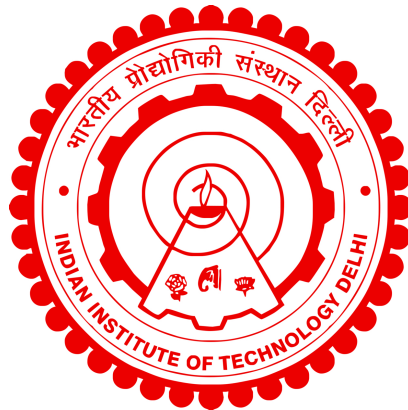


**WEARABLE ASSISTIVE TECHNOLOGIES AND
AI-DRIVEN APPROACHES FOR SLEEP
APNEA DETECTION AND MONITORING**

AMIT BHONGADE



**DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY DELHI
AUGUST 2025**

© Indian Institute of Technology Delhi (IITD), New Delhi, 2025

WEARABLE ASSISTIVE TECHNOLOGIES AND AI-DRIVEN APPROACHES FOR SLEEP APNEA DETECTION AND MONITORING

by

AMIT BHONGADE

DEPARTMENT OF ELECTRICAL ENGINEERING

Submitted

in fulfillment of the requirements of the Degree of Doctor of Philosophy

to the



INDIAN INSTITUTE OF TECHNOLOGY DELHI
AUGUST 2025

Dedicated to

**My Beloved
Father and Mother -**

who always inspire me to dream big

“It is better to live your own destiny imperfectly than to live an imitation of somebody else’s life with perfection”

—Bhagavad Gita

Certificate

This is to certify that the thesis entitled “**Wearable Assistive Technologies and AI-Driven Approaches for Sleep Apnea Detection and Monitoring** ” being submitted by **Mr. Amit Bhongade** to the Department of Electrical Engineering, Indian Institute of Technology-Delhi, for the award of the degree of **Doctor of Philosophy** is the record of the bonafide research work carried out by him under our supervision. In our opinion, the thesis has reached the standards fulfilling the requirements of the regulations relating to the degree.

The work contained in this thesis have not been submitted either in part or in full to any other university or institute for the award of any degree or diploma.

(Prof. Tapan Kumar Gandhi)

Dept. of Electrical Engineering
Indian Institute of Technology-Delhi
Hauz Khas, New Delhi 110016
INDIA

(Prof. Prathosh AP)

Dept. of Electrical Communication Engineering
Indian Institute of Science Bengaluru
Bangalore, 560012
INDIA

Acknowledgements

First and foremost, I would like to express my gratitude to the Almighty for providing me with the strength, wisdom, and perseverance to complete this thesis. Without His guidance and blessings, this thesis would not have been possible.

I extend my profound gratitude to my advisor, Prof. Tapan Kumar Gandhi, whose persistent supervision and insightful feedback have shaped this thesis in countless ways. I am equally grateful to my co-advisor, Prof. Prathosh AP, for his timely and invaluable inputs that have significantly contributed to the work's quality.

In no particular order, I would like to thank my SRC members, Prof. Kolin Paul, Prof. Sumantra Dutta Roy, and Prof. Lalan Kumar, for their valuable comments on my research work.

I would like to thank the Ministry of Education, Government of India for providing financial support during my Ph.D. (2021-2025). I gratefully acknowledge the travel support from the Research Scholar Travel Award (RSTA) and contingency fund, which has given me the wonderful opportunity to participate in national and international conferences and workshops and present my work across the globe.

I sincerely thank my esteemed collaborator, colleague, and friend, Dr. Rohit Gupta, for his constant support, valuable feedback, and collaborative spirit. His innovative approach to complex problems and insightful discussions have greatly influenced the direction of my research and contributed significantly to my personal and academic growth. I am also profoundly thankful to my other research collaborators in the Neurocomputing Lab, Chandra Bhushan Kumar and Chayan Majumder. Their dedicated efforts and contributions to their respective areas of research have greatly enriched the overall research ecosystem within the lab. Their expertise, enthusiasm, and collaborative mindset have not only enhanced my own work but have also fostered an environment of shared learning and progress. Working along-

side them has been a rewarding and intellectually stimulating experience. I would like to thank all my lab members at the Neurocomputing Lab, IIT Delhi: Dr. Kritika, Raghav, Sapna, Dr. Shefali, Prerna, Dr. Sangita, Dr. Chetan, Dr. Taranjit, Anupam, Siddhant, Prakash, Vivek, and Rakesh. Your engaging discussions, collaboration, and moral support have been invaluable throughout my journey. The camaraderie and encouragement within the lab have made this experience truly special, and I am deeply grateful for the moments of learning, collaboration, and friendship we've shared.

I am deeply grateful to my grandparents, the Late Mr. Gulabrao Bhongade and the Late Mrs. Laxmibai Bhongade, for their love, support, and encouragement. Their belief in me and their inspiring words continue to guide me in pursuing my dreams with confidence and determination. Their blessings and cherished memories continue to guide me in every step I take. I extend my deepest gratitude to my parents, Mr. Gangadhar Bhongade and Mrs. Sindhu Bhongade, for their unwavering support, love, and encouragement have been my constant source of strength throughout this journey. Your sacrifices, belief in my potential, and guidance have shaped me into who I am today. This milestone is as much yours as it is mine. I would like to thank my brother, Sumit Bhongade, for his unwavering support and for taking care of our family while I was pursuing my Ph.D. His selflessness and dedication have been a tremendous help, and I am deeply grateful for his presence in my life. To my dear friend, Ms. Linkita Dewangan, for your invaluable help in proofreading my thesis—thank you for your unwavering support, patience, and encouragement throughout this journey. Your belief in me and the joy you bring to my life have made all the difference. I am truly grateful for your presence and inspiration every day.

At last, I would like to pay my sincere gratitude to one and all who have directly or indirectly helped me throughout this journey.

Amit Bhongade

Abstract

Sleep disorders, such as obstructive sleep apnea (OSA), pose serious health risks, impacting cardiovascular, neurological, and cognitive functions. OSA, one of the most prevalent sleep disorders, is characterized by repeated episodes of partial or complete airway obstruction during sleep, leading to intermittent hypoxia, sleep fragmentation, and excessive daytime sleepiness. If left untreated, OSA is associated with an increased risk of hypertension, stroke, heart failure, metabolic disorders, and impaired cognitive function. Traditional diagnostic methods, such as polysomnography (PSG), are expensive, complex, and inconvenient for large-scale screening or home-based monitoring. This thesis addresses these challenges by developing wearable sensor-based systems and employing machine and deep learning models to improve the detection and early prediction of sleep disorders using various physiological signals.

