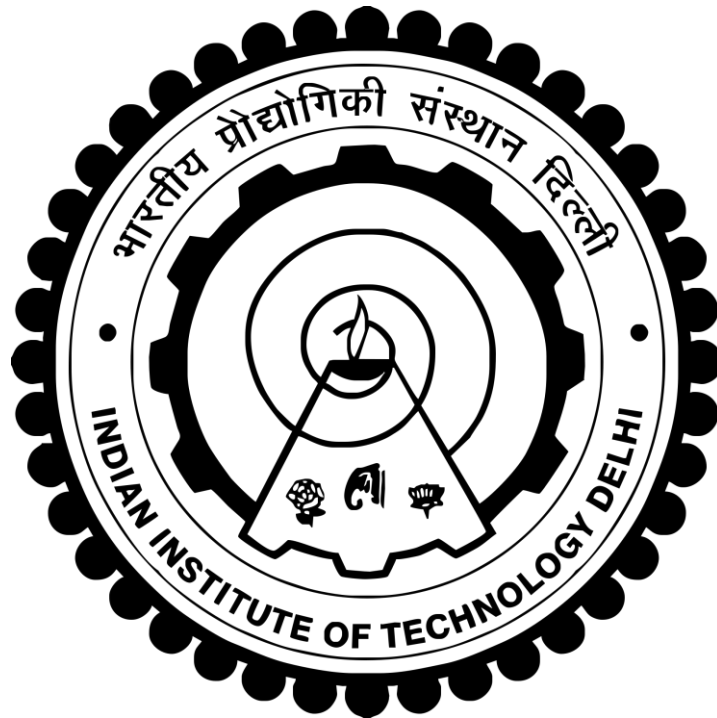


UNDERSTANDING SLEEP APNEA USING
PHYSIOLOGICAL SIGNALS AND NEUROIMAGING
DATA

CHANDRA BHUSHAN KUMAR



BHARTI SCHOOL OF TELECOMMUNICATION AND MANAGEMENT
INDIAN INSTITUTE OF TECHNOLOGY DELHI

May 2025

© Indian Institute of Technology New Delhi 2025

UNDERSTANDING SLEEP APNEA USING PHYSIOLOGICAL SIGNALS AND NEUROIMAGING DATA

by

CHANDRA BHUSHAN KUMAR

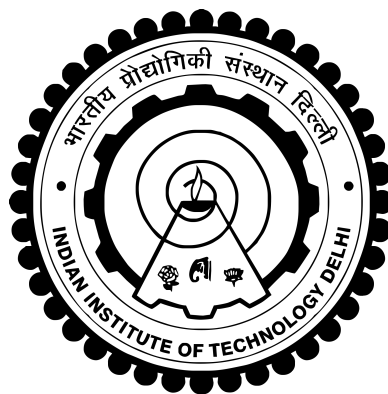
Bharti School of Telecommunication and Management

Submitted

in fulfillment of the requirements of the degree of

Doctor of Philosophy

to the



INDIAN INSTITUTE OF TECHNOLOGY DELHI

May 2025

THESIS CERTIFICATE

This is to certify that the thesis titled **Understanding Sleep Apnea Using Physiological Signal and NeuroImaging Data**, submitted by **Chandra Bhushan Kumar (2018BSZ8601)**, to the Indian Institute of Technology, Delhi, for the award of the degree of **Doctor of Philosophy** is a bona fide record of the research work done by him under our supervision. The contents of this thesis, in full or in parts, have not been submitted to any other institution or University for the award of any degree or diploma.

Prof. Tapan Kumar Gandhi

Professor

Dept. of Electrical Engineering

Indian Institute of Technology Delhi,

110016

Prof. Bijaya Ketan Panigrahi

Professor

Dept. of Electrical Engineering

Indian Institute of Technology Delhi,

110016, 110016

ACKNOWLEDGEMENTS

First and foremost, I would like to express my deepest gratitude to my parents, uncle, and aunty, whose unwavering support and encouragement have been the foundation of my academic journey. Despite the challenges of low-income farming, my father and mother have given me the strength and determination to pursue my dreams. Their sacrifices and hard work have been a constant source of inspiration, and this thesis is a testament to their love and dedication.

I am profoundly grateful to my supervisor, Prof. Tapan Kumar Gandhi and Prof. Bijaya Ketan Panigrahi, for their invaluable guidance, insightful feedback, and continuous support throughout my research. Your expertise and patience have been crucial in shaping this work, and I am truly fortunate to have had the opportunity to learn from you.

