HYBRID ACO AND SVM ALGORITHM FOR PATTERN CLASSIFICATION

HIBA BASIM ALWAN

DOCTOR OF PHILOSOPHY
UNIVERSITI UTARA MALAYSIA
2013

Permission to Use

Abstrak

Pengoptimum Koloni Semut (ACO) adalah algoritma metaheuristik yang boleh digunakan untuk menyelesai pelbagai masalah pengoptimuman kombinasi. Halatuju baru bagi ACO adalah untuk mengoptimumkan pembolehubah selanjar dan bercampur (diskrit dan selanjar). Mesin Vektor Sokongan (SVM) adalah satu pendekatan klasifikasi corak yang berpunca daripada pendekatan statistik. Walau bagaimanapun, SVM mempunyai dua masalah utama iaitu pemilihan atribut subset dan penalaan parameter. Kebanyakan pendekatan yang berkait dengan penalaan parameter SVM mendiskritkan nilai selanjar parameter dan ini akan memberi kesan negatif kepada prestasi klasifikasi. Tesis ini melaporkan empat algoritma untuk menala parameter SVM dan memilih atribut subset yang meningkatkan prestasi klasifikasi SVM dengan saiz attribute subset yang lebih kecil. Ini boleh dicapai dengan melaksanakan proses pemilihan subset dan penalaan parameter SVM secara serentak. Penghibridan algoritma ACO dan teknik SVM telah dicadangkan. Dua kelompok algoritma pertama iaitu algoritma ACO_R-SVM dan $IACO_R$-SVM akan menala parameter SVM manakala dua algoritma kedua iaitu algoritma $ACO_{MV\text{-}R}$-SVM and $IACO_{MV\text{-}R}$-SVM boleh melaksanakan penalaan parameter SVM dan pemilihan atribut subset secara serentak. Sepuluh dataset penanda aras dari University California, Irvine, telah digunakan dalam eksperimen untuk mengesahkan prestasi algoritma yang dicadangkan. Dapatan eksperimen daripada algoritma yang dicadangkan adalah lebih baik berbanding pendekatan lain dari segi ketepatan klasifikasi dan saiz subset atribut. Purata ketepatan klasifikasi bagi algoritma ACO_R-SVM, $IACO_R$-SVM, $ACO_{MV\text{-}R}$ dan $IACO_{MV\text{-}R}$ adalah 94.73%, 95.86%, 97.37% dan 98.1%. Purata saiz atribut subset adalah lapan bagi algoritma ACO_R-SVM dan $IACO_R$-SVM dan empat bagi algoritma $ACO_{MV\text{-}R}$ dan $IACO_{MV\text{-}R}$. Dapatan kajian ini turut menyumbang kepada halatuju baru bagi ACO yang boleh digunakan untuk pembolehubah ACO yang selanjar dan bercampur.

Kata kunci: Pengoptimum koloni semut selanjar, Pengoptimum koloni semut bercampur, Mesin vektor sokongan, Penalaan parameter SVM, Pemilihan subset atribut.

Abstract

Ant Colony Optimization (ACO) is a metaheuristic algorithm that can be used to solve a variety of combinatorial optimization problems. A new direction for ACO is to optimize continuous and mixed (discrete and continuous) variables. Support Vector Machine (SVM) is a pattern classification approach originated from statistical approaches. However, SVM suffers two main problems which include feature subset selection and parameter tuning. Most approaches related to tuning SVM parameters discretize the continuous value of the parameters which will give a negative effect on the classification performance. This study presents four algorithms for tuning the SVM parameters and selecting feature subset which improved SVM classification accuracy with smaller size of feature subset. This is achieved by performing the SVM parameters' tuning and feature subset selection processes simultaneously. Hybridization algorithms between ACO and SVM techniques were proposed. The first two algorithms, ACO_R-SVM and $IACO_R$-SVM, tune the SVM parameters while the second two algorithms, $ACO_{MV\text{-}R}$-SVM and $IACO_{MV\text{-}R}$-SVM, tune the SVM parameters and select the feature subset simultaneously. Ten benchmark datasets from University of California, Irvine, were used in the experiments to validate the performance of the proposed algorithms. Experimental results obtained from the proposed algorithms are better when compared with other approaches in terms of classification accuracy and size of the feature subset. The average classification accuracies for the ACO_R-SVM, $IACO_R$-SVM, $ACO_{MV\text{-}R}$ and $IACO_{MV\text{-}R}$ algorithms are 94.73%, 95.86%, 97.37% and 98.1% respectively. The average size of feature subset is eight for the ACO_R-SVM and $IACO_R$-SVM algorithms and four for the $ACO_{MV\text{-}R}$ and $IACO_{MV\text{-}R}$ algorithms. This study contributes to a new direction for ACO that can deal with continuous and mixed-variable ACO.

Keywords: Continuous ant colony optimization, Mixed-variable ant colony optimization, Support vector machine, Tuning SVM parameters, Feature subset selection.

Acknowledgement

When I write this acknowledgment, my tears are falling down. Some memories can never be deleted and I remember the first time I decided to complete my studies in a foreign country; when I placed my feet on Malaysian soil I thought I had made the biggest mistake of my whole life; I felt so afraid of studying in a foreign country with strange people. In that moment, I realized I had left my home country to live in a foreign land. But, when I met Malaysian people with their beautiful smiles, and everything smells so fresh, so exciting, I thought it may well be a good journey.

After three years spent in Malaysia, I am filled with confidence that I made the correct decision to complete my studies here and I feel fortunate to have spent three years of my life in this amazing country with so many wonderful and incredible people. Sometimes, life can move too quickly; we all need to rest. Reflecting back you happily discover that the journey you have taken has brought you to a place with a magnificent view; you are now standing on a mountain top with a vista stretching towards a horizon of green trees and mountains. You smile into the distance realizing you are no longer looking back but are viewing new, sweet dreams. Which direction to take? You do not know. There are the memories, the experience, the wisdom, and the smiles. Gather them to you and start walking.

After three years as a PhD student at UUM, I am grateful to the many inspirational people who have helped shape my future, guiding me at times of difficulty, laughing with me in times of discovery. I have many beautiful memories, painted like a vivid picture in my mind, of the days spent with such amazing people. So, I will take this moment, take a deep breath and recollect all the wonderful memories from these past few years and walk down the grassy slopes of the mountain to discover what lies ahead in the continuation of my journey. Now, let me start my acknowledgments:

First and foremost, I would to thank “ALLAH” for being the source of my spiritual strength and giving me the power to finish my studies, for helping and guiding me through all these years and especially in my PhD study period; I aspire to become one of the good mumineen in this world. ALLAH, I am forever grateful to You.

I would like to express my deepest gratitude to my supervisor, Prof. Dr. Ku Ruhana Ku-Mahamud, for giving me the opportunity to study under her direction. I deeply appreciate her views, comments and tireless encouragement. Through her guidance, probing questions and sharing of knowledge, which I will treasure always, I have gained a wealth of knowledge. You broke the barrier of fear for studying in a foreign country, you made my PhD study easier and simpler.

Last but not least, my thanks go my parents who have encouraged me, given me the skills to step courageously into the future with confidence and taught me the importance of being true to myself and working hard, Most importantly, they have walked beside me during my journey, giving love and support. They embody, for me, the value of "family". They always have and always will provide words of wisdom, encouragement and prayers. I thank my parents for inspiring optimism and supporting me unconditionally. To them, I dedicate this thesis. ALLAH, please keep both of them for me.

Table of Contents

List of Tables

List of Figures

List of Appendices

List of Abbreviations

NN	Neural Network
ACO	Ant Colony Optimization
SVM	Support Vector Machine
OSH	Optimal Separating Hyperplane
OAO	One-Against-One
OAA	One-Against-All
FS	Feature Selection
TSP	Travelling Salesman Problem
TS	Tabu Search
SA	Simulated Annealing
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
ACO_R	continuous Ant Colony Optimization
ACO_{MV}	mixed-variable Ant Colony Optimization
$IACO_R$	Incremental continuous Ant Colony Optimization
$IACO_R$-LS	Incremental continuous Ant Colony Optimization with Local Search
CSO	Cat Swarm Optimization
CSA	Clonal Selection Algorithm
GSA	Gravitational Search Algorithm
RBF	Radial Basis Function
OAO	One-Against-One
UCI	University of California, Irvine
k-NN	k-Nearest Neighbor
BEOBDW	Binary Encoded Output Based Data Weighting
ANNs	Artificial Neural Networks
MLR	Multiple Linear Regression
RLS	Regularized Least Squares
LSVM	Linear Support Vector Machine
LibSVM	Library SVM
CV	Cross Validation

