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Body Weight Estimation Using Smartphone Based Photoplethysmography Signal

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***Abstract*— This paper presents a novel approach for automatic estimation of human weight using only the smartphone's built-in camera-based fingertip video. PPG signals are analyzed for weight prediction utilizing their correlation with physiological characteristics such as blood volume, heart rate, and respiratory rate, which are intimately related to body weight, as evidenced by individuals with greater body mass having higher blood volume, heart rates, and respiration rates. In this study, 92 consenting participants provided fingertip videos during the data collection phase, placing their fingers on the smartphone's camera lens, and using the camera flashlight for illumination. Then, each subject's fingertip video was processed to provide PPG signals at a spectacular frame rate of 60 frames per second (fps). Advanced preprocessing techniques were used to successfully eliminate noise and baseline drift in the PPG signals captured at 60 fps, enabling precision tracking for precise weight measurements. A DNN model is trained to evaluate the measurement using the 40 different features that were extracted from the PPG signal using Fourier analysis, first and second order derivatives, and single period. The potential for this innovative approach to change health and wellness applications is demonstrated by the estimated R^2 = 0.96 and MAE=2.642 kg which is comparable to commercial weight scales. Due to the widespread use of smartphones, this technology transforms weight measuring by offering an accessible alternative to conventional procedures that rely on specialized weight measurement devices, which are often out of reach for many individuals.**

Keywords*— *Weight, PPG signal, Smartphone, Neural Network.

I. INTRODUCTION

Weight measurement is an important part of maintaining a healthy lifestyle. It is used to evaluate the health of persons with chronic illnesses like diabetes and heart disease as well as helps identify obesity risk factors and assess progress toward weight loss goals. On Traditional weight scales, the user must stand on the scale to have their weight measured. This can be difficult for people with mobility problems or who are confined to bed. Smartphone-based weight measurement system can get over these restrictions by providing a convenient and accessible way to measure weight. A non-invasive optical technique called photoplethysmography (PPG) can be used to assess changes in tissue blood volume. The PPG system uses a light source and a photodetector to illuminate the area of tissue, with the detector recording the light that is reflected back. From the heart to the fingertip, it depicts the blood flow [1]. The PPG signal can be obtained by measuring the quantity of light that is regularly absorbed in the presence of variations in blood volume in the system that circulates blood [2]. Modern smartphones have sophisticated capabilities like central processing units, LED illumination, and cameras with excellent resolution that allow the PPG signal to be extracted and used to identify a number of significant indicators, including blood volume, heart rate, and respiration rate. The blood vessels, bones and tissue on the finger are illuminated by the smartphone's flash and the light that reflects off of those areas is recorded by the camera. Heavier individuals typically have higher blood volume and heart rates than lighter individuals, as they have more blood and muscle mass. Similarly, heavier individuals tend to have higher respiratory rates than lighter individuals, as they need to breathe more oxygen to support their larger body mass. The advent of smartphone technology has brought in a new era of health and wellness monitoring by providing viable solutions to time-honored issues. One of these challenges is accurately measuring an individual's weight, a crucial metric in health assessment and management. In this research, an innovative, automatic method is proposed for assessing human weight utilizing PPG signals that are derived from smartphone-captured fingertip videos that have passed various filters and preprocessing steps. In addition, human weight estimation models based on deep neural networks (DNN) have been developed. The proposed model exhibits its potential in both clinical and non-clinical contexts, addressing the various demands of people with mobility limitations or low resources.

II. RELATED WORK

Fook et al. [3] proposed a method for predicting body mass index (BMI) from face images using three types of classification problems and achieved the highest recognition rate of 95.50%. Pei et al. [4] proposed an image-based body measurement technique that captures front and side images to predict the body size of user. The prediction was tested on

