

Non-Contact Automatic Respiratory Rate Monitoring for Newborns Using Digital Camera Technology and Deep Learning

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Abstract. In healthcare settings, particularly for newborns in the Neonatal Intensive Care Unit (NICU), continuous and accurate monitoring of respiratory rates (RR) is crucial, yet current methods often involve manual region selection, which limits their effectiveness. To address this challenge, we developed a novel approach using a low-cost digital camera for non-contact RR monitoring of ten newborns. This study leverages deep learning for automated region of interest (ROI) selection in the face and chest areas, coupled with signal decomposition techniques to reduce noise artifacts. A graphical user interface (GUI) system was also introduced to facilitate real-time RR monitoring and visualization of results. The experimental outcomes demonstrate the system's high efficacy, with the object detector achieving precision rates of 98.24% for the face region and 96.61% for the chest region. Additionally, the system recorded a low average mean absolute error (MAE) of 1.11 breaths per minute for the face and 1.03 breaths per minute for the chest, corroborated by reference ECG monitor readings. This method offers a cost-effective, non-contact, and deployable solution suitable for both clinical and home health monitoring applications. © 2024 Journal of Biomedical Photonics & Engineering.

Keywords: respiratory rate; newborns; digital camera; YOLOV4-Tiny.

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1 Introduction

Monitoring respiratory rate (RR) is crucial for the preservation of newborns' lives since they have a substantial impact on the diagnosis of newborns' health in both hospital and home settings [1, 2]. The use of imperceptible vital signs may be very advantageous, especially in scientific and therapeutic contexts [3]. Hemoglobin in the blood has a higher capacity to absorb light compared to the surrounding epidermis tissue [4]. Photoplethysmograph (PPG) signals are used to assess chest function by quantifying fluctuations in blood volume in specific areas [5]. These signals indicate cyclic patterns produced by the heart's activity and breathing [6]. Contact techniques like nasal thermocouples, electronic sensors, ECGs, and oximetry probes are used to monitor respiratory signals. However,

using and removing these biosensors and electrodes may harm the skin and restrict the newborn's mobility [7].

To overcome the limitations of contact techniques, researchers have developed non-contact techniques for monitoring biomedical signals. Thermal imaging detects physiological signs by observing temperature changes related to blood flow in superficial arteries [8], while radar detects chest movements in a specific region of interest (ROI) [9, 10]. However, these methods are susceptible to noise and motion artifacts, limiting mobility [11]. Furthermore, they are harmful to human health and may have a variety of biological impacts on bodily tissue [12, 13].

Video camera techniques capture and analyze biological signals from many areas of the human body. We can categorize techniques into two fundamental groups [14]: color-based techniques, also called imaging photoplethysmography (iPPG) [9, 15–17], and motion-

based techniques [8, 18]. The first category utilizes differences in pigmentation resulting from cardiorespiratory physical exertion. Though iPPG is appealing in principle, prior investigations have been influenced by various downsides for extracting respiratory signals from patients, including lighting conditions, distance, and skin color [9, 19]. Consequently, the photoplethysmography technique is unable to accurately reveal physiological indicators in regions of interest that are not well defined [8]. Using a video camera to record the motion of specific human parts, such as the chest, head, or face, is a dependable way to detect the respiratory signal [18, 20–22].

For example, Al-Naji et al. [23] proposed a non-contact method for assessing newborn respiration rates using a video camera to record chest movements or blankets in various positions. Lucy et al. [24] developed a video-based approach that correlates respiratory rates with chest-abdominal wall movements, analyzing RGB video components and applying a fast Fourier transform to the denoised signal. However, irregular vital signs due to respiratory diseases necessitate accurate ROI selection for effective monitoring, highlighting the limitations of manual methods.

Additionally, Olmi et al. [25] introduced an automatic face detection system for infants in the NICU using the aggregate channel feature technique. The Neurophysiology and Neonatology Clinical Units used newborn data to train the model. Khanam et al. [26] utilized the YOLOv3 model as an automatic face detector for monitoring newborn vital signals, ensuring accurate ROI selection for video image analysis.

Current methods for respiratory signal monitoring are often unsuitable for real-time systems due to high processing and memory demands, prompting researchers to refine their algorithms [24]. Recently, the YOLO series, particularly YOLOv4-tiny [27], has emerged as a leading solution in object detection. YOLOv4-tiny, an optimized variant of YOLOv4 [28], features a lightweight architecture with a CSPDarknet53-tiny backbone and innovative techniques to enhance detection speed and performance [29]. Unlike YOLOv3-tiny, it uses CSPBlock for feature extraction and incorporates complete intersection over union for bounding box selection [30]. Comparative studies, such as those by Hraybi et al. [31], have demonstrated YOLOv4-tiny's superior accuracy and speed over other YOLO variants in face-mask detection. Experiments show that the YOLOv4_tiny model improves performance for reduced time detection while keeping the speed of the lightweight model and meeting the accuracy standard of substantial target detection models [32].

After reviewing the literature, the manual ROI selection approach was mostly used for non-contact biological sign monitoring. Furthermore, the current studies exhibit a significant research gap due to the limited exploration of non-contact vital sign monitoring in the NICU. Furthermore, some literary works employ multi-object ROI detection, necessitating computationally expensive calculations in terms of both

power and time. The aforementioned limitations serve as the impetus for implementing automated ROI selection for infants. The main focus of this work is to develop a healthcare system for non-contact respiratory rate monitoring of newborns. This research investigates the appropriateness of using a deep learning model to automatically determine ROI in a healthcare system. The contributions of this study are as follows:

1. An accurate non-contact RR monitoring system was developed using digital camera technology to evaluate two experiments: the first focused on respiratory signals extracted from the face region, while the second focused on signals extracted from the chest region of newborns.

