**Abstract**:

Sleep disorders, particularly obstructive sleep apnea (OSA), pose significant health risks, affecting cardiovascular, neurological, and cognitive functions. OSA is characterized by recurrent episodes of airway obstruction during sleep, leading to intermittent hypoxia, sleep fragmentation, and excessive daytime sleepiness. Left untreated, it increases the risk of hypertension, stroke, heart failure, metabolic disorders, and cognitive decline. Traditional diagnostic methods, such as polysomnography (PSG), are resource-intensive, intrusive, and impractical for large-scale or home-based monitoring. This thesis addresses these limitations by developing wearable sensor-based systems and leveraging machine and deep learning models to facilitate early, non-invasive detection of sleep disorders using physiological signals.

A major contribution of this work is a wearable respiration monitoring system integrating the Inertial Measurement Unit (IMU), Electrocardiogram (ECG), and Photoplethysmogram (PPG) sensors to capture signals indicative of respiratory irregularities linked to OSA. The system was evaluated through extensive trials, demonstrating its effectiveness in detecting subtle respiratory variations. Derived temporal parameters were benchmarked against PSG data, and advanced signal processing was employed to reduce noise. Comparative analyses using statistical, machine learning, and deep learning methods revealed that multimodal signal integration improves accuracy and reliability in respiration estimation.

Furthermore, this thesis proposes a novel feature-engineering framework for sleep apnea detection using single-lead ECG signals, aimed at enabling efficient and non-invasive diagnosis. The framework extracts key cardiac features such as heart rate variability (HRV) and R-R intervals, along with underutilized metrics from the time, time-frequency, and nonlinear domains—including entropy-based features—to better capture the physiological disruptions caused by apneic events. Evaluated across multiple independent datasets and a range of machine learning classifiers, the model demonstrated strong classification performance, robustness, and computational efficiency. Its lightweight nature supports real-time processing, making it highly suitable for wearable and home-based diagnostic systems.

Building upon this, the research investigates deep learning methods to automate sleep apnea detection using raw physiological signals. Architectures such as supervised, self-supervised, and Transformer-based models were developed and assessed for their ability to learn complex temporal and nonlinear patterns without manual feature extraction. These models showed high sensitivity and generalizability and were optimized for real-time deployment through architecture simplification and parameter tuning, making them feasible for integration into wearable platforms.

The thesis further explores sleepwalking detection, focusing on an IMU-based gait analysis system, and investigates potential links between sleepwalking and the severity of apnea. A single IMU sensor placed on the shank captured gait events, and machine learning classifiers—SVM, KNN, and LDA—were used to identify movement patterns relevant to sleepwalking. The system

showed consistent performance across individuals and sensor placements. However, the study was limited to healthy participants, and further validation is needed in clinical populations to confirm its diagnostic value. Despite this, the study provides a foundational step toward non-invasive, wearable-based monitoring of parasomnia behaviors.

**Limitations:**

Despite promising results, this research has several limitations. First, the wearable systems and models were validated primarily on small-scale or publicly available datasets, which may not fully represent the diversity of real-world conditions. Second, the models' performance on clinical-grade, heterogeneous data—particularly from individuals with coexisting disorders—remains to be rigorously evaluated. Third, while deep learning models offer superior performance, they require substantial computational resources during training, which may limit scalability in some low-power wearable platforms. Additionally, the sleepwalking study was conducted only on healthy participants, and further clinical validation is essential before drawing conclusive insights for diagnostic applications. Lastly, the wearable prototypes developed in this study are yet to undergo long-term usability, durability, and compliance testing in real-world home settings.

This thesis advances the integration of wearable sensing with AI-driven analysis to develop accessible, scalable, and cost-effective solutions for sleep disorder diagnostics. By leveraging multimodal physiological signals and both machine learning and deep learning techniques, it presents practical alternatives to complex, clinic-based assessments such as polysomnography. The proposed systems are optimized for real-time, non-invasive, and home-based monitoring. This work lays the foundation for future research in clinical validation, large-scale deployment, and integration into digital health ecosystems for continuous and personalized sleep health management.