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HEART RATE DETECTION THROUGH REAL TIME DOMAIN

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Abstract : Human heart rate is a critical sign of people's physiological status and one of the most essential physiological markers. Depending on the patient's condition, the heartbeat can be monitored in a variety of methods, including contact basis, such as utilizing various devices or manually monitoring the pulse rate. We'd like to develop a non-contact gadget for measuring heart rate. Non-contact-based approaches are gaining popularity because they have the potential to address some of the disadvantages of contact-based techniques, especially in the therapeutic setting.

We propose a method that detects the human face as an input and produces the pulse rate as an output. It will concentrate on two facial subregions: the forehead and the nose-mouth area. After the unstable characteristics have been removed, temporal filtering is used to isolate the frequencies of interest. The cardiovascular pulse signal is then separated from extraneous noise induced by respiration, vestibular activity, and other changes in face expression using four-component analysis methods. After that, each component derived from one of the four component selection procedures is subjected to the suggested peak detection approach. This will allow the position of peaks in each component to be determined. The proposed automatic components selection technique is used to choose the best component for calculating the heartbeat.

This non-contact-based system will help in times where we are focusing on automating everything so as to make it contactless. This non-contact-based heart rate detection system will help in measuring the pulse rate without the use of expensive instruments.

***IndexTerms* - Non-Contact Based System, Computer Vision, HR Measure.**

I.INTRODUCTION

An adult human's heart rate is a critical sign of the person's physiological status and one of the most essential physiological markers. Depending on the patient's condition, the heartbeat can be monitored in a variety of methods, including contact basis, such as utilizing various devices or manually monitoring the pulse rate.
The number of contractions (beats) of the heart per minute is used to determine the heart rate (or pulse rate) (bpm). The heart rate is influenced by a number of factors, including heredity, physical fitness, stress or psychological status, food, medicines, hormonal status, environment, disease/illness, and the interplay between and among these elements. Its pulse is usually equal to or close to that of any peripheral location. The number of contractions (beats) of the heart per minute is used to determine the heart rate (bpm).
We have developed a non contact based system that will help in detecting heartbeat without the use of any primitive methods. We propose a method that accepts video as an input and produces the pulse rate as an output.
Heart rate measurement has been and will be an important part of a doctor's examination as it tells about our internal body function, it is through its virtue we get to know about any abnormalities in the blood pressure.
Since early days heart rate was measured by applying slight pressure to the underside of the wrist where the veins reside and feeling the blood pulsing beneath the fingers. The beats must be counted for either 1 min or for 15 sec and multiplied by four. The veins can be found at the place where the hand meets the palm or in short the wrist.
Users of stethoscopes must learn to evaluate what they hear. Listen to the left side of the chest, where the heart is located, when listening to the heart. The heart is located between the fourth and sixth ribs, nearly exactly beneath the breast. It's necessary to move the stethoscope around. A healthcare professional should be on the lookout for various sounds emanating from various locations. The instrument's bell is typically used to listen to low-pitched noises. The instrument's diaphragm is used to listen to various parts of the heart. Each region will have its own soundscape. The sound made by a normal heart as it beats is known as "lub-dub."
The heart rate of a person can reveal a lot about their health, fitness, amount of exercise, stress, and more. In most clinical settings, the cardiac pulse is monitored via an electrocardiogram (ECG), Patients are needed to wear chest straps with sticky gel patches, which can be harsh and uncomfortable. Heart rate can also be measured with pulse oximetry sensors worn on the fingertip or earlobe. These sensors are not comfortable to wear for long periods of time, and the pressure can become irritating with time.
All the existing instruments and products dealing in measurement of the pulse are generally reused for treating a number of patients

in a single sitting of the doctor, taking in mind that we can not correctly account the bacterial and viral contacts happening to its surface. To eliminate the nuance this project was undertaken.

Also, in times of COVID where we had focussed so much on making everything contactless so as to keep ourselves safe, this non-contact based heart rate detection model will provide a cost effective solution to people for measuring their heartbeat, also it is a hassle-less process to measure the heart beat. It is a simple yet effective method to minimize any sort of contact between the patient and the doctor or any medical personnel to almost nil.

