HYBRID PARTICLE SWARM OPTIMIZATION-ARTIFICIAL NEURAL NETWORK GENDER CLASSIFIER FOR TRABECULAR BONE MORPHOLOGY

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"Dedicated to the One,
None other than the Grand Weaver,
Who encourages me to move ahead, with bold and confidence,
And I'm nothing without Your love

Delivered to the blissful weirdos,
None other than the Ayahandas Sahadun Family Yusof Family, Who showers me the shimmering love and warmth in my needy time
Mak, Ayah, Fara, Udin, Effa, Cik Ela, Fatin, Mak Sam, Pak Usof

Dedicated to the lovey dovey,
You know you keep on bringing the best out of me.
Hubby Sulaiman, Sweety Haninda and Prince Imam

Dedicated to the soul mates,
Thanks for the prayers and the wonderful laughters, In time of distress, you will sing
"I will be by your side, when all hope has died"
Faizi, Fatihhi, IIs, Rin, Deni, Asha, Shaf, Ima, Sari, Nurul, Ida, Azie, Ipah, Fahim and Awin

Delivered to the superisor,
Gravity pulls and literally, I fall from the cloud,
But you prove that I can actually make it, thanks for the guidance all this way
Prof. Dr. Habibollah Haron, Prof. Ir. Dr Mohammed Rafiq Bin Dato' Abdul Kadir, Prof. Dr. Mohammad Ishak Bin Desa, Dr. Razana

Without whom none of my success would be possible"

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ABSTRACT

A pre-condition for identifying infectious disease and understanding the ecology of a species is by gender classification of the trabecular bone of an animal. Therefore, accurate gender classification on skeletal remains of nonhuman is essential for the research of nonhuman population. The traditional method of classifying gender by comparative skeletal anatomy by atlas has raised issues with regard to accurate classification and challenge in management of data to identify optimum features and interpretation optimum features in a simple way. In this research all these three issues were addressed by using a process model developed specifically for gender classification. This research used two computational intelligence models, namely Support Vector Machine (SVM) and Artificial Neural Network (ANN). Results of simulations of both models were compared and ANN performed better than SVM. To improve the accuracy of ANN classifier, Particle Swarm Optimization (PSO) feature selection was used as the basis for choosing the best features to be used by the selected ANN classification model. The model is called PSO-ANN and has been developed by MATLAB and WEKA tools platform. Samples were taken from Ryan and Shaw collection. This sample contains proximal femur and proximal humerus. Comparisons of the performance measurement namely the percentage of the classification accuracy, sensitivity and specificity of the model were performed. The results showed that the ability of PSO-ANN in classifying gender outperforming the SVM and ANN model by acquiring 100% accuracy, sensitivity and specificity. Apart from that, the optimum features of the gender classification are extracted and translated into more understandable explanations using Decision Tree and compare the differences and similarities with the original features. These findings have shown that the proposed PSO-ANN is capable of successfully solving three issues in the existing method in gender classification.

ABSTRAK

Pra-syarat untuk mengenalpasti penyakit berjangkit dan pemahaman ekologi sesuatu spesis ialah dengan pengelasan jantina melalui tulang trabekular. Oleh itu, ketepatan pengelasan jantina pada rangka mayat haiwan adalah penting untuk kajian populasi haiwan. Kaedah tradisional dalam pengelasan jantina dengan membandingkan rangka anatomi dengan atlas telah menimbulkan isu-isu yang berkaitan dengan pengelasan tepat, dan cabaran dalam pengurusan data untuk mengenalpasti ciri-ciri optimum dan mentafsir ciri-ciri optimum dengan cara mudah. Dalam kajian ini, ketiga-tiga isu ini ditangani dengan menggunakan satu proses model yang dibangunkan secara khusus untuk pengelasan jantina. Kajian ini menggunakan dua model pengiraan pintar iaitu Mesin Sokongan Vektor (SVM) dan Rangkaian Neural Buatan (ANN). Hasil dari simulasi dua model ini dibandingkan dan menunjukkan bahawa prestasi ANN lebih baik dari SVM. Bagi meningkatkan ketepatan klasifikasi ANN, Pengoptima Kumpulan Zarah (PSO) digunakan sebagai asas dalam memilih ciri terbaik yang akan digunakan oleh model ANN terpilih. Model itu dikenali sebagai PSO-ANN dan telah dibangunkan menggunakan platform MATLAB dan Weka. Kajian menggunakan sampel Ryan dan Shaw (2013) sebagai set data. Sampel ini mengandungi ciri-ciri tulang rawan proximal femur dan proximal humerus. Perbandingan pengukuran prestasi iaitu peratusan ketepatan pengelasan, sensitiviti dan spesifisiti model dilaksanakan. Hasil kajian menunjukkan keupayaan PSO-ANN pengelasan jantina mengatasi SVM dan ANN dengan memperolehi 100% untuk ketepatan, sensitiviti dan spesifisiti. Selain itu, ciri-ciri optimum pengelasan jantina ini diekstrakkan dan diterjemahkan kepada penjelasan yang lebih mudah difahami menggunakan Pepohon Keputusan serta membandingkan perbezaan dan persamaan dengan ciri-ciri asal. Penemuan ini menunjukkan bahawa PSO-ANN model yang dicadangkan mampu dengan jayanya menyelesaikan tiga isu yang wujud dalam kaedah pengelasan jantina sedia ada.

