

Video Extraction Into PPG Signal To Identify Blood Pressure With XGBoost Method

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Abstract

Improved sensor technologies and digital signal processing have transformed health monitoring, particularly non-invasive blood pressure measurement with photoplethysmography (PPG) signals derived from movies. In this article, we describe the use of the XGBoost technique to estimate blood pressure using PPG signals collected from movies. Our major goal was to look at how varied PPG signal lengths impact the accuracy of the XGBoost model in blood pressure prediction. We conducted systematic experiments with various PPG signal lengths and evaluated the model's performance. The findings offer valuable insights into optimising signal length for PPG extraction and incorporating signal length into the XGBoost model for blood pressure calculation. The model's efficacy was evaluated using quantitative criteria such as accuracy, root mean square error (RMSE), and mean square error (MSE). In addition, a Bland-Altman plot was utilised to visualise the agreement between predicted and real blood pressure measurements. These assessment techniques emphasise the relevance of optimising signal length in improving the prediction performance of XGBoost models for non-invasive blood pressure monitoring.

Keywords: XGBoost, PPG, Sinyal, Tekanan Darah

Abstrak

Teknologi sensor yang lebih baik dan pemrosesan sinyal digital telah mengubah pemantauan kesehatan, terutama pengukuran tekanan darah non-invasif dengan sinyal fotoplethysmography (PPG) yang berasal dari film. Dalam artikel ini, kami menggambarkan penggunaan teknik XGBoost untuk memperkirakan tekanan darah menggunakan sinyal PPG yang dikumpulkan dari film. Tujuan utama kami adalah untuk melihat bagaimana panjang sinyal PPG yang bervariasi mempengaruhi akurasi model XGBoost dalam prediksi tekanan darah. Kami melakukan eksperimen sistematis dengan berbagai panjang sinyal PPG dan mengevaluasi kinerja model. Temuan-temuan ini menawarkan wawasan berharga tentang mengoptimalkan panjang sinyal untuk ekstraksi PPG dan mengintegrasikannya ke dalam model XGBoost untuk perhitungan tekanan darah. Efisiensi model ini dinilai menggunakan kriteria kuantitatif seperti akurasi, kesalahan rata-rata persegi akar (RMSE), dan error persegi purata. (MSE). Selain itu, plot Bland-Altman digunakan untuk memvisualisasikan kesepakatan antara pengukuran tekanan darah yang diramalkan dan nyata. Teknik penilaian ini menekankan relevansi mengoptimalkan panjang sinyal dalam meningkatkan kinerja prediksi dari model XGBoost untuk pemantauan tekanan darah non-invasif.

Kata Kunci: XGBoost, PPG, Sinyal, Tekanan Darah

I. INTRODUCTION

BLOOD pressure estimation using photoplethysmogram (PPG) has become one of the most important aspects of medical innovation today. According to C. El-Hajj [1], the PPG approach allows non-invasive estimation of blood pressure by observing two waveforms obtained from signals, either from two different anatomical areas or through a combination of PPG signals and electrocardiograms. (EKG). Erika Abe [2] explains that the concentration of light reflected from the skin varies according to the changes in hemoglobin due to variations in blood vessel capacity. Near infrared light (600nm - 1000nm) is effective for PPG estimates because it can penetrate the skin and reach the blood circulation system. Sensors that emit near-infrared light, then measure the concentration of reflected light using a phototransistor. In this study, a combination of numerical and experimental methods was used to extract PPG signals from video. Andreaia V.

Moço [3] uses the Monte Carlo approach to simulate the PPG amplitude spectrum and perform normalizations to scale pulse waves. Serj Haddad [4] stated that this process allows for accurate PPG signal reception from various parts of the human body. Blood pressure estimates of PPG signals are performed through radial wave analysis (PWA) using an algorithm that extracts morphological features from the PPG signal, mapping these features to systolic blood pressure (SBP) and diastolic (DBP) values with the XGBoost model. Thus, PPG technology provides a continuous method for estimating blood pressure based on signals from different parts of the body. The hope of this study is to produce the most effective blood pressure detection by manipulating the signal length detected using XGBoost, comparing each scenario using MSE and RMSE parameters. Content of Introduction Section.

In introduction, the context of the study and state the precise objective should be explained. An Introduction should contain the following three parts: background, the problem, and proposed solution. In explaining the background, authors have to make clear what the context is. Ideally, authors should give an idea of the state-of-the-art of the field the report is about. The problem also need to described clearly so that readers able to understand why they should proceed reading. Authors also need to describe the proposed solution so that readers able to point out what are the novel aspects of authors work. Authors should place the paper in proper context by citing relevant papers.

