

**DEVELOPMENT OF FAULT DIAGNOSIS STRATEGIES FOR
ELECTRIC VEHICLE MOTOR**

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INDIAN INSTITUTE OF TECHNOLOGY, DELHI**

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**DEVELOPMENT OF FAULT DIAGNOSIS STRATEGIES FOR
ELECTRIC VEHICLE MOTOR**

by

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School of Interdisciplinary Research

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CERTIFICATE

This is to certify that the thesis entitled, “**Development of Fault Diagnosis Strategies for Electric Vehicle Motor**”, being submitted by **Mr. Anurag Choudhary (2020SRZ8246)** for the award of the degree of **Doctor of Philosophy**, is a record of bonafide research work carried out by him in the School of Interdisciplinary Research (SIRe) of the Indian Institute of Technology Delhi. Mr. Anurag Choudhary has worked under our guidance and supervision and has fulfilled the requirements for submitting this thesis to reach the requisite standard. The results obtained here have not been submitted to any other University or Institute for the award of any degree.

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ABSTRACT

Electric vehicles (EVs) are essential for future transportation, and various eco-friendly vehicles are being manufactured to attain the increasing demand for reducing environmental emissions, enhanced performance, and safety. The electric motor is a critical component of these eco-friendly vehicles for powering the wheels and propelling the vehicle forward. However, electric vehicle motors are susceptible to faults like any other mechanical system that can compromise their performance, safety, and longevity. Therefore, a fault diagnosis system is essential for the timely detection of faults and abnormalities in electric vehicle motors to ensure reliable performance, prevent safety hazards, and minimize maintenance costs.

This research work focuses on developing an efficient fault diagnosis strategy for electric vehicle motors. In pursuit of this, two fault simulators have been designed and developed to experimentally simulate the motor faults in two-wheelers and four-wheelers respectively. Various sensors, i.e., vibration, current, and acoustic and their data processing, are thoroughly investigated to assess their suitability for fault diagnosis of electric vehicle motors. These data processing methods include short-time Fourier transforms, continuous wavelet transforms, constant Q transforms, and wavelet synchrosqueezing transforms. After experimenting with the different sensors, it has been concluded that a fusion of vibration and the current signal is the most feasible, effective, and practical solution for electric vehicle motor fault diagnosis. The benefits of both signals are combined in the proposed fusion-based diagnosis solution, providing comprehensive coverage of both mechanical and electrical faults. Factors like suitability, performance, complexity, and mounting limitations drive the fusion-based decision. The developed diagnosis strategy involves the wavelet synchrosqueezing transform for decomposing raw signals collected

from the electric vehicle motor and then converted into time-frequency representation frames. A Multi-Input Convolutional Neural Network (MI-CNN) is designed and developed by combining the derived features from the vibration and current signal representation frames. The proposed MI-CNN can accurately diagnose a wide range of mechanical and electrical faults that may occur in the electric motor. Various performance metrics are employed to evaluate this diagnosis performance. These metrics assess the system's effectiveness in efficiently and accurately diagnosing different faults. Through rigorous testing, the developed fault diagnosis system demonstrates its proficiency in efficiently identifying and diagnosing faults in electric vehicle motors.

Furthermore, the developed fault diagnosis strategy through the fusion of vibration and current signatures is extended and validated in real-time on electric vehicles. To ensure the reliability of the approach, two dedicated electric vehicle setups have been utilized for testing and validating the fault diagnosis strategy using transfer learning. The results obtained from applying the diagnostic method initially on the laboratory motor and subsequently transferring it to the operational electric vehicle demonstrate the effectiveness and practicality of the proposed solution. This validation process reinforces the fault diagnosis system's confidence, showing its ability to perform efficiently and accurately in real-world scenarios on actual electric vehicles. In order to develop a field-worthy system that is relevant for real-time applications, a user-friendly on-board diagnostic solution is developed with a Graphical User Interface (GUI), enabling real-time fault prediction in electric vehicles. This diagnostic strategy leverages the established transfer learning-based diagnosis method, offering a reliable and efficient solution for identifying motor faults in electric vehicles. As a result, the system contributes to reduced maintenance costs, improved performance, enhanced safety, and prolonged longevity of electric vehicles.