I am indebted to my collaborators, Mr. Arnab Kumar Mondal and Amit Bhogande, for their contributions and the stimulating discussions that have enriched this research. Your collaboration has been instrumental in completing this work, and I sincerely appreciate your efforts and insights.

Lastly, I would like to thank my friends for their unwavering support and companionship. Your encouragement and understanding have been a constant source of motivation, and I am grateful for the moments we shared that helped me stay balanced and focused.

This journey would not have been possible without the collective support of my family, mentors, collaborators, and friends. Thank you all for being an integral part of this accomplishment.

The goal of my life is to solve the real problems of society in the fields of education and healthcare. This goal motivated me to pursue a Doctor of Philosophy, and I am committed to making a meaningful impact through my future work.

आत्मार्थं जीवलोकेऽस्मिन् को न जीवति मानवः । परं परोपकारार्थं यो जीवति स जीवति ॥

परोपकारार्थं फलन्ति वृक्षाः परोपकाराय वहन्ति नद्यः परोपकाराय दुहन्ति गावः परोपकारार्थमिदं शरीरम् ॥

ABSTRACT

KEYWORDS: Sleep Apnea; Automatic Sleep Stage Classification; Deep Learning for Sleep Stage Classification; Deep Learning for Sleep Apnea Detection; Supervised Contrastive Learning; Feature Representation Learning; Self-attention Mechanism; Self-Supervised Learning; Graph Theory; Brain Functional Connectivity; Small-world-network

Sleep apnea (SA) is a widespread and severe sleep disorder marked by recurrent episodes of breathing cessation during sleep, leading to significant health implications and reduced quality of life. This thesis understands sleep apnea using physiological signals and neuroimaging data to enhance diagnostic accuracy and efficiency. Sleep apnea, a prevalent and severe sleep disorder, is characterized by repeated interruptions in breathing during sleep, leading to significant health risks and reduced quality of life. This thesis addresses critical challenges in diagnosing and understanding sleep apnea by leveraging advanced signal processing and deep learning techniques to analyze physiological signals and neuroimaging data. The primary contributions of this research include the development of novel methodologies for automatic sleep stage classification, efficient obstructive sleep apnea (OSA) detection, and an in-depth analysis of brain functional connectivity across sleep stages. To achieve these objectives, the thesis introduces several innovative solutions. First, a deep learning-based model incorporating supervised contrastive learning and self-attention mechanisms is proposed for automatic sleep stage classification using single-channel EEG signals. The PSG data shows a non-uniform distribution of sleep stages, with wake (W) (around 30% of total samples) and N2 stages (around 58% and 37% of total samples in Physionet EDF-Sleep 2013 and 2018 datasets, respectively) being more prevalent, leading to an imbalanced dataset. The imbalanced data issue is addressed using a weighted softmax cross-entropy loss function that assigns higher weights to minority sleep stages. Additionally, an oversampling technique (the synthetic minority oversampling technique (SMOTE) [1]) is applied to generate synthetic samples for minority classes. This model achieves state-of-the-art performance with 94.1% accuracy, a macro F1 score of 92.64, and a Cohen's Kappa of 0.92 on public datasets, addressing challenges such as imbalanced datasets and minimal preprocessing requirements. Second, a self-supervised learning framework is developed for OSA detection using single-channel ECG signals, significantly reducing the reliance on labelled data. This method achieves robust performance with accuracies of 85%, 89%, and 92% using only 1%, 10%, and 100% labelled training data, respectively. Third, the thesis explores small-world properties in brain functional networks across sleep stages using fMRI and EEG data, the analysis of Variance (ANOVA) test (p -value = 0.00877) revealing significant

differences in functional brain connectivity and spectral connectivity during different stages. The study analyzes BFNs from the spectral functional brain network by computing various small-world network parameters (γ , λ , σ). For fMRI data, parameters such as clustering coefficient (C_p), local efficiency (E_{local}), and global efficiency (E_{global}) showed a negative correlation with sparsity, while γ , λ , and σ showed a positive correlation with sparsity across different sleep stages. Resting-state fMRI data exhibited similar trends. In contrast, for EEG signals, C_p , E_{local} , and E_{global} maintained constant values across different sleep stages. Small-world- network properties provided insights into the neurophysiological impacts of Sleep Apnea on functional brain connectivity. Also, we have analysed dynamic functional connectivity using fMRI signals to understand the brain network's temporal characteristics across different sleep stages better.

