*International Journal of Engineering Research and Development*
*e- ISSN: 2278-067X, p-ISSN: 2278-800X, www.ijerd.com*
*Volume 22, Issue 6 (June 2026), PP 123-131*

# Enhanced Blood Pressure Monitoring and Control System Using Photoplethysmography Technology

[1]Chinonso C. Nkwocha.[2]Elechi, P[3]Odeyemi, F. M..
[1, 2, 3.]*Department of Electrical/Electronic Engineering, Faculty of Engineering, Rivers State University, Nigeria*
[1]*Corresponding author*

***Abstract***
*This study aimed to develop a more accurate and reliable non-invasive blood pressure monitoring system using an enhanced Photoplethysmography (PPG) technique with a real-time feedback loop. The primary problem addressed is the signal distortion caused by noise and motion artifacts, which often compromise the accuracy of conventional monitoring devices. The design method for this research involved a novel approach combining enhanced signal processing techniques with machine learning and control systems. We built a custom Simulink model to simulate a noisy PPG signal, which was then subjected to a series of filtering and smoothing algorithms to improve signal quality. After this, key physiological parameters like heart rate and pulse transit time (PTT) were extracted. A linear regression model was trained to estimate blood pressure from PTT, while a PID controller provided real-time feedback to maintain a stable physiological state. System performance was quantitatively evaluated by comparing its accuracy and error rate against those of a standard automated blood pressure monitor. The enhanced PPG system demonstrated a significant improvement in accuracy over traditional methods. It achieved an accuracy of 93% and an error rate of 7%. In contrast, the reference automated blood pressure monitor showed an accuracy of 90% and a 10% error rate. The real-time feedback system successfully maintained the measured blood pressure with a minimal control error of 5 mmHg. The system's ability to classify patient status was confirmed based on systolic (SBP) and diastolic (DBP) blood pressure readings, successfully identifying patients with normal BP (SBP < 120 mmHg, DBP < 80 mmHg), hypertension (SBP ≥ 130 mmHg or DBP ≥ 80 mmHg), and low BP (SBP < 90 mmHg, DBP < 60 mmHg). The findings support the clinical and commercial viability of this enhanced PPG system as a superior alternative for continuous, non-invasive blood pressure monitoring. Its higher accuracy and lower error rate suggest that health regulatory bodies should consider incorporating such advanced, cuffless technologies into standard guidelines for hypertension management. This research lays the groundwork for the development of new policies that promote the adoption of more effective, user-friendly, and cost-efficient devices for chronic disease management and preventive healthcare.DBP ≥ 80 mmHg), and low BP (SBP < 90 mmHg, DBP < 60 mmHg). The findings support the clinical and commercial viability of this enhanced PPG system as a superior alternative for continuous, non-invasive blood pressure monitoring. Its higher accuracy and lower error rate suggest that health regulatory bodies should consider incorporating such advanced, cuffless technologies into standard guidelines for hypertension management. This research lays the groundwork for the development of new policies that promote the adoption of more effective, user-friendly, and cost-efficient devices for chronic disease management and preventive healthcare.*