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LIST OF ABBREVIATIONS

ACO	Ant colony optimization
AIS	Artificial Intelligent System
ANFIS	Adaptive-Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
BPA	Back Propagation Algorithm
CI	Computational Intelligence
DFA	Discriminant Function Analysis
DTE	Decision Tree
FL	Fuzzy Logic
FN	False Negative
FP	False Positive
GA	Genetic algorithm
GC	Gender classification
PSO-ANN	Particle Swarm Optimization-Artificial Neural Network
R^2	Co-Efficient Determination
RBF	Radial Basis Function
RSD	Ryan and Shaw dataset
SRM	Structural Risk Minimization
SVM	Support Vector Machine
TBM	Trabecular Bone Morphology
WEKA	Waikato Environment for Knowledge Analysis

LIST OF SYMBOLS

C	Cost
C_1	Cognitive Learning Factor
C_2	Social Learning Factor
n	Particle
$\boldsymbol{w}$	Weight
γ	gamma

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CHAPTER 1

INTRODUCTION

1.1 Overview

Forensic anthropology is a discipline that is concerned with postmortem identification of nonhuman skeletal remains. The objective of forensic anthropology is to contribute to the medico-legal process in building identification of the biological profile from nonhuman remains, usually in infectious disease cases (Coulibaly and Yameogo, 2000) and ecological knowledge (Gavan and Hutchinson, 1973). The biological details such as gender, ethnicity, race, age and stature are often the first data to helps to investigation on specific population. The successful forensic anthropology performance can be achieved when positive identification of skeletal remains which are the closest match to atlas. The first step for positive identification when burned, decomposed, extreme fragmentation, unrecognizable or otherwise mutilated body recovered is gender classification. Gender classification help to solve remains problematic, especially with regard to the evidence of crime while examination of skeletal remains in post-mortem. Gender builds based on biological sex. Knowledge of the gender of an unknown set of remains is essential to make a more accurate estimation of age (Koçak et al., 2003). Hence, the gender determination is necessary to identify age, ancestry, and stature estimations (Blanchard, 2010).

There are three methods used in forensic anthropology in classification; the gender traditional method (Adams *et al.* 2009), statistical method (Van *et al.*, 2000) and computational intelligence method (Mahfouz *et al.*, 2007). The traditional classification of gender was done by comparative skeletal anatomy by atlas. The atlas contains the bone morphology measurement from previous collection. This method faces a complex comparison of bone and selection of closest match to the atlas. The most parts of nonhuman bones have been research for gender classification such as foot (Archie *et al.*, 2006;Rozenblut and Ogielska, 2005), teeth (Stander, 1997) and long bone (Yeni *et al.*, 2008). In gender classification, the main issues that need to be addressed in the traditional gender classification process (GC) are classed for ensuring high efficiency of post-mortem results. The limitations of traditional methods are for certain population that is elephant foot in Kenya (Archie *et al.*, 2006), leopards teeth in United Kingdom (Stander, 1997) and bovine long bone in United States of America. The specific atlas for certain population is constrained to use in gender classification due to different development and growth of bone for different species.

Beside comparative skeletal anatomy in traditional method, computational methods are often used in data analysis to solve these traditional classification problems. In classification, modeling plays a very important role when trying to understand the various issues. Modeling classifications can be categorized into two: statistical classifier and computational intelligence classifier. One of popular linear statistical classifier is Discriminant Function Analysis (DFA). The application of DFA is most widespread of other techniques because very easy to use and simple technique (Du Jardin et al., 2009). While Artificial Neural Network (ANN), Genetic Algorithm (GA) and Support Vector Machine (SVM) are artificial intelligence classifier that are the most popular and widely used to solve different kinds of complex classification problems.

Brief explanations about SVM is one of Computational Intelligence (CI) methods that has ability to high classification accurate rate (Mukkamala and Sung, 2003). The success of SVM in classification methods is proven from several countries such as China (Zheng *et al.*, 2004), Mexico (Mukkamala and Sung, 2003), Taiwan (Lin *et al.*, 2008; Hsu *et al.*, 2003) and Spain (Huang and Wang, 2006). ANN is an intelligent model comparable to SVM that is also widely used. ANN is a mathematical model or computational model that tries to simulate the structure of biological neural networks, which are involve interconnected of artificial neurons group. In addition, ANN is an adaptive system consisting of sturucture based on information during the learning process in the network. Unlike the SVM, ANN uses Empirical Risk Minimization (ERM) to minimize the errors in the training data. Since 1989, ANN methods have been successfully applied in many classifications, especially in pattern recognition (Carpenter, 1989).

In literature search engine in web browser of the Scopus digital library, there is no research that has made using SVM and ANN in the gender classification of nonhuman bone domain as shown in Figure 1.1.

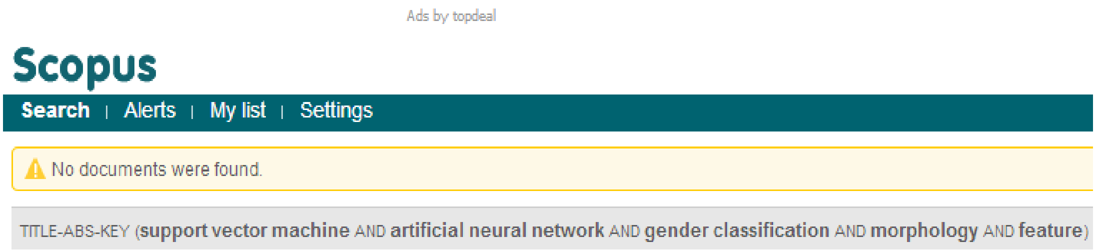

Figure 1.1: Result from search engine in the web browser of the Scopus Digital Library

The capability of these two methods (i.e. SVM and ANN) in classification of gender of nonhuman bone have not yet been evaluated. Therefore, this research is to identify the advantages of these two methods (i.e. SVM and ANN) in classification of gender that lead to the accurate classification in the post-mortem process.

