HEART RATE MEASUREMENT USING IMAGE RECOGNITION TECHNOLOGY

K. Daqrouq[*], A. Hazazi[*], A. Alkhateeb[*], R.A. Alharbey[†]

Abstract: The measurement of heart rate (HR) has numerous applications in various fields, such as the internet of things, security, sports, and telemedicine. There are many methods for measuring pulse rates, and this research is based on a novel technique of measuring the heartbeat using image recognition technology. The innovations in the field of visual objects have made the detection process easy and quick, with high efficiency. Four step-based algorithms, including a computer, an external high-definition camera, and an open-source computer vision library, have been presented for measuring heart rate. The first step was the face detection (FD) algorithm, and the second was the area attention algorithm to determine the region of interest (ROI). The ROI signal analysis algorithm was used in the third step, using a fast Fourier transform (FFT) for frequency detection. The pulse measurement phase was the final step, and it was based on the strength of the color concentration in proportion to the time extracted from video clips. With the help of our recorded database of 50 participants based on different ages and skin colors, the process was carried out. The results of this study contributed to the development of an HR detection technique based on image recognition using the Python programming language. This is a very comfortable and effective method for measuring the human heart rate. This research article discussed various factors and obstacles that affect heart rate measurement. The results found that our system is highly competent in measuring heart rate.

Key words: *heart rate, image recognition, detection rate, measurement*

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1. Introduction

Image recognition has been recognized as one of the most important and emerging technologies for measuring heart rate [1]. Human heart rate (HR) has been defined as the average heart rate per minute [2]. The values of HR vary from person to person and depend on their physical activities and exercises. It has been the main tool for measuring various levels of stress and other human emotional experiences.

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The popular and effective method for determining HR is the electrocardiogram (ECG). HR is measured by ECG as the machine helps to record electrical impulses from the heart, and these signals are leveraged for monitoring and detecting heart problems [3]. With time, all systems have been updated to smart devices, and the whole world has become a global village. Many other methods and techniques are being used for measuring the heartbeat, including adhesive sensors, but these are very inconvenient for patients as they require gel for enhancing electrical conductivity. Pulse oximetry is also another method for the detection of HR. These are all contact methods that are difficult for patients as they cause skin damage and other kinds of discomfort, especially for newborns and elderly people. In this paper, we suggest a system that works without direct contact. The proposed system uses a camera and image recognition, a simple web-based computer, or a mobile phone that can be used for tracking HR per minute for monitoring changes in the heart's beat rate. Photo-plethysmography (PPG) is another method for measuring the varieties in blood volume pulse (BVP) without any contact [4, 5].

The main purpose of this research is to present a novel and comfortable method for the measurement of HR. The traditional methods, including sensors and the inclusion of other devices with skin, are very difficult, especially for newborns, long-term epilepsy, sleep research, and persistent measurement of HR. Problems are caused by the electrical activity of the patient's body and electromagnetic fields. The elimination of these signals is an important issue for researchers and experts in biomedical engineering [6]. This article is very important for presenting a novel solution that will be contactless and consist of remote monitoring based on a camera. The proportion of signals will be relatively small, and all signals should be accessed and measured accurately. HR uses image recognition, and the main focus is on the image recognition pulse measurement system (IRPM). The mechanism being adopted for measuring HR is through a camera that would take an image from the top of the head built into a laptop or external HD camera. The different sections of this research article will discuss the algorithm system for IRPM, facilitating the measurement of HR of newborns, patients in the ICU, and all those that require long-term monitoring. Examination of factors affecting HR measurement and providing HR measurement support to people of different ages and skin colors will also be discussed in this study. There are many impacts of reducing HR through autogenic training, and this study will examine all those impact factors.

2. Literature review

The number of heart beats per minute is important physiological information used for the diagnosis and treatment of many heart-related diseases [7]. HR values vary from person to person and are also dependent on age group and skin color [8, 9]. Past studies have indicated that convolutional neural networks are used for image processing. A special type of feed-forward neural network derived from different biological processes is very useful for finding solutions for computer vision in artificial intelligence, including image and video processing [10, 11]. Recent research in the field of biomedical engineering has presented and introduced many new methods of contactless HR measurement [12, 13]. There are many examples and cases among patients that need continuous monitoring for diagnosing diseases. This research will present a real-time HR measurement framework based on real-time video streams. This will utilize images that extract customized features of pulse rate, and the whole mechanism has different steps: the face detection (FD) algorithm and object tracking method for finding the human face, with the help of software for producing a group of rectangles on the face to make the region of interest (ROI), and these rectangles then extract pulse samples. Finally, the collected samples are used for analyzing the chromatic differences caused by the appearance of the pulse through the skin. HR is found by the average of the color pixels of the ROI signal.

