ISSN (Online) 2456 -1304

International Journal of Science, Engineering and Management (IJSEM)

Volume 12, Issue 06, June 2025

Non-Invasive Cardiac Output Estimation Using Machine Learning-Driven Pulse Contour Analysis from PPG Signal

[1] Soorya K B, [2] Dr. Anjali S Nair

[1] [2] Department of Instrumentation and Control Engineering NSS College of Engineering, Palakkad, Kerala, India
* Corresponding Author's Email: [1] sooryababuraj19@gmail.com

***Abstract*— Cardiac output (CO) is a crucial indicator of cardiovascular function, traditionally measured with invasive techniques like thermodilution and pulse contour. These precise measures are technically challenging and non-continuous. The present work proposes a machine learning approach of non-invasive estimation of CO from photoplethysmogram (PPG) signals. The approach relies on low-pass filtering PPG signals and arterial pressure waveform reconstruction using a 1D Convolutional Neural Network (1D-CNN). Cardiac output is approximated from waveform features like systolic peaks and pulse pressure. The system also encompasses backflow detection and valve strength estimation to provide longer term physiological information. It was tested on the BIDMC dataset and demonstrates real-time usefulness, designed to improve patient safety and aid current hemodynamic monitoring.**

***Index Terms*— Cardiac output, photoplethysmogram (PPG), pulse contour analysis, non-invasive monitoring, arterial pressure waveform, machine learning, 1D convolutional neural network (1D-CNN), backflow detection, valve strength estimation, real-time biomedical signal processing.**

I. INTRODUCTION

Cardiac output (CO) is one of the vital physiological parameters that reflect the heart's ability to deliver oxygenated blood to the body. CO is the sum of stroke volume (SV)—amount of blood ejected from the left ventricle during a beat—and heart rate (HR) and is most commonly recorded in liters per minute. True and instantaneous measurement of cardiac output is of significant importance in most clinical settings like monitoring in intensive care, surgery, and treatment of cardiovascular diseases like heart failure, sepsis, and hypertension. Monitoring CO is also essential in the titration of drugs, resuscitation, and hemodynamic assessment of the patient.

Some of the older techniques for measuring cardiac output include the use of the thermodilution technique via a SwanGanz catheter and the Fick principle, which are invasive and are used mainly in intensive care because they are complicated and have a high risk factor. While pulse contour analysis (PCA) is a semi-invasive technique by analysis of the arterial pressure waveform contour for stroke volume determination, it is invasive with catheterization and needs intermittent invasive reference calibration, limiting its use to non-critical settings, or continuous prolonged monitoring.

The demand for ongoing, non-invasive and harmless cardiovascular monitoring has fueled the interest in alternative biosignals and machine learning. In them, photoplethysmogram (PPG) has gained a lot of attention since it is noninvasive, simple to record, and widespread in wearables. PPG signals are optical recordings of volumetric blood volume changes of blood within the microvascular bed of tissue and are rich in information regarding cardiac cycle dynamics. However, it is still challenging to estimate cardiac output directly from PPG due to the indirect nature of the signal and their vulnerability to noise and artifacts.

Deep neural networks such as convolutional neural networks (CNNs) have been found to have broad learning capacities of complex mappings of input signals to physiological values in recent advances in machine learning. The networks, depending on temporal and morphological characteristics of PPG signals, can simulate arterial pressure waveforms and hence enable pulse contour analysis independently of invasive measurement. In this paper, a new non-invasive cardiac output estimation by machine learning-based pulse contour analysis of PPG waveforms is presented. The method includes collection of raw PPG data, preprocessing of signals by removing highfrequency noise with low-pass filtering, and reconstruction of waveform using a 1D Convolutional Neural Network as training data with labeled PPG–arterial pressure waveform pairs. The cardiac output is finally obtained from waveforms as extrapolated from mitral and pulse pressure signatures for heart rate and pulse pressure respectively. Detection of valve regurgitation patterns in blood flow through the dysrhythmic states, and aortic and functional mitral valve strengths, is also included as part of the system.

The model is validated on publicly released BIDMC Congestive Heart Failure Database with synchronized PPG and arterial blood pressure data for training and testing supervised models. Real-time usage emulation is implemented with an Arduino-based PPG acquisition platform to demonstrate the applicability of real-time monitoring. The designed solution is a non-invasive, adaptive, and interpretable continuous cardiac output monitoring solution of interest in clinical settings, home healthcare, and wearable health technology.

