# A Web Application for Experimenting and Validating Remote Measurement of Vital Signs

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Abstract. With a surge in online medical advising remote monitoring of patient vitals is required. This can be facilitated with the Remote Photoplethysmography (rPPG) techniques that compute vital signs from facial videos. It involves processing video frames to obtain skin pixels, extracting the cardiac data from it and applying signal processing filters to extract the Blood Volume Pulse (BVP) signal. Different algorithms are applied to the BVP signal to estimate the various vital signs. We implemented a web application framework to measure a person's Heart Rate (HR), Heart Rate Variability (HRV), Oxygen Saturation (SpO<sub>2</sub>), Respiration Rate (RR), Blood Pressure (BP), and stress from the face video. The rPPG technique is highly sensitive to illumination and motion variation. The web application guides the users to reduce the noise due to these variations and thereby yield a cleaner BVP signal. The accuracy and robustness of the framework was validated with the help of volunteers.

Keywords: remote photoplethysmography  $\cdot$  deep learning  $\cdot$  vital signs measurement  $\cdot$  computer vision

#### 1 Introduction

Measurement of vital signs like the HR, HRV, SpO<sub>2</sub>, BP, stress and temperature are important to understand a patient's health status [24]. Presently, monitoring these vitals requires patients to either visit a clinical facility, or buy multiple devices such as the BP monitor, oximeter, and thermometer which they must learn to use. Wearable sensor devices like smart watches are also available but patients must buy the reliable devices approved by Health Canada. Therefore, an alternative mode of remote vital signs monitoring with a single device (smartphone or web camera) will be beneficial as the users can measure their vitals at the comfort of being at home and without buying additional devices or receiving prior training on device usage.

In the 1930s, Hertzman proposed the principle of Photoplethysmography (PPG) [8]. In PPG method, the skin is illuminated with light and in proportion to the volume of blood flowing through the tissues, a part of the light is absorbed by the tissues and the rest is reflected. From the reflected light, the

BVP signal is extracted, which is processed further to compute the HR [31]. The first commercial oximeter based on PPG was introduced in 1983 [14]. Oximeters contain a photodiode sensor which measures the intensity of reflected light. Based on this technique, many commercial devices are available today and are widely used to measure the HR and SpO2 [9]. Researchers have used PPG signals obtained from contact PPG sensor devices and analyzed them using machine learning algorithms to calculate HR and BP [10.27]. With the popularity and wide use of camera based smartphones, researchers have used videos of fingertip and monitored changes in skin color over a period of time to extract the BVP signal [20]. In recent years, the remote Photoplethysmography (rPPG) methods for measuring vital signs based on the principle of PPG have gained momentum, which are referred to as rPPG methods [28]. These methods employ a contactless camera to capture face video for vital signs measurement under laboratory environment [17,19] with controlled lighting conditions and no subject movements. These good quality videos without real life environmental noises result in clean BVP signals and provide good measurement accuracy. However, many users are hesitant in using online systems to record their face videos. Therefore, the technology needs to be enhanced with privacy measures to work in real world use case scenario and validated using a large sample population having different physical traits and health conditions before it can be deployed in clinical care in Canada.

In this paper, (1) we present a web application framework with a back-end server as shown in Fig. 1 for remote web-based measurement of vitals signs namely HR, HRV, SpO<sub>2</sub>, RR, BP and stress in near real-time using a privacy preserving face video captured with a device camera. (2) We validate the rPPG technology using our web application in the real world environment with different sources of light, varying camera resolutions, multiple browsers, several devices, and networks. (3) Extensive research was done to explore existing rPPG methods [23] and improve the BVP signal by diminishing motion and light noises encountered in real world environment and giving the user appropriate messages to capture a good quality video. In this version of the application, scalability

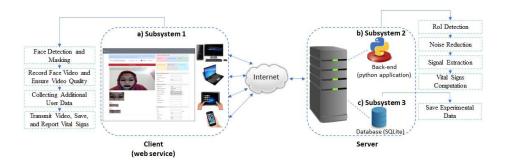


Fig. 1. Overview of the framework. It comprises of three subsystems: (a) front-end HTML application, (b) back-end processing python module and (c) SQLite database.

and load balancing was not addressed. Instead, we focused mainly on validating the accuracy of the framework in the real world.