As mentioned by Lim and Haron (2013), the different methods work best for different databases. Both SVM and ANN method have limitations in eliminating irrelevant data and may decrease the classification rate. Hsu *et al.* (2003) suggested that other method such as feature selection may be needed to identify optimum features in improving the classification rate. Liu *et al.* (2011) obtain low classification accuracy rate (75.9%) when model the classification with all dataset features. However, the accurate classification rate was improved by using the proposed Particle Swarm Optimization (PSO) as a feature selection method with achieved 80.2%. According to Jantan (2009), SVM and ANN not work in describing the data to predict the value of a target variable based on several input variables. Apart from that, the optimization features of the gender classification are extracted and translated into more understandable explanations using Decision Tree and compare the differences and similarities with the original features. Data features interpretation is important to understand the data features in alternative ways, such as symbol method because sometimes the data are complex which are depends on several aspects such as human expertice, experience, knowledge, preference and judgment. The decision tree is one of popular symbol method representations of a decision process that enable intuitive understanding of the data features and has the ability to extract IF THEN rule's pattern or other name is boolean logic rules.

Therefore, the aim of this research is to apply computational intelligence method based on establishing algorithm of forensic anthropology as a reliable method that is comparable to traditional methods. It can assist the authorities to gender classification in nonhuman and medical forensic cases involved the corpse.

1.2 Problem Background

The problems in traditional forensic anthropology are the specific atlas used as a reference for certain population to gender classification. The gender is developed based on previous collection nonhuman in Kenya (Archie *et al.*, 2006), United Kingdom (Stander, 1997) and United States of America (Yeni *et al.*, 2008) to solve medical forensic legal enforcement. Forensic Anthropology practitioner normally used the traditional method (comparative skeletal anatomy) for nonhuman identification which are depends on comparative skeletal anatomy by atlas used as a reference material. Positive identification achieved when the part of nonhuman bones (i.e. Long bone) accurate classified, the closest match to the atlas. This method requires a quality comparative collection of bones with demographic details or biological profile (i.e. Gender, age, species and stature) that are well-documented.

The biological profile as pre-condition for access of infectious disease likes tuberculosis, anthrax, cysticercosis and hydatidosis (Coulibaly and Yameogo, 2000). Background and clinical signs of pain experienced by nonhuman are necessary during the process of post-mortem begins. From here, some probabilities of a diagnosis can be made so that further examination of the skeletal remains can be done properly. This is very essential because there may be no signs of skeletal remains and the need to depend on the background of the case skeletal remains. Results of post-mortem conducted are very important in implementing disease control programs, particularly the control of infectious diseases. However, current comparative collections have been supplemented by identification guides and atlases which are developed based on bone morphology measurement of nonhuman in Kenya (Archie *et al.*, 2006), United Kingdom (Stander, 1997) and United States of America (Yeni *et al.*, 2008). Therefore, for this case the probability of getting accurate results can not be determined because of differences with the standard atlas (Darmawan *et al.* 2012).

In this research, we will fundamentally analyse a potential method that can be proven to relate gender to bone morphology measurement. In order to develop the possibility of utilizing current computational intelligence classification method of identification of nonhuman, the measurement of bone morphology from the femur and humerus (i.e. Long bone) of monkey will be used to develop an algorithm for the detection method. Although computational intelligence classification method has a great potential in gender classification, it does not have the ability to recognize the optimum feature as input. Therefore, the feature selection process is a way to select the most informative and potential features. The major issue in this research is to achieve positive identification of skeletal remains. In this research we will analyze whether there is any significant improvement in term of accurate classification by using feature selection for classification of gender in forensic anthropology post-mortem process. Addition, computational intelligence classifier (i.e. SVM and ANN) failed to describe data feature differences and similarities between optimum features and original features (Jantan, 2009). Jantan, 2009 believes that the decision tree method has ability to predict the value of a target class based on several input features by learning simple decision IF THEN rules inferred from the data features. Thus, the data features will interpret in simple IF THEN rule's pattern to describe data feature differences and similarities between optimum features and original features using decision tree method. The statistical analysis that can be used to see the strength of the relationship between gender and trabecular bone morphology of the monkey’s population is regression analysis, T test and ANOVA as motivated by Cerroni (2000). In continuing Medical Forensic (CMF), the new classifier algorithm will be beneficial to authorities to help in infectious disease cases involved corpse.

1.3 Problem Statement

Traditionally, classification of the gender of the nonhuman in forensic anthropology context fully depends on comparative skeletal anatomy via atlas used as a reference material to match the bone. So, the traditional methods (i.e. Comparative skeletal anatomy) do not have the ability to use in gender classification in term of achieving a positive identification which is required accurate classification for different population and other features that probably have a great potential and informative feature. Hence, the feature selection process is a way to select the most significant and optimum features. Addition, the data features interpretation of the simple rule pattern which are proven for differences and similarities between the optimum features and original features. The best classification model for gender should be one of that has a high classification accuracy by using optimum features.

Therefore the problem statement of this research is,

"*A hybrid (SVM or ANN) classification model by using PSO feature selection that can identify optimum features that enable to influence the classifier performance in order to get higher accuracy classification rates and find differences and similarity between the optimum features and original features in simple decision tree symbol with IF THEN rule's pattern*"

1.4 Research Question

There are four fundamental questions that need to be answered through this research:

i. Which one between SVM and ANN will produce the highest gender classification accuracy?

ii. What are the most significant trabecular bone morphology features which can help produce the highest gender classification accuracy?

iii. How to improve the classification accuracy rate of gender by using a PSO feature selection for classifier model?

iv. How to concisely describe the data feature differences and similarities between the optimum and original features in gender classification?

