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# Optimizing Cardiovascular Health Monitoring with IoT-Enabled Sensors and AI: A Focus on Obesity-Induced Cardiovascular Risks in Young Adults

**Meiling Chan [1,†], Ying Yu [1], Pohan Chang [2], Tsung-Yi Chen [3,*,†], Hok-Long Wong [3], Jian-Hua Huang [3], Wiping Zhang [4] and Shih-Lun Chen [5,*]**

[1] School of Physical Educational College, Jiaying University, Meizhou 514000, China; lynn202207017@jyu.edu.cn (M.C.); 202101202@jyu.edu.cn (Y.Y.)
[2] School of Sports and Physical Education, Huizhou University, Huizhou 516000, China; killua75630@hotmail.com
[3] Department of Electronic Engineering, Feng Chia University, Taichung 40724, Taiwan; d1031139@o365.fcu.edu.tw (H.-L.W.); d1049765@o365.fcu.edu.tw (J.-H.H.)
[4] Zhang Zhou Institute of Science & Technology, Zhangzhou 363000, China; tyxysyx@hzu.edu.cn
[5] Department of Electronic Engineering, Chung Yuan Christian University, Taoyuan City 32023, Taiwan
* Correspondence: tsungychen@fcu.edu.tw (T.-Y.C.); chrischen@cycu.edu.tw (S.-L.C.)
† These authors contributed equally to this work.

**Abstract:** With shifts in lifestyle and dietary patterns, obesity has become an increasing health issue among younger demographics, particularly affecting young adults. This trend is strongly associated with a heightened risk of developing chronic diseases, especially cardiovascular conditions. However, conventional health monitoring systems are often limited to basic parameters such as heart rate, pulse pressure (PP), and systolic blood pressure (SBP), which may not provide a comprehensive assessment of cardiac health. This study introduces an intelligent heart health monitoring system that leverages the Internet of Things (IoT) and advanced sensor technologies. By incorporating IoT-based sensors, this system aims to improve the early detection and continuous monitoring of cardiac function in young obese women. The research employed a TERUMO ES-P2000 to measure blood pressure and a PhysioFlow device to assess noninvasive cardiac hemodynamic parameters. Through precise sensor data collection, the study identified key indicators for monitoring cardiovascular health. Machine learning models and big data analysis were utilized to predict cardiac index (CI) values based on the sensor-derived inputs. The findings indicated that young obese women showed significant deviations in blood pressure (SBP and PP) and cardiac hemodynamic metrics (SVI, EDV, and ESV) at an early stage. The implementation of signal processing techniques and IoT sensors enhanced the CI prediction accuracy from 33% (using basic parameters like heart rate, PP, and SBP) to 66%. Moreover, the integration of extra sensor-based parameters, such as Stroke Volume Index (SVI) and Cardiac Output (CO), along with the use of color space transformations, successfully improved the prediction accuracy of the original data by 36.68%, increasing from 53.33% to 90.01%. This represents a significant improvement of 30.01% compared to the existing technology's accuracy of 60%. These results underscore the importance of utilizing sensor-derived parameters as critical early indicators of cardiac function in young obese women. This research advances smart healthcare through early cardiovascular risk assessment using AI and noninvasive sensors.

**Keywords:** obesity; machine learning; Internet of Things (IoT); smart health; cardiac health monitoring; cardiac index (CI)

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## 1. Introduction

Cardiovascular disease (CVD) remains the leading cause of death globally, accounting for approximately 17.9 million deaths each year [1]. CVD encompasses various conditions, including coronary artery disease, strokes, and hypertension. Major behavioral risk factors contributing to these conditions include physical inactivity, poor dietary choices, tobacco use, and excessive alcohol consumption [2–4]. Obesity has emerged as a key driver of CVD due to its significant impact on metabolic health. Excess visceral fat leads to dyslipidemia, hypertension, and insulin resistance, contributing to the onset of type 2 diabetes and metabolic syndrome, which further heightens the risk of cardiovascular events. Abnormal blood lipid levels—such as elevated triglycerides and low HDL cholesterol—are commonly seen in obese individuals, increasing the risk of coronary artery disease and atherosclerosis [5,6]. Obesity also disrupts sodium regulation in the kidneys, leading to hypertension. Studies show that two-thirds of hypertension cases are directly linked to obesity, further increasing the load on the heart and blood vessels [7,8]. Additionally, diabetes, often associated with obesity, significantly raises the risk of coronary heart disease due to endothelial dysfunction and lipid imbalances. As global obesity rates rise, the burden of CVD continues to grow, especially in low- and middle-income countries, where over 75% of CVD-related deaths occur [9–11]. Addressing obesity and its associated metabolic disorders is crucial in reducing the prevalence of cardiovascular disease. Public health initiatives promoting healthy lifestyles and improving early detection of risk factors are essential to mitigating the global impact of CVD. The integration of the IoT and artificial intelligence (AI) in healthcare, specifically through the Internet of Medical Things (IoMT) and machine learning, is revolutionizing the fight against CVD [12–14].

IoMT involves connecting medical devices and sensors to the Internet, allowing real-time health data collection and transmission without the need for human interaction. These devices range from wearable fitness trackers to sophisticated medical sensors that monitor vital signs such as HR, blood pressure, and oxygen levels. Continuous monitoring enables the early detection of abnormalities, allowing for timely interventions that can prevent critical cardiovascular events such as heart attacks and strokes [15–17]. Machine learning, a branch of AI, adds immense value to this system by analyzing the vast amounts of data generated by IoMT devices. One powerful approach used in this context is multivariable linear regression (MLR), which is a statistical method that helps identify relationships between multiple factors (variables) and health outcomes such as the risk of developing CVD. By integrating factors such as age, body mass index (BMI), blood pressure, cholesterol levels, and lifestyle habits, MLR enhances the accuracy of predicting a patient's risk of cardiovascular events [18,19]. This method refines predictive models by accounting for the complex, interrelated factors that contribute to heart disease, providing more reliable insights into individual patient risks. MLR, combined with machine learning techniques, enables personalized healthcare by tailoring treatments and preventive measures based on these comprehensive risk profiles [20]. This proactive approach improves the accuracy of CVD predictions and allows healthcare providers to intervene before a major event occurs. Moreover, IoMT and machine learning hold particular promise for patients in remote areas or those with limited access to healthcare services [21,22]. Smart wearables and IoMT devices allow for continuous remote monitoring, reducing the need for frequent hospital visits while ensuring ongoing care. The real-time data collected by these devices can also trigger emergency alerts, notifying caregivers or medical professionals in the event of critical health issues, thereby enabling rapid response. Although IoT offers numerous advantages in healthcare, the vast amounts of data generated by IoT devices present significant challenges related to storage, processing, and analysis [23]. To address these issues, the development of advanced machine learning and deep learning frameworks is

essential for effectively mining, interpreting, and processing this data. In response to these challenges, this study proposes a multivariate linear regression model based on machine learning for use in an automatic heart index assessment and prediction system. The model aims to collect basic physiological signals through noninvasive wearable sensors and apply advanced statistical analysis. By conducting data correlation analysis and leveraging data transformation and enhancement technologies, the multivariate linear regression model achieves high precision and accuracy in identifying and predicting cardiac index (CI). Furthermore, the system goes beyond merely providing numerical results for healthcare professionals—it incorporates a color conversion technology that intuitively communicates the health status of users. By translating medical data into easily recognizable color codes, the system offers general users a more straightforward way to understand and monitor their cardiac health. For example, if the data indicate an abnormal heart condition, the system will display warning colors, alerting users or caregivers to take necessary action.