LibLinear	Library Linear
LOOCV	Leave-One-Out Cross-Validation
EMG	ElectroMyoGraphy
MAV	Moving Average
RMS	Root Mean Square
VAR	Variance
SD	Standard Deviation
ZC	Zero-Crossing
SSC	Slop Sign Change
WL	Waveform Length
FCM	Fuzzy C-Means
PCA	Principle Component Analysis
AFS	Axiomatic Fuzzy Set
MFAM	Modified Fuzzy Ant Miner
OMFAM	Optimizing Modified Fuzzy Ant Miner
FAM	Fuzzy Ant Miner
BPNN	Back Propagation Neural Network
MSE	Mean Square Error
∆ZCC	delta Zero Crossing Counts
GMM	Gaussian Mixture Model
EM	Expectation Maximization
RBFNN	Radial Basis Function Neural Network
DT	Decision Tree
MLP	Multi-Layer Perceptron
PBC	Pattern Based Classification
SFLS	Shortest Feature Line Segment
NFL	Nearest Feature Line
NN	Nearest Neighbor
RNFLS	Refined Nearest Feature Line Segment
EMD	Empirical Model Decomposition
WSVM	Wavelet Support Vector Machine
ARs	Association Rules
DE	Differential Evolution

CVC	Classification Via Clustering
DPSO	Dynamic Particle Swarm Optimization
GS	Grid Search
CPSO	Chained Particle Swarm Optimization
DMS	Dynamic Model Selection
KCRF	Kernel Condition Random Field
PCA	Principle Component Analysis
LKFSVM	Linear Kernel Function Support Vector Machine
GSVM	Gauss kernel Support Vector Machine
BBDE	Bare Bones Differential Evolution
SVM-SA	Support Vector Machine and Simulated Annealing
PWC	Pair-Wise Coupling
R-M- bound	Radius Margin bound
UD	Uniform Design
ES	Empirical Set
RFE	Recursive Feature Elimination
EEG	Electroencephalography
IAPS	International Affective Picture System
SSDOI	Scalp Spectral Dynamics Of Interest
MI	Mutual Information
AV	Artificial Variables
CHB	Chronic Hepatitis B
CIR	CIRrhosis
HCC	HepatoCellular Carcinoma
BR	Bootstrap Resampling
VF	Ventricular Fibrillation
ECG	ElectroCardioGram
VT	Ventricular Tachycardia
RADAG	Reordering Adaptive Directed Acyclic Graph
NPLs	Nonperforming Loans
IFSFS	Improved F-score and Sequential Forward Search
SFS	Sequential Forward Search
SVML	SVM with linear kernel

TF-IDF	Term Frequency-Inverse Document Frequency
mRMR	minimum Redundancy-Maximum-Relevance
ACS	Ant Colony System
ARD	Automatic Relevance Determination
SVM-FuzCoC	Fuzzy Complementary of Criterion
LS-SVM	Least Square SVM
KFFS	Kernel F-score Feature Selection
Lin	Linear
LMANN	Levenberg-Marquart Artificial Neural Network
AS	Ant System
EAS	Elitist Ant System
IG	Information Gain
NGL	Ng, Goh, and Low
GSS	Galavotti, Sebastiani, and Simi
OR	Odds Ratio
ICA	Immune Clonal Algorithm
MBPSO	Modified Binary Particle Swarm Optimization
RGSA	Real value GSA
BGSA	Binary value GSA
SVR	Support Vector Regression
kp-SVM	kernel-penalized SVM
ACO-S	Ant Colony Optimization-Selection
BP	Back Propagation
WT	Wavelet Transform
ACOFS	Ant Colony Optimization for Feature Selection
AS_{rank}	Rank-based Ant System
MMAS	Max-Min Ant System
SBS	Sequential Backward Selection
MFB	Mel-Filter Bank
LPR	Linear Predictive Reflection
RF	Random Forest
CACO	Continuous Ant Colony Optimization
API	pachycondyla apicalis

CIAC	Continuous Interacting Ant Colony
HCIAC	Hybrid Continuous Interacting Ant Colony
DHCIAC	Dynamic Hybrid Continuous Interacting Ant Colony
ACA	Ant Colony Algorithm
ACBACO	Adaptive and Commutative Binary Ant Colony Optimization
BACO	Binary Ant Colony Optimization
COAC	Continuous Orthogonal Ant Colony
OS	Orthogonal Scheme
OSACO	Orthogonal Scheme Ant Colony Optimization
CACO-DE	Continuous ACO-Direct Encoding
BAS	Binary Ant System
CACS	Continuous Ant Colony System
DACO	Direct Ant Colony Optimization
DACA	Dynamic Ant Colony Algorithm
MACACO	Multivariate Ant Colony Algorithm for Continuous Optimization
PDF	Probability Density Function
ACO_R-LM	ACO_R-Levenberg Marquardt
IEEE	Institute of Electrical and Electronics Engineers
ACO_{MV-O}	mixed-variable Ant Colony Optimization for Ordering variables
ACO_{MV-C}	mixed-variable Ant Colony Optimization for Categorical variables
PDS	Pressure Vessel Design
CSD	Coil Spring Design
DTIS	Designing Thermal Insulation System
M-$IACO_R$	Modifies Improved continuous Ant Colony Optimization
SamACO	Sampling Ant Colony Optimization
DNA	Deoxyribonucleic acid
EI	exon/introns boundaries
IE	introns/exon boundaries
F-score	Fisher score
SVC	Support Vector Classification

CHAPTER ONE

INTRODUCTION

Classification is a supervised learning approach which is a significant field of research involving labeling an object to one of a group of classes, related to features of that object (Qian, Chen & Cai, 2011; Khashei, Hamadani & Bijari, 2012; Khashei, Hamadani & Bijari, 2011; Tsai et al., 2011; Cheng et al., 2010; Liu, Liu & Zhang, 2010; Mastrogiannis, Boutsinas & Giannikos, 2009; Tseng & Lee, 2009; and Uney & Turkay, 2006) and it is considered one of the basic difficulties in a numerous decision making processes. Many decision making processes are examples of classification difficulty or can be simply transformed into classification difficulty, for example, prognosis processes, diagnosis processes, and pattern recognition (Orkcu & Bal, 2011). Data classification process consists of: training and testing and this is undertaken in a two stage procedure. First, the training data are used to build the classifier (model for classification) and subsequently, the classifier will be tested using the test data (Uney & Turkay, 2006; and Cheng et al., 2010). The execution of the classification procedure is determined by the precision of the distinguishing function for the particular problem to which it is applied. A distinguishing function is improved to minimize the misclassification percentage, regarding the few present examples of input and output vector pairs, which are known as the training data group. This distinguishing function is then utilized to classify new examples into pre-defined categories and to test the precision of the classification (Qian, Chen & Cai, 2012; Khashei, Hamadani & Bijari, 2012; Khashei, Hamadani & Bijari, 2011; Tsai et al., 2011; Cheng et al., 2010; Liu, Liu & Zhang, 2010; Mastrogiannis, Boutsinas & Giannikos, 2009; Tseng & Lee, 2009; and Uney & Turkay, 2006). The

The contents of the thesis is for internal user only

REFERENCES

Abd-Alsabour, N. & Randall, M. (2010). Feature selection for classification using an ant colony system. Proceedings of The 6th International Conference on e-Science Workshops, 7-10 December 2010, Brisbane, QLD, 86-91.

Abd-Alsabour, N. (2010). Feature selection for classification using an ant system approach. In M. Hinchey, B. Kleinjohann, L. Kleinjohann, P. Lindsay, F. Ramming, J. Timmis & M. Wolf (Eds.), *Distributed, Parallel and Biologically Inspired Systems*, (pp. 233-241). Berlin Heidelberg: Springer.

Abdi, M. & Giveki, D. (2013). Automatic detection of erythemato-squamous diseases using PSO–SVM based on association rules. *Engineering Applications of Artificial Intelligence, 26*(1), 603-608.

Acharya, J., Das, A., Orlitsky, A., Pan, S. & Santhanam, N. (2010). Classification using pattern probability estimators. Proceeding of The International Symposium on Information theory, 13-18 June 2010, Austin, TX, 1493 - 1497.

Acir, N., Ozdamar, O. & Guzelis, C. (2006). Automatic classification of auditory brainstem responses using SVM-based selection algorithm for threshold detection. *Engineering Applications of Artificial Intelligence*, *19*(2), pp. 209-218.

Ahsan, Md., Ibrahimy, M. & Khalifa, O. (2012). EMG motion pattern classification through design and optimization of neural network. Proceedings of The International Conference on Biomedical Engineering, 27-28 February 2012, Penang, Malaysia, 175-179.

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

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

Al-Janabi, A. (2010). *Interacted multiple ant colonies for search stagnation problem.* (Doctoral dissertation, UUM, 2010). Retrieved from cache:z0fkJlvzCMoJ:www.idsia.ch/~luca/aco2004.pdf maniezzo v. gambardella l. & luigi f. ant colony optimization.pdf.

Al-Naami, B., Al-Nabulsi, J., Amasha, H. & Torry, J. (2010). Utilizing wavelet transform and support vector machine for detection of the paradoxical splitting in the second heart sound. *Medical and Biological Engineering and Computing, 48*(2), 177-184.

