ENSEMBLE SUPPORT VECTOR MACHINES AND DEMPSTER–SHAFER EVIDENCE THEORY FOR MACHINERY MULTI FAULT DIAGNOSIS

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DEDICATION

This thesis is dedicated to my parents, wife, and daughter, who continuously provide their moral, spiritual, and emotional support.

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ABSTRACT

Machinery fault diagnosis is essential for ensuring the integrity of machinery. To this end, vibration analysis has been proven to be the most effective method. However, its effectiveness is highly dependent on the experience and knowledge of the machine operator due to abundance of various machine parameters and the complexity of machinery. Thus, artificial intelligence (AI) or the machine learning approach provides a more consistent diagnostic result based on a trained machine learning model and hence leads to a more automated fault diagnosis system that minimizes human intervention. Support vector machines (SVM) are frequently used in automated machinery fault diagnosis to classify multiple machinery faults by handling a high number of input features with small data sets. However, SVM is well known for binary fault classifications only (i.e., healthy vs. faulty). When SVM is used for multi-fault diagnostics and classification, it results in decreased classification accuracy; this is due to the adaptation of SVM for multi-fault classification which requires the reduction of multiple classification problems into multiple subsets of binary classification problems, producing many contradictory results from each individual SVM model. Thus, this research aims to improve the multi-fault classification accuracy of SVM by the adaptation of Dempster−Shafer (DS) evidence theory which is referred as Ensemble SVM-DS. Besides, a novel feature selection tree (FST) is proposed to improve the computation time of a wrapper-based feature selection algorithm such as a genetic algorithm (GA) as part of the improvement for the proposed model. In order to fulfil the objectives of this study, the scope of the work is divided into two parts: the algorithm development and the experimental study. The initial model of feature selection and fault diagnosis algorithm is developed by using a bearing dataset downloaded from the Case Western Reserve University Bearing Data Center website specifically to represent healthy and faulty ball bearing conditions. Then, the proposed algorithms are validated with two sets of vibration signals which are recorded in the laboratory at a measured velocity with a sampling frequency of 2.56 kHz from the belt-driven machinery and SpectraQuest rotating machinery, respectively. The analysis showed that the FST is 13 times faster than the GA at selecting an optimal feature subset. The novel Ensemble SVM-DS model is developed to resolve conflicting results generated from each SVM model and thus increase the multi-fault classification accuracy. The analysis showed that the proposed Ensemble SVM-DS model improved the fault diagnostic accuracy of bearings (from 76% to 94%), belt-driven machinery (from 52% to 82%), and SpectraQuest rotating machinery (from 48% to 72%), as the Ensemble SVM-DS continuously refined and eliminated all conflicting results from traditional SVM models. The proposed Ensemble SVM-DS model was found to be more accurate and effective at handling multi-fault diagnostic and classification problems commonly faced by industry, and was found to be capable of general-purpose machinery fault diagnosis.

ABSTRAK

Diagnosis kerosakan mesin adalah penting untuk menjamin keutuhan mesin. Untuk tujuan ini, analisis getaran terbukti merupakan kaedah yang paling berkesan. Walau bagaimanapun, keberkesanannya amat bergantung kepada pengalaman dan pengetahuan pengendali mesin kerana kelimpahan pelbagai parameter mesin dan kerumitan mesin. Oleh itu, pendekatan kecerdikan buatan (AI) atau pembelajaran mesin memberikan keputusan diagnosis yang lebih konsisten berdasarkan model pembelajaran mesin terlatih dan seterusnya membawa kepada sistem diagnosis kerosakan automatik yang memerlukan penglibatan manusia secara minimum. Mesin vektor sokongan (SVM) sering digunakan dalam diagnosis kerosakan mesin automatik untuk mengelaskan pelbagai kerosakan mesin dengan mengendalikan jumlah ciri-ciri masukan yang tinggi dengan data yang kurang. Bagaimanapun, SVM terkenal dengan pengelasan kerosakan perduaan sahaja (keadaan normal dan keadaan rosak). Apabila SVM digunakan untuk diagnosis dan pengelasan pelbagai kerosakan, ia melibatkan penurunan kejituan pengelasan. Ini disebabkan oleh penyesuaian SVM bagi pengelasan pelbagai kerosakan memerlukan penurunan pelbagai masalah pengelasan kepada beberapa masalah pengelasan perduaan yang menghasilkan banyak keputusan yang bercanggah dari setiap model SVM. Kajian ini bertujuan untuk meningkatkan kejituan pengelasan pelbagai kerosakan SVM dengan menyesuaikan teori Dempster-Shafer (DS) yang dinamakan sebagai SVM-DS. Selain itu, akar pokok pemilihan ciri-ciri baharu (FST) dicadangkan untuk memperbaiki masa pengiraan algoritma pemilihan ciri-ciri berasaskan pembalut seperti algoritma genetik (GA) sebagai sebahagian daripada penambahbaikan model yang dicadangkan. Untuk memenuhi objektif kajian ini, skop kajian dibahagikan kepada dua bahagian iaitu pembangunan algoritma dan kajian eksperimen. Model awal pemilihan ciri-ciri dan pengelasan kerosakan dibangunkan dengan menggunakan data yang dimuat turun dari laman sesawang Case Western Reserve University Bearing Data Center untuk mewakili keadaan galas yang normal dan rosak. Kemudian, algoritma yang dicadangkan disahkan dengan dua set signal getaran yang dikumpulkan di makmal pada halaju getaran yang diukur dengan kadar pensampelan 2.56 kHz bagi mesin pacuan tali sawat dan mesin putaran SpectraQuest. Analisis menunjukkan bahawa FST adalah 13 kali ganda lebih pantas berbanding GA dalam pemilihan subset ciri-ciri optimum. Model SVM-DS baharu dibangunkan untuk mengatasi keputusan yang bercanggah yang dihasilkan dari setiap model SVM dan seterusnya meningkatkan kejituan pengelasan pelbagai kerosakan. Analisis menunjukkan bahawa model SVM-DS yang dicadangkan meningkatkan kejituan diagnosis kerosakan galas (dari 76% kepada 94%), mesin pacuan tali sawat (dari 52% kepada 82%), dan mesin putaran SpectraQuest (dari 48% kepada 72%) kerana SVM-DS terus ditapis dan dihapuskan semua hasil yang bercanggah daripada model SVM tradisional. Model SVM-DS yang dicadangkan didapati lebih jitu dan berkesan dalam menangani masalah diagnosis dan pengelasan pelbagai kerosakan yang sering dihadapi oleh industri, dan didapati mampu melakukan diagnosis kerosakan umum.

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LIST OF ABBREVIATIONS

AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
AR	-	Autoregressive
ASME	-	American Society of Mechanical Engineers
BN	-	Bayesian Networks
BPNN	-	Back-Propagation Neural Network
CEEMD	-	Complementary Ensemble Empirical Mode Decomposition
CMFE	-	Multiscale Fuzzy Entropy
CNN	-	Convolutional Neural Network
CRN	-	Convolutional Residual Network
CWRU	-	Case Western Reserve University
DAE	-	Deep Auto-Encoder
DBN	-	Deep Belief Network
DNN	-	Deep Neural Network
DS	-	Dempster–Shafer Evidence Theory
DWAE	-	Deep Wavelet Auto-Encoder
ELM	-	Extreme Learning Machine
EMD	-	Empirical Mode Decomposition
ESA	-	Envelope Spectrum Analysis
FFT	-	Fast Fourier Transform
FST	-	Feature Selection Tree
GA	-	Genetic Algorithm
HMM	-	Hidden Markov Model
HSDE	-	Hierarchical Symbol Dynamic Entropy
IDE	-	Integrated Development Environment
MLP	-	Multilayer Perceptron
NNBC	-	Non-Naive Bayesian Classifier
OEM	-	Original Equipment Manufacturer
RBF	-	Gaussian Radial Basis Function
RMS	-	Root-Mean-Square

ROC	-	Receiver Operating Characteristic
SD	-	Standard Deviation
SDP	-	Symmetrized Dot Pattern
SOM	-	Self-Organizing Map
SVM	-	Support Vector Machines
VRF	-	Variable Refrigerant Flow
WPD	-	Wavelet Packet Decomposition
WT	-	Wavelet Transform

LIST OF SYMBOLS

Bel	-	Belief Function
m	-	Mass Function
Pl	-	Plausibility
α	-	Discount Coefficient
Θ	-	Finite Set of Possible Answers
ϕ	-	Empty Set