There are many new and advanced studies based on HR measurement. The techniques used are the independent analysis technique, support vector machine, and other machine learning algorithms. All these algorithms have greater accuracy of 97.78% [14, 15]. In the past decades, before innovation and technological advancement, cardiac signals were analyzed with the help of wave technology. New technologies, including the recurrent neural network (RNN), a model of unsupervised learning, are also being applied for cardiac wave signal processing with high accuracy in results [16, 17].

Remote photoplethysmography (PPG) is also a remote measurement technique of HR based on low-cost RGB imaging equipment. This research study has focused on the development of PPG since 2008. This is very important as it includes the traditional and existing approaches of PPG and presents an overview of different modular steps. This framework is essential for practitioners to design algorithms for a PPG approach to meet specific needs [18]. Smartphone cameras are considered as the most important and effective means of detecting HR. These are the most effective and innovative mechanisms for providing comfort to people. HR is measured by detecting pulsatile PPG signals based on post-processing of the video of the face of the subjects. This pilot study has presented a novel approach that measures the HR and respiratory rate both from the video of the subject by measuring the color of reflected light. The data for this research was collected by measuring the HR of 25 healthy individuals between the age groups of 20 and 30 years. A two-second video of the face has been taken with minimal movement based on flash ON and OFF. The results of this study show that the proposed approach showed more accurate results than the traditional methods [19].

As the latest research papers on the subject, we can find:
"A non-contact system for continuous monitoring of heart rate variability in neonates" [20] developed a non-contact system for continuous monitoring of heart rate variability in neonates by using a thermal camera as a low-cost, non-invasive alternative to traditional methods of neonatal monitoring.

"Non-contact monitoring of heart rate variability using a low-cost thermal camera" [21] explored the feasibility by means of a low-cost thermal camera for non-contact monitoring of heart rate variability, showing promising results for the usage of thermal imaging in remote monitoring of heart rate variability.

"Heart rate variability monitoring using a low-cost thermal camera: A pilot study" [22] investigated the usage of thermal imaging for monitoring heart rate variability in healthy adults, demonstrating the potential of thermal imaging as a low-cost and non-invasive method for heart rate variability monitoring.

"Non-contact monitoring of heart rate variability by a remote photoplethysmography imaging system" [23] proposed a remote photoplethysmography imaging system for non-contact monitoring of heart rate variability, demonstrating accurate measurement of heart rate variability in real-time.

"Remote camera-based vital sign measurement using orthogonal subspace projection and blind source separation" [24] suggested a remote camera-based vital sign measurement system that accurately measures vital signs, such as heart rate and respiratory rate, from a distance using orthogonal subspace projection and blind source separation.

"Remote detection of vital signs using a visible light camera" [25] suggested a method for remote detection of vital signs, such as heart rate and respiratory rate, by the use of a visible light camera, achieving high accuracy in real-time vital sign detection.

"Contact-free measurement of cardiac pulse based on the principal component analysis of facial skin chromatic signals" [26] proposed a method for contact-free measurement of cardiac pulse using the principal component analysis of facial skin chromatic signals, accurately measuring cardiac pulse without the need for contact with the skin.

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3. Methodology

In this section, a detailed description of the methodology is presented. The method used in this study employed a video processing method for real-time measurement of heart rate, based on software with the latest libraries from OpenCV [27]. These libraries were instrumental in tracking objects and detecting face information accurately. The selection of an accurate region of interest (ROI) was crucial, particularly in places where color scrap changes. The research relied on the average intensity of skin color and the other three-color frequencies abstracted from the source signal. An algorithm was established to discover the vertex, and the confirmed peaks presenting the heart rate were calculated. Pixels in the ROI were managed in the development environment, and operated on OpenCV and Python programs, to accomplish the required results.

As shown in Fig. 1, the methodology utilized a series of blocks. The video processing method was applied for real-time heart rate measurement, and selecting an accurate ROI was an essential step. The study relied on the average intensity of skin color and the other three-color frequencies abstracted from the source signal to calculate confirmed peaks presenting the heart rate. The algorithm for the discovery of the vertex was constructed to achieve desired results.

The methodology employed a video processing method and several techniques, including using OpenCV libraries, to achieve real-time heart rate measurement, which is the desired outcome.