II. MATERIALS AND METHODS

A. Real-Time Signal Acquisition

To validate the operation of the system in real-time, a hardware platform was developed using a fingertip pulse sensor connected to an Arduino Uno microcontroller. The pulse sensor detects volumetric changes in peripheral circulatory blood through optical principles. The onboard analogto-digital converter of the Arduino converts the PPG signal from analog to digital and sends it to a host computer via a serial link. Python and PySerial library were used to capture the data stream and process it in real-time. The setup simulates an actual setting in which PPG data can be obtained and processed continuously without invasive devices.[1],[7]

B. Signal Preprocessing

BIDMC and real-time PPG signals were preprocessed for quality and stability prior to analysis. A fourth-order Butterworth low-pass filter with a cutoff frequency of 4 Hz was applied to remove high-frequency noise, baseline drift, and motion artifacts [2]. This frequency boundary was chosen to preserve important cardiac frequency components and reject unwanted distortions. The filtering process resulted in a more smoothed PPG waveform wherein systolic peaks, dicrotic notches, and diastolic decay were easily identifiable. Filtered signals gave consistent inputs to peak detection and machine learning-based waveform estimation.

C. Arterial Waveform Estimation Using 1D-CNN

One-dimensional convolutional neural network (1D-CNN) was utilized to forecast the arterial pressure waveform from filtered PPG signals. Five-second segments of PPG were utilized as input and matching segments of ABP as output to train the model. The network included a number of convolutional layers with pooling and dense layers, enabling the extraction of temporal patterns and morphological characteristics in the signal [3],[4]. The model was trained using the mean squared error loss function in order to minimize the difference between true and predicted arterial waveforms. After training, the model was found to be able to reconstruct pressure waveforms that maintained key features such as systolic upstrokes, dicrotic notches, and diastolic runoff curves.

D. Cardiac Output Estimation

Cardiac output was derived from the reconstructed arterial waveform based on heart rate and assumed stroke volume. Heart rate was derived from the duration of two consecutive systolic peaks. Stroke volume was derived from the area under each systolic segment of a cardiac cycle in the predicted waveform. Cardiac output was derived as stroke volume times heart rate. These values were established against physiological norms such that the system outputs would lie between healthy clinical parameters, typically 4 and 8 liters per minute for a healthy resting adult [1],[5],[13].

E. Backflow Detection and Valve Strength Estimation

To assess for potential valvular disease, reconstructed arterial pressure tracings were inspected for signs of backflow patterns and waveform changes. Backflow was looked for by the presence of secondary pressure peaks in the diastolic phase of the cardiac cycle, which could be indicative of regurgitation through insufficiency of the mitral or aortic valves. Aortic valve function was approximated from amplitude and slope of systolic upstroke, and mitral valve function from decay pattern and turbulence in the diastolic phase. The recordings were beat-to-beat and allowed variability in valve function over time to be measured [6],[8].

F. Correlation Analysis and Clinical Interpretation

Quantitative analysis was invoked in correlating extracted physiological parameters. In other words, valve strength and heart rate, and valve strength and volume of backflow were correlated. The magnitude and direction of correlations suggested information about the functional cardiac valve response with varying physiological states. A clinical interpretation table was extracted from the correlation coefficients determined, correlating each pattern with the possible underlying cardiac conditions. The integration of machine learning, physiology, and signal processing enables an interpretable and transparent model for cardiovascular monitoring in a non-invasive manner [9],[14],[15].

III. RESULTS AND DISCUSSIONS

Hardware setup real-time PPG and pre-recorded PPG-ABP pairs from the BIDMC database were utilized in order to assess the system. Filtered through a 4 Hz low-pass filter, PPG signals produced better morphology with well-resolved systolic peaks and more gradient-like diastolic fall-off. Reconstruction of artery pressure waveform with very close shape and time to the original ABP was possible using the 1D Convolutional Neural Network (1D-CNN).

Cardiac output (CO) was estimated by sampling peak systolic, pulse pressure computation, and area under curve measurement per beat. Calculated values of CO fell within physiological parameters of 4–8 L/min for patient samples collected at various time points and for real-time measurements. CO variations corresponded with changes in heart rate and with alterations in morphology of the waveform.

Quantitatively and graphically, backflow detection was confirmed. Potentials showing a secondary peak in the diastolic phase were noted as likely regurgitation. They showed negative correlations with aortic and mitral valve strength parameters. 662 beats in a single real-time session showed potential backflow, and thus the clinical application

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Volume 12, Issue 06, June 2025

of the model was acceptable. Valve strength analysis also showed aortic valve to be more pointed and of larger upstroke size, while mitral valve was more beat-to-beat varying.

