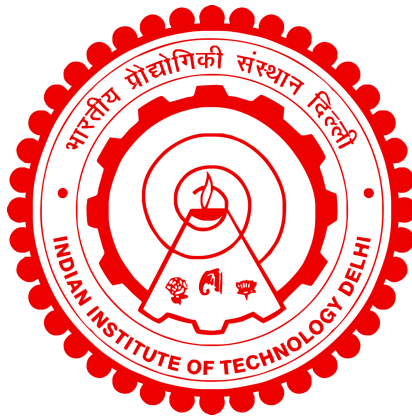


INTELLIGENT FAULT DIAGNOSIS STRATEGIES ON ROTATING MACHINES FOR INDUSTRY 4.0

TAUHEED MIAN



CENTRE FOR AUTOMOTIVE RESEARCH AND TRIBOLOGY

INDIAN INSTITUTE OF TECHNOLOGY DELHI

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Intelligent Fault Diagnosis Strategies on Rotating Machines for Industry 4.0

by

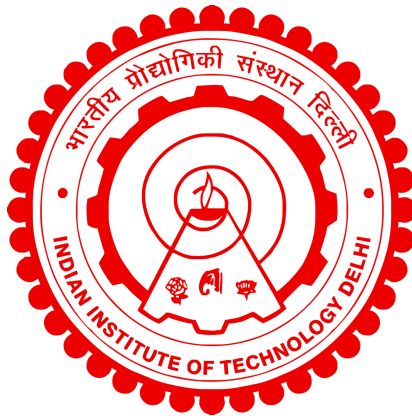
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Submitted

in fulfillment of the requirements of the degree of Doctor of Philosophy

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Dedicated to My Parents and Teachers

Certificate

This is to certify that the thesis entitled “**Intelligent Fault Diagnosis Strategies on Rotating Machines for Industry 4.0**”, submitted by **Mr. Tauheed Mian (Entry Number: 2018ITZ8549)** to the Indian Institute of Technology Delhi, for the award of the degree of **Doctor of Philosophy**, is a record of the original, bonafide research work carried out by him under my supervision and guidance. The thesis has reached the standards fulfilling the requirements of the regulations related to the award of the degree.

The results contained in this thesis have not been submitted in part or in full to any other University or Institute for the award of any degree or diploma to the best of my knowledge.

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Abstract

In any industrial system, rotating machines play a key role in seamless production. The reliable operation of rotating machines is ensured by their maximum availability through continuous health monitoring. In the present industrial scenario, due to intense market competition, industries are constrained to keep machinery maintenance costs to a minimum. Effective fault diagnosis is crucial to increase the reliability and availability of rotating machinery, minimize catastrophic loss, and reduce maintenance costs. Research and innovations in sensor systems, signal processing, Artificial Intelligence (AI), and internet-based technologies can be coupled as a comprehensive solution to address the demand for efficient and economical fault diagnostics within the context of Industry 4.0.

In this research work, an effort is made to develop a framework for intelligent fault diagnosis employing the growth of sensor technology, artificial intelligence, and cyber-physical systems by investigating in-situ edge computing and internet-based technology. To implement various strategies for intelligent fault diagnosis in rotating machines, the exploration of the most feasible sensor modalities in different working conditions is crucial. Experimentation for this exploration with contact and non-contact professional sensors is necessary to diagnose various faults. The information collected through professional sensors helps in building physics-based information regarding the faults through data-driven approaches. However, an important aspect of these sensors is the associated cost. The intense market competition in the present industrial scenario created a compulsion for industries to use economic sensors over professional sensors. The advancement in sensor technology opens the door to utilizing Micro Electro Mechanical System (MEMS) based sensors for intelligent, economical, and remote fault diagnosis using AI and the Internet of Things (IoT).

