.17% for PSO and 4.39% for HS algorithm. Last but not least, for George Murray Black collection, Clavicle gave the best performance for gender classification. The original dataset without feature selection is 89.76% and increased to 96.06% for PSO and 96.32% for HS algorithm. Based on the performance of gender classification, it can be seen that feature selection gave a good impact on the accuracy of gender classification. Although the increment of accuracy is only in a small amount, it is important for gender classification especially in forensic anthropology. From all the comparison made, it can be conclude that feature selection has increased the accuracy of gender classification in forensic anthropology although different dataset and different classifier is used.

4.0 CONCLUSION AND FUTURE WORKS

This paper has presented the effect of feature selection techniques toward the performance of gender classification on different dataset. When feature selection PSO and HS algorithm are applied to the dataset, the performance of gender classification has increased as feature selection only select the most significant features which end up help to increase the accuracy of gender classification. So, it can be concluded that feature selection is important in order to increase the performance in gender classification especially in forensic anthropology area.

For future works, we can search how the performance changes when other different techniques of features selection are used. There might have increment of accuracy when using other feature selection techniques in gender classification area.

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