Edge-Computing Enabled Real-Time Respiratory Monitoring and Breathing Pattern Detection

Ucchwas Talukder Utsha
Department of Computer Science
Texas Tech University
Lubbock, TX 79409, USA
uutsha@ttu.edu

Bashir I. Morshed
Department of Computer Science
Texas Tech University
Lubbock, TX 79409, USA
bmorshed@ttu.edu

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***Abstract*—Detecting respiratory disorders can be improved with real-time diagnostic solutions, where monitoring respiration rates and patterns can act as early indicators for various cardiorespiratory diseases. We present a cost-effective edge-computing method utilizing wearable technology for respiratory disorder detection. Our system employs a wearable device with an IMU sensor for real-time signal transmission to a custom smartphone app which enables thorough visualization of respiratory signals, continuous monitoring of respiration rates, and rapid alarms for breathing anomalies, alongside ECG functionalities. A novel approach is introduced for respiratory pattern detection that includes a pre-trained AI model for apnea detection and classification of normal, bradypnea, and tachypnea patterns from non-apnea signals. During model building using the Apnea-ECG dataset, the proposed hyper-feature algorithm for apnea detection demonstrates excellent performance, achieving accuracies of 92.33%, 94.89%, and 97.66% for Chest, Abdominal, and Nasal respiration signals, respectively. With an average inference time of 5 ms for respiratory event detection, the classifier achieves outstanding accuracy rates of 91.24%, 92.42%, and 93.26% for these signals on the validation dataset after being implemented and tested at the edge device. Real-time data analysis from 10 subjects further underscores the system's potential for continuous respiratory and cardiac monitoring in real-world scenarios.**

***Index Terms*—Apnea, Cardiorespiratory, Pre-trained model, Respiratory pattern, Smartphone application**

I. Introduction

Wearable technology for healthcare monitoring has grown in popularity due to the need for comfortable solutions that track a wide range of health metrics. The expansion of the Internet of Things (IoT) has enhanced healthcare effectiveness and scope [1]. Wearable devices integrate sensors, mobile tech, cloud storage, and data centers for seamless health data sharing, yet precise measurement of physiological parameters remains crucial [2]. Among these, respiratory signals, often overlooked, hold particular significance as they can serve as an early indicator of respiratory issues and overall human health status [3].

Numerous wearable systems have been developed for respiratory signal monitoring, such as pressure sensors, contactless photoplethysmography (PPG) [4], electrocardiography (ECG), bioimpedance, and inertial measurement units (IMU) [5]. These systems play a crucial role in detecting abnormalities in breathing patterns, which can serve as early indicators of various health conditions, including obstructive sleep apnea (OSA), chronic obstructive pulmonary disease (COPD), hyperpnea, bradypnea, tachypnea, and asthma [6]. Various studies have employed innovative approaches in the realm of breathing disorder recognition. For instance, some have utilized recurrent neural networks to classify different respiratory patterns, based on 60-second respiratory signals captured by depth cameras [7]. Another research group used multiple motion sensors to detect chest wall changes during breathing and extract features to classify eight pathological breathing patterns [8]. However, a gap remains in simultaneously monitoring respiratory and ECG signals. This highlights the importance of developing accurate and dependable wearable health monitoring devices to diagnose and treat health issues timely.

In this study, we introduce a real-time respiratory monitoring system to advance healthcare by detecting four distinct breathing patterns: apnea, bradypnea, tachypnea, and normal breathing. Our system enables simultaneous monitoring of both ECG and respiratory signals in real-time. Previously, our research focused on heart rate monitoring and detecting abnormal cardiac conditions through a mobile application utilizing a wearable device [9]. This paper introduces a system that can identify different breathing patterns and offers a remote monitoring platform for diagnosing respiratory issues, providing advantages in accuracy, cost-effectiveness, setup simplicity, and safety over previous methods.