Anguita, D. & Ghio, A. (2011). In-sample model selection for support vector machines. Proceeding of The international Joint Conference on Neural Networks, 31 July-5 August 2011, San Jose, CA, 1154 - 1161.

Aribarg, T., Supratid, S. & Lursinsap, C. (2012). Optimizing the modified fuzzy ant-miner for efficient medical diagnosis. *Applied Intelligence, 37*(3), 357-376.

Atienza, F., Alvarez, J., Munoz, A., Vinagre, J., Alberola, A. & Valls, G. (2012). Feature selection using support vector machines and bootstrap methods for ventricular fibrillation detection. *Expert System with Applications, 39*(2), pp. 1956-1967.

Azadeh, A., Saberi, M., Kazem, A., Ebrahimipour, V., Nourmohammadzadeh, A. & Saberi, Z. (2013). A flexible algorithm for fault diagnosis in a centrifugal pump with corrupted data and noise based on ANN and support vector machine with hyper-parameters optimization. *Applied Soft Computing, 13*(3), 1478-1485.

Bajla, I., Rublik, F., Arendacka, B., Farkas, I., Hornisova, K. & Stole, S. (2009). Segmentation and supervised classification of image objects in EPO doping-control. M*achine Vision and Applications, 20*(4), 243-259.

Basiri, M., Aghaee, N. & Aghdam, M. (2008). Using ant colony optimization-based selected features for predicting post-synaptic activity in proteins. In E. Marchiori & J. Moore (Eds.), *Evolutionary computation, machine learning and data mining in bioinformatics*, (pp. 12-23). Berlin Heidelberg: Springer.

Bhadra, T., Bandyopadhyay, S. & Maulik, U. (2012). Differential evolution based optimization of SVM parameters for meta classifier design. *Procedia Technology, 4*, 50-57.

Bilchev, G. & Parmee, I. (1995). The ant colony metaphor for searching continuous design spaces. In F. Terence (Ed.), *Evolutionary computing. (pp. 25-39).* Berlin Heidelberg: Springer.

Birattari, M., Pellegrini, P. & Dorigo, M. (2007). On the invariance of ant colony optimization. *Transaction on Evolutionary Computation, 11*(6), 732-742.

Blondin, J. & Saad, A. (2010). Metaheuristic techniques for support vector machine model selection. Proceedings of The 10th International Conference on Hybrid Intelligent Systems, 23-25 August 2010, Atlanta, GA, 197 – 200.

Blum, C. & Dorigo, M. (2004). The hyper-cube framework for ant colony optimization. *Transaction on System, Man, and Cyberntics*, *34*(2), 1161-1172.

Blum, C. & Dorigo, M. (2005). Search bias in ant colony optimization: on the role of competition-balanced systems. *Transactions on Evolutionary Computation*, *9*(2), 159-174.

Blum, C. (2005). Ant colony optimization: introduction and recent trends. *Physics of Life Reviews*, *2*(4), 353-373.

Brogini, A. & Slanzi, D. (2010). Several computational studies about variable selection for probabilistic Bayesian classifiers. In F. Palumbo, C. Lauro & M. Greenacre (Eds.), *Data analysis and classification, studies in classification, data analysis, and knowledge organization*, (pp.1-9). Berlin Heidelberg: Springer.

Bullnheimer, B., Hartl, R. F. & Strauss, C. (1999). A new rank-based version of the ant system: a computational study. *Central European for Operations Research and Economics*, 7(1), 25 – 38.

Castro, L. (2007). Fundamentals of natural computing: an overview. *Physics of Life Reviews*, *4*(1), 1-36.

Chang, C. & Lin, C. (2011). LIBSVM: a library for support vector machines. Retrieved April 16, 2012, from http://www.csie.ntu.edu.tw/~cjlin/papers/libsvm.pdf.

Chang-Wei, M. & Guang-Yuan, L. (2009). Feature extraction, feature selection and classification from electrocardiography to emotions. Proceeding of the International Conference on Computational Intelligence and Natural Computing, 6-7 June 2009, Wuhan, 190 - 193.

Chapelle, O. & Vapnik, V. (2000). *Model selection for support vector machines*. Retrieved January 1, 2011, from http://olivier.chapelle.cc/pub/nips99.pdf.

Chapelle, O., Vapnik, V., Bousquet, O. & Mukherjee, A. (2002). Choosing multiple parameters for support vector machines. *Machine Learning*. 46(1-3), 131-159.

Chen, B., Chen & Chen, Y. (2013). Efficient ant colony optimization for image feature selection. *Signal Processing 93*(6), 1566-1576.

Chen, H., Liu, G. & Xiong, X. (2011). A novel feature selection method for affective recognition based on pulse signal. Proceeding of The 4th International Symposium on Computational Intelligence and Design, 28-30 October 2011, Hangzhou, 110 - 113.

Chen, L., Sun, H. & Wang, S. (2009). Solving continuous optimization using ant colony algorithm. Proceedings of The 2nd International conference on Future Information Technology and Management Engineering, 13-14 December 2009, Sanya, 92-95.

Chen, Y.-W. & Lin, C.-J. (2006). Combining SVMs with various feature selection strategies. In I. Guyon, M. Nikravesh, S. Gunn & L. Zadeh (Eds.), *Feature Extraction*, (pp. 315-324). Berlin Heidelberg: Springer.

Cheng, X., Xu, J., Pei, J. & Liu, J. (2010). Hierarchical distributed data classification in wireless sensor networks. *Computer Communications*, *33*(12), 1404-1413.

Choi, Y. & Noh, J. (2004). Relevance feedback for content-based image retrieval using proximal support vector machine. In A. Lagana, M. Gavrilova, V. Kumar, Y. Mun, C. J. Tan & O. Gervasi (Eds.), *Computational science and its applications*, (pp. 942-951). Berlin Heidelberg: Springer.

Christen, P. (2009). Development and user experiences of an open source data cleaning, deduplication and record linkage system. *SIGKDD Explorations, 11*(1), 39-48.

Colak, I., Sagiroglu, S. & Yesilbudak, M. (2012). Data mining and wind power prediction: a literature review. *Renewable Energy*, *46*, 241-247.

Colorni, A., Dorigo, M. & Maniezzo, V. (1991). Distributed optimization by ant colonies. Proceedings of The 1st European Conference on Artificial Life, Paris, 134 – 142.

Cortes, C. & Vapnik, V. (1995). Support-vector networks. *Machine Learning, 20*(3), 273-297.

David, V. & A. S. (2003). Advanced support vector machines and kernel methods. *Neurocomputing, 55*(1-2), 5-20.

Deriche, M. (20009). Feature selection using ant colony optimization. Proceedings of The 6th International Multi-Conference on Systems, Signals and Devices, 23-26 March 2009, Djerba, 1-4.

Ding, S. & Li, S. (2009). Clonal selection algorithm for feature selection and parameters optimization of support vector machines. Proceedings of The 2nd International Symposium on Knowledge Acquisition and Modeling, 30 November-1 December 2009, Wuhan, 17-20.

Dioşan, L., Rogozan, A. & Pecuchet, J.-P. (2012). Improving classification performance of support vector machine by genetically optimizing kernel shape and hyper-parameters. *Applied Intelligence*, *36*(2), 280-294.

Dong, Y., Xia, Z., Tu, M. & Xing, G. (2007). An optimization method for selecting parameters in support vector machines. Proceedings of The 6th International Conference on Machine Learning and Applications, 13-15 December 2007, Cincinnati, OH, 1-6.

Dorigo, M. & Blum, C. (2005). Ant colony optimization theory: a survey. *Theoretical Computer Science, 344*(2-3), 243-278.

Dorigo, M. & Gambardella, L. M. (1997). Ant colony system: a cooperative learning approach to the traveling salesman problem. *IEEE Transactions on Evolutionary Computation, 1*(1), 53 – 66.

Dorigo, M. & Stützle, T. (2003). The ant colony optimization metaheuristic: algorithms, applications, and advances. In F. Glover & G. Kochenberger (Eds.), *Handbook of Metaheuristics,* (pp. 250-285). Springer: US.

Dorigo, M. & Stützle, T. (2004). Ant colony optimization. Cambridge, England: MIT Press.

Dorigo, M. & Stützle, T. (2010). Ant colony optimization: overview and recent advances. In M. Gendreau & J.-Y. Potvin (Eds.), *Handbook of Metaheuristics*, (pp. 227-263). Springer: US.

Dorigo, M., Birattari, M. & Stützle, T. (2006b). Ant colony optimization artificial ants as a computational intelligence technique. *Computational Intelligence Magazine*, 1(4), 28-39.

Dorigo, M., Oca, M., Oliveira, S. & Stützle, T. (2011). *Ant colony optimization*. Wiley Encyclopedia of Operations Research and Management Science.

