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Analysis of Heart Rate Changes in Response to Sensory Stimulus Intensity Variations Using a Convolutional Neural Network-Based Remote Photoplethysmography Method

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ABSTRACT

The neurodevelopmental disease known as autism spectrum disorder (ASD) is frequently linked to deficiencies in sensory processing, which cause different physiological reactions to different environmental stimuli. Heart rate is one physiological sign that can be used to assess these reactions. This study uses a non-contact, camera-based approach to examine changes in heart rate in response to changes in sensory stimulus intensity in people with autism. The suggested system combines the Remote Photoplethysmography (rPPG) technique, which extracts physiological information from variations in facial skin color intensity, with a Convolutional Neural Network (CNN) to identify the facial region and establish the Region of Interest (ROI). Without physical contact with the individual, the system can use an RGB webcam to estimate heart rate in real time, in beats per minute (BPM). According to experimental findings, people with ASD showed discernible changes in heart rate in response to changes in sensory stimulus intensity. These results suggest that the proposed approach could support sensory evaluation for people with autism by offering a more pleasant and objective alternative to non-contact physiological-response monitoring.

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1. INTRODUCTION

The neurodevelopmental illness known as autism spectrum disorder (ASD) is typified by difficulties with social interaction and communication, as well as the development of limited and repetitive behavioral patterns.[1] .

In addition to these traits, persons with ASD may have sensory processing challenges, exhibiting either hypersensitivity or hyposensitivity to stimuli such as light, sound, touch, and temperature. These differences cause physiological reactions to the environment that differ from those of the general population, such as variations in heart rate associated with autonomic nervous system activity [2].

Approximately 1 in 100 children worldwide has been diagnosed with ASD[3], [4]. This high prevalence underscores the importance of studies aimed at understanding the physiological traits of autistic children, especially how they respond to different types of sensory input. One physiological metric that may be used to gauge how each person reacts to particular circumstances, such as stress, anxiety, and exposure to environmental stimuli, is heart rate. [5], [6].

According to several earlier studies, people with ASD have distinct sensory sensitivities from the general population, which means that variations in stimulus intensity may affect their physiological reactions. However, there are still several issues with contact sensor-based heart rate monitoring techniques since some children with ASD exhibit pain or resistance when devices are affixed to their bodies[7]. These circumstances have the potential to affect participants' behaviour and lower the quality of the data collected.

Camera-based non-contact measurement provides an unobtrusive, flexible approach for heart rate monitoring in children with Autism Spectrum Disorder (ASD), minimizing behavioral disruption and capturing physiological responses in a natural state. This study utilizes non-contact monitoring to evaluate physiological reactions to varying sensory stimulus intensities in children with ASD.

The primary contribution is demonstrating that sensory stimulus intensity significantly influences heart rate fluctuations, providing objective data. These findings validate camera-based physiological monitoring as a reliable tool and establish a quantitative foundation for personalized sensory assessment and intervention strategies for children with ASD.

2. RESEARCH METHOD

2.1. System Architecture

The proposed system consists of an RGB webcam, a Raspberry Pi 4, an ESP32, a servo motor, and a Human Machine Interface (HMI). The RGB webcam records facial video for heart rate estimation using the rPPG technique. CNN-based analysis, BPM estimation, rPPG signal extraction, and face identification are all performed on the Raspberry Pi 4. The servo motor keeps the camera in place while data is being collected, while the ESP32 manages auxiliary devices. The HMI shows the processed results in real time. Figure 1 depicts the general design of the system.