One of the primary contributions of this research is the development of a wearable respiration monitoring system that utilizes an Inertial Measurement Unit (IMU), Electrocardiogram (ECG), and Photoplethysmogram (PPG) sensors to capture the corresponding physiological signals related to sleep apnea. The system's performance was validated through extensive experimental trials, demonstrating its effectiveness in detecting subtle respiratory variations associated with OSA. The temporal parameters derived from IMU, ECG, and PPG were benchmarked against traditional PSG-based methods, and signal processing techniques were employed to minimize noise and improve signal quality. A comparative analysis was conducted using statistical, machine learning, and deep learning models to evaluate the contribution of each sensor modality to sleep apnea detection. The findings indicate that integrating multiple physiological signals significantly enhances the accuracy and reliability of respiration estimation, offering a promising alternative to traditional PSG-based diagnosis.

In addition to respiration-based analysis, this thesis introduces a novel feature-engineering approach for sleep apnea detection using single-lead ECG signals. A comprehensive machine learning framework was developed to extract key cardiac features such as heart rate variability (HRV) and R-R intervals. Furthermore, previously underutilized features (time domain, time-frequency domain, and nonlinear entropy-based features) were incorporated to enhance the discriminatory power of the model. The framework was tested with multiple machine learning classifiers across independent datasets, and the results demonstrated its robustness and reliability in detecting sleep apnea in diverse scenarios. The lightweight nature of the model ensures efficient real-time processing, making it highly suitable for integration into wearable and home-based diagnostic systems.

Building upon machine learning methodologies, this research further explores the application of deep learning techniques to automate sleep apnea detection. Various architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based models, were evaluated for their effectiveness in processing physiological signals. Unlike traditional methods that rely on manually extracted features, deep learning models can automatically learn and extract intricate patterns from raw physiological data, leading to improved classification performance. The models were optimized for real-time deployment, ensuring seamless integration into wearable devices for continuous, non-invasive sleep monitoring. The results underscore the effectiveness of deep learning in sleep apnea detection, providing a scalable and robust solution for real-world applications.

Beyond sleep apnea detection, this thesis also presents a preliminary study on sleepwalking detection using a wearable IMU-based gait analysis system. Sleepwalking is a complex parasomnia disorder characterized by abnormal nocturnal movements, yet its objective detection remains challenging. In this study, an IMU sensor mounted on the shank was used to monitor gait phases and events in healthy individuals. Three machine learning classifiers—Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Linear Discriminant Analysis (LDA)—were employed to identify gait events and temporal parameters. The system demonstrated stable performance across different sensor locations and individual variations, highlighting its robustness. While this study was conducted on healthy participants,

the findings lay the foundation for future research aimed at detecting sleepwalking episodes in individuals with diagnosed sleep disorders. This research paves the way for a non-invasive, home-based diagnostic tool that could aid clinicians in assessing and managing sleepwalking more effectively.

The overarching goal of this thesis is to bridge the gap between traditional sleep disorder diagnostics and modern wearable technology by developing accessible, cost-effective, and efficient solutions for real-world implementation. The integration of wearable sensor technology with machine learning and deep learning models has the potential to transform sleep disorder diagnosis, enabling real-time monitoring, early detection, and large-scale screening. The findings from this work have significant implications for clinical practice, as they provide alternative methodologies for diagnosing and managing sleep disorders without the need for complex and expensive PSG-based assessments. By offering a scalable, user-friendly approach, this research contributes to the growing field of digital health and telemedicine, paving the way for future advancements in sleep disorder diagnosis and management.

सार

ऑब्स्ट्रक्टिव स्लीप एपनिया (ओएसए) जैसे नींद संबंधी विकार गंभीर स्वास्थ्य जोखिम पैदा करते हैं, जो कार्डियोवैस्कुलर, न्यूरोलॉजिकल और संज्ञानात्मक कार्यों को प्रभावित करते हैं। ओएसए, सबसे प्रचलित नींद विकारों में से एक, नींद के दौरान आंशिक या पूर्ण वायुमार्ग बाधा के बार-बार एपिसोड की विशेषता है, जिससे रुक-रुक कर हाइपोक्सिया, नींद विखंडन और दिन में अत्यधिक नींद आती है। यदि अनुपचारित छोड़ दिया जाता है, तो ओएसए उच्च रक्तचाप, आघात, हृदय की विफलता, चयापचय संबंधी विकारों और बिगड़े संज्ञानात्मक कार्य के बढ़ते जोखिम से जुड़ा हुआ है। पॉलीसोम्नोग्राफी (पीएसजी) जैसे पारंपरिक नैदानिक तरीके महंगे, जटिल और बड़े पैमाने पर जांच या घर-आधारित निगरानी के लिए असुविधाजनक हैं। यह थीसिस पहनने योग्य संवेदक-आधारित प्रणालियों को विकसित करके और विभिन्न शारीरिक संकेतों का उपयोग करके नींद विकारों का पता लगाने और प्रारंभिक भविष्यवाणी में सुधार करने के लिए मशीन और गहन शिक्षण मॉडल को नियोजित करके इन चुनौतियों का समाधान करता है।

इस शोध के प्राथमिक योगदानों में से एक पहनने योग्य श्वसन निगरानी प्रणाली का विकास है जो स्लीप एपनिया से संबंधित शारीरिक संकेतों को पकड़ने के लिए एक जड़त्वीय मापन इकाई (आईएमयू) इलेक्ट्रोकार्डियोग्राम (ईसीजी) और फोटोप्लेथिस्मोग्राम (पीपीजी) सेंसर का उपयोग करता है। प्रणाली के प्रदर्शन को व्यापक प्रयोगात्मक परीक्षणों के माध्यम से मान्य किया गया था, जो ओएसए से जुड़े सूक्ष्म श्वसन विविधताओं का पता लगाने में इसकी प्रभावशीलता का प्रदर्शन करता है। आईएमयू, ईसीजी और पीपीजी से प्राप्त अस्थायी मापदंडों को पारंपरिक पीएसजी-आधारित तरीकों के खिलाफ बेंचमार्क किया गया था, और सिग्नल प्रोसेसिंग तकनीकों को शोर को कम करने और सिग्नल की गुणवत्ता में सुधार के लिए नियोजित किया गया था। स्लीप एपनिया का पता लगाने में प्रत्येक संवेदक पद्धति के योगदान का मूल्यांकन करने के लिए सांख्यिकीय, मशीन लर्निंग और डीप लर्निंग मॉडल का उपयोग करके एक तुलनात्मक विश्लेषण किया गया था। निष्कर्ष से संकेत मिलता है कि कई शारीरिक संकेतों को एकीकृत करने से श्वसन आकलन की सटीकता और विश्वसनीयता में काफी वृद्धि होती है, जो पारंपरिक पीएसजी-आधारित निदान के लिए एक आशाजनक विकल्प प्रदान करता है।

श्वसन-आधारित विश्लेषण के अलावा, यह शोध प्रबंध एकल-लीड ईसीजी संकेतों का उपयोग करके स्लीप एपनिया का पता लगाने के लिए एक नए फीचर-इंजीनियरिंग दृष्टिकोण का परिचय देता है। हृदय गति परिवर्तनशीलता