II. LITERATURE REVIEW

First, Mentioned in the S Sun study [5] on estimating blood pressure using PPG mentioned photoplethysmography (PPG) as one of the techniques for assessing blood pressure. An optical sensor that radiates light into the skin can take light that is reflected or transmitted. PPG monitors variations in local blood volume in tissues at remote locations, such as feet, forehead, and fingers. PPG and arterial blood pressure signals have a comparable morphology as a result of the relationship between blood vessel volume and pressure. Therefore, to extract blood pressure from PPG signals, researchers have suggested a number of characteristics. Introduced by Erika Abe [2] in her study of application through infrared light but the basic theory is to calculate the depth of the light intensity reflected from the skin determined by the amount of hemoglobin change caused by variations in vascular capacity. In the study of Naresh Vempala [6] on the TOI method, the face form is used as a feature in estimating blood pressure but has a shortcoming that is to burden the processing that affects the specifications related to the device used. In the study of Bhanupriya and Neelam [7] on denoising emphasizes that PPG signals obtained from infrared do not have to be used directly but rather pass several steps.

Denoising PPG signal is the process of separating a desired signal component from a noisy or damaged signal, allowing for a simple and accurate diagnosis. This technique should recognize and eliminate noise in the data without endangering the results of unidentified objects. The use of a filter in the Aytrik Bose study [8] as a denoising tool in this study was divided into two methods: high-pass and low-pass as a motion artifact remover. This filter is called a low-pas filter because only the low-frequency component of the image will flow through it. You might think of a highpass filter as a filter that allows a higher frequency portion to pass through. In Xingbin Zhan's [9] study of the GBRT model (gradient boosting regression tree) that has a role in estimates has

an advantage as a gradient-boosting algorithm with multi-input multi-output applications. By considering the stochastic dependency on the various prediction horizons, the MIMO method only trains one model to multi-step prediction. Davide Giavarina explains in his study [10] in 1983, Altman and Bland (B&A) proposed alternative analysis, based on the quantification of the agreement between two quantitative measurements by studying average differences and building agreement limits. B&A plot analysis is a simple way to evaluate bias between average differences, and to estimate the deal interval, in which 95% of the difference of the second method, compared to the first, falls. Data can be analyzed both as a unit difference plot and as a percentage difference plot.

In the study of Davide Chicco [22] If it's necessary to identify any outliers, MSE can be applied. Because of the L2 norm, MSE is really excellent at assigning higher weights to these points. This is because, in the case that the model produces a single extremely poor forecast, the squaring portion of the function will presumably amplify the error. The square root shows a monotonic relationship between the two metrics, MSE and RMSE. Models based on RMSE and MSE will be arranged in the same order in regression analysis. The related literature in this study mainly deals with issues within the scope of image processing, blood pressure and signals that focus on PPG as a feature of machine learning itself which is the system of blood pressure estimation that is the main objective of this study. Modelling uses Bland altman as a comparison of two methods (actually and estimated) to measure the appropriateness of the estimated error that will be used to compare each scenario on this study to choose which one has the lowest error rate affected by the signal length.

III. RESEARCH METHOD

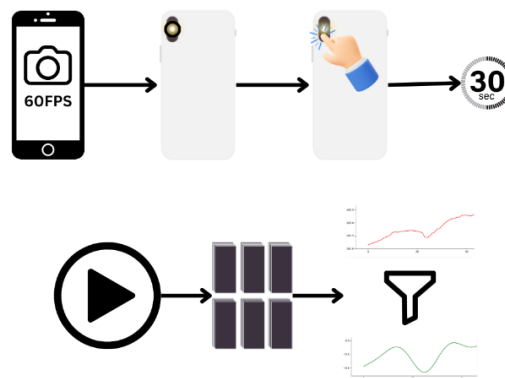


Fig. 1. Data gathering method

The diastole and systole of the video used as the signal will be tagged, and biodata such as age, height, weight, and gender will be collected as signal data characteristics. This step includes certain preparations, such as setting the camera's settings to 60 frames per second and ensuring that the battery has enough juice to record with the flash switched on. While the flash generates a light reflection to give the blood red colour concentration shown in the image 2 preview form, the video standard of 60 frames per second is required to match the signal generated every second. The attribute data follows the video data.