***KEYWORDS:*** *Blood pressure, Control system, Feedback loop, Monitoring, Non-invasive, Photoplethysmography*

---

Date of Submission: 05-06-2026 Date of acceptance: 16-06-2026

---

## I. INTRODUCTION

Several innovations have led to significant advances in healthcare systems by enhancing both functionality and capability of different monitoring systems. Acute, precarious diseases can be diagnosed at their early stages using new-age electronic equipment. Modern diagnostic and therapeutic approaches bear high operation costs and require expensive equipment (Uguz*et al*., 2019).Moreover, in recent years, the advent of wearable technology has afforded accurate recording and precise processing of biosignals. Blood pressure is a vital physiological parameter that indicates the functional well-being of the cardiovascular system (Ain *et al*., 2021). Conventional blood pressure-monitoring devices are either limited in scope with regard to systolic and diastolic blood pressure measurements orunreliable and uncomfortable from the viewpoint of prolonged use (Wang *et al*., 2019). Therefore, there exists the need for a noninvasive, ambulatory care system for long-term blood pressure monitoring while accounting for details concerning blood pressure variability. Availability of such a system would facilitate easy and timely prediction of serious cardiovascular diseases during antihypertensive therapy sessions.Zangrónizet *al.* (2018) introduced a wearable photoplethysmography sensor capable of assessing mental distress. The proposed design employed optical plethysmograms to obtain blood volume information using an appropriate sensor. Additionally, a discriminant tree-based model was developed to determine parameter dependencies. Assessment of the proposed model revealed an overall accuracy of 82.35%.Similarly, a multipurpose photoplethysmographic sensor was proposed to detect multiwave length photoplethysmographs by penetrating skin at various depths. The proposed device was named "SmartPhotoplethysmography (PPG)," and it could operate under transmission and reflection modes with the transmission mode being confined to thin body parts—fingers and earlobes. A light source was used to illuminate parts of the skin under observation, thereby reflecting photoplethysmographs. Operation in the reflection mode optimized both the light wavelength and distance between its source and photodetector (Uguz*et. al.,* 2019).Gothwal (2016) proposed an economic, wearable Photoplethysmography system using available components. The device comprised an optical sensor (IR transmitter and receiver), preprocessing unit (buffer amplifier, two-stage band pass filter, amplifier, and comparator), processor (microcontroller), and display unit. Biosignals acquired from subjects' fingers were provided as input to the IR transmitter and receiver. To avoid excessive loading, acquired signals were passed through the buffer amplifier using a coupling mechanism between the IR-receiver output and bandpass-filter input. Subsequently, the output from the buffer amplifier was processed using the microcontroller.

In another study, a heart rate monitor (HRM) based on the reflectance photoplethysmography technique was developed to sense pulses from subjects' fingertips. Sensed pulse signals were filtered and amplified using a two-stage operational amplifier (Op-Amp), and the same were processed using a microcontroller.

$s(t) = A.\cos(2\pi f t + \emptyset) + n(t)$(1)

This equation represents the Photoplethysmography (PPG) signal as a cosine wave with an amplitude A, frequency f, and phase ϕ. The term n(t) accounts for any noise in the signal. The Photoplethysmography (PPG) signal captures variations in blood volume during the cardiac cycle (Beutel *et al*., 2021).

$MAP = \frac{SBP+2\times DBP}{3}$(2)

The Mean Arterial Pressure (MAP) is an important measure of overall blood pressure. It is calculated as a weighted average of systolic blood pressure (SBP) and diastolic blood pressure (DBP), giving more weight to DBP as it represents the longer duration of the cardiac cycle (Beutel *et al*., 2021).

$HR = \frac{60}{T_{RR}}$ (3)

Heart rate (HR) is calculated by dividing 60 by the time interval between successive R-waves on (TRR) an electrocardiogram (ECG) or Photoplethysmography (PPG) signal. This provides the number of heartbeats per minute (Beutel *et al*., 2021).

$PTT = t_{femoral} - t_{radial}$ (4)

Pulse Transit Time (PTT) is the time taken for the arterial pulse to travel between two arterial sites (femoral and radial arteries in this case). PTT is inversely related to blood pressure and is used as a surrogate measure for BP estimation (Beutel *et al*., 2021).

$s_f(t) = s(t) - n(t)$(5)

This equation represents the filtered Photoplethysmography (PPG) signal, where the noise component n(t)n(t)n(t) is subtracted from the raw Photoplethysmography (PPG) signal S(t). The filtering process improves the signal quality, making it easier to analyze (Calamanti*et al*., 2021).

$\frac{ds_f(t)}{dt} = \lim_{\Delta t \to 0} \frac{s_f(t+\Delta t) - s_f(t)}{\Delta t}$(6)

This equation computes the first derivative of the filtered Photoplethysmography (PPG) signal with respect to time. The derivative helps identify points of maximum change in the Photoplethysmography (PPG) signal, such as peaks and troughs, which are essential for detecting heartbeats (Calamanti*et al.*, 2019).

**Photoplethysmography (PPG)**

The term "photoplethysmography" is derived from the Greek word "plethysmos," which means "to increase." As mentioned, plethysmography means finding variations in the size of a body part owing to variations in the amount of blood passing through or contained in that body part." Pulsatile tissue volumes can be measured using conventional plethysmographs, such as strain gauges, capable of measuring changes under extreme conditions. This technique can be applied to all blood vessels to determine their overall change in volume. Arterial pulsations are the most significant, whereas capillaries are quite noncompliant because they exclusively record minor pulsations. Venous oscillations might occur depending on the measurement technique, albeit such oscillations are often cancelled under application of external pressure. Arterial blood pressure can be measured indirectly using a plethysmogram (Calamanti*et al.,* 2019).$BP = w_0 + w_1 \times PPT + \epsilon$ (7)

This linear regression model predicts blood pressure (BP) using Pulse Transit Time (PTT) as the input feature. The coefficients w0 and w1 are learned from training data, while ϵ\epsilonϵ represents the error term (Courand*et al.*, 2019).