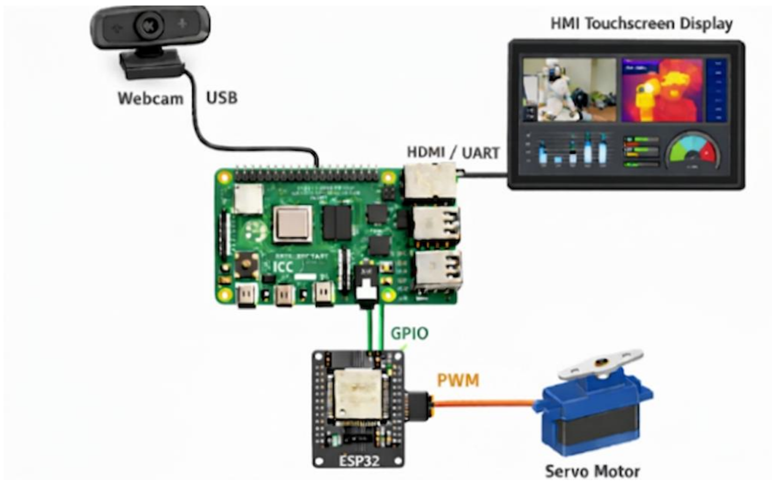

Figure 1. System Architecture

2.2. Block Diagram System

Figure 2 displays the block diagram of the system utilized in this investigation. The system consists of three main modules: input, processing, and output. In the input stage, an RGB webcam captures real-time facial video of the subject. The Raspberry Pi 4 processes these signals to estimate heart rate via Remote Photoplethysmography (rPPG) and displays the results on an HMI/LCD. Concurrently, the Raspberry Pi 4 communicates with an ESP32 to control a servo motor, ensuring continuous camera alignment with the subject's face throughout data acquisition.

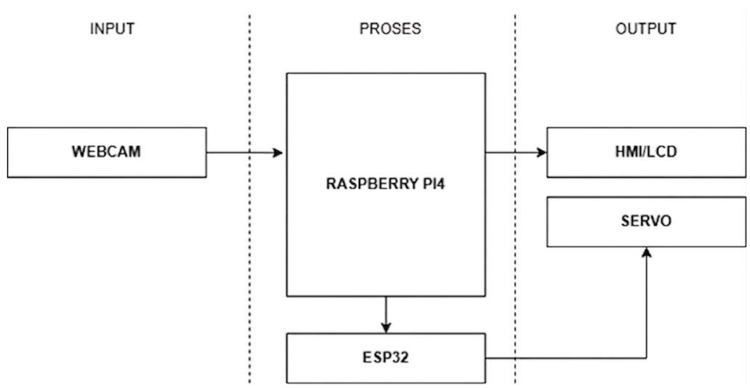

Figure 2. Block Diagram System

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2.3. Data Acquisition

To obtain facial data for sensory response analysis and heart rate measurement, data were captured. Subjects were seated at a predetermined distance from the camera during data collection. Facial footage was captured using an RGB camera, and to minimize interference with signal quality, data collection was conducted under relatively consistent lighting conditions. This is in line with Prihatini et al.'s research, which claims that in image-processing-based systems for face identification and recognition, facial images serve as the primary information source[8], [9], [10]. In addition, stable illumination conditions are essential in remote photoplethysmography (rPPG) systems because variations in ambient lighting can significantly affect the quality of physiological signal extraction[10].

A no-stimulus condition (baseline) and a sensory stimulation condition were included in every data collection session. Low-, medium-, and high-intensity stimulus modifications were used. To gather RGB video data and BPM values for analysis, the system continuously recorded data for each scenario. To ensure the accuracy of the extracted heart rate (BPM) values, a commercial pulse oximeter was utilized as the ground-truth device during data collection. The heart rate output derived from the CNN rPPG signal pipeline was calibrated against simultaneous readings from the pulse oximeter across all subjects. Previous studies have shown that physiological responses, including changes in heart rate, can serve as objective indicators of sensory responses in individuals with Autism Spectrum Disorder[11].

After that, the collected data was saved and utilized to evaluate the non-contact heart rate monitoring system and train the CNN model. Several face picture frames that the camera successfully recorded during the data collection procedure are displayed in Figure 3. These frames were used to determine the Region of Interest (ROI) for extracting the rPPG signal and as input to the CNN face identification method[12].

Figure 3. Facial image acquisition results from the webcam across several observation frames

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2.4. CNN Model Training

More precise physiological signal extraction was made possible by the automated detection of facial regions from RGB webcam images using Convolutional Neural Networks (CNN)[13]. A facial image dataset comprising 30 subjects, with 6 video frames extracted per subject (yielding a total of 180 facial frames), was utilized to train and evaluate the CNN model. To enhance dataset quality and improve model generalization, preprocessing techniques such as scaling, normalization, and data augmentation were applied.