1.5 Objectives of the Research

The main objectives of the research are:

i. To develop SVM and ANN model and to select as a classifier that hybrid with feature selection method for gender classification.
ii. To determine the significant features in the trabecular bone morphology dataset that enhance the gender classification performance.
iii. To develop a hybrid gender classification model based on the significant trabecular bone morphology features.

iv. To describe the data feature differences and similarities between optimum features and original features in gender classification in a simple rules pattern by using decision tree symbol method.

1.6 Scopes of the Research

The scopes of this research area:

i. The research only focuses on trabecular bone morphology of the monkey as a function of gender classification.
ii. Ryan and Shaw (2013) sample datasets will be used in the gender classification model.
iii. The classifier used in this research is a Support Vector Machine (SVM) and Artificial Neural Network (ANN).

1.7 Summary

This chapter has been clearly defined in relating to the idea of research implementation. The overview, problem background, research question, objectives and scopes of the research have been identified. In Continuing Medical Forensic (CMF), the simulation model can assist in the identification of deceased nonhuman remains are decomposed, extreme fragmentation, unrecognizable, burned or otherwise mutilated body.

This research is organized into six chapters. The outline is as follows:

Chapter 1: This chapter outlines a research overview, problem background, problem statement, research question, objectives and scopes of this research.

Chapter 2: This chapter presents tough theoretical and a literature review of methods and gender classification in forensic anthropology such as a physical maturity comparison, dentition based comparison, trabecular bone morphology based comparison and computational based comparison method model. Furthermore, analysis is done with the tools to find out the strength and weakness of each tool.

Chapter 3: This chapter describes the methodology of this research. The theoretical framework of the proposed method is shown in this chapter. The components in the proposed method are elaborated in this chapter.

Chapter 4: This chapter describes SVM classifier and ANN classifier implementation details of this model and compared.

Chapter 5: This chapter presents the development proposed hybrid feature selection in classifier model for gender classification in forensic anthropology on trabecular bone morphology dataset.

Chapter 6: The result and finding from the research are detailed in this chapter. Apart from that, chapter 6 focused on evaluating the performance of classification method with accuracy, sensitivity and specificity percentage.

Chapter 7: Lastly, Chapter 7 summarizes and discusses the overall findings in this research research and recommendations for further research.

REFERENCES

Adams, B. J., Santucci, G., and Crabtree, P. J. (2009). *Comparative skeletal anatomy: a photographic atlas for medical examiners, coroners, forensic anthropologists, and archaeologists.*1-348. Springer.

Ahmed, A.A. (2005). Feature subset selection using ant colony optimization Feature subset selection using ant colony optimization. *International Journal of Computational Intelligence*, 2(1), 53-58.

Akay, M. F. (2009). Support vector machines combined with feature selection for breast cancer diagnosis. *Expert Systems with Applications*, 36(2), 3240–3247.

Akhlaghi, M., Moradi, B., and Hajibeygi, M. (2012). Sex determination using anthropometric dimensions of the clavicle in Iranian population. *Journal of Forensic and Legal Medicine*, 19(7), 381-385.

Archie, E. a., Morrison, T. a., Foley, C. a. H., Moss, C. J., and Alberts, S. C. (2006). Dominance rank relationships among wild female African elephants, Loxodonta africana. *Animal Behaviour*, 71(1), 117–127.

Asala, S. A. (2001). "Sex determination from the head of the femur of South African whites and blacks". *Forensic Science International*, 117(1), 15-22.

Baccino, E., Ubelaker, D. H., Hayek, L. a, and Zerilli, A. (1999). Evaluation of seven methods of estimating age at death from mature human skeletal remains. *Journal of forensic sciences*, 44(5), 6-931.

Bagi, C. M., Berryman, E., and Moalli, M. R. (2011). Comparative bone anatomy of commonly used laboratory animals: implications for drug discovery. *Comparative medicine*, 61(1), 76–85.

Basheer, L.A., and Hajmeer, M., (2000). Artificial neural network: Fundamentals, computing, design, and application. *Journal of Microbiological Method*. 43, 3-31.

Benediktsson, J. O. N. A., Swain, P. H., and Ersoy, O. K. (1990). Neural network approaches versus statistical methods in classification of multisource remote sensing data. *IEEE Transactions on geoscience and remote sensing*, 28(4), 540-552.

Berson, A., and Smith, S. J. Data warehousing, data mining, and OLAP. *Series on Data Warehousing and Data Management*. McGraw-Hill, NY, USA, 1997.

Bon, A. T., Marc, J., and Razali, A. M. (2008). Optimization techniques for business process analysis on automotive industry in Malaysia. *Proceedings Third International Borneo Business Conference.*4232–4235.

Borah, B., Dufresne, T. E., Chmielewski, P. a, Gross, G. J., Prenger, M. C., and Phipps, R. J. (2002). Risedronate preserves trabecular architecture and increases bone strength in vertebra of ovariectomized minipigs as measured by three-dimensional microcomputed tomography. *Journal of bone and mineral research : the official journal of the American Society for Bone and Mineral Research*, 17(7), 47-1139.

Boy, C. C., Dellabianca, N., Goodall, R. N. P., and Schiavini, A. C. M. (2011). Age and growth in Peale's dolphin (Lagenorhynchus australis) in subantarctic waters off southern South America. *Mammalian Biology - Zeitschrift für Säugetierkunde*, 76(5), 634–639.

Carpenter, G. A. (1989). Neural network models for pattern recognition and associative memory. *Neural networks*, 2(4), 243-257.

Cattaneo, C. (2007). *Forensic anthropology : developments of a classical discipline in the new millennium*, 165, 185–193.