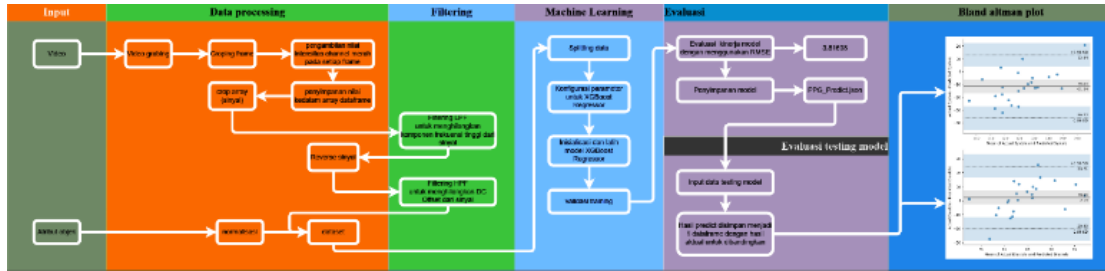


Fig. 2. Block diagram workflow

workflow data analysis and machine learning applications from video input to model evaluation with Bland-Altman plot as shown in figure 2. The process begins with the capture of video and object attributes, then the data is processed with the cropping frame and the red channel intensity capture. After that, the signal is filtered using LPF and HPF, then the data is shared for training and testing the XGBoost Regressor model. The performance of the model is evaluated with RMSE and the prediction results are compared to actual values using Bland-Altman plot for accuracy analysis.

A. PPG

It is described in the Yongbo Liang study [11] of Photoplethysmography (PPG), an essential physiological signal from the human cardiovascular system, is obtained using an LED transmitter that emits red or infrared light that lights the skin on the fingers, ears, or forehead. Photosensitive diodes assess the amount of light absorbed by biological tissues over time, a measurement known as PPG. Kaswar Ahmed [12] explains in his research that prejudice properties such as selectivity and affinity have increased demand for label-free biosensors. Blood hemoglobin biomolecules can also be detected using label-free biosensors.

Hla Myo Tun [13] explained in her study of pulse sensor implements placed at the fingertips used in the operation of her research system to collect detailed information about heart rate and blood flow. These sensors work by utilizing infrared light emitted to the skin and then reflected back by the blood circulating underneath it. These variations in the intensity of reflected light provide the data needed to analyze the heart rhythm and blood flow in real time, allowing accurate and non-invasive health monitoring.

B. Low-pass and high-pass filter

Described in the Hla Myo Tun [13] study, the denoising technique requires identifying different types of noise present in the data and filtering it without affecting the results obtained from unidentified artifacts. The quality of the PPG signal obtained is influenced by a variety of unique factors such as skin surface, measurement location, temperature, blood flow, blood oxygen saturation, and the environment.

Aziz Makandar explains in his research about [14] filters used including lowpass and highpass filters. Low-pass filters are filters that pass low-frequency signals while weakening signals at higher frequencies. Parameters such as the cutoff frequency and filter order are assigned precise values like 50 and 5. The high-pass filter, on the other hand, is a filter that effectively passes high frequencies while weakening frequencies below them. Sharpening is essentially a frequency-dependent high-pass procedure.

$$|H(j\omega)|^2 = \frac{1}{1 + \varepsilon^2(\omega/\omega_p)^{2N}} \tag{1}$$

Equation (1) given by Roger G.T. [15] described the N-order low-pass analog Butterworth filter following Fourier transformation in the frequency domain. where $j=\sqrt{-1}$, ω is the angle frequency, ω_c is the filter cutting

frequencies, and $|H(j\omega)|^2$ is the square magnitude of the frequency response. Given the same parameter given value 5. In its implementation, Butterworth is used as a core filter by giving parameters to btype as high for highpass and low for lowpass and by setting analog as false to determine that this signal is not a continuous signal but a signal in a discrete time domain. You can see the filter results in Figure 3 which gives each filter its own results.

$$|H(\Omega)|^2 = 1 - [1 / (1 + (\Omega / \Omega_c)^{2n})] \quad (2)$$

On the equation (2) in Joseph D. Ramsey study [18] that explain Butterworth channels are characterized by being maximally level within the passband and monotonic within the passband and stopband. In recurrence space, the control range of the Butterworth high-pass channel can be communicated as a work of the recurrence, where Ω is the frequency, Ω_c is the cutoff frequency and n is the order of the filter. But as famous within the passage cited over, within the Smith et al. reenactments a Butterworth high-pass channel with an arrange of $n=4$ and a cutoff recurrence of $1/200$ s was utilized to channel the information in all conditions autonomously of the testing recurrence.

