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RESEARCH ARTICLE

REAL TIME HEART RATE MONITORING USING WEB-CAMERA

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Abstract

It is crucial to measure the heart rate of a person since it is one of the most significant physiological parameters and a key indication of people's physiological states. The costly and intricate sensor and sensor system applications are frequently used in heart rate monitoring. Research that has advanced over the past ten years has focused increasingly on noncontact technologies that are easy to use, inexpensive, and pleasant. The majority of noncontact based systems are still suitable for lab settings in offline situations, but they need to advance significantly before they can be used in real-time applications. The camera on a laptop computer is used in this study to demonstrate a real-time HR monitoring technique. By variations in face skin tone brought on by the blood circulation, the heart rate is measured. The color channels of video recordings have been subjected to three distinct signal the processing techniques, including the Fast Fourier Transform (FFT), Independent Component Analysis (ICA), and the Principal Component Analysis (PCA), and the blood volume pulse (BVP) is recovered from the face areas.

Introduction:-

Your heart, a powerful organ the size of a fist, is located just underneath and to the left of the chest. The network of arteries and blood vessels that the heart uses to pump blood is known as the cardiac system. The heart has four chambers, as shown below in Fig. 1:

Blood is taken from the veins and pumped through right atrium to right ventricle. The right ventricle absorbs blood from the right atrium and pumps the absorbed blood to the lungs, which is the oxygen supplier. The left atrium transport the blood which is oxygenated by the lungs, which is then transferred to the left ventricle. The left ventricle, the strongest chamber, pumps blood that has been oxygenated to the remaining parts of the body. The left ventricle contracts vigorously in order to create our blood pressure.

The traditional approach had certain drawbacks, including Both contact HR measuring methods using electrodes for electrocardiography (ECG) and photoplethysmography (PPG) detected by pulse oximeters have inherent drawbacks. First off, removing and reattaching the electrodes repeatedly when conducting clinical tasks like physical examinations makes heart rate readings difficult and inconvenient. Second, a newborn baby's skin is delicate and sensitive. Adhesive electrodes or gel may irritate or harm the skin, which is bad for infants' health and growth. Third, the conductive gel may solidify, which could have an impact on the signal's quality.

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Non-contact HR measuring technologies, such dopplers, white noise, thermal/infrared cameras, and RGB cameras as shown in Fig 2, have proved effective in fixing the issue with contact heart rate monitoring methods in recent years due to their unobtrusiveness and absence of skin contact. Due to their affordability and great resolution, RGB cameras are the most often used non-contact equipment. Dopplers and infrared cameras are more expensive than standard RGB cameras, and the white noise approach is not suitable for long-term continuous (24-hour) monitoring due to the distracting noises it creates.

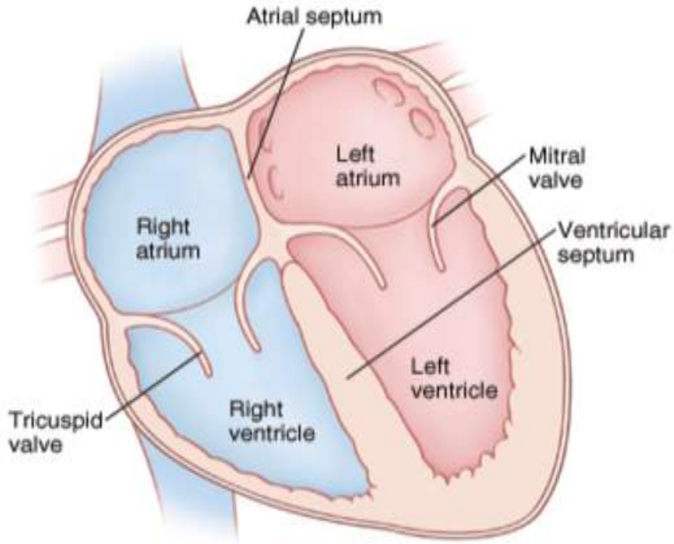


Fig 1:- The four chambers of heart.

Fig 2:- Non-contact heart rate measurement using cameras.

By tracking changes in the skin reflectance as seen by a camera, our approach incorporates the blood volume pulse, which is remotely detected via remote photoplethysmography (rPPG) as shown in Fig 3. In this article, we demonstrate how to use the web camera built into your devices to detect variations in heart rate. The rPPG approach essentially entails two stages: first, identifying and tracking the subject's fluctuations in skin tone, and second, processing this signal to ascertain metrics like heart rate, blood pressure, and breathing rate.