सार

इलेक्ट्रिक वाहन (ईवी) भविष्य के परिवहन के लिए आवश्यक हैं, और पर्यावरणीय उत्सर्जन को कम करने, बेहतर प्रदर्शन और सुरक्षा की बढ़ती मांग को पूरा करने के लिए विभिन्न पर्यावरण-अनुकूल वाहनों का निर्माण किया जा रहा है। पहियों को शक्ति देने और वाहन को आगे बढ़ाने के लिए इलेक्ट्रिक मोटर इन पर्यावरण-अनुकूल वाहनों का आवश्यक घटक है। हालाँकि, इलेक्ट्रिक वाहन मोटरें किसी भी अन्य यांत्रिक प्रणाली की तरह दोषों के प्रति संवेदनशील होती हैं जो उनके प्रदर्शन, सुरक्षा और दीर्घायु से समझौता कर सकती हैं। इसलिए, विश्वसनीय प्रदर्शन सुनिश्चित करने, सुरक्षा खतरों को रोकने और रखरखाव लागत को कम करने के लिए इलेक्ट्रिक वाहन मोटर्स में दोषों और असामान्यताओं का समय पर पता लगाने के लिए एक दोष निदान प्रणाली आवश्यक है।

यह शोध कार्य इलेक्ट्रिक वाहन मोटर्स के लिए एक कुशल दोष निदान समाधान विकसित करने पर केंद्रित है। इसके अनुसरण में, दो पहिया और चार पहिया वाहनों दोनों में मोटर दोषों को प्रयोगात्मक रूप से अनुकरण करने के लिए दो दोष सिमुलेटर डिजाइन किए गए हैं। आरंभ करने के लिए, इलेक्ट्रिक वाहन मोटरों के दोष निदान के लिए उनकी उपयुक्तता का आकलन करने के लिए विभिन्न सेंसर, यानी कंपन, वर्तमान और ध्वनिक और उनके डेटा प्रोसेसिंग की पूरी तरह से जांच की जाती है। इन डेटा प्रोसेसिंग विधियों में कम समय के फूरियर ट्रांसफॉर्म, निरंतर वेवलेट ट्रांसफॉर्म, निरंतर क्यू ट्रांसफॉर्म और वेवलेट सिन्क्रोस्क्वीज़िंग ट्रांसफॉर्म शामिल हैं। विभिन्न सेंसरों के साथ प्रयोग करने के बाद, यह निष्कर्ष निकाला गया है कि कंपन और विद्युत प्रवाह सिग्नल का संलयन इलेक्ट्रिक वाहन मोटर दोष निदान के लिए सबसे व्यवहार्य, प्रभावी और व्यावहारिक समाधान है। दोनों संकेतों के लाभों को प्रस्तावित संलयन-आधारित निदान समाधान में संयोजित किया गया है, जो यांत्रिक और विद्युत दोनों दोषों का व्यापक आवृत्त क्षेत्र प्रदान करता है। उपयुक्तता, प्रदर्शन, जटिलता और बढ़ती सीमाएँ जैसे कारक फ़्यूज़न-आधारित निर्णय को संचालित करते हैं।