This combination of multivariate linear regression and IoMT represents a significant step forward in CVD management by enabling healthcare systems to offer more accurate diagnoses, optimize resource utilization, and ultimately reduce healthcare costs through early intervention and prevention. This proactive approach facilitates a shift toward more personalized and efficient healthcare, empowering both patients and healthcare providers with real-time insights into cardiovascular health. The convergence of IoMT and machine learning not only enhances patient care but also offers practical solutions to challenges in modern healthcare systems. The main contributions of this study are as follows:

1. This study introduced an advanced noninvasive heart blood sensor with an accuracy rate as high as 73.33%. Compared to the existing system that only measures heart rate, pulse pressure, and systolic blood pressure [24], CI value prediction has been improved by 10%.
2. Through statistical analysis, the study identifies optimal physiological parameters for evaluating cardiac function, demonstrating that these parameters can enhance prediction accuracy by approximately 20%.
3. The application of data enhancement techniques resulted in CI value predictions exceeding 90.01% accuracy, which is 30% higher than current evaluation methods [25].

The remainder of this research is organized as follows: Section 1 presents a comprehensive review of the relevant literature. Section 2 details the research methodology, including data collection using IoT/IoMT technology, statistical analysis methods, data enhancement and comparison, and the application of multiple linear regression and correction techniques. Section 3 analyzes the research results, while Section 4 discusses the implications and innovative contributions of these findings. Finally, Section 5 concludes the paper and highlights potential avenues for future research.

## 2. Materials and Methods

This study employs IoT/IoMT technology and statistical analysis methods to enhance cardiac health monitoring and prediction. The research process is divided into several stages, as illustrated in Figure 1. First, data collection is conducted using advanced noninvasive cardiac blood sensors to gather physiological signals. Next, statistical analysis methods are applied to identify the most appropriate physiological parameters for evaluating cardiac function. Following this, data enhancement techniques are employed to improve the prediction accuracy of CI values. Finally, a MLR model is developed and evaluated to provide accurate assessments of cardiac health.

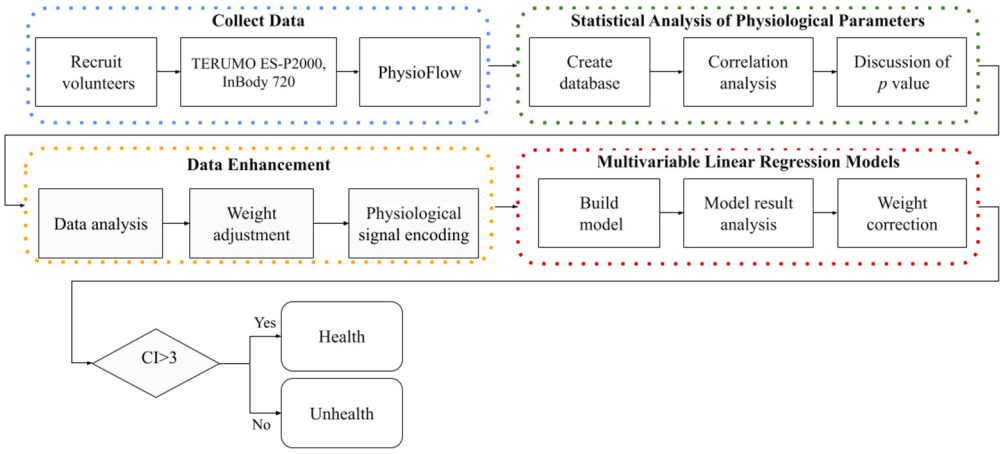



**Figure 1.** The flowchart used in this study.

### *2.1. Collecting Data*

The inclusion criteria for this study were young participants with normal cardiac function and no history of cardiopulmonary or neuromuscular diseases (e.g., heart disease, hypertension, asthma, pneumothorax). This study involved 54 young obese women from Taoyuan City, aged 20–29 years, with a BMI greater than 27 kg/m$^2$, who voluntarily participated. None of the participants had received formal athletic training or were professional athletes. Obesity was defined according to the body composition standards set by Taiwan's Ministry of Health and Welfare. The study employed the TERUMO ES-P2000 blood pressure monitor (TERUMO, Kyoto, Japan) and the InBody 720 body composition analyzer (InBody, Seoul, Korea) to record basic parameters such as blood pressure, weight, and fat distribution, as illustrated in Figure 2a,b. Unlike existing wearable devices that primarily measure blood pressure, this study introduced the noninvasive cardiac blood flow analyzer PhysioFlow (PhysioFlow, Taipei, Taiwan), as shown in Figure 2c. Proper monitoring and placement techniques were used to assess cardiac hemodynamic parameters, including blood flow and cardiac function, as depicted in Figure 3a,b. Additionally, a digital process was used to store and collect all data, including body composition and cardiac hemodynamic monitoring.