In this work, both contact and non-contact professional sensors are explored along with their fusion for the diagnosis of various faults in rotating machines. The faults simulated for this research are bearing faults, rotor unbalance, shaft misalignment, eccentricity, and gear faults. In this work, the development of intelligent fault diagnosis strategies is done using a data-driven approach due to its universality for simple and complex systems. Vibration is used as the contact modality, and radiated heat and sound are used as a non-contact modality.

Initially, vibration and Infrared Thermography (IRT) are explored for different bearing faults by adopting a sensor fusion-based strategy. Different statistical features are extracted, and further dimensionality reduction is done through Neighborhood Component Analysis (NCA) to cope with the curse of dimensionality in fusion. A support Vector Machine (SVM) with optimal features is used for the diagnosis of faults. With a fusion-based approach, better diagnosis results are obtained in terms of accuracy and detection quality. Further sound, which is another non-contact sensor modality, is explored in terms of its qualitative aspect for the diagnosis of faults. Substantially good results are observed using the sound quality features. The increase in fault severity needs robust features to get more accurate diagnosis information. For this purpose, image-based spatial information is used from vibration and IRT data using a deep learning-based strategy through Convolutional Neural Network (CNN) based deep feature extraction. Different combinations of faults are diagnosed with substantially better accuracy through this strategy.

Finally, after descriptively exploring different sensor modalities toward feasibility for economic and remote fault diagnosis, vibration monitoring is adopted, and an Artificial Intelligence of Things (AIoT) based package is developed. This is done by an integrated pulp of dedicatedly developed hardware, edge computing, AI, and IoT. The developed system is successfully validated with different fault conditions of rotating machine components. Moreover, the built AIoT-based system effectively illustrates real-time and remote fault detection and control for rotating machinery.

सार

किसी भी औद्योगिक प्रणाली में, घूमने वाली मशीनें निर्बाध उत्पादन में महत्वपूर्ण भूमिका निभाती हैं। घूमने वाली मशीनों का विश्वसनीय संचालन निरंतर स्वास्थ्य निगरानी के माध्यम से उनकी अधिकतम उपलब्धता द्वारा सुनिश्चित किया जाता है। वर्तमान औद्योगिक परिदृश्य में, तीव्र बाजार प्रतिस्पर्धा के कारण, उद्योग मशीनरी रखरखाव लागत को न्यूनतम रखने के लिए विवश हैं। घूमने वाली मशीनरी की विश्वसनीयता और उपलब्धता बढ़ाने, विनाशकारी नुकसान को कम करने और रखरखाव की लागत को कम करने के लिए प्रभावी दोष निदान महत्वपूर्ण है। उद्योग 4.0 के संदर्भ में कुशल और किफायती दोष निदान की मांग को पूरा करने के लिए सेंसर सिस्टम, सिग्नल प्रोसेसिंग, कृत्रिम बुद्धिमत्ता और इंटरनेट-आधारित प्रौद्योगिकियों में अनुसंधान और नवाचारों को एक व्यापक समाधान के रूप में जोड़ा जा सकता है।

इस शोध कार्य में, इन-सीटू एज कंप्यूटिंग और इंटरनेट-आधारित प्रौद्योगिकी की जांच करके सेंसर प्रौद्योगिकी, कृत्रिम बुद्धिमत्ता और साइबर-भौतिक प्रणालियों के विकास को नियोजित करते हुए बुद्धिमान दोष निदान के लिए एक रूपरेखा विकसित करने का प्रयास किया गया है। घूमने वाली मशीनों में बुद्धिमान दोष निदान के लिए विभिन्न रणनीतियों को लागू करने के लिए, विभिन्न कामकाजी परिस्थितियों में सबसे व्यवहार्य सेंसर तौर-तरीकों की खोज महत्वपूर्ण है। विभिन्न दोषों के निदान के लिए संपर्क और गैर-संपर्क पेशेवर सेंसर के साथ इस अन्वेषण का प्रयोग आवश्यक है। पेशेवर सेंसर के माध्यम से एकत्र की गई जानकारी डेटा-संचालित दृष्टिकोण के माध्यम से दोषों के संबंध में भौतिकी-आधारित जानकारी बनाने में मदद करती है। हालाँकि, इन सेंसरों का एक महत्वपूर्ण पहलू संबंधित लागत है। वर्तमान औद्योगिक परिदृश्य में तीव्र बाजार प्रतिस्पर्धा ने उद्योगों के लिए पेशेवर सेंसरों के बजाय आर्थिक सेंसरों का उपयोग करने की मजबूरी पैदा कर दी है। सेंसर प्रौद्योगिकी में प्रगति ने आर्टिफिशियल इंटेलिजेंस (एआई) और इंटरनेट ऑफ थिंग्स (आईओटी) का उपयोग करके बुद्धिमान, किफायती और दूरस्थ दोष निदान के लिए माइक्रो इलेक्ट्रो मैकेनिकल सिस्टम (एमईएमएस) आधारित सेंसर का उपयोग करने का द्वार खोल दिया है।