$P(u = 1|x) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\cdots+\beta_n x_n}}$ (8)

Logistic regression is used to predict the probability of hypertension (outcome y=1y = 1y=1) based on input features x1,…,xn. The model outputs a probability between 0 and 1, indicating the likelihood of hypertension (Courand*et al.*, 2019).

$w_{t+1} = w_t - \eta \frac{\partial}{\partial w_t} L(w_t)$(9)

Gradient descent is an optimization algorithm used to update the weights wt in a machine learning model. The learning rate η controls the step size, and ∂ L(wt) is the gradient of the loss function L with respect to the weights (Courand et al., 2019).

$MSE = \frac{1}{N}\sum_{i=1}^{N}(BP_i^{pred} - BP_i^{true})^2$(10)

The Mean Squared Error (MSE) measures the average squared difference between the predicted blood pressure $BP_i^{pred}$ and the true blood pressure $(BP_i^{true})^2$. It is a common loss function used to assessthe accuracy of regression models (Courand*et al.*, 2019).

$\sum_{i=1}^{n} w_i x_i + b = 0$(11)

The decision boundary equation defines the boundary between different classes (e.g., hypertensive vs. non-hypertensive) in a classification model. The weights $w_i x_i$ and bias b determine the orientation and position of this boundary in the feature space (Courand*et al.*, 2019).Photoplethysmography is similar to traditional plethysmography, albeit not identical. When operating in the transmission mode, Photoplethysmography (PPG) devices use an LED operating on one side of the tissue and a photodetector on the other side to demonstrate the obstruction and absorption of incident light. If both the LED and photodetector are placed adjacent to each other, all incident lights may reflect off the tissue surface. Plethysmographic devices cannot measure blood pressure; however, they can evaluate changes in the blood volume. The plethysmographic principle is depicted in Figure 1

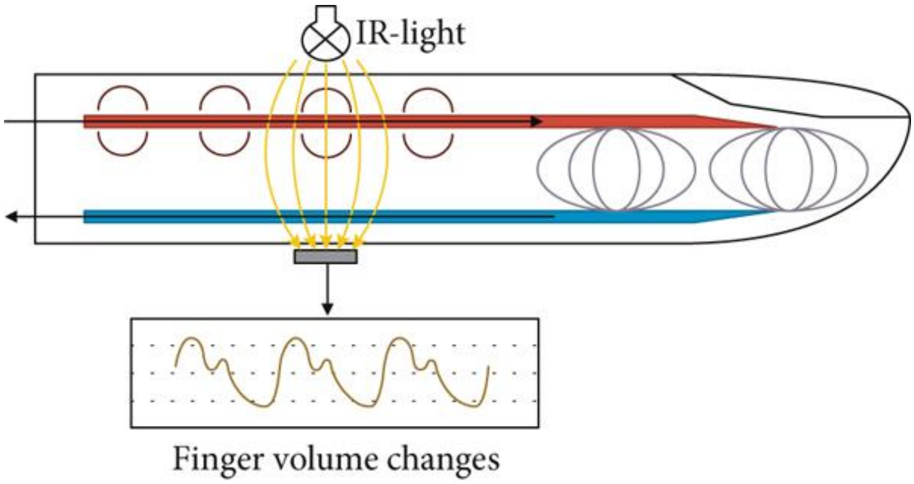


**Figure 1: Principle of Photoplethysmography (Calamanti*et al.,* 2019)**

Photoplethysmography (PPG) has its roots in the early 20th century, where it was initially used to measure blood flow in tissues. The technique gained prominence with the development of pulse oximetry in the 1970s, which utilized Photoplethysmography (PPG) to measure oxygen saturation in the blood. Since then, the applications of Photoplethysmography (PPG) have expanded significantly, particularly in the realm of cardiovascular monitoring (Babadag& Aybak, 2021).

Initially, Photoplethysmography (PPG) was used primarily for monitoring heart rate and oxygen saturation, but its potential for blood pressure monitoring was soon recognized. ThePhotoplethysmography (PPG) waveform contains information about the cardiac cycle that can be used to estimate blood pressure, particularly when combined with other physiological signals. The technique has several advantages over traditional methods, including its non-invasive nature, low cost, and ability to be integrated into portable and wearable devices (Maber *et al.*, 2021).