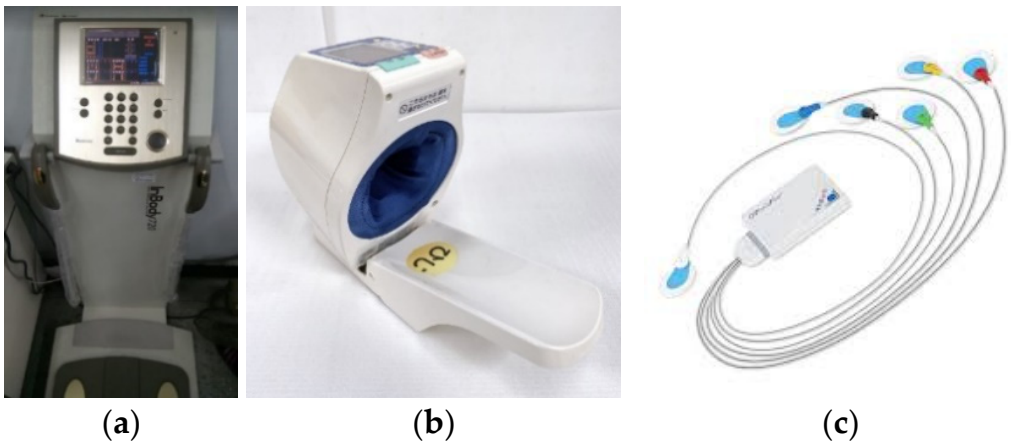



**Figure 2.** Sensing instrument used in this study. (**a**) InBody 720. (**b**) TERUMO ES-P2000. (**c**) PhysioFlow.

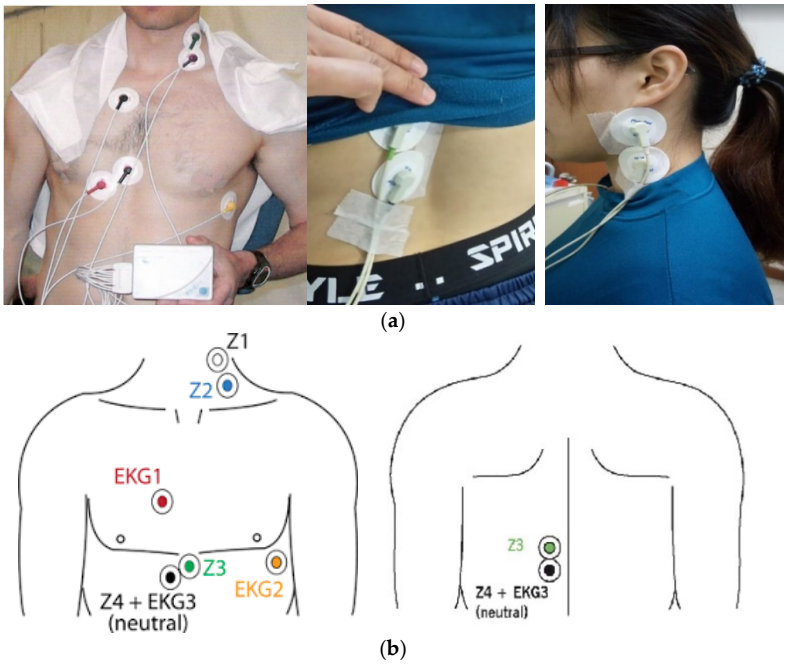



**Figure 3.** (**a**) Paste position. (**b**) Sensor stickers on the back of the body.

Additionally, the measurement process for blood pressure and hemodynamics was conducted while the participants were at rest. The entire cardiac function parameter data collection took approximately 50 min, with blood pressure and hemodynamic parameters measured at 3 and 20 min, respectively (Figure 3). The experimental data collection procedure for this study was as follows: Each subject underwent the following diagnostic sequence: 1. Sitting and resting for 10 min; 2. Blood pressure assessment for 3 min; 3. Electrode patch application and testing for 10 min, 4. Sitting and resting for 5 min; and 5. Evaluation of cardiac hemodynamic parameters for 20 min to complete the data collection process (Figure 3). The design and experimental process of this study are shown in Table 1.

**Table 1.** Blood pressure and cardiac hemodynamic assessment process.

| 10 min | 3 min | 10 min | 5 min | 20 min |
|---|---|---|---|---|
| Sit and rest | Blood pressure | Paste electrodes | Sit and rest | Detection of cardiac hemodynamic parameters |

Measured blood pressure parameters included SBP, diastolic blood pressure (DBP), resting HR, mean arterial pressure (MAP), and PP [26]. PP was calculated as the difference between brachial artery SBP and DBP, while MAP was determined as one-third of the sum of PP and DBP using the following Formulas (1) and (2). Table 2, shows the calculations for the cardiac hemodynamic parameters. In addition, Table 3 presents the reference ejection fraction values used in this study: the statistical data obtained include the descriptive statistics of the basic information of the subjects, the test values correlated to the respective body weight and blood pressure values, and cardiac hemodynamic parameters. Table 4 provides further details of the data collected in this study.

$$PP = SBP - DBP \tag{1}$$

$$MAP = \frac{1}{3}PP + DBP \tag{2}$$

**Table 2.** Blood pressure and cardiac hemodynamic assessment process [26].

| Parameter | Description | Formula | Reference Value |
|---|---|---|---|
| Stroke Volume (SV) (mL) | The volume of blood ejected by the heart per beat. | SV = EDV − ESV | 70 mL |
| Stroke volume index (SVI) (mL/m$^2$) | Stroke volume per body surface area. | SVI = SV/m$^2$ | 40–50 mL/m$^2$ |
| Cardiac Output (CO) (L/min) | The amount of blood ejected by the left ventricle per minute. | CO = SV × HR | 4.0–6.5 L/min |
| Cardiac Index (CI) (L/min/m$^2$) | Cardiac output per minute per body surface area. | CI = CO/m$^2$ | 3 L/min/m$^2$ |
| End Diastolic Volume (EDV) (mL) | The volume of blood when the left ventricles are filled with oxygenated blood. | EDV = SV + ESV | 108 + 24 mL |
| End Systolic Volume (ESV) (mL) | The amount of blood remaining in the ventricle after ejection. | ESV = EDV − SV | 45 + 46 mL |
| Ejection Fraction % (EF%) | The ratio of the volume of blood ejected from each ventricle. | EF% = (SV/EDV) × 100 | 65–70% |

**Table 3.** Ejection fraction reference value (%) [26].

| Level | Range |
|---|---|
| Normal Value | 67% |
| Low Risk | >50% |
| Moderate Risk | 35–49% |
| High Risk | <35% |
| LV Dysfunction | <40% |

**Table 4.** Descriptive statistical results of the basic information of participants ($n$ = 54).

| | M ± SD | Min | Max |
|---|---|---|---|
| Age | 21.72 ± 1.78 | 20 | 29 |
| Height | 159.41 ± 5.21 | 147 | 171 |
| Body Weight | 75.81 ± 8.76 | 62 | 103.9 |
| BMI | 29.61 ± 3.42 | 24.22 | 40.59 |
| Waist Circumference | 87.03 ± 9.45 | 70 | 122 |
| Hip Circumference | 106.24 ± 8.9 | 94 | 155.5 |
| Waist-to-Hip ratio | 0.82 ± 0.07 | 0.62 | 1.04 |

### *2.2. Statistical Analysis of Physiological Parameters*

The statistical analysis in this study followed a structured approach to evaluate the relationship between obesity and cardiac hemodynamic parameters. Initially, descriptive statistics were used to summarize the demographic and health characteristics of the 54 participants, focusing on key variables such as body weight, BMI, and cardiovascular indicators like blood pressure and HR. This foundational analysis provided an overview of the participant group and set the stage for further investigation.

Next, Pearson correlation analysis was applied to assess the strength and direction of associations between body weight and various cardiac hemodynamic parameters, including SVI, CO, and EF. These correlations helped identify whether increased body weight in young obese women was linked to changes in heart function. The use of SPSS 24.0 for Windows facilitated this analysis, with statistical significance determined by a threshold of $\alpha = 0.05$. Results with $p$ values less than 0.05 were considered statistically significant, ensuring the findings were reliable and meaningful. Through correlation analysis, this study determined the relationship between physiological parameters and CI values. Additionally, the study explored the associations between other physiological signals, such as stroke volume and HR, and body weight, emphasizing the potential for early detection of cardiovascular risks in obese individuals. By combining descriptive analysis, correlation

analysis, and regression analysis, the research offers a comprehensive understanding of how obesity influences cardiovascular health. This integrative approach aids in identifying key indicators for early intervention, allowing for more targeted healthcare strategies for individuals at risk.

### *2.3. Data Enhancement*

The study leverages the Nvidia GeForce RTX 3070 GPU to accelerate model training, ensuring efficient computation and optimization of the proposed deep learning models. The software platform integrates SPSS 24.0 for Windows for statistical analysis and MATLAB R2023b for advanced algorithm implementation and data processing. In this study, data enhancement techniques played a critical role in improving the accuracy of CI predictions. Traditional methods primarily rely on HR and BMI for prediction, which are key metrics in many health monitoring systems. However, these indicators have limitations when it comes to precisely predicting CI. As a result, this research explores how enhanced data processing techniques can improve CI prediction capabilities for more effective heart health assessments. To address these limitations, this study incorporates the use of advanced data enhancement strategies, such as feature engineering and the integration of additional physiological signals. This approach allows for the inclusion of parameters like SV, SVI, and CO, which are known to have a stronger correlation with CI. By combining multiple variables and using weighted parameters based on their statistical significance, the model is able to better capture the complex interactions between these physiological factors, leading to more accurate CI predictions. The study uses an Nvidia GeForce RTX 3070 GPU to accelerate model training, with specific hardware and software platforms detailed in Table 1.