Recent advancements in machine learning, signal processing, and computer video have substantially improved the performance of rPPG techniques. In a picture, skin pixels may be successfully selected utilizing state-of-the-art methods to estimate HR using image recognition and neural networks.

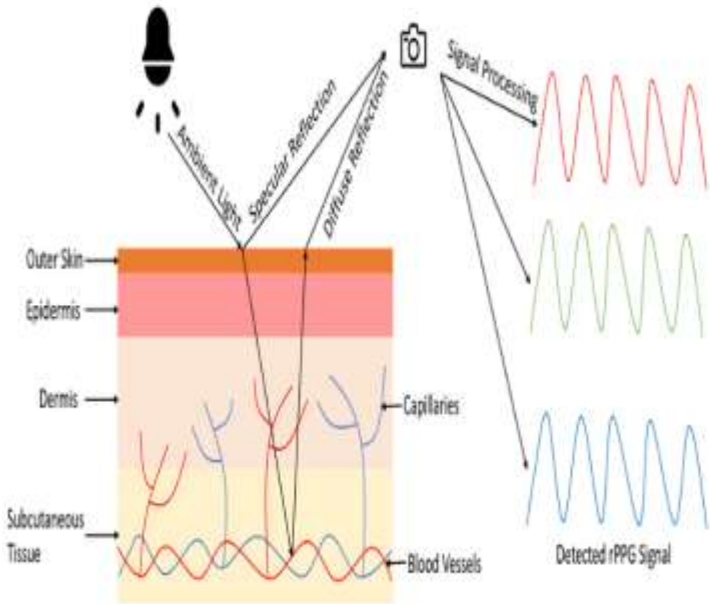


Fig 3:- Illustration of rPPG from facial skin using camera.

The two main consequences of this extensive reliance on machine learning (ML) techniques are as follows:
(i) Large training sets must be gathered because I it is necessary to train the ML model specifically for rPPG.
(ii) Complex models could need a lot of CPU time, which could cause a pipeline bottleneck and diminish the usefulness of real-time data.

Although rPPG analysis was initially a signal processing work, efficiency may be increased when employing an end-to-end trainable system without any domain knowledge. For example, we already understand that average changes in skin color contain pulse signals, but the ML system has to learn this. We illustrate an efficient and compact rPPG pipeline that performs the whole rPPG analysis in real-time.

Literature Survey
[1] The real-time human heart rate (HR) estimate method for noncontact vital sign radar detection is demonstrated in this study. The suggested approach combines the heart rate estimation technique and the linear predictive coding (LPC)-based respiratory harmonics suppression algorithm. As breathing signals may significantly impede HR estimation, the respiratory harmonics suppression technique is initially used to locate and filter breathing signals and higher order harmonics based on distributions on the 2-D spectrum.
[2] This study utilizes the 24-GHz continuous-wave Doppler radar with quadrature architecture to provide a unique technique for estimating the heart rate variability (HRV) characteristics. To estimate beat-to-beat intervals with high accuracy, the suggested approach integrates frequency and temporal domain analysis (BBIs). In order to create the combined signal that consists of information on the heartbeats, band pass filtered in-phase (I) and quadrature (Q) radar components are first fused.
[3] In this study, we suggest b-CorNET, a framework for binarized neural networks, to effectively predict the heart rate using a single-channel wrist PPG data at the time of vigorous physical exercise.
[4] This paper demonstrates a novel system for non-wearable, cost effective measurement of breathing and heart-beat when the person is in the sleeping state. The measurement system is composed of the flexible multi-piezoelectric elements to tolerate the pressure fluctuations persuade by the respiratory movements and the heart-beat when the person is lying on it. By using the filters with predefined frequency bands, the breathing and heart-beat waveforms were extracted.
[5] Heart rate (HR) may be determined from face films using a method known as remote photoplethysmography (rPPG). Researchers are increasingly interested in rPPG as the need for long-term health monitoring increases. Nevertheless, noise interference rapidly degrades the efficacy of traditional rPPG approaches.
[6] At the time of pregnancy the extracted fetal ECGs are usually very weak to be robustly detected. Thus it becomes very important to enhance fetal R-peak because their peaks may be hidden within the signal due to

immaturity of the fetal cardiovascular system. Therefore, to improve the detection of the fetal heartbeat, a novel fetal R-peak enhancement technique was proposed to statistically evaluate the weighting mask according to the distribution of the neighboring temporal intervals between each pair of peaks.