Dreo, J. & Siarry, P. (2002). A new ant colony algorithm using the heterarchical concept aimed at optimization of multiminima continuous functions. In M. Dorigo., G. Caro & M. Samples (Eds.), *Ant algorithms* (pp. 216-221). Berlin Heidelberg: Springer.

Dreo, J. & Siarry, P. (2004). Continuous interacting ant colony algorithm based on dense heterarchy. *Future Generation Computer Systems*, *20*(5), 841-856.

Dreo, J. & Siarry, P. (2006). An ant colony algorithm aimed at dynamic continuous optimization. *Applied Mathematics and Computation*, *181*(1), 457-467.

Dreo, J. & Siarry, P. (2007). Hybrid continuous interacting ant colony aimed at enhanced global optimization. *Algorithmic Operations Research. 2*(1), 52-64.

Dunbar, M., Murray, J., Cysique, L., Brew, B. & Jeyakumar, V. (2010). Simultaneous classification and feature selection via convex quadratic programming with application to HIV-associated neurocognitive disorder assessment. *European Journal of Operational Research, 206*(2), 470-478.

Fan, R.-E., Chen, P.-H. & Lin, C.-J. (2005). Working set selection using second order information for training support vector machines. *Journal of Machine Learning Research, 6*, 1889-1918.

Fang, X. & Bai, T. (2009). Share price prediction using wavelet transform and ant colony algorithm for parameters optimization in SVM. Proceedings of The Global Congress on Intelligent Systems, 19-21 May 2009, Xiamen, 288-292.

Fang, Z. & Li, Q. (2009). An integrated space-time pattern classification approach for individuals' travel trajectories. Proceeding of The 6^{th} International Conference on Fuzzy Systems and Knowledge Discovery, 14-16 August 2009, Tianjin,119-123.

Farvaresh, H. & Sepehri, M. (2011). A data mining framework for detecting subscription fraud in telecommunication. *Engineering Applications of Artificial Intelligence*, *24*(1). 182-194.

Feki, A., Ishak, A. & Feki, S. (2012). Feature selection using Bayesian and multiclass support vector machines approaches: application to bank risk prediction. *Expert Systems with Applications, 39*(3), 3087-3099.

Foithong, S., Pinngern, O. & Attachoo, B. (2012). Feature subset selection wrapper based on mutual information and rough sets. *Expert Systems with Applications, 39*(1), 574-584.

Forrester, E. (2006). *A process research framework.* Pittsburgh, USA: Carnegie Mellon University.

Franca, F., Coelho, G., Zuben, F. & Attux R. (2008). Multivariate ant colony optimization in continuous search spaces. Proceedings of The 10th Annual Conference on Genetic and Evolutionary Computation, 12-16 July 2008, Atlanta, Georgia, USA, 9-16.

Frohlich, H., Chapelle, O. & Scholkopf, B. (2003). Feature selection for support vector machines by means of genetic algorithms. Proceedings of The 15th International Conference on Tools with Artificial Intelligence, 3-5 November 2003, 142-148.

Fu, Z., Lu, G., Ting, K. M. & Zhang, D. (2013). Efficient nonlinear classification via low-rank regularised least squares. *Neural Computing & Applications, 22*(7-8), 1279-1289.

Garbarine, E., DePasquale, J., Gadia, V., Polikar, R. & Rosen, G. (2011). Information-theoretic approaches to SVM feature selection for metagenome read classification. *Computational Biology and Chemistry, 35*(3), 199-209.

Garde, A., Voss, A., Caminal, P. & Benito, S. (2013). SVM-based feature selection to optimize sensitivity–specificity balance applied to weaning. *Computers in Biology and Medicine, 43*(5), 533-540.

Glasmachers, T. & Igel, C. (2010). Maximum likelihood model selection for 1-norm soft margin SVMs with multiple parameters. *Transactions on Pattern Analysis and Machine Intelligence, 32*(8), 1522-1528.

Gürbüz, F., Özbakir, L. & Yapici, H. (2011). Data mining and preprocessing application on component reports of an airline company in turkey. *Expert Systems with Applications, 38*(6). 6618-6626.

Guyon, I., Weston, J., Barnhill, S. & Vapnik, V. (2002). Gene selection for cancer classification using support vector machines. *Machine Learning*, *46*(1-3), 389-422.

Hall, M. (2000). *Feature selection for discrete and numeric class machine learning*. Retrieved December 20, 2010, from http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.148.6025.

Han, H., Hou-Jun, W. & Xiucheng, D. (2011). Transformer fault dignosis based on feature selection and parameter optimization. *Energy Procedia, 12*, 662-668.

Harvey, J. (2009). *GPI acceleration object classification algorithm using NVIDIA CUDA*. (Master Thesis, Rochester Institute of Technology, 2009). Retrieved from http://ritdml.rit.edu/bitstream/handle/1850/10894/35445_pdf_00B0B24A-DFD8-11DE-9A30-D21AD352ABB1.pdf?sequence=1.

Hidalgo-Muňoz, A.R., López, M.M., Santos, I.M., Pereira, A.T., Vázquez-Marrufo, M., Galvao-Carmona, A. & Tomé, A.M. (2013). Application of SVM-RFE on EEG signals for detecting the most relevant scalp regions linked to affective valence processing. *Expert systems with Applications, 40*(6), 2101-2108.

Hong, L. & Shibo, X. (2008). On ant colony algorithm for solving continuous optimization problem. Proceedings of The International Conference on Intelligent Information Hiding and Multimedia Signal Processing, 15-17 August 2008, Harbin, 1450 - 1453.

Hric, M., Chmulik, M. & Jarina, R. (2011). Model parameters selection for SVM classification using Particle Swarm Optimization. Proceedings of The 21st International Conference of the Radioelektronika, 19-20 April 2011, Brno, 1-4.

Hsu, C.-W. & Lin, C.-J. (2002a). A simple decomposition method for support vector machines. *Machine Learning, 46,* 291-314.

Hsu, C.-W. & Lin, C.-J. (2002b). A comparison of methods for multiclass support vector machines. *Neural Networks, 13*(2), 415-425.

Hu, Q., Pan, W., Song, Y. & Yu, D. (2012). Large-margin feature selection for monotonic classification. *Knowledge-Based Systems, 31*, 8-18.

Hu, X., Zhang, J. & Li, Y. (2008). Orthogonal methods based ant colony search for solving continuous optimization problems. *Computer Science and Technology*, *23*(1), 2-18.

Hu, X., Zhang, J., Chung, H., Li, Y. & Liu, O. (2010). SamACO:variable sampling ant colony optimization algorithm for continuous optimization. *Transactions on System, Man, and Cybernetics*, *40*(6), 1555-1566.

Huang, C. & Dun, J. (2008). A Distributed PSO-SVM hybrid system with feature selection and parameter optimization. *Applied Soft Computing, 8*(4), 1381-1391.

Huang, C. & Wang, C. (2006). A GA-based feature selection and parameters optimization for support vector machines. *Expert Systems with Applications*, 31(2), 231-240.

Huang, C. (2009). ACO-based hybrid classification system with feature subset selection and model parameters optimization. *Neurocomputing*, 73(1-3), 438-448.

Huang, H. & Hao, Z. (2006). ACO for continuous optimization based on discrete encoding. In M. Dorigo, L. Gambardella, M. Birattari, A. Martinoli, R. Poli & T. Stützle (Eds.), *Ant colony optimization and swarm intelligence* (pp. 504-505). Berlin Heidelberg: Springer.

Huang, H., Xie, H.-B., Guo, J.-Y. & Chen, H.-J. (2012). Ant colony optimization-based feature selection method for surface electromyography signals classification. *Computers in Biology and Medicine, 42*(1), 30-38.

Ibrahim, R., Sethu, V. & Ambikairajah, E. (2010). Novel delta zero crossing regression features for gait pattern classification. Proceeding of The 32nd Annual International Conference of The on Engineering in Medicine and Biology Society, 31 August-4 September 2010, Buenos Aires, 2427 – 2430.

Imbault, F. & Lebart, K. (2004). A stochastic optimization approach for parameter tuning of support vector machines. Proceedings of The 17th International Conference on Pattern Recognition, 23-26 August 2004, 597-600.

Jensen, R. & Shen, Q. (2004). Fuzzy-rough data reduction with ant colony optimization. *Fuzzy Sets and Systems, 149* (1), 5–20.

Jensen, R. (2006). Performing feature selection with ACO. In A. Abraham, C. Grosan & V. Ramos (Eds.), *Swarm intelligence in data mining*, (pp 45-73). Berlin Heidelberg: Springer.

Jin, Y., Hu, Y., Huang, J. & Zhang, J. (2011). Study on influences of model parameters on the performance of SVM. Proceedings of The International Conference on Electrical and Control Engineering, 16-18 September 2011, Yichang, 3667 - 3670.