Cerroni, A. M., Tomlinson, G. A, Turnquist, J. E., and Grynpas, M. D. (2003). Effect of parity on bone mineral density in female rhesus macaques from Cayo Santiago. *American journal of physical anthropology*, 121(3), 69-252.

Charniya, N. N., and Dudul, S. V. (2011). Classification of material type and its surface properties using digital signal processing techniques and neural networks. *Applied Soft Computing*, 11(1), 1108-1116.

Chen, H., Zhou, X., Shoumura, S., Emura, S., and Bunai, Y. (2010). Age- and gender-dependent changes in three-dimensional microstructure of cortical and trabecular bone at the human femoral neck. *Osteoporosis international : a journal established as result of cooperation between the European Foundation for Osteoporosis and the National Osteoporosis Foundation of the USA*, 21(4), 36-627.

Cheung, S. O., Tam, C. M., Ndekugri, I., and Harris, F. C. (2000). Factors affecting clients' project dispute resolution satisfaction in Hong Kong. *Construction Management and Economics*, 18(3), 281-294.

Coulibaly, N. D., and Yameogo, K. R. (2000). Prevalence and control of zoonotic diseases: collaboration between public health workers and veterinarians in Burkina Faso. *Acta tropica*, 76(1), 7–53.

Craig, J. G., Cody, D. D., and Van Holsbeeck, M. (2004). The distal femoral and proximal tibial growth plates: MR imaging, three-dimensional modeling and estimation of area and volume. *Skeletal radiology*, 33(6), 44-337.

Cuozzo, F. P., and Sauther, M. L. (2006). Severe wear and tooth loss in wild ring-tailed lemurs (Lemur catta): a function of feeding ecology, dental structure, and individual life history. *Journal of human evolution*, 51(5), 490–505.

Dancey, D., Bandar, Z. A., and McLean, D. (2007). Logistic model tree extraction from artificial neural networks. Systems, Man, and Cybernetics, Part B: Cybernetics, *IEEE Transactions on*, 37(4), 794-802.

Darmawan, M. F., Yusuf, S. M., Haron, H., and Kadir, M. R. (2012). Review on Techniques in Determination of Age and Gender of Bone Using Forensic Anthropology. *Proceedings Fourth IEEE International Conference In Computational Intelligence, Modelling and Simulation.* 105-110.

Deris, A. M., Zain, A. M., and Sallehuddin, R. (2013). Hybrid GR-SVM for prediction of surface roughness in abrasive water jet machining. *Meccanica*, *48*(8), 1937-1945.

Doube, M., Kłosowski, M. M., Arganda-carreras, I., and Fabrice, P. (2011). *Europe PMC Funders Group BoneJ : free and extensible bone image analysis in ImageJ*, 47(6), 1076–1079.

du Jardin, P., Ponsaillé, J., Alunni-Perret, V., and Quatrehomme, G. (2009). A comparison between neural network and other metric methods to determine sex from the upper femur in a modern French population. *Forensic science international*, 192(1-3), 127.e1–6.

Eberhart, R. C., and Kennedy, J. (1995). A new optimizer using particle swarm theory. *In Proceedings of the sixth international symposium on micro machine and human science,*1, 39-43.

Egermann, M., Goldhahn, J., and Schneider, E. (2005). Animal models for fracture treatment in osteoporosis, *Osteoporosis international*, 16(2), 129-138.

Endo, A., Shibata, T., and Tanaka, H. (2008). Comparison of Seven Algorithms to Predict Breast Cancer Survival, *Biomedical Soft Computing and Human Sciences*, 13(2), 11–16.

Evans, K. E., and Harris, S. (2008). Adolescence in male African elephants, Loxodonta africana, and the importance of sociality. *Animal Behaviour*,76(3), 779-787.

Gavan, J. A, and Hutchinson, T. C. (1973). The problem of age estimation: a study using rhesus monkeys (Macaca mulatta). *American journal of physical anthropology*, 38(1), 69– 81.

Grabherr, S., Cooper, C., Ulrich-Bochsler, S., Uldin, T., Ross, S., Oesterhelweg, L., Bolliger, S., et al. (2009). Estimation of sex and age of “virtual skeletons”--a feasibility study. *European radiology*, 19(2), 29-419.

Gutta, S., Huang, J. J., Jonathon, P., and Wechsler, H. (2000). Mixture of experts for classification of gender, ethnic origin, and pose of human faces. *IEEE transactions on neural networks / a publication of the IEEE Neural Networks Council*, 11(4), 60-948.

Hans, D., Arlot, M. E., Schott, a M., Roux, J. P., Kotzki, P. O., and Meunier, P. J. (1995). Do ultrasound measurements on the os calcis reflect more the bone microarchitecture than the bone mass?: a two-dimensional histomorphometric study. *Bone*, 16(3), 295–300.

Hao, W., Zhu, X., Li, X., and Turyagyenda, G. (2006). Prediction of cutting force for self-propelled rotary tool using artificial neural networks. *Journal of materials processing technology*, 180(1), 23-29.

Harma, A., and Karakas, H. M. (2007). Determination of sex from the femur in Anatolian Caucasians: a digital radiological study. *Journal of forensic and legal medicine*, 14(4), 190-194.

Havill, L. (2003). Bone mineral density reference standards in adult baboons (Papio hamadryas) by sex and age. *Bone*, 33(6), 877–888.

Hoballah, A., and Erlich, I. (2009). PSO-ANN approach for transient stability constrained economic power generation. *IEEE Bucharest on PowerTech*, June 28th- July 2nd, 2009, Romania: IEEE, 2009. 1-6.

Hsieh, C. W., Jong, T. L., and Tiu, C. M. (2007). Bone age estimation based on phalanx information with fuzzy constrain of carpals. *Medical and biological engineering and computing*, 45(3), 283-295.