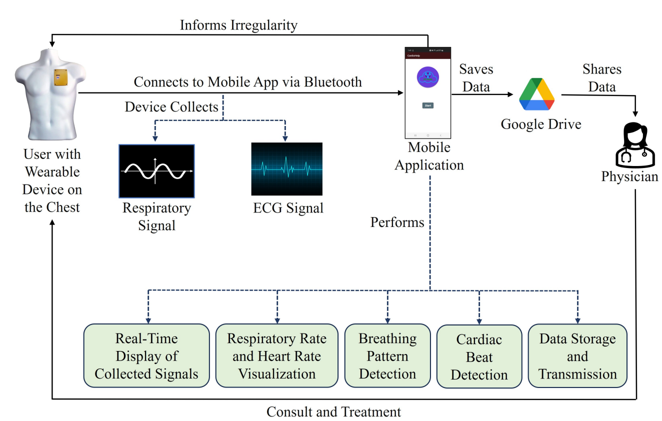

Fig. 1. Overview of the integrated healthcare system architecture.

II. System Architecture and Design

The study aims to distinguish respiratory events by analyzing raw signals in real time. Respiratory signals are acquired using a custom-printed circuit board (PCB) featuring an Inertial Measurement Unit (IMU) sensor. Additionally, we enhanced our existing mobile app by integrating features to visualize respiratory signals, determine respiratory rates (RR), and detect breathing patterns. The system also includes ECG circuitry within the PCB, Inkject Printed (IJP) electrodes for ECG data collection, and a 350 mAhr capacity Lipo battery (Pkcell LP552530). Figure 1 provides an overview of the proposed healthcare development architecture.

To capture chest movement corresponding to respiratory rhythms, we use an IMU chip MPU-6050, which collects 3-axis accelerometer data. This data is subsequently transmitted through an nRF52840 mini commercial Bluetooth System on Chip (SoC) from SparkFun (Niwot, Colorado, United States). Each Bluetooth packet comprises one sample of x, y, and z-axis data for movement detection and 48 samples of ECG. Notably, the respiratory data is sampled at a rate of 20 Hz.

III. Methods

A. Respiratory Signal Acquisition and Rate Detection

Our mobile app offers a user-friendly interface for accessing and monitoring respiratory data. Users can effortlessly track respiration rates, visualize real-time signals, receive notifications about abnormal breathing disorders, and easily share data recordings with healthcare providers.

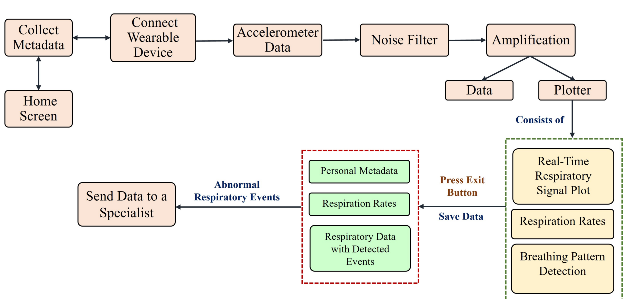

Fig. 2. Block diagram of our custom mobile app for breathing rate and pattern detection.

Upon receiving 3-axis acceleration data from the wearable device, our application constructs xy, yz, and zx vectors. A novel method then selects the optimal index from 6 options, including x, y, and z-axis data along with the three vectors. We calculate the standard deviations (SD) from a 10-second data array for each index to determine the most suitable index. The index with the highest SD is selected and further analyzed for RR detection. Subsequently, we apply a smoothing filter and then amplify the signal to detect subtle chest movements. Next, we employ spline polynomial interpolation to fill in gaps and smooth out irregularities. The number of peaks per minute is then computed from the interpolated curve to determine the RR. Please refer to Figure 2, for the block diagram that particularly focuses on RR and breathing pattern detection of our custom mobile app. Upon pressing the *Exit* button, the app consolidates all CSV files and metadata into a ZIP archive for storage and sharing with the designated physician.

B. Breathing Patterns Detection

Our focus lies on four primary types of breathing patterns: normal, apnea, bradypnea, and tachypnea. Once we have the RR in our application, we can classify certain breathing patterns based on this metric. For example, bradypnea has an RR of less than 12 breaths per minute (bpm), whereas tachypnea is distinguished by unusually rapid breathing, which typically exceeds 20 bpm at rest. In a normal respiratory pattern, the RR for an adult at rest falls within the range of 12 to 20 bpm. It's essential to note that RR may vary among participants and can also fluctuate due to emotional stress and physiological activities. During apnea events, breathing stops for a brief period and it is not possible to obtain any RR. Figure 3 illustrates our real-time respiratory signal classification approach, which utilizes a pre-trained artificial intelligence (AI) model and respiratory rates. This pre-trained model distinguishes between apnea and non-apnea events. Our approach uses respiratory rates (RR) to further classify non-apnea events into three categories: normal, bradypnea, and tachypnea. Additionally, the figure outlines the developmental process of the deep learning model used for classification.