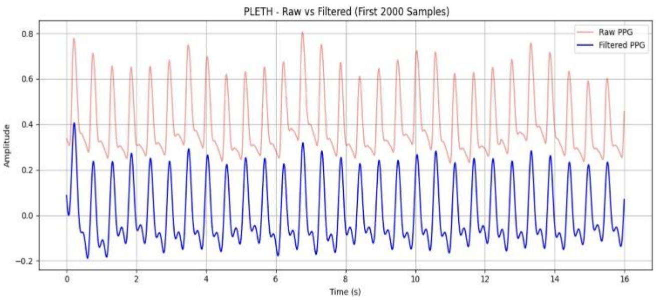

Fig. 1. Filtered data

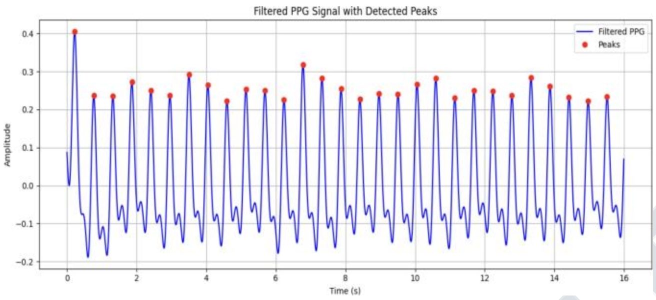

Fig. 2. Peak detection

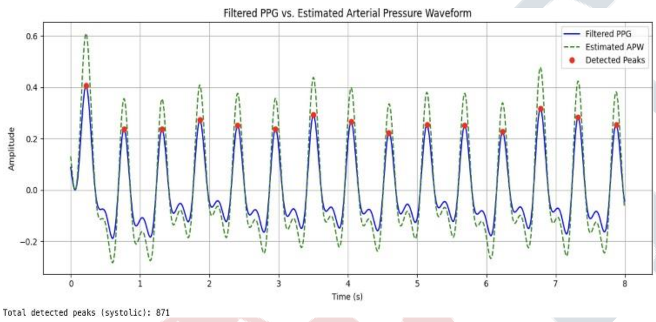

Fig. 3. Estimation of arterial waveform

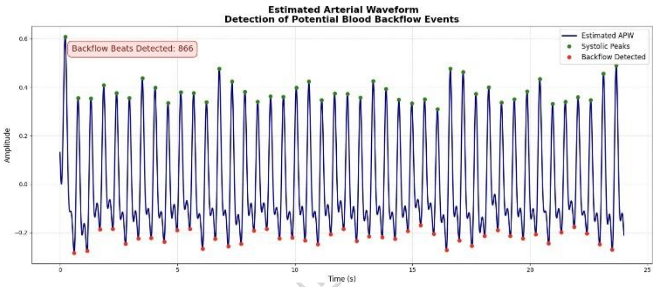

Fig. 4. Backflow detection

Correlation analysis also validated strong negative correlation with valve strength vs. backflow volume, along with heart rate with moderate negative correlation, pointing towards near-failure or fatigue in high frequency.

Scatter plots and interpretation tables were employed to plot the dose-response curve for the cardiac health indicators against the physiological indicators. Results confirm the ability of the system not only to produce CO values but also to produce additional diagnostic data on valvular function and integrity of blood passage.

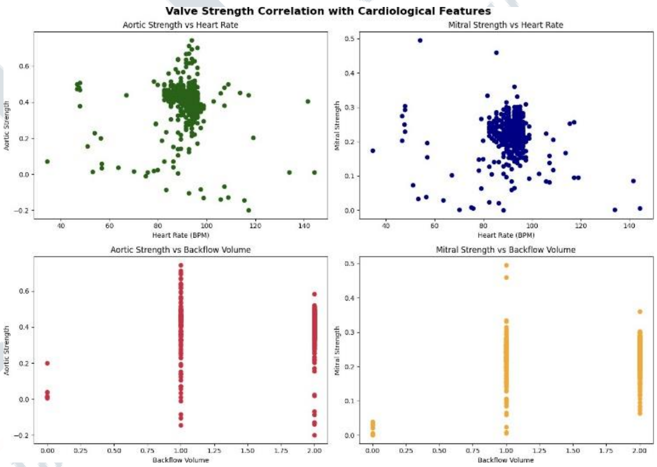

Fig. 5. Valve strength Analysis

Table I. Valve Strength vs Heart Metrics: Diagnostic Interpretation

Metric	Corr. Coeff.	Interpretation	Potential Pathology
Aortic Strength vs HR	0.02	Aortic valve stable under varied HR.	Normal
Mitral Strength vs HR	-0.04	Weakening under high HR; early fatigue.	Risk of Mitral Valve Prolapse
Aortic Strength vs Backflow	0.14	More backflow as aortic valve weakens.	Possible Aortic In-sufficiency
Mitral Strength vs Backflow	0.23	Indicates mitral regurgitation risk.	Mitral Regurgitation
Backflow vs HR	0.30	HR rise may compensate for backflow.	Early Heart Failure / Stress

IV. CONCLUSION

This paper presents a completely non-invasive, machine learning-based method for cardiac output estimation from PPG signals through pulse contour analysis. Real-time beat-to-beat cardiac output is enabled through the application of a 1DCNN for arterial waveform reconstruction from band-pass filtered PCG without invasive calibration. Clinical usefulness is further augmented by backflow detection and valve strength estimation for the identification of early valvular dysfunction. Validated with publicly available clinical data sets and realtime sensor data, the system holds enormous potential for use in critical care, wearable health monitoring, and remote health deployment. There are plans to conduct clinical trials, multi-signal fusion (e.g., ECG + PPG), and optimization on embedded real-time platforms.

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