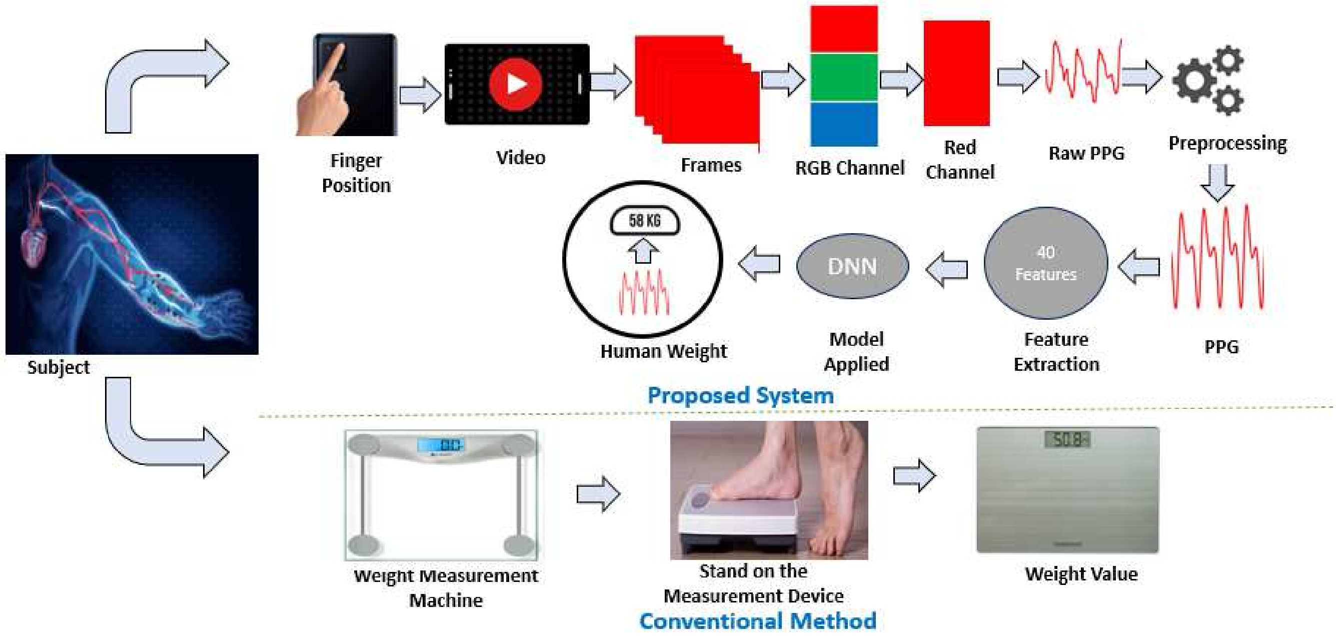

Fig. 1. System diagram of automatic weight measurement compare to conventional method.

10 individuals, but the error was found which is dependent on the clothing worn. Rativs *et al.* [5] developed a regression model to estimate weight using anthropometric data. This paper employed four different regression techniques: neural network regression, linear regression, support vector regression, and Gaussian process regression. The most accurate model employed six anthropometric parameters, including height, gender, ethnicity, and measurements of the waist, buttocks, thighs, and arms. This model had a confidence interval of 98% with limits of 1.80 kg and 2.25 kg. However, compared to other regression techniques, Gaussian process regression has a higher processing cost. Labati *et al.* [6] proposed a method for estimating the weight of a walking person using a pair of picture sequences captured by two cameras. The methodology extracts features from the frame sequences through the use of image processing, and then employs artificial intelligence to determine the correlation between the features and the subject's weight. On the analyzed set of frame sequences, the approach produced a mean error of 0.07 kg and a standard deviation of 2.30 kg. Considering the existing literature, it is observed that human weight can be estimated from the visual aspect of individuals using image processing techniques, but additional equipment such as cameras is required. To sum up there is up to now no method has been proposed to measure human weight from fingertip videos captured by smartphone built-in cameras through the analysis of PPG signal.

III. Proposed System

Smartphone-based human weight measurement not only makes it simpler for individuals with mobility issues to complete the task, but also increases their independence, promotes routine monitoring, and facilitates the management of their healthcare, all of which improve their overall wellbeing. An overview of the proposed system is presented in this section, which includes data collection using Smartphone, retrieval of raw PPG signal and channel selection, preprocessing of raw PPG signal, feature extraction, and the development of DNN model. The smartphone-based weight measurement experiment and the traditional method for determining human weight are shown side by side in Figure 1.

A. Data Collection Using Smartphone

In this study, fingertip data collection for PPG signals was selected due to its simplicity and user-friendliness. Participants were instructed to maintain their stillness while positioning their pointer finger over the camera and LED flash of the smartphone. The quality of the recording is affected by factors such fingertip placement, pressure, and lighting because blood volume affects light transmission through the finger [7]. A smartphone (Samsung Galaxy Note 10 Lite) was used to record 15-second videos at a frame rate of 30 frames per second (fps) with a resolution of 1080 x 2400 pixels. The initial three as well as last two seconds of every video were cut out in order to get rid of erratic frames. The quality of the signal can be reduced by artifacts related to motion, baseline drift, and high levels of noise, all of which are caused by repetitive interference from contact between the finger and the smartphone camera [8]. The proposed solution doubles the number of frames and produces smoother frames by switching from 30 to 60 fps [9]. 600 frames comprise a 10-second video captured with a fingertip. There were 92 participants in this study, ranging in age from 1 to 70, with body weight measurements between 7 and 98 kg and a 60:40 male to female ratio. In order to compare the results of the suggested model, body weight was measured using a CAMRY weight scale, specifically the EB9460 model, which is ISO 9001 certified by SGS.