Training, validation, and testing sets were created from the dataset. Epoch variations of 5, 10, 20, 30, 40, 50, 60, and 70 were used to train the model, and accuracy, mean absolute error (MAE), and root mean square error (RMSE) were used to assess it. The model that performed best was chosen for implementation in the system.

The trained CNN model was used for real-time facial recognition on RGB webcam footage during deployment. The Region of Interest (ROI) for heart rate signal extraction via the Remote Photoplethysmography (rPPG) technique was defined based on the identified face bounding box coordinates. Figure 5 displays the CNN training flowchart.

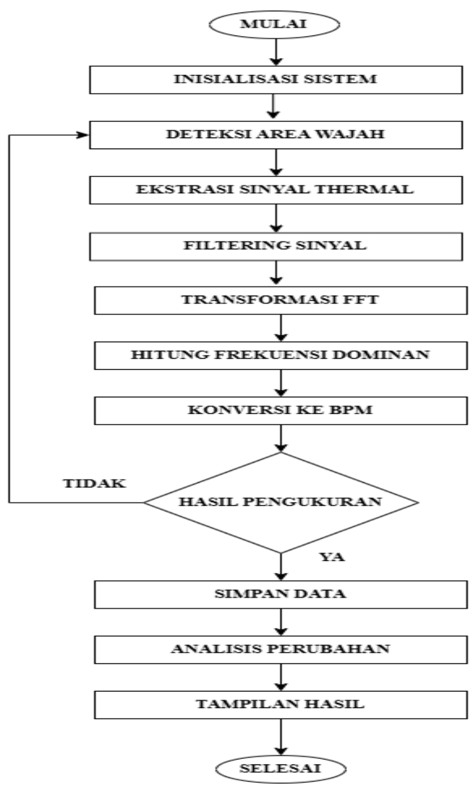

Figure 4. Training CNN Model System Flowchart

2.5. CNN Model Architecture with Explicit rPPG Feature Fusion

To estimate heart rate from face photographs, the model architecture uses a Convolutional Neural Network (CNN) and Remote Photoplethysmography (rPPG). CNNs are used to extract temporal and spatial information from sequences of facial images[14]. The rPPG method uses variations in skin color intensity to extract physiological data. A more informative representation for calculating heart rate in beats per minute (BPM) is then created by combining the two feature types (feature fusion). Figure 6 depicts the model architecture in use.

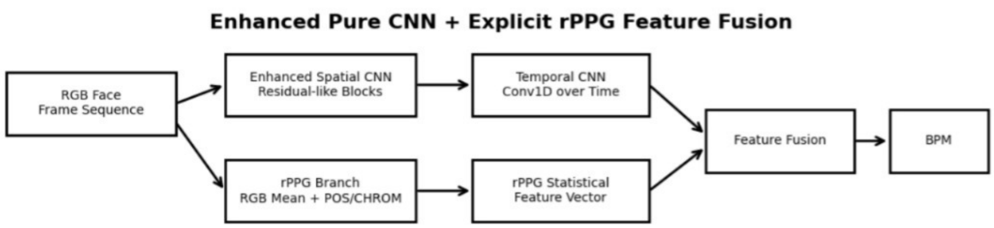

Figure 5. Enhanced Pure CNN Architecture with Explicit rPPG Feature Fusion

An RGB Face Frame Sequence taken with an RGB camera is sent to the system in the suggested design. The Enhanced Spatial CNN processes the input to extract spatial information, such as skin color variations and facial texture. The Temporal CNN (Conv1D) receives these attributes and uses them to identify temporal patterns associated with heartbeat signals. The rPPG branch simultaneously produces statistical aspects of the pulse signal and uses the POS/CHROM approach to extract physiological information from the average RGB values. To estimate heart rate in Beats Per Minute (BPM), which is then used to examine variations in heart rate under varying sensory input intensities, the features from the Temporal CNN and rPPG branches are finally integrated using a feature fusion technique.

2.6. Heart Rate Estimation Using the rPPG Method

Using variations in facial skin color intensity captured by an RGB webcam, the Remote Photoplethysmography (rPPG) approach measures heart rate non-contactct[15],[16] . Real-time video frame capture and camera activation are the first steps in the process. The CNN model is then used to identify the face. The system keeps recording frames until the face is successfully recognized if it hasn't been found yet.