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CHAPTER 1

INTRODUCTION

1.1 Overview

Unscheduled maintenance can lead to costly downtime and can threaten human life. Accordingly, machinery condition monitoring and fault diagnosis play a vital role in the operation, maintenance, aging management, reliability and performance of a critical industry such as the power generation, petrochemical, and aviation industries. For instance, in December 2016 Malaysia Airlines had to reschedule its flights to Medina due to unscheduled maintenance. Various methods have been developed for machinery condition monitoring and fault diagnosis, such as vibration analysis (Gelman *et al.*, 2014), acoustic analysis (Jena and Panigrahi, 2015), and thermal imaging interpretation (Janssens *et al.*, 2015). Vibration spectra analysis has been proven as the most efficient condition monitoring and fault diagnostic method for rotating machinery (Chen *et al.*, 2013). Hence various vibration signal processing tools have been introduced, namely wavelet analysis, empirical mode decomposition, and the Hilbert–Huang transform. These signal processing methods have advanced from non-adaptive to self-adaptive signal analysis (Hui *et al.*, 2014). The capabilities of vibration analysis have also progressed from qualitative analysis to quantitative analysis (Cui *et al.*, 2016). For instance, bearing fault diagnostic methods were previously developed to identify the conditions of the bearing (i.e., healthy or faulty), but recent diagnostic methods are intended to determine the severity of the bearing fault (e.g., the fault size). However, the effectiveness of these diagnostic methods is highly dependent on the experience and knowledge of the machine operator.

1.2 Research Problem

Currently, machinery condition monitoring and fault diagnosis in critical industrial plants such as oil and gas, power generation, and petrochemical plants is implemented by observing trends in the equipment parameters, such as temperature, pressure, vibration levels, and operating speeds, at various machine locations. Figure 1.1 plots the compressor vibration at a measured displacement of a gas turbine and its original equipment manufacturer (OEM) limits. The data are gathered from Petronas Gas Berhad. The gas turbine was operating within its OEM limits, but was found to exhibit obvious damage on multiple blades during its periodic and borescope inspections, as depicted in Figure 1.2. Therefore, machinery condition monitoring and fault diagnosis solely based on the OEM limits are deemed to be insufficient.

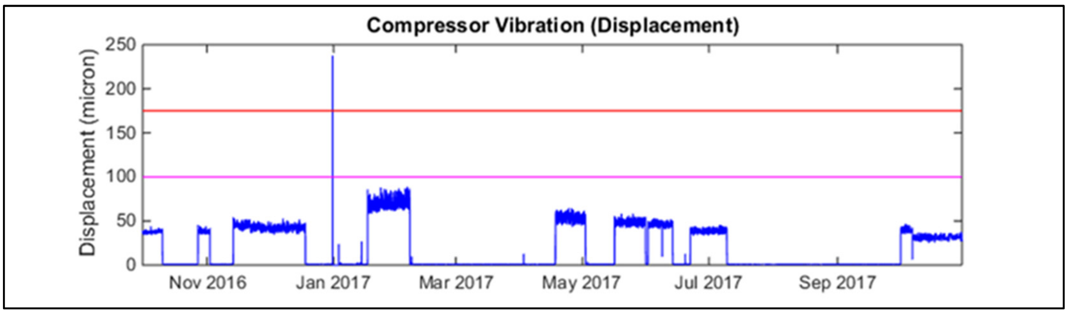

Figure 1.1 Compressor vibration of a gas turbine (magenta line: alarm limit; red line: trip limit)

Figure 1.2 Multiple instances of blade damage found during the periodic and borescope inspections of the gas turbine

In recent years there has been increasing interest in the use of an artificial intelligence (AI) or machine learning approach for machinery fault diagnosis. This approach provides a more consistent diagnostic result based on a trained machine learning model. As a result, it leads to a more automated fault diagnosis system that reduces or eliminates human intervention. A machine learning algorithm attempts to establish a relationship between the input (i.e., data captured by sensors) and the output (i.e., the conditions of the machine). Subsequently, the trained machine learning model can provide an output based on a new input. Although machine learning-based machinery fault diagnosis provides more consistent diagnostic results, its accuracy remains highly dependent on the machine learning algorithm applied to analyse the input. In other words, the accuracy of diagnostics based on an artificial neural network (ANN), self-organizing map (SOM), support vector machines (SVM), the Hidden Markov model (HMM), particle filtering, regression analysis and fuzzy logic, and the Bayesian technique could be completely different.

A machine learning algorithm that is able to achieve exceptional classification accuracy with limited sampling data is deemed to be crucial in machinery fault diagnosis, as the availability of fault sample data is often restricted. The renowned machine learning subset of deep learning is thus considered to be unsuitable as it requires a large amount of high-quality data for the nested layers in the neural networks. Previous studies have reported SVM as superior to other machine learning algorithms in fault diagnosis due to its capability to handle a large number of input features with a small sampling data set (Kankar *et al.*, 2013; Jedliński and Jonak, 2015; Zhang *et al.*, 2015). However, SVM was developed for two-class (binary) problem classification. Various strategies can be found in the literature regarding the use of SVM for multi-fault classification, including one-versus-one, one-versus-all, binary tree, error correcting output code, and directed acyclic graphs (Cheong *et al.*, 2004). However, most research on SVM multi-fault classification emphasizes the use of the one-versus-one (Wang *et al.*, 2014) and one-versus-all (Liu *et al.*, 2013; Baccarini *et al.*, 2011) strategies. These approaches require more than one SVM model for multi-fault classification, and different SVM models may provide contradictory results, which significantly degrade the performance of SVM in multi-fault classification. Chen *et al.* (2014) reported a bearing fault classification accuracy with an original SVM, which discard all contradictory outcomes from multiple SVM models is 76.82%. It is now well established that multi-fault classification with SVM can be achieved by reducing a multi-fault problem into multiple binary problems. However, the multi-fault classification performance of SVM has remained unsatisfactory. Therefore, this study attempts to improve SVM for multi-fault classification performance by adapting Dempster−Shafer (DS) evidence theory.

Overall, the problem addressed in this study can be summarised as follows:

(a) Machinery condition monitoring and fault diagnosis by manually monitoring machinery parameters based on the OEM limits is found to be insufficient.

(b) The machine learning approach provides a more consistent diagnostic result based on a trained machine learning model and thus leads to a more automated fault diagnosis system, which reduces or eliminates human intervention.

(c) The literature indicates that the SVM is regarded as the most promising machine learning algorithm in machinery fault diagnosis. However, its multi-fault diagnostic accuracy is found to be significantly degraded due to the contradictory results generated by multiple SVM models.

1.3 Research Question

This study attempts to address the research questions as follows.

(a) How can the classification accuracy of an SVM in multi-fault classification be improved?

(b) What is the performance of an SVM in multi-fault classification with fine-tuned *BoxConstraint* and *KernelScale* values?

(c) Can the improved SVM model be used to classify other machinery fault?

(d) How can contradictory output from multiple SVM models be reduced by selecting the most representable feature subsets of the dataset as input for the SVM?

(e) How can the computational time of a wrapper-based feature selection algorithm such as the genetic algorithm (GA) be improved?

1.4 Objective

This study embarks on the following objectives.

(a) To develop an algorithm to improve the classification accuracy of an SVM in multi-fault classification based on DS evidence theory.

(b) To develop an algorithm to improve the computational time of the wrapper-based feature selection algorithm.

(c) To develop a more robust SVM-based machinery fault diagnostic method for general-purpose machinery fault diagnosis, which can be used to classify any machinery fault with a higher classification accuracy than a conventional SVM model.

1.5 Scope

The scope of this study is presented below.

(a) The feature selection and fault diagnosis algorithms are developed in MATLAB's Integrated Development Environment (IDE).

(b) A bearing dataset is downloaded from the Case Western Reserve University (CWRU) Bearing Data Center website specifically to represent healthy and faulty ball bearing conditions and is used to develop the initial model of feature selection and fault diagnosis algorithm.

(c) Vibration signals of various machinery conditions are collected from the belt-driven machinery fault simulator and SpectraQuest machinery fault simulator located in the laboratory for verification and generalisation of the developed model.

(d) These three machinery fault datasets are used to develop the machinery fault diagnosis algorithm for general-purpose machinery fault diagnosis.

1.6 Significance of the Study

This study set out to enable and improve SVM for multi-fault classification due to its capability to handle a high number of input features with a small sampling data set. The results of the study will be of great benefit as follows.