(एचआरवी) और आर-आर अंतराल जैसी प्रमुख हृदय संबंधी विशेषताओं को निकालने के लिए एक व्यापक मशीन लर्निंग ढांचा विकसित किया गया था। इसके अलावा, मॉडल की भेदभावपूर्ण शक्ति को बढ़ाने के लिए पहले कम उपयोग की गई विशेषताओं (टाइम डोमेन, टाइम-फ्रीक्वेंसी डोमेन और गैर-रैखिक एन्ट्रॉपी-आधारित विशेषताएं) को शामिल किया गया था। फ्रेमवर्क का परीक्षण स्वतंत्र डेटासेट में कई मशीन लर्निंग क्लासिफायर के साथ किया गया था, और परिणामों ने विविध परिदृश्यों में स्लीप एपनिया का पता लगाने में इसकी मजबूती और विश्वसनीयता का प्रदर्शन किया। मॉडल की हल्की प्रकृति कुशल वास्तविक समय प्रसंस्करण सुनिश्चित करती है, जिससे यह पहनने योग्य और घर-आधारित नैदानिक प्रणालियों में एकीकरण के लिए अत्यधिक उपयुक्त हो जाता है।

मशीन लर्निंग पद्धतियों के आधार पर, यह शोध आगे स्लीप एपनिया डिटेक्शन को स्वचालित करने के लिए डीप लर्निंग तकनीकों के अनुप्रयोग की खोज करता है। शारीरिक संकेतों को संसाधित करने में उनकी प्रभावशीलता के लिए कन्वोल्यूशनल न्यूरल नेटवर्क (सी. एन. एन.), आवर्ती न्यूरल नेटवर्क (आर. एन. एन.) और ट्रांसफॉर्मर-आधारित मॉडल सहित विभिन्न संरचनाओं का मूल्यांकन किया गया। पारंपरिक विधियों के विपरीत जो हाथ से निकाली गई विशेषताओं पर भरोसा करते हैं, डीप लर्निंग मॉडल स्वचालित रूप से कच्चे शारीरिक डेटा से जटिल पैटर्न सीख सकते हैं और निकाल सकते हैं, जिससे वर्गीकरण प्रदर्शन में सुधार होता है। मॉडल को वास्तविक समय पर लगाने के लिए अनुकूलित किया गया था, जिससे निरंतर, गैर-आक्रामक नींद की निगरानी के लिए पहनने योग्य उपकरणों में निर्बाध एकीकरण सुनिश्चित किया जा सके। परिणाम स्लीप एपनिया का पता लगाने में डीप लर्निंग की प्रभावशीलता को रेखांकित करते हैं, जो वास्तविक दुनिया के अनुप्रयोगों के लिए एक स्केलेबल और मजबूत समाधान प्रदान करते हैं।

स्लीप एपनिया का पता लगाने के अलावा, यह थीसिस पहनने योग्य आईएमयू-आधारित चाल विश्लेषण प्रणाली का उपयोग करके स्लीपवॉकिंग का पता लगाने पर एक प्रारंभिक अध्ययन भी प्रस्तुत करता है। स्लीपवॉकिंग एक जटिल पैरासोमनिया विकार है जो असामान्य निशाचर गतिविधियों की विशेषता है, फिर भी इसका उद्देश्यपूर्ण पता लगाना चुनौतीपूर्ण बना हुआ है। इस अध्ययन में, स्वस्थ व्यक्तियों में चाल के चरणों और घटनाओं की निगरानी के लिए शैंक पर लगे एक आईएमयू सेंसर का उपयोग किया गया था। तीन मशीन लर्निंग क्लासिफायर-सपोर्ट वेक्टर मशीन (एसवीएम) के-नियर नेबर (केएनएन) और लीनियर डिस्क्रिमिनेंट एनालिसिस (एलडीए)-को चाल की घटनाओं और अस्थायी मापदंडों की पहचान करने के लिए नियोजित किया गया था। प्रणाली ने विभिन्न संवेदक स्थानों और व्यक्तिगत विविधताओं में स्थिर प्रदर्शन का प्रदर्शन किया, जो इसकी मजबूती को उजागर करता है। जबकि यह अध्ययन स्वस्थ प्रतिभागियों पर आयोजित किया गया था, निष्कर्ष भविष्य के शोध की नींव रखते हैं जिसका उद्देश्य निदान किए गए नींद विकारों वाले व्यक्तियों में नींद में चलने के प्रकरणों का पता लगाना है। यह शोध एक गैर-आक्रामक, घर-आधारित नैदानिक उपकरण का मार्ग प्रशस्त करता है जो स्लीपवॉकिंग का अधिक प्रभावी ढंग से आकलन और प्रबंधन करने में चिकित्सकों की सहायता कर सकता है।

इस थीसिस का व्यापक लक्ष्य वास्तविक दुनिया के कार्यान्वयन के लिए सुलभ, लागत प्रभावी और कुशल समाधान

विकसित करके पारंपरिक नींद विकार निदान और आधुनिक पहनने योग्य तकनीक के बीच पुल बनाता है। मशीन लर्निंग और डीप लर्निंग मॉडल के साथ पहनने योग्य संवेदक प्रौद्योगिकी के एकीकरण में नींद विकार के निदान को बदलने की क्षमता है, जो वास्तविक समय की निगरानी, जल्दी पता लगाने और बड़े पैमाने पर स्क्रीनिंग को सक्षम बनाता है। इस काम के निष्कर्षों के नैदानिक अभ्यास के लिए महत्वपूर्ण निहितार्थ हैं, क्योंकि वे जटिल और महंगे पीएसजी-आधारित मूल्यांकन की आवश्यकता के बिना नींद विकारों के निदान और प्रबंधन के लिए वैकल्पिक कार्यप्रणाली प्रदान करते हैं। एक मापनीय, उपयोगकर्ता के अनुकूल दृष्टिकोण की पेशकश करके, यह शोध डिजिटल स्वास्थ्य और टेलीमेडिसिन के बढ़ते क्षेत्र में योगदान देता है, जिससे नींद विकार के निदान और प्रबंधन में भविष्य की प्रगति का मार्ग प्रशस्त होता है।

Contents

Certificate	i
Acknowledgements	ii
Abstract	iv
संर	vii
List of Figures	xix
List of Tables	xxvii
Abbreviations	xxxii
I Prerequisites	1
1 Introduction	2
1.1 General Introduction	2
1.2 Types of Sleep Disorder: Clinical Phenomenology	3
1.2.1 Obstructive Sleep Apnea Syndrome (OSAS)	3
1.2.2 Sleepwalking (Somnambulism)	3
1.2.3 Narcolepsy	4
1.2.4 Insomnia	4
1.2.5 Restless Legs Syndrome	4
1.2.6 Parasomnias	5
1.2.7 Sleep Terror	5
1.2.8 Rapid Eye Movement Sleep Behaviour Disorder (RBD)	5