Hsu, C. W., Chang, C. C., and Lin, C. J. (2003). A practical guide to support vector classification. Available from *http://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf*.

Huang, C. L., and Wang, C. J. (2006). A GA-based feature selection and parameters optimizationfor support vector machines. *Expert Systems with applications*, 31(2), 231-240.

Huang, G. B., Zhu, Q. Y., and Siew, C. K. (2004). Extreme learning machine: a new learning scheme of feedforward neural networks. *Proceedings IEEE International Joint Conference In Neural Networks,*2, 985-990.

Huang, W., and Foo, S. (2002). Neural network modeling of salinity variation in Apalachicola River. *Water research*, 36(1), 62-356.

Hunt, E. E., and Gleiser, I. (1955). “The estimation of age and sex of preadolescent children from bones and teeth”. *American journal of physical anthropology*, 13(3), 479–487.

Imaizumi, K., Saitoh, K., Sekiguchi, K., and Yoshino, M. (2002). Identification of fragmented bones based on anthropological and DNA analyses: case report. *Legal medicine* (Tokyo, Japan), 4(4), 6-251.

Imrie, J. A, and Wyburn, G. M. (1958). “Assessment of age, sex, and height from immature human bones”. *British medical journal*, 1(5063), 128-131.

Jantan, H., Hamdan, A. R., and Othman, Z. A. (2009). Classification for talent management using Decision Tree Induction techniques. *IEEE In 2nd Data Mining and Optimization Seminar*, October 27-28, 2009. Bangi, Selangor:IEEE. 2009. 15-20.

Jensen, R. (2009). New Approaches to Fuzzy-Rough Feature Selection. *IEEE Transactions on Fuzzy Systems*, 17(4), 824–838.

Jones, W. M. *Using trabecular architecture of the proximal femur to determine age at death: an accuracy test of two methods.* Master’s Thesis. Baton Rouge; 2003

Kang, S. *An Investigation Of The Use Of FeedForward Neural Networks For Forecasting*. Ph.D. Thesis. Kent State University; 1991

Kitchenham, B., Pearl Brereton, O., Budgen, D., Turner, M., Bailey, J., and Linkman, S. (2009). Systematic literature reviews in software engineering–a systematic literature review. *Information and software technology*, 51(1), 7-15.

Klimt, B., and Yang, Y. (2004). The enron corpus: A new dataset for email classification research. In Machine learning: *ECML 2004*. 217-226.

Kranioti, E., and Paine, R. (2011). Forensic anthropology in Europe: an assessment of current status and application. *Journal of anthropological sciences = Rivista di antropologia : JASS / Istituto italiano di antropologia*, 89, 71–92.

Kurmis, A. P., Hearn, T. C., Grimmer, K., and Reynolds, K. J. (2004). Dimensional measurement of structural features of the ovine knee using three-dimensional reconstructed imaging: intra- and inter-observer repeatability. *Radiography*, 10(4), 269–276.

Kyoung, K.J. (2003). Financial Time Series Forecasting Using Support Vector Machines. *Neurocomputing*. 55, 307-319.

Lapedes, A., Farber, R., (1988). How neural nets work. In: Anderson, D.Z., (Ed.), *Neural Information Processing Systems*, American Institute of Physics, New York, 442–456.

Li, M., Han, K. J., and Narayanan, S. (2013). "Automatic speaker age and gender recognition using acoustic and prosodic level information fusion." *Computer Speech and Language*, 27(1), 151–167.

Lim, S. P., and Haron, H. (2013). Performance of different techniques applied in genetic algorithm towards benchmark functions, IEEE Conference on Open System. December 2-4, 2013. Kuching, Sarawak: IEEE. 2013. 255-264.

Lin, S.-W., Ying, K.-C., Chen, S.-C., and Lee, Z.-J. (2008). Particle swarm optimization for parameter determination and feature selection of support vector machines. *Expert Systems with Applications*, 35(4), 1817–1824.

Liou, S., and Wang, C. (2009). Integrative Discovery of Multifaceted Sequence Patterns by Frame-Relayed Search and Hybrid PSO-ANN. *J Universal Comp Sci*, 15(4), 742–764.

Liu Sheng, O. R., Wei, C.-P., Hu, P. J.-H., and Chang, N. (2000). Automated learning of patient image retrieval knowledge: neural networks versus inductive decision trees. *Decision Support Systems*, 30(2), 105–124.

Liu, Y., Wang, G., Chen, H., Dong, H., Zhu, X., and Wang, S. (2011). An Improved Particle Swarm Optimization for Feature Selection. *Journal of Bionic Engineering*, 8(2), 191–200.

Mahfouz, M., Badawi, A., Merkl, B., Fatah, E. E. A., Pritchard, E., Kesler, K., Moore, M., et al. (2007). Patella sex determination by 3D statistical shape models and nonlinear classifiers. *Forensic science international*, 173(2-3), 70-161.

Mäkinen, E., and Raisamo, R. (2008). Evaluation of gender classification methods with automatically detected and aligned faces. *IEEE transactions on pattern analysis and machine intelligence,* 30(3), 7-541.

Malhi, A., and Gao, R. X. (2004). PCA-based feature selection scheme for machine defect classification. *IEEE Transactions on Instrumentation and Measurement, 53*(6), 1517-1525.

Mitroff, I.I., Betz, F., Pondy, L.R. and Sagasti, F. (1974*). On managing science in the systems age: two schemas for the study of science as a whole systems phenomenon. Interfaces*. 4(3), 46-58.