(a) An Ensemble SVM-DS is proposed by continuously refining the classification results generated by multiple conventional SVM models. The multi-fault classification accuracy of a conventional SVM significantly improved with the proposed Ensemble SVM-DS technique. Thus, dependency on knowledgeable and experienced personnel in machinery condition monitoring and fault diagnosis could be reduced.

(b) A feature selection technique termed FST is proposed to select an optimal feature subset by using a faster and more systematic approach, which avoided repeated computation of the performance of identical feature subsets.

(c) The proposed Ensemble SVM-DS machinery fault diagnostic method is a better algorithm for general-purpose machinery fault diagnosis as compared to conventional SVM as it provides a higher classification accuracy in machinery fault diagnosis.

REFERENCES

Ali, S.M., Hui, K.H., Hee, L.M. and Leong, M.S. (2018) 'Automated valve fault detection based on acoustic emission parameters and support vector machine' *Alexandria Engineering Journal*, 57(1), 121–130.

Asr, M.Y., Ettefagh, M.M., Hassannejad, R. and Razavi, S.N. (2017) 'Diagnosis of combined faults in Rotary Machinery by Non-Naive Bayesian approach' *Mechanical Systems and Signal Processing*, 85, 56–70.

Avci, E. (2013) 'A new method for expert target recognition system: Genetic wavelet extreme learning machine (GAWELM)' *Expert Systems with Applications*, 40(10), 3984–3993.

Baccarini, L.M.R., Rocha e Silva, V.V., de Menezes, B.R. and Caminhas, W.M. (2011) 'SVM practical industrial application for mechanical faults diagnostic' *Expert Systems with Applications*, 38(6), 6980–6984.

Bewes, J., Andrew, L., Antony, M., Pate, F.D. and Henneberg, M. (2019) 'Artificial intelligence for sex determination of skeletal remains: Application of a deep learning artificial neural network to human skulls' *Journal of Forensic and Legal Medicine*, 62(January), 40–43.

Bhalla, D., Bansal, R.K. and Gupta, H.O. (2013) 'Integrating AI based DGA fault diagnosis using Dempster–Shafer Theory' *International Journal of Electrical Power & Energy Systems*, 48, 31–38.

Bhattacharyya, A., Saraswat, V.K., Manimaran, P. and Rao, S.B. (2015) 'Evidence theoretic classification of ballistic missiles' *Applied Soft Computing Journal*, 37, 479–489.

Bin, G.F., Gao, J.J., Li, X.J. and Dhillon, B.S. (2012) 'Early fault diagnosis of rotating machinery based on wavelet packets - Empirical mode decomposition feature extraction and neural network' *Mechanical Systems and Signal Processing*, 27(1), 696–711.

Björklund, T., Fiandrotti, T., Annarumma, M., Francini, G. and Magli, E. (2019) 'Robust License Plate Recognition using Neural Networks Trained on Synthetic Images' *Pattern Recognition*. (In Press)

Bordoloi, D.J. and Tiwari, R. (2014) 'Optimum multi-fault classification of gears with integration of evolutionary and SVM algorithms' *Mechanism and Machine Theory*, 73, 49–60.

Browne, F., Rooney, N., Liu, W., Bell, D., Wang, H., Taylor, P.S. and Jin, Y. (2013) 'Integrating textual analysis and evidential reasoning for decision making in Engineering design' *Knowledge-Based Systems*, 52, 165–175.

Castiglione, A., Pizzolante, R., Esposito, C., Santis, A.D., Palmieri, F. and Castiglione, A. (2017) 'A collaborative clinical analysis service based on theory of evidence, fuzzy linguistic sets and prospect theory and its application to craniofacial disorders in infants' *Future Generation Computer Systems*, 67, 230–241.

Cerrada, M., Zurita, G., Cabrera, D., Sánchez, R.V., Artés, M. and Li, C. (2016) 'Fault diagnosis in spur gears based on genetic algorithm and random forest' *Mechanical Systems and Signal Processing*, 70–71, 87–103.

Chang, C. and Lin, C. (2011) 'LIBSVM' *ACM Transactions on Intelligent Systems and Technology*, 2(3), 1–27.

Chapelle, O., Vapnik, V., Bousquet, O. and Mukherjee, S. (2002) 'Choosing Multiple Parameters for Support Vector Machines' *Machine Learning*, 46(1), 131–159.

Chen, F., Tang, B., Song, T. and Li, L. (2014) 'Multi-fault diagnosis study on roller bearing based on multi-kernel support vector machine with chaotic particle swarm optimization' *Measurement*, 47, 576–590.

Chen, J., Zi, Y., He, Z. and Wang, X. (2013) 'Adaptive redundant multiwavelet denoising with improved neighboring coefficients for gearbox fault detection' *Mechanical Systems and Signal Processing*, 38(2), 549–568.

Cheong, S., Oh, S. and Lee, S. (2004) 'Support vector machines with binary tree architecture for multi-class classification' *Neural Information Processing - Letters and Reviews*, 2(3), 47–51.

Choi, W., Moon, K., Kwak, M., Sung, C., Lee, J., Song, J., Park, J., Chekol, S.A. and Hwang, H. (2019) 'Hardware implementation of neural network using pre-programmed resistive device for pattern recognition' *Solid-State Electronics*, 153(December 2018), 79–83.

Cui, L., Liu, Y. and Zhou, D. (2018) 'Fault Diagnosis of the Planetary Gearbox Based on ssDAG-SVM' *IFAC-PapersOnLine*, 51(24), 263–267.

Cui, L., Wu, N., Ma, C. and Wang, H. (2016) 'Quantitative fault analysis of roller bearings based on a novel matching pursuit method with a new step-impulse dictionary' *Mechanical Systems and Signal Processing*, 68–69(2016), 34–43.

Darekar, R.V. and Dhande, A.P. (2018) 'Emotion recognition from Marathi speech database using adaptive artificial neural network' *Biologically Inspired Cognitive Architectures*, 23(January), 35–42.

Das, A.K., Sengupta, S. and Bhattacharyya, S. (2018) 'A group incremental feature selection for classification using rough set theory based genetic algorithm' *Applied Soft Computing Journal*, 65, 400–411.

Duan, L., Xie, M., Bai, T. and Wang, J. (2016) 'A new support vector data description method for machinery fault diagnosis with unbalanced datasets' *Expert Systems with Applications*, 64, 239–246.

Durodola, J.F., Li, N., Ramachandra, S. and Thite, A.N. (2017) 'A pattern recognition artificial neural network method for random fatigue loading life prediction' *International Journal of Fatigue*, 99, 55–67.

Espinoza, K., Valera, D.L., Torres, J.A., López, A. and Molina-Aiz, F.D. (2016) 'Combination of image processing and artificial neural networks as a novel approach for the identification of Bemisia tabaci and Frankliniella occidentalis on sticky traps in greenhouse agriculture' *Computers and Electronics in Agriculture*, 127, 495–505.

Ezhilarasu, C.M., Skaf, Z. and Jennions, I.K. (2019) 'The application of reasoning to aerospace Integrated Vehicle Health Management (IVHM): Challenges and opportunities' *Progress in Aerospace Sciences*, 105(December 2018), 60–73.

Galagedarage Don, M. and Khan, F. (2019) 'Dynamic process fault detection and diagnosis based on a combined approach of hidden Markov and Bayesian network model' *Chemical Engineering Science*, 201, 82–96.

Gao, X. and Hou, J. (2016) 'An improved SVM integrated GS-PCA fault diagnosis approach of Tennessee Eastman process' *Neurocomputing*, 174(2016), 906–911.

Gelman, L., Murray, B., Patel, T.H. and Thomson, A. (2014) 'Vibration diagnostics of rolling bearings by novel nonlinear non-stationary wavelet bicoherence technology' *Engineering Structures*, 80(2014), 514–520.

Gharesi, N., Arefi, M.M., Ebrahimi, Z., Razavi-Far, R., Saif, M. and Zarei, J. (2018) 'Analyzing the Vibration Signals for Bearing Defects Diagnosis Using the Combination of SGWT Feature Extraction and SVM' *IFAC-PapersOnLine*, 51(24), 221–227.

González, E.L.M., Desforges, X. and Archimède, B. (2018) 'Assessment method of the multicomponent systems future ability to achieve productive tasks from local prognoses' *Reliability Engineering and System Safety*, 180(March), 403–415.

