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A Mattress-Integrated ECG System for Home Detection of Obstructive Sleep Apnea Through HRV Analysis Using Wavelet Transform and XGBoost Classification

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Abstract **Obstructive Sleep Apnea (OSA) is a potentially life-threatening sleep disorder that often remains undiagnosed due to the complexity of conventional diagnostic methods such as polysomnography (PSG). Currently, there is a lack of accessible, non-invasive diagnostic solutions suitable for home use. This study proposes a novel approach to automate OSA detection using single-lead electrocardiogram (ECG) signals acquired through non-contact conductive fabric electrodes embedded in a mattress, enabling unobtrusive monitoring during sleep. The main contributions of the proposed study are a mattress-embedded contactless ECG monitoring system eliminating the discomfort of traditional electrodes, and an advanced signal processing framework integrating wavelet decomposition with machine learning for precise OSA identification. ECG signals from 35 subjects (30 male, 5 females, aged 27-63 years) diagnosed with OSA were obtained from the PhysioNet Apnea-ECG database, originally sampled at 100 Hz and up-sampled to 250 Hz for consistency with experimental recordings from healthy volunteers tested in various sleep positions. Signals were recorded non-invasively during sleep in various body positions and processed using the Discrete Wavelet Transform (DWT) up to the third level of decomposition. The processing of ECG signals involved Heart Rate Variability (HRV) analysis, which was applied to extract information in the time domain, frequency domain, and non-linear properties. By analyzing HRV on the respiratory sinus arrhythmia spectrum, the respiration signal was obtained from ECG-derived respiration (EDR). Feature selection was performed using ANOVA, resulting in a set of key features including respiratory rate, SD2, SDNN, LF/HF ratio, and pNN50. These features were classified using the XGBoost algorithm to determine the presence of OSA. The proposed system achieved a detection accuracy of 96.7%, demonstrating its potential for reliable home-based OSA diagnosis. This method improves comfort through non-contact sensing and supports early intervention by delivering timely alerts for high-risk patients.**

Keywords **Obstructive Sleep Apnea; Non-Contact ECG; Heart Rate Variability (HRV); Wavelet Transform; XGBoost Classification**.

I. Introduction

Obstructive Sleep Apnea (OSA) is a serious sleep disorder characterized by the intermittent relaxation of throat muscles, which obstructs the airway and leads to repeated interruptions in breathing during sleep. These apneic episodes cause fragmented sleep and fluctuating oxygen levels, resulting in significant health complications. If untreated, OSA can contribute to various cardiovascular diseases because the underlying mechanisms involve intermittent oxygen deprivation (hypoxemia), which activates the sympathetic nervous system, leading to elevated blood pressure, thus increasing the risk of hypertension, heart failure, and stroke. Moreover, repeated apneic events can exacerbate insulin resistance and promote inflammation, further raising the likelihood of

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developing type 2 diabetes and other metabolic disorders [1][2]. Additionally, OSA has been associated with cognitive decline and increased mortality rates, likely due to the cumulative effects of hypoxemia and autonomic dysfunction, which contribute to cardiovascular complications and other health issues [2][3]. Despite these severe health risks, OSA remains significantly underdiagnosed worldwide, particularly in low-resource settings. For instance, a study in Asia involving 226 bariatric surgery patients revealed that 80.5% of participants had OSA, with 24.3% having mild OSA, 23.9% moderate OSA, and 32.3% severe OSA. However, only 17.3% of these patients had been previously diagnosed [4]. These findings underscore the urgent need for more accessible, efficient, and effective diagnostic methods.

Polysomnography (PSG) is the current gold standard for diagnosing OSA, as it monitors various physiological signals, including EEG, EOG, EMG, ECG, and pulse oximetry, to provide a comprehensive assessment of sleep stages and respiratory events [1][5]. However, PSG requires overnight monitoring in specialized sleep clinics and can be uncomfortable for patients, limiting its accessibility in resource-constrained environments. Consequently, alternative methods like Home Sleep Apnea Testing (HSAT) and pulse oximetry have been developed. HSAT offers a more accessible option for diagnosing OSA in uncomplicated cases, but it monitors fewer parameters and is unsuitable for patients with comorbid conditions [1][5]. While more affordable, pulse oximetry only tracks oxygen desaturation and may yield false-negative results [1]. Given these limitations, there is growing interest in developing simpler and non-invasive diagnostic methods based on ECG analysis. Electrocardiography (ECG)-based methods for detecting obstructive sleep apnea (OSA) have gained significant attention due to their relative simplicity and non-invasiveness [6]. Recent research has shown that ECG signals alone can effectively detect OSA. Studies have demonstrated that single-lead ECG can accurately classify apnea events and detect apnea by analyzing temporal dependencies within ECG segments [7][8]. One of the widely used methods for processing ECG data is the Discrete Wavelet Transform (DWT), which excels in isolating the various components of the ECG signal for further analysis [9], [10]. This method is particularly useful for extracting HRV-related features, enabling more precise identification of apneic episodes [11]. HRV, which measures variations in the time intervals between heartbeats, is sensitive to autonomic nervous system activity changes caused by intermittent hypoxia during apneic events [12][13]. This analysis includes time-domain measures, frequency-domain measures, and non-linear features [14].

In addition to HRV, Electrocardiogram-derived Respiration (EDR) is another promising technique for detecting respiratory abnormalities associated with OSA. EDR allows respiratory signals to be extracted directly from ECG data, eliminating the need for additional sensors and making it a more convenient and non-invasive method for continuous respiratory monitoring [15][16][17]. By leveraging the variations in the R-R interval caused by respiratory sinus arrhythmia (RSA), a natural fluctuation in heart rate corresponding to the breathing cycle, EDR has been shown to estimate respiratory patterns and apneic events accurately [15][17]. Furthermore, studies suggest that EDR effectively assesses the synchronization between RSA and respiration, providing insights into how OSA influences respiratory and autonomic function [18][19]. However, most existing ECG-based OSA detection systems still rely on wet electrodes, which are uncomfortable and impractical for long-term, home-based applications due to issues such as skin irritation and the drying out of conductive gel [20]. Moreover, while ECG and HRV analyses have shown promise, the integration of HRV-based features, EDR extraction via Discrete Wavelet Transform (DWT), and advanced classification algorithms such as XGBoost using non-contact mattress-embedded ECG remains underexplored. This highlights a critical gap in current research and motivates the development of a more practical and robust solution for home-based OSA detection.

To partially address these challenges, recent studies have explored the use of dry electrodes made from conductive fabrics. These materials offer a more comfortable, gel-free alternative for acquiring ECG signals and can be seamlessly integrated into everyday objects, such as mattresses or clothing. Such systems enable continuous, unobtrusive monitoring during sleep, making them ideal for long-term home-based applications [21][22][23]. In parallel, machine learning has emerged as a powerful tool to enhance the diagnostic capability of ECG-based OSA detection. Traditional algorithms such as k-Nearest Neighbors (k-NN) and Support Vector Machines (SVM) have achieved promising classification performance, with reported accuracies of up to 90.87% using decision trees [6], and 85.12% with single-lead ECG and only 13 features [24]. More recently, deep learning approaches such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN) have further improved detection accuracy, reaching up to 97.21% in some studies [7][8][11].

