# Enabling Intelligent Resuscitation: Non-Invasive Cardiac Output Monitoring via Physiological Sensing and Machine Learning

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***Abstract*—Accurate, continuous monitoring of cardiac output (CO) is crucial for effective resuscitation management in hemorrhagic trauma, yet current gold-standard methods are invasive and impractical in field settings. This study introduces a fully non-invasive and wearable sensing-based approach utilizing electrocardiography (ECG), seismocardiography (SCG), and photoplethysmography (PPG) signals, integrated with machine learning algorithms, to enable stroke volume (SV) and CO estimation without requiring baseline calibration or normalization. This critical feature makes the model especially suitable for casualty care scenarios where baseline measurements are often unavailable. The proposed methodology was evaluated on a porcine model (n=6) subjected to controlled hemorrhage and resuscitation protocols. Clinically-validated cardiovascular features were used as inputs for regression models, including linear, ridge, LASSO, random forest, and XGBoost regressors. Among these, the LASSO demonstrated the best performance, achieving a high correlation ($R = 0.79$) and a mean absolute percentage error (MAPE) of $14.31\%$, well within clinically-acceptable limits for non-invasive CO monitoring. The framework reliably tracked SV trends crucial for clinical decision-making during resuscitation scenarios. This work highlights the potential for intelligent, non-invasive CO monitoring systems to improve clinical and trauma care outcomes.**

***Index Terms*—Hemodynamic monitoring, hypovolemia, resuscitation, cardiac output, stroke volume, seismocardiogram**

## I. Introduction

Hemorrhage remains a leading cause of preventable death in both military and civilian trauma scenarios [1]. Rapid detection and management of blood loss are essential to prevent complications such as absolute hypovolemia, a critical condition marked by severely-reduced blood volume. Effective hemorrhage resuscitation requires restoring adequate blood volume (BV) and tissue perfusion, which depends on accurate CO monitoring. However, direct and continuous measurement of CO is rarely feasible outside of the highly-invasive methods used in intensive care units (ICU) and operating rooms (OR).

In the absence of direct CO monitoring, blood pressure (BP) is often used as a surrogate during resuscitation. However, BP is an indirect and often unreliable indicator of circulating blood volume (BV), as it remains maintained near normal levels through the body's compensation mechanisms until the patient reaches a critically decompensated state. This delay means that BP only significantly drops once these compensatory systems fail, increasing the risk of both under- and over-resuscitation. This underscores the need for continuous, non-invasive, and accurate methods for estimating CO to support data-driven resuscitation decisions.

The current clinical gold standard for CO measurement (i.e., catheter-based thermodilution) is invasive, making it unsuitable for many emergency settings [2]. Recent advances in wearable sensing technologies enable non-invasive continuous monitoring of cardiovascular dynamics. Among non-invasive options, although echocardiography and MRI provide accurate cardiac output measurements, they are costly and unsuitable for continuous monitoring. Moreover, impedance cardiography (ICG) suffers from decreased accuracy in patients with high body mass index (BMI), while photoplethysmography (PPG), similar to ICG, faces challenges such as motion artifacts and limited reliability in critical care settings [3]. In contrast, although electrocardiography (ECG), seismocardiography (SCG), and PPG signals can each be affected by noise, combining them in a multimodal approach with machine learning enables more robust, non-invasive, continuous estimation of hemodynamic parameters, offering a promising strategy for CO estimation [4].

Several studies have explored this direction. Roha et al. [5] showed that ECG and PPG signals, utilizing 1-D CNN, can indirectly estimate CO for individuals with hypertension by first estimating SV and then multiplying it with HR, outperforming direct CO and BP-based methods. Pastor et al. [2] used PPG signals to classify CO as high or low with $88\%$ accuracy. Ke et al. [6] applied random forest and XGBoost models using arterial pressure waveforms and demographic data, achieving an MSE of $1.42$ L/min for CO estimation. Palanques-Tost et al. [7] used ICU datasets and a custom CORE model, reporting a MAPE of $14\%$. Bikia et al. [8] employed synthetic datasets and ensemble models to estimate aortic pressure and CO with a normalized RMSE of $7.5\%$.