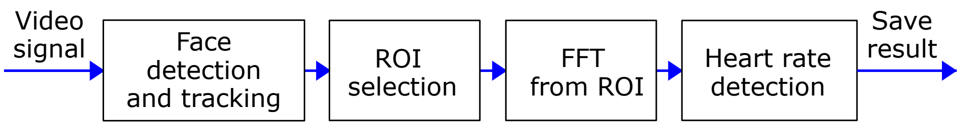


Fig. 1 *Block diagram for image recognition pulse measurement algorithm.*

Video signals: For the proposed research, a digital video has been utilized, which has all the information that is required to produce a visual image by the display device.

Face detection: This starts by capturing the forehead of the patient until all the details of the face become visible. Facial recognition is the first step in this process. After that, the facial movements can be tracked using the object tracker and FD must be renewed after every ten seconds until the number of frames reaches ten in a row. After every split second, the system is scanned if the face is still being tracked, and this phenomenon is termed a multimode learning tracking algorithm [28]. The average treatment time is almost 9 ms for each face.

Haar features: For detecting specific patterns in an image by calculating the difference in intensity values between adjacent rectangular regions, Haar features are used. These are a set of rectangular-shaped training images with various values used in object detection and recognition tasks. The main three types of Haar features are edge, line, and four-rectangle features, as shown in Fig. 2.

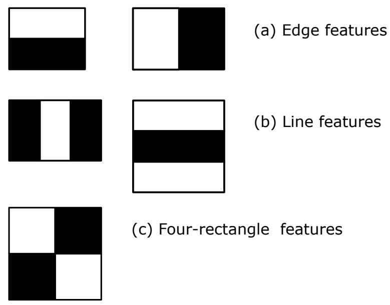


Fig. 2 *Haar features integral image.*

In the present research, by using an intermediate representation, an image's pixel value, and density are converted to an integrated image. The integral image is explained as the sum of the pixels and is located above and to the left of x, y. To calculate the integral image, the following Eq. (1) is used:

$$ii\,(x, y) = \sum_{x' \leq x} \sum_{y' \leq y} i\,(x', y'), \tag{1}$$

where $ii(x, y)$ is the integral image and $i(x, y)$ is the original image. The integral image can be processed using the pair of recurrences defined in Eqs. (2) and (3):

$$s\,(x, y) = s\,(x, y-1) + i\,(x, y)\,, \tag{2}$$

$$ii\,(x, y) = ii\,(x-1, y) + s\,(x, y)\,. \tag{3}$$

Using the pair of recurrences defined in Eqs. (2) and (3), the integral image can be processed. The cumulative row sum $s(x, y)$ is calculated using Eq. (2), where $s(x, y-1) = 0$. The integral image is then determined using Eq. (3), where $ii(x-1, y) = 0$. The integral image can be processed in one pass over the original image.

The integral image offers a more efficient representation of an image for object detection and recognition tasks, as it allows for faster calculation of rectangular features. The Haar feature-based approach used in the current research depends on the integral image to detect facial features and track facial movements.

3.1 AdaBoost training

In the presented research, AdaBoost, a machine learning algorithm for feature selection, was used to detect and choose the best and weightiest features to apply in a 24×24 window to determine if a face is present. AdaBoost is a popular algorithm for boosting the performance of weak classifiers by combining several weak classifiers to create a strong classifier.

The AdaBoost algorithm involves training a sequence of weak classifiers and updating the weights of the training samples based on the error rate of each classifier. The best feature is selected based on its ability to classify the training samples correctly, and its weight is adjusted based on the error rate. The final strong classifier is a linear combination of the best features, as shown in Eq. (4):

$$F(x) = \alpha_1 f_1(x) + \alpha_2 f_2(x) + \cdots + \alpha_n f_n(x), \tag{4}$$

where f_1, f_2, and f_n are the features, and a_1, a_2, and a_n represent the respective weights of the features. Each feature is termed a weak classifier, see Fig. 3.