Moghaddam, B., and Yang, M. H. (2000). Gender classification with support vector machines. *Proceedings Fourth IEEE International Conference In Automatic Face and Gesture Recognition*, 306-311.

Morita, M., Ebihara, A., Itoman, M., and Sasada, T. (1994). Progression of osteoporosis in cancellous bone depending on trabecular structure. *Annals of biomedical engineering*, 22(5), 532-539.

Mukherjee, I., and Routroy, S. (2012). Comparing the performance of neural networks developed by using Levenberg–Marquardt and Quasi-Newton with the gradient descent algorithm for modelling a multiple response grinding process. *Expert Systems with Applications*, 39(3), 2397–2407.

Mukkamala, S., and Sung, A. H. (2003). Identifying significant features for network forensic analysis using artificial intelligent techniques. *International Journal of digital evidence*, 1(4), 1-17.

Muqeem, S., Khamidi, M.F., Idrus, A.B. and Zakaria, S. (2011). Prediction modeling of construction labour productivity rates using artificial neural network. Proc., 2nd Int. *Conf. on Environmental Science and Technology*, IACSIT Press, Singapore, 32–36.

Muthukrishnan, N. and Davim, J.P. (2009). Optimization of machining parameters of Al/SiC-MMC with ANOVA and ANN analysis. *Journal of materials processing technology*. 225–232.

Niebles, J. C., Chen, C. W., and Fei-Fei, L. (2010). Modeling temporal structure of decomposable motion segments for activity classification. *In Computer Vision–ECCV 2010*, pp. 392-405.

Nieves, J. W., Formica, C., Ruffing, J., Zion, M., Garrett, P., Lindsay, R., and Cosman, F. (2005). Males have larger skeletal size and bone mass than females, despite comparable body size. *Journal of bone and mineral research : the official journal of the American Society for Bone and Mineral Research*, 20(3), 35-529.

O’farrell, M., Lewis, E., Flanagan, C., Lyons, W., and Jackman, N. (2005). Comparison of< i> k</i>-NN and neural network methods in the classification of spectral data from an optical fibre-based sensor system used for quality control in the food industry. *Sensors and Actuators B: Chemical*, 111, 354-362.

O'toole, A. J., Vetter, T., Troje, N. F., and Bülthoff, H. H. (1997). Sex classification is better with three-dimensional head structure than with image intensity information. *PERCEPTION-LONDON-*, 26, 75-84.

Omar, N., and Othman, M. S. (2013). Particle Swarm Optimization Feature Selection for Classification of Survival Analysis in Lymphoma Cancer, *International Journal of Innovative Computing*, 2(1), 1–7.

Perissinotto, E., Pisent, C., Sergi, G., Grigoletto, F., and Enzi, G. (2002). Anthropometric measurements in the elderly: age and gender differences.*British Journal of Nutrition*, 87(02), 177-186.

Pervouchine, V., and Leedham, G. (2007). Extraction and analysis of forensic document examiner features used for writer identification. *Pattern Recognition* ,40(3), 1004-1013.

Pfeiffer, I., Burger, J., and Brenig, B. (2004). Diagnostic polymorphisms in the mitochondrial cytochrome b gene allow discrimination between cattle, sheep, goat, roe buck and deer by PCR-RFLP. *BMC genetics*, 5(1), 30.

Pietka, E., Mcnitt-gray, M. F., Kuo, M. L., Huang, H. K., and Member, S. (1991). Computer-Assisted Phalangeal Analysis in Skeletal Age Assessment. *IEEE Transactions on Medical Imaging*. 10(4), 616–620.

Polat, K., and Güneş, S. (2007). A hybrid approach to medical decision support systems: Combining feature selection, fuzzy weighted pre-processing and AIRS. *Computer methods and programs in biomedicine*, 88(2), 164-174.

Purkait, R. (2005). “Triangle identified at the proximal end of femur: a new sex determinant”. *Forensic science international*, 147(2-3), 135–139.

Rahman S.A., Bakar, A.A and Hussein, Z.A.M. (2009). Filter-wrapper approach to feature selection using RST-DPSO for mining protein function. *2nd Conference on Data Mining and Optimization*, pp. 71-78.

Ramsthaler, F., Kettner, M., Gehl, A., and Verhoff, M. A. (2010). Digital forensic osteology : Morphological sexing of skeletal remains using volume-rendered cranial CT scans. *Forensic science international*. 195(1), 148–152.

Riggs, B. L., Melton, L. J., Robb, R. A., Camp, J. J., Atkinson, E. J., Peterson, J. M., ... and Khosla, S. (2004). Population-Based Study of Age and Sex Differences in Bone Volumetric Density, Size, Geometry, and Structure at Different Skeletal Sites. *Journal of Bone and Mineral Research*, 19(12), 1945-1954.

Roselin, R., Thangavel, K., and Velayutham, C. (2011). Fuzzy-Rough Feature Selection for Mammogram Classification. *Journal of Electronic Science and Technology*. 9(2), 124–132.

Rozenblut, B., and Ogielska, M. (2005). Development and growth of long bones in European water frogs (Amphibia: Anura: Ranidae), with remarks on age determination. *Journal of Morphology*, 265(3), 304-317.

Ryan, T. M., and Walker, A. (2010). Trabecular bone structure in the humeral and femoral heads of anthropoid primates. *Anatomical record (Hoboken, N.J. : 2007)*, 293(4), 29-719.

Ryan, T. M., and Shaw, C. N. (2013). Trabecular bone microstructure scales allometrically in the primate humerus and femur. *Proceedings of the Royal Society B: Biological Sciences*, 280(1758), 1-9.

Saenko, K., Kulis, B., Fritz, M., and Darrell, T. (2010). Adapting visual category models to new domains. *In Computer Vision–ECCV 2010*, pp. 213-226.