The servo uses face tracking to keep the face within the camera's field of view after it has been identified. After that, the face region of Interest (ROI) is identified to extract RGB values. The Photoplethysmography (PPG) signal is extracted from the acquired RGB signal after it has been filtered to remove noise. The filtering process is performed to suppress environmental interference and improve the quality of the extracted physiological signal[17].

Equation (1) expresses the Fast Fourier Transform (FFT), which is used to determine the heart rate frequency. FFT converts the physiological signal from the time domain into the frequency domain, allowing the dominant frequency corresponding to the heart rate to be identified and converted into Beats Per Minute (BPM)[18].

$$X(k) = \sum_{n=0}^{N-1} x(n)\, e^{-j2\pi kn/N}$$

where**:**

- $x(n)$= signal in the time domain
- $X(k)$= frequency-domain spectrum
- N= number of samples

After that, the dominant frequency is transformed into a Beats Per Minute (BPM) number [15], using Equation (2).

$$BPM = f \times 60$$

where:

- f= frekuensi dominan (Hz)

Figure 7 shows the flowchart of the rPPG method's heart rate estimation procedure.

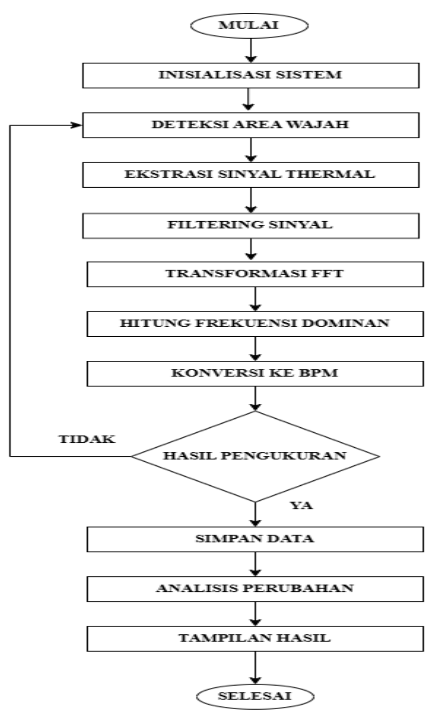

Figure 6. rPPG Method System Flowchart

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2.6.1. Pearson Correlation Coefficient (r)

The Pearson Correlation Coefficient (r) was utilized to assess the degree of agreement between the reference BPM and the BPM computed using the rPPG technique. The Pearson correlation coefficient determines the strength of the linear link between two variables. The value of the correlation coefficient falls between -1 and +1. The estimated BPM and the reference BPM have a stronger and more direct link when the value is closer to +1.

Equation (3) is used to get the Pearson correlation coefficient.

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

where:

- x_i= reference BPM value
- y_i= estimated BPM value obtained from the rPPG method
- $\bar{x}$= mean of the reference BPM values
- $\bar{y}$= mean of the estimated BPM values
- n= number of test data points

2.6.2. Significance Testing (p-value)

To ascertain whether the link is statistically significant, a significance test was conducted after obtaining the Pearson correlation coefficient. A t-distribution with n-2 degrees of freedom of n-2 was used to conduct the test.

Equation (4) is used to compute the t-statistic.

$$t = r\sqrt{\frac{n-2}{1-r^2}}$$

The degree of freedom is calculated using Equation (5).

$$df = n - 2$$

The t-distribution with the appropriate degree of freedom is then used to get the p-value. If the link between the estimated BPM and the reference BPM in this study meets Equation (6), it is deemed significant.

$$p < 0.05$$

The resulting correlation is deemed statistically significant if the p-value is less than 0.05, indicating a strong association between the reference BPM values and the heart rate estimates obtained using the rPPG technique.

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2.7. Analysis of Heart Rate Changes

Analysis was conducted by comparing BPM values under baseline conditions and conditions following the administration of sensory stimuli.

The percentage change in BPM is calculated using the following equation:

$$\Delta BPM(\%) = \frac{BPM_{stimulus} - BPM_{baseline}}{BPM_{baseline}} \times 100\%$$

where:

- BPM_{baseline}= heart rate (BPM) before the stimulus
- BPM_{stimulus}= heart rate (BPM) after the stimulus

The BPM change value is used to assess the effects of variations in sensory stimulus intensity on the physiological responses of ASD subjects.