The rest of the paper is organized as follows. Background and related work are presented in Section 2. The web application framework is explained in Section 3 and its experimental validation is described in Section 4. Finally, Section 5 concludes the paper with an outline of future work directions.

## 2 Background and Related Work

A web application is a software built using client-server architecture with the client side made accessible on the web to communicate with the users and obtain information that is transferred to the back end server for processing. The results can be reported back to the user. It can allow ubiquitous access to a wide range of users, and therefore, is ideal to validate the rPPG technology using a large number of volunteers. In this section we present some required concepts and literature review of the different methodologies we applied to implement a robust rPPG framework.

#### 2.1 Remote Photoplethysmography (rPPG)

rPPG models estimate user vital signs from face videos using signal processing techniques and machine learning models [24]. The complete method consists of the following steps.

- 1. Detect Region of Interest (RoI)s: Identify face landmarks such as eyes, nose, lips, forehead, cheeks, and segment RoIs in the video frames to obtain the raw signal;
- 2. Noise reduction: Improve the video quality to reduce the noise due to light and motion and thereby, improve the quality of the raw signal;
- 3. Signal extraction: From the RoIs of the improved video, BVP signals are extracted based on change in pixel colors representing the periodicity of blood flow under the skin;
- 4. Vital signs computation: On the BVP signal, different computational pipelines are applied to calculate HR, HRV, SpO<sub>2</sub>, RR, BP and stress.

#### 2.2 Literature Review

**RoI Detection:** The face is detected and suitable RoIs are segmented to extract a periodic BVP signal. This signal is often dampened by motion artifacts owing to involuntary facial movement like blinking, twitching, smiling, and frowning [31,19]. Therefore, it becomes necessary to choose a RoI that includes the least noise and the most cardiac information. Two methods are commonly used for extracting the RoIs on the face [31,19]. The first method uses a face detector to segment the face with a bounding box. The second method predicts the coordinates of the facial landmarks, which can then aid in segmenting the RoIs.

**Noise Reduction:** Two major sources of noise that result in poor quality BVP signal are, (a) inconsistent illumination and (b) movement [24].

Illumination Noise: In low light environment the skin cardiac data is not clearly visible, which affects the extracted PPG features [19]. Guo et al. [12] applied Histogram Equalization (HE) to the videos and found that the enhanced videos gave larger RoIs than the original ones and also improved the quality of the signal. Qiao et al [24] used HE to improve the lighting in the video when the background light was low.

Motion Noise: Rahman et al. [25] and Qiao et al. [23] used detrending filter and moving average filter to remove the stationary components and motion artifacts from the signal, respectively. Detrending helps attenuate the background intensity noise from the signal. Moving average filter computes the average of the datapoints between the video frames, thereby reducing the random noise yet retaining a sharp step response. The denoise filter helps in removing the jumps and steps in the signal caused by head movements such as rotation or shaking.

**Signal Extraction:** The individual face video frames are monitored over a period of time to track the changes in pixel color intensity to generate the BVP signal. All the three-color channels namely red (R), green (G) and blue (B), contain pulsatile data. Wang et al. [32] utilized the data from the green channel while Poh et al. [22] used all the three-color channels.

Vital Signs Computation: The different methods are briefly described below.

*HR*: The interval between the peaks of the time-domain BVP signal indicates the HR but this method is very sensitive to noise. The BVP signal can be transformed into the frequency domain using Fast Fourier Transform [19]. The highest peak in the frequency spectrum is the fundamental frequency  $f_{HR}$ . Qiao et al [24] calculated HR as  $f_{HR} * 60$ .