II. RELATED WORKS

Computer Vision has seen a lot of advancements in the field to the working of projects. In 1995, Costa et al. [1] investigated the first non-contact color variation of the facial skin using camera images in order to extract all the physiological parameters using color and hue variations of the skin but their approaches failed to show quantitative results they reported only a graph of heartbeats and also failed to show any correlation with reference ECG signals. This paved the way for further research and experiments to be conducted in the field to its advancement.

The progress was slow but in 2005 other methods were introduced for the measurement of a user's emotional state using facial thermal image using a thermal camera. The conducted experiment included 12 test subjects and the researchers found some new facts between stress and blood flow. They showed that Increased blood flow in the frontal vessel of the forehead is directly correlated with user stress. Finally in the year 2006 Takano et al [2] Showed that the respiratory rate (RR), HR and BVP are possible to extract simultaneously through the use of a camera. They photograph sections of the subject skin and then measured changes in the regions Of interest are measured for a short time. The researchers using Matlab custom filtering and spectral analysis function post-op eventually they learn that they could extract HR and HRV (heart rate variability). HR can be detected for a limited time by the system Data accuracy is unknown.

Isabelle Bosch [3] notes that while the results obtained could be better with the usage of a different camera meanwhile errors have been noted to occur within 3.4$\pm$0.6 BPM in a video with the a person standing still, meanwhile in a video with a person moving slightly there is a 2.8$\pm$0.6 BPM inaccuracy. The calculated heart rate by the author was constantly lower than the reference in all videos so it is possible that there might be some kind of basal layer in the calculation of frame rate in the video.

Rahman et al. [4] proposed the most successful noncontact based physiological parameter extraction system in 2015. They created a simple approach for detecting HR, RR, and IBI (inter bit interval) using a laptop web camera. The results reveal that this method extracts physiological characteristics with roughly 90% accuracy. For any period of time, this experiment can extract three physiological parameters in offline mode.

This paper aims to increase the efficacy of the project by introducing Facial Tracking, Filtering and A Region Of Interest Selection. The study describes a noncontact HR monitoring system that uses a web camera to watch subjects in real time for an endless period of time, overcoming most of the shortcomings of earlier work.

III. PROPOSED WORK

The Product works in three main stages which are namely Input Phase, Analysis Phase and the Output Phase. The application systematically goes through every bit of input to provide us quick and accurate results. To make the process a whole lot more efficient, multiple analysis methods have been tested and tried before finding the best one.

The final application when displaying the heart rate uses graphs to display peaks occurring while monitoring the subject's heart rate. Practically when a person sits still his heart is still beating, producing multiple high peaks with different values which are captured by the application and used to measure the heart rate.

In all humans there are numerous small movements happening on our facial region, may it be contraction due to breathing rise and fall of chest muscles imperceptible movements but which can be detected unwillingly by the camera [5]. It required a filtering mechanism which removed all the obsolete signals which were captured and may act as interference or influence the result. The filter removed all these signals perfectly providing us with clean input to be worked upon.

The subject is asked to sit still for a time of 5-10 sec for the application to establish a box around the face and align it according to our use which in reality divides the face in grids and also tracks face in case of any movements to provide uninterrupted heart rate. The heart rate doesn't stop in case of movement by subject after the initial waiting time but constantly keeps tracking the face of the subject through the box grid.