1.2.9	Nightmares	5
1.2.10	Sleep-related Movement Disorders	6
1.2.11	Rhythmic Movement Disorder	6
1.2.12	Nocturnal Leg Cramps	6
1.2.13	Bruxism (Tooth Grinding)	6
1.3	Literature Review and Motivation	7
1.3.1	Wearable Technology for Sleep Apnea Detection	9
1.3.2	Machine Learning (Feature Engineering) for Obstructive Sleep Apnea Detection	10
1.3.3	Deep Learning for Obstructive Sleep Apnea Detection	12
1.4	Research Gaps	14
1.4.1	Wearable Technology	14
1.4.2	Machine Learning	15
1.4.3	Deep Learning	16
1.5	Research Objectives and Contributions	17
1.5.1	Research Objectives	17
1.5.2	Summary of Contributions	17
1.6	Organization of the Thesis	19
2	An Overview of Respiration Analysis for Sleep Apnea Detection	25
2.1	Introduction	25
2.2	Literature Review: Respiration’s Role in Sleep Apnea Detection	26
2.3	Challenges in Respiration Analysis	28
2.4	Advances in Respiration Monitoring	28
2.5	Significance of Respiration Analysis in Clinical Practice	29
II	Detailed Respiration Analysis Using Various Physiological Signals for Sleep Apnea Detection	32
3	Respiration Analysis Using Developed Inertial Measurement Unit Sensor-Based System	33
3.1	Introduction	35
3.2	Wearable Systems Used for Data Collection	37

3.2.1	Wearable Respiration Rate Monitoring System (WRMS)	37
3.2.2	Wireless Equivital System (EQO2)	38
3.3	Study 1: Respiration Monitoring Using Basic Signal Processing	40
3.3.1	Experimental Setup and Data Aquisition	40
3.3.2	Signal Processing	41
3.3.3	Results and Discussion	42
3.3.4	Conclusion	46
3.4	Study 2: Respiration Monitoring Using Convolution-Based Deep Learning Model	49
3.4.1	Experimental Setup and Data Aquisition	49
3.4.2	Signal Processing	50
3.4.3	Results	56
3.4.4	Discussion	62
3.4.5	Conclusion	69
3.5	Study 3: Respiration Monitoring Using Convolution and Transformer Based Hybrid Model	71
3.5.1	Experimental Setup and Acquisition	71
3.5.2	Signal Processing	72
3.5.3	Results	79
3.5.4	Discussion	84
3.5.5	Limitations and Future Scope	88
3.5.6	Conclusion	89
3.6	Summary	90
4	Respiration Analysis Using Developed Photoplethysmography (PPG) Sensor- Based System	91
4.1	Introduction	94
4.2	Wearable Systems Used for Data Collection	95
4.2.1	Wearable Low-cost PPG Acquisition Device (WeLOVE)	95
4.2.2	Wireless Equivital System (EQO2)	96
4.3	Study 1: Heart Rate Monitoring Using Basic Signal Processing	97
4.3.1	Experimental Setup and Data Acquisition	97
4.3.2	Signal Processing	98

4.3.3	Temporal Cardiac Parameter Estimation	100
4.3.4	Results and Discussion	102
4.3.5	Conclusions	104
4.4	Study 2: Respiration Monitoring Using Convolution and Bi-LSTM Based Deep Learning Model	106
4.4.1	Databases	106
4.4.2	Signal Processing	107
4.4.3	Temporal Respiration Parameters Estimation	109
4.4.4	Results and Discussion	110
4.4.5	Conclusions	113
4.5	Study 3: Respiration Monitoring Using Convolution and Transformer-Based Deep Hybrid Model	114
4.5.1	Databases	114
4.5.2	Signal Processing	115
4.5.3	Temporal Respiration Parameters Estimation	118
4.5.4	Results and Discussion	121
4.5.5	Conclusions	123
4.6	Study 4: Respiration Monitoring Using Robust VMD-PCA Based Method . .	124
4.6.1	Experimental Setup and Data Acquisition	124
4.6.2	Signal Processing	125
4.6.3	Temporal Respiration Parameters Estimation	128
4.6.4	Results and Discussion	129
4.7	Mitigating Motion Artifacts in PPG Signals for Improved Respiration Monitoring	133
4.7.1	Conclusions	134
5	Respiration Analysis Using Electrocardiogram (ECG) Signals Measured Using EQO2 System	135
5.1	Introduction	137
5.2	Materials and Methods	139
5.2.1	Data Acquisition System	139
5.2.2	Experiment Design and Data Acquisition	139

5.2.3	Wavelet Decomposition	141
5.2.4	Signal Processing	143
5.3	Results	148
5.4	Discussions	157
5.5	Limitations and Future Scope	161
5.6	Conclusion	161

III Sleep Apnea Detection Using Machine Learning 163

6 Automatic Detection of Sleep Apnea from Single-lead ECG Signal Using Standard Features 164

6.1	Introduction	166
6.2	Materials and Methods	166
6.2.1	Database	167
6.2.2	Pre-processing of ECG Signal	168
6.2.3	Feature Extraction and Classification	169
6.3	Results and Discussions	170
6.4	Limitation and Future Scope	172
6.5	Conclusions	174

7 Automatic Identification of Obstructive Sleep Apnea using Multi-domain Features 175

7.1	Introduction	177
7.2	Database	179
7.2.1	PhysioNet Database	179
7.2.2	UCDSA Database	179
7.3	Methodology	180
7.3.1	Data Processing	181
7.3.2	Feature Extraction	184
7.3.3	Feature Selection	188
7.4	Results	189
7.4.1	Selected Feature	189
7.4.2	Epoch-based Classification Performance	190

7.4.3	Analysis with Inter and Intra Subjects	192
7.4.4	Performance of Different Classifiers for Varying Training Data	193
7.4.5	Performance of Different Classifiers for Different Folds in Cross-validation Method	196
7.4.6	Performance of the Various Deep Learning Models:	197
7.5	Discussion	198
7.6	Additional and Supplementary Material of This Study	203
7.6.1	Implemented Deep Learning Models for Comparing Proposed Model with these Deep Models	203
7.7	Conclusion	208

IV Sleep Apnea Detection Using Deep Learning 210

8	Obstructive Sleep Apnea Detection Using Wigner-Ville Distribution of ECG Signals	211
8.1	Introduction	213
8.1.1	Related Works	213
8.1.2	Our Contributions	214
8.2	Materials and Methods	215
8.2.1	Database	215
8.2.2	Wigner-Ville Distribution	217
8.2.3	Savitzky–Golay (S-G) Filtering	217
8.2.4	Deep Learning Model	218
8.2.5	Training Configuration	219
8.2.6	Effect of Downsampling on Performance	219
8.2.7	Evaluation Index	220
8.3	Results	221
8.3.1	Per-segment Performance of the Model	222
8.3.2	Effect of K-fold Cross Validation on Performance	224
8.3.3	Effect of Down-sampled Signals on Performance	225
8.3.4	WVD Selection: Theoretical and Quantitative Analysis	226
8.3.5	Model Complexity and Runtime Analysis	227

