MyBreathingHeart: Literature Review and State of the Art

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1 Introduction

The COVID-19 pandemic explosion highlighted the need to develop fast and accurate pre-screenings of patients affected by respiratory diseases. While epidemics dynamics evolve according to exponential functions [30], the number of available expert physicians clearly scale at a much slower pace, making it impossible to cope with unexpected and massive increases of care demand caused by pandemics. According to the WHO, the number of doctors per 10000 population goes from a mean value of 36.61 (Europe) to an absolute minimum in underdeveloped countries of 0.35 (Niger) [33]. Therefore, the remote monitoring of vital signs on large scale population acquires fundamental importance to control COVID-19, and in view of possible future pandemics.

In these condition, it is paramount to be able to rely on widespread monitoring performed without relying on particular expertise, and by using devices which are already in widespread use among the general population. The main goal of the MyBreathingHearth project is thus to exploit smartphones for the at-home acquisition of physiological data. In particular, in this project we focus on time series from inertial sensors describing the expansion and contraction of the rib cage during breathing. In particular, we use the accelerometer and gyroscope already built into all contemporary smartphones. In order to form a more precise picture of the respiratory condition, we also integrate the aforementioned data with photoplethysmogram (PPG) signals measured via Bluetooth pulsoximeter, and possibly audio recordings of few breath cycles recorded thorough the smartphone's microphone.

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The data from patients will be gathered via a custom-developed smartphone app, and sent through a previously trained deep learning model that will provide support for the physicians to actually evaluate the situation. A first milestone would be to employ those data to train a deep learning model to correctly discriminate between healthy and presumably non-healthy individuals. Furthermore, if the first milestone can be achieved, a second milestone would be to train the model to successfully classify patients according to their specific cardiorespiratory diseases.

Remarkably, the significance of the project holds even outside the extraordinary state of emergency dictated by the current epidemic occurrence. In fact, heart and pulmonary diseases are correlated with the first and third, respectively, causes of mortality worldwide [50]. Therefore, a successful realisation of such an app (for data collection) and machine learning system (for signal analysis) can truly help physicians to cope with the burden of an increasingly large number of cardiorespiratory patients, streamlining the diagnosis' decision flow and eventually alleviating the stress on the health system. Ideally, this would allow to make appropriate decisions faster, hopefully before patients undergo a critical decrease in their wellness.

2 Literature survey

2.1 Sensors and data collection and processing

In the following we will use the term *inertial data* to refer to the data collected from accelerometers and gyroscopes. In the literature several works focus on *estimating physiological indices* like the Heart Rate (HR), or Respiratory Rate (RR), from sensors like photoplethysmogram (PPG), electrocardiogram (ECG), or inertial data.

In [14] the authors demonstrated that it is possible, devising specific feature extraction algorithms, to estimate HR quite accurately from accelerometers, deviating from the ground truth value with a narrow standard deviation of 1.63%. However, the accelerometer device was worn on the wrist, while we aim to place the device over the chest with the patient lying supine. Furthermore, in [32] it is shown how to extract other important vitals signs like the RR and the Heart Rate Variability from accelerometers placed in the pretracheal area. Although their focus is to screen sleep-apnea episodes, their results are of interest to our experimental design. In fact, they observe that the nasal airflow data acquired from polysomnography is highly correlated with the respiration component extracted from the accelerometer, suggesting that accelerometer data convey relevant information of the breathing dynamics.

Similarly, in [52], Zhang et al. propose to estimate the posture and key cardio-respiratory parameters during sleep using a single accelerometer strapped onto the chest obtaining good results. Similar results are obtained in the literature [36, 40, 51, 39, 53] focusing on estimating HR and RR relying on PPG data only, or in combination with accelerometer data. Notably, the majority of this works focus on physical activity tasks, and in some of these works the accelerometer data is used to purify the PPG data from motion artefacts. On the contrary, in our work we aim to actively use accelerometer data to gain physiological insights on the status of the heart and lungs.