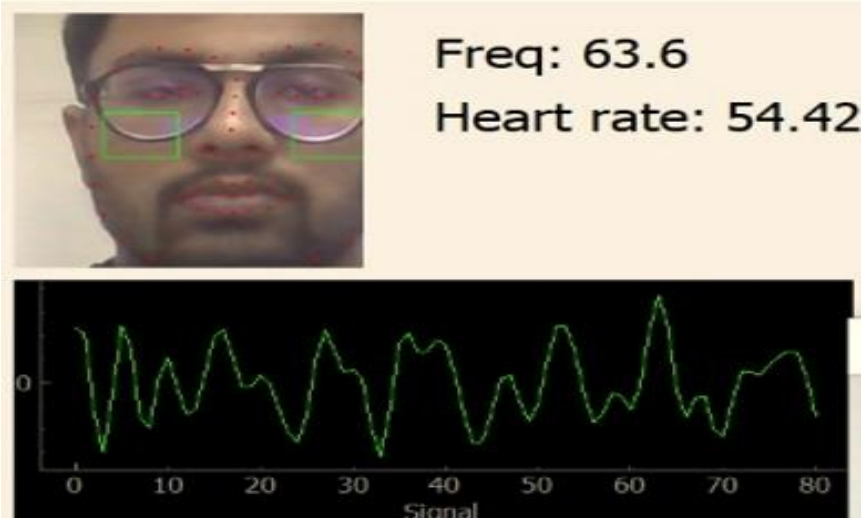

Fig 1. Enhanced Facial region

The application also looks upon the case if any obstacle comes before the face hiding it from view the system stops the heart rate meter and shows an error message upon the video reporting that the face has been blocked the presence of a live subject is essential for it to work.