2. An automatic ROI selection technique was developed using a pre-trained deep-learning model (YOLOV4-Tiny) as a baby detector, efficiently handling various challenging scenarios and different region selections (i.e., face and chest).

3. Motion-based techniques, combined with ensemble empirical mode decomposition (EEMD), were utilized to effectively extract respiratory signals from PPG signals.

4. A Newborn's Graphical User Interface (GUI) system was implemented for monitoring the baby's status and displaying the findings of the proposed non-contact monitoring system.

2 Methods and Materials

2.1 Subjects and Experiment Setup

We conducted this study at Al-Elwiya Maternity and Teaching Hospital (AMTH) in Al Rusafa, Baghdad, Iraq. We got permission from guardians to record videos using non-contact techniques at various periods after explaining the nature of the work and the experiment's aim to collect data without touching baby newborns. We protected the baby newborns' anonymity by concealing their faces. In this work, we used an ECG monitor as reference information to compare and analyze the performance of the 2 proposed experiments in evaluating the respiratory signals of baby newborns.

We used 10 newborn babies as participants, dividing them into 2 experiments: the first involved extracting RR values from the face region, named the RRface experiment, while the second involved extracting RR values from the chest region, named the RRchest experiment. The age range of newborns was 24 to 40 weeks, and they weighed 1500 to 3100 g. Fig. 1 depicts the experimental configuration, where 2 digital cameras recorded videos of 10 baby newborns in incubators. We tripod-mounted a Canon 2000D with a resolution of 1920 width $\times$ 1080 height at 25 frames per sec (fps) to record the infants' videos at a distance of approximately 1–1.5 m. We also installed another Canon 650D camera on a tripod to record the true state of vital signs on the ECG monitor. To synchronize the information from the ECG monitor and contactless technique, recording from both cameras began simultaneously.



Fig. 1 Experimental configuration of newborn's data collection.

We stored the videos in the “MOV” format. Collecting data from newborn babies requires a significant amount of time and effort. Recording rated videos of baby newborns is extremely challenging in a hospital setting, such as the NICU. Typically, medical devices or soft layers obstruct newborn babies. To validate our work, we gathered a small database. We considered the use of video recorders when newborns were not moving, as well as the constant use of ECG monitors.

We recorded each infant 5 times in their most stable condition. We recorded each newborn's video for approximately 10 min and edited it into 10-sec segments when the monitor's readings remained stable. As a result, we captured 50 videos for each experiment.

3 System Framework

This section will provide a detailed explanation of the proposed non-contact RR values monitoring system for newborns. This will include details: an automatic ROI selection-based deep learning model for 2 regions, respiratory rate calculation, and a newborn's GUI system proposed. Fig. 2 illustrates the framework for developing non-contact automatic respiratory rate monitoring for newborns.

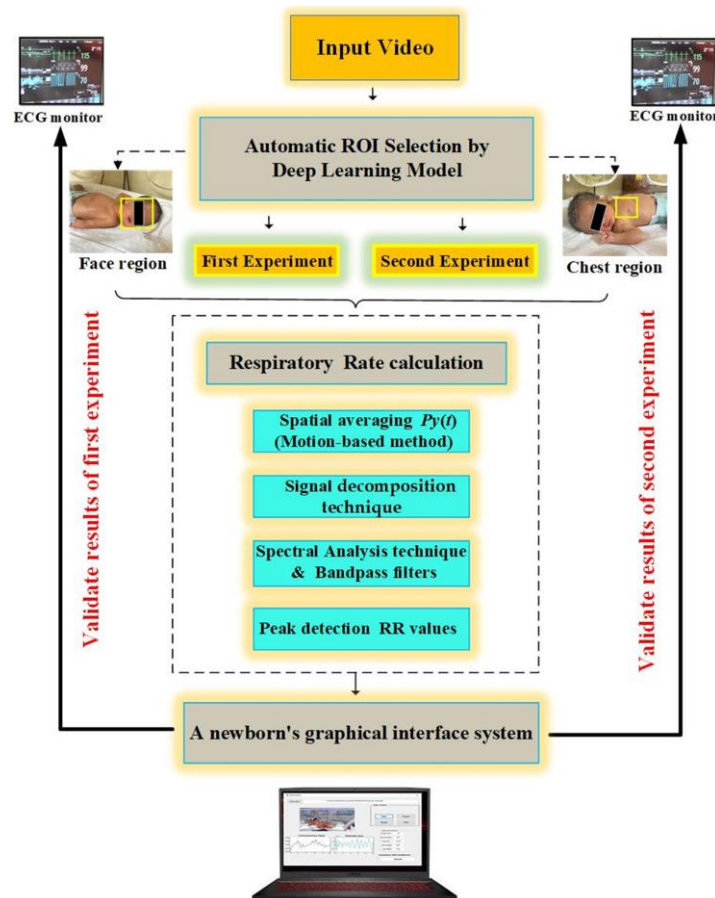


Fig. 2 The system framework of the proposed study.

3.1 Automatic Selection Model

Capturing high-quality video of newborns in healthcare units presents significant challenges due to the complexity of the environment. Traditional detection models, such as YOLOv2 and Mask-RCNN, supported by MATLAB [33], are generally effective for detecting people of all ages but fail to recognize infants within hospital settings. Also, insufficient infant-specific data may be not available [34].

Therefore, we trained a small dataset consisting of 420 images acquired from healthcare units, internet sources, and the NJN dataset [35], featuring various illumination conditions and infants in different sleeping positions.