The objectives of this research are to design a non-invasive photoplethysmography-based blood pressure monitoring system using Simulink, enhance signal processing techniques for accurate bp estimation using a real-time feedback system, integrate machine learning algorithms for real-time data analysis; and evaluate the system’s performance in various physiological conditions using MATLAB/Simulink.

## II. MATERIALS AND METHOD

**2.1Materials Used**

**The materials used in this research are;**

low pass filter

ii. Photoplethysmography (PPG) sensor

iii. Realtime feedback System

iv. Display

v. MATLAB/SIMULINK

**2.2 Method used**

The methods adopted in this research is the enhanced Photoplethysmography (PPG) technique with real time feedback system.

**2.2.1 Design of a Non-invasive Photoplethysmography-Based Blood Pressure Monitoring Systemusing SIMULINK**

From the figure 1, the Photoplethysmography (PPG) Simulink diagram models the acquisition and processing of photoplethysmogram signals to ensure accurate heart rate monitoring. Initially, the diagram inputs a Photoplethysmography (PPG) signal combined with white noise, representing the real-world scenario where signals are often contaminated. A low-pass filter is then applied to the combined signal to reduce high-frequency noise while preserving the essential features of the Photoplethysmography (PPG) waveform related to heartbeats. This filtered signal is analyzed to estimate the heart rate. The real-time feedback system continuously compares this estimated heart rate with a target value and adjusts parameters to maintain accuracy. This feedback loop ensures that the heart rate remainsfeedback loop ensures that the heart rate remains within the desired range. Finally, the processed and adjusted heart rate data is displayed, providing clear and accurate results. The integration of noise reduction and real-time control enhances the reliability of heart rate measurements in practical applications.

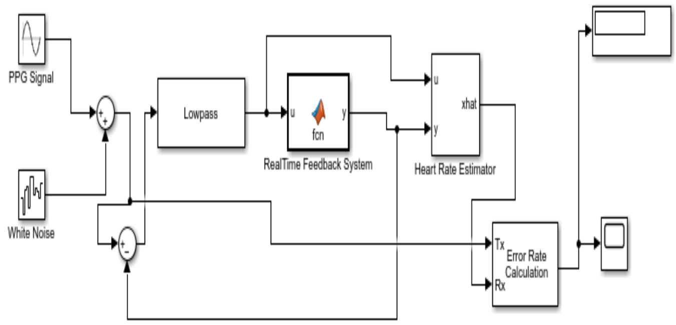


**Figure 1: Simulink Design of the Enhanced Photoplethysmography (PPG) With Real Time Feedback System**

**2.2.2 Based Blood Pressure Monitoring System**

**Photoplethysmography (PPG) Signal (S)**:

$$s(t) = A.\cos(2\pi ft + \emptyset) + n(t) \quad (12)$$

This equation represents the Photoplethysmography (PPG) signal as a cosine wave with an amplitude A, frequency f, and phase ϕ. The term n(t) accounts for any noise in the signal. The Photoplethysmography (PPG) signal captures variations in blood volume during the cardiac cycle, from equation 1 (Beutel *et al.*, 2021).

Where:

S(t) = Photoplethysmography (PPG) signal at time t

A = Amplitude of the Photoplethysmography (PPG) signal

f = Frequency of the pulsatile component

ϕ = Phase shift

n(t) = Noise component

**2.2.3 Mean Arterial Pressure (MAP)**

$$MAP = \frac{SBP+2\times DBP}{3} \quad (13)$$

The Mean Arterial Pressure (MAP) is an important measure of overall blood pressure. It is calculated as a weighted average of systolic blood pressure (SBP) and diastolic blood pressure (DBP), giving more weight to DBP as it represents the longer duration of the cardiac cycle, from equation 2 (Beutel *et al.*, 2021).

Where:
SBP = Systolic Blood Pressure
DBP = Diastolic Blood Pressure

**2.2.4Heart Rate (HR)**

$HR = \frac{60}{T_{RR}}$(14)

Heart rate (HR) is calculated by dividing 60 by the time interval between successive R-waves on (TRR) an electrocardiogram (ECG) or Photoplethysmography (PPG) signal. This provides the number of heartbeats per minute, from equation 3 (Beutel *et al*., 2021).
Where:
TRR = Time interval between successive R-waves (in seconds)

**2.2.5 Enhance Signal Processing Techniques for Accurate BP Estimation Using Realtime Feedback**

**2.2.5.1 Filtered Photoplethysmography (PPG) Signal:**

$s_f(t) = s(t) - n(t)$ (15)