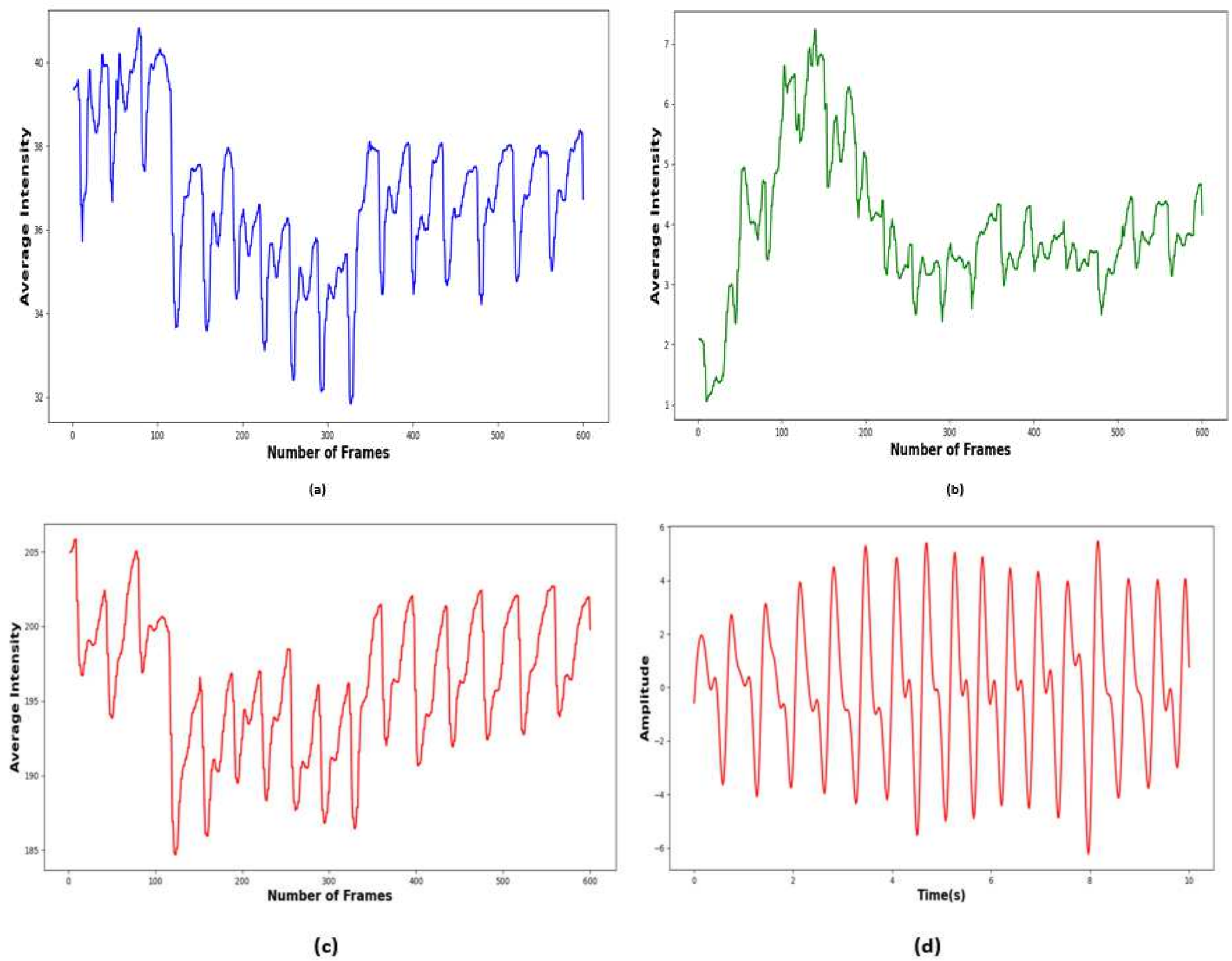

Fig. 2. (a) Average Intensity of blue channel (b) Average Intensity of green channel (c) Average intensity of Red channel (d) PPG Signal after Butterworth Bandpass Filter.