We completed the label annotation process using the MATLAB 2023a toolbox's image-labeler function, drawing bounding boxes around each detected object. In the first experiment, we labeled the images as face regions, and in the second experiment, we labeled them as chest regions. In object detection, YOLO models predict the bounding box and category of objects in images. We assessed the accuracy of these predictions using Intersection over Union (IoU), applying a threshold of 0.5 to determine successful detections. If the intersection between the predicted bounding box and the ground truth bounding box is more than 50%, the detection is deemed successful. After label annotation, we applied data preprocessing techniques, such as rotations, scaling, and resizing images to 416×416 px, to enhance dataset diversity.

We trained the object detector model using pre-trained YOLOv4-Tiny weights [27], which were originally trained on the MS COCO dataset [27]. After configuring the model's parameters, we fine-tuned it using our small data. YOLOv4-Tiny outperforms other

detection models in terms of accuracy and speed. The YOLOv4-Tiny's average speed is twice that of the YOLOv4 and 10 times that of the Faster-RCNN [29].

Using the Adam optimization algorithm, we set the hyperparameters to 30 epochs, a batch size of 20, and a learning rate of 0.001. The training was conducted on a system with an i7 processor, NVIDIA GeForce GTX 1060Ti GPU, and 16 GB of RAM, using a GPU execution environment to expedite the process. We split the gathered data set from the sources mentioned into 70% (294 images) for training, 15% (63 images) for validation, and 15% (63 images) for testing. Finally, we evaluated the model's performance using precision, recall, and F_1 score, by applying the following Eqs.:

$$Precision = \frac{T_p}{T_p + F_p}, \quad (1)$$

$$Recall = \frac{T_p}{T_p + F_n}, \quad (2)$$

$$F_1 \text{ Score} = 2 * \frac{(Precision * Recall)}{(Precision + Recall)}, \quad (3)$$

where T_p represents the number of true positive regions detected during object detection, such as the face in the first experiment and the chest in the second experiment. F_p denotes the number of false positives, T_n is the number of true negative cases, and F_n is the number of false negative instances. To evaluate the model performance, we used the mean average precision (mAP), specifically the $mAP_{(0.5)}$ refers, for computing it at an IoU threshold of 0.5. Fig. 3 illustrates the steps involved in building the automatic ROI selection-based deep learning model.

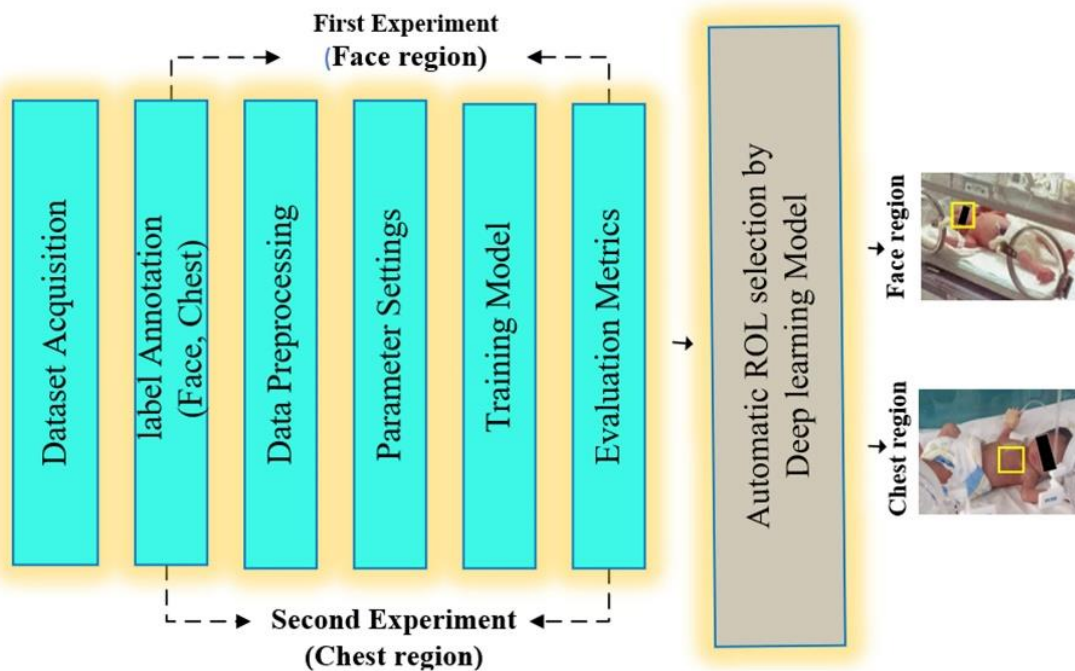


Fig. 3 Steps for building the automatic ROI selection-based deep learning model.

3.2 Respiratory Rate Calculation

In this study, we employed a motion-based technique to extract raw respiratory signals from newborns from 2 experiments (RRface and RRchest) as the first step. Respiratory activity generates a rhythmic motion in certain areas of the body, including the face, thorax, and chest regions. Therefore, in the recorder clip, spatial variations in intensity values refer to this motion. This principle allows for the calculation of the respiratory signal. As the digital camera records the video in the RGB color space, it is essential to distinguish between intensity and color information. Therefore, we transformed the RGB color space to 'YIQ' using MATLAB's built-in function 'rgb2ntsc'. Next, we calculated the raw respiratory signal from the Y channel of the YIQ color space by assessing the average brightness values of pixels within the chosen ROI, as follows:

$$p_{y(t)} = \frac{\sum_{x,y \in \text{ROI}} p(x,y,t)}{|\text{ROI}|}, \quad (4)$$

where $p_{y(t)}$ is the computed respiratory signal of a newborn, $p(x,y,t)$ indicates the intensity value of each pixel in the Y channel at the specified image location (x,y) , and time (t) , and $|\text{ROI}|$ represents the size of ROI regions by an automatic ROI selection.