Jin, Z., Chen, Y. & Ma, X. (2010). Model selection for SVM based on similarity margin of inner product. Proceedings of The Conference on Control and Decision Conference, 26-28 May 2010, Xuzhou, 1653 - 1657.

Ju, W., Shan, J., Yan, C. & Cheng, H. (2009). Discrimination of disease-related non-synonymous single nucleotide polymorphisms using multi-scale RBF kernel fuzzy support vector machine. *Pattern Recognition Letters*, *30*(4), 391-396.

Kabir, M., Shahjahan, M. & Murase, K. (2009). An efficient feature selection using ant colony optimization algorithm. In C. Leung & J. Chan (Eds.), *Neural information processing*, (pp. 242-252). Berlin Heidelberg: Springer.

Kabir, M., Shahjahan, M. & Murase, K. (2012). A new hybrid ant colony optimization algorithm for feature selection. *Expert Systems with Applications*, *39*(3), pp. 3747-3763.

Kadoury, S. & Levine, M. (2006). Finding faces in gray scale images using locally linear embeddings. In H. Sundaram, M. Naphade, J. Smith & Y. Rui

(Eds.), *Image and video retrieval*, (pp. 221-230). Berlin Heidelberg: Springer.

Kanan, H. & Faez, L. (2008). An improved feature selection method based on ant colony optimization (ACO) evaluated on face recognition system. *Applied Mathematics and Computation*, *205*(2), 716-725.

Kanan, H., Faez, K. & Taheri, S. (2007). Feature selection using ant colony optimization (ACO): A new method and comparative study in the application of face recognition system. In P. Perner (Ed), *Advances in Data Mining. Theoretical Aspects and Applications,* (pp. 63-76). Berlin Heidelberg: Springer.

Kapp, M. N., Sabourin, R. & Maupin, P. (2012). A dynamic model selection strategy for support vector machine classifiers. *Applied Soft Computing*, *12*(8), 2550–2565.

Kapp, M., Sabourin, R. & Maupin, P. (2009). A PSO-based framework for dynamic SVM model selection. Proceedings of The 11th Annual Conference on Genetic and Evolutionary Computation, 8-12 July 2009, Montréal Québec, Canada, 1227-1234.

Khalid, S. & Razzaq, S. (2012). Frameworks for multivariate *m*-mediods based modelling and classification in Euclidean and general feature spaces. *Pattern Recognition, 45*(3), 1092-1103.

Khashei, M., Hamadani, A. Z. & Bijari, M. (2011). A fuzzy intelligent approach to the classification problem in gene expression data analysis. *Knowledge-Based Systems, 27*, 465–474.

Khashei, M., Zeinal Hamadani, A. & Bijari, M. (2012). A novel hybrid classification model of artificial neural networks and multiple linear regression models. *Expert Systems with Applications, 39*(3), 2606-2620.

Khushaba, R., AlSukker, A., Al-Ani, A. & Al-Jumaily, A. (2008a). A combined ant colony and differential evolution feature selection algorithm. In M. Dorigo, M. Birattari, C. Blum, M. Clerc, T. Stützle & A. Winfield (Eds.), *Ant Colony Optimization and Swarm Intelligence*, (pp. 1-12). Berlin Heidelberg: Springer.

Khushaba, R., AlSukker, A., Al-Ani, A. & Al-Jumaily, A. (2008b). Intelligent artificial ants based feature extraction from wavelet packet coefficients for biomedical signal classification. Proceeding of The 3rd International Symposium on Communications, Control and Signal Processing, 12-14 March 2008, St Julians, 1366 – 1371.

Kong, M. & Tian, P. (2005). A binary ant colony optimization for the unconstrained function optimization problem. In Y. Hao, J. Liu, Y. Wang, Y.-M. Cheung, H. Yin, L. Jiao, J. Ma & Y.-C. Jiao (Eds.), Computational intelligence and security, (pp. 632-687). Berlin Heidelberg: Springer.

Kong, M. & Tian, P. (2006a). Application of ACO in continuous domain. In L. Jiao, L. Wang, X. Gao, J. Liu & F. Wu (Eds.), *Advances in Natural Computation*, (pp. 126-135). Berlin Heidelberg: Springer.

Kong, M. & Tian, P. (2006b). A direct application of ant colony optimization to function optimization problem in continuous domain. In M. Dorigo, L. Gambardella, M. Birattari, A. Martinoli, R. Poli & T. Stützle (Eds.), ant colony optimization and swarm intelligence, (pp. 324-331). Berlin Heidelberg: Springer.

Kovářík, O. (2006). *Ant colony optimization for continuous problems*. (Master Thesis, Czech Technical University in Prague, 2006). Retrieved from http://fakegame.sourceforge.net/lib/exe/fetch.php?media=ants-optimalizace.pdf.

Kumar, R. (2011). Research methodology: a step-by-step guide for beginners (3rd Ed.). London: Sage Publications Ltd.

Lázaro-Gredilla, M., Gómez-Verdejo, V. & Parrado-Hernández. Low-cost model selection for SVMs using local features. (2012). *Engineering Application of Artificial Intelligence, 25*(6), 1203-1211.

Lei, L. & Qiao, G. (2012). Text categorization using SVM with exponent weighted ACO. Proceedings of The 31st Chinese Control Conference, 25-27 July 2012, Hefei, 3763 - 3768.

Lessmann, S., Stahlbock, R. & Crone, S. (2006). Genetically constructed kernels for support vector machines. In Hans H., Herbert K. & Jorn S. (Eds.), *Operations research*, (pp. 257-262). Berlin Heidelberg: Springer.

Li, N. & Zhou, R. (2011). A new approach to fault pattern classification of gasoline engine vibration. Proceedings of The 8th International Conference on Fuzzy systems and Knowledge Discovery, 26-28 July 2011, Shanghai, 1892 - 1896.

Li, S. & Tan, M. (2010). Tuning SVM parameters by using a hybrid CLPSO-BFGS algorithm. *Neuro Computing*, *73*(10-12), 2089-2096.

Li, W., Liu, L. & Gong, W. (2011). Multi-objective uniform design as a SVM model selection tool for face recognition. *Expert Systems with Applications, 38*(6), 6689-6695.

Li, X. & Chen, Z. (2010). Weed identification based on shape features and ant colony optimization algorithm. Proceeding of the International Conference on Computer Application and system Modeling, 22-24 October 2010, Taiyuan, 384-387.

Li, Y., Wang, G., Chen, H., Shi, L. & Qin, L. (2013). An ant colony optimization based dimension reduction method for high-dimensional datasets. *Journal of Bionic Engineering, 10*(2), 231-241.

Lian, H. (2012). On feature selection with principle component analysis for one-class SVM. *Pattern Recognition Letters, 33*(9), 1027-1031.

Liao, S., Yang, C. & Ding, L. (2011). Approximate parameter tuning of support vector machines. Proceedings of The 3rd International Workshop on Intelligent System and Applications, 28-29 May 2011, Wuhan, 1-4.

Liao, T. (2011). *Improved ant colony optimization algorithms for continuous and mixed discrete-continuous optimization problems* (Report No. 2010/2011). Retrieved from IRIDIA, Universite Libre de Bruxelles: Brussels, Belgium website: http://iridia.ulb.ac.be/~tliao/papers/DEAreport-Liao.pdf.

Liao, T., Oca, M., Aydin, D., Stützle, T. & Dorigo, M. (2011). *An incremental ant colony algorithm with local search for continuous optimization* (Report No. TR/IRIDIA/2011-005). Retrieved from IRIDIA, Universite Libre de

Bruxelles: Brussels, Belgium website: http://iridia.ulb.ac.be/IridiaTrSeries/rev/IridiaTr2011-005r002.pdf.

Lin, K. & Chien, H. (2009). CSO-based feature selection and parameter optimization for support vector machine. Proceedings of The Joint Conference on Pervasive Computing, 3-5 December 2009, Tamsui, Taipei, 783-788.

Lin, S., Lee, Z.-J., Chen, S.-C. & Tseng, T.-Y. (2008). Parameter determination of support vector machine and feature selection using simulated annealing approach. *Applied Soft Computing, 8*(4), 1505-1512.

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

Lin, X., Yang, F., Zhou, L., Yin, P., Kong, H. Xing, W., Li, X., Jia, L., Wang, Q. & Xu, G. (2012). A support vector machine-recursive feature elimination feature selection method based on artificial contrast variables and mutual information. *Journal of Chromatography B*, *910*, 149-155.

Liu, A., Cao, H., Chen, X., He, Z. & Shen, Z. (2013). Multi-fault classification based on wavelet SVM with PSO algorithm to analyze vibration signals from rolling element bearings. *Neurocomputing, 99*, 399-410.

Liu, G., Zhou, D., Xu, H. & Mei, C. (2010). Model optimization of SVM for a fermentation soft sensor. *Expert Systems with Applications, 37*(4), 2708-2713.