First, the study identified the physiological parameters most strongly correlated with CI through the "Statistical Analysis of Physiological Parameters" in Section 2.2 and processed the data accordingly. The selection of these parameters was based on correlation analysis with CI, and their weights were adjusted according to their p values. Specifically, lower p values indicate higher correlations with CI, resulting in greater weight being assigned to those parameters in the predictive model. This approach ensures that the model effectively leverages the most representative physiological signals, thereby improving the reliability of the CI predictions. To further validate these methods, this research proposed various parameter combinations, including the use of HR and BMI alone, the combination of HR and BMI with a single physiological signal, and combinations involving multiple physiological signals. To optimize the data visualization and inspection process, the study employed RGB color space [27] and CIELAB color space [28] transformation to encode the data. This technique aimed to convert the collected HR signals into RGB color codes, allowing researchers to visually inspect and analyze the data more intuitively. In this process, the maximum, minimum, and midpoint values of the HR were first determined. The green color code was fixed at the midpoint, with HRs below the midpoint represented by a gradient from blue to green, and those above the midpoint by a gradient from green to red. This color variation not only made the trends in the data more visually apparent but also helped to quickly identify anomalies within large datasets. The Formulas (3)–(6) for HR to RGB conversion are as follows:

a. For HRs below the midpoint:

$$\text{Normalized HR} = \frac{(\text{Actual HR} - \text{Min HR})}{(\text{Mid HR} - \text{Min HR})} \tag{3}$$

$$\text{Target RGB} = \text{Min RGB} + \text{Normalized HR} \times (\text{Mid RGB} - \text{Min RGB}) \tag{4}$$

b. For HRs above the midpoint:

$$\text{Normalized HR} = \frac{(\text{Actual HR} - \text{Mid HR})}{(\text{Max HR} - \text{Mid HR})} \tag{5}$$

$$\text{Target RGB} = \text{Mid RGB} + \text{Normalized HR} \times (\text{Max RGB} - \text{Mid RGB}) \tag{6}$$

The data enhancement approach utilizing RGB color space effectively transformed complex physiological data into intuitive visual representations, enabling researchers to identify trends and potential health risks with greater speed and accuracy. Initially, the dataset comprised 54 data points of physiological and cardiac-related measurements collected from participants. This included 54 Heart Rate (HR) values and 162 additional data points (54 each for Stroke Volume (SV), Stroke Volume Index (SVI), and Cardiac Output (CO)) along with their respective RGB encodings. Through the augmentation process, the dataset was expanded threefold, resulting in 162 HR data points with RGB encodings and 486 data points for SV, SVI, and CO with RGB encodings. The detailed procedural steps are outlined in Algorithm 1.

**Algorithm 1.** Data Enhancement for CI Prediction.

**Input**: HR, BMI, Additional Physiological Signals (SV, SVI, CO)
**Output**: Preprocessed data for model, Significant parameters for CI prediction
Optimal parameter combinations for accurate CI prediction
#Step 1: Collect and preprocess the data
1.1 Collect HR, BMI, SV, SVI, CO data
1.2 Preprocess the data for model input
#Step 2: Statistical analysis to find significant parameters
2.1 For each physiological parameter in [HR, BMI, SV, SVI, CO]:
2.1.1 Calculate correlation with CI
2.1.2 If *p*-value < threshold (0.05):
2.1.2.1 Assign higher weight to the parameter in the model
#Step 3: Test different parameter combinations for CI prediction
3.1 Combinations to test:
3.1.1 HR + BMI
3.1.2 HR + BMI + 1 physiological signal (SV, SVI, or CO)
3.1.3 HR + BMI + 2 physiological signals
3.1.4 HR + BMI + 3 physiological signals
3.2 Goal: Find the minimum number of parameters for accurate CI prediction
#Step 4: Conversion of HR to RGB Code
Function: convert_HR_to_RGB(hr_value, min_hr, mid_hr, max_hr, min_rgb, mid_rgb, max_rgb)
Input: hr_value, min_hr, mid_hr, max_hr, min_rgb, mid_rgb, max_rgb
Output: target_rgb
4.1 If hr_value < mid_hr:
4.1.1 Normalize HR:
norm_hr = (hr_value − min_hr)/(mid_hr − min_hr)
4.1.2 Compute target RGB:
target_rgb = min_rgb + norm_hr * (mid_rgb − min_rgb)
4.2 Else:
4.2.1 Normalize HR:
norm_hr = (hr_value − mid_hr)/(max_hr − mid_hr)
4.2.2 Compute target RGB:
target_rgb = mid_rgb + norm_hr * (max_rgb − mid_rgb)
4.3 Return target_rgb

### *2.4. Multivariable Linear Regression Models*

In recent years, the rapid advancement of big data processing has led various fields to incorporate data analysis techniques into everyday practice, particularly in healthcare. The proliferation of wearable devices and physiological monitoring technologies has made it possible to collect vast amounts of physiological data, providing valuable resources for studying cardiovascular health. By analyzing these data, it becomes possible not only to identify the risks of cardiovascular diseases at an early stage but also to promote the development of personalized medicine. In this context, selecting appropriate data analysis methods is crucial. The Levenberg–Marquardt (LM) algorithm is a widely used nonlinear least squares method, primarily employed for data fitting, especially when addressing nonlinear regression problems [25]. The mathematical formulation of the LM algorithm can be expressed as the following Formula (7):

$$J(p) = \frac{\partial F}{\partial p} \tag{7}$$

where $\boldsymbol{J}$ is the Jacobian matrix of the residuals, $\boldsymbol{F}$ is the vector of observed data, and $\boldsymbol{p}$ is the parameter vector to be estimated. The LM algorithm iteratively updates the parameters according to the following:

$$p_{new} = p_{old} - \left(J^T J + \lambda I\right)^{-1} J^T F \tag{8}$$

Here, $\lambda$ is a damping factor that balances between gradient descent and the Newton method, and $\boldsymbol{I}$ is the identity matrix.

This algorithm effectively combines the advantages of gradient descent and Newton's method to locate the local minima of the loss function. The strength of the LM algorithm lies in its ability to adapt to more complex models, demonstrating high flexibility for nonlinear data fitting and making it applicable across various fields [29]. However, the LM algorithm is sensitive to data noise and requires careful selection of the initial parameters; when the model is inappropriate or when there is significant noise in the data, the prediction accuracy may decline [30]. In contrast, the multivariable linear regression model (MLR) is another commonly used technique in medical data analysis, favored for its simplicity and interoperability [31,32]. The MLR model can be mathematically expressed as the following Formula (9):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_{\mathrm{n}} \tag{9}$$

where $Y$ represents the dependent variable (in this case, the cardiac index, CI), $\beta_0$ is the intercept, $\beta_1$ to $\beta_n$ are the regression coefficients corresponding to the independent variables $X_1$ to $X_n$. This model is based on the assumption of linear relationships between multiple independent variables and a single dependent variable.

In this research, multivariable linear regression analysis was employed to model various physiological parameters against the CI and thus predict CI values. This research aimed to utilize the MLR model to analyze the relationships between different physiological parameters and CI values, testing its predictive capability to provide a reliable tool for early risk detection and improved clinical diagnostics. The goal of this research is to achieve accurate predictions of CI values. To enhance the predictive accuracy of the model, data augmentation techniques were also introduced. The primary purpose of data augmentation is to expand the quantity and diversity of available data, allowing the model to learn more comprehensive features during the training process. This not only improves the stability of the model but also enhances its generalization capabilities across different data scenarios.

Additionally, weight correction techniques were employed to further enhance accuracy and model precision.