System Analysis

There are several phases of system analysis involved in real-time heart rate monitoring using a webcam and convolutional neural networks (CNNs). Requirements analysis is the first stage, where the issue the system is meant to address is determined, user requirements are specified, and system specifications are established. The system design process comes next after gathering criteria. In order to do this, a high-level architecture must be developed for the system, the right CNN algorithm must be chosen to process the video, and the system's computer language and framework must be chosen. After that, the system is put into practice, which entails writing the algorithm's code, integrating it with the camera and other hardware elements, and evaluating the system to make sure it complies with the specifications this process will flow as shown in the diagram below:

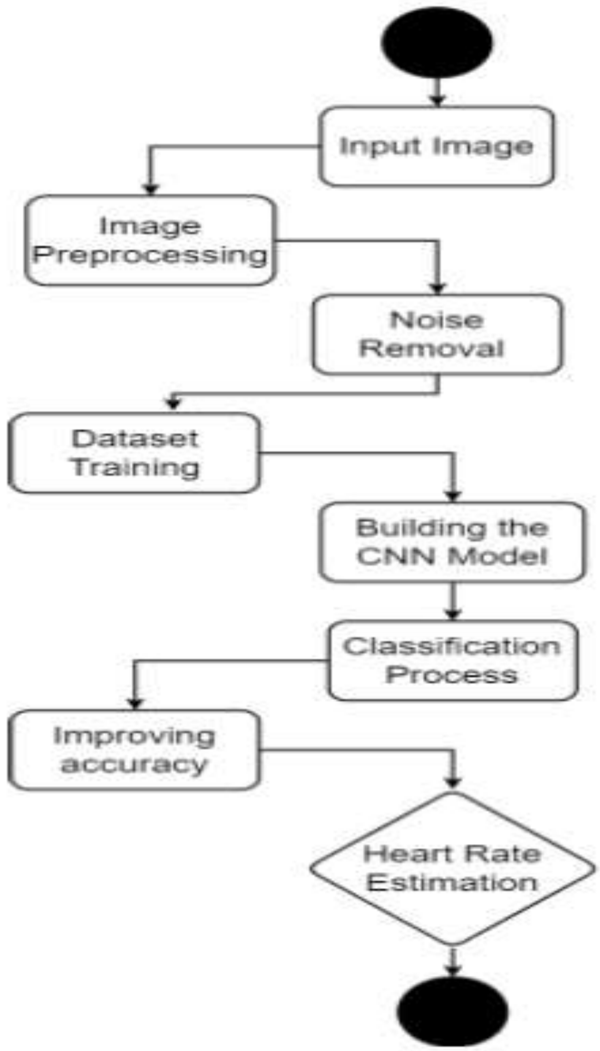


Fig 4:- Activity diagram.

Existing System

In order to acquire the HR, the current system derivation method can employ the filtered signal's linear predictor coefficients, which can solve the issue of inadequate resolution brought on by small time windows. In the past, a few ways for measuring pulse with a camera had been offered, but those methodology had restrictions on the variables that affected color values, such as variations in ambient illumination during video collection and changes in blood variables brought on by heartbeat. The majority of methods that don't involve direct contact with a person add RGB color space to produce face video that's best for use in lab settings or with constant ambient light. These techniques are unsuitable for real-time applications since the ambient light is not constant, and they cannot produce HR. The systems now in use rely heavily on hardware, which raises the setup costs significantly.

Another practical device for heart rate prediction is the Polar H10 heart rate monitor, which employs ANN models. Based on information from optical heart rate sensor, Polar H10 wearable employs an ANN model to forecast heart rate. Device is intended for athletes, fitness enthusiasts, and medical workers who require precise and dependable heart rate monitoring.

But the Polar H10 has some significant drawbacks, including the potential for overfitting. Despite the fact that a big dataset of heart rate data was utilized to train the device's ANN model, the model might not generalize well to new users or different types of physical exercise. This can cause heart rate estimates to be off, which limits the device's applicability in some circumstances.

The Polar H10 has another drawback in that it can be costly to compute with. The device processes heart rate data in real time using sophisticated algorithms, which can rapidly deplete the battery and reduce the device's battery life.