विकसित निदान प्रक्रिया में इलेक्ट्रिक वाहन मोटर से एकत्र किए गए कच्चे संकेतों को विघटित करने के लिए वेवलेट सिंक्रोस्क्वूजिंग ट्रांसफॉर्म शामिल है और फिर समय-आवृत्ति प्रतिनिधित्व फ्रेम में परिवर्तित किया जाता है। एक मल्टी-इनपुट कन्वोल्यूशनल न्यूरल नेटवर्क (एमआई-सीएनएन) को कंपनी और वर्तमान सिग्नल प्रतिनिधित्व फ्रेम से प्राप्त सुविधाओं को मिलाकर डिजाइन किया गया है। ऐसा करने से, एमआई-सीएनएन इलेक्ट्रिक मोटर में होने वाली यांत्रिक और विद्युत दोषों की एक विस्तृत श्रृंखला का सटीक निदान कर सकता है। इस निदान पद्धति के प्रदर्शन का मूल्यांकन करने के लिए विभिन्न प्रदर्शन मेट्रिक्स नियोजित किए जाते हैं। ये मेट्रिक्स विभिन्न दोषों का कुशलतापूर्वक और सटीक निदान करने में सिस्टम की प्रभावशीलता का आकलन करते हैं। कठोर परीक्षण के माध्यम से, विकसित दोष निदान प्रणाली इलेक्ट्रिक वाहन मोटर्स में दोषों की कुशलतापूर्वक पहचान और निदान करने में अपनी दक्षता प्रदर्शित करती है।

इसके अलावा, कंपनी और वर्तमान हस्ताक्षरों के संलयन के माध्यम से विकसित दोष निदान पद्धति को इलेक्ट्रिक वाहनों पर वास्तविक समय में बढ़ाया और मान्य किया गया है। दृष्टिकोण की विश्वसनीयता सुनिश्चित करने के लिए, ट्रांसफर लर्निंग का उपयोग करके दोष निदान रणनीति के परीक्षण और सत्यापन के लिए दो समर्पित इलेक्ट्रिक वाहन सेटअप का उपयोग किया गया है। प्रारंभ में प्रयोगशाला मोटर पर निदान पद्धति को लागू करने और बाद में इसे परिचालन इलेक्ट्रिक वाहन में स्थानांतरित करने से प्राप्त परिणाम प्रस्तावित समाधान की प्रभावशीलता और व्यावहारिकता को प्रदर्शित करते हैं। यह सत्यापन प्रक्रिया दोष निदान प्रणाली के विश्वास को मजबूत करती है, जो वास्तविक इलेक्ट्रिक वाहनों पर वास्तविक दुनिया के परिदृश्यों में कुशलतापूर्वक और सटीक रूप से प्रदर्शन करने की क्षमता दिखाती है। एक क्षेत्र-योग्य प्रणाली विकसित करने के लिए जो वास्तविक समय के अनुप्रयोगों के लिए प्रासंगिक है, ग्राफिकल यूजर इंटरफेस (जीयूआई) के साथ एक उपयोगकर्ता के अनुकूल ऑन-बोर्ड डायग्नोस्टिक प्लेटफॉर्म विकसित किया गया है, जो इलेक्ट्रिक

वाहनों में वास्तविक समय की गलती की भविष्यवाणी को सक्षम करता है। यह प्लेटफ़ॉर्म स्थापित ट्रांसफर लर्निंग-आधारित निदान पद्धति का लाभ उठाता है, जो इलेक्ट्रिक वाहनों में मोटर दोषों की पहचान के लिए एक विश्वसनीय और कुशल समाधान प्रदान करता है। परिणामस्वरूप, सिस्टम रखरखाव लागत को कम करने, बेहतर प्रदर्शन, बढ़ी हुई सुरक्षा और इलेक्ट्रिक वाहनों के लंबे समय तक चलने में योगदान देता है।

TABLE OF CONTENTS

CERTIFICATE		i
ACKNOWLEDGEMENT		ii
ABSTRACT		iv
TABLE OF CONTENTS		ix
LIST OF FIGURES		xiv
LIST OF TABLES		xxii
LIST OF ABBREVIATIONS		xxv
LIST OF SYMBOLS		xxvii
CHAPTER 1 INTRODUCTION		1-10
1.1.	Overview of Electric Vehicle	1
1.2.	Background of Fault Diagnosis for EV Motor	2
1.3.	Motivation	3
1.4.	Statement of the Problem	4
1.5.	State of the Arts on Fault Diagnosis	5
1.6.	Scope of Proposed Research Work	6
1.7.	Thesis Organization	6
CHAPTER 2 LITERATURE REVIEW		11-45
2.1	Electric Vehicle Motor Faults	11
2.1.1	Bearing Faults	14
2.1.2	Stator Faults	16
2.1.3	Rotor and Other Related Faults	17
2.2	Fault Diagnosis Methods for Electric Vehicle	19
2.2.1	Knowledge-Based Method	21
2.2.2	Model-Based Method	22