These contributions are novel in their ability to address key limitations in existing methodologies: reducing dependency on extensive labelled datasets, enhancing generalization across datasets, and providing clinically relevant insights into brain connectivity patterns. The proposed techniques are designed for real-time and offline applications, making them suitable for clinical use and home-based monitoring systems. The findings of this thesis have significant implications for advancing personalized treatment strategies for sleep apnea and improving patient outcomes. By combining innovative computational techniques with physiological signal analysis and neuroimaging data exploration, this research paves the way for more accessible, accurate, and cost-effective diagnostic tools to transform sleep medicine practices.

सारांश

मुख्य शब्द: स्लीप एपनिया; स्वचालित निद्रा चरण वर्गीकरण; निद्रा चरण वर्गीकरण के लिए डीप लर्निंग; स्लीप एपनिया डिटेक्शन के लिए डीप लर्निंग; सुपरवाइज्ड कॉन्ट्रास्टिव लर्निंग; फीचर प्रतिनिधित्व अधिगम; स्व-ध्यान तंत्र; स्व-पर्यवेक्षित अधिगम; ग्राफ सिद्धांत; मस्तिष्क क्रियात्मक कनेक्टिविटी; स्मॉल-वर्ल्ड नेटवर्क

स्लीप एपनिया (SA) एक व्यापक और गंभीर नींद विकार है, जिसमें नींद के दौरान बार-बार सांस रुकने की घटनाएँ होती हैं, जिससे महत्वपूर्ण स्वास्थ्य संबंधी समस्याएँ और जीवन की गुणवत्ता में गिरावट आती है। यह शोध प्रबंध निदान की सटीकता और दक्षता बढ़ाने के लिए फिज़ियोलॉजिकल सिग्नल्स और न्यूरोइमेजिंग डेटा का उपयोग करके स्लीप एपनिया को समझने का प्रयास करता है। स्लीप एपनिया, एक आम और गंभीर नींद विकार है, जिसकी विशेषता नींद के दौरान बार-बार सांस रुकना है, जिससे गंभीर स्वास्थ्य जोखिम और जीवन की गुणवत्ता में कमी आती है। यह शोध प्रबंध, फिज़ियोलॉजिकल सिग्नल्स और न्यूरोइमेजिंग डेटा का विश्लेषण करने के लिए उन्नत सिग्नल प्रोसेसिंग और डीप लर्निंग तकनीकों का उपयोग करते हुए, निदान और समझ की महत्वपूर्ण चुनौतियों को संबोधित करता है। इस शोध के प्रमुख योगदानों में स्वचालित स्लीप स्टेज वर्गीकरण के लिए नई कार्यप्रणालियों का विकास, कुशल ऑब्स्ट्रक्टिव स्लीप एपनिया (OSA) की पहचान, और नींद के विभिन्न चरणों में मस्तिष्क की कार्यात्मक कनेक्टिविटी का गहन विश्लेषण शामिल है। इन लक्ष्यों को प्राप्त करने के लिए, शोध में कई नवाचार प्रस्तुत किए गए हैं। सबसे पहले, सिंगल-चैनल EEG सिग्नल्स का उपयोग करते हुए स्वचालित स्लीप स्टेज वर्गीकरण के लिए एक डीप लर्निंग आधारित मॉडल प्रस्तावित किया गया है, जिसमें सुपरवाइज्ड कॉन्ट्रास्टिव लर्निंग और सेल्फ-अटेंशन मैकेनिज्म शामिल हैं। पॉलीसोमनोग्राफी PSG डेटा में नींद के चरणों का वितरण असमान है, जिसमें वेक (W) (लगभग 30%) और N2 चरण (Physionet EDF-Sleep 2013 और 2018 डेटासेट में क्रमशः 58% और 37%) अधिक प्रचलित हैं, जिससे डेटा असंतुलित हो जाता है। इस समस्या को हल करने के लिए वेटेड सॉफ्टमैक्स क्रॉस-एंटरॉपी लॉस फंक्शन और SMOTE (सिंथेटिक माइनॉरिटी ओवरसैंपलिंग टेक्नीक) का उपयोग किया गया है। यह मॉडल सार्वजनिक डेटासेट्स पर 94.1% सटीकता, 92.64 का मैक्रो F1 स्कोर और 0.92 का कोहेन कप्पा प्राप्त करता है, जिससे असंतुलित डेटा और न्यूनतम प्री-प्रोसेसिंग जैसी चुनौतियों का समाधान होता है। दूसरे, OSA पहचान के लिए सिंगल-चैनल ECG सिग्नल्स का उपयोग करते हुए एक सेल्फ-सुपरवाइज्ड लर्निंग फ्रेमवर्क विकसित किया गया है, जिससे लेबल्ड डेटा पर निर्भरता काफी कम हो जाती है। इस विधि ने केवल 1%, 10% और 100% लेबल्ड प्रशिक्षण डेटा के साथ क्रमशः 85%, 89% और 92% सटीकता प्राप्त की है। तीसरे, शोध में fMRI और EEG डेटा का उपयोग करते हुए नींद के विभिन्न चरणों में मस्तिष्क के कार्यात्मक नेटवर्क की स्मॉल-वर्ल्ड विशेषताओं का अध्ययन किया गया है। ANOVA परीक्षण (p -value = 0.00877) के माध्यम से विभिन्न चरणों के दौरान कार्यात्मक मस्तिष्क कनेक्टिविटी और स्पेक्ट्रल कनेक्टिविटी में महत्वपूर्ण अंतर पाए गए। fMRI डेटा के लिए, क्लस्टरिंग कोएफिशिएंट (C_p), लोकल एफिशिएंसी (E_{local}), और ग्लोबल एफिशिएंसी (E_{global}) में स्पार्सिटी के साथ नकारात्मक सहसंबंध देखा गया, जबकि γ , λ , और σ में स्पार्सिटी के साथ सकारात्मक सहसंबंध पाया गया। EEG सिग्नल्स के लिए, C_p , E_{local} , और E_{global} ने विभिन्न नींद चरणों में स्थिर मान बनाए रखे। स्मॉल-वर्ल्ड नेटवर्क गुणों ने स्लीप एपनिया के कार्यात्मक मस्तिष्क कनेक्टिविटी पर न्यूरोफिज़ियोलॉजिकल प्रभावों की समझ प्रदान की। साथ ही, fMRI सिग्नल्स का उपयोग करके डायनामिक फंक्शनल कनेक्टिविटी का विश्लेषण किया गया, जिससे