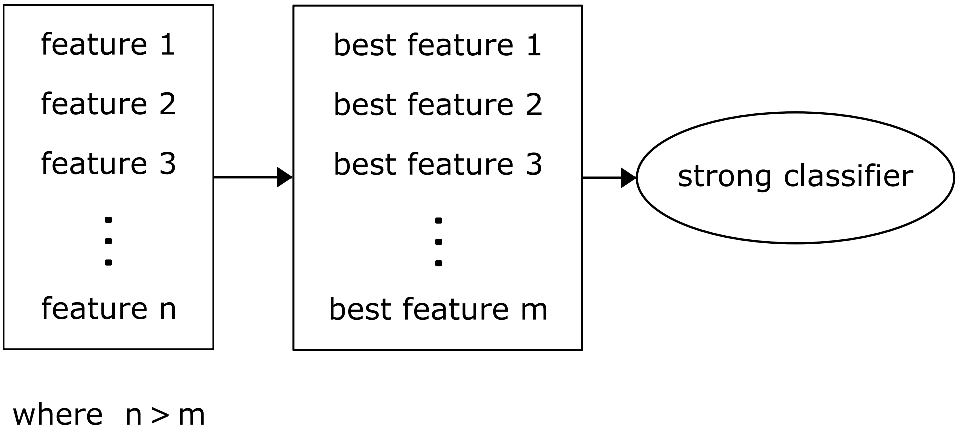


Fig. 3 *Adabost algorithm.*

Cascading classifiers: In the current research, cascading classifiers were utilized to accept positive images and reject negative images in the detection of facial features. The main purpose of cascade filters is to reduce the computational cost and save time in the detection process. After performing AdaBoost, the cascade classifier can evaluate 2 500 features in every 24×24 window.

The cascading classifier works by evaluating a set of features in a series of stages. Only a smaller number of features are available in the initial stages, and these are discarded if they fail to qualify for the initial stages. Features are only applied if they pass the first stage, and the process proceeds to the next stage. The face region is the window that passes all the stages of features, see Figs. 4 and 5.

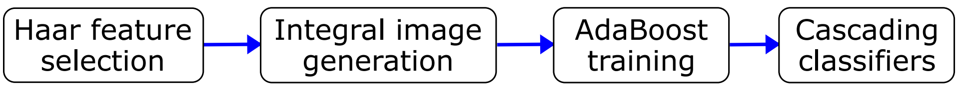


Fig. 4 *Different steps for face detection.*

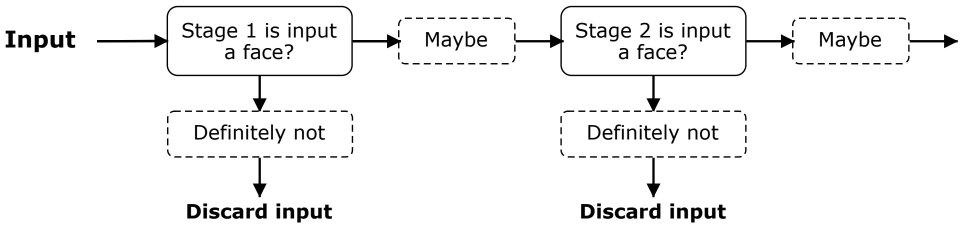


Fig. 5 *Cascading classifier.*

Region of interest: After detecting facial features in each frame the region of interest (ROI) is calculated. The ROI is a more precise region where the raw blood volume pulse signal can be obtained. In density-based methods, the pixel values in the ROI are averaged to reduce and quantize the noise. The mean function is used in Eq. (7) to average all the pixels in the ROI:

$$averaged\, ROI\, pixel\, value = \frac{sum\, of\, mean\, pixel\, values}{number\, of\, pixels}. \tag{5}$$

In the presented paper, we focused on the front area of the face, as it clearly shows the skin color during the pulse or its absence, see Fig. 6. The specific ROI is the origin of the heart data, and the box ROI is the general area of the face defined by a rectangle being combined with skin spots.

The ROI is an important step in the real-time heart rate measurement process from video signals, as it allows for accurate detection of the heart rate signal. The calculation of the ROI involves selecting the most anterior region, shaving the dense blood vessels, and averaging the pixel values to reduce noise and improve signal quality.

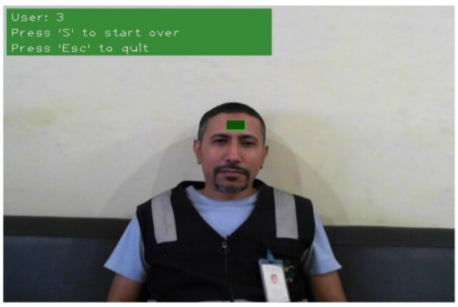


Fig. 6 *Face identification.*

FFT for region of interest: To convert the ROI samples into the frequency domain to obtain the energy spectrum of the signal, the fast Fourier transform (FFT) is used. The FFT is implemented on the final two hundred signal frames, which are used to detect frequencies ranging from 0.5 Hz to 3 Hz based on 0.01 steps.

The FFT is the algorithm used for computing discrete Fourier transform (DFT), which is a widely used algorithm for converting a signal from the time domain to the frequency domain. It involves computing the discrete Fourier transform (DFT), which is a mathematical technique for decomposing a signal into its constituent frequencies. The DFT is computed using Eq. (6):

$$F(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m, n) e^{-\mathrm{j}2\pi(x \frac{m}{M} + y \frac{n}{N})}, \tag{6}$$

where $F(x, y)$ represents the value of the image in the frequency domain corresponding to the coordinates x and y. $f(m, n)$ is the pixel at coordinates (m, n), and M and N are the dimensions of the image.