This equation represents the filtered Photoplethysmography (PPG) signal, where the noise component n(t)n(t)n(t) is subtracted from the raw Photoplethysmography (PPG) signal S(t). The filtering process improves the signal quality, making it easier to analyze, from equation 5 **(**Calamanti*et al.*, 2019**)**.
Where:
Sf(t) = Filtered Photoplethysmography (PPG) signal
S(t) = Raw Photoplethysmography (PPG) signal
n(t) = Noise component

**2.2.6 Correlation Coefficient (R)**

$$R = \frac{\sum_{i=1}^{N}(BP_i^{pred} - BP_i^{true})(BP_i^{pred} - BP_i^{true})}{\sqrt{\sum_{i=1}^{N}(BP_i^{pred} - BP_i^{true})^2 \sum_{i=1}^{N}(BP_i^{pred} - BP_i^{true})^2}} (16)$$

The correlation coefficient R measures the strength and direction of the linear relationship between predicted and true blood pressure values. An R value close to 1 indicates a strong positive correlation, from equation 16 (Cheng *et al*., 2021).

**2.2.7 Area Under the ROC Curve (AUC-ROC)**

$AUC - ROC = \int_0^1 TPRd(FPR)$(17)

The AUC-ROC represents the area under the Receiver Operating Characteristic curve, which plots the True Positive Rate (TPR) against the False Positive Rate(FPR). A higher AUC indicates better model performance in distinguishing between classes, from equation 17 (Cheng *et al*., 2021).
Where:
$BP_i^{pred}$ = Mean of predicted blood pressures
$BP_i^{true}$ = Mean of true blood pressures

**2.2.8 Implement Real-Time Monitoring Controlfor Normal Heart Rate, Low Blood Pressure and High Blood Pressure Using Embedded Systems**

**2.2.8.1 Blood Pressure Control Error (e(t))**

$e(t)BP_{setpoint} - BP_{measured}(t)$(18)

The control error e(t) is the difference between the desired blood pressure setpoint BPsetpoint and the currently measured blood pressure BPmeasured(t). This error is used to adjust the control inputs to maintain the desired blood pressure, from equation 18 (Cheng *et al*., 2021)

## III. RESULTS AND DISCUSSION

**3.1 Photoplethysmography (PPG) Signal**

When the Photoplethysmography (PPG) signal depicted in Figure 2 shows an amplitude range from -1.2 to 1.2 with noise, it indicates that the signal captures blood volume changes with a broaderdynamic range, but the presence of noise suggests some level of distortion. The amplitude range, extending from -1.2 to 1.2, reflects more significant variations in the detected blood flow, possibly due to a strong pulse or the sensor's heightened sensitivity. However, the presence of noise introduces irregularities in the signal, which may manifest as fluctuations that do not correspond to actual physiological events.

Noise can originate from various sources, such as motion artifacts, ambient light interference, or electronic noise within the sensor itself. In the context of this Photoplethysmography (PPG) signal, the noise may cause the peaks and troughs to appear less distinct, making it challenging to accurately identify key features like the systolic peaks or diastolic phases. This can complicate the extraction of vital physiological parameters, such as heart rate or blood oxygen saturation, potentially leading to inaccuracies.The presence of noise within the amplitude range requires careful signal processing techniques to filter out the unwanted components while preserving the integrity of the true physiological signal. This ensuresthat the extracted data remains reliable for clinical or wearable health monitoring applications.