Grbovic, M., Li, W., Xu, P., Usadi, A.K., Song, L. and Vucetic, S. (2012) 'Decentralized fault detection and diagnosis via sparse PCA based decomposition and Maximum Entropy decision fusion' *Journal of Process Control*, 22(4), 738–750.

Guil, F. and Marín, R. (2013) 'A Theory of Evidence-based method for assessing frequent patterns' *Expert Systems with Applications*, 40(8), 3121–3127.

Shao, H., Jiang, H., Li, X. and W, S. (2018) 'Intelligent fault diagnosis of rolling bearing using deep wavelet auto-encoder with extreme learning machine' *Knowledge-Based Systems*, 140, 1–14.

Han, T., Liu, C., Yang, W. and Jiang, D. (2019a) 'A novel adversarial learning framework in deep convolutional neural network for intelligent diagnosis of mechanical faults' *Knowledge-Based Systems*, 165, 474–487.

Han, T., Liu, C., Yang, W. and Jiang, D. (2019b) 'Learning transferable features in deep convolutional neural networks for diagnosing unseen machine conditions' *ISA Transactions*. (In Press)

He, K., Zhang, X., Ren, S. and Sun, J. (2015) 'Deep Residual Learning for Image Recognition' *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778.

Hitesh and Kumari, A.C. (2018) 'Feature Selection Optimization in SPL using Genetic Algorithm' *Procedia Computer Science*, 132, 1477–1486.

Hsu, C.W., Chang, C.C. and Lin, C.J. (2010) *A Practical Guide to Support Vector Classification*. Taipei: National Taiwan University.

Hu, M. Chen, H., Shen, L., Li, G., Guo, Y., Li, H., Li, J. and Hu, W. (2018) 'A machine learning bayesian network for refrigerant charge faults of variable refrigerant flow air conditioning system' *Energy and Buildings*, 158, 668–676.

Hui, K.H., Ooi, C.S., Lim, M.H., Leong, M.S. and Al-Obaidi, S.M. (2017) 'An improved wrapper-based feature selection method for machinery fault diagnosis' *PLoS ONE*, 12(12).

Hui, K.H., Lim, M.H., Leong, M.S. and Abdelrhman, A.M. (2014) 'Time-Frequency Signal Analysis in Machinery Fault Diagnosis: Review' *Advanced Materials Research*, 845, 41–45.

Hui, K.H., Lim, M.H. and Leong, M.S. (2017) 'Evidence-based Automated Machinery-Fault Diagnosis' *APVC2017: the 17th Asia Pacific Vibration*

Conference. 13–15 November 2017, Nanjing University of Aeronautics and Astronautics, Nanjing, 1–12.

Hui, K.H., Lim, M.H., Leong, M.S. and Al-Obaidi, S.M. (2017) 'Dempster-Shafer Evidence Theory for Multi-Bearing Faults Diagnosis' *Engineering Applications of Artificial Intelligence*, 57(November 2016), 160–170.

Hui, K.H., Lim, M.H. and Leong, M.S. (2017) 'Dempster-shafer-based sensor fusion approach for machinery fault diagnosis' *American Society of Mechanical Engineers, Power Division (Publication) POWER*. 2017

Islam, M.L., Shatabda, S., Rashid, M.A., Khan, M.G.M. and Rahman, M.S. (2019) 'Protein structure prediction from inaccurate and sparse NMR data using an enhanced genetic algorithm' *Computational Biology and Chemistry*, 79(March 2018), 6–15.

Jadhav, S., He, H. and Jenkins, K. (2018) 'Information gain directed genetic algorithm wrapper feature selection for credit rating' *Applied Soft Computing Journal*, 69, 541–553.

Janssens, O., Schulz, R., Slavkovikj, V., Stockman, K., Loccufier, M., Walle, R.V.D. and Hoecke, S.V. (2015) 'Thermal image based fault diagnosis for rotating machinery' *Infrared Physics & Applications*, 73(2015), 78–87.

Jedliński, Ł. and Jonak, J. (2015) 'Early fault detection in gearboxes based on support vector machines and multilayer perceptron with a continuous wavelet transform' *Applied Soft Computing*, 30(2015), 636–641.

Jegadeeshwaran, R. and Sugumaran, V. (2015) 'Fault diagnosis of automobile hydraulic brake system using statistical features and support vector machines' *Mechanical Systems and Signal Processing*, 52–53(1), 436–446.

Jena, D.P. and Panigrahi, S.N. (2015) 'Automatic gear and bearing fault localization using vibration and acoustic signals' *Applied Acoustics*, 98(2015), 20–33.

Jia, F., Lei, Y., Lu, N. and Xing, S. (2018) 'Deep normalized convolutional neural network for imbalanced fault classification of machinery and its understanding via visualization' *Mechanical Systems and Signal Processing*, 110, 349–367.

Jiang, S., Chin, K.S., Wang, L., Qu, G. and Tsui, K.L. (2017) 'Modified genetic algorithm-based feature selection combined with pre-trained deep neural network for demand forecasting in outpatient department' *Expert Systems with Applications*, 82, 216–230.

Jing, C. and Hou, J. (2015) 'SVM and PCA based fault classification approaches for complicated industrial process' *Neurocomputing*, 167, 636–642.

Jong, K.A.D. (1975) 'An Analysis of the Behavior of a Class of Genetic Adaptative Systems'. PhD Thesis, University of Michigan.

Junior, P.O.C., Conte, S., Addona, D.M.D., Aguiar, P.R., Baptista, F.G., Bianchi, E.C. and Teti, R. (2019) 'Damage patterns recognition in dressing tools using PZT-based SHM and MLP networks' *Procedia CIRP*, 79, 303–307.

Kamadinata, J.O., Ken, T.L. and Suwa, T. (2019) 'Sky image-based solar irradiance prediction methodologies using artificial neural networks' *Renewable Energy*, 134, 837–845.

Kankar, P.K., Sharma, S.C. and Harsha, S.P. (2013) 'Fault diagnosis of rolling element bearing using cyclic autocorrelation and wavelet transform' *Neurocomputing*, 110, 9–17.

Kankar, P.K., Sharma, S.C. and Harsha, S.P. (2011) 'Rolling element bearing fault diagnosis using wavelet transform' *Neurocomputing*, 74(10), 1638–1645.

Keskes, H., Braham, A. and Lachiri, Z. (2013) 'Broken rotor bar diagnosis in induction machines through stationary wavelet packet transform and multiclass wavelet SVM' *Electric Power Systems Research*, 97, 151–157.

Konar, P. and Chattopadhyay, P. (2011) 'Bearing fault detection of induction motor using wavelet and Support Vector Machines (SVMs)' *Applied Soft Computing*, 11(6), 4203–4211.

Lazakis, I., Raptodimos, Y. and Varelas, T. (2018) 'Predicting ship machinery system condition through analytical reliability tools and artificial neural networks' *Ocean Engineering*, 152(February 2017), 404–415.

Lei, Y., He, Z. and Zi, Y. (2009) 'Application of an intelligent classification method to mechanical fault diagnosis' *Expert Systems with Applications*, 36(6), 9941–9948.

Lepskiy, A. (2013) 'Estimation of Conflict and Decreasing of Ignorance in Dempster-Shafer Theory' *Procedia Computer Science*, 17, 1113–1120.

Li, S., Liu, G., Tang, X., Lu, J. and Hu, J. (2017) 'An ensemble deep convolutional neural network model with improved D-S evidence fusion for bearing fault diagnosis' *Sensors (Switzerland)*, 17(8), 1–19.

Li, S., Yao, Y., Hu, J., Liu, G., Yao, X. and Hu, J. (2018) 'An Ensemble Stacked Convolutional Neural Network Model for Environmental Event Sound Recognition' *Applied Sciences*, 8(7), 1–20.

Li, Y., Yang, Y., Wang, X., Liu, B. and Liang, X. (2018) 'Early fault diagnosis of rolling bearings based on hierarchical symbol dynamic entropy and binary tree support vector machine' *Journal of Sound and Vibration*, 428, 72–86.

Li, Y., Liang, X., Wei, Y. and Wang, X. (2018) 'A method based on refined composite multi-scale symbolic dynamic entropy and ISVM-BT for rotating machinery fault diagnosis' *Neurocomputing*, 315, 246–260.

Li, Y., Xu, M., Wei, Y. and Huang, W. (2016) 'A new rolling bearing fault diagnosis method based on multiscale permutation entropy and improved support vector machine based binary tree' *Measurement*, 77(2016), 80–94.