B. *Retrieval of Raw PPG Signals and Channel Selection*

The proposed non-invasive method involves recording a brief (15s) video of the subject's fingertip, which is afterward split into frames retaining information from three color channels: red, green, and blue. Compared to green or blue light, red light can penetrate tissue more effectively due to its longer wavelength. To get a consistent PPG signal, the average intensities of the RGB channels must be determined before selecting the channel with the highest intensity. The red channel, which is noted for having a higher intensity, frequently produces a more dependable PPG signal. Po *et al.* [10] conducted a number of tests and contrasted the PPG signal strength in the three-color bands when a flashlight was used vs when it wasn't. Grimaldi *et al*. [11] used various smartphone models to exhibit various distributions of the pixels in the green channel. Bolkhovsky *et al.* [12] recommended other channels for different phones. All of these experiments indicate that the selection of the channel can vary depending on a range of variables, including the phone model, the camera's characteristics, the capture technique (LED or not), and the ROI. In the experiment, the tissues, bones and vascular structures of the finger were illuminated by the smartphone's flash, while the camera on the same side captured the reflected light. The raw PPG signal from each channel is extracted in this study, and it is shown that the red channel is less noisy and more prominent than the green and blue channels, as shown in Figures 2 (a), (b) and (c). As a result, it was discovered that the PPG signals retrieved from the video recording were inverted and required inversion for effective operation., depicted in Figure 2(d).

C. *Preprocessing of Raw PPG Signal*

In order to estimate human weight from the PPG signal accurately, the proper preprocessing must be performed. The accuracy of the PPG signal is significantly impacted by motion artifacts, which results in incorrect assessment of important properties. The PPG signal's quality is influenced by the user's breathing, finger pressure, finger movement, and illumination intensity. It is crucial to develop a consistent series of preprocessing approaches to improve the constancy and reliability of PPG signal obtaining. To reduce noise, a Butterworth band pass filter is used to the raw PPG

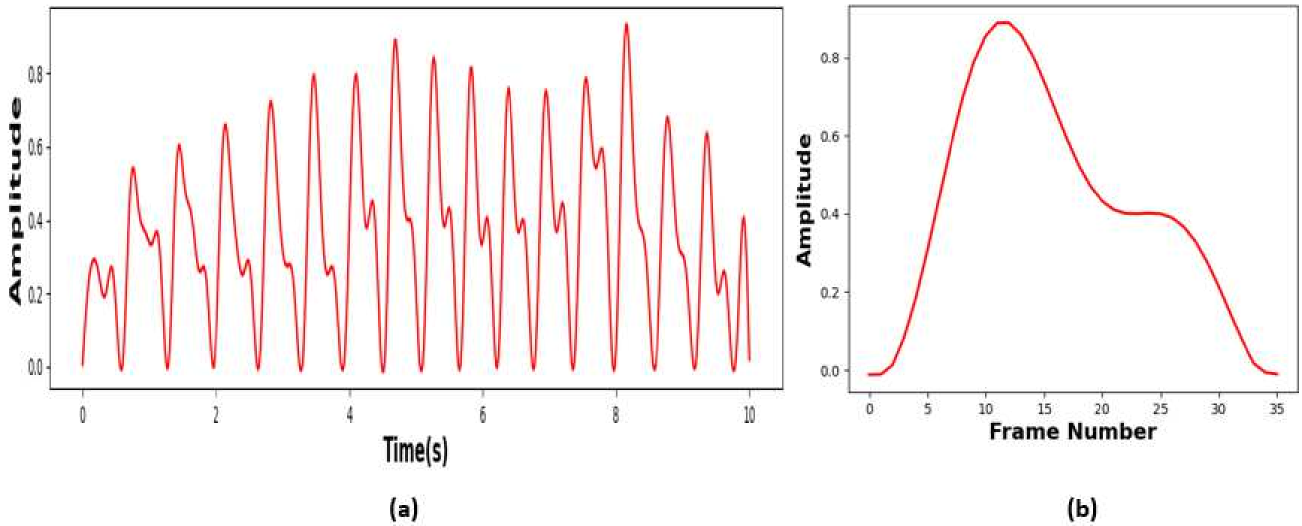

Fig. 3. (a) Normalization and Baseline Corrected PPG signal (b) Single PPG Signal

signal stream. Through normalization, the PPG signals in the 0–1 range are scaled. The normalized PPG signal, which maintains all values between [0, 1].