*HRV:* Inter Beat Interval (IBI) is the time period between the heartbeats. HRV can be computed by calculating the time interval between two successive peaks in the BVP signal [26]. Qiao et al. [24,23] calculated  $IBI = t_n - t_{(n-1)}$  where  $t_n$  is the time of the *n* th detected peak. They calculated HRV according to Eq. 1, where N is the number of IBIs in the sequence.

$$HRV = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (IBI_i - IBI_{i+1})^2}$$
(1)

 $SpO_2$ : Based on the principle that the absorbance of Red (R) light and Infrared (IR) light by the pulsatile blood changes with the degree of oxygenation [15], SpO<sub>2</sub> is calculated from the BVP signal. The extracted BVP signal obtained from the reflected light is divided into two parts: the Alternating Current (AC) component resulting from the arterial blood and the Direct Current (DC) component resulting from the underlying tissues, venous blood, and constant part of arterial blood flow. The SpO<sub>2</sub> level in the blood can be calculated using Eq. 2. Title Suppressed Due to Excessive Length

$$SpO_2 = A - B \times \frac{AC_R/DC_R}{AC_{IR}/DC_{IR}}$$
(2)

where parameters A and B can be calibrated by using a pulse oximeter. Qiao et al [24] set 1 and 0.04 as the calibration parameters A and B respectively.

RR: Due to its non-stationary nature, estimating RR from PPG is challenging. Park et al. [21] extracted the dominant frequency from the BVP signal, used an infinite impulse response filter to eliminate cardiac component, and then used adaptive lattice notch filter to estimate RR. In this project, we estimated RR by using a bandpass filter to retain frequencies in the range of 0.15 - 0.35 Hz, and the peak in the resultant signal times 60 was taken as the RR.

*BP*: Non-linear regression models have shown good accuracy in estimating the BP [16] proving that BP and PPG have a non-linear correlation. Shimazaki et al. [27] used autoencoders to extract the complex features that could be used as input to a four layer neural network. Viejo et al. [29] fed the amplitude and frequency of detected peaks to a regression model comprising a two layer feed forward network. Huang et al. [13] used the results from transfer learning on MIMIC II dataset with k-nearest neighbours for BP prediction from face videos. Qiao et al. used a deep neural network with ResNet blocks and employed transfer learning by first training the network with finger PPG data and then with face video rPPG data.

Stress: HR is an indicator of stress level. In this project, we calibrate the stress as follows: relaxed when HR < 67 bpm, normal when 67-75 bpm, low when 75-83 bpm, medium when 84-91 bpm, high when 92-100 bpm, very high when 101-109 bpm and extreme when HR > 109 bpm.

An overview of the commercially available applications for estimating vital signs from face videos is illustrated in Table 1. These applications offer the solution to measure multiple vital signs with a single device which is why we implemented the same approach with improved noise reduction techniques.

# 3 Web Application Framework

The proposed web application framework version 1.0 is a python web framework having a client-server architecture which is composed of three subsystems as shown in Fig. 1. The server hosts the front-end application, manages resources,

App	Technology	Face	Finger	SDK	Free	Vitals Measured HR HRV RR SpO <sub>2</sub> BP Stress					
App						HR	HRV	RR	$SpO_2$	BP	Stress
Anura [1]	TOI	$\checkmark$			$\checkmark$	$\checkmark$				$\checkmark$	$\checkmark$
Happitech [5]	PPG		$\checkmark$	$\checkmark$	$\checkmark$		$\checkmark$				
Binah.ai [2]	PPG, rPPG	$\checkmark$	$\checkmark$	$\checkmark$		$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Veyetals [6]	PPG, rPPG	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$

 Table 1. Overview of existing commercial applications for remote measurement of vital signs.

and delivers the back-end functionality including data processing, storage, and running the computational models for estimating and returning the vital signs namely HR, HRV, RR, SpO<sub>2</sub>, BP, and stress from face videos. We specifically focused on the computational models in this version, which will be demonstrated and evaluated through experiments. Load balancing and scalability will be addressed in future work.

We used the Flask framework <sup>1</sup>, which is a popular lightweight Python microframework with a built-in development server and support for unit testing. The framework also has a strong community support and excellent documentation which made it our choice for this application.