Li, Y., Xu, M., Zhao, H. and Huang, W. (2016) 'Hierarchical fuzzy entropy and improved support vector machine based binary tree approach for rolling bearing fault diagnosis' *MAMT*, 98, 114–132.

Lin, Y., Li, Y., Yin, X. and Dou, Z. (2018) 'Multisensor Fault Diagnosis Modeling Based on the Evidence Theory' *IEEE Transactions on Reliability*, 67(2), 513–521.

Liu, F., Zhao, Q. and Yang, Y. (2018) 'An approach to assess the value of industrial heritage based on Dempster–Shafer theory' *Journal of Cultural Heritage*, 32, 210–220.

Liu, P., Basha, M.D.E., Li, Y., Xiao, Y., Sanelli, P.C. and Fang, R. (2019) 'Deep Evolutionary Networks with Expedited Genetic Algorithm for Medical Image Denoising' *Medical Image Analysis*, 54, 306–315.

Liu, R., Yang, B., Zhang, X., Wang, S. and Chen, X. (2016) 'Time-frequency atoms-driven support vector machine method for bearings incipient fault diagnosis' *Mechanical Systems and Signal Processing*, 75, 345–370.

Liu, Y., Zhang, J. and Ma, L. (2016) 'A fault diagnosis approach for diesel engines based on self-adaptive WVD, improved FCBF and PECOC-RVM' *Neurocomputing*, 177, 600–611.

Liu, Y., Zhang, Y., Yu, Z. and Zeng, M. (2016) 'Incremental supervised locally linear embedding for machinery fault diagnosis' *Engineering Applications of Artificial Intelligence*, 50, 60–70.

Liu, Z., Cao, H., Chen, X., He, Z. and 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.

Lu, C., Wang, S. and Wang, X. (2017) 'A multi-source information fusion fault diagnosis for aviation hydraulic pump based on the new evidence similarity distance' *Aerospace Science and Technology*, 71, 392–401.

Lu, L., Yan, J. and Meng, Y. (2016) 'Dynamic Genetic Algorithm-based Feature Selection Scheme for Machine Health Prognostics' *Procedia CIRP*, 56, 316–320.

Lu, L., Yan, J. and De Silva, C.W. (2015) 'Dominant feature selection for the fault diagnosis of rotary machines using modified genetic algorithm and empirical mode decomposition' *Journal of Sound and Vibration*, 344, 464–483.

Luo, S., Cheng, J., Zeng, M. and Yang, Y. (2016) 'An intelligent fault diagnosis model for rotating machinery based on multi-scale higher order singular spectrum analysis and GA-VPMCD' *Measurement*, 87(2016), 38–50.

Ma, B. and Xia, Y. (2017) 'A tribe competition-based genetic algorithm for feature selection in pattern classification' *Applied Soft Computing Journal*, 58, 328–338.

Ma, S., Cheng, B., Shang, Z. and Liu, G. (2018) 'Scattering transform and LSPTSVM based fault diagnosis of rotating machinery' *Mechanical Systems and Signal Processing*, 104, 155–170.

Ma, S. and Chu, F. (2019) 'Ensemble deep learning-based fault diagnosis of rotor bearing systems' *Computers in Industry*, 105, 143–152.

Mao, W., Feng, W. and Liang, X. (2019) 'A novel deep output kernel learning method for bearing fault structural diagnosis' *Mechanical Systems and Signal Processing*, 117, 293–318.

MathWorks (2016) *Statistics and Machine Learning Toolbox™ User's Guide R2016a* 10.2., Natick: The MathWorks Inc.

Namdari, M. and Jazayeri-Rad, H. (2013) 'Incipient fault diagnosis using support vector machines based on monitoring continuous decision functions' *Engineering Applications of Artificial Intelligence*, 1–14.

Pacheco, F., Oliveira, J.V.D., Sánchez, R.V., Cerrada, M., Cabrera, D., Li, C., Zurita, G. and Artés, M. (2016) 'A statistical comparison of neuroclassifiers and feature selection methods for gearbox fault diagnosis under realistic conditions' *Neurocomputing*, 194(2016), 192–206.

Pearl, J. (1990) 'Reasoning with belief functions: An analysis of compatibility' *International Journal of Approximate Reasoning*, 4(5–6), 363–389.

Phillips, P. and Diston, D. (2011) 'A knowledge driven approach to aerospace condition monitoring' *Knowledge-Based Systems*, 24(6), 915–927.

Porebski, S., Porwik, P., Straszecka, E. and Orczyk, T. (2018) 'Liver fibrosis diagnosis support using the Dempster–Shafer theory extended for fuzzy focal elements' *Engineering Applications of Artificial Intelligence*, 76(January), 67–79.

Porebski, S. and Straszecka, E. (2018) 'Extracting easily interpreted diagnostic rules' *Information Sciences*, 426, 19–37.

Potes Ruiz, P.A., Kamsu-Foguem, B. and Noyes, D. (2013) 'Knowledge reuse integrating the collaboration from experts in industrial maintenance management' *Knowledge-Based Systems*, 50, 171–186.

Rajisha, T.M., Sunija, A.P. and Riyas, K.S. (2016) 'Performance Analysis of Malayalam Language Speech Emotion Recognition System using ANN / SVM' *Procedia Technology*, 24, 1097–1104.

Rathman, J.F., Yang, C. and Zhou, H. (2018) 'Dempster-Shafer theory for combining in silico evidence and estimating uncertainty in chemical risk assessment' *Computational Toxicology*, 6, 16–31.

Safa, M., Martin, K.E., KC, B., Khadka, R. and Maxwell, T.M.R. (2019) 'Modelling Nitrogen Content of Pasture Herbage Using Thermal Images and Artificial Neural Networks' *Thermal Science and Engineering Progress*.

Sarabi-Jamab, A., Araabi, B.N. and Augustin, T. (2013) 'Information-based dissimilarity assessment in Dempster–Shafer theory' *Knowledge-Based Systems*, 54, 114–127.

Sayed, S., Nassef, M., Badr, A. and Farag, I. (2019) 'A Nested Genetic Algorithm for feature selection in high-dimensional cancer Microarray datasets' *Expert Systems with Applications*, 121, 233–243.

Sene, A., Kamsu-Foguem, B. and Rumeau, P. (2018) 'Data mining for decision support with uncertainty on the airplane' *Data and Knowledge Engineering*, 117(February 2017), 18–36.

Shafer, G. (1987) 'Belief functions and possibility measures' *Analysis of Fuzzy Information*. Boca Raton, FL, 51–84.

Shen, Z., Chen, X., Zhang, X. and He, Z. (2012) 'A novel intelligent gear fault diagnosis model based on EMD and multi-class TSVM' *Measurement*, 45(1), 30–40.

Sta, H.B. (2017) 'Quality and the efficiency of data in “Smart-Cities”' *Future Generation Computer Systems*, 74, 409–416.

Sudha, P., Ramyachitra, D. and Manikandan, P. (2018) 'Enhanced Artificial Neural Network for Protein Fold Recognition and Structural Class Prediction' *Gene Reports*, 12(June), 261–275.

Tao, Z., Huiling, L., Wenwen, W. and Xia, Y. (2019) 'GA-SVM based feature selection and parameter optimization in hospitalization expense modeling' *Applied Soft Computing Journal*, 75, 323–332.

Tian, Y., Fu, M. and Wu, F. (2015) 'Steel plates fault diagnosis on the basis of support vector machines' *Neurocomputing*, 151, 296–303.

Tidriri, K., Tiplica, T., Chatti, N. and Verron, S. (2018) 'A New Multi-Objective Decision-Making Approach Applied to the Tennessee Eastman Process' *IFAC-PapersOnLine*, 51(24), 1212–1219.

Utai, K., Nagle, M., Hämmerle, S., Spreer, W., Mahayothee, B. and Müller, J. (2019) 'Mass estimation of mango fruits (Mangifera indica L., cv. ‘Nam Dokmai’) by linking image processing and artificial neural network' *Engineering in Agriculture, Environment and Food*, 12(1), 103–110.

Vargas, J., Spiotta, A. and Chatterjee, A.R. (2019) 'Initial Experiences with Artificial Neural Networks in the Detection of Computed Tomography Perfusion Deficits' *World Neurosurgery*, 124, e10–e16.

Vijayanand, R., Devaraj, D. and Kannapiran, B. (2018) 'Intrusion detection system for wireless mesh network using multiple support vector machine classifiers with genetic-algorithm-based feature selection' *Computers and Security*, 77, 304–314.