While prior studies have made significant progress toward CO estimation, continuous estimation of CO using SCG signals remains limited in the literature. Although SCG has been used for CO estimation in congenital heart disease populations

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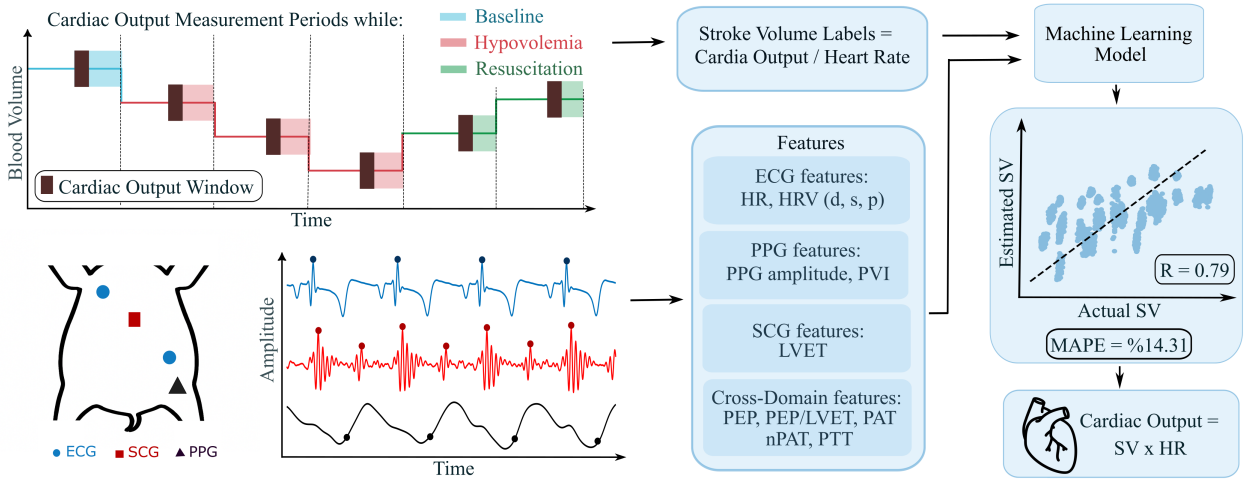


Fig. 1. Overview of the methodology: ECG, SCG, and PPG signals were recorded during baseline, hypovolemia, and resuscitation phases, with key features extracted from each modality within a 100-beat cardiac output window. These features were used to train a machine learning model to estimate stroke volume, which was combined with heart rate to calculate cardiac output.

[9], and for SV estimation in peri-operative scenarios [10], to the best of our knowledge, it has not been studied in the context of hemorrhage and resuscitation. Building on these efforts, our study presents a fully non-invasive, wearable sensor-based framework for continuous estimation of CO using ECG, SCG, and PPG signals. Evaluated on a porcine model (n=6), our approach performs beat-by-beat regression without requiring baseline calibration or normalization, allowing continuous hemodynamic monitoring.

## II. Methods

### A. Experimental Protocol

Six Yorkshire pigs (three males, three females; 51.5–71.4 kg) were included under a protocol approved by the Georgia Institute of Technology, T3 Labs, and the Department of the Navy BUMED. Anesthesia was induced with Xylazine and Telazol, and maintained via inhaled isoflurane during mechanical ventilation. Baseline blood volume was estimated using Evans Blue dye, followed by a second blood sample after distribution. Hypovolemia was induced by passively drawing blood through a venous line in 7% increments, with 5–10 minute stabilization pauses at each level. Blood withdrawal was stopped upon a 20% drop in mean aortic root pressure (MARP), indicating cardiovascular collapse. Resuscitation followed the same 7% incremental steps in reverse, again with 5–10 minute monitoring periods. At the end of each interval, CO was measured via thermodilution using a Swan-Ganz catheter. Throughout the protocol, ECG, SCG, and PPG signals were continuously recorded at 2 kHz using a Biopac system (BIOPAC Systems Inc., Goleta, CA, USA).