Building upon these advancements, this study proposed a mattress-integrated, non-contact ECG acquisition system using conductive fabric electrodes for the unobtrusive monitoring of sleep-related physiological signals. The acquired single-lead ECG

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was processed using a multi-stage analytical pipeline consisting of DWT-based signal decomposition, HRV analysis across time, frequency, and non-linear domains, as well as ECG-derived respiration (EDR) estimation based on RSA. Selected features, including respiratory rate, SDNN, SD2, LF/HF ratio, and pNN50, were then classified using the XGBoost algorithm for automated OSA detection.

This research aimed to develop an accurate and comfortable home-based system for the detection of Obstructive Sleep Apnea by leveraging non-contact ECG sensing and advanced signal processing techniques combined with machine learning. The key contributions of this study are as follows:

1. Development of a mattress-integrated, non-contact ECG acquisition system using conductive fabric electrodes for unobtrusive home monitoring.
2. Implementation of a signal processing framework using DWT to extract both HRV and EDR features relevant to OSA.
3. Application of ANOVA for effective feature selection, resulting in physiologically meaningful parameters.
4. Deployment of XGBoost classifier achieving high detection accuracy, demonstrating feasibility for real-world use.

The remainder of this paper is organized as follows: Section II describes the dataset, system design, and methodology, including signal acquisition, processing, and feature extraction. Section III presents the experimental setup and evaluation metrics. Section IV discusses the results and comparisons with related works. Finally, Section V concludes the study and outlines potential directions for future research.

II. Method

The proposed non-contact ECG acquisition system utilized conductive fabric electrodes embedded in a mattress to capture cardiac signals during sleep. These signals were sampled at a rate of 250 Hz [25][26] and initially passed through an instrumentation amplifier, followed by a band-pass filter (BPF) to isolate the relevant ECG frequency components. The conditioned ECG signals were then transmitted to a Mikromedia 5 for STM32F4 microcontroller development board (MikroElektronika, Serbia) [27], which features an STM32F407ZG ARM Cortex-M4 processor. The microcontroller board includes a 5-inch capacitive TFT display (800×480 resolution). Heart rate calculation was performed using the Discrete Wavelet Transform (DWT) algorithm.

The R-R intervals were used to estimate ECG-derived respiration (EDR) signals through DWT decomposition and refinement using a Moving Average (MAV) filter. In parallel, heart rate variability (HRV) features were extracted from the R-R interval sequence across time-domain, frequency-domain, and non-linear metrics. To enhance classification performance, an ANOVA-based feature selection process was applied to identify the most discriminative features relevant to Obstructive Sleep Apnea (OSA) detection. These selected features were then fed into an Extreme Gradient Boosting (XGBoost) classifier, which performs automated classification between OSA and non-OSA segments.

Following classification, a notification mechanism was triggered in the case of detected OSA events. This system utilized the Twilio API to send alert messages via WhatsApp to caregivers or users, enabling real-time health monitoring and early intervention. An overview of the complete system architecture is illustrated in Fig. 1, and each component is detailed in the subsequent subsections.

A. Data Collection and Experimental Setup

This study utilized two sources of ECG data: a publicly available dataset from patients diagnosed with Obstructive Sleep Apnea (OSA), and experimental recordings collected from healthy subjects using the proposed mattress-based system. The primary dataset was obtained from the Apnea-ECG database, which contains overnight ECG recordings from 35 subjects (30 male and 5 female) aged between 27 and 63 years [28]. Each recording ranges from 7 to 9 hours in duration and was originally sampled at 100 Hz. According to Penzel et al. [29], the inclusion criteria for this database were patients referred for suspected sleep apnea who underwent full overnight polysomnography, along with a smaller group of healthy control subjects. Exclusion criteria included subjects with severe cardiovascular disease, systemic illnesses that could confound autonomic regulation, or recordings with excessive artifacts and poor ECG quality.

In addition to the database, experimental recordings were collected from healthy volunteers recruited at our institution. These subjects were aged between 21 and 60 years, had no history of cardiovascular or respiratory disorders, and provided informed consent prior to participation. Exclusion criteria included smoking and, use of medications affecting heart rate variability. ECG signals were acquired in four different sleep positions: supine, left lateral, right lateral, and prone. For each position, five minutes of ECG data were recorded at a sampling frequency of 250 Hz, as recommended for accurate Heart Rate Variability (HRV) analysis [30].

To maintain consistency with the experimental recordings in this study, all signals from the Apnea-ECG database were up-sampled to 250 Hz using a comprehensive signal processing approach. The up-sampling to 250 Hz [25][26] was necessary to preserve

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the detailed morphological characteristics of ECG waveforms, particularly the sharp transitions and peak definitions of QRS complexes, which are critical for accurate feature extraction and classification performance. Higher sampling rates ensure better temporal resolution for detecting subtle changes in cardiac dynamics and morphological variations that may be indicative of sleep apnea events. The up-sampling process employed cubic spline interpolation to maintain signal fidelity and preserve the morphological characteristics of the ECG waveforms. Prior to interpolation, anti-aliasing measures were implemented through low-pass filtering at 50 Hz, corresponding to the Nyquist frequency of the original 100 Hz signal, to prevent frequency domain artifacts. The quality of the up-sampling process was validated through comparison with original 250 Hz recordings from similar subjects, and signal distortion was assessed using correlation analysis, achieving correlation coefficients greater than 0.98, indicating minimal distortion and high preservation of signal integrity. This unified signal processing approach enabled consistent feature extraction pipelines across both datasets.

In this study, both primary and secondary datasets were utilized. For consistency, all signals from the Apnea-ECG database were up-sampled to 250 Hz using cubic spline interpolation. Each recording was segmented into 5-minute intervals, resulting in a balanced dataset of 100 samples per class (normal and OSA). For model evaluation, the dataset was split at the subject level into 70% training and 30% testing sets, ensuring independence between subsets and preventing data leakage.

B. ECG Acquisition System

The non-contact ECG acquisition system developed in this study integrated conductive electrodes and custom signal conditioning hardware to enable unobtrusive, mattress-based monitoring. The conductive textile electrodes were fabricated from silver-plated nylon conductive material with a surface resistivity of 0.03 Ω/sq. In addition, the electrodes demonstrated a contact impedance lower than 10 kΩ at 10 Hz, a conductivity of 1.67×10^6 S/m, and a surface resistance not greater than 1 Ω/sq. These properties were further enhanced by an anti-oxidation surface treatment, which preserves the silver coating from degradation during exposure to air and repeated washing, thereby maintaining both conductivity and long-term durability of the textile electrodes [25].