D. Baseline Drift Correction

The smartphone camera is only temporarily linked to the fingertip during the video capture, which could easily cause motion deviations in the recorded PPG signals. Significant baseline fluctuations can result from even a tiny bit of distortion. Baseline correction of PPG signals is necessary to remove variations resulting from non-pulsatile components and ensure accurate detection of pulsatile changes in blood volume. The main idea behind baseline correction is to apply different weights based on the degree of signal deviation from the fitted baseline. The asymmetrically reweighted penalized least squares smoothing (arPLS) methodology is employed to effectively remove baseline drift from a PPG signal. This is accomplished by allowing the extraction of the underlying PPG waveform while minimizing the impact of baseline fluctuations by repeatedly identifying and penalizing the signal's outliers. This method has been demonstrated to be useful in enhancing the precision of PPG signal processing and subsequent physiological parameter estimation. The PPG signal after normalization and baseline correction is shown in Figure 3(a)

E. Feature Extraction of PPG Signal

Feature extraction is the process of extracting relevant information from a signal. The heart rate, heart rate variability, and other cardiovascular parameters can all be determined from the PPG signal by using feature extraction. The four different approaches used in this study are first and second-derivative analysis, single-period analysis, and the Fast Fourier Transform. The first derivative analysis is used to define systolic and diastolic peaks as well as other significant points, while the second derivative analysis is used to highlight inflection points and further enhance characterization. FFT is used to convert data from the time domain to the frequency domain, enabling to identification of the dominant frequency components. By dividing PPG signals into distinct time periods, detailed analysis of each waveform cycle is thus made possible, providing insights on vascular dynamics. In addition to the age and gender of each participant, 40 features are derived from the FFT, first-order derivative, second-order derivative, and a single PPG signal. Figure 3 (b) shows a single ppg signal.

IV. MODEL DEVELOPMENT

A multi-layer feed-forward network is used to train the proposed model. A single neuron makes up the output layer, whereas neurons in the input layer represent the features in the dataset. The DNN model was trained using 50 epochs of training with a batch size of 32, and two dropout layers were added to the neural network architecture after the second and fourth hidden layers with a dropout rate of 0.2 each. The number of neurons found in each hidden layer is listed in the table. The output layer uses a linear activation function, whereas the input and hidden layers both use the Rectified Linear Units (ReLU) activation function. Adam is used as the optimization algorithm to expedite the DNN's parameter update and training data processing. The purpose of these modifications is to improve the model's capacity to identify intricate patterns in the dataset, resulting in a customized utilization of a conventional deep neural network to address the challenging issue of calculating body weight from PPG signals. The proposed DNN model's hyperparameters are shown in Table I.

TABLE I. HYPERPARAMETERS VALUE

Parameters	Status
Batch size	32
Node number of the input layer	The number of features obtained
The number of hidden Layer	4
Node of each hidden layer	100,150,200,150
Dropout Layers at the 2nd and 4th hidden Layers	0.2
Node of Output Layer	1
Activation Function	ReLU , Linear
Optimizer	Adam