Weight correction is an optimization method targeting the training process of the model, aimed at adjusting the influence of different features, especially when certain features significantly impact the prediction outcome [33]. By assigning higher weights to important features, the model can better capture the variations of these key factors, thereby improving predictive accuracy. In predicting cardiac index, this approach is particularly beneficial for reinforcing the interrelationships between physiological parameters, further enhancing overall prediction capability.

To align CI value identification with risk management, this research defines the normal range as 2.5–4 L/min/m [34]. If the predicted CI value falls within this range, the data indicate that the subject is healthy, suggesting good cardiac status. Conversely, if the CI value falls outside this normal range, it indicates health risks, necessitating further medical examination to ensure the patient's cardiac health. In this study, the CI Prediction algorithm, as demonstrated in Algorithm 2, was executed by the MLR model.

**Algorithm 2.** Multivariable Linear Regression CI Prediction.

#Define Model
**Input**: Physiological parameters (X1, X2, . . ., Xn)
**Output**: CI
**Equation**: Y = β0 + β1X1 + β2X2 + . . . + βnXn
Where:
- Y = CI
- β0 = Intercept
- β1 to βn = Regression coefficients

#Data Collection
**Input**: Physiological parameters dataset (X1, X2, . . ., Xn)
**Output**: Raw data for model training

#Data Augmentation
a. Increase data quantity and diversity using augmentation techniques
b. Train the model on augmented data to enhance feature learning

#Model Training
a. Train the MLR model using the processed data
b. Optimize model parameters (β0, β1, . . ., βn) for best fit using an optimization method such as Stochastic Gradient Descent (SGD).

#Prediction
**Input**: Physiological parameters (X1, X2, . . ., Xn)
**Output**: Predicted CI
Predicted CI = Y

#Health Status Assessment
a. If $2.5 \leq$ Predicted CI $\leq 4$:
- **Output**: "Subject is healthy, good cardiac status."
b. Else:
- **Output**: "Health risk detected, further medical examination needed."

End Algorithm

## 3. Results

The research aims to provide more precise predictions of CI values and deliver accurate assessments of overall cardiac health. In this section, the study will present findings in two key areas. First, it will discuss the results of the Statistical Analysis of Physiological Parameters, emphasizing significant relationships between various physiological metrics and cardiac health indicators. This section will identify critical factors that impact cardiac

function. Second, the section will explore the outcomes of the MLR Models, focusing on their predictive accuracy and effectiveness in evaluating cardiac function, particularly concerning the CI.

### *3.1. Result of Statistical Analysis of Parameters*

In the statistical analysis of physiological parameters, the correlation analysis results indicate a positive relationship between body weight and SBP, with a correlation coefficient of r(52) = 0.363 and $p = 0.007$. Additionally, body weight is also positively correlated with PP, showing a correlation coefficient of r(52) = 0.292 and $p = 0.032$, as detailed in Table 5. Furthermore, Table 6 presents the correlation coefficient matrix of body weight parameters and blood pressure values across different groups. The results indicate significant correlations between body weight and blood pressure parameters, as well as notable correlations among the different blood pressure parameters themselves. Specifically, SBP shows significant positive correlations with DBP, HR, PP, and MAP. Conversely, DBP demonstrates significant negative and positive correlations with PP and MAP, respectively, while HR shows a significant positive correlation with PP. These findings support the interrelationship between body weight and blood pressure, highlighting the mutual influence among blood pressure parameters.

**Table 5.** Correlation between body weight and blood pressure values ($n = 54$).

| | **Parameters** | **Unit** | **Value (M ± SD)** | ***r*** | ***p*** |
|---|---|---|---|---|---|
| **Body Weight** | | **(kg)** | **75.81 ± 8.76** | | |
| Blood Pressure Values | SBP | (mmHg) | 111.83 ± 13.18 | 0.363 | 0.007 ** |
| | DBP | (mmHg) | 69.09 ± 11.32 | 0.068 | 0.625 |
| | HR | (bpm) | 88.61 ± 13.48 | 0.228 | 0.097 |
| | PP | (mmHg) | 42.74 ± 13.77 | 0.292 | 0.032 * |
| | MAP | (mmHg) | 83.34 ± 10.05 | 0.209 | 0.129 |

* $p < 0.05$; ** $p < 0.01$.

**Table 6.** Correlation coefficient matrix between body weight and blood pressure parameters—*r* value ($n = 54$).

| | **Body Weight** | **SBP** | **DBP** | **HR** | **PP** | **MAP** |
|---|---|---|---|---|---|---|
| Body Weight | 1 | 0.363 ** | 0.068 | 0.228 | 0.292 * | 0.209 |
| SBP | | 1 | 0.376 ** | 0.305 * | 0.648 ** | 0.719 ** |
| DBP | | | 1 | −0.076 | −0.462 ** | 0.915 ** |
| HR | | | | 1 | 0.355 ** | 0.076 |
| PP | | | | | 1 | −0.063 |
| MAP | | | | | | 1 |

* $p < 0.05$. ** $p < 0.01$.

The statistical analysis of the correlation coefficients between body weight and cardiac hemodynamic parameters reveals several significant relationships. Body weight demonstrates a significant negative correlation with SVI (r(52) = −0.310, $p = 0.023$, $p < 0.05$) and significant positive correlations with EDV (r(52) = 0.381, $p = 0.004$, $p < 0.01$) and ESV (r(52) = 0.350, $p = 0.009$, $p < 0.01$), as shown in Table 7. Additionally, the correlation coefficient matrix presented in Table 6 highlights not only significant relationships between body weight and the hemodynamic parameters but also notable inter-parameter correlations. Specifically, SV shows significant positive correlations with SVI, CO, CI, EDV, and EF%. Similarly, SVI is positively correlated with CO, CI, EDV, and EF%. CO exhibits significant positive correlations with CI and EF% but a negative correlation with ESV. CI is negatively correlated with ESV while showing a positive correlation with EF%. EDV

demonstrates significant positive correlations with ESV and negative correlations with EF%, while ESV is significantly negatively correlated with EF%. These findings are detailed in Table 8.

**Table 7.** Correlation between body weight and cardiac hemodynamic parameters ($n$ = 54).

| | Parameters | Unit | Value (M ± SD) | *r* | *p* |
|---|---|---|---|---|---|
| Body Weight | (W) | (kg) | 75.81 ± 8.76 | | |
| Cardiac Hemodynamic | SV | (mL) | 77.48 ± 8.9 | 0.234 | 0.089 |
| | SVI | ($mL/m^2$) | 42.14 ± 5.11 | −0.31 | 0.023 * |
| | CO | (L/min) | 6.61 ± 1.1 | 0.238 | 0.084 |
| | CI | ($L/min/m^2$) | 3.59 ± 0.59 | −0.153 | 0.27 |
| | VET | (ms) | 320.55 ± 45.55 | 0.034 | 0.809 |
| | EDV | (mL) | 123.01 ± 16.98 | 0.381 | 0.004 ** |
| | ESV | (mL) | 43.56 ± 11.97 | 0.35 | 0.009 ** |
| | EF% | (%) | 64.75 ± 6.41 | −0.213 | 0.121 |

* $p < 0.05$. ** $p < 0.01$.