Another relevant work published in the literature is [20]. They use accelerometer data measured from the chest and PPG data measured from the finger to estimate the RR of intensive care unit discharged patients, reaching maximum mean absolute (MAE) error of 2.56 breaths/min. Differently from the aim of this project, they do not use deep learning techniques, but rather employ a mixture of traditional signal processing techniques.

In another work [11], the authors propose a technique to estimate via a peak detection algorithm the RR via accelerometer with a MAE of 1.67 ± 0.37 bpm (abdomen position), and of 1.89 ± 0.53 bpm (chest position). This makes the choice of abdomen position for the smartphone to be considered for the collection of data in our project.

In [17], Hernandez et al. present a method to estimate HR and RR via signal processing techniques on inertial data acquired from a head-mounted wearable device (Google Glass). Interestingly, they show that the signal from gyroscopes on its own is more amenable to accurate HR and RR estimations compared to accelerometric data only. Although the context of their experiment is relatively different from ours, this work strongly suggests that gyroscopic data must be exploited for enhancing the classification accuracy of a deep learning model. As additional evidence, in [42] it is observed that the fusion of accelerometer and gyroscopic data by using a Kalman filter improved the RR detection accuracy by 4.6% (for treadmill exercise) and 9.54% (for leg press exercise). Finally, a patch device with integrated accelerometer and gyroscope has been used in [49] allowing a signal processing based algorithm to reach a MAE of 0.11 ± 0.7 bpm on estimation of the RR (comparable with manually counted RR value).

A paper by Behar et al. [5] remarkably relates to the idea of our project. The authors prototype an app for smartphones for home-screening of obstructive sleep apnea. To this end, they use accelerometer from the smartphone worn on the arm via an arm band, audio data from a microphone attached close to the nose, PPG data from a pulse-oximeter, and demographic data obtained by questionnaire from patients. The authors use the collected data to train a machine learning model, namely a Support Vector Machine. The paper reports an accuracy of up to 92.2% classifying subjects between having moderate or severe apnea disorders versus being healthy. Interestingly, they use Multiscale Entropy as feature extracting technique. Although the sensory channels used in [5] exactly match those used in our project, the aim is substantially different. Moreover, in contrast to their work, we aim to place the smartphone over the chest in resting supine position, and most importantly, we plan to employ deep learning to automatically extract features from data.

Another similar work [8] pointed out that audio recordings from smartphone microphones are limited to detect breathing cycles compared to classical tracheal microphones, due to the lower signal-to-noise ratio of sound signals acquired, especially in quiet breathing. Thus, they claim to solve this limitation by placing the smartphone on the chest capturing additionally breathing movement information. Interestingly, this recording setting matches the one of our project. References of the last two mentioned papers indicate the existence of several similar works combining accelerometer and respiratory data to detect sleep apnea episodes.

It may be noted that in the majority of the works discussed above, as well as many others that we do not discuss in detail (e.g., [25] where physiological indices are successfully extracted from inertial and PPG data), there was no use of deep learning techniques. The experiences reported in the papers surveyed in this section confirm that it is possible to extract fundamental vital signs via standard DSP techniques. This, in turn, makes it very likely that our hypothesis that automatic feature extraction for the successful classification of cardiorespiratory diseases will provide even better results, does in fact hold. Our approach aims to develop deep learning techniques to automatically extract relevant features from data. We aim to provide an end-to-end deep learning approach circumventing the need of specifically devised processing techniques, with the goal of obtaining results comparable or better than those obtained in the case of specialised feature extraction techniques.

2.2 Deep learning for cardiorespiratory diseases

Deep learning has revolutionised the fields of computer vision, natural language processing, and speech recognition [26], just to name a few. The impressive results achieved in those fields drove the research community to explore applications of deep learning in medicine in the last decade, and suggest a future uptrend in healthcare applications [16]. In particular, deep learning can have an impact in medicine on at least three levels: for clinicians, predominantly via rapid, accurate image interpretation; for health systems, by improving workflow and the potential for reducing medical errors; and for patients, by enabling them to process their own data to promote health [46].