Each electrode was fabricated with uniform dimensions, 60 cm × 5 cm for the positive and negative terminals, and 60 cm × 10 cm for the ground. The electrodes were positioned horizontally on the mattress surface, with the positive electrode under the shoulder

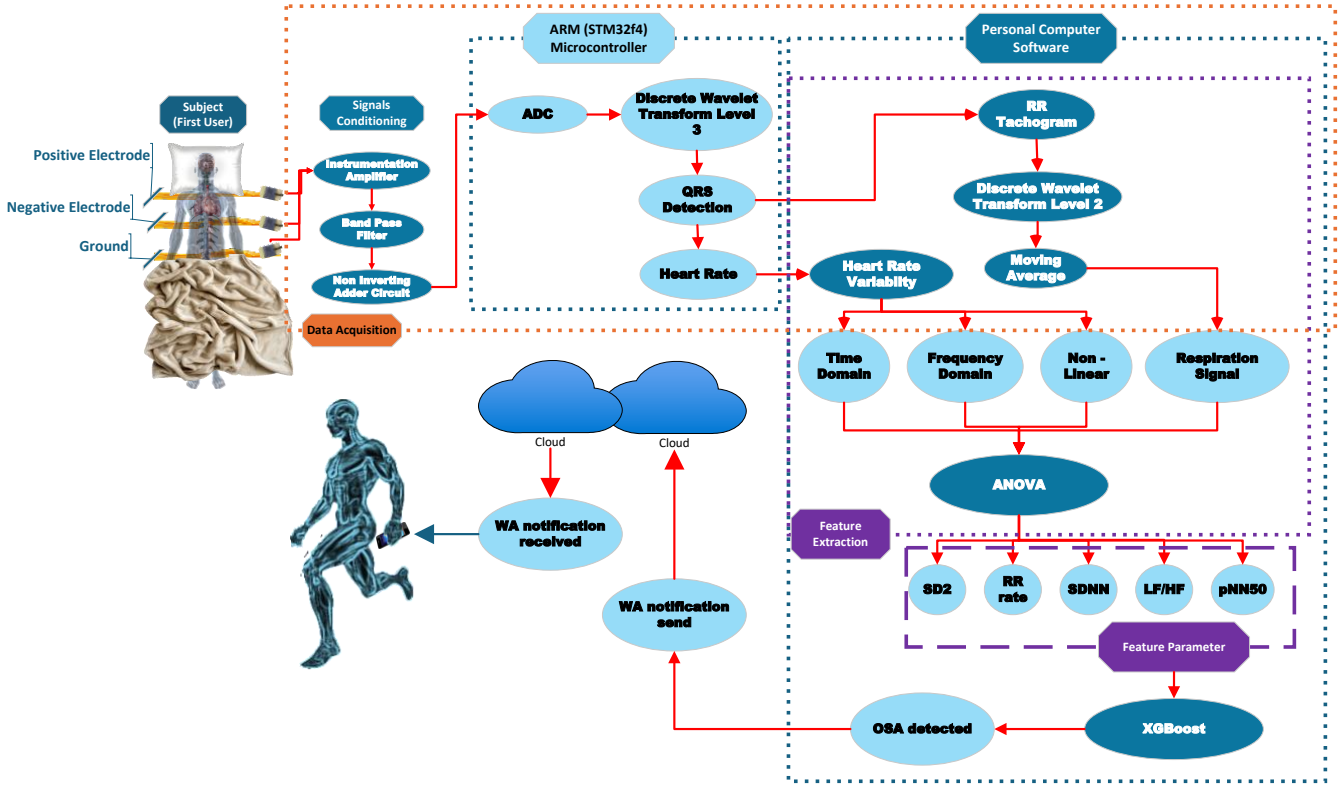

Fig. 1. Overall system diagram.

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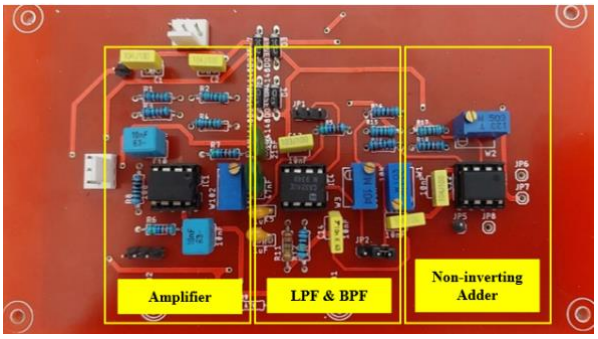

Fig. 2. ECG circuit.

blade, the negative electrode at the waist, and the ground electrode at the hip level. This configuration ensures effective body coverage during supine or lateral sleeping positions. This configuration ensures effective body coverage during supine or lateral sleeping positions, following Einthoven's triangle principle and validated mattress-embedded electrode layouts [31].

The signal conditioning circuit consists of three main components: an instrumentation amplifier, a band-pass filter (BPF), and a non-inverting adder. The AD620 instrumentation amplifier, chosen for its high common-mode rejection ratio and low power consumption, amplifies the low-amplitude ECG signals (~1 mV) to a readable level [23]. The BPF is designed as a two-stage cascade, comprising a high-pass filter (HPF) with a cutoff frequency between 0.1–0.2 Hz to eliminate baseline wander, and a low-pass filter (LPF) with a 100 Hz cutoff to suppress high-frequency noise. Finally, a non-inverting adder circuit was implemented to shift the signal baseline, ensuring compatibility with the microcontroller's input range. This configuration was designed for reliable acquisition of clean ECG signals as shown in Fig. 2.

C. Discrete Wavelet Transform

The primary objective of ECG signal processing in this study is to extract key features that are indicative of OSA. Discrete Wavelet Transform (DWT) is particularly effective for identifying the QRS complex due to its ability to analyze non-stationary signals at multiple resolution levels through a filter bank structure. In this implementation, the Quadratic Spline Wavelet with Compact Support was used as the *mother wavelet* due to its smoothness and localization properties, which are well-suited for biomedical signals such as ECG. The Quadratic Spline Wavelet with Compact Support is mathematically defined by the wavelet function $\psi(\omega)$ using Eq. (1) [9] as:

$$\Psi(\omega) = j\omega \left(\frac{sin(\omega/4)}{(\omega/4)}\right)^4 \quad (1)$$

where $\psi(\omega)$ is the wavelet function in the frequency domain, ω is the angular frequency (rad/s), and j is the imaginary unit.

The DWT decomposition was performed up to the third level, where wavelet coefficients at scales 1 to 3 were analyzed in detail to isolate QRS complexes and R-R intervals. Gradient-based thresholding combined with zero-crossing detection was applied to determine QRS peak positions, ensuring robust detection of heartbeats under varying noise conditions. For each decomposition level, filter coefficients and frequency ranges were explicitly defined to preserve the clinical fidelity of the ECG signal.

DWT analyzes the signal at different scales using high-pass filters $g[n]$ for high-frequency components and low-pass filters $h[n]$ for low-frequency components. The transfer functions $H(\omega)$ and $G(\omega)$ are defined the spectral characteristics using Eq. (2) and Eq. (3) [9][32] as follows:

$$H(\omega) = \sum_{k\epsilon Z} h(k)e^{-jk\omega} \quad (2)$$

$$G(\omega) = \sum_{k\epsilon Z} g(k)e^{-jk\omega} \quad (3)$$

where $H(\omega)$ and $G(\omega)$ are frequency responses for LPF and HPF, respectively. The wavelet transform is performed through a convolution operation described by Eq. (4) [33] as follows:

$$W_{2^j}f = S_{2^{j-1}}f * g_j \quad (4)$$

where $W_{2^j}f$ is the wavelet transform result at scale 2^j, and $S_{2^{j-1}}f$ represent the scaled function. Considering the delay T_j=2^{j-1}, QRS peak positions were determined using zero crossing. This leads to the extraction of R-R intervals, essential for calculating heart rate and heart rate variability (HRV), both of which play a critical role in OSA detection.

D. Heart Rate Variability Analysis

Feature extraction from ECG signals includes time-domain, frequency-domain, and non-linear analysis to assess heart rate variability (HRV), which is critical for evaluating autonomic nervous system function in relation to OSA. All HRV analyses were performed using standardized 5-minute segments to ensure statistical reliability and consistency with established HRV guidelines, as recommended by the Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology [34].