**Table 8.** Correlation coefficient matrix between body weight and cardiac hemodynamic parameters—*r* value ($n$ = 54).

| | Body Weight | SV | SVI | CO | CI | VET | EDV | ESV | EF% |
|---|---|---|---|---|---|---|---|---|---|
| Body Weight | 1 | 0.234 | −0.310 * | 0.238 | −0.153 | 0.034 | 0.381 ** | 0.350 ** | −0.213 |
| SV | | 1 | 0.837 ** | 0.529 ** | 0.445 ** | −0.022 | 0.601 ** | 0.103 | 0.353 ** |
| SVI | | | 1 | 0.371 ** | 0.521 ** | −0.035 | 0.361 ** | −0.097 | 0.458 ** |
| CO | | | | 1 | 0.914 ** | −0.204 | 0.163 | −0.292 * | 0.593 ** |
| CI | | | | | 1 | −0.214 | 0.002 | −0.445 ** | 0.694 ** |
| VET | | | | | | 1 | 0.177 | 0.205 | −0.132 |
| EDV | | | | | | | 1 | 0.796 ** | −0.395 ** |
| ESV | | | | | | | | 1 | −0.858 ** |
| EF% | | | | | | | | | 1 |

* $p < 0.05$; ** $p < 0.01$.

These results underscore the critical role of body weight in influencing blood pressure dynamics, particularly concerning SBP and PP. The positive correlation between body weight and SBP suggests that as body weight increases, systolic blood pressure tends to rise, potentially elevating cardiovascular risk. The significant relationships observed between various blood pressure parameters also point to complex interactions, where changes in one parameter may affect others. For instance, the positive correlation between SBP and PP suggests that higher systolic pressure contributes to an overall increase in cardiovascular load. Moreover, the analysis of cardiac hemodynamic parameters (as seen in Table 7) further highlights the influence of body weight on heart function. The CI, a key measure of heart efficiency, shows strong positive correlations with SVI (r = 0.521, $p < 0.01$) and CO (r = 0.914, $p < 0.01$), suggesting that higher CI values are associated with better heart function. Conversely, CI exhibits a significant negative correlation with end-systolic volume (ESV) (r = −0.445, $p < 0.01$), indicating that more efficient cardiac function is linked to lower ESV values. This points to an enhanced ability of the heart to pump blood more effectively in individuals with higher CI.

### *3.2. Result of MLR Models*

When evaluating the performance of an MLR model, four key indicators are typically used to assess the model's accuracy and effectiveness: accuracy, error rate (ER), root mean square error (RMSE), and coefficient of determination ($R^2$) [35].

Accuracy is determined by assessing whether the predicted values fall within the 95% confidence interval of the actual values; higher accuracy indicates better model performance. ER quantifies the deviation of predicted values that fall outside the confidence interval, calculated as the absolute difference between predicted and actual values divided by the actual value; a lower error rate signifies a more accurate model. $R^2$ reflects the correlation between predicted and actual values; the closer $R^2$ is to 1, the smaller the prediction error, indicating that the model accounts for most of the variation in the results. Finally, RMSE measures the average error between predicted and actual values, with values closer to 0 indicating more accurate predictions. These indicators provide a comprehensive evaluation of the MLR model. Higher accuracy and $R^2$ values, along with lower error rates and smaller RMSE values, indicate superior model performance. Formulas (10)–(13) for these indicators can be expressed as follows.

$$Accuracy = \frac{Number\ of\ predictions\ within\ 95\%\ confidence\ interval}{Total\ number\ of\ predictions} \times 100 \quad (10)$$

$$ER = \frac{|Predicted\ Value - Actual\ Value|}{Actual\ Value} \times 100 \quad (11)$$

$$R^2 = 1 - \frac{\sum(Actual\ Value - Mean\ of\ Actual\ Values)^2}{\sum(Actual\ Value - Predicted\ Value)^2} \quad (12)$$

$$RMSE = \sqrt{\frac{1}{n} = \sum_{i=1}^{n}(Predicted\ Value_i - Actual\ Value_i)^2} \quad (13)$$

This research presents a comparison of MLR results for raw images and two-color space transformation techniques (RGB [27] and CIELAB [28]), along with an analysis against existing technology (LM), as shown in Table 9. The analysis results indicate significant differences in the performance of various methods for predicting CI based on color space transformations. The RGB method achieved an accuracy of 60.00%, demonstrating its effectiveness in predicting CI values. In contrast, the Lab method had the lowest accuracy at only 45.00%, indicating reduced reliability. The accuracy for the HR and LM methods was 50.00% and 53.33%, respectively. When examining the error rates, the RGB method again performed best, with the lowest error rate of 18.98%, showcasing its predictive advantages. Conversely, the Lab method exhibited the highest error rate at 24.67%. The coefficient of determination revealed that the LM method explained more variability in the CI values, with an $R^2$ value of 0.11772, while the $R^2$ value for RGB was lower at 0.062188. Finally, the RMSE for the RGB method was 0.51346, indicating higher predictive accuracy, whereas the RMSE for the Lab method was 0.79957, reflecting a larger prediction error. These results highlight the performance differences among various color space transformation methods in predicting cardiac index, as illustrated in Figure 4. The comparison clearly demonstrates how each method's accuracy, error rates, and predictive capabilities vary, emphasizing the effectiveness of the RGB approach over others.

Based on the experimental results, this research ultimately selected RGB as the primary color space transformation technique. The RGB method excelled across all performance metrics, particularly in accuracy and error rates, demonstrating its effectiveness in predicting CI. Compared to other methods, RGB not only achieved the highest accuracy of 60.00% but also had the lowest error rate and RMSE, confirming its potential application in cardiac health assessment. Therefore, RGB will be the preferred color space transformation technique in this research, supporting more accurate CI predictions and related health risk analyses.

**Table 9.** Predicted indicators of cardiac index outcomes (using heart rate only).

| | Color Space Conversion | | | |
|---|---|---|---|---|
| | **HR** | **CIELAB [28]** | **RGB** | **LM [25]** |
| Accuracy | 50.00% | 45.00% | 60.00% | 53.33% |
| ER | 21.88% | 24.67% | 18.98% | 19.71% |
| $R^2$ | 0.06933 | 0.10728 | 0.062188 | 0.11772 |
| RMSE | 0.74238 | 0.79957 | 0.51346 | 0.73299 |

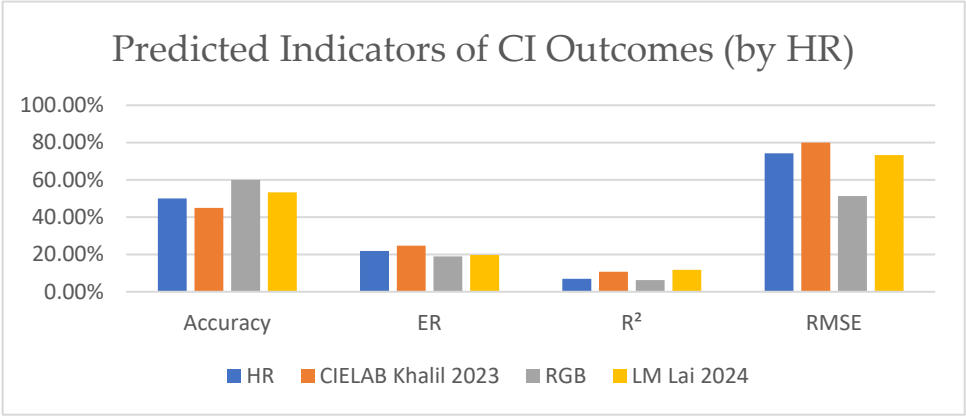



**Figure 4.** Performance comparison of color space transformation methods in predicting cardiac index [25,28].

On the other hand, we analyzed the key physiological parameters for predicting cardiac index by comparing data collected from various noninvasive sensors and to develop a robust multivariable linear regression model. The results demonstrate a significant increase in the predictive accuracy of CI with the addition of more parameters. As shown in Table 10, the model's accuracy was only 27% to 33% when using two parameters (e.g., heart rate (HR) combined with stroke volume (SV) or stroke volume index (SVI)). This indicates that the predictive capability is relatively limited when relying on a small number of parameters. Further analysis revealed that introducing a third parameter increased the model's accuracy to 53.33%, with an average $R^2$ value of 0.76231 and a root mean square error (RMSE) of 0.27521, indicating a noticeable improvement in the model's ability to explain and predict the data. When the number of parameters was expanded to four (HR + SV + SVI + cardiac output (CO)), the model achieved a perfect accuracy of 100%, with an $R^2$ value of 0.99595 and an RMSE of 0.03, demonstrating optimal predictive performance and maintaining stability across different scenarios.