The most common deep learning models explored in the literature of medicine are ANNs (vanilla feedforward neural networks, aka MLP), CNNs (2D convolutions for image-like data, or 1D causal convolutions for temporal data) and RNNs (mainly LSTMs), or combinations of them. Also, common performance metrics in the field are Classification Accuracy, area under the ROC curve (AUROC), MAE, MSE, and Correlation Coefficient.

In the following a sample of works that have employed deep learning models for healthcare applications is discussed.

A 2019 survey [43] revealed that the performance of convolutional based NNs was at par with expert human clinicians on tasks ranging from melanoma classification to pulmonary pathology classification, and even exceeding that of less expert clinicians. Again in [29], a CNN was trained that outperformed human board-certified echocardiographers on view classification of echocardiograms. However, those models are fed with data images where CNNs are broadly recognised to reach or even surpass the human level. Contrariwise, our project focus on inertial data, thus the choice of a CNN might not be optimal, and it should be validated in experiments before being relied upon.

In [48], Wang et al. train a MLP with inertial data to monitor the RR of athletes under different conditions, namely sitting quietly, walking and running. The accuracy of the estimated RR while sitting quietly was a remarkable 94.4%, thus better than previous attempts to estimate RR via signal processing based algorithms in resting conditions. However, the better performance might be due to the multisensor device exploited which registered inertial data from both the chest and the back of athletes. The sampling frequency of the sensor signal is set to 10 Hz, and the sampling point is set at 2000 to improve the speed of data processing and reduce the amount of data processing. Moreover, in [15] the authors use a CNN followed by an LSTM to detect sleep apnea episodes from an accelerometer attached in the tracheal position with a correlation coefficient between gold standard and estimated values of 0.84. Interestingly, they tried to feed their deep learning models with both raw signals and with manually extracted features. The results suggest that deep learning models are more than twice more correlated with the ground truth when also provided with manually extracted features. They preprocess accelerometer signals with band-pass filters. Then 7 morphological features from each movement axis (x, y, and z) were extracted using a sliding window of 10 seconds with a 9 seconds overlap. Although their objective is considerably different from ours, this work strongly suggest that "manual" feature extraction should be taken into consideration.

Another pertinent work found is [31]. In this paper, the authors use deep learning (one-dimensional CNN) for classification of breath patterns (apnea, muller, yawning, coughing, sighing, and normal breathing) from accelerometer and gyroscopic data collected from light-weight wireless sensors placed on the chest and abdomen (using the raw data from sensors directly). For classification purposes, they used 7-seconds windows in the time series. They achieved a mean F1 score of 92% for normal breathing, suggesting that a deep learning model should be able to at least discern normal breathing patterns from atypical ones. They collected data from 100 healthy volunteers, but their dataset does not seem to be publicly available.

A more elaborated deep learning model, namely 2 CNNs followed by 2 LSTM layers further followed by an ANN, has been implemented in [7] to estimate HR from single channel PPG wrist-worn device. They test the model on the TROIKA dataset achieving a MAE of 1.47 ± 3.37. The PPG signal has been only preprocessed with a band-pass 4^{th} order Butterworth filter cutting-off frequencies $0.1 - -18$ Hz, and then normalised to zero mean and unit variance.

In [45] they estimate the blood pressure from PPG signals implementing a CNN+LSTM model to automatically extract features, followed by a MLP for delivering the output. We might use PPG signals to integrate the accelerometer data in our work. Therefore, their choice of architecture can be considered for testing in our framework. A peculiarity of this work is that they train and test the architecture for each person. Albeit they are not extracting features manually, they do preprocess the data via denoising techniques, namely a band-pass filter eliminating the frequencies outside the range $0.1 - 8$ Hz. They feed the network with windows of 8s with a step of 2s, resulting in 6s overlaps between two consecutive windows. Then they scale signals in each window to zero mean and unit variance. They validate their models on 2 datasets, the MIMIC V.3 2015[1], and The University of Queensland Vital Signs Dataset[2].