8.3.6	Effect of External Noise on Performance	228
8.4	Discussion	229
8.5	Conclusion	232
9	Early Prediction of Sleep Apnea Using Single-Lead ECG Signal	233
9.1	Introduction	235
9.1.1	Related Works	236
9.1.2	Our Contributions	237
9.2	Data	238
9.2.1	Database	238
9.2.2	Data Preparation and Formation	240
9.3	Proposed Techniques	240
9.3.1	Gabor-CNN	241
9.3.2	Wavelet-CNN	242
9.3.3	Wigner-CNN	245
9.3.4	STFT-CNN	246
9.4	Training Configurations	247
9.5	Results and Discussions	249
9.5.1	Model Comparisons	250
9.5.2	Preceding and Predicted Class Analysis	250
9.5.3	Effect of Down-sampling on Predicting OSA	252
9.5.4	Comparison with Existing Studies	253
9.6	Limitations and Future Scope	253
9.7	Conclusion	254
10	Siamese-based Self-Supervised Learning for Sleep Apnea Detection	256
10.1	Introduction	258
10.2	Dataset and Data Preparation	260
10.2.1	Dataset	260
10.2.2	Data Preparation	263
10.3	Model Architecture	263
10.4	Proposed Model	265
10.5	Results and Discussion	265

10.5.1	Network Parameters	265
10.5.2	Evaluation Metrics	266
10.5.3	Performance Estimation of the Proposed Model	267
10.5.4	Comparison of the Performance between Existing Techniques and the Proposed Technique	269
10.5.5	Performance Estimation of the Proposed Model After Applying Differ- ent Augmentation Techniques	271
10.6	Conclusion	272

V Appendix 273

11 Classification of Gait Phases Using a Shank-Mounted Single IMU Sensor:

A	Preliminary Study for Sleep Walking Detection	274
11.1	Introduction	276
11.1.1	Related Works	276
11.1.2	Contributions	278
11.2	Materials and Methods	279
11.2.1	Gait Temporal Characterization	279
11.2.2	Developed Hardware System	280
11.2.3	Experimental Setup and Data Acquisition	282
11.2.4	Signal Processing	283
11.3	Results	286
11.4	Discussion	294
11.5	Potential of IMU-Based Gait Analysis for Sleepwalking Detection	298
11.6	Conclusion	298

VI Final Remarks 300

12 General Discussion: Summary, Scope for Future Work and Conclusions 301

12.1	Summary of the Findings	301
12.2	Future Directions	305
12.3	Conclusions	306

Bibliography	307
List of Publications	352
Patent Application	355
Biography	356

List of Figures

1.1	OSA patient is diagnosed using a multi-electrode PSG at a sleep laboratory. Source: Tran et al., Frontier in Neurology, (2023). [1] © [2023] Frontiers. . . .	8
3.1	Developed wearable respiration monitoring system. (A) Main module, (B) IMU sensor, (C) Toggle switch, (D) Micro-controller, (E) SD card, (F) Battery charging module, and (G) Voltage regulator.	38
3.2	Experiment setup and data acquisition. (A) Equivital system (EQO2), (B) Sensor belt (SB) or respiration belt (RB), (C) IMU sensor, (D) WRMS, (E) PPG sensor, (F) Connecting module (establish the connection between PC and EQO2), (G) laptop (PC).	39
3.3	Experimental setup and data acquisition. (For normal activity, sitting posture and different sensor location (chest, abdominal, and ribs), (A) equivital device, (B) developed system, and IMU sensor placed at chest (P1), lest ribs (P2), and abdominal (P3)).	41
3.4	Block diagram for the signal processing to estimate respiration rate.	42
3.5	Recorded Signal for different sensor placement positions and activities (black- Chest expansion signal, red- acceleration signal).	43
3.6	Average MAE in respiration rate estimation with window size (60Sec) and window shift (50% of window size).	45
3.7	Presents the categorical sample % of different respiration rates (Black bar-sample % and white bar-%BREA).	46
3.8	Experimental protocol for different breathing rates. Here, STB: start breath detection, SPB: stop breath detection, INT: instruction time (2 min), RST: rest time (5 min), and T: time in seconds.	50
3.9	Complete block diagram for respiration parameter estimation.	51

3.10	Recorded signals from the WRMS system and reference respiration signals measured using SB of the EQO2.	52
3.11	Proposed ResPara-Net DCNN. (CNN: 2D convolutional neural network, BN: batch normalization, LN: layer normalization, AP: Average pooling layer, DP: dropout layer, GAP: global average pooling layer, and FC: fully connected layer).	53
3.12	Trajectories predicted using the proposed ResPara-Net. (a) normal breathing (subject-8), (b) fast breathing (subject-2), and (c) slow breathing (subject-3).	59
3.13	Box plots of breath rate (bpm) from the WRMS device and SB for all the subjects. (I) Normal Breathing. (II) Slow Breathing. (III) Fast Breathing. The Y-axis presents the breathing rate per minute and the X-axis presents both the WRMS device and the SB system.	60
3.14	Correlation and Bland Altman plot for predicted respiration signal from ResPara-Net using WRMS device and actual respiration signals measured from EQO2 device. The dotted line denotes the upper and lower limits of agreement, the black line denotes the mean of difference. (a) Normal breathing rate (subject 8), (b) Fast breathing rate (subject 2), and (c) Slow breathing rate (subject 3).	61
3.15	Respiration trajectory prediction of subject 9 for normal breathing.	66
3.16	Respiration trajectory prediction of subject 4 for fast breathing.	67
3.17	Experimental protocol for different breathing rates. Here, STB: start breath detection, SPB: stop breath detection, INT: instruction and calibration time (2 min), RST: rest time (5 min), and T: time in seconds.	72
3.18	A comprehensive signal processing block diagram for respiratory signal prediction using IMU signals.	72
3.19	Proposed RePair-Net model. (a) Structure of the proposed RePair-Net model, (b) Convolution block, (c) Transformer block.	73
3.20	Predicted respiration signal using RePair-Net with respiration signals and reference respiration signals for (a) normal breathing, (b) fast breathing, and (c) slow breathing with peak detection. (Red: SB, Blue: RePair-Net).	80
3.21	Box plots of respiration rate (bpm) from the SB and RePair-Net for across subjects. (a) Normal, (b) Fast, and (c) Slow breathing.	82