**Table 10.** Predictors of CI results (including various physiological parameters).

| | **HR + Any Parameter** | | | | **HR + Any 2 Parameters** | | | | **HR + 3 Parameters** |
|---|---|---|---|---|---|---|---|---|---|
| | **HR + SV** | **HR + SVI** | **HR + CO** | **Average** | **HR + SVI + CO** | **HR + SV + CO** | **HR + SV + SVI** | **Average** | **HR + SV + SVI + CO** |
| Accuracy | 20.00% | 27.00% | 33.00% | 26.67% | 53.33% | 40.00% | 33.33% | 42.22% | 100.00% |
| ER | 2.09% | 5.27% | 4.12% | 3.83% | 1.90% | 0.15% | 0.46% | 0.84% | 0.00% |
| $R^2$ | 0.34288 | 0.62239 | 0.88123 | 0.6155 | 0.94192 | 0.82482 | 0.52019 | 0.76231 | 0.99595 |
| RMSE | 0.60441 | 0.39152 | 0.22015 | 0.40536 | 0.22459 | 0.21733 | 0.38391 | 0.275276667 | 0.03 |

When four key variables (HR, SV, SVI, and CO) were used in the predicting cardiac index (CI), a high accuracy of 100% accuracy was achieved. However, this may present a problem with too many sensors to actually incorporate into a wearable device. Using fewer sensors and limited variables is often a key consideration, especially in wearable devices

or resource-limited environments. To address this issue, our study emphasizes exploring alternative approaches, such as using fewer sensors, to achieve reliable CI prediction. As seen in Figure 5, using the combination of HR + SVI + CO for predictions yielded impressive results across various metrics, especially with an $R^2$ value of 0.94192, which closely resembles the performance of the four-parameter model. This study ultimately selected the combination of HR + SVI + CO due to its ability to maintain high predictive accuracy while mitigating the risk of model overfitting. In scenarios with limited medical resources, achieving high-precision predictions with the fewest number of parameters is crucial for clinical applications and cardiac health management. Furthermore, Figure 6 and Table 11 illustrate the performance of the multivariable linear regression model during the 5-fold cross-validation, showing the distribution of RMSE and $R^2$ values across the five folds.

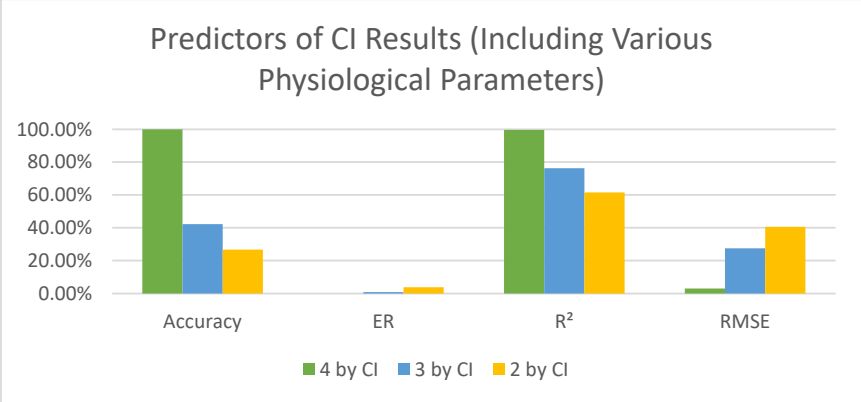



**Figure 5.** Performance analysis of predictors for CI outcomes.

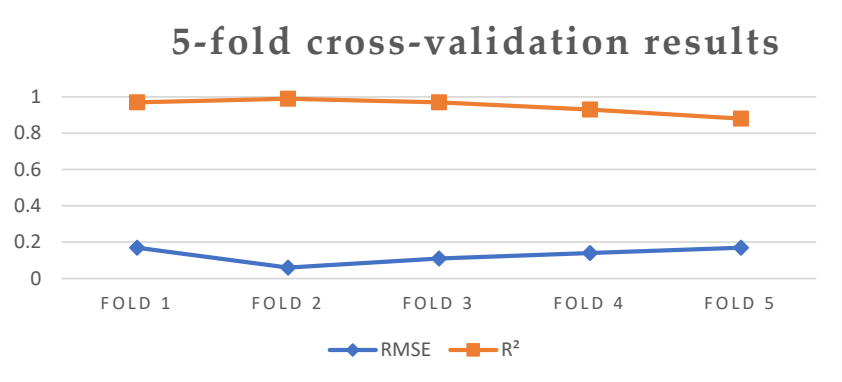



**Figure 6.** 5-fold cross-validation results for multivariable linear regression model.

**Table 11.** Performance metrics for 5-fold cross-validation.

| | Fold 1 | Fold 2 | Fold 3 | Fold 4 | Fold 5 | Average |
|---|---|---|---|---|---|---|
| RMSE | 0.17 | 0.06 | 0.11 | 0.14 | 0.17 | 0.13 |
| $R^2$ | 0.97 | 0.99 | 0.97 | 0.93 | 0.88 | 0.95 |

The experimental results reveal that the original models achieved accuracy rates of only 33.00% and 53.33%, with corresponding $R^2$ values of 0.88123 and 0.94192. In contrast, our approach reached an accuracy of 73.33% and an $R^2$ of 0.98390, indicating a significant improvement in predictive reliability. This study has made substantial advancements in predicting CI by exploring the impact of using two versus three parameters, as shown in Table 12.