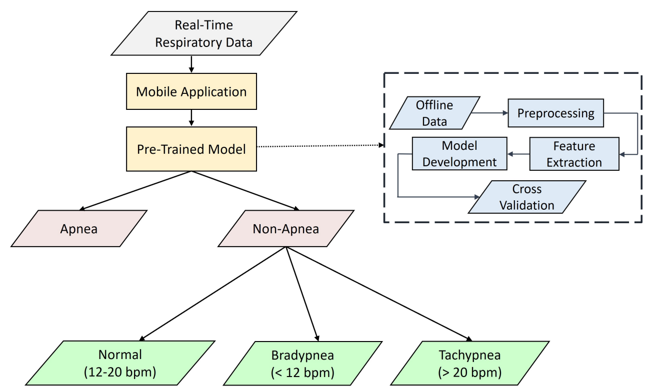

Fig. 3. A flowchart of real-time respiratory signal classification using a pre-trained model and respiratory rates.

C. Dataset and Train-Test-Validation Split

We used the Apnea-ECG database from PhysioNet to build a model for apnea detection [10]. This publicly available database consists of 70 single continuous ECG recordings. Each minute segment of all signals in the database was annotated by medical experts as either apnea or non-apnea, which resulted in binary classification for this study. Additionally, eight recordings (labeled a01 through a04, b01, and c01 through c03) are accompanied by four signals: Resp C and Resp A (representing chest and abdominal respiratory signals), Resp N (indicating oronasal airflow), and SpO2 (measuring oxygen saturation), where the sampling frequency is 100 Hz. We used Resp C, A, and N to create our model for detecting apnea using respiratory data. A total of 3955 respiratory events were extracted from the dataset, then randomly shuffled, stratified, and split into training, testing, and validation datasets. Among these, 2768 signals were dedicated to model development, which included both training and testing phases executed in a Python environment, while the remaining 1187 signals were used to validate the pre-trained model within our mobile app. Table I shows the distribution of respiratory signal classes for model building and validation in the app. For classification of the signal as apnea or non-apnea, all the records are labeled for each one-minute interval.

TABLE I
DISTRIBUTION OF RESPIRATORY SIGNAL CLASSES

Dataset	Apnea	Non-Apnea	Total
Training and Testing Samples (min)	1110	1658	2768
Validation Samples (min)	499	688	1187
Total Events (min)	1609	2346	3955

D. Feature Extraction

Feature extraction is a critical step in analyzing respiratory signals because it identifies informative characteristics that can aid in pattern recognition and classification. Our study extracted a range of features from respiratory signals, covering both time and frequency domains. These extracted features serve as essential inputs for machine learning algorithms that help with the identification of both apnea and non-apnea episodes. Table II provides an overview of the extracted features, encompassing time-domain, peak-related, frequency-domain, and other statistical features.

TABLE II
FEATURES EXTRACTED FROM RESPIRATORY SIGNALS FOR APNEA DETECTION.

Feature Category	Features
Time Domain	Mean, Standard Deviation, Skewness, Area Absolute, Kurtosis, Minimum Value, Maximum Value, Root Mean Square, Signal Energy, Shannon Entropy
Peak-Related	Peak Heights, Mean Peak Height, Std of Peak Height, Skewness of Peak Height, Num of Peaks, Skewness of Inter-Peak Distance, Peak Indices, Mean Inter-Peak Distance, Peak Frequency, Sum of Peak Heights, Min Peak Height, Max Peak Height, Std of Peak Distance
Frequency Domain	Magnitude Spectrum, Dominant Frequency Power Spectrum, Total Power, Mean Frequency, Central Frequency, Band Power, Spectral Centroid, Spectral Spread, Spectral Skewness, Spectral Kurtosis
Other Statistical	Median, 25th Percentile, 75th Percentile, Data Range