### B. Signal Pre-Processing and Feature Extraction

Single-lead ECG, dorsoventral SCG, and PPG signals collected throughout the protocol were filtered using linear-phase finite impulse response (FIR) digital bandpass filters with a Kaiser window. Cutoff frequencies were set to 0.5–40 Hz for ECG, 1–40 Hz for SCG, and 0.5–10 Hz for PPG signals. Following filtering, each signal was segmented into individual heartbeats with respect to ECG R-peaks. Three sensing modalities—electrical (ECG), mechanical (SCG), and optical (PPG)—were used to assess the cardiovascular function of the subjects during hemorrhage and resuscitation. From these modalities, twelve clinically validated features were extracted for each heartbeat, including both modality-specific and cross-domain features similar to the previous studies [11]. Fiducial points were identified from each signal: the R-peak from the ECG, the aortic opening (AO) and aortic closing (AC) points from the SCG, and the amplitude and foot points from the PPG signal (Fig. 1). From ECG, heart rate (HR) and three heart rate variability (HRV) measures were extracted: time-domain HRV as the standard deviation of de-trended R-R intervals over 5-minute windows; Poincaré HRV via the ratio of the first two eigenvalues of the covariance matrix; and frequency-domain HRV from the low-to-high frequency power ratio of an FFT-upsampled window. From SCG, the pre-ejection period (PEP, R-peak to AO), left ventricular ejection time (LVET, AO to AC), and the PEP/LVET ratio were extracted to assess cardiac contractility. From PPG, PPG amplitude (PPGamp), pulse arrival time (PAT, R-peak to foot), normalized PAT (nPAT = PAT/R-R interval), pulse transit time (PTT = PAT – PEP), and pleth variability index (PVI), defined as amplitude variation over respiratory cycles were computed.

All extracted features were calculated on a beat-to-beat basis and used for subsequent analysis of cardiovascular responses to hemorrhage and resuscitation.

### C. Label Assignment

CO measurements were obtained at the end of each hemorrhage and resuscitation step using the thermodilution method. To account for dynamic physiological changes within each monitoring interval, a window of 100 heartbeats starting from the time of the CO measurement was selected, and the