Similarly in [38], Reiss et al. estimate the HR from PPG and accelerometer data using CNNs. They provide their dataset (PPG-DaLiA) where several daily-life activities are performed. In this work, the accelerometer data is used to purify the PPG data from motion artefacts in order to gain accuracy on HR estimation. Their method achieves good results also on 4 other publicly available datasets, outperforming previous algorithms based on spectral methods. These works suggest that PPG signals can be useful to enhance the classification accuracy of deep learning models on cardiorespiratory diseases compared

[1]https://physionet.org/content/mimiciii/1.4/

[2]https://outbox.eait.uq.edu.au/uqdliu3/uqvitalsignsdataset/browse.html

to solely inertial data.

Other works such as [2] use more sophisticated architectures like Generative Adversarial Networks to estimate RR from PPG data obtaining MAE of 1.9 ± 0.3. Although we do not currently plan to implement this kind of architecture, in the worst case scenario where all the proposed models give unsatisfactory performance we might consider it as an alternative. The authors of the paper employed BIDMC PPG and Respiration Dataset[3]. This dataset is widely used to evaluate the performance of different algorithms for estimating respiratory rate from PPG signals (see references therein); therefore, it might be used for experiments. As preprocessing, raw PPG data are normalized to 0–1. Then, the signals are down-sampled to 30 Hz. Finally, 30-second windows of data are extracted from the signals to be used.

Moreover, in [44] several machine learning models have been implemented (among which ANNs) to estimate RR from PPG signals. The best feature extraction technique for ANN turned out the FIT a Regression Gaussian Process model, where the ANN reached a RMSE of 4.05 breaths per minute. We might consider this feature extraction technique in case of very poor performance of other approaches. They used the VORTAL dataset[4]. The signals were segmented into windows of 32 seconds.

Although not relying on accelerometric data, many other works successfully exploited deep learning models in cardiorespiratory related applications; some of which are reported as follows. ANNs have been trained to classify cardiotocography signals between normal, suspicious and pathological obtaining Geometric Mean values of 89.69% [10]. A 3-layer LSTM could predict cardiac arrests based on time series formed by systolic blood pressure, HR, respiratory rate, and body temperature, outperforming previous techniques reaching an area under the ROC curve of 0.85 [23], without any feature extraction or preprocessing technique. A CNN followed by a MLP was able to detect aortic stenosis from 12-lead ECG and single-lead ECG signals obtaining, respectively, an area under the ROC curve of about 0.87 and 0.83 [24]. Again, CNNs have been employed for predicting heart diseases, namely classifying between normal and abnormal behaviour, from blood pressure and ECG data collected from smartwatch and heart monitor, obtaining 98.7% test accuracy on the Cleavaland dataset [21]. Test accuracy of 99.2% is reached by an ANN in classification of an ECG database in 10 types of arrhythmia, using Complex Discrete Wavelet Transforms for feature extraction to feed the model [34]. Finally, a MLP has been trained on categorical data for the prediction of persistent asthma in children with accuracy of 96.77% [9]. We might feed our model with categorical data describing the individuals who are taking the recordings in conjunction with the sensors' channels, thus this work might be of interest.

Note that the vast majority of the works above did not deal with data of a nature that is particularly close to the context of our work. In fact, most of them dealt with inertial and PPG data coming from daily activity tasks, rather than from ad-hoc measurement. Furthermore, almost all of the works that deal with PPG signals focus on estimating the RR. In this sense, our project points towards a direction which has not been explored yet in the literature.