In biomedical signal processing, signal decomposition methods are used to separate a time signal into a set of interesting modes. In this work, we employed the EEMD technique for signal decomposition as the second step. This technique was improved by Wu and Huang [36], in which white noise was added to the original EMD method to restrain the mode-mixing effect. The following steps identify the signal decomposition process, which is based on EEMD.

Also, we used the Fast Fourier Transform (FFT) to transfer the respiratory signals from the time domain to the frequency domain for spectral analysis as the third step. We then implemented the appropriate band-pass filters within the frequency range of 0.3 to 1 Hz, aligning

with the respiratory range of 30 to 60 breaths per min fourth step. Then, we subjected the processed data to the inverse of FFT to obtain the time-series respiratory signal accuracy.

In the fifth step, time series respiratory signals are processed by computing peaks and their locations (*locs*) between successive peaks. The built-in MATLAB function 'findpeaks' was utilized to detect peaks. Then, the total cycle length (*L*) between 2 peaks is calculated by applying the following Eq.:

$$L = \text{mean}(\text{diff}(\text{locs})). \quad (5)$$

The number of peaks (N_P) can be retrieved by the following Eq.:

$$N_P = \frac{D}{L}, \quad (6)$$

where *D* is the duration time in seconds of the video.

Finally, the RR values in breaths per min (breaths/min) is calculated using Eq. (7):

$$\text{RR} = \frac{60 N_P}{T}. \quad (7)$$

3.3 A Newborn's Graphical User Interface System

We implemented a newborn GUI system for non-contact RR monitoring using MATLAB 2023a, as shown in Fig. 4. The proposed system features a user-friendly interface that includes respiratory signal processing and displays the RR value results based on an automatic deep-learning model. It also provides an efficient environment for video uploads, along with analytical tools, including 3 axes for video selection, input signal display, and respiratory signal output. The proposed system includes 6 text fields for displaying video information and RR values. Additionally, it offers a variety of video controls, such as Start, Extract, Pause, and Reset, each designed for specific functions.



Fig. 4 A snapshot of the newborn's proposed graphical user interface.

4 Results and Analyses Experimental

4.1 Automatic Selection Model Performance

This Section evaluates the performance of the automatic ROI selection model based on the fine-tuned YOLOv4-Tiny model as a baby detector. As shown in Fig. 5, the YOLOv4-Tiny model effectively segments images, predicting bounding boxes and probabilities for each region. The model independently processes the detected face and chest regions, delivering accurate predictions with strong performance.

The results of performance metrics on the test dataset set regarding precision, recall, and F_1 score, and $mAP_{(0.5)}$ are shown in Table 1. The table demonstrates the performance results an automatic ROI selection region RRface and RRchest experiments.

The detector accuracies comparing the bounding box detected by the trained object detector with the true-label bounding box annotated (face and chest) were 96.31% for $mAP_{(0.5)}$ and 96.11% for $mAP(50)$ for the RRface

and RRchest experiments, respectively. Also, it is clearly shown from the table results that the object detector for regions (face and chest) had good performance for precision, recall, and F_1 Score for 2 experiments.

4.2 Respiratory Rate Extraction

In our experiments, we obtained raw respiratory signals for 250 frames by applying spatial averaging to the automatically detected ROIs using a motion-based method. We captured the signals for 2 distinct regions: the face and the chest. Fig. 6(a) presents the respiratory signal from the RRface experiment, while Fig. 6(b) shows the corresponding signal from the RRchest experiment.

The raw respiratory signals were subsequently decomposed using the EEMD method. The EEMD had a 10-sec window length. Fig. 7 illustrates the results of IMF decomposition for respiratory signals into IMF1, IMF2, and IMF7. Using FFT, we conducted a frequency spectral analysis of the decomposed IMFs to determine the most suitable IMF for calculating the RR values.



Fig. 5 Automatic ROI selection using the YOLOV4-Tiny deep learning model.

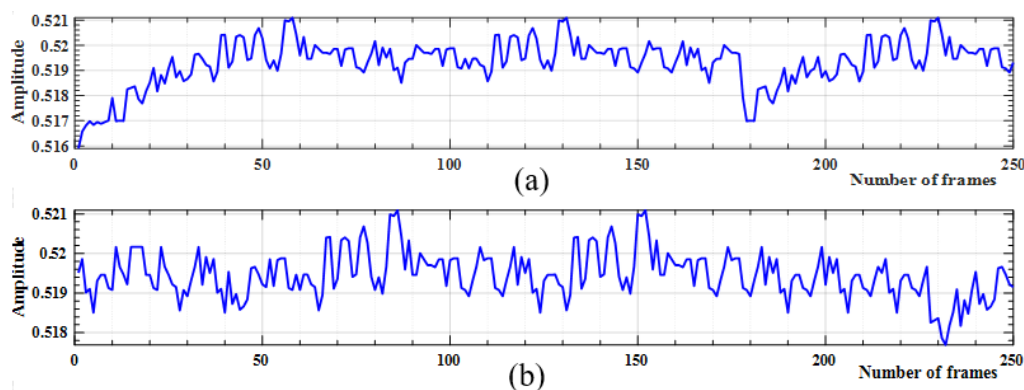


Fig. 6 Raw respiratory signals of two experiments. (a) RRface experiment; (b) RRchest experiment.

Table 1 Performance evaluation of 2 experiments.