3.22	Poincare plots depicting successive TI_{PP} intervals are shown for (I) RePair-Net and (II) the SB device over a duration of 60 seconds. In these plots, the red color signifies the fitted ellipse, the black line represents the line of identity, and the small blue circles denote the data points. Three breathing conditions are illustrated: (a) Normal breathing, (b) Fast breathing, and (c) Slow breathing. The Y-axis corresponds to $TI_{PP_{i+1}}$, while the X-axis represents TI_{PP_i}	85
3.23	Correlation and Bland–Altman plots comparing breathing rates obtained from the RePair-Net and SB across subjects are presented. In these plots, the dotted lines denote the upper and lower limits of agreement, the black line indicates the mean difference. Three breathing conditions are examined: (a) Normal breathing, (b) Fast breathing, and (c) Slow breathing.	86
4.1	Experimental setup and data acquisition. (I) WeLOVE device and circuit diagram, (II) Experimental setup. ((A) WeLOVE system, (B) EQO2 system, (C) Connecting model, (D) Personal computer, (E) PPG sensor).	96
4.2	Complete signal processing pipeline for estimating the HR from the PPG signal.	98
4.3	Acquired Signals. (a) Raw PPG Signal, (b) Reference ECG signal measured using EQO2 system, (c) Estimated cardiac signal using PPG signal of WeLOVE system.	99
4.4	Box plots of Heart rate (bpm) from PPG Signal and ECG Signal across subjects. (a) Normal breathing, (b) Slow breathing.	101
4.5	Poincare plots comparing RR intervals (RRI) for different breathing conditions for a 60-second signal. (I) PPG-derived cardiac signal, (II) ECG signal. . . .	102
4.6	Correlation and Bland–Altman plots comparing heart rates obtained from the PPG and ECG across subjects. (a) Normal breathing, (b) Slow breathing. . .	103
4.7	The complete signal processing block diagram to estimate the respiration from PPG.	107
4.8	RespTrack-Net deep learning model.	108
4.9	Box plots of respiration rate (bpm) from PPG signal and reference respiration signal across subjects. (a) Our database, (b) CapnoBase database. (SB: Sensor belt, PR: Predicted respiration using PPG signals, and CB: CapnoBase database).	111

4.10	Correlation and Bland–Altman plots comparing respiration rates obtained from the PPG and reference respiration signals across subjects. (a) Our database, (b) CapnoBase database.	112
4.11	The complete signal processing block diagram to estimate the respiration from PPG.	115
4.12	Reform-Net deep learning model. (a) Block diagram, (b) Convolution block, and (c) Transformer block.	119
4.13	Box plots of respiration rate (bpm) from PPG signal and reference respiration signal across subjects. (a) Our database, (b) CapnoBase database. (SB: Sensor belt, PR: Predicted respiration using PPG signals, and CB: Estimated respiration using respiration signals using the CapnoBasee database).	120
4.14	Correlation and Bland–Altman plots comparing respiration rates obtained from the PPG and reference respiration signals across subjects. (a) Our database, (b) CapnoBase database.	122
4.15	Complete experiment setup and data processing pipeline. ((A) PPG sensor, (B) Sensor belt (SB), (C) PC, (D) Wireless connecting module).	125
4.16	Spectrums (FFT) obtained using respiration signal and different IMF modes. (a) FFT of respiration signal measured using SB, (b)-(f) FFT of IMF modes estimated using PPG signals.. . . .	126
4.17	Acquired signals. (a) Raw PPG signal, (b) Reference respiration signal measured using SB, (c) Estimated respiration signal using PPG Signal.	127
4.18	Box plots of respiration rate (bpm) from PPG Signal and SB Signal across subjects. (a) Normal Breathing, (b) Fast Breathing, (c) Slow Breathing. . .	129
4.19	Correlation and Bland–Altman plots comparing breathing rates obtained from the PPG and SB across subjects. (a) Normal breathing, (b) Fast breathing, and (c) Slow breathing.	130
5.1	Experiment setup and data acquisition. (A) Equivital’s wireless physiological monitoring system (WPMS), (B) Sensor belt (SB), (C) laptop (PC), and (D) Connecting module (establish the connection between PC and WPMS). . . .	140
5.2	Experimental protocol for different breathing rates. Here, STB: start breathing, SPB: stop breathing, INT: instruction time (2 min), RST: rest time (5 min), and T: time in seconds	140

5.3	Decomposition of the ECG using Daubechies' mother function.	142
5.4	A comprehensive signal processing block diagram for respiratory signal Prediction using single-lead ECG signals.	142
5.5	Recorded signal using SB and DAS. (a) ECG signal (Black), (b) Reference respiration signal (Blue).	144
5.6	RespECG-Net Model. (CNN: 2D convolutional neural network, BN: batch normalization, LN: layer normalization, AP: Average pooling layer, DP: dropout layer, GAP: global average pooling layer, and FC: fully connected layer). . . .	146
5.7	Predicted respiration signal using RespECG-Net with ECG signals and reference respiration signals for (a) Normal breathing, (b) Fast breathing, and (c) Slow breathing with peak detection. (Red: SB, Blue: RespECG-Net). . . .	150
5.8	Box plots of breath rate (bpm) from the SB and PR using DLM for across subjects. (a) Normal breathing. (b) Slow breathing (c) Slow breathing. . . .	152
5.9	Poincare plots depicting successive TI_{PP} intervals are shown for (I) RespECG-Net and (II) the SB device over a duration of 60 seconds. In these plots, the red color signifies the fitted ellipse, the black line represents the line of identity, and the small blue circles denote the data points. Three breathing conditions are illustrated: (a) Normal breathing, (b) Fast breathing, and (c) Slow breathing. The Y-axis corresponds to $TI_{PP_{i+1}}$, while the X-axis represents TI_{PP_i}	156
5.10	Correlation and Bland–Altman plots comparing breathing rates obtained from the RespECG-Net and SB across subjects are presented. In these plots, the dotted lines denote the upper and lower limits of agreement, the black line indicates the mean difference. Three breathing conditions are examined: (a) Normal breathing, (b) Fast breathing, and (c) Slow breathing.	158
6.1	Proposed data processing and system model	167
6.2	(a) Raw ECG waveform, (b) Filtered ECG waveform with baseline correction, (c) RR peak marked waveform.	169
6.3	Classifiers performance for different RR threshold values.	171
6.4	Performance of individual features. (a) For ECG signal, (B) For HRV signal.	172
6.5	Performance of classifiers for ECG and RR/HRV signal	173
7.1	A flowchart for the automated detection of sleep apnea.	180