विभिन्न नींद चरणों में मस्तिष्क नेटवर्क की समयगत विशेषताओं को बेहतर समझा जा सका। इन योगदानों की नवीनता यह है कि ये मौजूदा कार्यप्रणालियों की प्रमुख सीमाओं को दूर करते हैं, जैसे कि बड़े लेबल डेटा सेट्स पर निर्भरता कम करना, डेटा सेट्स के बीच सामान्यीकरण बढ़ाना, और मस्तिष्क कनेक्टिविटी पैटर्न में चिकित्सकीय रूप से प्रासंगिक अंतर्दृष्टि प्रदान करना। प्रस्तावित तकनीकों को रीयल-टाइम और ऑफलाइन दोनों अनुप्रयोगों के लिए डिज़ाइन किया गया है, जिससे ये क्लिनिकल उपयोग और होम-बेस्ड मॉनिटरिंग सिस्टम दोनों के लिए उपयुक्त हैं। इस शोध के निष्कर्ष स्लीप एपनिया के लिए व्यक्तिगत उपचार रणनीतियों को आगे बढ़ाने और रोगी परिणामों में सुधार के लिए महत्वपूर्ण हैं। नवीन कम्प्यूटेशनल तकनीकों को फिज़ियोलॉजिकल सिग्नल्स के विश्लेषण और न्यूरोइमेजिंग डेटा अन्वेषण के साथ जोड़कर, यह शोध अधिक सुलभ, सटीक और किफायती निदान उपकरणों के विकास का मार्ग प्रशस्त करता है, जिससे नींद चिकित्सा पद्धतियों में क्रांतिकारी बदलाव आ सकता है।

Contents

ACKNOWLEDGEMENTS	i
ABSTRACT	ii
LIST OF TABLES	xii
LIST OF FIGURES	xv
1 INTRODUCTION	1
1.1 Introduction	1
1.1.1 Sleep Disorder Detection Methods	3
1.2 Focus of this thesis: Understanding sleep apnea using physiological Signals and Neuro-imaging Data	9
1.3 Related Work	10
1.4 Research Gaps	12
1.5 Motivation	13
1.6 Thesis Objectives and Scope	14
1.6.1 Objectives	14
1.6.2 Scope	14
1.7 Contribution of this Thesis	15
1.8 Thesis Overview	16
2 Literature Survey: Sleep Apnea Detection Methods, Prognosis, and Future Scope	17
2.1 Introduction	17
2.2 Sleep Apnea Detection methods	17
2.2.1 Traditional Approach for Sleep Apnea Detection Using Physiological Signals	18