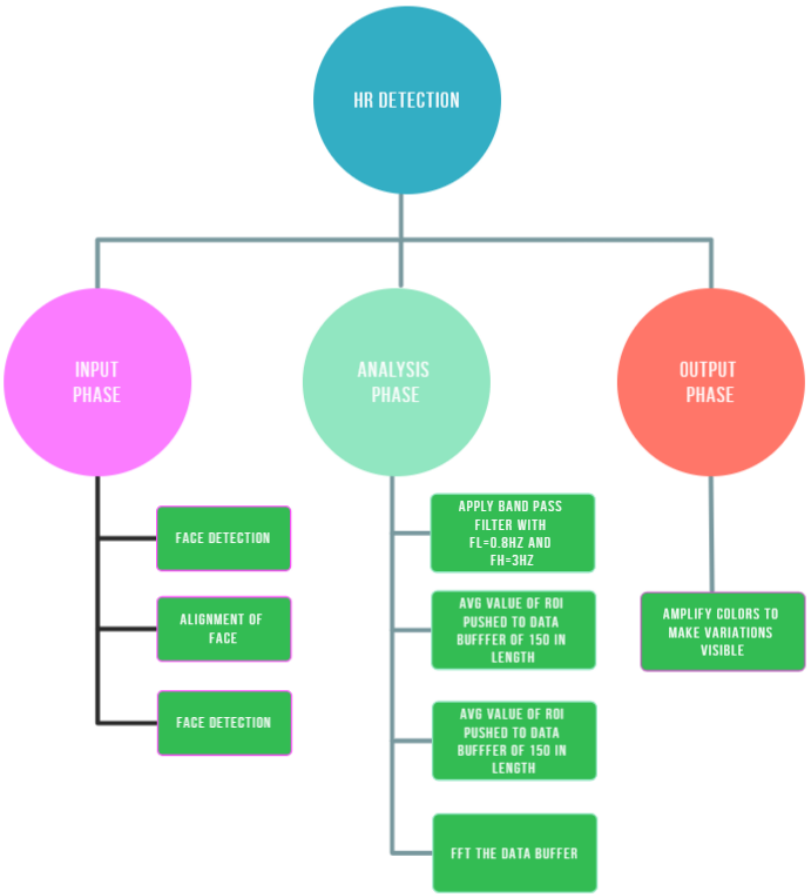

Fig 1. Phases Of the project

IV. METHODOLOGY

1. Phases of Project

There are three key phases to determining heart rate, which are detailed in the parts following.
First, because the face is the only portion of the frame with heart rate information, each frame of the video must have the facial region recognised.
Second, the suitable Region of Interest (**ROI**) must be identified inside the face bounding box.
Finally, the plethysmographic signal must be recovered from the time-dependent change in pixel colors inside the ROI, and the salient frequency within the heart rate range must be determined.
The initial stage was to analyze existing pre-recorded videos while simultaneously measuring a known heart rate. We constructed signal processing to measure heart rate from pre-recorded videos, then calculated the percent inaccuracy by comparing our heart rate measurement to a known number. Haar cascade classifiers, originally proposed by Viola and Jones and enhanced by Lienhart et al., are used to detect and track faces. We employ the OpenCV Cascade Classifier, this algorithm was trained on both positive and negative frontal face photos. A set of increasingly complex classifiers make up the face detector, each of which employs one or more features.
When utilizing this method to extract the bounding box encompassing the user's forehead, the ROI is automatically scaled based on the size of the user's face, allowing the user's heart rate to be extracted at various distances [6-7]. The dimensions and location of the forehead box are established just once at the start of the acquisition due to computational difficulties in detecting the face with the implementation of the Haar-Cascade classifier.
The signal corresponding to each color wavelength was spatially averaged over the ROI to create a scalar temporal signal for each wavelength. There were three wavelengths in the instance of our camera (red, green, and blue). To establish invariance with respect to illumination and scale, sub-windows are normalized, and the final detector is dragged across the image at various window sizes. To produce a single face bounding box, any overlapping positive-classification windows are averaged.
Each frame in the movie is subjected to this face detection algorithm, which generates a bounding box for each face it finds. If no face is detected in a frame, the previous frame's face is used, and if many faces are found, the face closest to the previous frame's face is used to ensure consistency across frames.

A. Data Collection

Data was collected of 20 volunteers ranging in age from 25 to 50 years old and skin color. The experiments were carried out in a controlled environment with enough natural light. The participants were briefed about the study's purpose and sat at a table in front of a laptop computer, around 0.5 m away from the built-in webcam (HP HD webcam). Participants were requested to remain still, breathe naturally, and face the webcam for 5 minutes while their video was being captured. HR data was gathered in real time and saved in an excel spreadsheet.
During real-time HR extraction, all facial picture frames (24-bit RGB) were consecutively recorded at 30 frames per second (fps) with a pixel resolution of 640x480 [8] and saved in PNG (Portable Network Graphics) format on the laptop. ECG sensor system was used to record HR at the same time.

B. ROI Selection

This is important - Because face detection creates a bounding box that includes both background and facial pixels, a ROI must be chosen from inside the bounding box. The simplest ROI selection is to use the entire height and the center 60% of the bounding box width. Because the bounding box is normally within the face region height-wise but outside the face width-wise, this method simply adjusts the bounding box to exclude background pixels to the sides of the face. When utilizing this method, some hair or background pixels are frequently visible at the box's corners.
We also investigate several methods for calculating the ROI. The effects of removing the eye region, which contains non-skin pixels that can change between frames due to blinking or eye movement, are examined. The eyes were successfully removed by removing pixels from between 25% and 50% of the enclosing box height. Because it was discovered that the fore-head has the strongest plethysmographic signal, we also consider preserving only the pixels above the eye region. Finally, we look into separating facial pixels from background pixels.

C. Applied Algorithms

To extract HR in real time using only face footage, three algorithms such as FFT, ICA, and PCA were used simultaneously [9-11] yet separately. For the FFT [12] approach, the average of the R, G, and B signals was determined [13]. Using the joint approximate diagonalization of Eigen matrices (JADE) algorithm, the normalized raw traces were decomposed into three separate source signals (R, G, and B)[4,5-9] for the ICA approach [16]. The data collection was supposed to be done in a sitting position with no movement, however the test subjects actually moved their hands and heads a little, resulting in motion artifacts. As a result, ICA is employed, which is capable of removing motion-artifact by separating fluctuations induced by minor motions or movement.
To save time and money, the SHIBBS algorithm calculates a part of the fourth order cumulant set and skips eigen matrix decomposition. However, at the time of its first release, it was thought to be slower than JADE, therefore it is less well-known. The SJAD algorithm, on the other hand, has been proved to be highly fast when employing the same approach. The SHIBBS/SJAD algorithm[14-15] has been upgraded and is now capable of large-scale separation. ICA yields the independent components at random, and the component with the highest peak in its power spectrum is chosen for further investigation. PCA decomposes the normalized raw traces in the same way to obtain the principle components. This transformation is defined so that the first principal component has the greatest possible variance, and each subsequent component has the greatest possible variance while remaining orthogonal to the preceding components.