7.2	(a) Raw ECG signal (red) and (b) filtered ECG signal (blue).	181
7.3	Steps involved in the R-peak detection algorithm.	182
7.4	Convergence of SFFS feature selection in terms of (a) classification error and (b) accuracy for each iteration.	190
7.5	The boxplots illustrate the importance of individual features in effectively dif- ferentiating between apnea and non-apnea events.	192
7.6	Confusion matrix for different classifiers for PhysioNet database (values shown in %)	194
7.7	ROC curves of SVM, LDA, and RF	195
7.8	Inter and intra-subject analysis.	196
7.9	Performance of different classifiers for varying training data.	196
7.10	Performance of different classifiers for different folds in the cross-validation method.	197
7.11	Effect of various types of artifacts and noises on the performance of all classi- fiers. (a) White Gaussian noise, (b) Motion artifacts, and (c) Baseline drift.	199
7.12	1D-CNN model.	202
7.13	BiLSTM Model.	203
7.14	CNN-BiLSTM model.	204
7.15	CNN+Transformer model for sleep apnea detection.	205
8.1	Complete processing block diagram.	216
8.2	Per-minute ECG segment representations for normal (blue) and OSA (red) events.	216
8.3	Wigner-Ville spectrogram. (a) Apnea, (b) Normal.	217
8.4	Smoothed WVS after S-G filtering. (a) Apnea, (b) Normal.	218
8.5	Proposed WIVIDOSA-Net model.	221
8.6	10-fold cross-validation.	222
8.7	Confusion matrix (CM) for each model. (Values presented in %) for (a) ResNet-18 DLM, (b) ResNet-50 DLM and (c) WIVIDOSA-Net DLM.	224
8.8	The evaluation metrics extend beyond accuracy. (a) ROC curve, (b) Precision- Recall (PR) curve.	225
8.9	Performance of the WIVIDOSA-Net DLM for the k values 2, 4, 6, 8, and 10 in k-fold cross-validation method.	225

8.10	Scalograms computed using WVD, STFT, and CWT for the same ECG segment. (a) Continuous wavelet transform, (b) Short-time Fourier transform, and (c) Wigner-Ville distributions.	228
8.11	The model’s robustness to noisy ECG signals. (a) SG-filtering and (b) Wavelet denoising	229
9.1	Presents the 120-second segment of the ECG signal. (a) OSA segment (red), (b) Normal segment (blue).	239
9.2	Presents a preceding 120-second monitored segment and 60-second target segment of ECG signal. (a) Targeted segment consists of normal event, (b) Targeted segment consists of OSA event.	239
9.3	Complete methodology of the proposed predict-OSA model.	241
9.4	The architecture of the Gabor-CNN model. (CNN: 2D convolutional neural network, BN: batch normalization, MP: Pooling layer, and FC: Fully Connected Layer).	243
9.5	The architecture of the Wavelet-CNN model. (CNN: 2D convolutional neural network, BN: batch normalization, MP: Pooling layer, and FC: Fully Connected Layer).	244
9.6	The architecture of the Wigner-CNN model. (CNN: 2D convolutional neural network, BN: batch normalization, MP: Pooling layer, and FC: Fully Connected Layer).	246
9.7	The architecture of the STFT-CNN model. (CNN: 2D convolutional neural network, BN: batch normalization, MP: Pooling layer, and FC: Fully Connected Layer).	248
9.8	Confusion matrix for the (a) Gabor-CNN, (b) Wavelet-CNN, (c) Wigner-CNN, and (d) STFT-CNN. (Values shown in %)	251
10.1	Complete processing block diagram. Where weight associated with network is represented with θ , q_θ : predictor network, f_θ : encoder, And f_ϵ : encoder with of weight ϵ	259
10.2	Original ECG signals and transformed signal after various transformations of the RR interval measured from ECG signal. (a) RR interval signal. (b) time-warping transformation. (c) addition of Gaussian noise. (d) scale transformation.	261

10.3	Representation of signal shown in Fig. 2 (a) when passed through various transformation techniques. (a) negate transformation. (b) Permute transformation. (c) horizontal flip transformation. (d) Cutout and resize transformation.	262
10.4	Confusion matrix when model is fine-tuned with (a) 100% , (b) 10%, and (c) 50% labelled data.	270
10.5	Performances of our proposed model when different pairs of augmented signals are passed as input to the model.	271
11.1	Gait events and key gait phases throughout an entire gait cycle [2].	279
11.2	Developed wearable system. (1) Microcontroller module; (2) IMU sensor; (3) SD card; (4-5) Li-ion battery and charging module; (6) voltage regulator; (7-8) FSR sensor and shoe insole.	281
11.3	Experimental setup and data acquisition. (A) Volunteer; (B) Experimental setup; (C) Power module; (D) Main module; (E) microcontroller; (F) IMU sensor; (G) FSR sensor; (H) Insole.	282
11.4	Normalized raw signals of IMU and FSR sensor ((a-b) Z-axis: Blue, Y-axis: Red, X-axis: Black, (c) Toe FSR: Red dotted and Heel FSR: Black dotted).	286
11.5	Flowchart and pseudocode for detecting GPs and GEs from the FSR signal.	287
11.6	A complete signal processing pipeline.	289
11.7	Confusion matrix for phase classification.	289
11.8	Graphical illustration showing the predicted GP classes alongside the actual GP classes. (yellow patch: continuous error, Red patch: Outlier type error).	291
11.9	Methodology for cross-subject performance estimation (Gray box: test data).	292
11.10	Cross-subject and subject-specific performance of classifiers.	292
11.11	Different sensor placement locations.	293
11.12	Performance of classifiers trained using data from sensor at location 1 and tested across different sensor locations.	293
11.13	Continuous overlapping windowing.	297

List of Tables

1.1	Summary of literature review on wearable technology for sleep apnea detection	11
1.2	Summary of literature review on machine learning for sleep apnea detection .	12
1.3	Summary of literature review on deep learning for sleep apnea detection . . .	13
2.1	Summary of commercially available devices (years 2002-10)	30
2.2	Summary of commercially available devices (years 2011-18)	31
3.1	Average % BREA for various combinations of window size, window shift, activities, and sensor placement locations. (P1: Chest, P2: Left ribs, and P3: Abdominal.)	47
3.2	Subjects details	50
3.3	Tunable learning parameters for each layer	54
3.4	Hyper parameters for ResPara-Net	54
3.5	Breathing RMSE and CC for breathing rate prediction from DNN (reddish: bad results, Yellowish: good results)	57
3.6	Predicted respiration rate of individual subjects for normal, fast, and slow breathing rates.	58
3.7	Comparison of this research with existing different techniques used for estimating respiration measurement.	65
3.8	Details of learning parameters and model settings	79
3.9	The RMSE and Pearson Correlation Coefficient (CC) between the respiration signal predicted by RePair-Net and the actual respiration signal measured using the SB device	80
3.10	Respiration rate (bpm) measured from SB and RePair-Net	81