In the present research, the pulse frequency is set at the frequency relating to the highest spectral energy in the operating frequency band. The energy spectrum obtained from the FFT is used to detect the pulse frequency and measure the heart rate in real time.

Measurement of heart rate: Based on the time instances of the first and last peak points, the heart rate (HR) is measured. These points are denoted as t_1 and t_2, respectively, which were measured using the proposed automatic component selection (ACS) technique. The total number of peaks between t_1 and t_2 is denoted as N_P, and the heart rate is calculated using Eq. (7):

$$heart\,rate = \frac{60}{t_2 - t_1} \cdot N_\mathrm{P}, \tag{7}$$

there are many factors that can affect the accuracy of the HR calculation, such as the subject's body motion, facial expressions, facial features (face shape, glasses, beard, etc.), camera noise, and changes in lighting. Controlled experiments are conducted to remove these disturbing factors, and noise reduction and signal recovery algorithms are implemented to extract the HR signal.

The green color channel is used in the current research, as it has the strongest pulse signal, while the red and blue channels also contain pulse information but at a lower level. The peak frequency signal for hemoglobin absorption of oxygen (oxy) is also located in the green channel.

As normal heart rates range from 35 to 195 beats per minute, which corresponds to the frequency between 0.5 and 3 Hz, it is easy to filter out the wrong frequency range. Moreover, the continuous component (0 Hz) will affect the spectrum because this range is near the heart rate. So, to avoid the need to calculate the actual value of the heart rate frequency, the ratio between the maximum and the spectral median from the experiments was calculated, which was found to be approximately 3:1.

It is important to note that the proposed methodology offers several advantages over traditional methods such as pulse oximeters. For example, it is a non-contact method that does not require any physical contact with the patient, which can be particularly useful in situations where physical contact is not possible or desirable. Additionally, the proposed methodology is relatively simple and cost-effective, as it only requires a high-definition camera and an open-source computer vision library.

The study also highlights the importance of developing an experimental protocol for evaluating the performance of the system under different conditions and situations.

Overall, while the proposed methodology may not be completely novel, this study provides a comprehensive evaluation of the system's performance and highlights the potential of image recognition technology for measuring heart rate. The study also provides valuable insights into the various factors and obstacles that can affect heart rate measurement and how they can be addressed.

3.2 Experimental tools

Specification	Item
Microsoft LifeCam Studio	1080p HD video recording Sensor resolution: 1920×1080 Intel Dual-core 3.0 GHz 2 GB RAM, USB 2.0
PM60 Pulse Oximeter 115-018019-00, LI11S001A	The Mindray PM-60 is a miniature, lightweight device capable of spot-check and continuous monitoring of SpO2 and pulse rate
Laptop	HP-ENVY-15-Notebook-PC Linux operating system
Software package	OpenCV pulse rate package. OpenCV (Open-Source Computer Vision Library) is a library collection of programming functions related to real-time computer vision. Originally developed by Intel

Tab. I *Specification of tools.*

4. Results and discussion

Based on the experimental results for the measurement of heart rate (HR) using the IRPM system, three types of experiments were carried out throughout the research. The video was recorded by taking a sample size of 50.

4.1 Obstacles during HR measurement

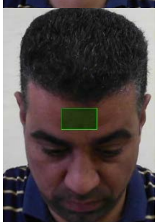
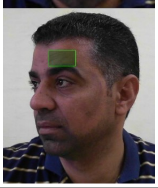
The video was recorded when the participants were making simple movements during the examination period, including tilting the head forward, backward, or moving the right leg. Another test was performed with the face covered, and the algorithm showed greater accuracy but with some noise around the ROI. The main obstacles studied in this research are:

– Noise due to moving the head at different degrees.

– Noise due to moving limbs.

– Covering part of the participants' faces.

The statistical analysis based on error rate is shown in Tabs. II, III, and IV. The purpose of this work is to test the system's capability by applying several obstacles to test their impact on the system's performance during HR measurement.