The system used a windowing approach for temporal segmentation. ECG signals were divided into 5-minute non-overlapping segments to extract HRV features, ensuring sufficient R-R intervals for reliable frequency-domain analysis. For real-time OSA detection, a sliding 5-minute window with 1-minute overlap was applied, providing classification updates every 4 minutes. This setup balances the need for

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timely detection, statistical reliability of HRV, and continuity across segment boundaries.

In the time domain, several statistical metrics were computed to quantify beat-to-beat variability. The Standard Deviation of NN intervals (SDNN) (Eq. (5)) reflects the total variability in heart rate over the recording period, while Root Mean Square of Successive Differences (RMSSD) (Eq. (6)) and Standard Deviation of Successive Differences (SDSD) (Eq. (7)) provide insight into short-term fluctuations. The percentage of adjacent NN intervals differing by more than 50 ms (pNN50) (Eq. (8)) indicates parasympathetic modulation. These metrics are calculated using Eq. (5) to Eq. (8) [12] as follows:

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(N-\overline{RR}\right)^2} \quad (5)$$

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(RR_{i+1}-RR_i)^2} \quad (6)$$

$$SDSD = \sqrt{\frac{1}{N-2}\sum_{i=1}^{N-1}(\Delta RR_i-\overline{\Delta RR})^2} \quad (7)$$

$$pNN50 = \frac{NN50}{N-1}.100\% \quad (8)$$

where RR_i is the *i*-th R-R interval, *N* is the total number of intervals, and *NN50* is the number of interval pairs differing by more than 50 ms.

For the frequency-domain analysis, power spectral density estimation was performed using Welch's method with a Hamming window of 256 points and 50% overlap to reduce spectral leakage and improve frequency resolution. The frequency bands were defined according to established standards: Very Low Frequency (VLF: 0.0033-0.04 Hz), Low Frequency (LF: 0.04-0.15 Hz), and High Frequency (HF: 0.15-0.4 Hz). The analysis focused on the LF and HF bands, which are commonly associated with sympathetic and parasympathetic activity, respectively. To account for inter-individual variability in total power, LF (Eq. (9)) and HF (Eq. (10)) components were calculated by Eq. (9) and Eq. (10) [12] as follows:

$$LF = \frac{LF}{TP-VLF} \quad (9)$$

$$HF = \frac{HF}{TP-VLF} \quad (10)$$

where *TP* is the total power and *VLF* represents the Very Low Frequency component.

In the non-linear analysis, Poincaré plot analysis was used to visualize the correlation between successive R-R intervals. From the plot, two geometric features were extracted: SD1 (Eq. (11)), which represents short-term variability (perpendicular to the line of identity), and SD2 (Eq. (12)), which represents long-term variability (along the line of identity). These are computed with Eq. (11) and Eq. (12) [12] as:

$$SD1 = \sqrt{\frac{1}{2}SDSD^2} \quad (11)$$

$$SD2 = \sqrt{2SDSD^2-\frac{1}{2}SDSD^2} \quad (12)$$

E. ECG-Derived Respiration (EDR)

To extract respiratory information from ECG signals without the use of dedicated respiratory sensors, this study employed ECG-Derived Respiration (EDR) based on respiratory sinus arrhythmia (RSA), a natural modulation of the R-R interval associated with the breathing cycle. Specifically, the approach involves analyzing temporal variations in the R-R intervals, which are correlated with the frequency bandwidth of the respiratory signal. The resulting tachogram is then subjected to DWT using a wavelet filter bank, and the second-level approximation signal is selected for further processing. To reduce high-frequency fluctuations and enhance the underlying respiratory pattern, the signal is smoothed using a Moving Average (*MAV*) filter, defined using Eq. (13) [10] as follows:

$$MAV(n) = \frac{1}{M}.\sum_{i=0}^{M-1} data[n-i] \quad (13)$$

where *M* is the window size, *n* is the current data point in the filtered signal, and *data[n-i]* represents the ECG-derived respiration sample at time step (*n-i*). After smoothing, peak detection was applied to identify the prominent respiratory cycles. The respiratory rate was then calculated by determining the average time interval between consecutive peaks and converting this interval into breaths per minute by taking its inverse and multiplying by 60. This method enables robust, non-invasive estimation of respiratory activity from ECG data, offering additional insight into autonomic and respiratory function during sleep.

F. Feature Selection and Classification Framework

Following feature extraction from ECG signals, comprising time-domain, frequency-domain, non-linear, and EDR, the next stage involves selecting the most relevant features for the classification of OSA and non-OSA cases. Given the multidimensional nature of the data, feature selection is essential to reduce redundancy, mitigate overfitting, and enhance classification performance.

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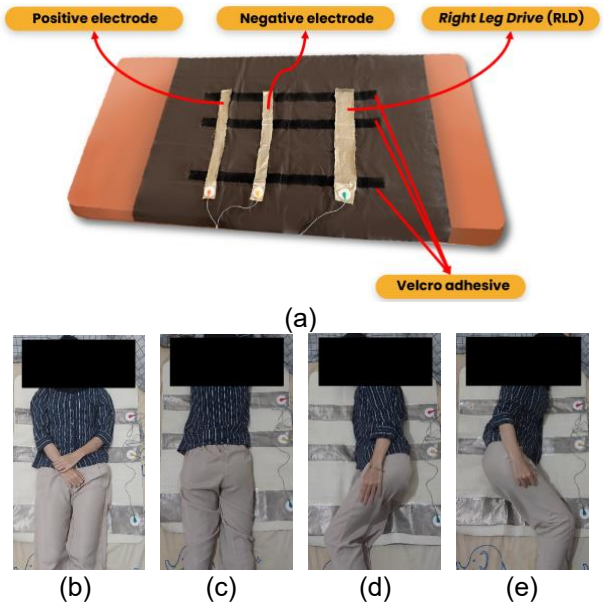

Fig. 3. A mattress-integrated ECG and different acquisition positions (a) ECG electrode design on the mattress, (b) supine, (c) prone, (d) right lateral, and (e) left lateral.

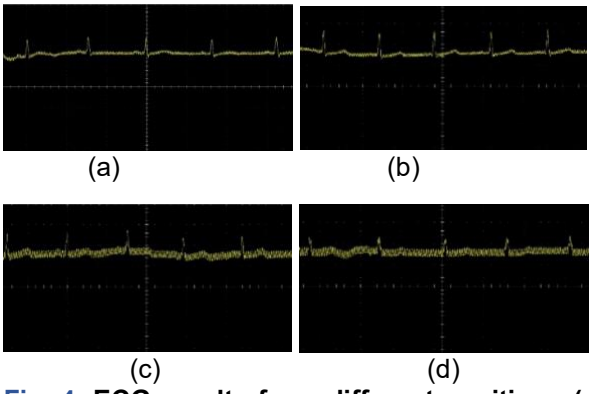

Fig. 4. ECG results from different positions (a) supine, (b) prone, (c) right lateral, and (d) left lateral.

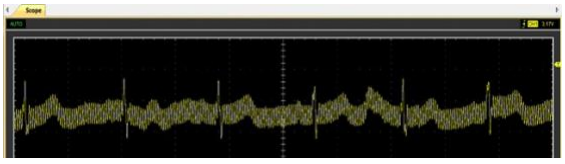

Fig. 5. Result for conductive textile electrode.