इस कार्य में, घूमने वाली मशीनों में विभिन्न दोषों के निदान के लिए उनके संलयन के साथ-साथ संपर्क और गैर-संपर्क पेशेवर सेंसर का पता लगाया जाता है। इस शोध के लिए सिम्युलेटेड दोष असर दोष, रोटार असंतुलन, शाफ्ट मिसलिग्मेंट, विलक्षणता और गियर दोष हैं। इस कार्य में, सरल और जटिल प्रणालियों के लिए इसकी सार्वभौमिकता के कारण डेटा-संचालित दृष्टिकोण का उपयोग करके बुद्धिमान दोष निदान रणनीतियों का विकास किया जाता है। कंपन का उपयोग संपर्क साधन के रूप में किया जाता है, और विकिरणित गर्मी और ध्वनि का उपयोग गैर-संपर्क साधन के रूप में किया जाता है।

प्रारंभ में, सेंसर फ्रयूजन-आधारित रणनीति अपनाकर विभिन्न असर दोषों के लिए कंपन और इन्फ्रारेड थर्मोग्राफी (आईआरटी) का पता लगाया जाता है। विभिन्न सांख्यिकीय विशेषताएं निकाली जाती हैं, और संलयन में आयामीता के अभिशाप से निपटने के लिए नेबरहुड कंपोनेंट एनालिसिस (एनसीए) के माध्यम से आयामीता में और

कमी की जाती है। दोषों के निदान के लिए इष्टतम सुविधाओं वाली एक सपोर्ट वेक्टर मशीन (एसवीएम) का उपयोग किया जाता है। फ़्यूज़न-आधारित दृष्टिकोण के साथ, सटीकता और पता लगाने की गुणवत्ता के मामले में बेहतर निदान परिणाम प्राप्त होते हैं। इसके अलावा ध्वनि, जो एक अन्य गैर-संपर्क सेंसर पद्धति है, दोषों के निदान के लिए इसके गुणात्मक पहलू के संदर्भ में पता लगाया जाता है। ध्वनि गुणवत्ता सुविधाओं का उपयोग करके काफी अच्छे परिणाम देखे गए हैं। दोष की गंभीरता में वृद्धि के लिए अधिक सटीक निदान जानकारी प्राप्त करने के लिए मजबूत सुविधाओं की आवश्यकता है। इस प्रयोजन के लिए, कन्वोल्यूशनल न्यूरल नेटवर्क (सीएनएन) आधारित गहन फीचर निष्कर्षण के माध्यम से गहन शिक्षण-आधारित रणनीति का उपयोग करके कंपन और आईआरटी डेटा से छवि-आधारित स्थानिक जानकारी का उपयोग किया जाता है। इस रणनीति के माध्यम से दोषों के विभिन्न संयोजनों का काफी बेहतर सटीकता के साथ निदान किया जाता है।