2.2.2 Feature Extraction from Physiological Signals	20
2.2.3 Feature selection	24
2.2.4 Classification	25
2.3 Application of Deep Learning for Classification of Sleep Stage and Detection of Sleep Apnea	25
2.3.1 Sleep Apnea Detection Using Mixed Signals	26
2.3.2 Sleep Apnea Detection Using ECG Signals	27
2.3.3 Sleep Apnea Detection Using EEG Signals	28
2.4 Medical Treatment, Challenges, and Prognosis of Sleep Apnea	28
2.4.1 Medical treatment of sleep apnea	29
2.4.2 Challenges in sleep apnea management	32
2.4.3 Prognostic perspective	34
2.5 Datasets	35
2.6 Discussion & Future Scope	35
3 Unraveling Sleep Patterns: Supervised Contrastive Learning with Self-Attention for Sleep Stage Classification	49
3.1 Introduction	49
3.2 Preliminary Studies	50
3.3 Methodology	55
3.3.1 Datasets and Data Pre-processing	55
3.3.2 Data Pre-processing	56
3.3.3 Oversampling of the Minority classes in the training set of the Data	57
3.3.4 Formation of the Triplet(Reference, Positive, and Negative subsets) from the Training Data	57
3.3.5 Model Architecture	58
3.4 Experiments and Results	66
3.4.1 Implementation Tool	66
3.4.2 Experimental design	66
3.4.3 Evaluation Metrics	66

3.4.4 Results and Discussion	67
3.5 Integration into Clinical Workflows	75
3.6 Conclusion	76
4 Automatic detection of sleep apnea and its severity level	78
4.1 Introduction	78
4.2 Proposed Model	82
4.2.1 Architecture of Model in the Experiment A	82
4.2.2 Architecture of Model in the Experiment B	85
4.2.3 Transformations of ECG Signals	88
4.3 Datasets and Data Preparation	89
4.4 Experimental Results Analysis	90
4.4.1 Evaluation Metrics	90
4.4.2 Classification Performance of Proposed model in Experiment A	91
4.4.3 Performance Analysis of the Model in Experiment B	96
4.4.4 Ablation Studies of Our Proposed Model	100
4.4.5 Performance Comparison of Proposed Model in Experiment A with State-of-the-Art Model	105
4.4.6 Comparison of the Performance between existing techniques and the proposed model in Experiment B	107
4.5 Conclusion	107
5 Exploring Small-World-Network and Other Network Properties in Functional Brain Networks: A Comparative Analysis Across Sleep Stages	110
5.1 Introduction	110
5.2 Materials and Methods	111
5.2.1 Dataset	111
5.2.2 fMRI Data Preprocessing	112
5.3 Results	117
5.3.1 Analysis of Functional Brain Connectivity using fMRI	117
5.3.2 Analysis of Spectral Functional Brain Connectivity Using EEG Signals	126

5.3.3	Limitations of fMRI in Sleep and Functional Connectivity Studies . . .	127
5.4	Comparison with Existing Literature	128
5.5	Discussion and Conclusion	128
6	Discussion and Scope of Future Work	131
6.1	Discussion	131
6.2	Conclusion	134
	Bibliography	134
	Biography	163
	Publications	164