This study employed Analysis of Variance (ANOVA) as a statistical filter-based method for feature selection. ANOVA evaluates the significance of each feature by comparing the variance between classes with the variance within each class. The feature selection process utilized a statistical significance threshold of p-value less than 0.05 to identify features that demonstrate statistically significant differences between OSA and non-OSA groups. F-scores were calculated for all extracted features and ranked in descending order based on their discriminative power between classes. To ensure feature stability and prevent overfitting, a 10-fold cross-validation approach was implemented during the feature selection process, where feature rankings were evaluated across all CV folds to assess consistency. Features that maintained stable rankings across at least 80% of the CV folds were considered reliable and retained for subsequent analysis. Sequential forward selection was then applied based on the F-statistic ranking, progressively adding features until no significant improvement in cross-validation performance was observed, thus preventing the inclusion of redundant or noisy features that could compromise model generalization.

For a given feature, the ANOVA F-score is computed using Eq. (14) [35] as:

$$F = \frac{SS_B/(k-1)}{SS_W/(N-k)} \tag{14}$$

where SS_B and SS_W denote the sum of squares between and within the groups, respectively, k is the number of classes (in this case, two), and N is the total number of observations. Features that exhibit a statistically significant difference in means across groups (typically with a p-value < 0.05) are retained for model training.

The selected subset of features was then used as input to the Extreme Gradient Boosting (XGBoost) algorithm, a decision-tree-based ensemble learning method optimized for speed and performance. XGBoost builds an additive model in a forward stage-wise manner, minimizing a regularized objective function defined with Eq. (15) and Eq. (16) [36] as follows:

$$\mathcal{L}(\phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{15}$$

$$\Omega(f_k) = \gamma \mathrm{T} + \frac{1}{2} \lambda \|w\|^2 \tag{16}$$

where $l(y_i, \hat{y}_i)$ is logistic loss for binary classification, $\Omega(f_k)$ is the regularization term, γ and T are regularization hyperparameters, T denotes the number of leaves in the decision tree, w represents the leaf weights, and K is the number of boosting rounds.

Building upon the regularized objective function defined in Eq. (15) and Eq. (16), the XGBoost model was configured through systematic hyperparameter optimization using grid search with 5-fold cross-validation, resulting in optimal parameters of maximum depth at 6, learning rate at 0.1, and n_estimators of 100. To address class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) was applied during preprocessing to ensure balanced class

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representation. The model incorporated L1 (alpha at 0.1) and L2 (lambda at 0.1) regularization penalties to enhance generalization, along with early stopping criteria (patience of 10 rounds) to prevent overfitting. Model performance was evaluated using stratified 10-fold cross-validation, where the dataset was partitioned into 10 subsets while maintaining class proportions in each fold, with iterative training on 9 folds and validation on the remaining fold to ensure robust performance estimation across varying data distributions.

III. Result

A. ECG Signal Acquisition and Evaluation

To assess the reliability of the proposed non-contact ECG acquisition system for home-based monitoring, signal acquisition tests were conducted across different sleep positions. In the set of experiments, ECG signals were acquired from healthy subjects placed in four common sleep positions: supine, prone, left lateral, and right lateral. Conductive fabric electrodes were embedded within the mattress surface to ensure unobtrusive contact with the subject's body. Each recording session lasted five minutes and was performed at a sampling rate of 250 Hz to maintain consistency across all positional variations. Position-specific signal quality assessment revealed significant variations in ECG acquisition performance across different sleep positions. Statistical comparison of HRV features across positions using ANOVA ($p < 0.05$) demonstrated that supine and right lateral positions provided optimal signal acquisition with higher signal-to-noise ratios and more consistent R-wave detection accuracy (>98%). The left lateral position showed moderate performance with occasional signal degradation due to electrode contact variability, while the prone position presented the greatest challenges with reduced signal amplitude and increased baseline drift. These findings indicate that supine and right lateral positions are most suitable for reliable cardiac monitoring using the proposed mattress-integrated system. The prone position may require alternative electrode configurations or additional contact points to achieve comparable signal quality, which represents an important consideration for system deployment and user guidance. As illustrated in Fig. 3(a)-(e) and Fig. 4(a)-(d), differences in signal amplitude and waveform clarity were observed between positions. The supine and lateral positions generally provided higher signal stability compared to the prone position, likely due to more consistent contact between the torso and electrodes.

The tests aimed to evaluate the effectiveness of conductive textile electrodes in acquiring ECG signals under the supine condition. Signals were captured using a digital oscilloscope, and representative waveforms are depicted in Fig. 5. The results demonstrated that conductive textile electrodes were able to successfully transmit cardiac activity with good baseline stability and noise suppression. These findings highlight the suitability of conductive textiles for ensuring both comfort and reliable conductivity in long-term monitoring applications.

To validate the signal acquisition pathway, the proposed system was benchmarked against a commercial ECG device. Signals obtained using the custom hardware and STM32F4-based digitizer were compared with those from a standard clinical-grade monitor. The comparison confirmed that the proposed setup is capable of capturing ECG signals with comparable fidelity, supporting its potential for subsequent feature extraction and OSA analysis.

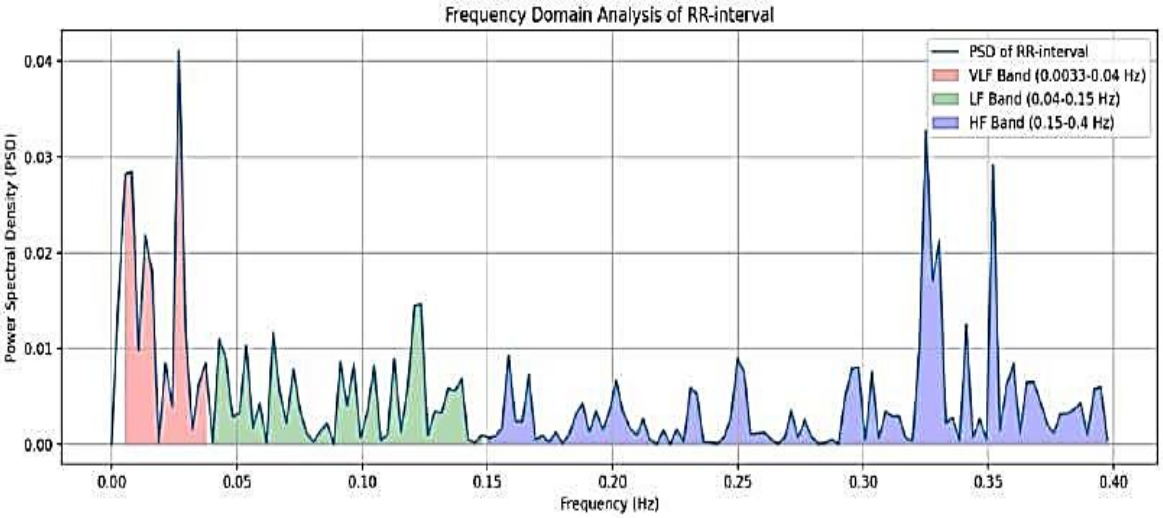

Fig. 6. Frequency domain analysis of HRV.

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B. HRV Feature Extraction

After acquisition and digitization, ECG signals were processed to extract key features associated with heart rate variability (HRV), which serve as important biomarkers in the detection of OSA. The initial stage involved preprocessing and QRS complex detection using gradient-based thresholding applied to the discrete wavelet transform (DWT) of the ECG signal. This enabled the precise localization of R peaks, from which R-R intervals were derived. Subsequent feature extraction was performed on the R-R interval sequences to quantify autonomic nervous system activity. The analysis was structured into three domains: time, frequency, and non-linear, each applied to data obtained from both healthy and OSA subjects.