E. Pre-Trained ANN Model for Apnea Detection

This paper focuses on supervised methods for feature discretization, a crucial step for comprehensive evaluation using multilayer artificial neural network (ANN) models. ANNs are pivotal for analyzing vast clinical data due to their robust capabilities. We trained and developed three ANN models on Resp C, Resp A, and Resp N signals. After training, the models were converted to *.tflite* format and integrated into the *Android Studio Java* environment. Real-time respiratory data inputs were resampled, as the sampling rate of the real-time data is different from the training dataset of the pre-trained model. Using a ByteBuffer object, the resampled data was passed through the TensorFlow Lite interpreter and classified. Validation of our model involved passing the validation set in the app as mock data, categorizing each 1-minute signal into apnea and non-apnea. Following successful validation, a pilot study involving apnea patients using real-time signals is imminent. Ethical approval was granted by the Institutional Review Board (IRB) at Texas Tech University (IRB2020-783).

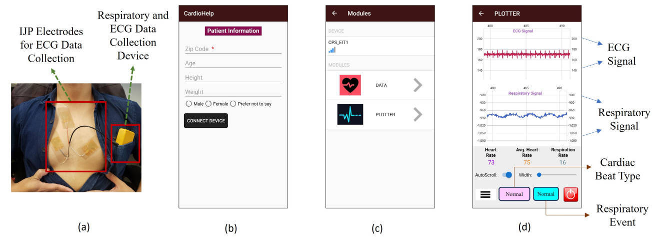

Fig. 4. Experimental setup and snapshots from our mobile app: (a) Real-time data collection, (b) Metadata input, (c) Functional modules, (d) Real-time signals plot, including heart and respiratory rates, cardiac beat, and respiratory event types.

TABLE III
PERFORMANCE METRICS OF ANN MODELS FOR APNEA DETECTION

Signal	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Chest	92.33	92.93	92.09	92.51
Abdominal	94.89	94.96	94.56	95.0
Nasal	97.66	98.0	98.0	98.0

IV. EXPERIMENTS AND RESULTS

In this section, we evaluate the performance of our system and discuss validation results. The mobile app initially processes respiratory signals through a pre-trained model for apnea and non-apnea detection. Subsequently, non-apnea signals undergo further classification into normal, bradypnea, and tachypnea categories.

A. Experimental Setup

The experimental setup involved ten healthy volunteers, evenly split between males and females, aged 22 to 35 years. Each experimental trial lasted approximately 15 minutes per subject. Refer to Figure 4 for the validation setup, featuring a customized device placed in the pocket for movement detection, alongside IJP electrodes attached to the chest for ECG data collection. The figure also includes snapshots of our mobile app displaying real-time ECG and breathing data streams, heart rate, RR, and detected respiratory pattern, as well as cardiac beat types. We utilized the mentioned validation dataset to further validate the apnea detection algorithms. The pre-trained apnea model demonstrated notable accuracy during validation. This positions us favorably to proceed to

TABLE IV
CONFUSION METRICS FOR APNEA DETECTION PRE-TRAINED MODELS ON THE APP USING THE VALIDATION DATASET.

		Predicted					
		Chest		Abdominal		Nasal	
		Non-Apnea (%)	Apnea (%)	Non-Apnea (%)	Apnea (%)	Non-Apnea (%)	Apnea (%)
Actual	Non-Apnea (%)	97.53	2.47	98.98	1.02	99.71	0.29
	Apnea (%)	17.43	82.57	16.63	83.37	15.63	84.37

the next phase of validation, which involves the use of real-life apnea patient data.

B. Experimental Results

1) Apnea Detection with Validation Dataset: The ANN algorithm achieved notable accuracies of 92.33% for Resp C, 94.89% for Resp A, and 97.66% for Resp N during model development and classification of breathing patterns on the training and testing samples dataset. Detailed results are provided in Table III, showcasing each signal's accuracy. After successful model development, we integrated them into our mobile app. To validate the pre-trained models, we parsed a CSV file containing the validation dataset into the mobile app, and the results showed accuracy rates of 91.24% for Resp C, 92.42% for Resp A, and 93.26% for Resp N. Table IV presents an evaluation of the models' performance and illustrates the classification of apnea and non-apnea events.