Liu, H., Liu, L. & Zhang, H. (2010). Ensemble gene selection by grouping for microarray data classification. *Journal of Biomedical Informatics*, *43*(1), 81-87.

Liu, J. & Yuan , X. (2009). Obscure bleeding detection in endoscopy images using support vector machines. *Optimization Engineering*, *10*(2), 289-299.

Liu, Q., Chen, C., Zhang, Y. & Hu, Z. (2011). Feature selection for support vector machines with RBF kernel. *Artificial Intelligence Review, 36*(2), 99-115.

Liu, W. & Zhang, D. (2009). Feature subset selection based on improved discrete particle swarm and support vector machine algorithm. Proceedings of The Information Engineering and Computer Science, 19-20 December 2009, Wuhan, 1-4.

Liu, Y. & Zheng, F. (2006). FS-SFS: A novel feature selection method for support vector machines. *Pattern Recognition*, *39*(7), 1333-1345.

Lu, N., Zhou, J., He, Y. & Liu, Y. (2009). Particle swarm optimization for parameter optimization of support vector machine model. Proceedings of The 2nd International Conference on Intelligent Computation Technology and Automation, 10-11 October 2009, Changsha, Hunan, 283-286.

Luo, Z.-Y., Zhang, W.-F., Ye, B.-Y. & Cai, L.-Q. (2008). Wavelet SVM ensemble for pattern classification with quantum-inspired evolutionary algorithm. Proceedings of The International Conference on Wavelet Analysis and Pattern Recognition, 30-31 August 2008, Hong Kong, 485 - 490.

Madadgar, S. & Afshar, A. (2011). Forced water main design mixed ant colony optimization. *International Journal of Optimization in Civil Engineering, 1,* 47-71.

Maldonado, S. & Weber, R. (2009). A wrapper method for feature selection using support vector machines. *Information Sciences, 179*(13), 2208-2217.

Maldonado, S., Weber, R. & Basak, J. (2011). Simultaneous feature selection and classification using kernel-penalized support vector machines. *Information Science, 181*(1), 115-128.

Marcus, K. & Akila, M. (2010). Personal authentication based on keystroke dynamic using soft computing techniques. Proceedings of The 2nd International Conference on Communication Software and Network, 26-28 February 2010, Singapore, 334 - 338.

Mastrogiannis, N., Boutsinas, B. & Giannikos, I. (2009). A method for improving the accuracy of data mining classification algorithms. *Computers & Operations Research, 36*(10), 2829-2839.

Mesleh, A. & Kanaan, G. (2008). Support vector machines text classification system: using ant colony optimization based feature subset selection. Proceedings of The International Conference on Computer Engineering & Systems, 25-27 November 2008, Cairo, Egypt, 143-148.

Monmarch, M., Venturini, G. & Slimane, M. (2000). On how pachycondyla apicalis ants suggest a new search algorithm. *Future Generation Computer Systems,* 16(8), 937-946.

Moustakidis, S. & Theocharis, J. (2010). SVM-FuzCoC: A novel SVM-based feature selection method using a fuzzy complementary criterion. *Pattern Recognition*, *43*(11), 3712-3729.

Nemati, S., Basiri, M., Ghasem-Aghaee, N. & Aghdam, M. (2009). A novel ACO-GA hybrid algorithm for feature selection in protein function prediction. *Expert System with Applications, 36*(10), 12086-12094.

Nguyen, H., Ohn, S., Chae, S., Song, D. & Lee, I. (2006). Optimizing weighted kernel function for support vector machine by genetic algorithm. In A. Gelbukh & C. Garcia (Eds.), *Advances in artificial intelligence*, (pp. 583-592). Berlin Heidelberg: Springer.

Nguyen, M. & Torre, F. (2010). Optimal feature selection for support vector machines. *Pattern Recognition, 43*(3), 584-591.

Oliveira, L., Sabourin, R., Bortolozzi, F. & Suen, C. (2003). A methodology for feature selection using multi-objective genetic algorithms for handwritten digit string recognition. *International Journal of Pattern Recognition and Artificial Intelligence (IJPRAI)*, *17*(6), 1-35.

Örkcü, H. & Bal, H. (2011). Comparing performance of back propagation and genetic algorithms in the data classification. *Expert Systems with Applications,38*(4), 3703-3709.

Otero, F., Freitas, A. & Johnson, C. (2012). Inducing decision trees with an ant colony optimization algorithm. *Applied Soft Computing, 12*(11), 3615-3626.

Partridge, D., Wang, W. & Jones, P. (2001). Efficient and effective feature selection in the presence of feature interaction and noise. In S. Singh, N. Murshed & W. Kropatsch (Eds.), *Advances in pattern recognition* (pp. 196–204), Berlin Heidelberg: Springer.

Pellegrini, P. Favaretto, D. & Moretti, E. (2007). Multiple ant colony optimization for a rich vehicle routing problem: a case study. In B. Apolloni, R. Howlett & L. Jain (Eds.). *Knowledge-based intelligent information and engineering systems* (pp. 627-634), Berlin Heidelberg: Springer.

Peng, Y., Wu, Z. & Jiang, Z. (2010). A novel feature selection approach for biomedical data classification, *Journal of Biomedical Informatics*, *43*(1), pp. 15-23.

Pham, D., Muhamad, Z., Mahmuddin, M., Ghanbarzadeh, A., Koc, E. & Otri, S. (2007). *Using the bees algorithm to optimise a support vector machine for wood defect classification*. *Conference on Innovative Production Machines and Systems Virtual*.

Phokharatkul, P. & Phaiboon, S. (2011). Control chart pattern classification using Fourier descriptors and neural networks. Proceedings of The 2nd International Conference on Artificial Intelligence, Management Science and Electronic Commerce, 8-10 August 2011, Deng Leng, 4587 - 4590.

Polat, K. & Güneş, S. (2009). A new feature selection method on classification of medical datasets: kernel F-score feature selection. *Expert Systems with Applications, 36*(7), 10367-10373.

Polat, K. (2013). Data weighting method on the basis of binary encoded output to solve multi-class pattern classification problems. *Expert Systems with Applications, 40*(11), 4637-4647.

Pourtakdoust, S. & Nobahari, H. (2004). An extension of ant colony system to continuous optimization problems. In M. Dorigo, M. Birattari, C. Blum, L. Gambardella, F. Mondada, T. Stützle (Eds.), *Ant colony optimization and swarm intelligence,* (pp. 294-301), Berlin Heidelberg: Springer.

Qi, Z., Tian, Y. & Shi, Y. (2013). Robust twin support vector machine for pattern classification. *Pattern Recognition, 46*(1), 305–316.

Qian, Q., Chen, S. & Cai, W. (2011). Simultaneous clustering and classification over cluster structure representation. *Pattern Recognition, 45*(6), 2227–2236.

Qiu, D., Li, Y., Zhang, X. & Gu, B. (2011). Support vector machine with parameter optimization by bare bones differential evolution. Proceedings of The 7th International Conference of the Natural Computation, 26-28 July 2011, Shanghai, 263-266.

Rasmy, M., El-Beltagy, M., Saleh, M. & Mostafa, B. (2012). A hybridized approach for feature selection using ant colony optimization and ant-miner for classification. Proceedings of The 8th International Conference on Informatics and Systems, 14-16 May 2012, Cairo, Egypt, BIO-211 - BIO-219.

Reed, S., Reed, T. & Dascalu, S. (2010). High dimensional pattern recognition using the recursive hyperspheric classification algorithm. Proceedings of The World Automatic Congress, 19-23 September 2010, Kobe, 1-8.

Reif, M., Shafait, F. & Dengel, A. (2012). Meta-learning for evolutionary parameter optimization of classifiers. *Machine Learning, 87*(3), 357-380.

Ren, J., Shen, Y., Ma, S. & Guo, L. (2004). Applying multi-class SVMs into scene image classification. In B. Orchard, C. Yang & M. Ali (Eds.), *Innovations in applied artificial intelligence*, (pp. 924-934). Berlin Heidelberg: Springer.

Saini, L., Aggarwal, S. & Kumar, A. (2010). Parameter optimization using genetic algorithm for support vector machine-based price-forecasting model in national electricity market. *IET Generation, Transmission & Distribution, 4*(1), 36-49.

Salama., M. Hassanien, A. & Fahmy, A. (2010). Pattern-based subspace classification model. Proceedings of The 2nd World Congress on Natural and Biologically Inspired Computing, 15-17 December 2010, Fukuoka, 357 - 362.

Salama., M. Hassanien, A. & Fahmy, A. (2010). Uni-class pattern-based classification model. Proceedings of The 10th International Conference on Intelligent Systems Design and Applications, 29 November-1 December 2010, Cairo, Egypt, 1293 - 1297.

Saltan, M., Terzi, S. & Küçüksille, E. (2011). Backcalculation of pavement layer moduli and poission's ratio using data mining. *Expert Systems with Applications, 38*(3), 2600-2608.