अंत में, आर्थिक और दूरस्थ दोष निदान के लिए व्यवहार्यता की दिशा में विभिन्न सेंसर तौर-तरीकों की वर्णनात्मक खोज के बाद, कंपन निगरानी को अपनाया जाता है, और एक आर्टिफिशियल इंटेलिजेंस ऑफ थिंग्स (एआईओटी) आधारित पैकेज विकसित किया जाता है। यह समर्पित रूप से विकसित हार्डवेयर, एज कंप्यूटिंग, एआई और आईओटी के एकीकृत पल्प द्वारा किया जाता है। विकसित प्रणाली को घूर्णन मशीन घटकों की विभिन्न दोष स्थितियों के साथ सफलतापूर्वक मान्य किया गया है। इसके अलावा, निर्मित एआईओटी-आधारित प्रणाली घूर्णन मशीनरी के लिए वास्तविक समय और दूरस्थ दोष का पता लगाने और नियंत्रण को प्रभावी ढंग से दर्शाती है।

Contents

Certificate	i
Acknowledgements	ii
Abstract	iii
Contents	vii
List of Figures	xi
List of Tables	xv
Abbreviations	xvii
Symbols	xix
1 Introduction	1
1.1 Motivation	2
1.2 Fault diagnosis in rotating machines	3
1.3 Recent advances in fault diagnosis	5
1.4 Need for economical remote fault diagnosis in Industry 4.0	6
1.5 Scope of the work	7
1.6 Organization of the thesis	8
2 Literature Review	11
2.1 Data acquisition in fault diagnosis	12
2.1.1 Sensor modalities	12
2.1.2 Sensor fusion	15
2.2 Fault diagnosis approaches	17
2.2.1 Model-based approach in fault diagnosis	17

2.2.2	Data driven approach in fault diagnosis	18
2.2.2.1	Signal processing in fault diagnosis	19
2.2.2.2	Artificial intelligence in fault diagnosis	20
2.2.2.3	Feature extraction and dimensionality reduction	20
2.2.2.4	Machine learning in fault diagnosis	22
2.2.2.5	Deep learning in fault diagnosis	24
2.3	Economic remote fault diagnosis in rotating machines	25
2.3.1	Advances in data acquisition for economic fault diagnosis	26
2.3.2	Advances in data handling for remote fault diagnosis	27
2.4	Conclusion and research gap	30
2.5	Problem identification and definition	31
2.6	Objectives of thesis	31
3	Experimental Details	33
3.1	Optimization design for diagnosing the rotating machine faults	34
3.1.1	Sensor optimization	34
3.1.2	Optimization of detection technique	35
3.1.3	Cost-benefit assessment	35
3.2	Rotating machine setups	36
3.2.1	Bearing test rig	36
3.2.2	Machine fault simulator	38
3.2.2.1	Bearing faults	40
3.2.2.2	Unbalance	41
3.2.2.3	Misalignment	41
3.2.2.4	Rotor eccentricity	43
3.2.3	Gear fault simulator	43
3.3	Data acquisition and measurement details	46
3.4	Hardware details for low-cost fault diagnosis system development	47
3.5	Summary of experiments	48
4	Fault Diagnosis using Sensor Fusion	51
4.1	Data acquisition and processing	52
4.1.1	Vibration signals	54
4.1.2	Infrared thermography	56
4.2	Feature extraction and dimensionality reduction	59
4.3	Feature ranking	63
4.4	Training and testing using SVM	65
4.5	Fault Diagnosis using SVM	67
4.5.1	Performance evaluation using vibration data	68
4.5.2	Performance evaluation using IRT data	71
4.5.3	Performance evaluation using sensor fusion	73
4.6	Summary	77