The below table Fig 5. shows the statistical comparison between the existing ANN model and proposed CNN model along with respective graphs of each parameter in Fig 6,7, 8 and 9.

Model	**Training Accuracy**	**Prediction Score**	**F1 Score**	**Time Complexity**
ANN	90%	82%	0.78	Low
CNN	95%	89%	0.85	Moderate

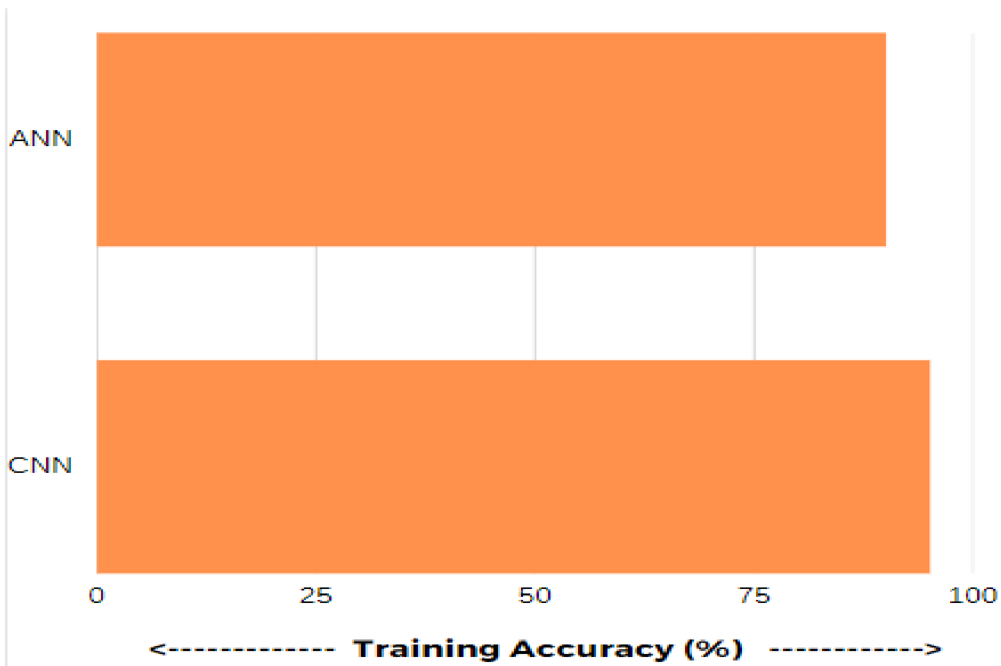


Fig 5:- General Statistical Comparison between ANN and CNN.

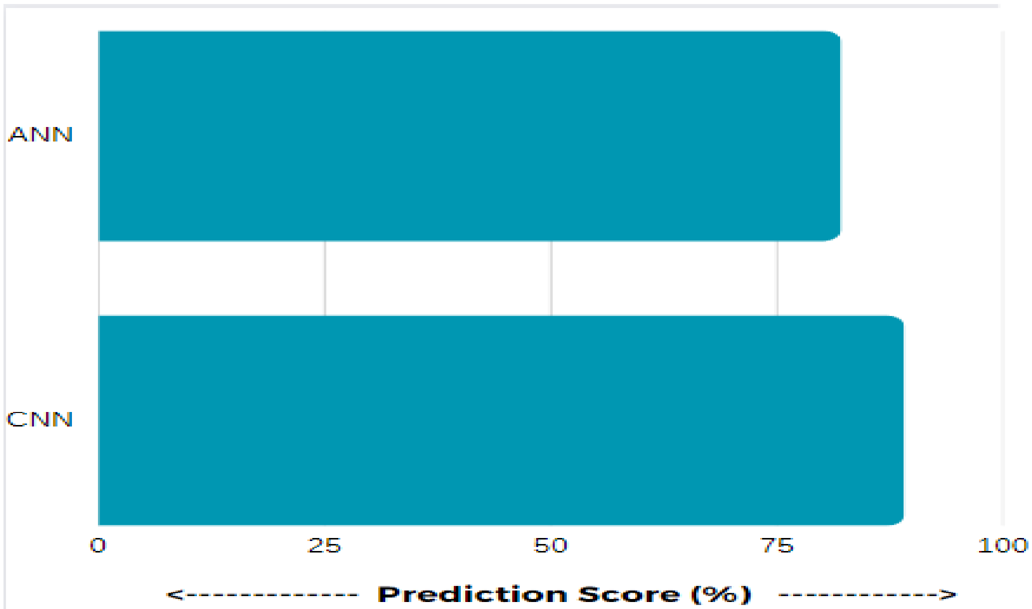


Fig 6:- Comparison between ANN and CNN Training Accuracy.