The first stage involved time-domain analysis, yielding features such as SDNN (standard deviation of NN intervals), SDSD (standard deviation of successive differences), RMSSD (root mean square of successive differences), and pNN50 (the percentage of interval differences greater than 50 ms). These metrics reflect short-and long-term variability in heart rate and are widely used to assess autonomic dysfunction.

A comparative statistical summary of these features is presented in Table 1 for healthy subjects and subjects with diagnosed OSA. Notably, while healthy subjects exhibited higher mean values for SDSD (151.09 ms), RMSSD (151.09 ms), and SDNN (105.12 ms), the OSA group showed elevated pNN50 (57.25%) and LF/HF ratio (1.73), suggesting a potential shift in sympathovagal balance and autonomic dysregulation. These findings support the clinical relevance of time-domain HRV features in distinguishing between normal and pathological sleep physiology.

The second stage of the heart rate variability (HRV) feature extraction involved frequency-domain analysis of the R-R interval data. This analysis was conducted using Welch's method to estimate the Power Spectral Density (PSD), which enabled the identification of energy distribution across specific frequency bands. The analysis focused on three primary components: Very Low Frequency (VLF: 0.0033–0.04 Hz), Low Frequency (LF: 0.04–0.15 Hz), and High Frequency (HF: 0.15–0.4 Hz) bands. By quantifying the LF and HF power components, the LF/HF ratio was computed to assess sympathovagal balance, an important autonomic marker frequently altered in subjects with obstructive sleep apnea (OSA). The resulting spectral distribution is illustrated in Fig. 6, where the PSD curve is plotted against frequency.

The non-linear features SD1 and SD2, derived from Poincaré plot analysis, provide valuable insights into the complex dynamics of heart rate variability that are not captured by conventional time or frequency domain metrics. SD1 reflects the short-term variability of the R-R intervals, which is predominantly influenced by parasympathetic nervous system activity.

Table 1. Statistical Comparison of ECG Signal Features Between Normal and OSA Subjects.

Features	Unit	Normal Subjects	OSA Subjects
SDSD	ms	151.1 ± 32.3	96.7 ± 6.7
SDNN	ms	105.1 ± 14.1	123.8 ± 12.9
RMSSD	ms	151.1 ± 32.3	96.7 ± 6.7
pNN50	%	22.8 ± 2.6	57.2 ± 2.1
LF/HF	ratio	0.5 ± 0.1	1.7 ± 0.2
SD1	ms	67.8 ± 32.4	65.6 ± 4.4
SD2	ms	83.1 ± 10.1	160.9 ± 18.9
Resp. rate	BrPM	17.4 ± 0.4	7.9 ± 0.4

Table 2. Features Ranking Based on ANOVA.

Features	ANOVA Score	p-value
SD2	129.32	2.18×10^{-23}
Resp. rate	117.47	8.66×10^{-22}
SDNN	114.09	2.54×10^{-21}
LF/HF	72.50	4.15×10^{-15}
pNN50	44.56	2.42×10^{-10}
RMSSD	20.99	8.17×10^{-6}
SD1	20.98	8.19×10^{-5}
SDSD	19.64	1.55×10^{-5}

In contrast, SD2 corresponds to long-term variability, incorporating both sympathetic and parasympathetic influences and is often associated with overall autonomic balance. As shown in Table 1, while the SD1 values of normal (67.8 ± 32.4 ms) and OSA (65.6 ± 4.4 ms) subjects were relatively similar, the SD2 value in OSA subjects was nearly doubled (160.9 ± 18.9 ms) compared to that of normal subjects (83.1 ± 10.1 ms). This marked increase in SD2 among OSA patients may indicate a compensatory elevation in long-term autonomic modulation in response to chronic sleep-disordered breathing events.

C. ECG-Derived Respiration (EDR) Analysis

Respiratory signal extraction in this study was performed using ECG-derived respiration (EDR), where R-R

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interval fluctuations were analyzed to estimate the respiratory rate. The R-R tachogram, generated from ECG recordings, was processed using DWT to isolate respiratory components at the second level of decomposition. Subsequent gradient computation and smoothing with a moving average (MAV) filter allowed clear identification of respiratory peaks, from which the respiratory rate (breaths per minute) was derived.

The respiratory rate obtained through the EDR method was compared between normal subjects and those diagnosed with obstructive sleep apnea (OSA), as summarized in Table 1. Results indicated a marked difference between the two groups: normal subjects exhibited a mean respiratory rate of 17.4 ± 0.4 breath per minute (BrPM), while OSA subjects showed a significantly lower rate of 7.9 ± 0.4 BrPM. This reduction in respiratory rate among OSA patients is consistent with known pathophysiological features of the disorder, where apneic events lead to irregular or diminished respiratory effort.

D. Feature Selection and Classification Performance

Following the extraction of eight candidate features from the ECG and EDR signal processing stages, namely SD2, respiratory rate, SDNN, LF/HF, pNN50, RMSSD, SD1, and SDSD, an analysis of variance (ANOVA) was conducted to determine the most significant features for obstructive sleep apnea (OSA) classification. Table 2 presents the ranking of extracted features based on ANOVA scores and their corresponding p-values. The top-ranked feature was SD2 (ANOVA score = 129.32, p-value = 2.18×10^{-23}), followed by Respiratory Rate (117.47, p-value = 8.66×10^{-22}) and SDNN (114.09, p-value = 2.54×10^{-21}), all of which exhibited extremely low p-values, indicating highly significant differences between OSA and non-OSA groups. LF/HF ratio and pNN50 also demonstrated strong statistical significance ($p < 10^{-9}$), while RMSSD, SD1, and SDSD showed relatively lower discriminative power, although still statistically significant ($p < 0.001$). These results suggest that time-domain, frequency-domain, and nonlinear HRV features contribute differently to distinguishing OSA from non-OSA cases, with nonlinear parameters such as SD2 showing the greatest separation.

Subsequent classification was performed using the Extreme Gradient Boosting (XGBoost) algorithm. The accuracy of the model was evaluated based on cross-validation, where different numbers of selected features were tested. As shown in Fig. 7, the highest accuracy of 96.67% was achieved when five features were used, revealing that the top five discriminative features were SD2, RR rate, SDNN, LF/HF, and pNN50, which demonstrated the highest contributions to group separation between normal and OSA subjects.

The classification performance of the proposed model in distinguishing between normal and obstructive sleep apnea (OSA) subjects is illustrated in Table 3, which presents the confusion matrix along with the corresponding AUC-ROC score. The model achieved a correct classification rate of 96.6% for normal cases and 96.8% for OSA cases, with only 3.4% of normal subjects misclassified as OSA and 3.2% of OSA subjects misclassified as normal. This corresponds to an overall classification accuracy of 96.7%.

Furthermore, the area under the receiver operating characteristic curve (AUC-ROC) was calculated to be 0.9911, reflecting excellent discriminatory capability of the model across varying classification thresholds. These results underscore the effectiveness of the feature selection method based on ANOVA, where all selected features demonstrated highly significant discriminatory power, namely SD2 (F-score = 129.32, p = 2.18×10^{-23}), respiratory rate (F-score = 117.47, p = 8.66×10^{-22}), SDNN (F-score = 114.09, p = 2.54×10^{-21}), LF/HF ratio (F-score = 72.50, p = 4.15×10^{-15}), and pNN50 (F-score = 44.56, p = 2.42×10^{-10}). All p-values were substantially below the significance threshold ($p < 0.001$), confirming the strong statistical separation between OSA and normal classes. The combination of these five features with the XGBoost classifier achieved robust and highly accurate detection of OSA using ECG-derived parameters in a non-contact setting.