The main part of the whole process relies on the configuration of the ROI(Region of Interest) which also allows . The generated vectors form an orthogonal uncorrelated basis set. Because the eigenvectors of the symmetric covariance matrix are orthogonal, the principal components are orthogonal. The relative scaling of the original variables affects PCA.
Finally, the power spectrum is obtained by applying the Fast Fourier Transform (FFT) on the specified source signal. Within an operational frequency band, the pulse frequency was defined as the frequency that matched to the greatest power of the spectrum.

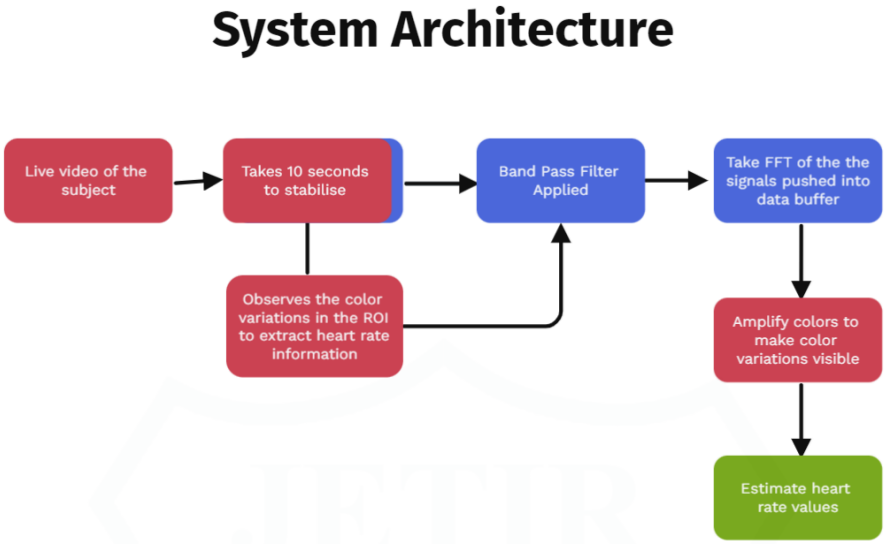

Fig.2 Architecture of the System

2. Feature Extraction

The proposed method utilizes the working of Red,Green and Blue signals of each pixel of all the parts of the grid facial image along with Spectral Analysis as well as Eulerian Video Magnification.

A. Image Frames Analysis

An image frame is a fundamental component of a video or any image source that indicates the start and finish points of a video while also representing a quiet portion of that film. The real-time HR monitoring system extracts a series of image frames one at a time during which the user specifies.
It's also worth noting that, for further computations, the video's resolution should remain constant for each image frame extraction. To keep the same resolution, a novel keyframe video extraction technique was used, which can read image frames one by one automatically.[6]

B. Face Tracking

As the suggested non-contact HR monitoring method relies on facial image as an input, it's critical to keep track of the user's face. To achieve a greater face detection rate, the real-time method requires a sophisticated face tracking system. Following the real-time extraction of an image frame, the automatic face detection function 'Cascade Object Detection' of the Computer Vision Toolbox supplied by MATLAB2 was implemented using Viola and Jonas method[14]. The function has been tweaked to monitor the subject's face and provide an error warning if anything gets in the way.

C. Region Of Interest (ROI) Selection

The most important aspect of this experiment is the R, G, and B color values of each pixel of the facial image frames. As a result, a perfect Region of Interest (ROI) was searched over the observed face. The face that was recognised using the Viola and Jones method has some undesired parts that need to be removed. According to the method, a boosted cascade classifier was used to identify the coordinates of the face location in the first frame for the x and y-coordinates, as well as the height and width that constitute a box around the face.
As a result, the center of the box, which is 60 percent width and 80 percent height, was chosen as the region of interest that is free of undesired components. Only the ROI was then detached from the entire facial image and this is used for further calculations.