2.2.3	Data-Driven Based Method	23
2.3	Different Sensor Modalities in Fault Diagnosis	24
2.3.1	Vibration Monitoring	25
2.3.2	Motor Current Signature Analysis	28
2.3.3	Infrared Thermography	29
2.3.4	Acoustic Signal	31
2.3.5	Sensor Fusion-Based Approaches	34
2.4	Statistical and Signal Processing for Fault Diagnosis	35
2.4.1	Time Domain Analysis	35
2.4.2	Frequency Domain Analysis	35
2.4.3	Time-Frequency Domain Analysis	36
2.5	Fault Diagnosis of EV using Artificial Intelligence Techniques	37
2.5.1	Machine Learning-Based Fault Diagnosis	38
2.5.2	Deep Learning-Based Fault Diagnosis	39
2.5.3	Transfer Learning-Based Fault Diagnosis	41
2.6	Inferences Drawn from the Literature Review	42
2.7	Research Gap	43
2.8	Thesis Objective	44
CHAPTER 3	EXPERIMENTAL SETUP AND DETAILS	46-63
3.1.	Machine Fault Simulator	46
3.2.	Development of Electric Vehicles Simulators	48
3.3.1	Electric -Two-Wheeler Setup	50
3.3.2	Electric -Four-Wheeler Setup	53
3.3.	Experimental Designed	60

CHAPTER 4	FAULT DIAGNOSTIC STRATEGIES BASED ON DIFFERENT SENSOR MODALITIES	64-100
4.1.	Experimental Setup on Machine Fault Simulator	64
4.1.1	Experimental Setup	65
4.1.2	Data Acquisition	66
4.2.	Data Preparation	71
4.2.1	Signal-to-Image Representation of Signal	71
4.2.2	Extraction of the Thermal Images	73
4.3.	Deep Learning-Based Fault Diagnosis Methodology	74
4.4.	Experimental Results and Discussion	78
4.4.1	Performance with Vibration Signature Analysis	80
4.4.2	Performance with Motor Current Signature Analysis	85
4.4.3	Performance with Acoustic Signature Analysis	89
4.4.4	Performance with Infrared Thermography	94
4.5.	Comparison and Suitability of Sensor Modality for EV Motors	98
CHAPTER 5	FAULT DIAGNOSIS OF ELECTRIC VEHICLE MOTOR IN LABORATORY CONDITIONS	101-132
5.1.	Multi-Sensor Fusion-Based Fault Diagnosis	102
5.1.1	Multi-Input Convolutional Neural Network	102
5.1.2	Time-Frequency Representation using WSST	109
5.1.3	Training and Testing	118
5.2.	Result and Discussion Based on Sensor Fusion	119
5.2.1	Fault Diagnosis Based on Vibration and Current Fusion	119
5.2.2	Fault Diagnosis Based on Vibration and Acoustic Fusion	124
5.2.3	Comparative Analysis of Proposed Diagnosis Method	130

CHAPTER 6 TRANSFER LEARNING-BASED FAULT DIAGNOSIS OF 133-178
ELECTRIC TWO-WHEELER AND FOUR-WHEELER

6.1	Theoretical Background of Transfer Learning	134
6.2	Transfer Learning and Fine Tuning	137
6.3	Experimentation and Data Acquisition	140
6.3.1	Investigated Faults	141
6.3.2	Data Acquisition	147
6.4	Result of fault diagnosis on Electric Two-Wheeler	152
6.4.1	In-Wheel BLDC Hub Motor	152
6.4.2	Mid Drive SRM	158
6.5	Validation of Proposed TL-based Diagnosis Methodology on Electric Four-Wheeler Motor	165
6. 5.1.	Experimental Setup	165
6. 5.2.	Investigated Faults	167
6. 5.3.	Data Acquisition	168
6.5.4	Diagnosis Results on Electric Four-wheelers	169