Case	Category	Angle movement [hor; ver]	Face detection	Pulse rate (IRPM)	Pulse rate (BVP)	Mean absolute error
1		[0°; +20°]	√	70	90	4.00
2		[0°; +10°]	√	77	85	1.60
3		[0°; +75°]	√	84.8	95	2.04
4		[0°; −75°]	√	94	95	0.20
5		[−50°; 20°]	√	87	94	1.40
Total of mean absolute error						9.24

Tab. II *Comparison of the classification strategy with different data set.*

Case	Type of movement	Features Pulse rate (IRPM)	Pulse rate (BVP)	Mean absolute error
1	Right leg	64.8	73	1.025
2	Right leg	66.0	74	1.000
3	Left leg	65.0	70	0.625
4	Left leg	72.2	78	0.725
5	Right arm	79.0	85	0.750
6	Right arm	66.0	72	0.750
7	Left arm	67.2	70	0.350
8	Left arm	72.3	69	0.412
Total of mean absolute error				5.637

Tab. III *Heart rate calculation errors due to different limbs movements.*

In Tab. III, measuring HR with moving limbs as the second obstacle is studied. The calculation of the HR includes errors because of several movements that might lead to significant errors and it reached to ± 5.63 bpm.

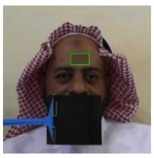
In Tab. IV, covering the face during HR measurement as the third obstacle is studied. The study results revealed that the IRPM system did not recognize the participants because of covering parts of their faces. This led to a significant error which was about ± 17.2 bpm. ± 65.467 bpm is the total error of covering the faces of the participants.

4.2 Factors affecting the HR measurement

This experiment was conducted for checking the accuracy and robustness of the IRPM system. It includes many factors like lightning conditions like sunlight and industrial light, different age groups from 2–63 years, different time seconds, i.e., 30–90 seconds, and different distances between the camera and participants, i.e., 50–200 cm are studied. The statistical analysis based on the error rate is shown in Tabs. V, VI and VII. The motivation behind this experiment is to find the optimum distance and duration of measuring HR via the system and to measure the influence of the different lightning factors during the measuring of the HR using the IRPM system.

Shows how the lighting conditions factor is affecting the measurement of the HR. During the measurements, multiple light sources caused errors that reached to ± 2.4 bpm. Furthermore, analyzing the data shows the high accuracy of the IRPM system when regular industrial lighting plus extra lighting is applied.

The distance between the face and the camera is a major factor. It was found that the distance affects the resolution of the region of interest (ROI), which might lead to an error of up to ± 4.4 beats per minute (bpm). Data analysis showed that the IRPM system has good accuracy when the distance between the face and the camera is between 50 cm to 150 cm.

Case	Objects covering the face	Face detection	Pulse rate (IRPM)	Pulse rate (BVP)	Mean absolute error
1		√	101.2	102	0.133
2		×	0	103	17.167
3		×	0	94	15.667
4		×	0	92	15.333
5		×	0	102	17.000
6		√	101	102	0.167
Total of mean absolute error					65.467

Tab. IV *Demonstrates the accuracy of the classification, when adding some objects covering the face.*

Case	Light type	Light angles	Face detection	Pulse rate (IRPM)	Pulse rate (BVP)	Mean absolute error
1	Sunlight (at 12 pm)	90	$\surd$	73	77	0.8
2	Sunlight lit (at 4 pm)	45	$\surd$	62	65	0.6
3	Sunlight with industrial lighting	90	$\surd$	65	68	0.6
4	Industrial lighting	90	$\surd$	78	80	0.4
5	Regular industrial lighting + extra lighting	45	$\surd$	95	95	0
Total of mean absolute error						2.4

Tab. V *Demonstrates the accuracy of the classification of face detection with different lights.*

Participants	Age	IRPM at different times			BVP at different times		
		30 sec	60 sec	90 sec	30 sec	60 sec	90 sec
1	35	90.0	94.0	101.2	93	95	99
2	36	79.5	80.0	76.3	77	83	75
3	43	79.5	81.0	84.0	77	80	86
4	46	86.7	81.0	79.5	84	80	80
5	48	65.0	65.1	65.2	64	62	65
6	38	79.5	72.4	79.5	77	74	79
7	36	79.5	79.6	79.5	77	79	80
8	55	72.3	79.5	72.3	71	77	74
9	41	72.2	79.6	72.3	70	78	73
10	37	65.0	66.0	72.0	63	65	70
11	25	65.0	65.0	79.0	66	66	75
12	30	86.6	87.0	87.0	85	88	88
13	63	73.0	72.0	73.0	71	73	72
14	59	100	102	99.0	102	100	100
15	46	64.0	65.0	65.0	62	65	67
16	39	65.0	65.1	65.1	64	64	65
17	37	79.5	81.0	80.0	81	80	79
18	44	73.0	72.3	71.0	73	74	70
19	4	57.0	57.0	57.0	56	56	56
20	3	57.0	57.0	57.0	58	56	57
21	2	72.0	79.0	77.0	76	80	78
22	2	100	98.0	96.0	99	98	95

