Development of Machine Learning Assisted Smart Health Monitoring Console Integrated with Signal Quality Assessment Module

Divyayan Dey
University Roll No. T91/ECE/174053
Registration No. D01-1111-0076-17
Department of Electronics and Communication Engineering
University of Calcutta

Agniva Rath
University Roll No. T91/ECE/174067
Registration No. D01-1111-0001-17
Department of Electronics and Communication Engineering
University of Calcutta

Guided By:
Dr. Sumitra Mukhopadhyay
Institute of Radiophysics and Electronics
University of Calcutta

July 2021

1 Introduction

In this project, a machine learning assisted wearable, standalone health monitoring system has been proposed along with signal quality assessment and smart decision making. After extensive literature review, few shortcomings of the existing research work have been identified - (a)evidence of hardware implementation of machine learning assisted health monitoring system is rare, (b)many of the approaches didn't use signal quality assessment procedure to justify the reliability of the received physiological signal. In this context, we present a real time, machine learning assisted health monitoring system based on PPG signal. The main objectives of the proposed work are as follows - (1) reception of minimum number of physiological signals and its preprocessing, (2) introduction of signal quality assessment(SQA) module to increase reliability of the received signal, (3) extraction of important health parameters. Here we monitor a patient round the clock and observe his vital health parameters, (4) machine learning assisted health status prediction based on clinical, fiducial and non-fiducial features extracted from PPG signal.
Figure 1 below shows a schematic of the workflow that has been implemented in our project work. The progress of our work has been divided into two phases, which we will discuss in the next sections. In phase I, initially we made the literature survey and identified the research gaps. Based on the observations, we designed a smart health monitoring system as shown in Fig. 1. We also implemented some portion of the system(upto SQA module) on **Arduino Uno** microcontroller(32 KB flash memory and 2 KB SRAM). However, the machine learning assisted algorithms require higher memory space for its implementation. In the later part of our work, as per our workflow, we needed to implement a machine learning assisted health status prediction module. Therefore, on-device implementation has been accomplished on **Raspberry Pi Zero W** microprocessor(environment:Thonny Python IDE). Results have been validated with the *BIDMC PPG and Respiration dataset v1.0.0*[1,2] and also with some time real time PPG signal.

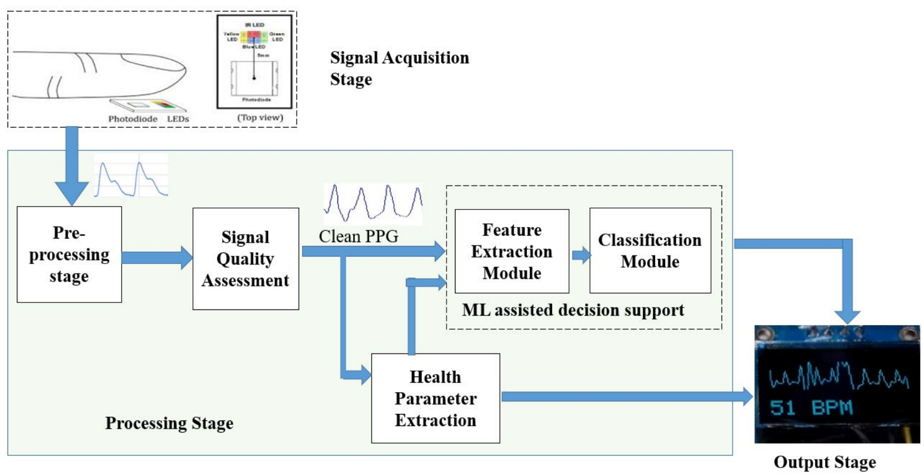

Figure 1: Workflow diagram

2 Phase I

The following objectives have been achieved in the phase I of our work:
• Signal acquisition using PPG sensor; (*MAX30102 Pulse Oximeter and Heart-Rate Sensor*).
• Signal pre-processing using a butterworth filter(high-pass, cutoff freq.= 10 Hz) to remove low frequency baseline wander and corruption due to motion artefacts.
• Segmentation of PPG frames in 3 second windows and signal quality assessment. Signal Quality Assessment Module(SQAM)[3] has four sub-modules - (a) motion detection module, (b) saturation detection module, (c) sensor connectivity detection module and (d) pulse noise segment detection module. A decision rule is implemented based on the status flag of each of the sub-modules. This module increases the reliability of the overall system. The above work has been implemented in Arduino Uno environment (16 MHz ATmega328 processor, 31.5 KB memory size, 2 KB SRAM, 1 KB EEPROM)

3 Phase II

In Phase II of our work, we have achieved the following objectives:
• Clinical parameter extraction from 3 second PPG frames(heartbeat rate(HR), oxygen saturation level(SpO_2), etc.) are extracted.
• Design and implementation of feature extraction[4] module: 3 types of features are extracted - (a) Clinical features, (b) Fiducial features(systolic slope and diastolic slope), and (c) Non-fiducial features(mean, standard deviation, variance, skewness, approximate entropy, etc.)
• Feature matrix formation and division of total feature set into 70:30 ratio for 10 times 10 fold cross validation and blind testing. 3 different classifiers implemented - (a) Support vector Machine(kernel = Linear and RBF, c=1.0, gamma = 1.0), (b) Random forest classifier(trees/estimators = 100, criterion = '*gini*', min samples split = 2) and (c) Logistic regression(penalty = *l2*).
• Random forest classifier shows the best prediction accuracy(approx. 99.9%) with sensitivity 0.99, specificity 0.98, recall 0.99 and F1-score 0.99. The entire workflow as shown in figure 1 has been implemented in Raspberry Pi Zero W(One GHz single-core ARM11 CPU, Broadcom BCM2835 SoC, 512 MB RAM and a 16 GB SD card inserted).

4 References

[1] Pimentel, M.A.F. et al. Towards a Robust Estimation of Respiratory Rate from Pulse Oximeters. IEEE Transactions on Biomedical Engineering, 64(8), pp.1914-1923, 2016.
[2] Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., ... Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation [Online]. 101 (23), pp. e215–e220.
[3] Reddy, Gangireddy Narendra Kumar, M. Sabarimalai Manikandan, and NVL Narasimha Murty. "On-Device Integrated PPG Quality Assessment and Sensor Disconnection/Saturation Detection System for IoT Health Monitoring." IEEE Transactions on Instrumentation and Measurement 69.9 (2020): 6351-6361.
[4] Zhao, Xiangfa, and Guobing Sun. "A Multi-Class Automatic Sleep Staging Method Based on Photoplethysmography Signals." Entropy 23.1 (2021): 116.