Wang, C.C., Kang, Y., Shen, P.C., Chang, Y.P. and Chng, Y.L. (2010) 'Applications of fault diagnosis in rotating machinery by using time series analysis with neural network' *Expert Systems with Applications*, 37(2), 1696–1702.

Wang, Y.S., Ma, Q.H., Zhu, Q., Liu, X.T. and Zhao, L.H. (2014) 'An intelligent approach for engine fault diagnosis based on Hilbert–Huang transform and support vector machine' *Applied Acoustics*, 75, 1–9.

Waqar, T. and Demetgul, M. (2016) 'Thermal analysis MLP neural network based fault diagnosis on worm gears' *Measurement: Journal of the International Measurement Confederation*, 86, 56–66.

Wu, C., Jiang, P., Ding, C., Feng, F. and Chen, T. (2019) 'Intelligent fault diagnosis of rotating machinery based on one-dimensional convolutional neural network' *Computers in Industry*, 108, 53–61.

Wu, J., Zhou, R., Xu, S. and Wu, Z. (2017) 'Probabilistic analysis of natural gas pipeline network accident based on Bayesian network' *Journal of Loss Prevention in the Process Industries*, 46, 126–136.

Xiao, M., Ma, Y., Feng, Z., Deng, Z., Hou, S. and Shu, L. (2018) 'Rice blast recognition based on principal component analysis and neural network' *Computers* *and Electronics in Agriculture*, 154(June), 482–490.

Xie, X., Ke, Y., Hao, Y., Song, L. and Wang, H. (2018) 'Feature extraction method for roller bearing based on Dempster-Shafer evidence' *Proceedings of 2017 9th International Conference On Modelling, Identification and Control, ICMIC 2017*, 2018–March (ICMIC), 746–751.

Yager, R.R. and Liu, L. (2008) *ClassicWorks of the Dempster-Shafer Theory of Belief Functions* Kacprzyk, J., (ed.), Springer, Berlin.

Yan, X. and Jia, M. (2019) 'Intelligent fault diagnosis of rotating machinery using improved multiscale dispersion entropy and mRMR feature selection' *Knowledge-Based Systems*, 163, 450–471.

Yang, B., Lei, Y., Jia, F. and Xing, S. (2019) 'An intelligent fault diagnosis approach based on transfer learning from laboratory bearings to locomotive bearings' *Mechanical Systems and Signal Processing*, 122, 692–706.

Yang, C. and Hou, J. (2016) 'Fed-batch fermentation penicillin process fault diagnosis and detection based on support vector machine' *Neurocomputing*, 190, 117–123.

Yang, H., Mathew, J. and Ma, L. (2003) 'Vibration Feature Extraction Techniques for Fault Diagnosis of Rotating Machinery -A Literature Survey' *Asia Pacific Vibration Conference*. 2003, 1–7.

Yao, X., Li, S. and Hu, J. (2017) 'Improving Rolling Bearing Fault Diagnosis by DS Evidence Theory Based Fusion Model' *Journal of Sensors*, 2017, 1–14.

Zadeh, L.A. (1984) 'Review of A Mathematical Theory of Evidence' *AI Magazine 5*, 5(3), 81–83.

Zeng, R., Zhang, L., Mei, J., Shen, H. and Zhao, H. (2017) 'Fault detection in an engine by fusing information from multivibration sensors' *International Journal of Distributed Sensor Networks*, 13(7), 1–9.

Zhang, X., Zhang, Q., Chen, M., Sun, Y., Qin, X. and Li, Heng (2018) 'A two-stage feature selection and intelligent fault diagnosis method for rotating machinery using hybrid filter and wrapper method' *Neurocomputing*, 275, 2426–2439.

Zhang, X., Chen, W., Wang, B. and Chen, X. (2015) 'Intelligent fault diagnosis of rotating machinery using support vector machine with ant colony algorithm for synchronous feature selection and parameter optimization' *Neurocomputing*, 167, 260–279.

Zhang, X., Qiu, D. and Chen, F. (2015) 'Support vector machine with parameter optimization by a novel hybrid method and its application to fault diagnosis'

Neurocomputing, 149(PB), 641–651.

Zhang, S.S., Zhang, S.S., Wang, B. and Habetler, T.G., 2019. Machine Learning and Deep Learning Algorithms for Bearing Fault Diagnostics - A Comprehensive Review. *arXiv e-prints*, p.arXiv:1901.08247.

Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P. and Gao, R.X. (2019) 'Deep learning and its applications to machine health monitoring' *Mechanical Systems and Signal Processing*, 115, 213–237.

Zhao, Y., Xiao, F. and Wang, S. (2013) 'An intelligent chiller fault detection and diagnosis methodology using Bayesian belief network' *Energy and Buildings*, 57, 278–288.

Zheng, J., Pan, H. and Cheng, J. (2017) 'Rolling bearing fault detection and diagnosis based on composite multiscale fuzzy entropy and ensemble' *Mechanical Systems and Signal Processing*, 85(September 2016), 746–759.

Zhong, J.H., Wong, P.K. and Yang, Z.X. (2018) 'Fault diagnosis of rotating machinery based on multiple probabilistic classifiers' *Mechanical Systems and Signal Processing*, 108, 99–114.

Zhong, S. sheng, Fu, S. and Lin, L. (2019) 'A novel gas turbine fault diagnosis method based on transfer learning with CNN' *Measurement: Journal of the International Measurement Confederation*, 137, 435–453.

Zhu, X., Hou, D., Zhou, P., Han, Z., Yuan., Y., Zhou, W. and Yin, Q. (2019) 'Rotor fault diagnosis using a convolutional neural network with symmetrized dot pattern images' *Measurement: Journal of the International Measurement Confederation*, 138, 526–535.

Zou, X., Wang, F., Chang, Y. and Zhang, B. (2017) 'Process operating performance optimality assessment and non-optimal cause identification under uncertainties' *Chemical Engineering Research and Design*, 120, 348–359.

Appendix A Example Calculation of the Ensemble SVM–DS

Table A-1 presents an example of DS calculations used to handle conflicting results. For example, when SVM results were classified as neither class 1 nor class 2 (and not class 3 or class 4), the probabilities of class 1 and class 2 can be calculated using DS evidence theory to enable a final decision to be made. The values shown in Table A-1 were obtained by multiplying basic probability with the results generated from the SVM model (column 2), and merging the result with the normalised SVM training accuracy (row 2). The SVM training accuracy was obtained based on the capability of every individual SVM model to predict the training samples correctly. Subsequently, the mass function (*m*), belief function (*Bel*), and plausibility (*Pl*) can be calculated as follows.

Table A-1 Illustration of DS theory calculation

	Class	**1**	**2**	**Not 3**	**Not 4**	**ϴ**
Class	m	0.2038	0.2275	0.2500	0.2500	0.0688
1	0.25	0.0509	0.0569	0.0625	0.0625	0.0172
2	0.25	0.0509	0.0569	0.0625	0.0625	0.0172
Not 3	0.25	0.0509	0.0569	0.0625	0.0625	0.0172
Not 4	0.25	0.0509	0.0569	0.0625	0.0625	0.0172

$$m(1) = \frac{0.0509 + 0.0509 + 0.0509 + 0.0625 + 0.0625 + 0.0172}{1 - 0.1078}$$

$$m(1) = 0.3305$$

$$m(2) = \frac{0.0569 + 0.0569 + 0.0569 + 0.0625 + 0.0625 + 0.0172}{1 - 0.1078}$$