5	Fault Diagnosis using Sound Quality	79
5.1	Sound quality features	80
5.1.1	Loudness	81
5.1.2	Fluctuation strength	82
5.1.3	Roughness	82
5.1.4	Sharpness	83
5.1.5	Articulation index	83
5.2	Bearing fault diagnosis	84
5.2.1	Experimentation	84
5.2.2	Descriptive analysis	85
5.2.3	Fault diagnosis using SVM	89
5.2.4	Effect of background noise	92
5.2.5	Effect of sensor interchangeability	93
5.3	Gear fault diagnosis	95
5.3.1	Descriptive analysis	96
5.3.2	Fault diagnosis using SVM	97
5.4	Summary	100
6	Fault Diagnosis using Image-based Spatial Information	103
6.1	Images as data for fault diagnosis	104
6.2	Convolutional neural network	106
6.3	Bearing fault diagnosis	110
6.3.1	Vibration-based analysis and results	111
6.3.2	IRT-based analysis and results	116
6.4	Misalignment, unbalance, and eccentricity detection	121
6.4.1	Measurements	121
6.4.2	Vibration-based analysis and results	124
6.4.3	IRT-based analysis and results	127
6.5	Summary	133
7	Development of an Economical Remote Fault Diagnosis System	135
7.1	Role of edge computing in remote fault diagnosis	136
7.2	Feasibility assessment and sensor selection	137
7.3	AIoT-based fault diagnosis system development	140
7.3.1	Data acquisition and feature extraction	141
7.3.2	Model training and testing	141
7.3.3	Software development	143
7.4	Experimentation	146
7.5	Classification results	149
7.5.1	Bearing faults	150
7.5.2	Induction motor faults	152
7.5.3	Gear faults	154

7.6	Result for real-time remote fault detection	156
7.6.1	Bearing faults	157
7.6.2	Induction motor faults	158
7.6.3	Gear faults	158
7.7	Summary	159
8	Conclusions and Future Scope	161
8.1	Research contributions and comparison with state-of-the-art	164
8.1.1	Research contributions	164
8.1.2	Benchmarking	165
8.1.3	Comparison with the state-of-the-art	166
8.2	Practical relevance of the work	167
8.3	Scope for the future work	168
	 Bibliography	 169
	 Publications from the thesis	 203
	 Brief bio data	 205

List of Figures

1.1	Common faults and their causes in rotating machines	2
3.1	Bearing test rig	37
3.2	Different bearing faults (a) outer race fault (b) inner race fault (c) ball fault (d) cage fault	38
3.3	Different combination of bearing faults (a) dual-fault (b) multi-fault	38
3.4	Machine fault simulator	39
3.5	Induction motor as the prime mover in MFS	39
3.6	Different bearing fault conditions (a) healthy (b) inner race fault (c) outer race fault (d) ball fault (e) combined fault	40
3.7	Unbalance in the system (a) principal of unbalance (b) unbalance mass attached to the rotor	41
3.8	Fundamental of parallel misalignment	42
3.9	View of coupling (a) normal, and (b) misaligned coupling	43
3.10	Eccentricity fault (a) principal of eccentricity in the rotor (b) view of normal and eccentric Rotor	44
3.11	Gear fault simulator (a) full view (b) inside view of the gearbox	44
3.12	Gear faults (a) healthy gear (b) pitting (c) root cut (d) tooth missing	45
3.13	Hardware for low-cost diagnosis system development	48
4.1	Workflow for sensor fusion-based fault diagnosis	52
4.2	Measurement of vibration and IRT Data	53
4.3	Raw signal and frequency plot for OR defect at 19 Hz	55
4.4	Hilbert enveloped signal and frequency plot for OR defect at 19 Hz	55
4.5	Pre-processing the thermal images through 2D Hilbert transform (a) healthy bearing (b) outer race fault	58
4.6	Relevance score of each feature based on NCA at 19 Hz	63
4.7	Confusion matrices based on vibration data (a) 19 Hz (b) 23 Hz (c) 29 Hz	69
4.8	Performance measures based on vibration data (a) precision (b) recall, and (c) F1-score	70
4.9	Confusion matrices based on IRT (a) 19 Hz (b) 23 Hz (c) 29 Hz	71
4.10	Performance measures based on IRT data (a) precision (b) recall, and (c) F1-score	72