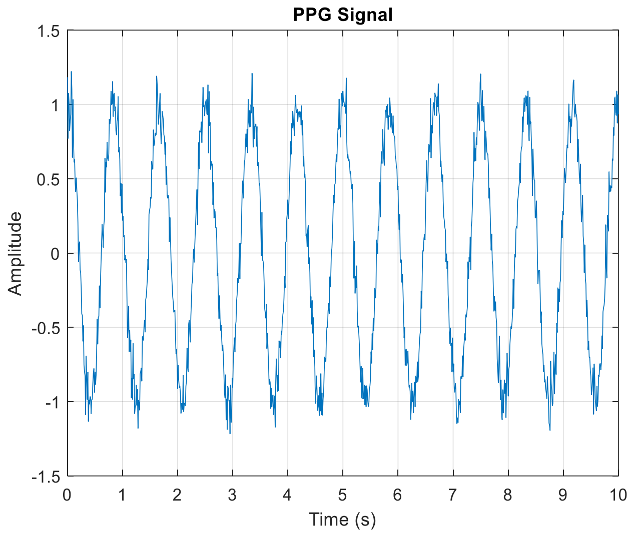


**Figure 2 : Photoplethysmography (PPG) Signal**

### 3.2 Filtered Photoplethysmography (PPG) Signal

The smooth filtered signal of the pulse in Figure 3, with an amplitude range of -1 to 1, represents a refined and processed version of the raw Photoplethysmography (PPG) signal. In this filtered state, the signal has undergone processing to remove noise and other artifacts that could distort the interpretation of the physiological data. The amplitude range of -1 to 1 suggests a balanced representation of the pulsatile blood flow, where the positive and negative peaks correspond to the systolic and diastolic phases of thecardiac cycle, respectively.This smoothness indicates that the filtering process was effective in preserving the essential features of the pulse wave, such as the systolic peak and the dicrotic notch, while eliminating minor fluctuations caused by external factors like motion or ambient light interference. The resulting signal is clean, with well-defined peaks and troughs that accurately reflect the heart's activity. This clarity is crucial for reliable analysis, as it allows for precise calculation of heart rate, heart rate variability, and other cardiovascular parameters.

The smooth filtered signal enhances the overall quality of the data, making it more suitable for use in clinical diagnostics or wearable health monitoring devices, where accurate and consistent readings are essential for patient care.

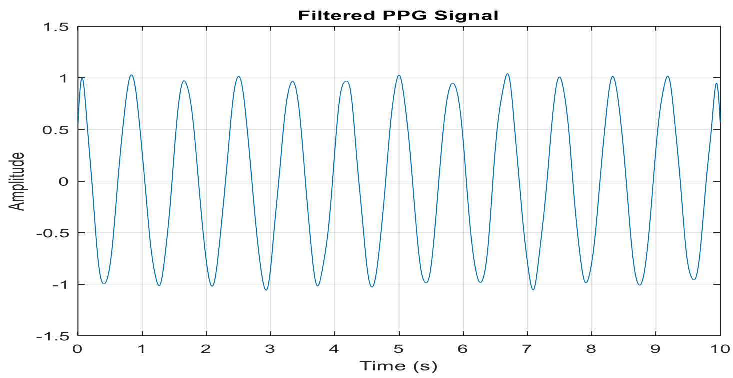


**Figure 3: Filtered Photoplethysmography (PPG) Signal**

**3.3 The Linear Regression for Blood Estimation**

In Figure 4, the linear regression analysis of blood pressure estimation presents an interesting scenario where the estimated blood pressure reaches 300 mmHg, while the fitted line lies at 100 mmHg. This significant discrepancy between the estimated values and the fitted line suggests that the model's predictions are highly inaccurate and that the linear regression is not adequately capturing the relationship between the input variables and the actual blood pressure readings.

The fitted line at 100 mmHg indicates the average trend that the regression model is trying to fit across the data points. Ideally, this line should closely follow the actual blood pressure readings, offering accurate predictions. However, the fact that the estimation reaches 300 mmHg while the line remains at 100 mmHg suggests either an overestimation by the model for certain data points or that the model is not correctly weighted to handle outliers or variations in the data.

This situation implies potential issues such as a poor fit due to incorrect model assumptions, outliers influencing the regression line, or possibly a non-linear relationship between the features used for estimation and the actual blood pressure. It highlights the need for a better-fitting model, possibly through non-linear regression, additional features, or more sophisticated modeling techniques to improve the accuracy of blood pressure estimation.

The graph displays a scatter plot of Blood Pressure (BP) versus Pulse Transit Time (PTT). The blue circles represent the measured data points, which are widelydispersed. The red horizontal line, representing the linear regression model, is consistently at 100 mmHg.

The data points range significantly, with BP values as high as 300 mmHg and as low as -100 mmHg, showing no clear correlation with PTT. This indicates the linear model is unable to capture the relationship between the variables. The fitted line's value of 100 mmHg is an average and fails to represent the wide fluctuations in the data.