List of Tables

2.1	Time-domain extracted from HRV(m) epoch sequence.	21
2.2	Time-domain measure for EDR(q) epoch sequence.	21
2.3	Spectral-domain measures for HRV and EDR epoch sequences.	22
2.4	Spectral-domain measures for HRV and EDR epoch sequences.	22
2.5	Performance summary of different traditional sleep apnea detection approaches.	39
2.6	Deep learning for sleep apnea detection methods	41
3.1	Class-wise evaluation metrics on Fpz_cz Channel of EDF-Sleep 2013	69
3.2	Class-wise evaluation metrics on Pz_oz Channel of EDF-Sleep 2013	69
3.3	Class-wise evaluation metrics on Fpz_cz Channel of SleepEDF-78	72
3.4	Performance comparison of the proposed model with existing state-of-art models	73
3.5	Ablation studies of the proposed model	73
3.6	Ablation study on the classifier of the proposed model	73
3.7	Effect of different oversampling techniques on proposed model's performance	74
4.1	Performance Comparison Of Different Studies For Respiratory-Related Events	80
4.2	Proposed model performance in each fold of 10-fold cross-validation set up on ECG signals(trained on 100% training data) with Negate and Noise Addition transformation	92
4.3	Class-wise evaluation metrics on ECG signals(trained on 100% training data) with Negate and Moving Average transformation	93
4.4	Class-wise evaluation metrics on ECG signals(trained on 100% training data) with Negate and Horizontal flip transformation	93
4.5	Class-wise evaluation metrics on ECG signals(trained on 100% training data) with Negate and Noise Addition transformation	94
4.6	Class-wise evaluation metrics on ECG signals(trained on 1% training data) with Negate and Moving Average transformation	94

4.7 Class-wise evaluation metrics on ECG signals(trained on 1% training data) with Negate and Horizontal flip transformation	94
4.8 Class-wise evaluation metrics on ECG signals(trained on 1% training data) with Negate and Noise Addition transformation	94
4.9 Class-wise evaluation metrics on ECG signals(trained on 10% training data) with Negate and Noise Addition transformation	95
4.10 Model performance with negating and adding Gaussian noise and 100% training data	96
4.11 Model performance with negate and permute and 100% training data..	97
4.12 Model performance with negate and Horizontal flip and 100% training data.	97
4.13 Model performance with negate and crop and resize and 100% training data.	97
4.14 Model performance with negate and addition of Gaussian noise and 10% training data	98
4.15 Model performance with negate and addition of Gaussian noise and 50% training data	98
4.16 The OSA diagnosis evaluation metrics of trained proposed model(trained on 10% training data) per-individual with Negate and Noise Addition transformation	99
4.17 The OSA diagnosis evaluation metrics of trained proposed model(trained on 1% training data) per-individual with Negate and Noise Addition transformation	99
4.18 The OSA severity diagnosis evaluation metrics of trained proposed model(trained on 10% training data) per-individual with Negate and Noise Addition transformation	99
4.19 The OSA severity diagnosis evaluation metrics of trained proposed model(trained on 1% training data) per-individual with Negate and Noise Addition transformation	100
4.20 Classifier performance when trained using different amounts of data without self-supervision	102
4.21 Ablation study on the input of our proposed model	103
4.22 Ablation study on the normalization techniques of input of our proposed model	103
4.23 Performance Comparison Of Different Studies For per-sequence OSA Detection using Single Channel ECG	105
4.24 Performance Comparison Of Different Studies For per-individual OSA Detection using Single Channel ECG	105
4.25 Proposed model per-segment classification accuracy comparison on the UCDDB dataset	106

4.26 Comparison with other state-of-the-art works on the PhysioNet Apnea-ECG dataset	
.....	107

List of Figures

1.1	Classification of sleep detection methods; source: [2].	3
1.2	(a) Normal breathing; (b) Snoring- partial obstruction of the air ways; (c) OSA- complete obstruction of the air ways; source: ([3] and in reference)	8
1.3	Basic schematic diagram of ECG signal; source: [4]	9
2.1	Basic schematic diagram of ECG signal; source: [4]	18
3.1	Step-wise block diagram of the (a) end-to-end process (b) Data pre-processing steps, (c) Feature representation learning network training phase using triplet loss; where $f(\theta)$ representing encoder network; Z_n , Z_a , and Z_p representing latent vectors of negative, anchor, and positive samples, (d) classification network training phase, and (e) Prediction process.	54
3.2	Illustration of the proposed method. Here, $f(\theta)$ denotes the Feature Learner Network; Neg. and Pos. are notations for the negative and positive, respectively. The anchor, positive, and negative are three subsets of data prepared from the training data set. The Feature Learner Network $f(\theta)$ is trained in the initial stage to representation and then pre-trained $f(\theta)$ fine-tuned with a classifier for the classification task in the second stage.	58
3.3	Detail architecture of feature learner $f(\theta)$. Each conv block specifies the filter size, number of filters, and stride length, while each max-pooling block indicates the pooling size and stride length.	59
3.4	Illustration of an encoder-decoder-based classifier with self-attention. A dotted line between them shows the weight sharing between blocks.	63
3.5	Illustration of an end-to-end Signal flow in proposed model with encoder-decoder-based classifier with self-attention	63
3.6	The t-SNE plot visualization of (a) raw signal(b) embedding of raw signals (c) raw signal plot with axes scale x $[-8; 8]$ and y $[-8; 8]$, where labels denote wake (W), NREM sleep stages (N1, N2, N3), and REM. Parameters used during the t-SNE plot are metric: euclidean; learning rate:200; the number of iterations: 1000; and the number of components: 5.	67
3.7	The pairwise mean and standard deviation of Euclidean distance between cluster centres of (a) raw signal(b) embedding of raw signals, where mean and standard deviation are shown at up and down in each box respectively. The map is annotated with labels denoting wake (W), NREM sleep stages (N1, N2, N3), and REM.	68