4.11	Confusion matrices based on fusion (a) 19 Hz (b) 23 Hz (c) 29 Hz . .	74
4.12	Performance evaluation based on fusion (a) precision (b) recall (c) F1-score	75
5.1	Sound quality-based fault diagnosis	80
5.2	Experimental setup for data acquisition	85
5.3	SQ features for left ear data (a) TVL (b) L_L (c) F_s (d) R_g (e) S_h (f) A_rI	87
5.4	Overall value of SQ features for left ear data (a) TVL (b) L_L (c) F_s (d) R_g (e) S_h (f) A_rI	88
5.5	Confusion matrices for left ear data (a) 19 Hz, (b) 27 Hz, (c) 35 Hz .	91
5.6	Performance evaluation in different backgrounds	93
5.7	Performance evaluation using different microphones	94
5.8	Experimental setup for gear fault diagnosis	95
5.9	SQ features for left ear data (a) TVL (b) L_L (c) F_s (d) R_g (e) S_h (f) A_rI	96
5.10	Overall value of SQ features for left ear data (a) TVL (b) L_L (c) F_s (d) R_g (e) S_h (f) A_rI	98
5.11	Confusion matrices for left ear data (a) 19 Hz, (b) 27 Hz, (c) 35 Hz .	99
6.1	Time-frequency image of vibration signal	105
6.2	Thermal image	106
6.3	Workflow of CNN for (a) vibration and (b) IRT	108
6.4	Overlapping windowing-based extraction of CWT-based scalogram .	113
6.5	Confusion matrices for single faults using vibration data (a) 19 Hz (b) 29 Hz (c) ramp up (d) ramp down	114
6.6	Confusion matrices for dual faults using vibration data (a) 19 Hz (b) 29 Hz (c) ramp up (d) ramp down	115
6.7	Confusion matrices for multi faults using vibration data (a) 19 Hz (b) 29 Hz (c) ramp up (d) ramp down	116
6.8	Thermal image of bearing housing in healthy condition at 29 Hz (a) machine is not running (b) steady state condition	117
6.9	Temperature values in different fault conditions at 19 Hz and 29 Hz (a) single faults (b) dual faults (c) multi-faults	118
6.10	Thermal images of different single fault conditions in bearing (a) healthy (b) IR (c) OR (d) BF (e) LB	119
6.11	Thermal images of different dual fault conditions in bearing (a) IRBF (b) IRLB (c) IROR (d) ORBF (e) ORLB	119
6.12	Thermal images of different multi-fault conditions in the bearing (a) MF1 (b) MF2 (c) MF3 (d) MF4 (e) MF5	120
6.13	Experimental setup and data acquisition	122
6.14	Vibration-based results at no-load condition (a) single faults, (b) dual faults, and (c) multi-faults	126

6.15	Vibration-based results at load condition (a) single faults, (b) dual faults, and (c) multi-faults	127
6.16	IRT images at (a) initial condition (b) during running at steady state	128
6.17	Temperature on bearing (a) single faults (b) dual faults (c) multi-faults	129
6.18	Temperature on coupling (a) single faults (b) dual faults (c) multi-faults	130
6.19	IRT-based results at no-load condition (a) single faults, (b) dual faults, and (c) multi-faults	131
6.20	IRT-based results at load condition (a) single faults, (b) dual faults, and (c) multi-faults	132
7.1	Edge centric AIoT based fault diagnosis	137
7.2	Frequency spectrum of raw and Hilbert enveloped signal of outer race fault at 19 Hz using MEMS sensor	138
7.3	Frequency spectrum of raw and Hilbert enveloped signal of outer race fault at 19 Hz using professional sensor	139
7.4	AIoT-based fault diagnosis strategy	140
7.5	Developed hand-held prototype based on AIoT-based strategy	144
7.6	Login page of the software	145
7.7	AIoT-based platform	146
7.8	Experimental setup for bearing fault detection	147
7.9	Experimental setup for induction motor fault detection	148
7.10	Experimental setup for gear fault detection	148
7.11	Feature visualization for bearing fault data at 19 Hz	150
7.12	Confusion matrices for bearing fault dataset based on SVM	151
7.13	Feature visualization for induction motor fault data at 19 Hz	153
7.14	Confusion matrices of the induction motor dataset based on SVM . .	154
7.15	Feature visualization for the gear fault data at 19 Hz	155
7.16	Confusion matrices of the gear dataset based on SVM	156
8.1	Flow diagram of the developed intelligent diagnosis framework	162