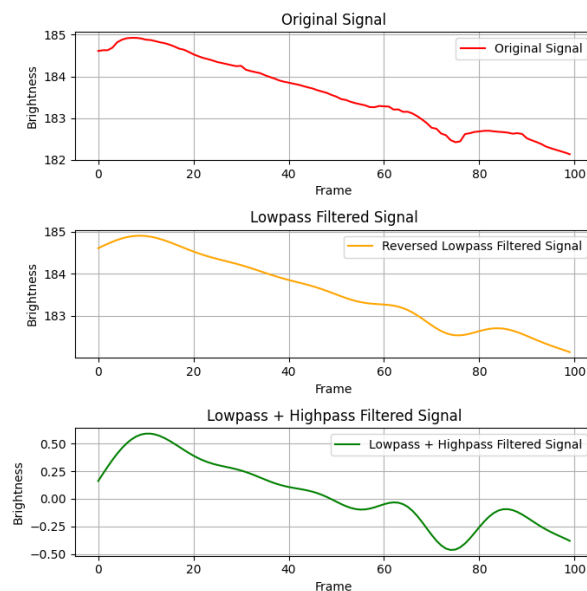


Fig. 3. Progres in signal processing from PPG

C. XGBoost

The boosting gradient used in this survey uses XGBoost (Extream gradient boosting). In a book written by Shubham Malik, Rohan Harode and Akash Singh Kunwar [16] described XGBoost as having the goal of minimizing computing resources and avoiding over-fitting. Simplify target functions that allow a combination of regulation and predictive terms whileining the best possible computational performance that can result in this. In addition, XGBoost is highly resistant to overfitting, parallelizable, and efficient computing. Unlike the other ensemble algorithms, Anurag Tiwari and Amrita Chaturvedi [25] highlight that the regularisation term of XGBoost's objective function includes leaf node weights and tree depth, which can manage the model's complexity and prevent over-fitting.

Boosting is a sequential ensemble learning method that aims to transform a weak learner into a strong learner in order to provide better model accuracy. Andreas Mayr [24] explain in his study that the concept Boosting was then applied to the field of statistical modelling, where it may be used to choose and evaluate the effect of predictors on a univariate response variable in various sorts of regression situations.

$$F_i(x) = F_{i-1}(x) + f_i(x) \quad (3)$$

The equation (3) is described in Shubham Malik's book [16] in Boosting never changes the previous prediction $F_{i-1}(x)$, instead, it only corrects the next forecast $F_i(x)$ by learning from previously made mistakes $f_i(x)$. It is also concluded that the boosting method uses the Greedy method which will continue to look for the best performance results and then it requires the setting of conditions to stop the process such as the model performance or the depth of learning visualized in Figure 4.

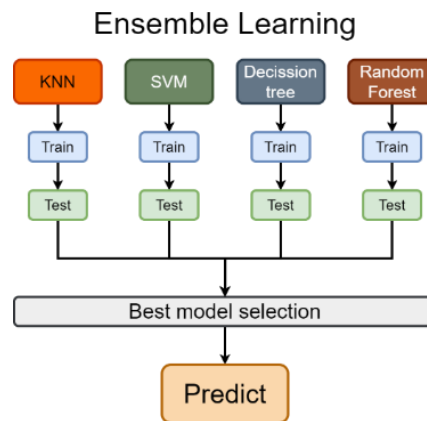


Fig. 4. How Ensemble learning works

In the study of Timofeev [23] Classification And Regression Trees (CART) is a classification approach that uses historical data to build decision trees. A classification tree or regression tree can be formed based on the dataset's available information. The constructed tree can then be used to classify newly observed data. The first section of the thesis discusses the basic principles of tree construction, as well as various splitting algorithms and pruning processes. The second half of the study addresses why we should or should not employ the CART approach. The method's advantages and shortcomings are thoroughly addressed and tested .

$$w = w - n \nabla w$$

$$\nabla w = \frac{\partial L}{\partial w} \quad (4)$$

On the equation (4) in Shubham Malik's book [17] that makes the boosting gradient special is its use in Additive Modeling, in which a new decision tree is added one by one into the model. This addition is done by minimizing losses using the gradient descent method. The decision trees already in the model are unchanged, so slowing down the overfitting rate with w as weight, n as learning rate and L as loss.