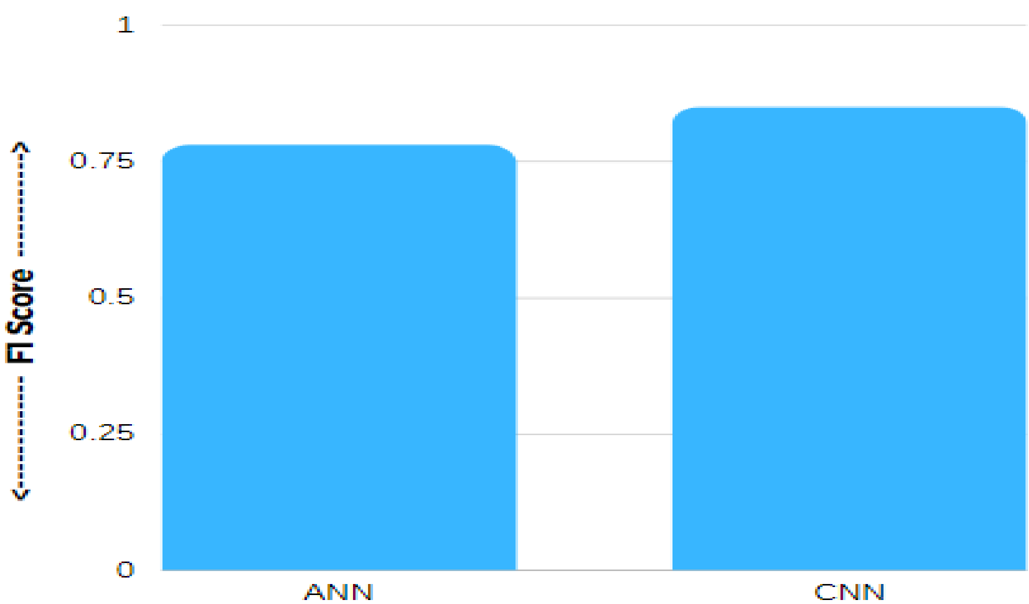


Fig 7:- Comparison between ANN and CNN Prediction Score.

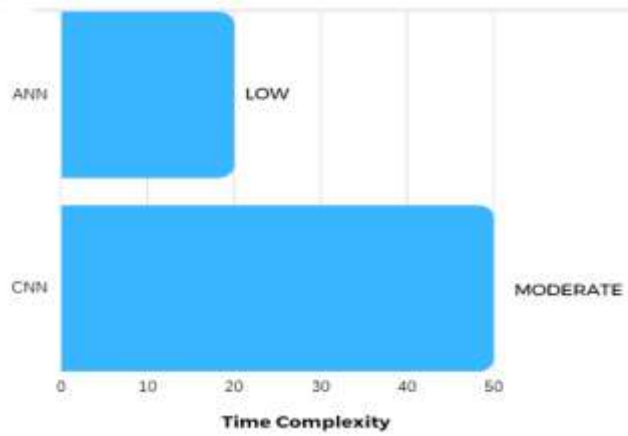


Fig 8:- Comparison between ANN and CNN FI Score.