3.8 Performance graph of the proposed model on EDF-Sleep 2013 database in (a) 12th fold (b) 18th fold	70
3.9 Confusion matrix generated from the predicted class on the EDF-Sleep-2013 database using EEG signal for (a)FPz-cz EEG channel (b) Pz-Oz EEG channel	72
4.1	84
4.2 Residual network with 18 convolutional layers as encoder	84
4.3 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	85
4.4 Signal visualization after application of augmentation techniques	87
4.5 Confusion matrix produced from the predicted class by the proposed method (a) when encoder fine-tuned on 100% training data (b) when encoder fine-tuned on 1% training data (c) when encoder fine-tuned on 10% training data	95
4.6 Visualization of raw ECG signals and its embedding using t-SNE plot: (a) The t-SNE plot of raw signal(b) The t-SNE plot of embedding of raw signals	95
4.7 Confusion matrix when model is fine-tuned with (a) 100% , (b) 10%, and (c) 50% labelled data	98
4.8 Proposed model performance in terms of accuracy for different augmentation techniques applied to the ECG signals when fine-tuned with 100% labelled data	101
4.9 Proposed model performance in terms of accuracy for different augmentation techniques applied to the ECG signals when fine-tuned with 10% labelled data	102
4.10 Proposed model performance in terms of accuracy for different augmentation techniques applied to the ECG signals when fine-tuned with 1% labelled data	102
4.11 Performances of our proposed model when different pairs of augmented signals passed as input to the model.	103
4.12 Proposed model performance in terms of accuracy and F1 score when trained using different amounts of labelled data	104
5.1 FMRI data preprocessing block diagram.	113
5.2 C_p , E_{local} , and E_{global} correlation plot with sparsity between different sleep stages: (a) Wake and Stage 1, (b) Wake and Stage 2, (c) Wake and Stage 3, (d) Stage 1 and Stage 2, (e) Stage 1 and Stage 3, (f) Stage 2 and Stage 3.	114
5.3 γ , λ , and σ correlation plot with sparsity, between different sleep stages: (a) Wake and Stage 1, (b) Wake and Stage 2, (c) Wake and Stage 3, (d) Stage 1 and Stage 2, (e) stage 1 and Stage 3, (f) stage 2 and Stage 3.	115

5.4 State occurrence across different sleep stages (Stages 0–3) based on K-means clustering.	116
5.5 Variability in dynamic functional connectivity across different sleep stages (Stages 0–3).	116
5.6 Average dynamic functional connectivity matrices for different sleep stages (Stages 0–3).	117
5.7 Temporal dynamics of dynamic functional connectivity across different sleep stages (Stages 0–3).	117
5.8 State occurrence during resting state based on K-means clustering	118
5.9 Variability in functional connectivity across different sleep stages (Stages 0–2) during resting state.	118
5.10 Average dynamic functional connectivity matrices for different sleep stages (Stages 0–2) during resting state.	119
5.11 Temporal dynamics of functional connectivity during resting state.	119
5.12 C_p , E_{local} , and E_{global} correlation plot with sparsity between different sleep stages during rest: (a) Wake and Stage 1, (b) Wake and Stage 2, (d) Stage 1 and Stage 2.	120
5.13 γ , λ , and σ correlation plot with sparsity between different sleep stages during rest: (a) Wake and Stage 1, (b) Wake and Stage 2, (c) stage 1 and Stage 2.	121
5.14 Small-world Network Properties Between Two Groups During Sleep. (a) C_p , E_{local} , and E_{global} plot with different sparsity, in wake and sleep stage 1. (b) γ , λ , and σ plot with different sparsity, in wake and sleep stage 1.	121