List of Tables

3.1	Summary of experiments	49
4.1	Extracted features and their mathematical expressions	60
4.2	Selected features with obtained rank using RA at 19 Hz	65
4.3	Comparison of the present method with other methods of feature fusion	76
5.1	Performance measures for left ear data of bearing faults at 19 Hz . .	92
5.2	Performance measures for left ear data of bearing faults at 27 Hz . .	92
5.3	Performance measures for left ear data of bearing faults at 35 Hz . .	92
5.4	Performance measures for left ear data of gear faults at 19 Hz	99
5.5	Performance measures for left ear data of gear faults at 27 Hz	100
5.6	Performance measures for left ear data of gear faults at 35 Hz	100
6.1	Description of various layers in the present CNN model	107
6.2	Fault conditions of bearing	111
6.3	Fault conditions of unbalance, misalignment, and eccentricity	123
6.4	Data size used for training and testing	123
7.1	Performance evaluation of various classifiers for bearing faults	151
7.2	Performance measures for bearing fault dataset based on SVM	152
7.3	Performance evaluation of various classifiers for induction motor faults	153
7.4	Performance measures for the induction motor dataset based on SVM	153
7.5	Performance evaluation of various classifiers for gear faults	155
7.6	Performance measures for the gear dataset based on SVM	155
7.7	Real-time fault detection results on bearing faults	157
7.8	Real-time fault detection results on induction motor faults	158
7.9	Real-time fault detection results on gear faults	159
8.1	Benchmarking chart for different sensing techniques presented in this thesis	165
8.2	Comparison of the contributed methodology with state-of-the-art . .	166

Abbreviations

AI	A rtificial I ntelligence
AIoT	A rtificial I ntelligence of T hings
CNN	C onvolutional N eural N etwork
CQT	C onstant Q - T ransform
CWT	C ontinuous W avelets T ransform
ML	M achine L earning
HATS	H ead and T orso S imulator
IoT	I nternet of T hings
IRT	I nfrared T hermography
MEMS	M icro E lectro M echanical S ystem
MFS	M achine F ault S imulator
DL	D eep L earning
NCA	N eighbourhood C omponent A nalysis
PCA	P rinciple C omponent A nalysis
ROI	R egion of I nterest
SBC	S ingle B oard C omputer
SQ	S ound Q uality
SVM	S upport V ector M achine

Symbols

s	Vibration signal	σ	Stefan-Boltzmann constant
s_a	Analytic signal	ϕ	Contact angle
Q	Total heat energy	Q_h	Convection heat energy
Q_r	Radiation heat energy	c	Specific heat
ε	Emissivity	T	Absolute temperature
L	Loudness	L'	Specific loudness
L_L	Loudness level	F_s	Fluctuation strength
F'_s	Specific fluctuation strength	z	Bark scale
R_g	Roughness	R'_g	Specific roughness
S_h	Sharpness	$A_r I$	Articulation Index
ψ	Mother wavelet	ψ^*	Complex conjugate of mother wavelet
τ	Translational factor	β	Scale factor
w_0	Center of support	I_{2D}	Total number of 2D images
Z	Total number of data points	w	Window size
r	Overlap factor	n	Frequency bin
K_n	Window length	f_n	Center frequency
f_s	Sampling frequency	χ	Bins per octave