In case the test classification accuracy will not meet the satisfactory thresh-

[3] `https://physionet.org/content/bidmc/1.0.0/`

[4] `http://peterhcharlton.github.io/RRest/vortal_dataset.html`

old of 80%, for the easier case of binary classification between healthy and non-healthy, or the threshold of 60% for each class of cardiorespiratory diseases for the multi-class task, then audio recordings of the breath may be employed in addition to the inertial and PPG time series. Despite the lack of deep learning models implemented on inertial data outside the human activity recognition field, and on PPG data outside the estimation of the RR, several works have been found in the literature using deep learning models to classify cardiorespiratory diseases from audio recordings. Few of them are reported in the following. In particular, classification of heart diseases via electronic stethoscopes has been proved successful with ANNs fed with spectrogram based preprocessing techniques on the audio auscultation recordings.

An interesting study conducted in [47] revealed that with relatively little training data (60 audio recordings of the heart via electronic stethoscope), a feedforward neural network can achieve very good accuracy on a test dataset (of 60 recording as well), classifying between healthy, pulmonary stenosis and mitral stenosis; namely, obtaining 95% test accuracy. Similarly, in [13] authors obtain 88% accuracy on a dataset of 15 heart diseases plus the healthy class. Other works focused on cough recognition via deep learning models. In [22, 4] they use CNNs, while in [12] they use ANNs with one hidden layer of 32 tanh-neurons and a single sigmoid-neuron as output layer. From the study in [12], positioning the microphone on the thorax rather than the trachea gives slighter higher values of specificity and sensitivity.

Note however that we aim to record audio from smartphone's microphone in a possibly very noisy environment. That makes our case very different from those in the literature, and force us to not rely too much on audio data.

2.3 Preprocessing and feature extraction techniques

Our goal is to rely on automatic feature extraction from deep learning modules. Nevertheless, in order to reduce the computational burden while hopefully boosting the performance, we might consider feeding the deep learning model with manually devised feature extraction algorithms.

From the analysis of the literature, feature extraction techniques can be divided on mainly three categories focusing on time domain (e.g. band-pass filters), frequency domain (e.g. Fast-Fourier based transforms), and time-frequency domain (e.g. Wavelet Transforms). A comparison of those methods applied on accelerometer data revealed that frequency domain features, precisely Magnitude of First Five Components of FFT analysis (M5FFT), gives the best accuracy [37]. Another comparative study applied on PPG and accelerometer signals to estimate the HR corroborated the supremacy of frequency domain features, highlighting Finite Harmonic Sum as the best method [35]. However, it worth to notice that these comparative studies have been done within the scope of human activity recognition, therefore these methods may be non-optimal for the ambit of our project.

Two reviews on feature extraction techniques for audio signals can be found in [41, 3]. A comparative study between various different feature extraction techniques for audio signals reported cepstral-based transformations, namely the Mel-frequency cepstral coefficients (MFCC) and linear prediction coefficients (LPC), as the best choices [27]. However, a more recent study [28] showed that a denoising autoencoder extracting features from the heart sounds can enhance the classification accuracy compared to the MFCC method. Therefore, an autoencoder for extracting deep features might be better suited to our goals.

Note that, in our case, frequency and cepstral based feature extraction techniques are justified by the fact that the physiological time series we aim to classify are assumed to be inherently periodic or quasi-periodic, since the measurements are supposed to be acquired at resting condition. Therefore, frequency components of importance should distinctly appear and result crucial for the classification task, without significant losses of information from the whole temporal series.

Many other techniques have been explored in the literature, and might be considered during the experiments. For instance, a review on preprocessing of accelerometer and PPG signals (for HR estimation) can be found in [35]; in [6] there are interesting thoughts on preprocessing biomedical signals which are related to those of our work.

A survey on data augmentation techniques for classification of time series using neural network based models can be found in [19]; Window Warping is the most recommended. A review on distance-based ML techniques for time series classification is provided in [1]; based on that review, kNN with Distance Time Warping is a standard baseline choice. Another review on deep learning techniques for time series classification is in [18]; ResNets and Fully Convolutional Nets reach the best performance.

It is worth remarking that, as widely exploited in the literature, denoising filtering and downsampling techniques should be considered prior to the feature extraction. Finally, dimensionality reduction techniques on raw data might be considered to reduce the computational time for training, alone or in synergy with feature extracting algorithms.

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