CHAPTER 7 ON-BOARD FAULT DIAGNOSIS OF ELECTRIC 179-191
VEHICLE MOTORS

7.1	On-Board Fault Diagnosis	179
7.2	Experimental Setup and Data Acquisition	180
7.2.1.	Experimental Setup	181
7.2.2	Sensing Unit	182
7.2.3	Data Acquisition	182
7.2.4	Single Board Computer	183
7.3	Deployment of the Software on SBC	184

7.4	Results and Discussion	188
CHAPTER 8	CONCLUSION AND FUTURE WORK	192-197
8.1	Major Contributions	195
8.2	Scope for Future Work	195
8.3	Comparison with Published Research	196
8.4	Comparison with Published Research	197
REFERENCES		198-233
PATENTS AND PUBLICATIONS FROM THE THESIS		234
BIO-DATA		238

LIST OF FIGURES

Figure No.	Caption	Page No.
1.1	Flowchart of the thesis	7
2.1	Possible sources of electric motor faults in electric vehicle	14
2.2	Different ball bearing defects in electric motor	15
2.3	Different stator faults in electric vehicle motors (a) Induction motor (b) PMSM (c) SRM (d) BLDC motor	16
2.4	Different rotor-related faults in electric motor	18
2.5	Six steps of the fault diagnosis process in EV	20
2.6	Classification of fault diagnosis methods	21
3.1	View of the machine fault simulator	47
3.2	CAD-designed of developed electric two-wheeler simulators	50
3.3	View developed electric two-wheeler simulator setup	51
3.4	CAD design of developed electric four-wheeler simulator setup	54
3.5	Total deformation analysis on the front side of the developed electric four-wheeler vehicle frame	55
3.6	Total stress analysis on the front side of the developed electric four-wheeler vehicle frame	55
3.7	Safety factor analysis on the front side of the developed electric four-wheeler vehicle frame	56
3.8	View developed electric four-wheeler simulator setup	58
3.9	Developed electric four-wheeler setup (a) Exploded view drive train transmission (b) View of the drivetrain transmission with	59

	SRM motor (c) View of the drivetrain transmission with BLDC motor	
4.1	Experimental setup and measurement with sensor modalities	65
4.2	Acquired raw vibration signals under various conditions (a) No-Load (b) Load	67
4.3	Acquired raw current signals under various operating conditions (a) No-Load (b) Load	68
4.4	Acquired raw acoustic signals under various conditions (a) No-Load (b) Load	69
4.5	Acquired thermal images at initial rotating speed condition (a) No-Load (b) Load	70
4.6	Sliding window-based CQT extraction process	72
4.7	Process of thermal image extraction	74
4.8	CNN-based fault diagnosis methodology for induction motor fault diagnosis	74
4.9	Class-wise performance measures based on vibration signals under constant operating conditions	82
4.10	Class-wise performance measures based on vibration signals under varying operating conditions	84
4.11	Class-wise performance measures based on current signal under constant operating conditions	87
4.12	Class-wise performance measures based on current signal under varying operating conditions	89
4.13	Class-wise performance measures based on acoustic signals under constant operating conditions	91

4.14	Class-wise performance measures based on acoustic signals under varying operating conditions	93
4.15	Class-wise performance measures based on the thermal image under constant operating conditions	95
4.16	Class-wise performance measures based on thermal images under varying operating conditions	97
4.17	Compression of different sensor modalities based on their accuracy performance under constant operating conditions	99
4.18	Compression of different sensor modalities based on their accuracy performance under varying operating conditions	99
5.1	Sensor fusion-based fault diagnosis methodology for EV Motor	103
5.2	Proposed multi-input-based convolutional neural network model	107
5.3	Sample signals representation (a) Stationary signal (b) Non-stationary signal (c) Varying speed non-stationary signal	113
5.4	Instantaneous frequency representation (a) Stationary signal (b) Non-stationary signal (c) Varying speed non-stationary signal	114
5.5	Raw samples of current signatures in each sliding window for different operating conditions	117
5.6	Raw samples of vibration signatures in each sliding window for different operating conditions	117
5.7	Sample of different time-frequency frames obtained from different time-frequency representation methods (a) Bearing fault at no-load condition (b) Bearing fault load condition	118
5.8	Performance measures obtained from the fusion of current and vibration-based diagnostic models under NL-RU condition	121