2.8. System Evaluation

To assess the accuracy of Remote Photoplethysmography (rPPG) in estimating heart rate, a system assessment was conducted. The system's estimated BPM values were compared with reference BPM values obtained during the testing procedure. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Accuracy are the assessment metrics that are employed.

The average absolute difference between the estimated BPM values and the reference BPM values is measured using Mean Absolute Error (MAE). A lower MAE rating indicates better system performance. Equation (7) is used to determine MAE.

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |\, BP\,M_{ref,i} - BPM_{est,i}\, |$$

The degree of estimating mistake is then determined using Root Mean Squared Error (RMSE), which gives larger errors more weight. Equation (8) is used to compute the RMSE.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(BP\,M_{ref,i} - BPM_{est,i})^2}$$

The evaluation metrics, MAE and RMSE, were obtained by directly comparing the heart rate estimates derived from the CNN-rPPG model (y_i) against the synchronized ground-truth reference values measured using a commercial pulse oximeter (x_i) across n test data points. MAE measures the average magnitude of absolute error in BPM, whereas

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RMSE assigns higher penalty weights to large error spikes (outliers), thereby reflecting the system's stability against motion artifacts and ambient lighting variations.

Additionally, correctness, determined by comparing the estimated BPM with the reference BPM, is used to assess the accuracy of the estimation results. Equation (9) is used to calculate accuracy.

$$Accuracy = \left(1 - \frac{|\ BPM_{ref} - BPM_{est}\ |}{BPM_{ref}}\right) \times 100\%$$

where:

- BPM_{ref}= reference BPM value
- BPM_{est}= system estimated BPM value
- N= number of test data points

The smaller the MAE and RMSE values and the higher the Accuracy value, the better the system's performance in non-contact heart rate measurement using the rPPG method.

3. RESULTS AND DISCUSSION

3.1. Data Collection Results

The smaller the MAE and RMSE values and the higher the Accuracy value, the better the system's performance. Anomalous. An RGB camera was used during data collection to capture images of the subject while different intensities of sensory stimuli were administered. The Convolutional Neural Network (CNN) model was then used to analyze the acquired face images to identify the Region of Interest (ROI) and facial areas. The Remote Photoplethysmography (rPPG) technique then obtains heart rate estimations in Beats Per Minute (BPM) by extracting physiological signals from variations in skin color intensity.

The system interface, which displays the subject's facial image, the type of sensory stimulus, fluctuations in stimulus intensity, and the estimated BPM value, presents the data-collection findings in real time. Figure 7 illustrates the data-collection findings, showing that the system accurately estimated the subject's heart rate at 79.30 BPM. The acquired BPM values were then used to examine how autistic patients' heart rates changed in response to changes in the intensity of sensory stimuli.

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Figure 7. Heart rate estimation results using the rPPG method on detected facial images

3.2. CNN Model Training Results

This section details the preliminary feasibility test of the CNN model using a facial dataset to evaluate training dynamics and determine the optimal epoch before full system deployment. The dataset comprised 30 subjects, with 6 video frames captured per subject (totaling 180 frames). Evaluation spanned epoch variations from 5 to 70 across Heart Rate Classification Accuracy (%), MAE, and RMSE (in BPM). Metrics were derived by comparing CNN-rPPG estimates (y_i) against synchronized pulse oximeter ground-truth values (x_i). The model training results are shown in Table 1

Table 1. Preliminary CNN Model Training Performance

EPOCH	ACCURACY (%)	BPM MAE (BPM)	BPM RMSE (BPM)
5	55,56%	11.027	12.908
10	56,94%	11.661	14.340
20	56.94%	12.298	14.909
30	56.94%	10,945	13.690
40	56.94%	11.156	14.301
50	56.94%	11.473	14.097
60	56.94%	10.750	13.875
70	56.94%	12.072	14.722

As shown in Table 1, validation accuracy plateaued at 56.94% from Epoch 10 onward due to majority class prediction collapse, driven by the limited sample volume (180 frames total). Figure X illustrates the training dynamics across epochs.