Salam, S. (2007). *Daily Wind Speed Prediction In Kota Bharu Using Artificial Neural Network*. Master of Science (Computer Science). Universiti Teknologi Malaysia.

Samui, P., and Dixon, B. (2012). Application of support vector machine and relevance vector machine to determine evaporative losses in reservoirs.*Hydrological Processes*, 26(9), 1361-1369.

Smola, A. J. and Scholkopf, B (2003). *A Tutorial on Support Vector Regression. Technical Report*. NC2-TR-1998-030. NeuroCOLT2.

Stander, P. E. (1997). Field age determination of leopards by tooth wear.African *Journal of Ecology*, 35(2), 156-161.

Stauber, M., and Müller, R. (2006). Age-related changes in trabecular bone microstructures: global and local morphometry. *Osteoporosis international : a journal established as result of cooperation between the European Foundation* *for Osteoporosis and the National Osteoporosis Foundation of the USA*, 17(4), 26-616.

Sun, Z., Yuan, X., Bebis, G., and Louis, S. J. (2002). Neural-network-based gender classification using genetic search for eigen-feature selection. *Proceedings of the 2000 IEEE International International Joint Conference on Neural Network.* 2433-2438.

Swartz, S. M., Parker, a, and Huo, C. (1998). Theoretical and empirical scaling patterns and topological homology in bone trabeculae. *The Journal of experimental biology*, 201(Pt 4), 90-573.

Thangavel, K., and Roselin, R. (2012). Fuzzy - Rough Feature Selection with Π - Membership Function for Mammogram Classification. *International Journal Computer Science Issues*. 9(4), 361–370.

Topoliński, T., Mazurkiewicz, A., Jung, S., Cichański, A., and Nowicki, K. (2012). Microarchitecture parameters describe bone structure and its strength better than BMD. *The Scientific World Journal*, 2012, 502-781.

Tosun, N., and Ozler, L. (2002). A study of tool life in hot machining using artificial neural networks and regression. *Journal of Materials Processing Technology*. 124, 99-104.

Tsai, M.-J., Wang, C.-S., Liu, J., and Yin, J.-S. (2012). Using decision fusion of feature selection in digital forensics for camera source model identification. *Computer Standards and Interfaces*, 34(3), 292–304.

Ubaidillah, S. H. S. A., Sallehuddin, R., and Ali, N. A. (2013). Cancer Detection Using Aritifical Neural Network and Support Vector Machine: A Comparative Study. *Jurnal Teknologi*, 65(1), 1-9.

Ubelaker, D. H. (2006). *Evolution of the relationship of forensic anthropology with physical anthropology and forensic pathology : A North American perspective*, 4, 199–205.

Ulrich, D., van Rietbergen, B., Laib, a, and Rüegsegger, P. (1999). The ability of three-dimensional structural indices to reflect mechanical aspects of trabecular bone. *Bone*, 25(1), 55–60.

Van Deelen, T. R., Hollis, K. M., Anchor, C., and Etter, D. R. (2000). Sex affects age determination and wear of molariform teeth in white-tailed deer. *The Journal of wildlife management*, 1076-1083.

Vapnik V. (1998). *Statistical Learning Theory*. Wiley. New York, USA.

Wang, X., Yang, J., Teng, X., Xia, W., and Jensen, R. (2007). Feature selection based on rough sets and particle swarm optimization. *Pattern Recognition Letters*, 28(4), 459–471.

Xue, B., Zhang, M., and Browne, W. N. (2012). Multi-objective particle swarm optimisation (PSO) for feature selection. *Proceedings of the fourteenth international conference on Genetic and evolutionary computation conference*. 81-88.

Yang, F., Ichii, K., White, M. a., Hashimoto, H., Michaelis, A. R., Votava, P., Zhu, A.-X., et al. (2007). Developing a continental-scale measure of gross primary production by combining MODIS and AmeriFlux data through Support Vector Machine approach. *Remote Sensing of Environment*, 110(1), 109–122.

Yang, H., Zhang, S., Deng, K., and Du, P. (2007). Research into a Feature Selection Method for Hyperspectral Imagery Using PSO and SVM. *Journal of China University of Mining and Technology*, 17(4), 473–478.

Yannakoudakis, H., Briscoe, T., and Medlock, B. (2011). A new dataset and method for automatically grading ESOL texts. *In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, 1, pp. 180-189.

Yen, G. G., and Ivers, B. (2009). Job shop scheduling optimization through multiple independent particle swarms. *Proceedings International Journal of Intelligent Computing and Cybernetics*, 2(1), 5-33.

Yeni, Y. N., Zelman, E. a, Divine, G. W., Kim, D.-G., and Fyhrie, D. P. (2008). Trabecular shear stress amplification and variability in human vertebral cancellous bone: relationship with age, gender, spine level and trabecular architecture. *Bone*, 42(3), 6-591.

Zain, AM., Haron, H. and Sharif, S. (2010). Prediction of surface roughness in the end milling machining using Artificial Neural Network. *Expert Systems with Applications*, 37, 1755–1768.

Zhang, G. P. (2000). Neural networks for classification: a survey. *IEEE Transactions on Systems, Man, and Cybernetics-Part C: Applications and Reviews*, 30(4), 451-462.

Zhang, G., Eddy Patuwo, B., and Y Hu, M. (1998). Forecasting with artificial neural networks:: The state of the art. *International journal of forecasting*, 14(1), 35-62.

Zheng, E., Li, P., and Song, Z. (2004). Performance analysis and comparison of neural networks and support vector machines classifier. *Proceedings of the 2004 IEEE World Congress on Intelligent Control and Automation*. 4232–4235.