Tab. VI *Demonstrates the heart rate calculations for participants of different age groups and different measuring times.*

Case	Distances [cm]	Face detection	Pulse rate (IRPM)	Pulse (BVP)	Mean absolute error
1	50	√	94	95	0.2
2	100	√	102	102	0.0
3	120	√	101	102	0.2
4	150	√	94	103	1.8
5	200	√	80	102	4.4
Total of mean absolute error					6.6

Tab. VII *Demonstrates the accuracy of the face detection, when different distances between camera and face are applied.*

4.3 HR measurement under different conditions

This experiment was carried out to assess the accuracy and reliability of the IRPM system for measuring heart rate (HR) under different conditions, such as autogenic training and categories of cardiac arrhythmia. Statistical analysis was carried out with the aim of discovering the maximum permissible variations affecting the robustness of the classifier. Tabs. VIII and IX below show the statistical analysis demonstrating the accuracy of autogenic training and the categories of arrhythmia. Different conditions were applied to measure their influence on participants and the system's capability to respond to the conditions.

Multiple conditions for IRPM system were applied, it showed important effect in lowering the HR for the participants with small MAE ± 1.85 bpm.

It is found that measuring the three types of cardiac arrhythmia gives MAE up to ± 0.64 in the case of tachycardia, ± 0.6 in the case of Normocardia, and ± 0.54 in the case of bradycardia.

The proposed IRPM system was tested under various conditions to test its accuracy and robustness. The presented study investigated the effects of different aspects such as face coverage, age groups, lighting conditions, the distance between camera and face, and different conditions like autogenic training and categories of cardiac arrhythmia on the performance of the system. Overall, the study was designed to uncover the optimum distance and duration of measuring HR via the IRPM system and to measure the effect of different factors on its accuracy. The results present insights into the system's strengths and limitations under different conditions, which can help develop the accuracy and robustness of the IRPM system for HR measurement.

Unlike the work in reference [18] which is a technical literature review titled "Remote heart rate measurement using low-cost RGB face video: a technical literature review". The study discusses the different methods and techniques for remote heart rate measurement using low-cost RGB face video. Various algorithms and approaches were used for detecting heart rate from facial video data, such as photoplethysmography (PPG), remote PPG (rPPG), and video-based methods.

The study in [19], investigates algorithms for monitoring heart rate and respiratory rate from the video of a user's face. The article presents algorithms for

Case	Face detection	Pulse rate (IRPM)	Pulse rate (BVP)	Mean absolute error
1	√	72.3	71	0.038
	√	72.0	70	0.059
	√	71.0	69	0.059
	√	69.0	68	0.029
	√	68.5	66	0.074
2	√	72.0	70	0.059
	√	70.0	70	0.000
	√	68.0	67	0.029
	√	65.0	67	0.059
	√	64.0	66	0.059
3	√	72.3	68	0.126
	√	72.0	69	0.088
	√	65.1	64	0.032
	√	65.0	63	0.057
	√	65.0	64	0.029
4	√	78.5	77	0.043
	√	72.3	73	0.02
	√	72.3	72	0.009
	√	70.0	71	0.029
	√	70.0	70	0.000
5	√	116	117	0.029
	√	113	115	0.057
	√	110	110	0.000
	√	109	108	0.029
	√	109	107	0.057
6	√	79.4	82	0.074
	√	77.0	80	0.086
	√	74.0	76	0.057
	√	72.2	74	0.051
	√	72.0	74	0.057
7	√	65.0	68	0.086
	√	64.0	68	0.114
	√	63.2	67	0.109
	√	63.0	67	0.114
	√	62.0	66	0.114
Total of mean absolute error				1.850

Tab. VIII *Demonstrates the accuracy of the classification when using autogenic training.*

Effort to get	Case	Objects	Face detection	Pulse rate (IRPM)	Pulse rate (BVP)	Mean absolute error
Tachycardia HR>120 beat/min	1	T1	√	101	100	0.20
	2	T2	√	102	102	0.00
	3	T3	√	80	82	0.40
	4	T4	√	115	115	0.00
	5	T5	√	92.2	92	0.04
Total of mean absolute error						0.64
Normocardia 60–100 beat/min	1	N1	√	68.7	69	0.06
	2	N2	√	63.3	62	0.26
	3	N3	√	68.7	69	0.06
	4	N4	√	74.1	74	0.02
	5	N5	√	84	85	0.20
Total of mean absolute error						0.60
Bradycardia HR<60 beat/min	1	B1	√	65.1	66	0.18
	2	B2	√	59.6	59	0.12
	3	B3	√	57.8	58	0.04
	4	B4	√	75.9	76	0.02
	5	B5	√	74.1	75	0.18
Total of mean absolute error						0.54

Tab. IX *Demonstrates the accuracy of the categories of arrhythmias.*

monitoring heart rate and respiratory rate from video data of a user's face. The authors propose a method for detecting the pulse rate by measuring changes in skin color caused by the blood flow in the face, as well as a method for detecting the respiratory rate by noticing the motion of the chest and abdomen using video data.