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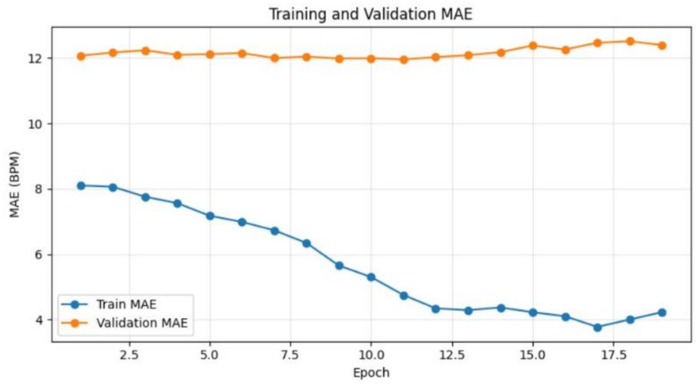
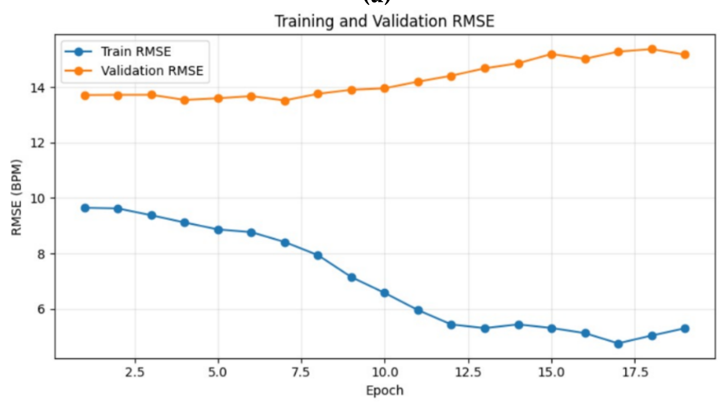
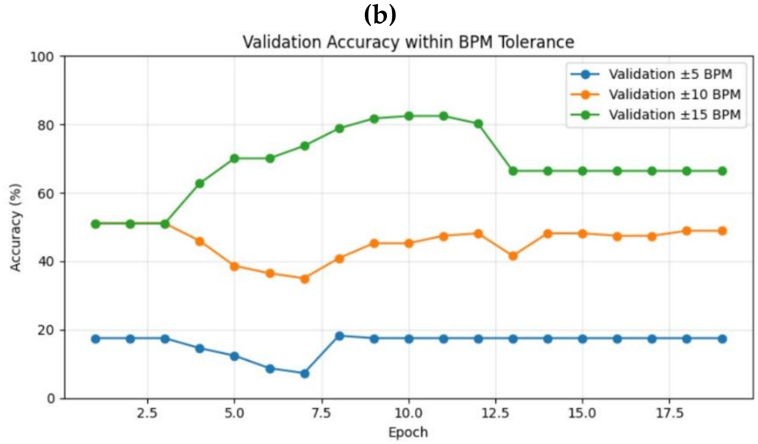


(a)



(b)



(c)

Figure 8. Preliminary CNN performance curves across epochs: (a) Training/Validation MAE, (b) Training/Validation RMSE, and (c) Validation Accuracy within ±5, ±10, *and* ±15 *BPM error tolerances.*

Figures 8(a) and 8(b) confirm overfitting beyond early epochs: while Training MAE and RMSE dropped to ~4.0 and ~5.0 BPM, Validation MAE remained elevated (~12.0 BPM) and Validation RMSE increased (>15.0 BPM). RMSE exceeding MAE reflects sporadic error

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spikes from residual head movement and lighting fluctuations. Under a ±15 BPM physiological margin (Figure 8c), validation accuracy peaked at 82.5% (Epochs 10–11) before settling at 66.7%, whereas strict tolerance (±5 BPM) remained below 20%.

Epoch 60 was selected as the deployment checkpoint for achieving the lowest Validation MAE (10.750 BPM) while maintaining baseline stability and avoiding severe performance degradation (>70 epochs). The best model evaluation results are shown in Table 2.