5.9	Performance measures obtained from the fusion of current and vibration-based diagnostic models under NL-RD condition	122
5.10	Performance measures obtained from the fusion of current and vibration-based diagnostic models under L-RU conditions	123
5.11	Performance measures obtained from the fusion of current and vibration-based diagnostic models under L-RD conditions	124
5.12	Performance measures obtained from the fusion of acoustic and vibration-based diagnostic models under NL-RU conditions	126
5.13	Performance measures obtained from the fusion of acoustic and vibration-based diagnostic models under NL-RD condition	127
5.14	Performance measures obtained from the fusion of acoustic and vibration-based diagnostic models under L-RU condition	129
5.15	Performance measures obtained from the fusion of acoustic and vibration-based diagnostic models under L-RD conditions	129
5.16	Comparison of diagnosis accuracies between current and vibration fusion vs acoustic and vibration fusion in different operation conditions	130
5.17	Comparison of time-frequency representation based on the current and vibration fusion in different operation conditions.	131
6.1	General pipeline of transfer learning from the source domain to the target domain	136
6.2	Transfer learning procedure trains the three highest-level blocks of the pre-trained diagnostic model while leaving the weights of the bottom two blocks frozen	139
6.3	Electric two-wheeler setup for in-wheel BLDC hub motor	140

6.4	Electric two-wheeler setup for mid-drive SRM	141
6.5	Different components of the In-wheel BLDC hub Motor	142
6.6	Experimentally simulated bearing fault in In-wheel BLDC hub motor	143
6.7	Experimentally simulated stator fault in In-wheel BLDC hub motor	143
6.8	Experimentally simulated cracks or fractures in the permanent magnets in the In-wheel BLDC hub motor	144
6.9	Different components of the mid-drive SRM	145
6.10	Experimentally simulated bearing fault in mid-drive SRM	145
6.11	Experimentally simulated cracks or fractures on the rotor in mid-drive SRM	146
6.12	Experimentally simulated stator faults on the rotor in mid-drive SRM	146
6.13	Acquired vibration signature under operating and fault conditions of BLDC hub motor	150
6.14	Acquired current signature under different operating and fault conditions of BLDC hub motor	150
6.15	Acquired vibration signature under operating and fault conditions of SRM motor	151
6.16	Acquired current signature under different operating and fault conditions of SRM motor	151
6.17	Confusion matrix on the in-wheel BLDC hub motor dataset under S-100 conditions	154

6.18	Performance measures on the in-wheel BLDC hub motor dataset under S-100 conditions	154
6.19	Confusion matrix on the in-wheel BLDC hub motor dataset under S-50 conditions	155
6.20	Performance measures on the in-wheel BLDC hub motor dataset under S-50 conditions	155
6.21	Confusion matrix on the in-wheel BLDC hub motor dataset under S-RU conditions	156
6.22	Performance measures on the in-wheel BLDC hub motor dataset under S-RU conditions	156
6.23	Confusion matrix on the in-wheel BLDC hub motor dataset under S-RD conditions	157
6.24	Performance measures on the in-wheel BLDC hub motor dataset under S-RD conditions	157
6.25	Confusion matrix on the mid-drive SRM motor dataset under S-100 conditions	159
6.26	Performance measures on the mid-drive SRM motor dataset under S-100 conditions	159
6.27	Confusion matrix on the mid-drive SRM motor dataset under S-50 conditions	160
6.28	Performance measures on the mid-drive SRM motor dataset under S-50 conditions	160
6.29	Confusion matrix on the mid-drive SRM motor dataset under S-RU conditions	161