Experiments	Select ROI region	Precision (%)	Recall (%)	F_1 Score (%)	$mAP_{(0.5)}$ (%)
First	Face	98.24	96.55	97.39	96.31
Second	Chest	96.61	98.27	97.43	96.11

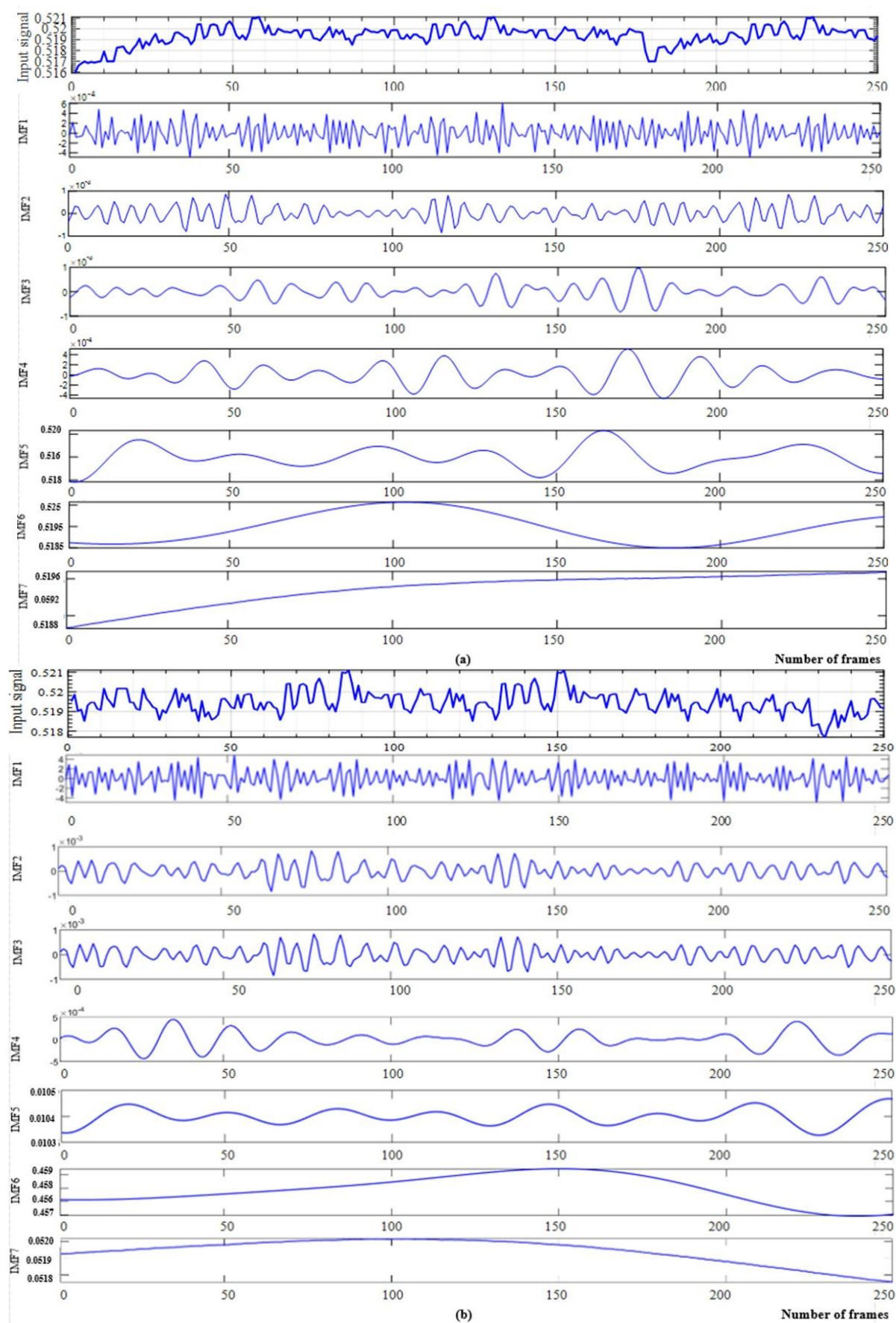


Fig. 7 IMFs component results of the raw respiratory signals. (a) RRface experiments; (b) RRchest experiment.