D. Bland-Altman

In study of "Understanding Bland Altman analysis" Davide Giavarina [10] explain that Bland and Altman created the Bland-Altman (B&A) plot to describe the agreement between two quantitative measurements. They created a method for calculating agreement between two quantitative measurements utilising boundaries of agreement. Statistical limits are computed using the mean and standard deviation of two measurements. They used a graphical approach to evaluate assumptions about the normalcy of differences and other characteristics. Mohammad Ali Mansournia [19] write on his study that more accurate transformations would be possible using other regression techniques such as Deming regression, which allows for error in both X and Y. As noted above, when two measures on the same scale are obtained, there is no reason not to use a Bland-Altman analysis to assess agreement, subject to the necessary verification of the association between differences and means.

IV. RESULTS AND DISCUSSION

In the testing process, we conduct a detailed analysis of all available data based on a range of previously defined scenarios. Each of these scenarios is used to evaluate the data more thoroughly, so that we can get more accurate and comprehensive results. We provide the results of this test in a separate form for two types of blood pressure, namely systolic blood pressure (systole) and diastolic pressure. (diastole). In this study, three scenarios will be developed in signal data processing where the signal length will be determined to be 1 cycle (100 units), 3 cycles (300 units), 5 cycles (500 unites) and 8 cycles (800 unities) to prove that the length of the signal can affect the model. The reception method in this study sets out two rules where only the red channel is taken and the signal reception is taken from the index 900 where the maximum signal index itself is 1800 to ensure the wave taken is in the middle of the signal taken as a whole (30 sec).

In this scenario, 80 data are used in total with a composition of 70% training data, 15% validation data and 15% for testing. This data consists of two datasets: the signal data containing columns along the signal and an additional column named video_name containing the name of the video, and the other data set is an object attribute data set that contains the column Name, Age, Height, Gender, Systole, Diastole, Video_name, Weight. On this dataset what will change is the data set of signals in accordance with the previously mentioned scenario.

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Model Parameters :
-Gamma: 0.8
-learning rate: 0.01
-max depth: 6
-n estimator: 140
-reg alpha: 0.1
-reg lambda: 0.9
-subsample: 0.6
    