6.30	Performance measures on the mid-drive SRM motor dataset under S-RU conditions	161
6.31	Confusion matrix on the mid-drive SRM motor dataset under S-RD conditions	162
6.32	Performance measures on the mid-drive SRM motor dataset under S-RD conditions	162
6.33	Comparison of obtained overall fault diagnosis accuracy on the tested motor for electric two-wheeler	164
6.34	Experimental setup and data acquisition on the electric four-wheeler	166
6.35	Traction motor mounting on electric four-wheelers (a) SRM (b) BLDC	167
6.36	Confusion matrix at different loading condition speed conditions of BLDC motor in four-wheeler	170
6.37	Performance at different loading condition speed conditions of BLDC motor in four-wheeler	171
6.38	Confusion matrix at different loading condition speed conditions of SRM in the four-wheeler	173
6.39	Performance at different loading condition speed conditions of SRM in four-wheeler	174
6.40	Overall accuracy comparison under different speed and load conditions of BLDC motor for electric four-wheeler	177
6.41	Overall accuracy comparison under different speed and load conditions of SRM motor for electric four-wheeler	177
7.1	Flow diagram of the proposed on-board diagnosis system	180

7.2	Experimental setup for the on-board fault diagnosis of electric vehicle motor	181
7.3	Stepwise development stages of the on-board diagnosis system based on SBC	183
7.4	Represents the workflow for Tkinter GUI of the frontend	185
7.5	Visualization of the frontend of the GUI	186
7.6	Visualization of the functional GUI for electrical vehicle motor	187
7.7	Diagnosis results under different operating conditions of the electric vehicle motor at no load conditions	189
7.8	Diagnosis results under different operating conditions of the electric vehicle motor at single-person loaded conditions	189
7.9	Diagnosis results under different operating conditions of the electric vehicle motor at double person loaded conditions	190

LIST OF TABLES

Table No.	Caption	Page No.
2.1	Different electric motor and battery details used in four-wheeler EVs	12
2.2	Different electric motor and battery details used in two-wheeler EVs	12
3.1	Details of the machine fault simulator used for the experiment	47
3.2	Technical specification of developed electric two-wheeler fault simulators	51
3.3	Technical specification of developed electric four-wheeler fault simulators	58
3.4	Designed experiments on the machine fault simulator	60
3.5	Designed experiments on the electric two-wheeler	61
3.6	Designed experiments on the electric four-wheeler	62
4.1	Confusion matrix obtained from the vibration-based diagnostic model on constant speed condition	81
4.2	Confusion matrix obtained from the vibration-based diagnostic model on varying speed condition	83
4.3	Confusion matrix obtained from the current based diagnostic model on constant speed condition	86
4.4	Confusion matrix obtained from the current based diagnostic model on varying speed condition	88

4.5	Confusion matrix obtained from the acoustic-based diagnostic model on constant speed condition	90
4.6	Confusion matrix obtained from the acoustic-based diagnostic model on varying speed condition	92
4.7	Confusion matrix obtained from the thermal image-based diagnostic model on constant speed condition	94
4.8	Confusion matrix obtained from thermal images based diagnostic model on varying speed condition	96
5.1	Proposed multi-input CNN-based model architecture design for fault diagnosis	107
5.2	Confusion matrix obtained from current and vibration fusion-based diagnostic model under NL-RU condition	120
5.3	Confusion matrix obtained from current and vibration fusion-based diagnostic model under NL-RD condition	121
5.4	Confusion matrix obtained from current and vibration fusion-based diagnostic model under L-RU condition	122
5.5	Confusion matrix obtained from current and vibration fusion-based diagnostic model on L-RD condition	123
5.6	Confusion matrix obtained from acoustic and vibration fusion-based diagnostic model under NL-RU	125
5.7	Confusion matrix obtained from acoustic and vibration fusion-based diagnostic model under NL-RD condition	126
5.8	Confusion matrix obtained from acoustic and vibration fusion-based diagnostic model under L-RU condition	128

5.9	Confusion matrix obtained from acoustic and vibration fusion-based diagnostic model on L-RD condition	128
6.1	Operating condition of electric two-wheelers as an in-wheel and mid-drive wheel motor	148
8.1	Comparison with the published literatures	196