**Table 12.** Comparison of CI predictions using various methods.

| | | Accuracy | ER | $R^2$ | RMSE |
|---|---|---|---|---|---|
| HR + co | Original | 33.00% | 4.12% | 0.88123 | 0.22015 |
| | LM [25] | 60.00% | 23.06% | 0.0046979 | 0.69737 |
| | This work | 73.33% | 0.41% | 0.9839 | 0.07367 |
| HR + svi + co | Original | 53.33% | 1.90% | 0.94192 | 0.22459 |
| | LM [25] | 60.00% | 11.08% | 0.47657 | 0.37362 |
| | This work | 90.01% | 0.56% | 0.98705 | 0.07668 |
| HR + sv + svi + co | Original | 100.00% | 0.00% | 0.99595 | 0.03 |
| | LM [25] | 100.00% | 0.00% | 0.99572 | 0.03 |
| | This work | 100.00% | 0.00% | 0.99692 | 0.02 |

In scenarios where medical resources and access are limited, measuring only cardiac output (CO) and heart rate (HR) can still yield impressive results. It can be seen from Figure 7 that with our techniques, even a two-parameter model can achieve 73.33% accuracy, which represents a remarkable improvement of approximately 13.33% to 40% compared to existing models. The error rate was calculated at just 0.41%, with an $R^2$ value of 0.9839. These findings underscore the effectiveness of implementing innovative data enhancement techniques and robust statistical methods in advancing CI prediction. Further analysis showed that incorporating a three-parameter model with HR, CO, and SVI resulted in a significant performance boost, as shown in Figure 8. The accuracy surged to 90.01%, with an $R^2$ value of 0.98705, demonstrating the model's enhanced ability to capture the complex relationships between physiological parameters and CI, thereby improving predictive reliability. A key contribution of this research is its ability to achieve high accuracy with fewer parameters. By applying weight correction techniques, we demonstrated that a three-parameter model can approach the performance of a four-parameter model (HR, SV, SVI, and CO). The final results indicated that integrating RGB space transformation on the original data effectively improved data augmentation, allowing for a more diverse dataset that enhances the model's learning capabilities. The performance metrics indicate a substantial increase in prediction accuracy, which is significant as it suggests that a simpler model can provide exceptional predictive precision.

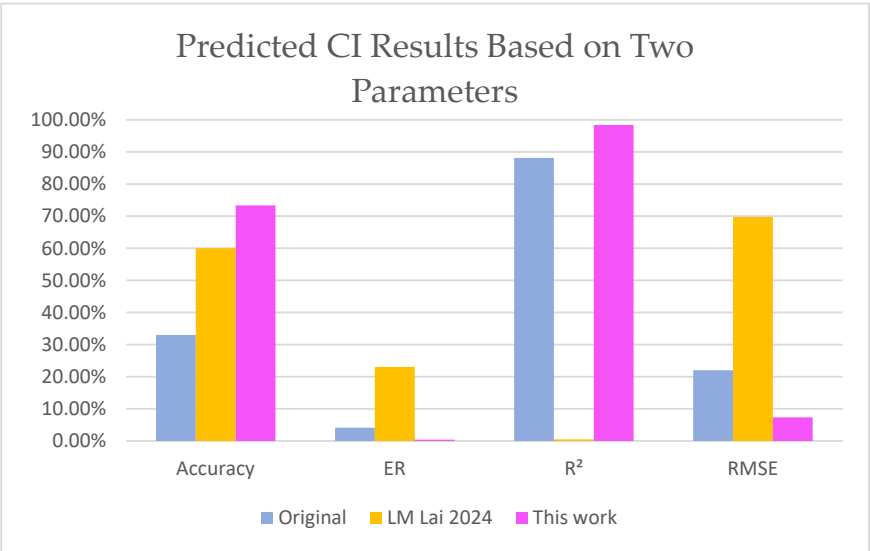



**Figure 7.** Predicted CI results based on two parameters [25].

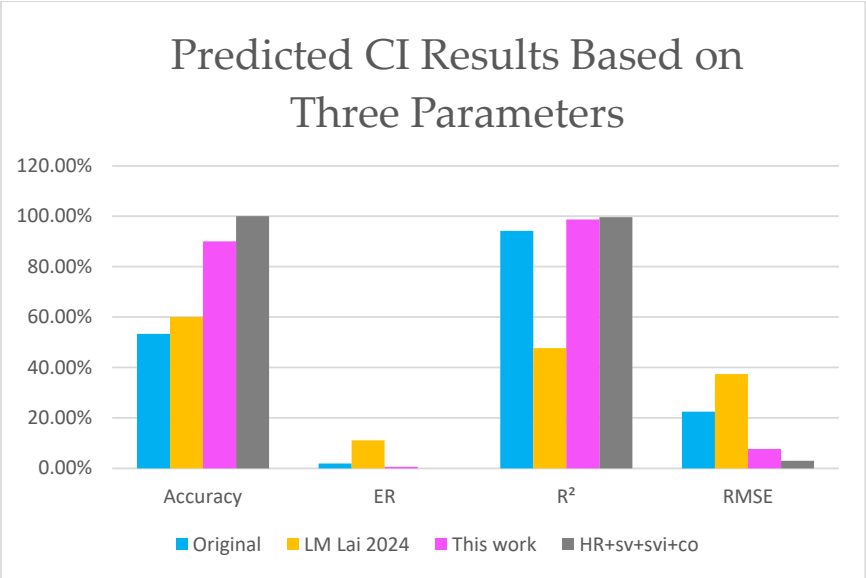



**Figure 8.** Predicted CI results based on three parameters [25].

## 4. Discussion

The results of this study highlight significant advancements in the prediction of CI using sensor technologies and machine learning. By comparing models that use two versus three parameters, we demonstrated substantial improvements in predictive accuracy. Initially, the baseline models [24] using conventional approaches achieved accuracy rates of 33.00% and 53.33%, with $R^2$ values of 0.88123 and 0.94192, respectively. However, our approach, integrating RGB space transformation for data enhancement and weight correction techniques, yielded accuracy improvements of 73.33% with an $R^2$ of 0.9839 when using only two parameters (HR and CO). Moreover, when a third parameter, stroke volume index (SVI), was included, the accuracy surged to 90.01%, with an $R^2$ of 0.98705, confirming the added value of more detailed physiological inputs in CI prediction. These findings are crucial, especially in resource-limited scenarios where collecting multiple parameters might not always be feasible. The ability to maintain high predictive performance with fewer parameters (two or three) while retaining minimal error rates (e.g., 0.41%) underscores the model's robustness and adaptability. Furthermore, the implementation of data augmentation techniques has led to CI value predictions with accuracy exceeding 90.01%, representing a 30% improvement over existing evaluation methods [25]. This is particularly valuable for clinical applications where usability and interpretability are paramount, establishing a solid foundation for future research and advancements in cardiac health monitoring.

## 5. Conclusions

This research highlights significant advancements in heart health monitoring within the context of smart cities, emphasizing the innovative integration of IoT and sensor technologies. Through the use of advanced noninvasive sensors, the study achieved remarkable predictive accuracy for the cardiac index, demonstrating that effective health monitoring can be feasible even in resource-limited settings. The findings reveal that simple parameter combinations, such as heart rate and cardiac output, can yield impressive results, underscoring the potential for early cardiovascular health interventions, particularly among young obese women. However, the study acknowledges certain limitations. The focus on young obese women from the Asian region may limit the generalizability of the findings to other populations. Future research should aim to include more diverse participant

groups and explore broader applications of the developed technologies across various demographic settings. Additionally, the research underscores the transformative potential of IoT-enabled health systems in urban environments. These systems provide continuous, real-time monitoring, equipping both patients and healthcare providers with actionable insights. The convergence of IoT and machine learning fosters a proactive approach to healthcare, enabling timely diagnoses and optimized resource utilization. Notably, the study demonstrates the ability of IoT-enabled systems to offer accurate, real-time, non-invasive cardiovascular health monitoring using fewer parameters. This approach is particularly valuable in clinical scenarios where simplicity and efficiency are critical. Ultimately, this research lays a foundation for the development of smart city health systems that enable early interventions, reduce healthcare costs, and improve long-term outcomes for individuals at risk of cardiovascular disease.

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**Informed Consent Statement:** All participants in the study were informed of the purpose and scope of data processing before voluntarily joining, and their written informed consent was obtained prior to participation.

**Data Availability Statement:** The data presented in this study are available upon request from the corresponding author due to the inclusion of sensitive personal information. The study participants did not consent to the public sharing of their data.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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