2) Breathing Pattern Detection in Real-Time: Ten healthy volunteers participated in the experiment and were instructed to breathe naturally. The custom device's index selection feature ensures accurate respiratory data processing, maintaining precision regardless of its three-dimensional positioning. As the device is placed on the chest, we activated the pre-trained model for chest data in our app. Table V provides a detailed overview of the respiratory rates and identified breathing patterns across all participants over a 15-minute duration. To enable real-time respiratory pattern detection, we implemented a sliding window technique that updates events every 10 seconds. This approach facilitates continuous monitoring and analysis of breathing behavior, which improves the reliability of our findings.

TABLE V
RESPIRATORY RATE RANGE AND DETECTED BREATHING PATTERNS FOR EACH PARTICIPANT.

Participant	RR Range (bpm)	AI Model Classification	Detected Breathing Pattern Class
1	17-19	Non-Apnea	Normal
2	15-18	Non-Apnea	Normal
3	20-22	Non-Apnea	Tachypnea
4	11-13	Non-Apnea	Bradypnea
5	17-20	Non-Apnea	Normal
6	18-19	Non-Apnea	Normal
7	16-18	Non-Apnea	Normal
8	14-17	Non-Apnea	Normal
9	14-16	Non-Apnea	Normal
10	10-13	Non-Apnea	Bradypnea

V. FUTURE WORK

We plan to explore other deep learning models to improve the accuracy of apnea detection and further classify them into various breathing patterns such as Biot's and Cheyne-Stokes. Larger clinical trials focusing on apnea patients will validate the efficacy of our method across diverse patient groups. Additionally, with the custom device simultaneously collecting multiple signals, we plan to develop advanced algorithms for comprehensive health management.

VI. CONCLUSION

This study presents a novel method for detecting breathing patterns on edge devices, highlighting four distinct classifications. We explore innovative techniques to extract important features from respiratory signals to identify apnea. Using the device and mobile app, users can effortlessly access multiple physiological signals. With the ability to identify and prevent respiratory and cardiovascular disorders, our system allows patients to take an active role in their health care.

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REFERENCES

[1] Majumder S, Mondal T, Deen MJ. Wearable sensors for remote health monitoring. Sensors. 2017 Jan 12;17(1):130.

[2] Harford M, Catherall J, Gerry S, Young JD, Watkinson P. Availability and performance of image-based, non-contact methods of monitoring heart rate, blood pressure, respiratory rate, and oxygen saturation: a systematic review. Physiological measurement. 2019 Jul 3;40(6):06TR01.

[3] Nicolò A, Massaroni C, Passfield L. Respiratory frequency during exercise: the neglected physiological measure. Frontiers in physiology. 2017 Dec 11;8:295402.

[4] Iqbal T, Elahi A, Ganly S, Wijns W, Shahzad A. Photoplethysmography-based respiratory rate estimation algorithm for health monitoring applications. Journal of medical and biological engineering. 2022 Apr;42(2):242-52.

[5] Angelucci A, Aliverti A. An IMU-Based Wearable System for Respiratory Rate Estimation in Static and Dynamic Conditions. Cardiovascular Engineering and Technology. 2023 Jun;14(3):351-63.

[6] Whited L, Hashmi MF, Graham DD. Abnormal Respirations. In: StatPearls. StatPearls Publishing, Treasure Island (FL); 2023. PMID: 29262235.

[7] Wang Y, Hu M, Li Q, Zhang XP, Zhai G, Yao N. Abnormal respiratory patterns classifier may contribute to large-scale screening of people infected with COVID-19 in an accurate and unobtrusive manner. arXiv preprint arXiv:2002.05534. 2020 Feb 12.

[8] Fekr AR, Janidarmian M, Radecka K, Zilic Z. Respiration disorders classification with informative features for m-health applications. IEEE journal of biomedical and health informatics. 2015 Jul 21;20(3):733-47.

[9] Utsha UT, Morshed BI. CardioHelp: A smartphone application for beat-by-beat ECG signal analysis for real-time cardiac disease detection using edge-computing AI classifiers. Smart Health. 2024 Mar 1;31:100446.

[10] Penzel T, Moody GB, Mark RG, Goldberger AL, Peter JH. The apnea-ECG database. InComputers in Cardiology 2000. Vol. 27 (Cat. 00CH37163) 2000 Sep 24 (pp. 255-258). IEEE. .