ABBREVIATIONS

AC	Alternating Current	DL	Deep Learning
AM	Amplitude Modulation	DTL	Deep Transfer Learning
AHM	Automotive Health Monitoring	EVs	Electric Vehicles
AI	Artificial Intelligence	EWT	Empirical Wavelet Transform
ANN	Artificial Neural Network	FD	Fault Diagnosis
ANFIS	Adaptive Neuro-Fuzzy Inference System	FEM	Finite Element Modeling
		FPL	Four Person Load
ANSYS	Analysis System	FFT	Fast Fourier Transform
BLDCM	Brushless Direct Current Motor	FL	Fuzzy Logic
BEV	Battery Electric Vehicles	FM	Frequency Modulation
CAD	Computer-Aided Design	FN	False Negative
CBM	Condition Based Maintenance	FP	False Positive
CNN	Convolutional Neural Network	GUI	Graphical User Interface
CQT	Constant Q Transform	HEV	Hybrid Electric Vehicles
CWT	Continuous Wavelet Transform	IM	Induction Motor
DC	Direct Current	IRT	Infrared Thermography
DBM	Deep Boltzmann Machine	ICE	Internal Combustion Engine
DBN	Deep Belief Networks	LSTM	Long Short-Term Memory
DFT	Discrete Fourier Transform	LGPCA	Local and Global Principal
DPL	Double Person Load		Component Analysis
DWT	Discrete Wavelet Transform	k-NN	k-Nearest Neighbor

ML	Machine Learning	S-RD	Speed-Ramp Down
MFS	Machine Fault Simulator	SRM	Switched Reluctance Motor
MI-	Multi-Input-Convolutional Neural	SBC	Single Board Computer
CNN	Network	SVM	Support Vector Machine
MCC	Matthews Correlation Coefficient	SVM	Support Vector Machine
MCSA	Motor Current Signature Analysis	S-RU	Speed-Ramp-Up
MMD	Maximum Mean Discrepancy	S-100	100 % Speed
PM	Phase Modu	SPL	Single Person Load
PMSM	Permanent Magnet Synchronous	SAE	Stacked Autoencoder Transfer
	Motors	TL	Learning
PTG	Passive Thermography	TP	True positive
PEV	Pure Electric Vehicle	TN	True Negative
PWM	Pulse width Modulation	TBS	Time-Based Service
RF	Random Forest	VGG	Visual Geometry Group
RNN	Recurrent Neural Network		
RU-L	Ramp Up with Load		
RU-NL	Ramp Up with No-Load		
RD-L	Ramp Down with Load		
RD-NL	Ramp Down with No-Load		
RUL	Remaining Useful Life		
ResNet	Residual Network		
S-50	50% Speed		

LIST OF SYMBOLS

X_{in}	Input signal	M	feature set
Y	weighted coefficients	I	feature output
λ	number of windows	F	convolutional filter weights
\mathbb{C}	space vector of finite signal	P	width of the window
F_O	CQT coefficient	Q	length of the window
O	specific octave or frequency band	\mathbb{R}^i	space of real-valued vectors
C	convolution output	L	label vector
w	weight matrix	$Prob(.)$	probability of an event
b	bias value	a	context associated with input
$Q(.)$	activation function	p	prior probability associated
e	exponential of the dot product	$1\{.\}$	indicator function
Err	low fitness value	A	actual output
Z_{min}	minimum output	B	targeted output
Z_{max}	maximum output	FN	false negative
TP	true positive	FP	false positive
MCC	Matthew's correlation coefficient	TN	true negative
N	number of inputs	W	learnable weights
$*$	convolutional operation	f_n	number of operations
I_{img}	input image	P_{con}	concatenation process
D	inputs vectors	$x(t)$	non-stationary signal
A_{amp}	instantaneous amplitude	$\varphi(t)$	phase function

$gw(t)$	Gaussian window	S_q	time-frequency spectrum
η	time-frequency distributions	R	WSST operation
\hat{C}	chirp rate	\hat{t}	delay estimator
\hat{K}	original WSST		