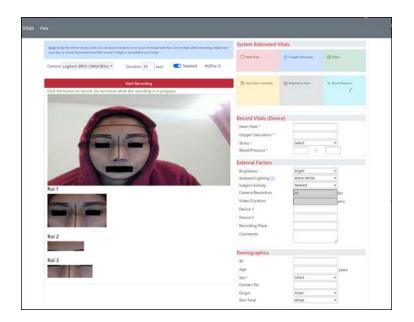


Fig. 2. Front-end web interface

#### 3.1 Subsystem 1: Front-end Web Interface

The front-end web interface shown in Fig. 2 can be accessed on the browser via a public web URL<sup>2</sup>. It is built using HTML5, CSS, jQuery and Bootstrap. The front-end application requests camera access and upon receiving access, it starts capturing user's video. It anonymizes the user video by face masking, monitors the user position, sends the video to the back-end for computing vitals, displays the vitals on the user interface, and collects optional user data such as age, skin

<sup>&</sup>lt;sup>1</sup> https://flask.palletsprojects.com/en/2.0.x/

<sup>&</sup>lt;sup>2</sup> https://vital-signs-bamlab.tk/

color, and other relevant information to enable further analysis as explained below.

- 1. Face Detection and Masking: To protect user privacy, we apply face masking by detecting face landmarks such as eyes, lips, jawline, and nose, and covering them with another object called the face mask. Three APIs namely Haar-cascade classifier [30], face-api.js [3], and MediaPipe Face Mesh framework JavaScript API [7] were tested for face and facial landmark detection. We used the MediaPipe Face Mesh API as it made real-time predictions and gave superior user experience. We apply a simple mask by covering the mouth and eyes with black strips, and drawing black contour lines on the nose area, eyebrows, and face edges. A button on the user interface allows the user to turn face mask on or off.
- 2. Record Face Video and Ensure Video Quality: The device camera records the user's face video in MP4 format using the MediaRecorder<sup>3</sup> interface of the MediaStream Recording API. A bounding box around the face is computed to determine the face area. User distance from the camera is computed as the ratio of the face area to the video frame area. Tracking of the face landmarks throughout the video allows the system to detect too much movement (beyond 15 units of displacement of the bounding box) and stop the recording. If the user is too far from the camera or moving too much, the User Interface (UI) displays a message to guide the user to reposition or stay steady to obtain a good quality video.
- 3. Collect Additional User Data: To validate the accuracy of the measurements for different parameters, some data is collected from the user using a form on the UI as listed below.
  - (a) Ground truth data measurements of HR, SpO<sub>2</sub>, stress and BP taken by the user or the researcher using Health Canada approved medical devices. The HRV and RR measurements are sensitive measurements which are typically measured at a clinical facility. In this study we did not record the HRV and RR ground truth values (future study) and used a benchmark dataset containing these values.
  - (b) Environmental data such as the brightness of the place (bright/dark), type of ambient lighting (warm white/ cool white/ daylight) causing illumination noise, and subject activity (relaxed/post exercise) causing motion noise, which affect the measurement accuracy.
  - (c) User Profile such as name, age, sex, skin tone (white, yellow, brown, dark), and ethnicity (Asian, South-Asian, White Caucasian, African American, Hispanic) can be optionally provided by the user.
- 4. Transmit Video, Save, and Report Vital Signs: Once the noise is acceptable, the recording is transmitted to Subsystem 2 for further processing and calculation of vital signs. Calculated measurements are displayed on the UI in near real time. A *Save* button allows all information to be saved on Subsystem 3, which can be accessed later for further studies.

<sup>&</sup>lt;sup>3</sup> https://developer.mozilla.org/en-US/docs/Web/API/MediaRecorder

#### 3.2 Subsystem 2: Back-end Data Processing

The back-end hosts a Python 3.8 application on the server. The videos received from Subsystem 1 are saved on the server, processed and analyzed to extract the raw PPG signals and reduce noises due to changes in light intensity and motion to obtain a robust BVP signal for higher accuracy of vital signs. We used the state-of-the-art methods from Qiao et al [24] for vital sign estimation as explained briefly in Section 2.2 and improve the noise filtering techniques (selecting the best RoI, guiding user by UI messaging) while validating the framework in real life environment.