Samadzadegan, F., Soleymani, A. & Abbaspour, A. (2010). Evaluation of genetic algorithms for tuning SVM parameters in multi-class problems.

Proceedings of The 11th International Symposium on Computational Intelligence and Informatics, 18-20 November 2010, Budapest, 323-328.

Santana, L., Canuto, A. & Silva, L. (2011). Bio-inspired meta-heuristic as feature selector in ensemble systems: a comparative analysis. Proceedings of The international Joint Conference on Neural Networks, 31 July-5 August 2011, San Jose, CA, 1112 - 1119.

Santana, L., Silva, L., Canuto, A., Pintro, F. & Vale, K. (2010). A comparative analysis of genetic algorithm and ant colony optimization to select attributes for an heterogeneous ensemble of classifiers. Proceedings of The Congress on Evolutionary Computation, 18-23 July 2010, Barcelona, 1-8.

Sanz, S., Cumplido, M., Cruz, F. & Calzon, C. (2002). Feature selection via genetic optimization. In J. Dorronsoro (Ed.), *Artificial Neural Networks*, (pp. 547–552). Berlin Heidelberg: Springer.

Sarafrazi, S. & Nezamabadi-pour, H. (2013). Facing the classification of binary problems with a GSA-SVM hybrid system. *Mathematical and Computer Modelling, 57*(1-2), 270-278.

Sartakhti, J. S., Zangooei, M. H. & Mozafari, K. (2011). Hepatitis disease diagnosis using a novel hybrid method based on support vector machine and simulated annealing (SVM-SA). *Computer Methods and Programs in Biomedicine, 108*(2), *570-579*.

Schaffernicht, E., Stephan, V. & Groß, H. (2007). An efficient search strategy for feature selection using chow-liu trees. In J. de Sá, L. Alexandre, W. Duch,

D. Mandic (Eds.). *Artificial neural networks*. (pp. 190-199). Berlin Heidelberg: Springer.

Seçkiner, S., Eroğlu, Y., Emrullah, M. & Dereli, T. (2013). Ant colony optimization for continuous functions by using novel pheromone updating. *Applied Mathematics and Computation, 219*(9). 4163-4175.

Sim, K. & Sun, W. (2003). Multiple ant colony optimization for load balancing. In J. Liu, Y.-M. Cheung & H. Yin (Eds.). *Intelligent data engineering and automated learning,* (pp. 467-471). Berlin Heidelberg: Springer.

Shahjahan, M. & Murase, K. (2009). An efficient feature selection using ant colony optimization algorithm. In C. Leung & J. Chan (Eds.), *Neural information processing*, (pp. 242-252). Berlin Heidelberg: Springer.

Shieh, M. & Yang, C. (2008). Multiclass SVM-RFE for product from feature selection. *Expert Systems with Applications*, *35*(1-2), 531-541.

Sivagaminathan, R. & Ramakrishnan, S. (2007). A hybrid approach for feature subset selection using neural networks and ant colony optimization. *Expert Systems with Applications, 33*(1), 49-60.

Socha, K. & Blum, C. (2006). Ant colony optimization. In E. Alba & R. Martí (Eds.), *Metaheuristic procedures for training neutral networks*, (pp. 153-180). Springer: US.

Socha, K. & Dorigo, M. (2008). Ant colony optimization for continuous domain. *European Journal of Operational Research, 185*(3), 1155-1173.

Socha, K. (2004). ACO for continuous and mixed-variable optimization. In M. Dorigo, M. Birattari, C. Blum, L. Gambardella & F. Mondada (Eds.), *Ant*

Colony Optimization and Swarm Intelligence, (pp. 25-36). Berlin Heidelberg: Springer.

Socha, K. (2008). *Ant colony optimization for continuous and mixed-variables domain*. (Doctoral dissertation, Universite' Libre de Bruxelles, 2008). Retrieved from *iridia.ulb.ac.be/~mdorigo/HomePageDorigo/thesis/SochaPhD.pdf.*

Stützle, T. & Hoos, H. (1997). MAX-MIN ant system and local search for the traveling salesman problem. Proceedings of the International Conference on Evolutionary Computation. 13-16 April, Indianapolis, 309 – 314.

Su, C. & Yang, C. (2008). Feature selection for the SVM: An application to hypertension diagnosis. *Expert Systems with Applications, 34*(1), 754-763.

Sun, J., Zheng, C., Li, X. & Zhou, Y. (2010). Analysis of the distance between two classes for tuning SVM hyperparameters. *Transaction on Neural Networks, 21*(2), 305-318.

Tan, J., Zhang, Z., Zhen, L., Zhang, C. & Deng, N. (2012). Adaptive feature selection via a new version of support vector machine. *Neural Computing & Applications*.

Tan, P.-N., Steinbach, M. & Kumar, V. (2006). Introduction to data mining. Addison Wesley.

Tang, Y., Guo, W. & Gao, J. (2009). Efficient model selection for support vector machine with Gaussian kernel function. Proceedings of The Symposium on Computational Intelligence and Data Mining, 30 March-2 April 2009, Nashville, TN, 40-45.

Theresa, M. & Raj, V. (2013). Fuzzy based genetic neural networks for the classification of murder cases using trapezoidal and lagrange interpolation membership functions. *Applied Soft Computing, 13*(1), 743-754.

Thomas, A. & Oommen, B. (2013). The fundamental theory of optimal "anti-Bayesian" parametric patter classification using order statistics criteria. *Pattern Recognition*, *46*(1), 376-388.

Tsai, C. W., Liao, M. Y., Yang, C. S. & Chiang, M. C. (2011). Classification algorithms for interactive multimedia services: a review. *Multimedia Tools and Applications*, 1-29.

Tsai, C.-F. (2010). An evaluation methodology for binary pattern classification systems. Proceedings of The International Conference on Industrial Engineering and Engineering Management, 7-10 December 2010, Macao, 953 - 956.

Tsai, C.-F., Eberle, W. & Chu, C.-Y. (2013). Genetic algorithms in feature and instance selection. *Knowledge-Based systems*, *39*, 240-247.

Tseng, V. S. & Lee, C. H. (2009). Effective temporal data classification by integrating sequential pattern mining and probabilistic induction. *Expert Systems with Applications, 36*(5), 9524-9532.

Twomey, C., Stutzle, T., Dorigo, M., Manfrin, M. & Birattari, M. (2010). An analysis of communication policies for homogeneous multi-colony ACO algorithms. *Information Sciences*, 180(12), 2390-2404.

Tzotsos, A. & Argialas, D. (2008). Support vector machine classification for object-based image analysis. In T. Huang, V. Kecman & I. Kopriva (Eds.), *Kernal based algorithms for mining huge data sets supervised, semi-supervised, and unsupervised learning*, (pp. 663-677). Berlin Heidelberg: Springer.

UCI Repository of Machine Learning Databases, Department of Information and Computer Science, University of California, Irvine, CA, <http://www.ics.uci.edu/mlearn/MLRepository>, 2012.

Üney, F. & Türkay, M. (2006). A mixed-integer programming approach to multi-class data classification problem. *European Journal of Operational Research*, 173(3), 910-920.

Unler, A., Murat, A. & Chinnam, R. (2011). mr^{2}PSO: A maximum relevance minimum redundancy feature selection method based on swarm intelligence for support vector machine classification. *Information Sciences*, *181*(20), 4625-4641.

Vapnik, V. & Chapelle, O. (2000). Bounds on error expectation for support vector machines. *Neural Computation*, *12*(9), 2013-2036.

Vapnik, V. & Vashist, A. (2009). A new learning paradigm: learning using privileged information. *Neural Networks: The Official Journal of The International Neural Network Society, 22*(5-6), 544–557.

Vapnik, V. (1995). The nature of statistic learning theory. NY-USA: Springer.

Vapnik, V. (1999). An overview of statistical learning theory. *Transactions on Neural Networks*, *10*(5), 988-999.

Varewyck, M. & Martens, J.-P. (2011). A practical approach to model selection for support vector machines with a Gaussian kernel. *Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics, 41*(2), 330-340.

Venkatesan, S. & Karnan, M. (2010). Edge and characteristic subset selection in image using ACO. Proceedings of The 2nd International Conference on Computer Research and Development, 7-10 May 2010, Kuala Lumpur, Malaysia, 369 - 372.

Verleysen, M., Rossi, F. & Francois, D. (2009). Advances in feature selection with mutual information. In M. Biehl, B. Hammer, M. Verleysen & T. Villmann (Eds.), *Similarity-based clustering recent developments and biomedical applications,* (pp. 52-69). Berlin Heidelberg: Springer.

Verma, P. & Yadava, R.D.S. (2012). Fuzzy C-means clustering based uncertainty measure for sample weighting boosts pattern classification efficiency. Proceedings of The 2nd National Conference on Computational Intelligence and Signal Processing, 2-3 March 2012, Guwahati, Assam, 31-35.