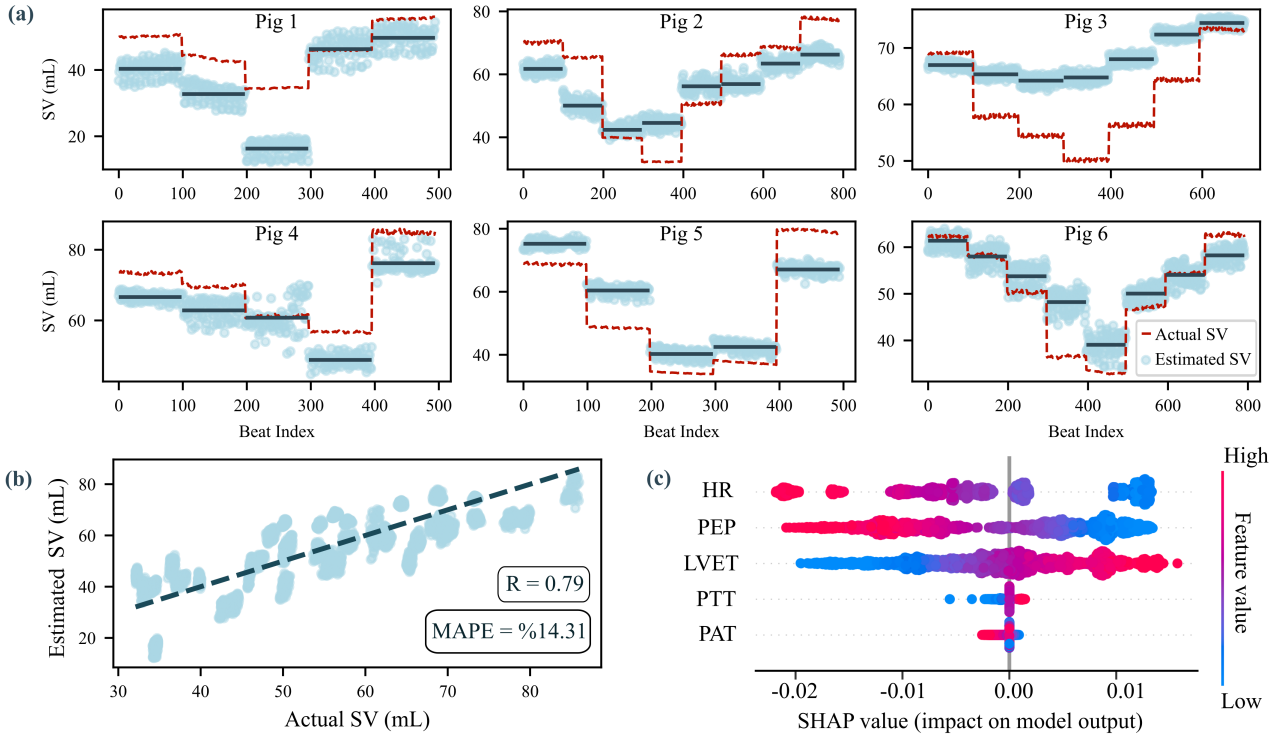


Fig. 2. Results of the LASSO model for stroke volume (SV) estimation: (a) Subject-wise results with leave-one-subject-out cross-validation (LOSO-CV). Actual SV is shown as a red dotted line, estimated SV as light blue dots, and the mean estimate for each blood removal/resuscitation phase as a dark blue line. (b) Aggregated predicted versus actual SV results for the best-performing model (c) SHAP values of the five most important features, illustrating their impact on model output and ranked by feature importance.

extracted features within this window were labeled with the corresponding CO value. Then, SV labels were calculated by dividing the CO values by the corresponding HR.

### *D. Regression Modeling*

To estimate SV, multiple regression models were developed using features extracted from ECG, SCG, and PPG signals. Five regression models were evaluated, and all models were trained with leave-one-subject-out cross-validation (LOSO-CV). Linear regression was included as a baseline to provide a simple and interpretable comparison. Ridge and LASSO were used to incorporate regularization, with LASSO also offering inherent feature selection to eliminate irrelevant or less informative features, which is an important consideration given that some extracted features may not directly contribute to SV estimation.

Ensemble models, including random forest and XGBoost, were also evaluated due to their ability to model complex, non-linear relationships and their previous success in predicting blood volume decompensation status using the same dataset [11] . All models were trained to provide beat-by-beat SV predictions, allowing continuous monitoring of cardiovascular function.

## III. Results and Discussion

SV estimation results are reported in Fig. 2. From the subject-wise estimation results, it is evident that the estimated SV values closely follow the same trends observed in the ground truth SV values. Aggregating results across all subjects, the SV estimation model achieved a high correlation (R = 0.79) and low MAPE (14.31%). The SHAP (SHapley Additive exPlanations) values for the five most important features are also presented in Fig. 2. These results align well with existing literature, emphasizing the importance of SCG features known to indicate cardiovascular contractility [4], [12].

RMSE (mL/beat), MAPE, and R scores are summarized in Table I, which details LOSO-CV results. The mean of subject-wise RMSE scores was reported as the aggregated result, while MAPE and R were recalculated from aggregated plots. Among the tested models, LASSO provided the highest R score and the lowest MAPE, ranging from 9.68% to 22.58%, with an aggregated MAPE of 14.31%. This performance is significantly better than the clinically acceptable range for non-invasive measurements (i.e., 30%) [2].

The superior performance of the LASSO can be attributed to its L1 regularization capability, effectively zeroing out noisy features from individual subjects. Given potential issues with signal quality across subjects, a multimodal approach provides robust SV estimation. Utilizing multiple modalities ensures that even if one signal is compromised, other signals can maintain accurate estimations. In ideal scenarios, combining different modalities provides diverse cardiovascular insights, particularly beneficial during hemorrhage and blood transfusion events.