#### 3.3 Subsystem 3: SQLite Database

Due to the ease of installation, usage, and portability, we used the SQLite<sup>4</sup> database version 3.12.2 as the repository on the back-end server to store the experimental data. It consists of a single relational table which saves time stamped data for each user session including the video file name, the vitals calculated by Subsystem 2, and the measured vitals entered by the user in Subsystem 1 along with the additional user and environmental details collected through the UI.

## 3.4 Application Deployment

To host the framework on a public server accessible by a URL, a Nginx web server and Gunicorn HTTP server is used, as the built-in Flask web server cannot be used for production. Nginx<sup>5</sup> is a powerful open source web server that can handle reverse proxy, load balancing, security, scalability and HTTP caching. Gunicorn<sup>6</sup> is a Python Web Server Gateway Interface (WSGI) HTTP server for UNIX.

# 4 Experiments and Results

To demonstrate the usability and performance of the framework, participants were asked to use the application in real life environment. The vitals were measured simultaneously using medical devices Omron HEM-FL31 BP monitor and LOOKEE LK50D1A pulse oximeter. We used the Mean Absolute Error (MAE), System Response Time (SRTime), and Back-end Processing Time (BPTime) as the metric for evaluating the experimental results. The difference between the ground truth vital sign reading measured with a medical device and the vital sign value estimated by the framework, is the error. Average error value computed from multiple measurement sessions is called the Mean Absolute Error (MAE). The SRTime is the total time taken by the application to collect the video and report the results. The BPTime is the time taken by the back-end system to process the videos and report the results. We conducted experiments to validate the framework's:

<sup>&</sup>lt;sup>4</sup> https://www.sqlite.org/index.html

<sup>&</sup>lt;sup>5</sup> https://www.nginx.com/

<sup>&</sup>lt;sup>6</sup> https://gunicorn.org/

- 1. Accuracy: Five volunteers in the age group of 13-40 years used the application at different times of the day and in different physical states on the Google Chrome browser of an Acer Aspire A315-55G laptop, with a Logitech UltraHD 4K webcam. The ground truth vital signs readings were in the range of 72-108 bpm, 97-100%, 94-114 mmHg, and 58-76 mmHg for HR, SpO<sub>2</sub>, SBP, and DBP respectively. The results of this experiment are shown in Table 2.
- 2. Robustness and Performance: One volunteer used the application for 5 days with multiple sources of light and camera resolutions, and different internet networks, devices and browsers. The application was used three times in a day at 10:00, 13:00, and 16:00 hrs. The experimental results are shown in Table 3 and 4.
- 3. Workload Capacity: The maximum number of users the application can support was tested using Google Chrome browser on different devices starting with 9 participants.

Discussion: From Table 2, it is clear that the system performance improves with face masking because the eyes and mouth movement is completely obscured which avoids the noise due to movement. With the other experiment, we observed that the MAE was the lowest with natural daylight, thereby indicating that the light sources are adding artifacts to the video resulting in noise in the raw signal. Although the performance of the system is comparable on both the networks, the BPTime is similar but the SRTime varies for different devices and browsers. SRTime depends on data processing time plus the network data transmission time. The computational complexity, device configuration, and video streaming capability of the device camera affect the data processing time. The frame rate of the camera in a browser depends on video resolution, device memory, and available bandwidth [18]. For example, a camera might capture at 60 fps at 720p resolution but it might only capture 30 fps at 1080p.

We configured the Gunicorn service with 5 worker processes as the official documentation of the service provider mentions that 4-12 worker processes can handle thousands of requests per second [4]. The recommendation is to use  $(2 * \#num\_cores) + 1$  as the number of workers. Gunicorn relies on the operating system for load balancing. The Nginx server has efficient load balancing techniques that must be configured. The workload capacity of the framework can be enhanced by appropriate configurations, which is outside the scope of this work.