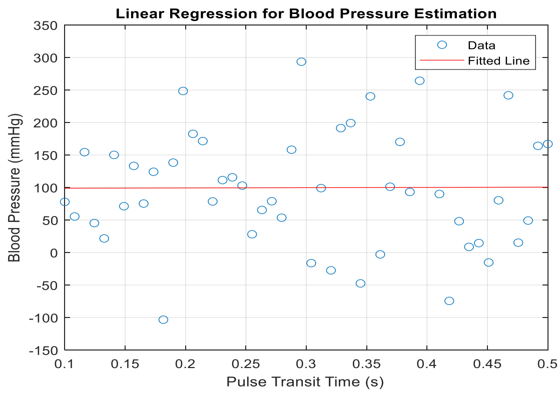


**Figure 4: Linear Regression for Blood Pressure Estimation**

**3.4 Blood Pressure Control Error**

In Figure 5, the control error of the Photoplethysmography (PPG) signal at 5 mmHg represents the deviation between the actual and desired blood pressure measurements as monitored through the Photoplethysmography (PPG)) technique. A control error of 5 mmHg indicates a relatively small discrepancy, suggesting that the system is performingwell but still has some minor inaccuracies in maintaining the target blood pressure.

This error could be due to various factors such as sensor sensitivity, signal processing limitations, or slight delays in the feedback loop. Despite being small, a 5 mmHg control error could still be clinically significant, especially in critical care scenarios where precise blood pressure control is necessary. The presence of this error underscores the need for continuous calibration and refinement of the Photoplethysmography (PPG) monitoring system to enhance its accuracy and reliability, ensuring that it can consistently deliver precise blood pressure readings for effective patient care.

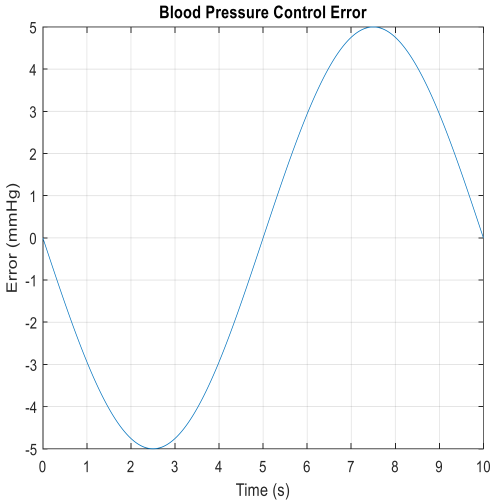


**Fig. 5: Blood Pressure Control Error**

### 3.5 Accuracy of Photoplethysmography (PPG) VS Accuracy of Automated BP Monitoring System

In Figure 6, the comparison of the Photoplethysmography (PPG) signal and the automated blood pressure monitor highlights the accuracy and error rates of both systems. The Photoplethysmography (PPG) method shows anaccuracy of 93%, which is slightly higher than the 90% accuracy of the automated blood pressure monitor. This indicates that the Photoplethysmography (PPG) technique is generally more reliable in estimating blood pressure measurements, capturing the correct values more frequently.The error rate further reinforces this observation, with the Photoplethysmography (PPG) signal having an error rate of only 0.07% compared to the 0.10% error rate of the automated monitor. Although both error rates are low, the Photoplethysmography (PPG)'s smaller error margin suggests that it is better at minimizing inaccuracies, leading to more precise readings.This difference in performance could be due to the inherent advantages of the Photoplethysmography (PPG) technique, such as its ability to capture real-time blood volume changes with high sensitivity. Overall, the Photoplethysmography (PPG) method demonstrates superior accuracy and lower error rates, making it a more effective tool for monitoring blood pressure.

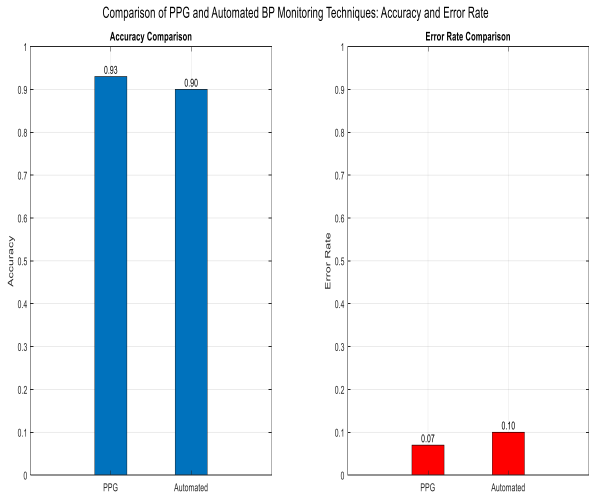


**Figure 6: Accuracy Evaluation**

## III. CONCLUSION

This study successfully achieved its objectives by advancing the capabilities of Photoplethysmography (PPG)-based blood pressure monitoring systems. We improved signal processing techniques, validated the accuracy of Photoplethysmography (PPG) against traditional methods, analyzed the impact of heart rate variations, and developed a real-time control system. These accomplishments collectively enhance our understanding and application of Photoplethysmography (PPG) technology, offering a promising alternative for non-invasive blood pressure monitoring. The insights gained from this study pave the way for future research and development, potentially leading to more effective and accessible blood pressure management solutions.