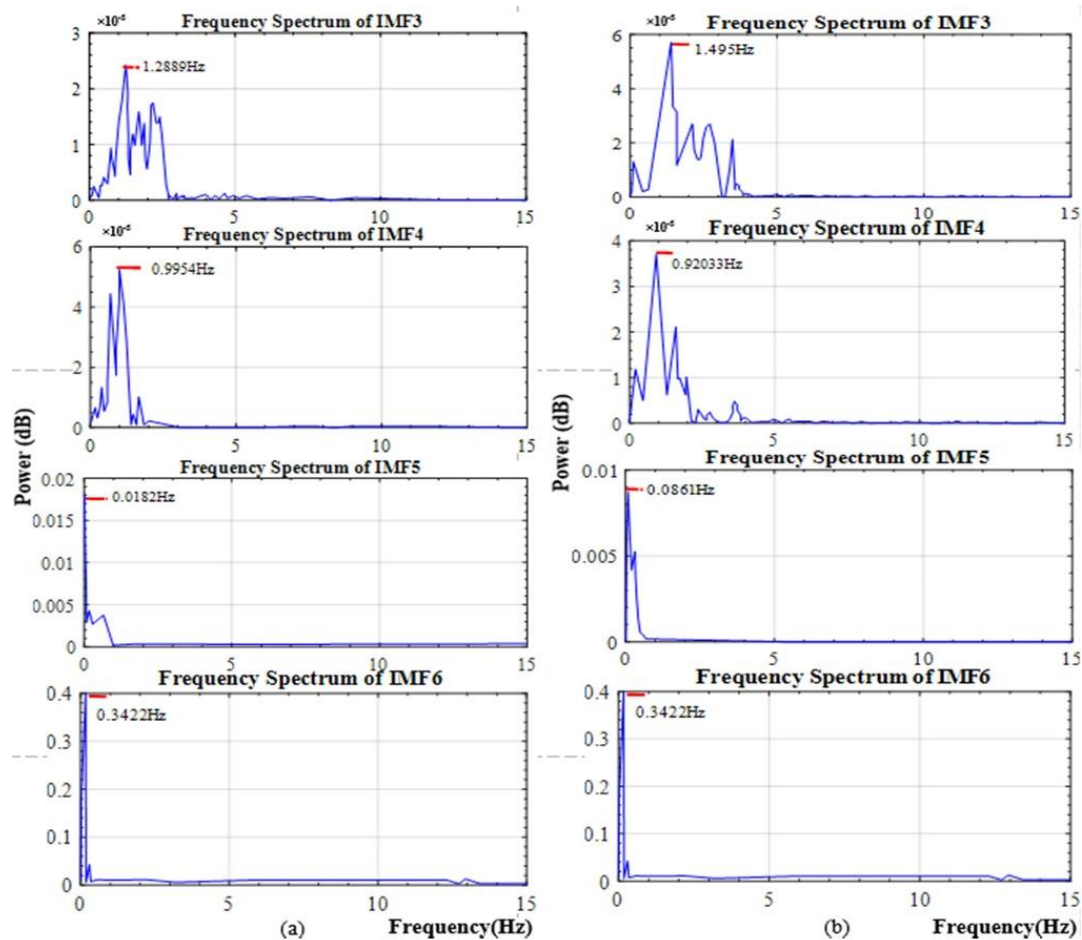


Fig. 8 Frequency spectrum analysis of IMFs. (a) RRface experiment; (b) RRchest experiment.

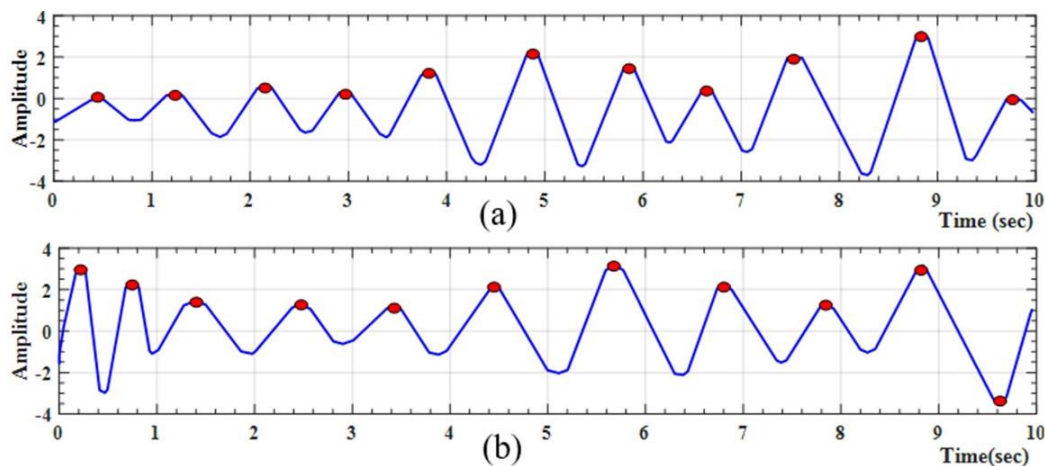


Fig. 9 Filtered respiratory signals. (a) RRface experiment; (b) RRchest experiment.

For 2 experiments, Fig. 8 displays the frequency bands of IMFs 3–6 most relevant to the respiratory range. Other spectra fall outside of this range. Typically, the breathing rate ranges between 30 and 60 breaths per min; thus, the normal frequency range of the RR measurements for newborns is approximately 0.3 Hz to 1 Hz. Therefore, we identified IMF4 (Figs. 7(a) and 8(a)) and IMF4 (Figs. 7(b) and 8(b)) for calculating the RRface experiment and the RRchest experiment, respectively.

Fig. 9(a, b) shows the results of filtered respiratory signals obtained after applying FFT, band-pass filtering, and inverse FFT, respectively. The FFT's window duration was 10 sec. The red color points indicate the peak locations of the filtered signals. The red circles indicate the peak locations of the filtered signal, as shown in Fig. 8(a) (RRface experiment) and Fig. 8(b) (RRchest experiment).

Fig. 10 shows the newborn's GUI, which includes the RR values (breaths/min) calculation from Eq. (8), the

input signal, and the filtered respiratory signal. Additionally, this proposed algorithm allows for real-time remote status monitoring of newborns and saves the RR results automatically on the computer as available medical data to aid in the future diagnosis of breathing conditions.

4.3 Statistical Analysis Measurements

To validate the performance of the proposed non-contact monitoring system from two experiments, we applied statistical analysis methods, including Pearson's correlation coefficient (PCC), Bland-

Altman plots, Spearman's correlation coefficient (SCC), mean bias, and linear regression. The overall sample size was set at $n = 50$. Fig. 11 presents the statistical analyses for the measured readings from the RRface experiment. As shown in Fig. 10(a), the Bland-Altman analysis reveals a mean bias of -0.32 breaths/min, with 95% limits of agreement ranging from -2.75 to $+2.09$. The PCC and SCC between the measured and reference readings were 0.991 and 0.978, respectively. Fig. 10(b) shows that the linear regression analysis demonstrates a strong relationship between the measured readings and the linear fit, with an R^2 value of 0.9823.