The article presents the results of the evaluation of the accuracy and robustness of the proposed algorithms under different conditions, such as changes in lighting conditions and user movement.

Overall, our proposed study was conducted to test the method over different conditions to investigate the idea over different aspects that are rarely conducted in the literature. The purpose of this investigation is to enhance the knowledge of the approach presented and that will help researchers to get more insight into the known method.

Regarding the comparison to the paper [20], the suggested study presented a different method for measuring heart rate using image recognition technology. The proposed method used four step-based algorithms, including face detection, area attention, ROI signal analysis, and pulse measurement, to measure heart rate based on the strength of color concentration extracted from video clips. The study was conducted on a database of 50 participants of different ages and skin colors, and the results showed that the system is highly competent in measuring heart rate. Additionally, the study did not address neonatal monitoring or heart rate variability specifically but rather presented a method for measuring heart rate that could have applications in various fields such as the Internet of Things, security, sports, and telemedicine.

The paper [20] has some limitations that need to be addressed in future research. Firstly, the sample size of the study is relatively small, with only six preterm and six full-term neonates included. Secondly, the study was conducted in a controlled environment, and it is unclear how the system would perform in real-world settings with disturbances and movement artifacts. Thirdly, the study did not investigate the long-term performance of the system and how it would perform over extended periods of time.

In comparison to the paper [21], the presented study has a slightly different focus, emphasizing the importance of non-contact technology for measuring heart rate in daily routine life, especially for patients who require continuous monitoring such as newborns and ICU patients. The proposed study also highlighted the use of the IRPM system algorithm, and the four steps involved in the measurement of heart rate, as well as the different experiments conducted to analyze the results.

While both papers focused on non-contact monitoring of heart rate, paper [21] specifically used a low-cost thermal camera for non-contact monitoring of heart rate variability, while our proposed method presents a non-contact technology for measuring heart rate using the IRPM system algorithm. Additionally, the paper [21] investigated the feasibility of using a low-cost thermal camera for non-contact monitoring of heart rate variability, while the presented study did not mention the cost-effectiveness of the IRPM system algorithm.

One limitation of the paper [21] is that the study was conducted on healthy volunteers in a controlled environment, which may not accurately reflect the performance of the system in real-world settings with disturbances and movement artifacts. In comparison, the proposed study presented a limitation that addressed this concern by mentioning the impact of factors and obstacles on HR measurements, which can affect the application of the IRPM system under different conditions and situations. Thus, our proposed study covers the investigation of using technology in different conditions and limitations. And that helps the academic community and industry develop the presented technology.

5. Conclusion

The measurement of heart rate (HR) is significant for monitoring unusual changes in the heart, especially for those who require continuous monitoring, including newborns and intensive care unit (ICU) patients. This research has presented the latest non-contact technology for measuring HR, which is very important for daily routine life. HR measurement in this research has been produced with the help of the IRPM system algorithm, and the main four steps are FD, ROI, FFT, area of ROI, and measuring the HR. Three different kinds of experiments were conducted to analyze the results using different factors and obstacles faced by the patients.

Hence, the results of this study show that factors and obstacles affecting HR measurements can impact the applications of the IRPM system under different conditions and situations. This research has compared the IRPM with other techniques, such as the BVP pulse oximeter. Many errors are encountered during the measurement of HR through IRPM. Using the experimental protocol, high accuracy was achieved based on the IRPM system. This study is very useful for identifying all the possible factors that impact HR measurement, such as the intensity of light and the mean absolute error rate. The optimum distance between the camera and the face was found to be between 50 cm and 150 cm. Future work can be extended to measure HR under low light conditions and with the whole face covered.

The novelty of this research lies in the specific combination of algorithms and techniques used to measure heart rate, as well as the use of a recorded database of 50 participants with varying ages and skin colors for the evaluation of the system's performance. The study also highlights the importance of identifying and addressing factors that affect heart rate measurements, such as light intensity and distance between the camera and the face. Overall, while the proposed methodology may not be entirely new, this study makes a valuable contribution to the field and presents a comprehensive evaluation of the system's performance.

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