$$m(2) = 0.3507$$

$$m(Not\ 3) = \frac{0.0625 + 0.0625 + 0.0625 + 0.0172}{1 - 0.1078}$$

$$m(Not\ 3) = 0.2294$$

$$m(Not\ 4) = \frac{0.0625 + 0.0172}{1 - 0.1078}$$

$$m(Not\ 4) = 0.0893$$

$$Bel(1) = 0.3305$$

$$Pl(1) = 0.3305 + 0.2294 + 0.0893 = 0.6492$$

$$Bel(2) = 0.3507$$

$$Pl(2) = 0.3507 + 0.2294 + 0.0893 = 0.6694$$

Appendix B Ensemble SVM–DS MATLAB Script

```
function [ DisplayDecision,Testing_Accuracy,Indecisive ] = newsvmds( ...
    TrainData,TrainTarget,TestData,TestTarget )

%   NEWSVMDS is a funtion of Ensemble Support Vector Machines (SVM) and
%   Dempster-Shafer (DS) Evidence Theory for multi-fault classification.

%   When SVM is used for multi-fault diagnostics and classification it
%   results in decreased classification accuracy; this is because the
%   adaptation of SVM for multi-fault classification requires the
%   reduction of the multiple classification problem into multiple subsets
%   of binary classification problems, producing many contradictory
%   results from each individual SVM model. Thus, this function is
%   developed to improve multi-fault classification.

%   Last updated: 23 April 2019

    %   Determine number of classes.
    Class = length(unique(TrainTarget));

    %   Train the SVM model with TrainData & test with TestData.
    for a = 1:Class

        %   Create temporary target matrix by zeros.
        TempTrainTarget=zeros(length(TrainTarget),1);

        for x = 1:length(TrainTarget)

            %   Assign 1 to the current class, else 0.
            if TrainTarget(x,1) == a

                TempTrainTarget(x,1) = 1;

            else

                TempTrainTarget(x,1) = 0;

            end

        end

    %   Train SVM structure with Kernel Function = rbf.
    SVMStruct{a} = svmtrain(TrainData,TempTrainTarget,...
        'kernel_function','rbf');

    %   Test the trained SVM structure with TrainData.
    TrainOutput{a} = svmclassify(SVMStruct{a},TrainData);

    %   Test the trained SVM structure with TestData.
    TestOutput{a} = svmclassify(SVMStruct{a},TestData);

    %   Gather all Train Output generated by each SVM structures.
    AllTrainOutput(:,a) = TrainOutput{1,a};

    %   Gather all Test Output generated by each SVM structures.
    AllTestOutput(:,a) = TestOutput{1,a};

    end
```

```
%%  Dempster-Shafer Operations.

%   Calculate weightage for the DS.

    %   Determine training accuracy for each SVM structure.
    for b=1:Class

        m(b,1) = length(unique(find(AllTrainOutput(((b-1)/4)*...
            length(TrainData)+1:(b/4)*length(TrainData),1)==(b==1))));

        m(b,2) = length(unique(find(AllTrainOutput(((b-1)/4)*...
            length(TrainData)+1:(b/4)*length(TrainData),2)==(b==2))));

        m(b,3) = length(unique(find(AllTrainOutput(((b-1)/4)*...
            length(TrainData)+1:(b/4)*length(TrainData),3)==(b==3))));

        m(b,4) = length(unique(find(AllTrainOutput(((b-1)/4)*...
            length(TrainData)+1:(b/4)*length(TrainData),4)==(b==4))));

    end

    %   Calculate training accuracy for each SVM structures.
    MSVMStruct = [sum(m(:,1))/length(AllTrainOutput) ...
        sum(m(:,2))/length(AllTrainOutput) ...
        sum(m(:,3))/length(AllTrainOutput) ...
        sum(m(:,4))/length(AllTrainOutput)];

    %   Calculate training error for each SVM structures.
    MSVMStructErr=[1 1 1 1]-MSVMStruct;

%   Result fusion by DS.

    %   Calculate the size of matrix for the Test Output from SVM.
    Row = size(AllTestOutput,1);
    Col = size(AllTestOutput,2);

    %   Reset counter for indecisive output.
    Indecisive = 0;

    %   Process data for each column.
    for c = 1:1:Row

        %   Process data for each row.
        for d = 1:1:Col

            %   Check if there is no decision (all zeros).
            if sum(AllTestOutput(c,:),2) == 0

                %   Correction on output from SVM for all zeros cases.
                CorrSVM(c,d) = 1/Col; % Assign error.
                CorrSVM(c,Col+1) = 1; % Mark to use error.

            else

                %   Correction on output from SVM for non all zeros cases.

                %   Calculate accuracy.
                CorrSVM(c,d) = AllTestOutput(c,d)/sum(AllTestOutput(c,:));

                %   Mark to use accuracy.
```

```
                CorrSVM(c,Col+1) = 0;
            end
        end
        %   Check if to use error.
        if CorrSVM(c,Col+1) == 1
            %   Fusion of corrected SVM Test Output with error.
            DS = (CorrSVM(c,:))'*MSVMStructErr;
        else
            %   Fusion of corrected SVM Test Output with accuracy.
            DS = (CorrSVM(c,:))'*MSVMStruct;
        end
%   Decision making based on SVM structure.
    %   Select diagonal cells in the matrix.
    DiagFused = diag(DS);
    %   Calculate probability for Class 1.
    Decision(c,1) = DiagFused(1,1)/sum(DiagFused);
    %   Calculate probability for Class 2.
    Decision(c,2) = DiagFused(2,1)/sum(DiagFused);
    %   Calculate probability for Class 3.
    Decision(c,3) = DiagFused(3,1)/sum(DiagFused);
    %   Calculate probability for Class 4.
    Decision(c,4)=DiagFused(4,1)/sum(DiagFused);
    TestDecision(c,:) = Decision(c,:)==max(Decision(c,:));
        if sum(TestDecision(c,:)) == 1
            %   Identified types of fault.
            FinalDecision(c,1) = find(TestDecision(c,:) == 1);
        else
            %   Undefined.
            FinalDecision(c,1) = 0;
            Indecisive = Indecisive+1;
        end
            %   Validate the test result.
            FinalDecision(c,2) = FinalDecision(c,1) == TestTarget(c,1);
    end
        %   Calculate test accuracy.
        Testing_Accuracy = sum(FinalDecision(:,2))/length(AllTestOutput);
        %   Display final decision.
```

```
        DisplayDecision = FinalDecision(:,1);

end
```

Appendix C FST MATLAB Script

```
function [ BestFeatures ] = fst( TrainData,TrainTarget,TargetedFeatureNum )
%   FST is a systematic evaluation of features for machine learninng.

%   Last updated: 23 April 2019

    %   Find number of features.
    NumFeas = size(TrainData,2);

    %   TargetedFeature < 1 means to ignore desirable number of feature.
    if TargetedFeatureNum < 1

        %   If the desirable number of feature ignored, then select the
        %   best features based on training accuracy.
        TargetedFeatureNum = NumFeas;

    end

    %   Generate combination for 1 feature.
    Combi{1,1} = combnk(1:NumFeas,1);

    %   From the 1st to the total number of combination for a single
    %   feature.
    for A1 = 1:size(Combi{1,1},1)

        % Assigned training data.
        TrainInput = TrainData(:,Combi{1,1}(A1,1));

        % Assigned training target.
        TrainTarget = TrainTarget;

        % Call SVM function, calculate, and record training accuracy.
        [ Combi{1,1}(A1,2) ] = svm4feasel( TrainInput,TrainTarget );

    end

    A2 = 0;

    %   From the 2nd feature to the total number of features.
    for A3 = 2:TargetedFeatureNum

        %   Find mean training accuracy percentage from the previous
        %   evaluated feature.
        B1 = mean(Combi{1,A3-1}(:,A3));

        %   Find all features with the accuracy larger than mean accuracy
        %   to avoid the system missed any identical accuracy.
        %   B3 = Cell ID of the highest accuracy features.

        [B2,~] = find(Combi{1,A3-1}(:,A3)>B1);

        %   Temp best features from previous evaluated features.
        TempBestFeas = Combi{1,A3-1}(B2,1:A3-1);

        %   Record the best performance features.
        BestAcc(A2+1:A2+size(B2,1),1:A3-1) = TempBestFeas;

        %   Record the best performance features' accuracy.
        BestAcc(A2+1:A2+size(B2,1),TargetedFeatureNum+1) = Combi{1,A3-1}...
            (B2,A3);