3.11 Subject-Wise RMSE between respiration rate measured using RePair-Net and SB for different breathing speeds.	82
3.12 MAE of ten additional features across subjects for Normal, Fast and Slow breathing rates	83
3.13 Comparison of the proposed model with existing studies	84
4.1 Measured heart rate for different breathing speeds from reference and estimated cardiac signal	101
4.2 Heart rate RMSE (bpm) comparison between PPG and ECG signals across various breathing speeds	104
4.3 MAE of different temporal features between PPG and SB	104
4.4 Tunable learning parameters for each layer. (CNN: 2D convolutional neural network, Sd: stride, A: activation, P: padding, AP: average pooling layer, DP: dropout layer, GAP: global average pooling layer, HL: Hidden Layers, and FC: fully connected layer)	109
4.5 Respiration rate and RMSE using actual SB and predicted PPG signals . . .	110
4.6 Mean absolute error (MAE) of different temporal features between respiration predicted using PPG and reference respiration signal.	111
4.7 Comparison of the proposed model with existing studies.	113
4.8 Details of learning parameters and model settings	118
4.9 Respiration rate and RMSE using actual SB and predicted PPG signals of our database.	120
4.10 Mean absolute error (MAE) of different temporal features between respiration predicted using PPG and reference respiration signal.	121
4.11 Comparison of the proposed model with existing studies.	123
4.12 Measured respiration rate for different breathing speeds from reference (SB) and estimated (ER) signals.	131
4.13 Respiration rate RMSE (BPM) comparison between PPG and actual SB measurements across various breathing speeds	131
4.14 MAE of different temporal features between PPG and SB	132
4.15 Comparison of the proposed model with existing studies	132
5.1 Tunable learning parameters for each layer	145

5.2	Hyper parameters for RespECG-Net	145
5.3	Respiration rate (bpm) measured from SB and RespECG-Net	151
5.4	Subject-Wise RMSE of respiration rate between RespECG-Net and SB for different breathing speed	152
5.5	The RMSE and CC between predicted respiration signal using RespECG-Net and actual measured respiration signal using SB device	153
5.6	MAE of ten additional features across subjects for Normal, Fast and Slow breathing rates	154
5.7	Comparison with previous studies on respiratory rate assessments employing diverse methodologies	159
6.1	List of extracted features from ECG and HRV signals	170
6.2	Performance of different classifiers for individual features (Accuracies).	172
7.1	Time domain features extracted from RR sequence	184
7.2	Time domain features extracted from ECG signals	185
7.3	Classifiers performance using selected features for epoch duration of 60 seconds	193
7.4	Classifiers performance using selected features for epoch/windowing duration of 30 seconds	193
7.5	Comparison of average classification accuracy of the proposed model along with the recent state-of-the-art methods	195
7.6	Comparison of proposed conventional ML models with various implemented DLMs using the same PhysioNet database	198
7.7	Architecture of 1D-CNN model. (Conv1D: one-dimensional convolutional layer, F: number of filters, K: Kernal size, S: stride length, FC: Fully connected layer, GAP: global average pooling layer, MP: max pooling)	205
7.8	Architecture of BILSTM model. (H: number of hidden layers, D: dropout, OM: output mode)	206
7.9	Architecture of CNN-LSTM model. (Conv1D: one-dimensional convolutional layer, F: number of filters, K: Kernal size, S: stride length, FC: Fully connected layer, GAP: global average pooling layer, D: dropout, MP: max pooling, H: number of hidden layers)	206
7.10	Details of learning parameters and model settings	209

8.1	The pseudo-code for WIVIDOSA-Net model	215
8.2	Tunable learning parameters	219
8.3	Hyperparameters utilized for WIVIDOSA-Net	220
8.4	The fold-wise per-segment performance of the models	223
8.5	Overall performance for ResNet-18, ResNet-50, and proposed WIVIDOSA-Net DLMs (with SWVS: used SG Filtering on WVS Images before Feeding to DLM, with WVS: without S-G Filtering)	226
8.6	Average performance for down-sampled signals at various sampling rates are fed into the WIVIDOSA-Net model	226
8.7	Theoretical and quantitative analysis for selection of WVD over CWT and STFT.	227
8.8	Model Complexity and Runtime Analysis	228
8.9	Performance comparison of existing techniques with proposed model for per-segment OSA detection	230
8.10	Comparison of proposed model in terms of per-recording OSA detection with existing methods	231
9.1	Tunable learning parameters for each layer	242
9.2	Tunable learning parameters for each layer	245
9.3	Tunable learning parameters for each layer	246
9.4	Tunable learning parameters for each layer	247
9.5	Tunable learning parameters for each layer	249
9.6	Average evaluation indexes for Predict-OSA models. Values inside the brackets indicate standard deviation	251
9.7	Class-wise prediction accuracy for the monitored and predicted segments using Wigner-CNN model	252
9.8	The average performance of the Wigner-CNN model using downsampled signals. (Values inside the brackets indicate standard deviation.)	253
9.9	Performance comparison of existing techniques.	254
10.1	Model performance with negating and adding Gaussian noise and 100% training data.	267
10.2	Model performance with negate and permute and 100% training data.. . . .	268

10.3	Model performance with negate and Horizontal flip and 100% training data.	268
10.4	Model performance with negate and crop and resize and 100% training data.	268
10.5	Model performance with negate and addition of Gaussian noise and 10% training data.	269
10.6	Model performance with negate and addition of Gaussian noise and 50% training data.	269
10.7	Comparison with other state-of-the-art works on the PhysioNet Apnea-ECG dataset	269
11.1	Demographic information of study participants	281
11.2	Features extracted from IMU signals	285
11.3	The learning parameters for various classifiers	286
11.4	Comparison of the performance of various classifiers in detecting gait phases .	290
11.5	Average temporal gait parameters	291
11.6	Comparison of the proposed approach with previously reported methods. . .	296

Abbreviations

OSA	Obstructive Sleep Apnea
IMU	Inertial Measurement Units
WRMS	Wearable Respiration Monitoring System
EQO2	Equivital system
MAE	Mean Absolute Error
BREA	Breathing Rate Estimation Accuracy
RMSE	Root Mean Square Error
DCNN	Deep Convolution Neural Network
SB	Sensor Belt
<i>TI_{PP}</i>	Time Interval Between Peak to Peak
PPG	Photoplethysmography
PR	Predicted Respiration
RR	Respiration Rate
PSG	Polysomnography
SFFS	Sequential Forward Feature Selection
ECG	Electrocardiogram
TFD	Time and Frequency Domain
EDR	Electrocardiogram-derived Respiratory
HRV	Heart Rate Variability
MSDA	Multiscale Dilation Attention
WLTD	Weighted-loss Time-Dependent
PMCR	Phase-Modulated Continuous Wave Radar
WT	Wavelet Transform
cd1	Details Coefficients 1

SBD	Sleep Breathing Disorder
rc1	Auto-regressive Coefficients
AR	Autoregressive
EEG	Electroencephalogram
ML	Machine Learning
DL	Deep Learning
CNN	2D convolutional neuralnetwork
BN	batch normalization
MP	Pooling layer,
FC	Fully Connected Layer
FSR	Force Sensitive Registance