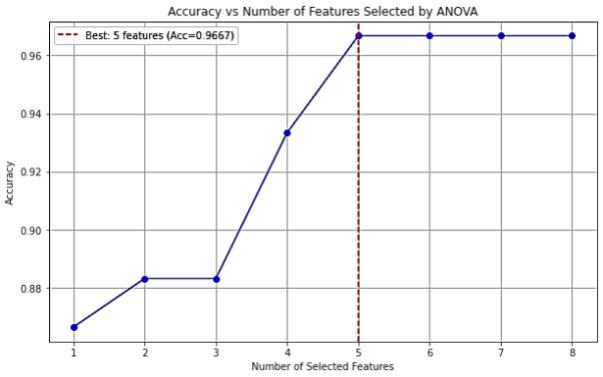

Fig. 7. Optimal number of features.

Table 3. Confusion Matrix in Percentage.

Matrix	Predicted Normal	Predicted Apnea
Actual Normal	96.6%	3.4%
Actual Apnea	3.2%	96.8%

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IV. Discussion

This study presents a non-contact, mattress-integrated ECG monitoring system for detecting obstructive sleep apnea (OSA) using heart rate variability (HRV) and ECG-derived respiration (EDR) features. The results indicate that the proposed system can effectively differentiate between normal and OSA subjects with high accuracy, validating the feasibility of unobtrusive sleep monitoring in home environments.

The extracted HRV features, particularly SDNN, pNN50, LF/HF ratio, and SD2, demonstrated significant discriminative power between the two subject groups. In OSA patients, lower pNN50 and RMSSD values reflected diminished parasympathetic modulation, while higher LF/HF ratios indicated a sympathetic shift. These autonomic alterations are consistent with known pathophysiological mechanisms in OSA, including intermittent hypoxia and increased sympathetic drive during apneic events.

The selected features reflect distinct pathophysiological mechanisms underlying OSA. SDNN represents overall autonomic modulation and is elevated in OSA due to enhanced sympathetic activation triggered by repetitive hypoxic episodes, leading to increased heart rate variability during arousal responses. The LF/HF ratio elevation (1.7 vs 0.5 in controls) indicates sympathovagal imbalance, where chronic intermittent hypoxia activates the sympathetic nervous system through chemoreceptor stimulation and subsequent catecholamine release. Reduced pNN50 in healthy subjects (22.8%) versus elevated values in OSA (57.2%) paradoxically reflects irregular autonomic responses during apneic events rather than healthy parasympathetic tone. SD2's dramatic increase (160.9 vs 83.1 ms) captures the long-term heart rate oscillations caused by cyclic arousal patterns and oxygen desaturation-reoxygenation cycles characteristic of OSA. The significantly reduced respiratory rate (7.9 vs 17.4 BrPM) detected through EDR directly corresponds to apneic episodes where respiratory effort diminishes or ceases entirely, validating the physiological relevance of our feature selection approach.

Additionally, the SD2 value in OSA subjects was nearly double that of normal subjects, suggesting greater long-term variability in heart rhythm, potentially due to chronic autonomic imbalance. Interestingly, SD1 values remained relatively stable, indicating that short-term variability alone may not be sufficient to distinguish OSA, reinforcing the need for multi-domain HRV analysis. The respiratory rate derived via EDR also showed strong differentiation, with significantly lower values observed in the OSA group, corresponding to reduced respiratory effort and apnea-induced suppression.

Although all eight features demonstrated statistical significance ($p < 0.05$), only the top five features, namely SD2, RR Rate, SDNN, LF/HF, and pNN50, were selected for subsequent classification. This decision was motivated by the need to balance discriminative power with model simplicity, thereby reducing redundancy and mitigating the risk of overfitting. The very low p-values of these five features ($p < 10^{-9}$) indicate robust statistical differences between OSA and non-OSA groups, ensuring a reliable contribution to classification performance. By restricting the feature set to the most informative variables, the classification framework

Table 4. Performances comparison with other studies.

	Method			Performance		
	Data	**Feature Extraction**	**Classifier**	**Accuracy**	**Sensitivity**	**Specificity**
Wang et al [11]	ECG	R-R interval (time and frequency domain); R-peak amplitude (frequency domain)	TW-MLP (ANN)	97.1%	100%	91.7%
Song et al [8]	ECG	R-R interval; EDR	HMM+SVM	97.1%	95.8%	100%
Sharma et al [37]	ECG	heart rate variability; ECG-derived respiration signals	LS-SVM	97.1%	95.8%	100.0%
Moridani [14]	ECG	time, frequency, and non-linear domain	SVM	-	95.46%	97.57%
Lin et al [38]	ECG	ECG spectrogram features	SVM	91.4%	89.8%	92.4%
X. Liang et al [39]	ECG	R-R intervals	CNN-LSTM	99.80%	96.94%	98.97%
Zarei et al [7]	PSG	ECG segment	CNN-LSTM	100%	100%	100%
Proposed method	ECG	R-R interval (time, frequency, and non-linear); respiratory rate	XGBoost	96.7%	96.8%	96.6%

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achieves improved generalization, reduced computational complexity, and enhanced interpretability, which are critical for practical deployment in real-time sleep monitoring systems.

The use of ANOVA for feature selection ensured statistical robustness, while the XGBoost classifier effectively captured non-linear relationships in the data, resulting in a high classification accuracy of 96.7%, sensitivity of 96.8%, and specificity of 96.6%. The performance of the proposed method was compared with prior studies employing ECG-based approaches for obstructive sleep apnea (OSA) detection, as summarized in Table 4. Wang et al. [11] achieved a high accuracy of 97.1% and perfect sensitivity (100%) using a Time-Window Multi-Layer Perceptron (TW-MLP) classifier. However, their specificity was limited to 91.7%, indicating a tendency to generate false positives. Similarly, Moridani [14] used features from time, frequency, and nonlinear domains with an SVM classifier, yielding 95.46% sensitivity and 97.57% specificity, although overall accuracy was not reported. Lin et al. [38], using spectrogram-based ECG features and an SVM classifier, reported a lower overall accuracy of 91.4%, further highlighting the limitation of relying solely on ECG signal morphology without autonomic or respiratory context.

In contrast, methods that integrated ECG-derived respiration (EDR) features demonstrated better classification outcomes. Song et al. [8] combined R-R interval features with EDR and achieved 97.1% accuracy and 100% specificity using a hybrid HMM+SVM approach. Sharma et al. [37] also incorporated HRV and EDR signals, attaining high classification metrics with LS-SVM, reaffirming the importance of including respiratory dynamics in OSA detection models.

Recent studies using deep learning architectures such as CNN-LSTM have reported state-of-the-art results. For example, Liang et al. [39] used R-R intervals with a CNN-LSTM network, achieving 99.8% accuracy, while Zarei et al. [7] used full PSG-derived ECG segments to achieve perfect scores across all metrics. However, these approaches require substantial computational resources, making them less practical for real-time or resource-constrained embedded systems.

In comparison, our proposed method applies a more interpretable and computationally efficient supervised machine learning model, XGBoost, combined with features selected via ANOVA from time, frequency, and non-linear HRV domains, along with ECG-derived respiration rate. This approach achieved 96.7% accuracy, 96.8% sensitivity, and 96.6% specificity, which are competitive with more complex deep learning models. The method strikes a practical balance between diagnostic performance and computational simplicity, making it well-suited for deployment in wearable or mattress-based systems for home-based OSA screening.