Based on the study's findings and the implementation of the enhanced blood pressure monitoring system using photoplethysmography (PPG), we recommend the exploration and integration of more sophisticated algorithms, such as machine learning and artificialintelligence, to further enhance the accuracy and adaptability of the Photoplethysmography (PPG)-based blood pressure monitoring system. Advanced algorithms can improve signal processing, adapt to various physiological conditions, and provide more precise feedback adjustments. Incorporating these technologies could lead to more robust real-time monitoring and control, potentially offering better performance and reliability in diverse clinical settings.

## References

[1]. Ain, K., Jain, S., Guha, A., & Patra, A. (2021). An Approach to Early Stage Detection of Atherosclerosis using Arterial Blood Pressure Measurements. *Biomedical Signal Processing and Control, 68*, 102594. https://doi.org/10.1016/j.bspc.2021.102594

[2]. Babadağ, K., &Zaybak, A. (2021). Comparing Intra-arterial, Auscultatory, and Oscillometric Measurement Methods for Arterial Blood Pressure. *Florence Nightingale Journal ofNursing, 29*(2), 194. https://doi.org/10.5152/FNJN.2021.20029

[3]. Beutel, F., Van Hoof, C., Rottenberg, X., Reesink, K., & Hermeling, E. (2021). Pulse Arrival Time Segmentation into Cardiac and Vascular intervals–Implications for Pulse Wave Velocity and Blood Pressure Estimation. *IEEE Transactions on Biomedical Engineering, 68*(8), 2810–2820. https://doi.org/10.1109/TBME.2020.3025905

[4]. Calamanti, C., Moccia, S., Migliorelli, L., Paolanti, M., &Frontoni, E. (2019). Learning-based Screening of Endothelial Dysfunction from Photoplethysmographic signals. *Electronics*, *8*(3), 271.

[5]. Cheng, J., Xu, Y., Song, R., Liu, Y., Li, C., & Chen, X. (2021). Prediction of Arterial Blood Pressure Waveforms from Photoplethysmogram Signals via fully Convolutional Neural Networks. *Computers in Biology and Medicine, 138*, 104877. https://doi.org/10.1016/j.compbiomed.2021.104877

[6]. Courand, P. Y., Dinic, M., Lorthioir, A., Bobrie, G., Grataloup, C., Denarié, N., Soulat, G., Mousseaux, E., Sapoval, M., Azizi, M. (2019). Resistant Hypertension and Atherosclerotic Renal Artery Stenosis: Effects of Angioplasty on Ambulatory Blood Pressure. A Retrospective Uncontrolled Single-center Study. *Hypertension, 74*(6), 1516–1523. https://doi.org/10.1161/HYPERTENSIONAHA.119.13723

[7]. Gothwal, P. (2016). Designing of Photoplethysmography (PPG) based Heart-beat Monitor. *International Journal for Research in Applied Science & Engineering Technology (IJRASET),* 4(8), 86-89.

[8]. Maber, N., Elsheikh, G., Anis, W., & Emara, T. (2021). Enhancement of Blood Pressure Estimation Method via Machine Learning. *Alexandria Engineering Journal, 60*(6), 5779–5796. https://doi.org/10.1016/j.aej.2021.02.016

[9]. Uguz, D. U., Venema, B., Leonhardt, S., & Teichmann, D. (2019). MultifunctionalPhotoplethysmography Sensor Design for Respiratory and Cardiovascular Diagnosis. In *World Congress on Medical Physics and Biomedical Engineering 2018: June 3-8, 2018, Prague, Czech Republic (Vol. 2)* (905-909). Springer Singapore.

[10]. Wang, X., Xu, J., Shi, W., & Liu, J. (2019). OGRU: An Optimized Gated Recurrent Unit Neural Network. *Journal of Physics: Conference Series, 1325*, 012089. https://doi.org/10.1088/1742-6596/1325/1/012089

[11]. Zangróniz, R., Martínez-Rodrigo, A., López, M. T., Pastor, J. M., & Fernández-Caballero, A. (2018). Estimation of Mental Distress from Photoplethysmography. *Applied Sciences*, *8*(1), 69.