D. RGB Signals and Feature Extraction

The core parts of R, G, and B signals (together known as RGB signals) that were extracted from the facial cropped RIO image are R, G, and B color values. The image's Red (R), Green (G), and Blue (B) colors are represented by a 3x1 matrix of color values

in each pixel. The three desired signals, red, green, and blue, are then generated in two stages. The average R, G, and B color values for each image frame are computed in the first phase, and the red, green, and blue signals are calculated from the sum of all the averaged R, G, and B color values in the second phase. The ROI is also used to perform Spectral Analysis to enhance the features a bit for the target areas for a better read of the signals.

Feature Extraction is also done which aims to reduce the number of features in a dataset by creating new features from the existing ones (and then discarding the original features). These new reduced sets of features should then be able to summarize most of the information contained in the original set of features. This way the summarized version of the original features can be created from a combination of the original set.

After this color amplification was applied on the video to extract blood flow on skin in a much better manner for which the Eulerian Video Magnification method was used. Eulerian Video Magnification takes a typical video sequence as input and applies spatial decomposition to the frames, followed by temporal filtering. The resulting signal is then amplified to reveal the information that was previously buried. We can visualize the flow of blood as it fills the face and enhance and show subtle motions using our technology. Our method can display phenomena occurring at user-selected temporal frequency in real time.

E. Signal Detrending

Detrending is a signal processing concept that is used to remove undesirable trends from a series.

When a feature is deemed to be skewed from the relationships of interest, signal detrending is useful. When environmental conditions change, such as temperature or external noise, the RGB signals capture drift and become noisy. As a result, the signals must detrend. The RGB signal was detrended utilizing the method, which uses a smoothness priors approach with a band pass filter with fl=0.8 Hz and fh=3Hz, which corresponds to 48-180 bpm.

F. Filtering

The Red, Green, and Blue signals created from all red, green, and blue image frames are filtered for heart rate using a Hamming window (128 point, 0.6-2 Hz, for normal HR 48-180) then finally the PCA, ICA and FFT are applied on the data sets to head to the next step . The sets are also subjected to temporal filtering.

V. TEST CASES AND TRIALS

S.No	Name of the person	Gender	Heart Rate measured through ECG machine	Heart Rate as per our model
1.	Kratika	F	70	61
2.	Neelesh	M	65	59
3.	Paurush	M	64	60
4.	Ananya	F	72	65
5.	Sparsh	M	69	61
6.	Shubh	M	67	59
7.	Anshul	M	80	73
8.	Lavi	F	68	57
9.	Aniket	M	86	65
10.	Aditya	M	78	66
11.	Diya	F	76	67
12.	Ayushmaan	M	84	72
13.	Devansh	M	76	66
14.	Ritika	F	75	68
15.	Devanshi	F	66	61
16.	Ayushi	F	74	62