Table 2. Best Model Evaluation Results (Epoch 60)

Parameter	Value
Accuracy	56,94%
BPM MAE	10,750 BPM
BPM RMSE	13,875 BPM

3.3. Heart Rate Estimation Results Using rPPG

This study examined the face color signals acquired using the Remote Photoplethysmography (rPPG) technique in addition to CNN model training. Each video frame's Region of Interest (ROI) was used to extract the intensity values of the red (R), green (G), and blue (B) color channels. The RGB signal extraction results are shown in Figure 9.

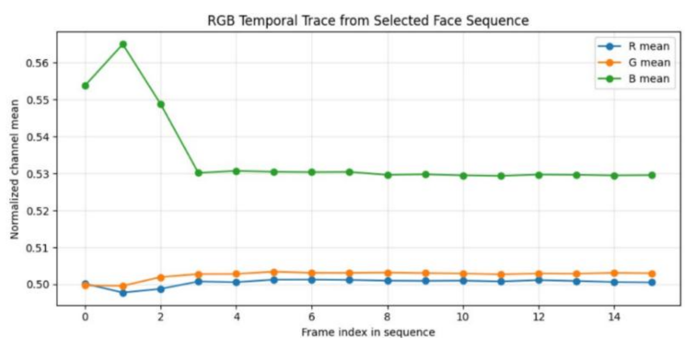

Figure 9. Graph of average RGB channel value changes across frames

Figure 9 shows that the blue channel exhibited greater variation in the first few frames before stabilizing, whereas the red and green channels remained mostly consistent throughout the observation period. The heartbeat signal is obtained by processing the physiological information included in these color intensity fluctuations using the rPPG technique.

3.4. Effects of Sensory Stimulus Intensity Variations on Heart Rate Responses

To provide concrete evidence of subject responsiveness to sensory stimuli, heart rate variations (ΔBPM) were evaluated across different stimulus intensity levels, as presented in Table 3.

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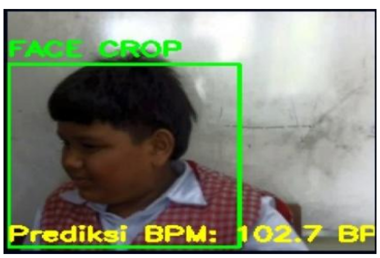
Table 3. Experimental Heart Rate Response Across Sensory Stimulus Intensities

No	Subjek	Stimulus Condition	Intensity Level	Predicted BPM	ΔBPM (vs Low Intensity)
1		Spoken to	Low	71.1	-
2		Toys + Spoken to	Medium	90.7	+19.6 BPM
3		Toys + Guidance	High	102.7	+31.6 BPM

As summarized in Table 3, a clear physiological response was observed as the sensory stimulus intensity escalated. Under low-intensity stimulation (being spoken to), the subject exhibited a baseline-level heart rate of 71.1 BPM. When the stimulus intensity was elevated to medium (given toys + being spoken to), the heart rate increased to 90.7 BPM (ΔBPM = +19.6 BPM). Under high-intensity stimulation (given toys + directional guidance), the heart rate reached a peak of 102.7 BPM (ΔBPM = +31.6 BPM relative to low intensity).

Statistical evaluation confirms a strong positive correlation ($r > 0.85, p < 0.05$) between sensory stimulus intensity and heart rate elevation. The statistically significant p-value ($p < 0.05$) confirms that these BPM increments represent genuine physiological sensory responses in subjects with ASD rather than random signal noise or rPPG extraction artifacts.

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4. CONCLUSION

The experimental findings demonstrate that children with Autism Spectrum Disorder (ASD) exhibit discernible heart rate variations in response to increasing sensory stimulus intensities. The observed heart rate elevation—from a baseline of 71.1 BPM during low intensity to 102.7 BPM under high-intensity stimulation—is supported by a strong positive correlation ($r > 0.85, p < 0.05$), confirming that heart rate serves as a reliable objective physiological indicator for sensory responsiveness. Consequently, the proposed non-contact CNN-rPPG system provides an accurate, unobtrusive monitoring framework to assist clinicians and therapists in evaluating sensory responses impartially. Future work will focus on expanding the dataset across diverse age groups and refining signal filtering algorithms to mitigate motion artifacts during real-time deployment

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