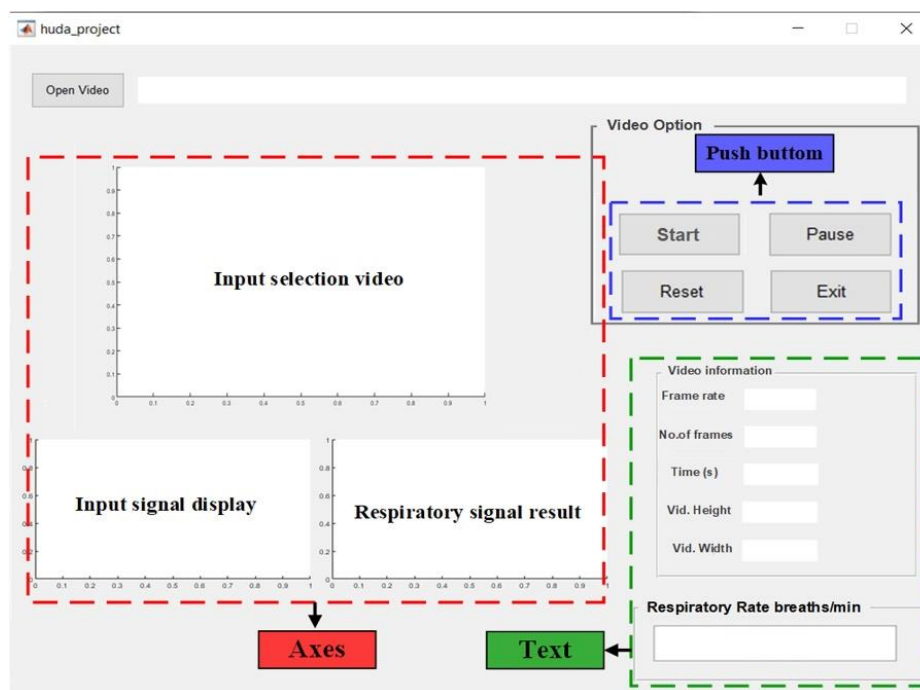


Fig. 10 Screenshot of proposed newborn's GUI.

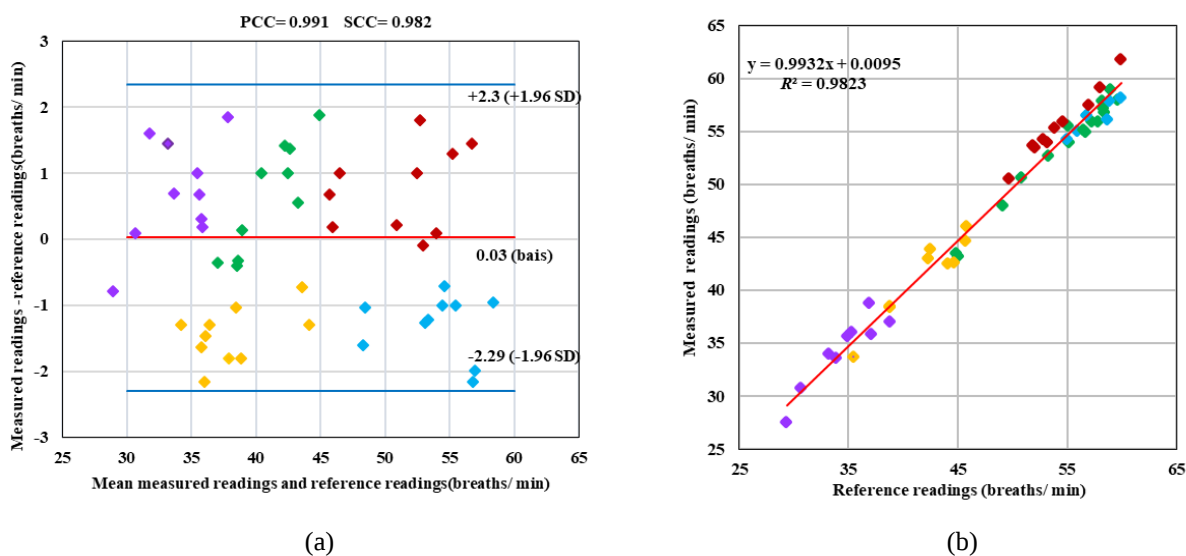


Fig. 11 Statistical analyses of the RRface experiment: (a) Bland-Altman plot, (b) correlation plot. The colored dots – purple, green, orange, red, and blue – represent data visualization from the first, second, third, fourth, and fifth newborns, respectively, related to the first experiment.

In addition, Fig. 12 illustrates a statistical investigation related to measured readings from the RRchest experiment. As demonstrated in Fig. 11(a), the Bland-Altman statistics exhibit a mean bias of 0.03 breaths/min, with 95% confidence intervals ranging from -6.67 to $+5.2$. Also, the PCC and SCC between RR readings and reference readings were 0.991 and 0.982, respectively. As shown in Fig. 11(b), linear

regression coefficients demonstrate a strong match between the measured readings and the linear fit, with $R^2 = 0.983$.

For each experiment, data from 5 newborns was collected, with 10 videos recorded for each newborn. To enhance data visualization, the data for each newborn were represented using uniquely colored dots, with each color corresponding to a specific newborn.