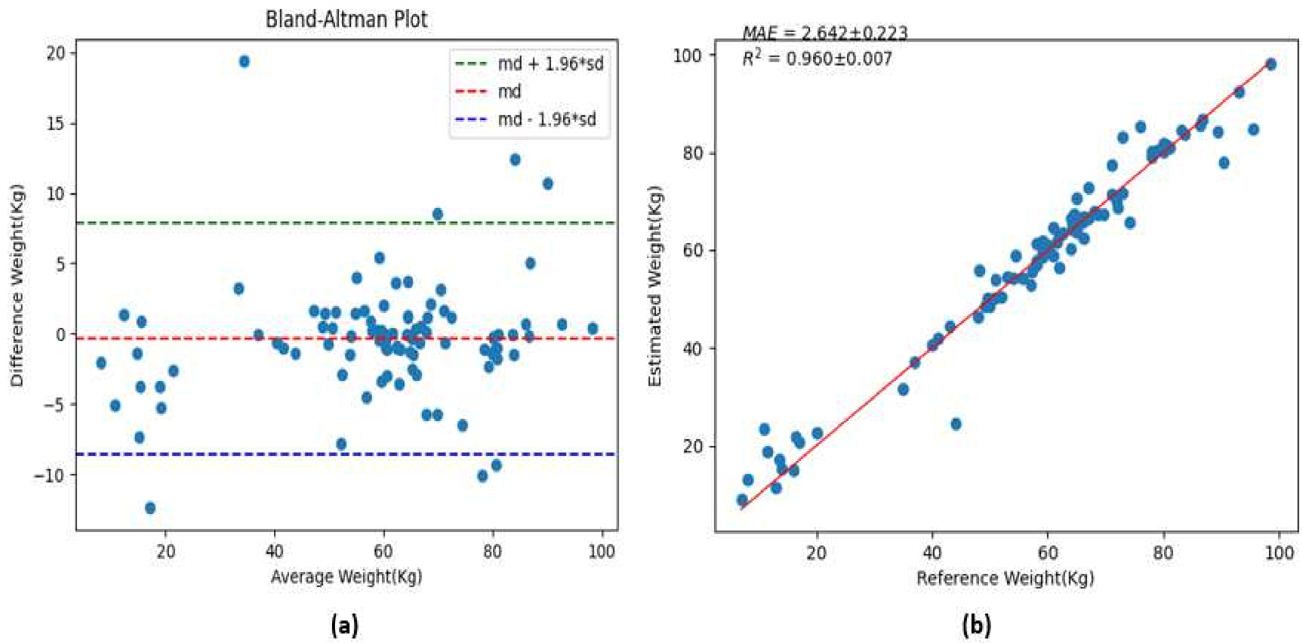

Fig. 4.(a) Relationship and Agreement plot and (b) Estimated and Reference Weight

V. Result

Most estimated body weights are within acceptable bounds of agreement, as seen in Figure 4. a (± 1.96 standard deviation). The figure also illustrates the degree to which the anticipated weight deviates from the reference value. Figure 4(b) shows how the proposed method's performance was analyzed using the performance metrics, namely the coefficient of determination R^2 and mean absolute error MAE. The proposed DNN models' estimated accuracy for human weights is R^2 = 0.960, whereas MAE for these measurements is 2.642 kg, as shown in Figure 4(b).

VI. Comparison Of Results

TABLE II. Comparison Of Proposed Model With Several Existing Automatic Body Weight Measurement System

Authors	Method	Device	Human Body	Algorithm	Performance
H Siddiqui *et al.*[13]	Image Based Method	Camera	Facial Image	CNN	MAE= 1.04
T Supranata *et al.*[14]	Image processing	Smartphone Camera	Body Surface Area (BSA) & Elliptical Tube Volume(ETV)	ETV formula & BSA algorithm.	93,271% for ETV & 92,854% for BSA
H Fitriyah *et al.* [15]	2D Image Based	Thermal Camera	Front and Side Image	Multiple Linear Regression	R^2=0.80 & RMSE =2.68
Proposed System	PPG	Smartphone Camera	Finger Video	DNN	R^2=0.960 & MAE= 2.64

Considering the existing literature, it can be seen that using image processing techniques, human weight can be calculated from an individual's visual appearance, however additional tools like cameras are needed. There has not yet been a method proposed for determining a person's weight from fingertip recordings obtained by a smartphone's built-in camera. In this proposed system, human weight is measured effectively with estimated R^2 =0.960 based on PPG signal because heavier people often have higher blood volumes, heart rates, and respiration rates due to their greater blood and muscle mass. Moreover, A higher frame rate enhances PPG signal analysis by enabling more exact and thorough tracking of small deviations in blood flow. The baseline correction algorithm successfully eliminates baseline drift from PPG data, creating a cleaner signal that makes it possible to analyze human body weight with more accuracy and dependability.

VII. Conclusion

In this paper, a novel method for estimating human body weight using the PPG signal was presented. The PPG signal is obtained by recording fingertip videos with a smartphone's built-in camera and flash while maintaining a frame rate of 60 fps. The signal's noise and baseline drift are successfully removed using advanced filtering methods and a baseline correction algorithm, preserving the integrity of the data. A Deep Neural Network (DNN) model is then trained using the extracted features that have been retrieved from the PPG signal, including its first and second-order derivatives and Fourier analysis. Since heavier people frequently have higher blood volumes, heart rates, and respiration rates due to their greater blood and muscle mass, the proposed approach effectively measures human weight with an estimated $R^2 = 0.960$ from PPG signal-based automatic weight estimation system. Furthermore, a higher frame rate enhances PPG signal interpretation by allowing for more accurate and thorough detection of small variations in blood flow. Utilizing the accessibility and convenience of smartphones, this approach makes weight monitoring easier, more dependable for individuals, and eventually contributes to better health management.

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