TABLE I
SV ESTIMATION PERFORMANCE RESULTS

| Pig Index | Linear Regression | | | LASSO | | | Ridge Regression | | | Random Forest | | | XGBoost | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | RMSE | MAPE | R | RMSE | MAPE | R | RMSE | MAPE | R | RMSE | MAPE | R | RMSE | MAPE | R |
| 1 | 17.20 | 33.97 | 0.89 | 11.04 | 22.58 | 0.90 | 16.44 | 32.58 | 0.89 | 7.94 | 13.50 | 0.83 | 8.54 | 13.67 | 0.90 |
| 2 | 12.64 | 23.32 | 0.66 | 9.72 | 15.91 | 0.85 | 10.62 | 19.98 | 0.84 | 8.01 | 14.39 | 0.92 | 8.30 | 14.64 | 0.92 |
| 3 | 18.61 | 29.84 | 0.33 | 9.07 | 13.99 | 0.76 | 18.54 | 29.68 | 0.31 | 5.75 | 8.18 | 0.88 | 8.59 | 13.12 | 0.88 |
| 4 | 22.09 | 31.47 | 0.87 | 7.23 | 9.62 | 0.92 | 22.69 | 32.51 | 0.87 | 10.40 | 12.43 | 0.88 | 13.31 | 16.07 | 0.85 |
| 5 | 14.68 | 30.08 | 0.84 | 8.98 | 16.01 | 0.89 | 12.40 | 24.16 | 0.86 | 9.45 | 12.20 | 0.86 | 9.18 | 10.88 | 0.87 |
| 6 | 4.07 | 7.17 | 0.92 | 5.45 | 9.68 | 0.92 | 4.31 | 7.31 | 0.92 | 16.20 | 29.74 | 0.80 | 9.28 | 16.80 | 0.84 |
| **All** | 15.25 | 24.48 | 0.55 | **8.65** | **14.31** | **0.79** | 14.64 | 22.95 | 0.57 | 10.45 | 15.81 | 0.70 | 9.50 | 14.38 | 0.74 |

From the SHAP results, the five most important features for SV estimation were identified as HR, PEP, LVET, PTT, and PAT. HR tends to have an inverse relationship with SV as higher HR requires shorter filling times. PEP reflects myocardial contractility, venous return, and sympathetic activity; longer PEP can indicate lower cardiac contractility, correlating with reduced SV and CO. In hemorrhagic conditions, cardiac contractility initially increases as a compensatory response to blood loss but tends to decline as the subject progresses toward decompensation. LVET, indicative of ventricular function and contractility, is intrinsically tied to SV. A shortened LVET typically suggests reduced SV or compromised cardiac performance, thus directly influencing CO estimation. PAT and PTT are well-established indicators correlated with blood pressure [13] and were found to be important for SV estimation. However, these features exhibited inconsistent behavior during the hemorrhage and resuscitation phases, making their contributions to the model less impactful compared to the consistently-performing SCG features.

A critical advantage of the proposed model is that it does not require normalization, which makes it particularly suitable for casualty care scenarios where baseline measurements may be unavailable. The algorithm successfully demonstrates accurate beat-by-beat estimation of SV within clinically-acceptable ranges. Importantly, the model reliably identifies trends in SV values, indicating whether they are increasing or decreasing. This capability is crucial for decision-making regarding the initiation and cessation of blood transfusions.

## IV. CONCLUSION

This work explored algorithms for continuous and non-invasive estimation of CO. By leveraging features extracted from cardiac signals, SV was estimated with an MAPE of $14.31\%$, which falls within the clinically acceptable range for non-invasive CO measurement. Notably, this level of accuracy was achieved without applying any baseline normalization, highlighting the potential of the proposed approach for use in real-world trauma scenarios where rapid, calibration-free monitoring is essential.

## V. DISCLOSURES

O. T. Inan holds equity in Physiowave, Cardiosense, and Biozen, manufacturers of cardiovascular sensing devices.

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