```

Fig. 5. Set up parameters

In this study, several experiments were carried out in obtaining the lowest value of RMSE (Root Mean Squared Error) by setting several parameters and performing data splitting. The following parameters will be used that have been set in such a way to obtain maximum results for this study As can be seen in Figure 5 there are some points that show the parameter settings used in this study. To present the results of this test, we used the Bland-Altman plot. This plot helps us to visualize the difference between the actual measurement results and the estimates given by the model. In addition, we also include other relevant parameters as comparisons in the analysis. These parameters allow us to conduct a more in-depth evaluation of the performance of the model. To present the results of this test, we used the Bland-Altman plot. This plot helps us to visualize the difference between the actual measurement results and the estimates given by the model. In addition, we also include other relevant parameters as comparisons in the analysis. These parameters allow us to conduct a more in-depth evaluation of the performance of the model.

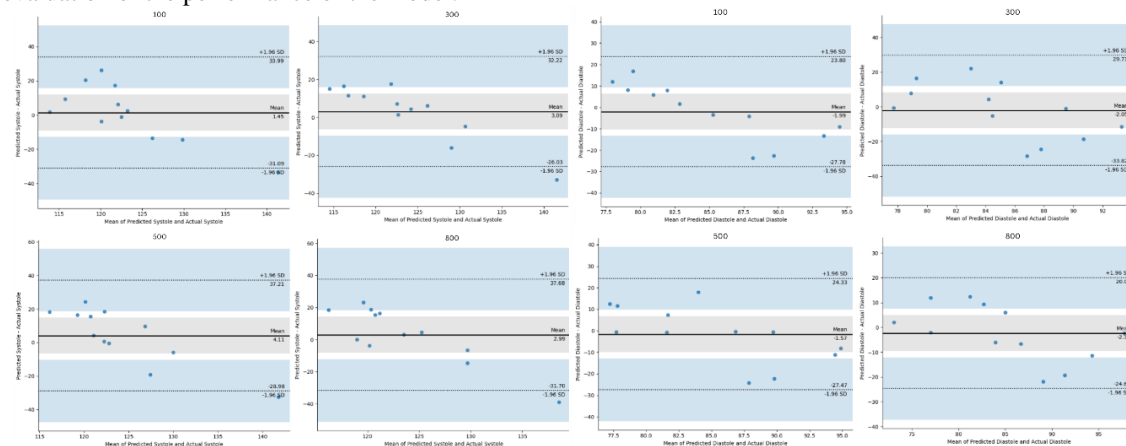


Fig. 6. Bland-altman plot for Systole and Diastole

As part of quantitative analysis, we calculate Root Mean Square Error (RMSE) and Mean Squared Error (MSE). RMSE and MSE are used to compare the results of model testing with actual measurement figures. The MSE is a good statistic for optimisation. Zhou Wang [20] in the study of “Mean squared error: Love it or leave it?” explain that MSE has the very desirable features of convexity, symmetry, and differentiability. Minimum-MSE (MMSE) optimisation problems frequently have closed-form analytical solutions, and when they don't, iterative numerical optimisation processes are often straightforward to define, because the MSE's gradient and Hessian matrix are easy to compute.

Otherwise, RMSE in the study of T. Chai [21], which relies solely on model sensitivity studies, may not necessitate extensive interpretation due to the comparable error distributions observed across modifications of the model. However, when comparing various models using a single measure, the significance of changes in error distributions becomes increasingly apparent. It should be noted that RMSE is presented under the assumption that errors are unbiased and follow a normal distribution. Using RMSE & MSE, we can evaluate how well our models are in predicting systolic and diastolic blood pressure, so that we can ensure the accuracy and reliability of the models developed.

TABLE I
MSE AND RMSE FROM BLAND-ALTMAN

		100 unit	300 unit	500 unit	800 unit
Systole	RMSE	3,5715	3,9561	3,5706	3,3402
	MSE	12,756	15,6514	12,7492	11,1570
14Diastole	RMSE	3,9949	3,8155	4,0842	4,1481
	MSE	15,9595	14,558	16,6812	17,2073

Overall, the RMSE and MSE values that can be seen in table 1 are relatively low in all scenarios indicating that the model used has good performance. Scenario 2 with 300 units shows best performance in systolic measurements with the lowest RMSE & MSE value, respectively 3,8155 and 14,558. On the other hand, for diastolic measures, scenario 3 with 500 units has the best performance with the lower RMSE / MSE score, which is 3,5706 and 12,7492, respectively.

Bland-Altman analysis provides further information about the bias and variability of measurements. For systolic pressure, scenario 2 has the narrower upper and lower boundaries, namely 32.22 and -26.34, which indicates lower measurement variability than other scenarios. Moreover, the average difference in scenario 2, of 3.09, indicates minimal bias. As for diastolic pressures, scenarios 3 indicate the narrowest top and bottom boundary, which are 23.34 and -27.47, as well as an average difference of -1.57, which also indicates low biases.

V. CONCLUSION

Referring back to table 1 as an overall evaluation form, the analysis suggests that scenario 2 with 300 units is optimal for systolic pressure measurement, while scenario 3 with 500 units optimum for diastolic pressure. Both scenarios provide the best balance between low measuring errors and minimal variability. In conclusion, for systolic pressure measurements, scenario 2 (300 units) offers lower RMSE and MSE values, which indicate better measurement accuracy and precision. Furthermore, the upper and lower boundaries of Bland-Altman analysis in this scenario indicate that the measuring variability is smaller, which means that the results are more consistent.

Thus, the decision to use a particular scenario should be based on the application context and priority in blood pressure measurement. If the primary objective is to obtain the most accurate and consistent systolic pressure measurement, then scenario 2 is the right choice. However, if the focus is on diastolic pressure measurements,

scenario 3 will give more optimal results. Consideration of clinical or operational conditions as well as tolerance of the level of variability should also be taken into account in determining the most appropriate scenario for use. These conclusions provide clear guidance in choosing the most effective measurement method according to specific needs. The results showed that scenario 2 stands out as the most outstanding, showing the lowest Mean Squared Error (MSE) and Root Mean Square error (RMSE) values as well as a relatively low standard deviation. The main recommendation is the use of scenario 2 method in blood pressure measurement practice, as it can produce more accurate and consistent results.

In addition, to ensure the generalization of the results, the research suggests that additional evaluations be carried out with more diverse datasets. Data from different demographic groups, health conditions, and environments will provide a more comprehensive picture of model performance. Thus, model accuracy can be assured unlimited to a particular population type or condition. Finally, there is a need for advanced development in the optimization of model parameters and the application of additional algorithms. Although scenario 2 has shown good performance, further exploration is needed to improve the performance of models in measuring blood pressure. Thus, blood pressure measurement systems can be more accurate and reliable in clinical practice as well as other practical applications.

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