17.	Narshi	F	75	57
18.	Nihal	M	87	74
19.	Nikhil	M	75	55
20.	Rajat	M	70	51

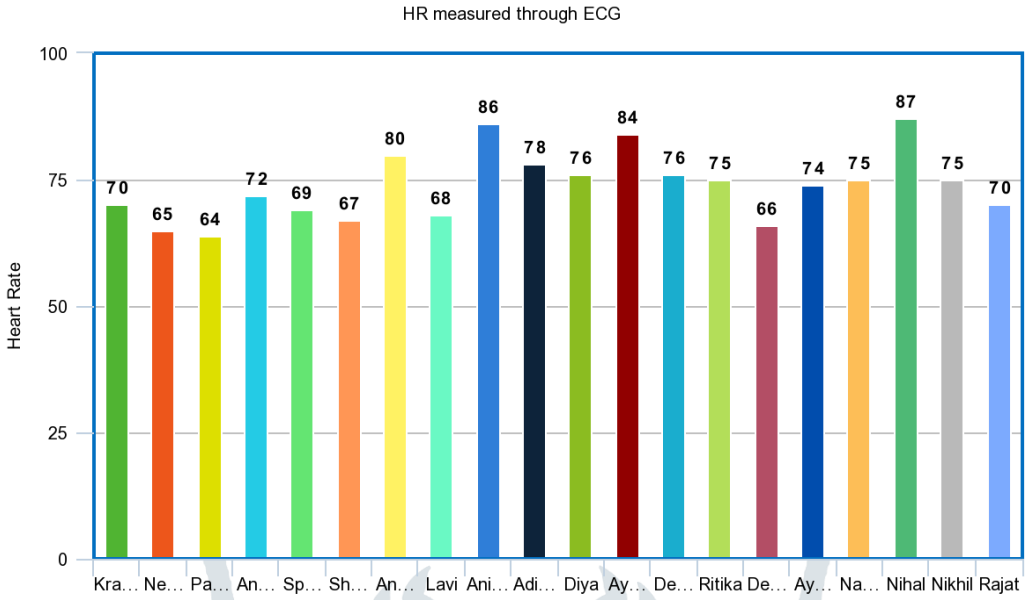

Fig 3. HR measured through ECG

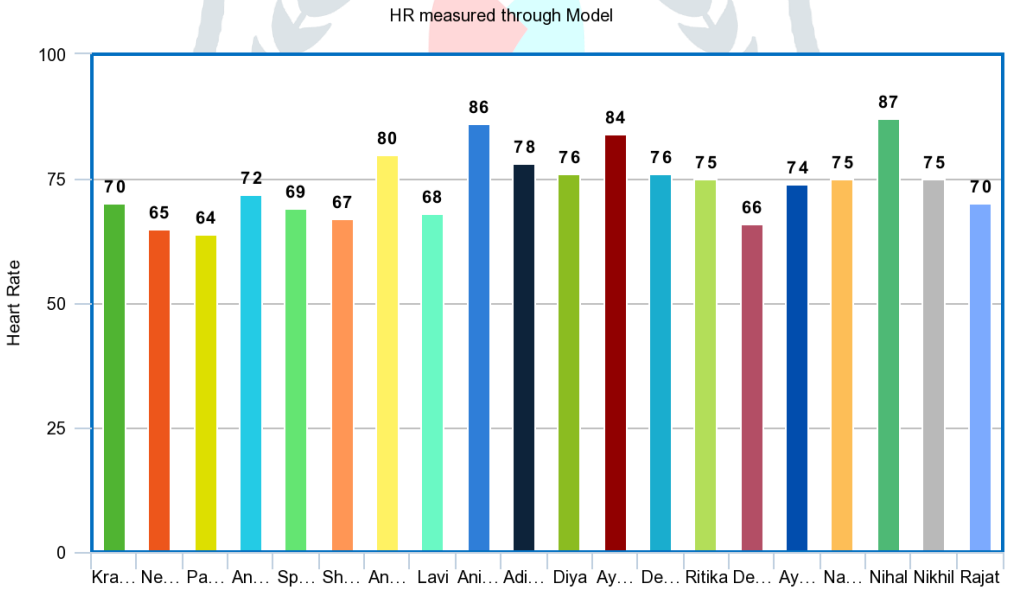

Fig 4. HR measured through Model

VI. RESULT AND CONCLUSION

HR was extracted and recorded in real time for 5 minutes for all 20 test subjects using a camera and ECG sensors, and the HR results were saved in two separate excel files. The real-time session ended after 5 minutes, and HR was extracted offline using the stored film sequences and the proposed techniques. To determine the efficacy of the suggested method in comparison to the reference sensor system, statistical analysis is required[17-19]. For both the real-time and offline methods, many parameters such as minimum, maximum, average, median, and standard deviations were determined from the extracted HR.

After that, some statistical analysis is required for the evaluation. As a result, two crucial statistical measures, RSQ and CORREL, were used to evaluate the system for both real-time and offline HR extraction.

It's worth noting that the RSQ parameter is used to determine how near the HR signals are to the reference signal. The RSQ scale runs from 0 to 1, with 0 indicating that the two signals are uncorrelated and 1 indicating that the signals are fully correlated, meaning that the model fully explains the variability of the response data around its mean.

CORREL is a statistical measure of the linear relationship (correlation) between two sets of values. CORREL values vary from -1 to +1, with +1 denoting a strong positive correlation and -1 denoting a strong negative correlation. Both real-time and offline statistical metrics were determined.