Vieira, S., Mendonça, L., Farinha, G. & Sousa, J. (2013). Modified binary PSO for feature selection using SVM applied to mortality prediction of septic patients. *Applied Soft Computing, 13*(8), 3494-3504.

Vieira, S., Sousa, J. & Runkler, T. (2007). Ant colony optimization applied to feature selection in fuzzy classifiers. In P. Melin, O. Castillo, L. Aguilar, J. Kacprzyk & W. Pedrycz (Eds.), *Foundations of Fuzzy Logic and Soft Computing*, (pp. 778-788). Berlin Heidelberg: Springer.

Wang, R. (2012). AdaBoost for feature selection, classification and its relation with SVM, a review. *Physics Procedia, 25*, 800-807.

Wang, S. & Meng, B. (2011). Parameter selection algorithm for support vector machine. *Procedia Environmental Sciences*, *11*(Part B), pp. 538-544, 2011.

Wang, T., Huang H., Tian S. & Xu J. (2010). Feature selection for SVM via optimization of kernel polarization with gaussian ARD kernels. *Expert Systems with Applications, 37*(9), 6663-6668.

Wang, X., Liu, X., Pedrycz, W., Zhu, X. & Hu, G. (2012). Mining axiomatic fuzzy association rules for classification problems. *European Journal of Operational Research, 218*(1), 202-210.

Wang, Z. & Chen S. (2007). New least squares vector machines based on matrix patterns. *Neural Processing Letters*, 26(1), 41-56.

Wei, K., Tuo, H. & Jing, Z. (2010). Improving binary ant colony optimization by adaptive pheromone and commutative solution update. Proceedings of The 5th Bio-Inspired Computing: Theories and Applications, 23-26 Septmber 2010, Changsha, 565-569.

Weiss, N. (2008). Introductory statistics (8th Ed.). Boston, USA: Pearson, Addison Wesley.

Weston, J., Mukherjee, S., Chapelle, O., Pontil, M., Poggio, T. & Vapnik, V. (2001). *Feature selection for SVMs*. Retrieved December 20, 2010, from http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.102.7476.

Wu, Z. & Li, C. (2006). Feature selection with transductive support vector machines. In I. Guyon, M. Nikravesh, S. Gunn & L. Zadeh (Eds), *Feature extraction foundation and applications,* (pp. 325-341). Berlin Heidelberg: Springer.

Xie, J. & Wang, C. (2011). Using support vector machines with a novel hybrid feature selection method for diagnosis of erythemato-squamous diseases. *Expert Systems with Applications, 38*(5), 5809-5815.

Xiong, S., Wang, J.-Y. & Lin, H. (2010). Hybrid feature selection algorithm based on dynamic weighted ant colony algorithm. Proceedings of The 9th International Conference on Machine Learning and Cybernetics, 11-14 July 2010, Qingdao, 518 - 522.

Xiong, W. & Wang, C. (2008). Feature selection: a hybrid approach based on self-adaptive ant colony and support vector machine. Proceedings of The International Conference on Computer Science and Software Engineering, 12-14 December 2008, Wuhan, Hubei, 751 - 754.

Xiong, W. & Wang, C. (2009). A hybrid improved ant colony optimization and random forests feature selection method for microarray data. Proceedings of The 5th International Joint Conference on INC, IMS and IDC, 25-27 August 2009, Seoul, Korea, 559 - 563.

Xuan, W., Jiake, L. & Deti, X. (2010). A hybrid approach of support vector machine with particle swarm optimization for water quality prediction. Proceedings of The 5th International Conference on Computer Science and Education, 24-27 August 2010, Hefei, 1158 - 1163.

Xue, X., Sun, W. & Peng, C. (2010). Improved ant colony algorithm for continuous function optimization. Proceedings of The Control and Decision Conference, 26-28 May 2010, Xuzhou, 20 – 24.

Xusheng, G., Wei, C. & Yongxiang, L. (2010). Parameter selection for SVM using niches genetic algorithm in determined range. Proceedings of The 2nd International Conference on Information Management and Engineering, 16-18 April 2010, Chengdu, 492 - 496.

Yang, L., Fu, Z.-Q., Wang, D., Li, H.-L. & Xia, J.-B. (2010). An improved ant colony algorithm for continuous space optimization. Proceedings of The International Conference on Machine Learning and Cybernetics, 11-14 July 2010, Qingdao, 1829–1832.

Yang, Y., Han, C. & Han, D. (2009). A novel feature line segment approach for pattern classification. Proceedings of The 12th International Conference on Information Fusion, 6-9 July 2009, Seattle, WA, 490 - 497.

Ye, Y., Chen, L., Wang, D., Li, T., Jiang, Q. & Zhao, M. (2009). SBMDS: an interpretable string based malware detection system using SVM ensemble with bagging. *Journal in Computer Virology, 5*(4), 283-293.

Yuxia, H. & Hongtao, Z. (2012). Chaos optimization method of SVM parameters selection for chaotic time series forecasting. *Physics Procedia, 25*, 588-594.

Zavar, M., Rahati, S., Akbarzadeh-T, M.-R. & Ghasemifard, H. (2011). Evolutionary model selection in a wavelet-based support vector machine for automated seizure detection. *Expert systems with Applications, 38*(9), 10751-10758.

Zhang, B., Pham, T. & Zhang, Y. (2007). Bagging support vector machines for classification of SELDI-TOF mass spectra of ovarian cancer serum samples. In M. Orgun & J. Thornton (Eds.), *Advances in artificial intelligence*, (pp. 820-826). Berlin Heidelberg: Springer.

Zhang, G. & Li, H.-X. (2010). A probabilistic fuzzy learning system for pattern classification. Proceedings of The International Conference on Systems Man and Cybernetics, 10-13 Oct. 2010, Istanbul, Turkay, 2336 - 2341.

Zhang, H. & Mao, H. (2009). Feature selection for the stored-grain insects based on PSO and SVM. Proceedings of The 2nd International Conference on Knowledge Discovery and Data Mining, 23-25 January 2009, Moscow, Russia, 586-589.

Zhang, H., Xiang, M., Ma, C., Huang, Q., Li, W., Xie, W., Wei, Y. & Yang, S. (2009). Three-class classification models of LogS and LogP derived by using GA-CG-SVM approach. *Molecular Diversity, 13*(2), 261-268.

Zhang, J., Chen, W., Zhong, J., Tan, X. & Li, Y. (2009). Continuous function optimization using hybrid ant colony approach with orthogonal design scheme. In Tzai-Der W. (Eds.), Simulated Evolution and Learning, *The Sixth International Symposium on Neural Networks (ISNN 2009)*, (pp. 126-133). Berlin Heidelberg: Springer.

Zhang, X. & Jiao, L. (2005). Simultaneous feature selection and parameters optimization for SVM by Immune Clonal Algorithm. In L. Wang, K. Chen & Y. Ong (Eds.), *Advances in Natural Computation*, (pp. 905-912). Berlin Heidelberg: Springer.

Zhang, X., Chen, X. & He, Z. (2010). An ACO-based algorithm for parameter optimization of support vector machines. *Expert System with Applications, 37*(9), 6618-6628.

Zhang, X., Chen, X., Zhang, Z. & He, Z. (2008). A grid–based ACO algorithm for parameters optimization in support vector machines. Proceedings of The International Conference on General Computing, 26-28 August 2008, Hangzhou, 805-808.

Zhang, Y. (2008). Evolutionary computation based automatic SVM model selection. Proceedings of The 4th International Conference on Natural Computation, 18-20 October 2008, Jinan, 66-70.

Zhang, Y., Zhang, C., Ma, P. & Su, X. (2010). A hybrid and ensemble intelligent pattern classification algorithm. Proceedings of The 1st International Conference on Pervasive Computing, Signal Processing and Applications, 17-19 September 2010, Harbin, 833 - 836.

Zhao, M., Fu, C., Ji, L., Tang, K. & Zhou, M. (2011). Feature selection and parameter optimization for support vector machines: A new approach based on genetic algorithm with feature chromosomes. *Expert System with Applications, 38*(5), 5197-5204.

Zhou, J., Zhang, A. & Bai, T. (2008). Client classification on credit risk using rough set theory and ACO-based support vector machine. Proceedings of The 4th International Conference on Wireless Communications, Networking and Mobile Computing, 12-14 October 2008, Dalian, 1-4.

Zhou, X. & Xu, J. (2002). A SVM model selection method based on hybrid genetic algorithm and empirical error minimization criterion. In H. Wang, Y. Shen, T. Huang & Z. Zeng (Eds.), *The Sixth International Symposium on Neural Networks,* (pp. 245–253). Berlin Heidelberg: Springer.

Zong, Q., Liu, W. & Dou, L. (2006). Parameters selection for SVR based on PSO. Proceedings of The 6th World Congress on Intelligent Control, 21-23 July 2006, Dalian, China, 2811-2814.