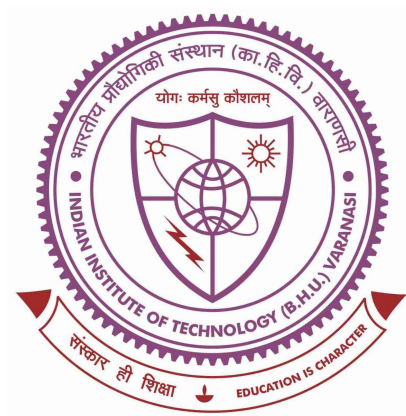


# Scalogram-based multimodal signal classification using deep learning



**Thesis submitted in partial fulfilment**

**for the Award of**

**DOCTORATE OF PHILOSOPHY**

**in**

**BIOMEDICAL ENGINEERING**

*by*

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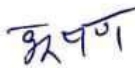
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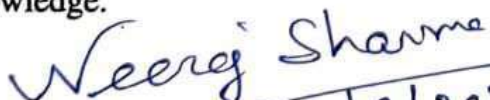
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## Nomenclature

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### Acronyms / Abbreviations

*AC* Autocorrelation

*ALS* Amyotrophic Lateral Sclerosis

*AUC* area under the ROC curve

*BCI* Brain-Computer Interface

*Bior* Biorthogonal wavelets

*CA* Channel Attention

*CBAM* Convolutional block attention module

*CF* Crest Factor

*Cgau8* Complex gaussian wavelet

*CJD* Creutzfeldt-Jakob Disease

*Coif* Coiflets

*CV* Coefficient of Variation

*Db* Daubechies wavelets

*DNN* Deep Neural Networks

*DT* Decision Tree

*DWT* Discrete Wavelet Transform

*EEG* Electroencephalogram

*EMG* Electromyogram

*ERD* Event-Related Desynchronization

*Fbsp* Frequency B Spline wavelet

*FN* False Negatives

*FP* False Positives

*HD* Huntington's disease

*HR* Harmonic Ratios

*IMU* Inertial Measurement Units

*KNN* K-Nearest Neighbors

*LR* Logistic Regression

*LSTM* Long Short-Term Memory

*MAV* Mean Absolute Value

*MDF* Median Frequency

*Mexh* Mexican hat wavelet

*MGAS* Medial gastrocnemius

*ML* Machine Learning

*MLP* Multi-layer perceptron

*MNF* Mean Frequency

*MNP* Mean Power

*MSA* Multiple System Atrophy

*NB* Naïve Bayes

*NDD* Neurodegenerative Diseases

*PD* Parkinson's disease

*PIVD* Prolapsed Intervertebral Disc

*PPV* Peak-to-Peak Value

*PRC* Precision-Recall Coverage

*PSD* Power Spectral Density

*PSP* Progressive Supranuclear Palsy

*RA* Rheumatoid Arthritis

*ReLU* Rectified Linear Unit

*CNN* Convolution Neural Networks

*CWT* Continuous Wavelet Transform

*RF* Random Forest

*RMS* Root Mean Square

*ROC* Receiver Operating Characteristic

*SA* Spatial Attention

*SB* Spectral Bandwidth

*SC* Spectral Centroid

*SD* Standard Deviation

*SE* Spectral Entropy

*SF* Spectral Flatness

*SGD* Stochastic gradient descent

*Shan* Shannon wavelet

*SM1* Spectral Moments 1

*SM2* Spectral Moments 2

*SM3* Spectral Moments 3

*SVM* Support Vector Machine

*Sym* Symlets

*TA* Tibialis anterior

*TN* True Negatives

*TP* True Positives

*MNF* Total Power

*VCF* Variance Central Frequency

*vGRF* Vertical ground reaction force

*ZC* Zero Crossing

# Preface

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Biomedical engineering has recently experienced significant advancements, particularly in classifying neuromuscular activity using electroencephalography (EEG) and electromyography (EMG) signals. These technologies have become increasingly important in applications such as brain-computer interfaces (BCIs) and gait analysis, offering new possibilities for diagnosis and rehabilitation. However, these signals' inherent noise and variability present challenges that can hinder classification accuracy. This thesis aims to address these challenges by investigating the use of scalograms—visual representations that capture both the time and frequency components of signals to improve the precision of neuromuscular activity classification. The research presented in this thesis is structured to systematically build upon each chapter's findings, providing a comprehensive understanding of the methodologies and advancements in this domain.

Chapter 1 introduces the motivation behind the research, outlining the challenges in neuromuscular activity classification and the study's objectives.

Chapter 2 offers an in-depth literature review on gait analysis and BCIs. It discusses the methodologies and technologies employed in the field, including signal processing techniques and feature extraction methods. The chapter also introduces the applications of EEG and EMG across various domains while providing a foundational overview of machine learning and deep learning.

Chapter 3 focuses on the classification of hemiplegic gait abnormalities using EMG signals. The research demonstrates the effectiveness of an ensemble classifier in identifying hemiplegic gait patterns, achieving high accuracy, and highlighting the potential for applications in diagnosis and rehabilitation.

Chapter 4 extends the classification to other gait abnormalities, including rheumatoid arthritis, osteoarthritis, and prolapsed intervertebral disc (PIVD), using EMG scalograms.

Additionally, this chapter explores the classification of neurological disorders like Parkinson's disease, amyotrophic lateral sclerosis (ALS), and Huntington's disease, utilizing scalograms generated from foot insole data.

Chapter 5 presents the application of attention networks for classifying EMG scalograms related to various gait abnormalities. This chapter emphasizes the impact of combining different wavelet family scalograms on classification accuracy, showcasing how attention mechanisms can significantly enhance the performance of classification models.

Chapter 6 investigates the classification of hand movements using a combination of EEG and EMG scalograms. By employing CNNs and transfer learning, the study demonstrates how integrating these signals can improve classification accuracy, reduce noise, and mitigate signal variability, offering promising advancements for healthcare and assistive technology applications.

Chapter 7 concludes the thesis by summarizing the key findings, discussing the contributions to gait analysis and signal processing, and proposing directions for future research. The chapter also reflects on the current study's limitations and the future scope.

## Abstract

Recent advancements in the classification of neuromuscular activity using electroencephalography (EEG) and electromyography (EMG) signals have demonstrated significant potential in applications such as brain-computer interfaces (BCI) and gait analysis. EMG, which captures electrical activity from muscles, is crucial for assessing muscle function, fatigue, and abnormalities, while EEG, which records brain activity, plays a critical role in BCI research. However, both signals are susceptible to noise and variability, impacting classification tasks' accuracy and precision. This research aims to mitigate these limitations by utilizing scalograms, which are plots of time and frequency components of the signal. The study increased classifier performance using models ranging from conventional machine learning classifiers to attention networks and transfer learning. This research highlights the effectiveness of scalograms in enhancing classification accuracy for gait abnormalities associated with conditions such as hemiplegia, Parkinson's disease, and rheumatoid arthritis. Further, integrating EEG and EMG scalograms for hand movement classification, primarily through CNNs and transfer learning, led to improved classification accuracy. These findings highlighted the potential of scalogram-based deep learning techniques in enhancing diagnostic accuracy.

## Graphical Abstract