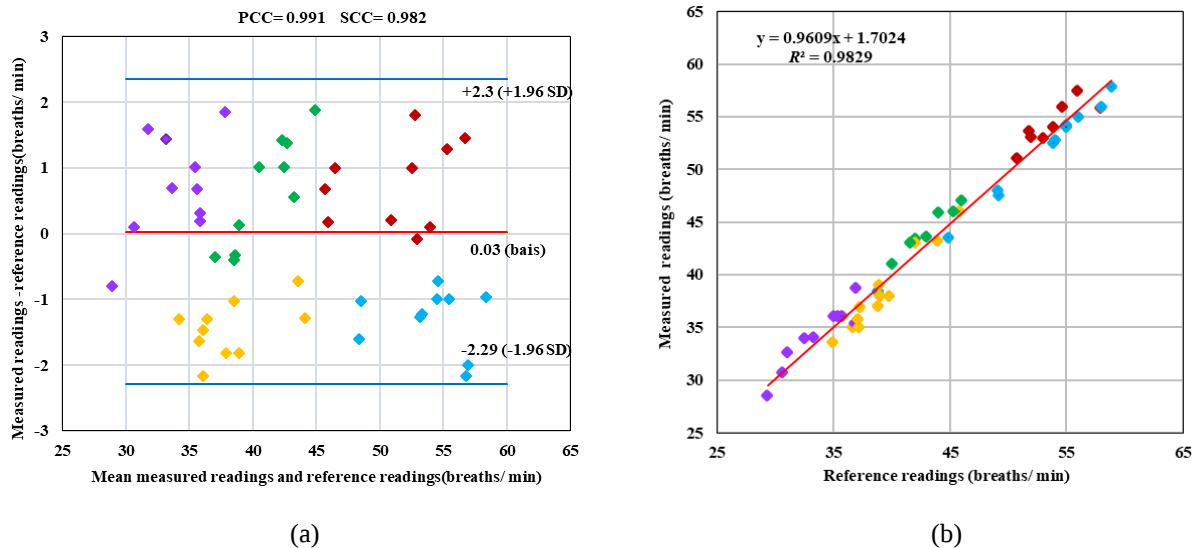


Fig. 12 Statistical analyses of the RRchest experiment: (a) Bland-Altman plot, (b) correlation plot. The colored dots – purple, green, orange, red, and blue – represent data visualization from the first, second, third, fourth, and fifth newborns, respectively, related to the second experiment.

Table 2 Comparison performance of the proposed system with the techniques of previous studies.

Authors	Sensor	ROI	Technique	Region	MAE (breaths/min)	PCC, SCC
Al-Naji et al. [23]	DSLR video camera	Manually	Wavelet pyramid	Chest	1.314	0.956, 0.966
Brieva et al. [7]	digital camera EOS 1300D	Manually	Hermite	Chest	2.15	–, –
Khanam et al. [26]	digital camera Nikon D610	Automatic	EEMD	Face	2.13	0.9453, –
Jorge et al. [34]	RBG camera	–	PCA	Chest	6.9	–, –
Chen et al. [37]	Video camera	Automatic	Convolution attention network	Face	3.02	–, –
Ganfure et al. [13]	Video camera	Automatic	Lucas Kanade optical flow	Chest	15.34	–, –
Tarassenko et al. [11]	Digital camera	Manually	Auto-regressive	Face	3	–, –
McDuff et al. [38]	Digital camera of five band	Manually	ICA	Face	–	0.92, –
Brieva et al. [39]	Digital camera EOS 1300D	Automatic	Hermite Magnification	Face	1.83	0.99, 0.91
Chen et al. [4]	Canon camera	Automatic	Lomb-Scargle periodogram	Face	2.16	–, –
Al-Naji et al. [40]	Nikon D3500 camera	Manually	ICA	Face	1.44	0.872, 0.823
Our work	Canon 2000D	Automatic	EEMD	Face	1.11	0.991, 0.978
				Chest	1.03	0.991, 0.982

5 Discussion

Based on the findings obtained in this paper, it appears to be possible to remotely extract the RR values in newborns' regions (face and chest) based on non-contact automatic monitoring using a digital camera and deep learning. The YOLOV4-Tiny deep learning model enhances the system's ability to automatically select the ROI in RRface and RRchest experiments, as demonstrated in Table 1. The study utilizes the pre-trained model's important feature extraction for efficient training, significantly enhancing the model's detection speed. The most considerable challenges faced in this work can be summarized in the bellow following points:

1. The unsteady measurements of the hospital ECG monitor connected to the newborns, which were considered reference data. Consequentially, we videotaped every newborn 5 times in their most stable position.

2. Consequentially, we videotaped every newborn 5 times in their most stable position. Thus, data gathering from newborns is a time-consuming and difficult procedure.

3. Additionally, there was limited space available for camera installation, which often resulted in unequal distances between the camera and the newborns.

To assess the effectiveness of our findings from the RRface and RRchest experiments, we compared them with 10 trustworthy studies using non-contact camera-based monitoring systems. The results revealed that the proposed system performed at the minimum average MAE of 1.11 breaths/min and had high metrics in PCC and SCC of 0.991 and 0.978, respectively, for the RRface experiment. Also, we obtained the lowest minimum average MAE of 1.03 breaths/min and had excellent metrics in PCC and SCC of 0.991 and 0.982 for the RRchest experiment. From the error rate analysis above, we can deduce that the proposed algorithm based on the deep learning model significantly improves the RR evaluation accuracy compared with previous works. As a result, the proposed technique is suitable for use in hospitals or indoor healthcare monitoring.

6 Conclusions

In conclusion, this study successfully developed a non-contact automatic RR monitoring system for newborns,

utilizing digital camera technology and deep learning. We introduced a fast and accurate ROI selection method based on a pre-trained YOLOV4-Tiny model to efficiently detect newborns in various challenging scenarios, with a focus on the face and chest regions. To further enhance signal quality, we employed an EEMD-based signal decomposition technique to minimize noise artifacts. Additionally, we developed a specialized GUI for newborns, providing a visual interface and comprehensive information that supports biomedical engineers in remotely monitoring vital signs in the NICU. The experimental results demonstrated a strong correlation, with PCC values of 0.991 for both RRface and RRchest, alongside low average error rates, with MAE values of 1.11 breaths/min for RRface and 1.03 breaths/min for RRchest. The system's low cost and ease of deployment make it a promising solution for real-time neonatal health monitoring. Future work will focus on enhancing system reliability by incorporating advanced signal-processing techniques and exploring a dual-camera (RGB and thermal) approach to further improve performance.

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Disclosures

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Author Contribution

Huda Ali Hashim: Conceptualization, Resources, Methodology, Investigation, Software, Writing - Review & Editing.

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