```

```
        %   Updated A2 value based on the total combination of the
        %   previous evaluated features.
        A2 = A2+size(TempBestFeas,1);

        A4 = 0;

        %   From 1 to the total of highest performance features.
        for A6 = 1:size(TempBestFeas,1)
            A5 = A6-1;

            %   Generated the combination of all features and record
            %   latest left over features.
            F1 = (1:NumFeas)';

            for A7=1:size(TempBestFeas,2)

                %   Generate the previous feature for the combination
                %   of 2 features (up to all features) based
                %   on the highest previous evaluated features.
                Combi{1,A3}(A4*A5+1:(NumFeas-A3+1)*A6,A7) = ...
                    TempBestFeas(A6,A7);

            end

            %   From 1 to the total number of highest performance features.
            for A8 = 1:size(TempBestFeas,2)

                %   Find the row ID of left over features.
               [A9,~] = find(F1~=TempBestFeas(A6,A8));

               %    Updated the latest left over features.
               F1 = F1(A9,1);

            end

            %   Generate the 2nd feature for the combination of 2 features
            %   (up to all features) based on the highest previous
            %   evaluated features.
            Combi{1,A3}(A4*A5+1:(NumFeas-A3+1)*A6,A3) = F1;

            A4 = NumFeas-A3+1;

        end

        for A10 = 1:size(Combi{1,A3},1)

            %   Sorting the features (ascending) by each row.
            Combi{1,A3}(A10,:) = unique(Combi{1,A3}(A10,:));

        end

        %   Eliminated identical features.
        Combi{1,A3} = unique(Combi{1,A3},'rows');

        %   Training for combination of 2 features and above.
        for A11 = 1:size(Combi{1,A3},1)

            %   Assigned training input.
            TrainInput = TrainData(:,Combi{1,A3}(A11,1:A3));

```

```
            %   Assigned training target.
            TrainTarget = TrainTarget;

            %   Call SVM function, calculate, and record training accuracy.
            Combi{1,A3}(A11,A3+1) = svm4feasel( TrainInput,TrainTarget );

        end

    end

    %   Find mean training accuracy percentage from the second last
    %   evaluated feature.
    B1 = mean(Combi{1,TargetedFeatureNum}(:,TargetedFeatureNum+1));

    %   Find all features with the accuracy larger than mean accuracy to
    %   avoid the system missed any identical accuracy.
    %   B3=Cell ID of the highest accuracy features.
    [B2,~] = find(Combi{1,TargetedFeatureNum}(:,TargetedFeatureNum+1)==B1);

    %   Temp best features from previous evaluated features.
    TempBestFeas = Combi{1,TargetedFeatureNum}(B2,1:TargetedFeatureNum);

    %   Record the best performance features.
    BestAcc(A2+1:A2+size(B2,1),1:TargetedFeatureNum) = TempBestFeas;

    %   Record the best performance features' accuracy.
    BestAcc(A2+1:A2+size(B2,1),TargetedFeatureNum+1) = Combi{1,...
        TargetedFeatureNum}(B2,TargetedFeatureNum+1);

    %   Find highest training accuracy percentage from all evaluated
    %   feature.
    [B3,~] = max(BestAcc(:,TargetedFeatureNum+1));

    %   Find all features with the accuracy within 5% of the highest
    %   accuracy to avoid the system missed any identical accuracy.
    %   B4=Cell ID of the highest accuracy features.
    [B4,~] = find(BestAcc(:,TargetedFeatureNum+1)>B3-0.05);

    BestFeatures=nonzeros((BestAcc(B4(1,1),1:TargetedFeatureNum)))';

end
```

```
function [ SVM_Training_Accuracy ] = svm4feasel( TrainData,TrainTarget )
%   SVM4FEASEL is a function of SVM that used for FST.

%   Last updated: 23 April 2019

    %   Determine number of class.
    Class = length(unique(TrainTarget));

    % Train SVM model & test with Test Data.
    for a = 1:Class

        %   Create temporary target matrix by zeros.
        TempTrainTarget = zeros(length(TrainTarget),1);
        for x = 1:length(TrainTarget)

            if TrainTarget(x,1) == a

                %   Assign 1 to the current class, else 0.
                TempTrainTarget(x,1) = 1;

            else

                TempTrainTarget(x,1) = 0;

            end

        end

    %   Train SVM structure with Kernel Function = rbf.
    SVMStruct{a} = svmtrain(TrainData,TempTrainTarget,...
        'kernel_function','rbf');

    %   Test the trained SVM structure with Train Input.
    TrainOutput{a} = svmclassify(SVMStruct{a},TrainData);

    %   Gather all Train Output generated by each SVM structures.
    AllTrainOutput(:,a) = TrainOutput{1,a};

    end

    %   Calc size of matrix for the Test Output from SVM.
    Row = size(AllTrainOutput,1);
    Col = size(AllTrainOutput,2);

    %   Process data for each column.
    for b = 1:1:Row

        if sum(AllTrainOutput(b,:)) == 1

            %   Identified types of fault.
            SVMFinalDecision(b,1) = find(AllTrainOutput(b,:) == 1);

        else

            %   Undefined.
            SVMFinalDecision(b,1) = 0;

        end

        %   Validate the test result.
```

```
        SVMFinalDecision(b,2) = SVMFinalDecision(b,1) == TrainTarget(b,1);

    end

    %   Calculate test accuracy.
    SVM_Training_Accuracy = sum(SVMFinalDecision(:,2))/...
        length(AllTrainOutput);

end
```

LIST OF PUBLICATIONS

Journal with Impact Factor

1. **Hui, K.H.**, Ooi, C.S., Lim, M.H., Leong, M.S., Al-Obaidi, S.M. (2017) 'An improved wrapper-based feature selection method for machinery fault diagnosis' *PLoS ONE*, 12(12), 1–10. **(Q1, IF: 2.766)**

2. **Hui, K.H.**, Lim, M.H., Leong, M.S. and Al-Obaidi, S.M. (2017) 'Dempster-Shafer Evidence Theory for Multi-Bearing Faults Diagnosis' *Engineering Applications of Artificial Intelligence*, 57(November 2016), 160–170. **(Q1, IF: 2.819)**

3. **Hui, K.H.**, Ooi, C.S., Lim, M.H. and Leong, M.S. (2016) 'A Hybrid Artificial Neural Network with Dempster-Shafer Theory for Automated Bearing Fault Diagnosis' *Journal of Vibroengineering*, 18(7), 4409–4418. **(Q4, IF: 0.398)**

Indexed Journal

1. **Hui, K.H.**, Lim, M.H., Leong, M.S. and Al-Obaidi, S.M. (2017) 'Dempster-Shafer Evidence Theory for Automated Bearing Fault Diagnosis' *International Journal of Mechanical Engineering and Technology*, 8(4), 277–288. **(Indexed by SCOPUS)**

Indexed Conference Proceeding

1. **Hui, K.H.**, Lim, M.H. and Leong, M.S. (2017) 'Dempster-Shafer-based sensor fusion approach for machinery fault diagnosis' *American Society of Mechanical Engineers, Power Division (Publication) POWER*. 2017 **(Indexed by SCOPUS)**

2. **Hui, K.H.**, Hee, L.M. and Leong, M.S. (2014) ‘Machine Learning Tools in Machinery Faults Diagnosis: A Review’ *Applied Mechanics and Materials*, 575, 833–836. **(Indexed by SCOPUS)**

3. **Hui, K.H.**, Hee, L.M., Leong, M.S. and Abdelrhman, A.M. (2014) ‘Time-Frequency Signal Analysis in Machinery Fault Diagnosis: Review’ *Advanced Materials Research*, 845, 41–45. **(Indexed by SCOPUS)**

4. **Hui, K.H.**, Hee, L.M. and Leong, M.S. (2014) ‘Equipment Aging, Aging Detection, and Aging Management: A Review’ *Applied Mechanics and Materials*, 575, 935–938. **(Indexed by SCOPUS)**

Non-indexed Conference Proceeding

1. **Hui, K.H.**, Ooi, C.S., Lim, M.H. and Leong, M.S. (2019) ‘Feature selection tree for automated machinery fault diagnosis’ *MATEC Web of Conferences*, (255), 1–7.

2. **Hui, K.H.**, Ooi, C.S., Ngui, W.K., Lim, M.H., Leong, M.S. (2018) 'An Improved Image Processing Approach For Machinery Fault Diagnosis' *Global Power and Propulsion Forum*. 7–9 May 2018. Montreal, 1–5.

3. **Hui, K.H.**, Lim, M.H. and Leong, M.S. (2017) 'Evidence-based Automated Machinery-Fault Diagnosis' *APVC2017: the 17th Asia Pacific Vibration Conference.* 13–15 November 2017. Nanjing, 1–12.

4. **Hui, K.H.**, Lim, M.H., Leong, M.S., Zakaria, M.K. and Ngui, W.K. (2015) 'A Hybrid Method of Support Vector Machine and Dempster-Shafer Theory for Automated Bearing Fault Diagnosis' *Proceedings of the 16th Asia Pacific Vibration Conference*, 525–531.

5. **Hui, K.H.**, Lim, M.H., Leong, M.S. and Abdelrhman, A.M. (2015) 'Vibration Condition Monitoring: Latest Trend and Review' *Applied Mechanics and Materials*, 774, pp.139–143.