Comparative analysis reveals critical methodological differences affecting performance variations across studies. While deep learning methods [7][39] achieve near-perfect accuracy, they require substantial computational resources, making them impractical for embedded applications. Dataset diversity and validation protocols also significantly impact results, with some studies using segment-based splitting that may overestimate performance due to data leakage, whereas our approach employs subject-level splitting for true generalization.

Most comparative studies rely on contact-based wet electrodes, limiting practical applicability for long-term home monitoring. Our method balances diagnostic performance (96.7% accuracy) with practical implementation through non-contact sensing and computationally efficient XGBoost classification, offering superior comfort and lower overhead compared to deep learning alternatives, making it more suitable for widespread home-based OSA screening.

The positional analysis revealed important considerations for the practical implementation of the mattress-based monitoring system. While supine and right lateral positions demonstrated optimal signal acquisition, the variability observed across positions suggests that position-adaptive algorithms may be necessary for comprehensive sleep monitoring. Future work should focus on developing intelligent electrode switching mechanisms or position-dependent signal processing algorithms that can automatically adjust acquisition parameters based on detected sleep posture. Additionally, the acknowledgment that the prone position requires different electrode configurations highlights the need for enhanced mattress design that can accommodate all common sleep positions with equal reliability.

Despite promising results, this study has several limitations. First, the sample size remains relatively small, which may limit the generalizability of the findings to broader and more diverse populations. This constraint underscores the need for future research involving larger cohorts across multiple demographics and clinical conditions to validate and extend the applicability of the proposed system. Second, the dataset used for OSA classification was sourced from a publicly available database and may differ in signal characteristics from the data acquired using the proposed hardware, despite up-sampling for consistency. Additionally, the system's

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performance in subjects with comorbid conditions (e.g., cardiac arrhythmias, COPD) was not evaluated, which could influence feature extraction and classification. Moreover, demographic variability such as age and sex differences was not systematically analyzed in this study, and these factors may also affect HRV dynamics and model performance. Beyond positional variability, real-world deployment of the system may introduce additional challenges such as motion artifacts, inconsistent electrode-skin contact, and environmental electrical noise. Addressing these real-world sources of variability will be critical to ensure consistent performance and user trust in daily use.

In addition to accuracy, the computational efficiency and real-time feasibility of the proposed method are critical for practical deployment. The XGBoost classifier was chosen over deep learning models not only for its interpretability but also for its lightweight computational footprint, which allows processing of a 5-minute ECG window in only a few seconds on a microcontroller-based system (STM32F4). This low-latency processing, combined with the windowing strategy that provides classification updates every 4 minutes, demonstrates that the system can operate continuously in near real-time. Furthermore, the modest hardware requirements make it suitable for integration into mattress-based monitoring systems intended for home use, without reliance on high-performance computing resources.

Despite these limitations, the study presents several important implications. The proposed non-contact ECG monitoring system, integrated into a mattress and powered by lightweight machine learning algorithms, offers a comfortable, accessible, and low-cost alternative to traditional polysomnography for early screening of OSA.

Clinically, this approach could help reduce the burden on sleep laboratories and enable earlier identification of at-risk individuals who might otherwise go undiagnosed [40][41]. The use of interpretable features (e.g., SDNN, LF/HF, pNN50, respiratory rate) allows clinicians to understand model decisions, potentially aiding trust and adoption in medical contexts [42].

Future research should focus on validating the system across diverse populations and sleep conditions, including individuals with comorbid diseases. Additionally, expanding the feature set to include multi-modal biosignals such as oxygen saturation (SpO_2), motion (actigraphy), or snoring patterns could improve diagnostic accuracy and differentiate between OSA severities. Ultimately, this study lays a foundation for advancing accessible, interpretable, and practical solutions in sleep disorder diagnostics and highlights the growing potential of combining biomedical signal processing with machine learning for personalized and preventive healthcare. In this work, the system was successfully integrated with a cloud-based monitoring platform that enables real-time apnea detection and immediate alert notifications. When an apneic event is detected, the system automatically sends a warning to the patient's registered family member through a secure messaging channel. This allows for timely intervention, such as manually adjusting the patient's sleeping position to restore airflow. In more severe or prolonged cases, the system also provides an emergency call option, enabling the caregiver to promptly contact ambulance services. This integrated approach enhances the safety and responsiveness of home-based monitoring, bridging the gap between detection and action in the management of sleep apnea.

V. Conclusion

This study proposed and validated a non-contact, mattress-integrated system for detecting obstructive sleep apnea (OSA) using ECG-derived features, including heart rate variability (HRV) and respiratory rate extracted via Discrete Wavelet Transform (DWT). With five key features selected through ANOVA and classified using the XGBoost algorithm, the system achieved strong performance, reaching 96.7% accuracy, 96.8% sensitivity, and 96.6% specificity. Additional findings showed that the prone sleeping position produced the best ECG morphology, while copper tape electrodes yielded lower noise but were less suitable for long-term comfort compared to conductive textile electrodes. Hardware optimization further ensured stable signal acquisition through effective amplification and filtering. The system was successfully integrated with a cloud-based real-time alert platform, which enables automatic apnea detection and immediate notification to caregivers. This feature allows early intervention, such as repositioning the patient or contacting emergency services, thereby enhancing safety in home-based monitoring. Future work will focus on large-scale validation across diverse populations, extension to multi-night continuous monitoring, and the integration of Apnea-Hypopnea Index (AHI) classification to support severity grading. Incorporating additional biosignals such as SpO_2 and motion data may further improve diagnostic accuracy and system robustness.

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Data Availability
This study utilized two datasets: (1) The publicly available PhysioNet Apnea-ECG Database [28] (https://physionet.org/content/apnea-ecg/1.0.0/), which contains overnight ECG recordings from 35 subjects and is freely accessible for research purposes under PhysioNet's data use agreement, and (2) experimental ECG recordings from healthy volunteers collected at our institution under ethics approval (No. 3974/IT2.XXII/T/TU.00.08/VII/2024). The experimental dataset contains proprietary recordings and is available from the corresponding author upon reasonable request, subject to ethical approval and institutional data sharing policies.

Author Contribution
This study was conceptualized and supervised by Nada Fitrieyatul Hikmah, who also managed project administration. Rachmad Setiawan contributed to system design, validation, and resource support. Rima Amalia curated the data, implemented the software pipeline, performed formal analysis, and prepared the initial manuscript draft. Zain Budi Syulthoni provided medical and clinical insights, guided interpretation in the context of OSA, and assisted in manuscript review. Dwi Oktavianto Wahyu Nugroho focused on instrumentation development, system integration, and manuscript refinement. Mu'afa Ali Syakir conducted experimental investigations, collected mattress-based ECG data, and supported the visualization of results. All authors reviewed and approved the final manuscript and are accountable for the integrity and accuracy of the work.

Declarations
Ethical Approval
All research activities involving human subjects were performed under the approval of the Research Ethics Committee, Institut Teknologi Sepuluh Nopember, which granted authorization for the experimental protocols (Approval No. 3974/IT2.XXII/T/TU.00.08/VII/2024).

Consent for Publication Participants.
Consent for publication was given by all participants.

Competing Interests
This paper has no conflict of interest for publication.

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