# 5 Conclusion and Future Work

With the global transition of business processes to online cloud technologies, the medical domain has seen a digital transformation in offering online services to patients. In this regard, the rPPG technology which facilitates measurement of vitals signs remotely from face videos can greatly benefit the online medical consultations. Existing research in rPPG [17,19,20] has shown promising results when used in controlled laboratory conditions. However, their performance

Time	State	Vital	Mask (MAE)	No Mask(MAE)
Morning	Rest	HR	9.4 bpm	$7 \mathrm{\ bpm}$
		$SpO_2$	2.7%	3%
		SBP	8.1 mmHg	10.3 mmHg
		DBP	5.7  mmHg	8.4 mmHg
Morning	Post Exercise	HR	6.3 bpm	9.7 bpm
		$SpO_2$	2.3%	2.3%
		SBP	9 mmHg	$7.3 \mathrm{~mmHg}$
		DBP	3.6 mmHg	$3.3 \mathrm{~mmHg}$
Evening	Rest	HR	5.25 bpm	8.25 bpm
		$SpO_2$	2.7%	2.7%
		SBP	11.75 mmHg	15  mmHg
		DBP	1.5 mmHg	4 mmHg
	Post Exercise	HR	6.3 bpm	6.6 bpm
Evening		$\mathrm{SpO}_2$	2.3%	2.3%
		SBP	$9 \mathrm{mmHg}$	10.6  mmHg
		DBP	4.3 mmHg	4  mmHg
Mean		HR	6.8 bpm	7.9 bpm
		$SpO_2$	2.5%	2.5%
		SBP	9.4 mmHg	10.8 mmHg
		DBP	3.8 mmHg	4.9 mmHg

 Table 2. Validating the framework accuracy.

 Table 3. Validating robustness of the framework with different light sources and camera resolutions.

		Light(MAE	)	Camera Resolution(MAE)			
	Daylight	Warm Tone	Cool Tone	0.3MP	$2 \mathrm{MP}$	8MP	
$\mathbf{HR}$	2.1 bpm	7 bpm	6.2 bpm	13.8 bpm	$6.1 \mathrm{\ bpm}$	8.2 bpm	
SpO2	3%	3%	3%	3%	3%	3%	
SBP	5.9  mmHg	9.8 mmHg	5  mmHg	2.1 mmHg	2 mmHg	3.4  mmHg	
DBP	4.2  mmHg	6.1 mmHg	5.8  mmHg	6.1  mmHg	1.4 mmHg	3 mmHg	

**Table 4.** Validating the performance of the framework for different networks, devicesand browsers.

		Back-end processing time	System response time
Network	Wifi Network	47.9 secs	84.5 secs
	Wifi Network Mobile Network	50.1  secs	86.0 secs
Devices	Acer laptop	50 secs	114 secs
	Alienware laptop	46.5  secs	104.5 secs
	Samsung phone	48.7 secs	107.5 secs
	Redmi phone	47.9 secs	116.7 secs
	iPhone	48.3 secs	111.2 secs
	iPad	43 secs	198 secs
Browser	Google Chrome	48 secs	84.4 secs
	Mozilla Firefox	46.5 secs	104.55 secs
	Microsoft Edge	50.9 secs	93.47 secs
	Safari	46 secs	91.2 secs

degrades when movement or illumination changes affect the videos. Moreover, researchers have usually focussed on one or two vitals in validating their experiments [11,29]. We propose a web-based, publicly accessible ubiquitous framework for estimating six vitals namely, Heart Rate (HR), Heart Rate Variability (HRV), Respiration Rate (RR), Oxygen Saturation (SpO<sub>2</sub>), Blood Pressure (BP), and stress, which handles movement and illumination artifacts prevalent in real life. We validate the accuracy, robustness, usability and functionality of the rPPG models in estimating the vitals from face videos.

As future work, ways to enhance the video quality need to be explored so that low resolution camera devices can be used over weak networks at remote locations. Better camera control can be used to optimize the frame rate for video capture. Videos can be live streamed using WebRTC technology to reduce processing delay instead of recording and uploading to the back end server. Further noise reduction due to facial movements can be explored in the future along with a study design to be executed at the hospital for a wider patient sample having varying vital sign measurements, which can help build a robust technology to deploy at a healthcare setting.

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