Both the RSQ and CORREL values, as calculated, are near to or more than 85.42%. Both in real time and offline, the CORREL function outperforms RSQ. By using three algorithms, the average RSQ and CORREL values of ten participants were obtained for real-time and offline HR techniques.

The calculated HR for each subject is depicted numerically as well as shown through a peak system using graphs which displays the constant live HR peaks as it goes.

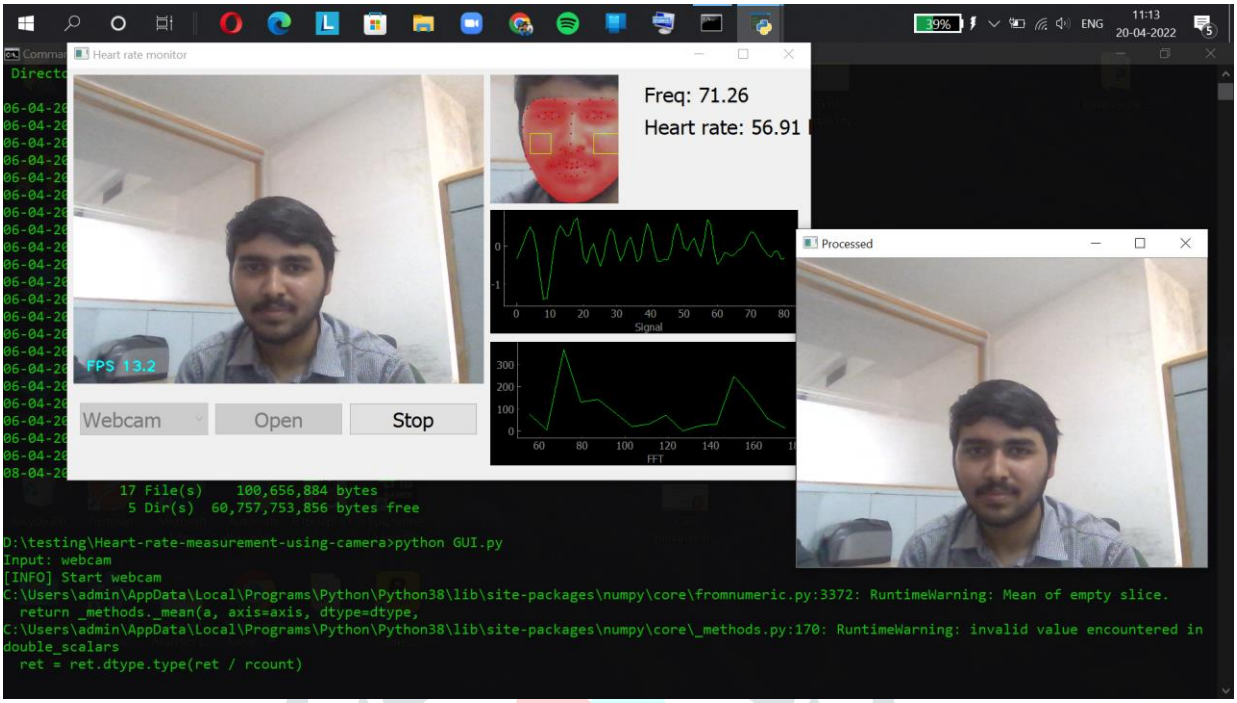

Fig 6. Final Result screen with peak showing graph

CONCLUSION:

The calculation of HR was found to be more accurate with longer data frames and time. With greater data frames there were larger signal variations captured by the camera resulting in a more definite result with a chance of greater accuracy in measuring of HR. The calculated accuracy was found to be around 84.1% for cases with more than 20 sec of stability.

Furthermore the use of ROI results in a better filtering and tracking method instead of the box frame method, providing greater stability and obstruction indicator also. The application of FFTs proved to be beneficial in enhancing peaks for better HR calculation. The use of color amplification methods helped to capture the fluctuations in blood underneath skin in a much better manner which resulted in better accuracy than all other previous models.

This method will help patients all over the world in avoiding a physical visit for any measurement of metrics, and reduce the load on the Doctor giving them a clear result helping them in diagnosing the patient perfectly.

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