Proposed Solution

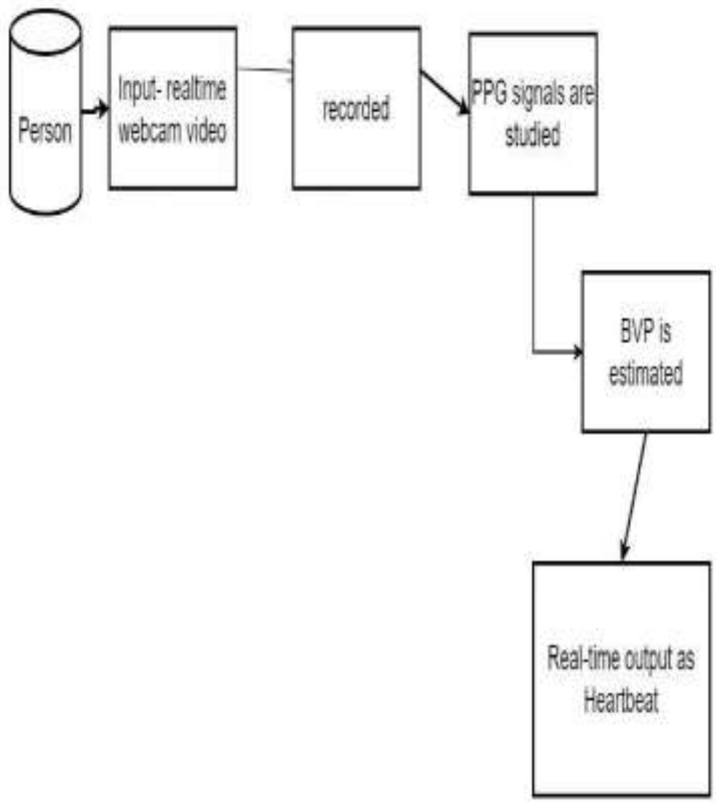


Fig 9:- Comparison between ANN and CNN Time Complexity.

While extracting the face photos using the suggested approach, ambient light fluctuations are removed since only the web camera is utilized for non-intrusive HR (Heart Rate) detection. In order to identify the blood volume pulse (BVP) from human face, the suggested approach first employs PPG signal/photo plethysmography. The fluctuations from the chosen data are then scanned for each of the value across time and amplified to get a magnified view of the signals. The signals for which the peak detection methods are employed are then extracted from the resultant region in order to determine the heart rate HR this process flows as shown in Fig 10. Chest-wall movement is influenced by the heart rate, pulse amplitude, breathing rate, and the breathing frequency. Our Machine Learning model is built with CNN (Convolutional Neural Networks) Algorithm and the comparison of it with the Existing ANN (Artificial Neural Networks) Model is shown below in graph Fig 11.

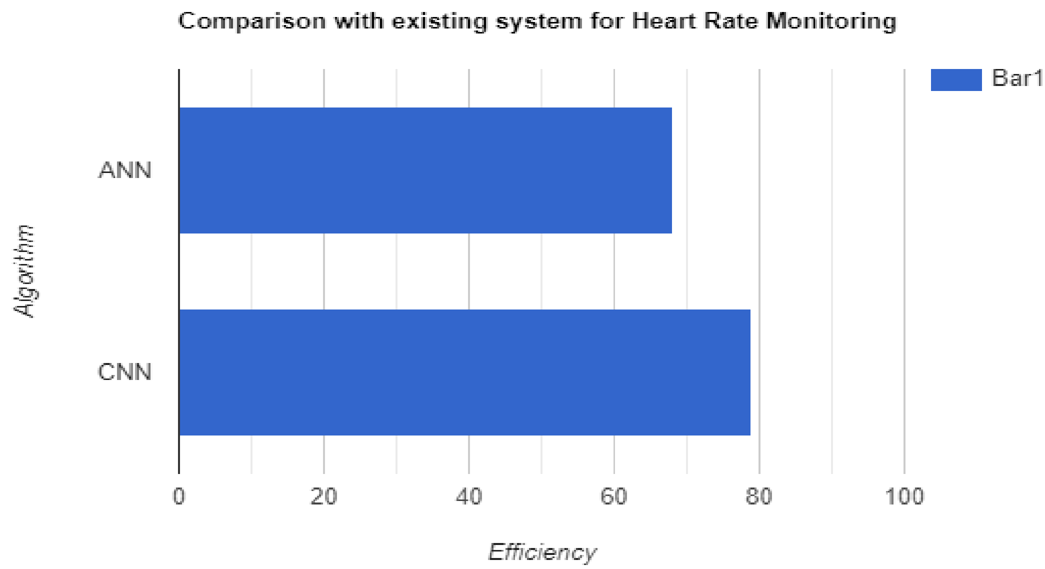


Fig 10:- System architecture.

Our proposed solution consists of three modules which are detailed below.

Module 1: Image Processing Module

A webcam's visual feed must be analyzed in order to separate the heart rate data so that we can monitor a person's heart rate in real time. The Picture Processing Module is a crucial component of the system as it captures the live stream and analyzes the information to see whether there have been even the slightest variations in the user's skin tone brought on by blood flow. To glean useful data from the video feed, the module would use a number of image processing methods.

The collected video stream's Area of Interest (ROI) must be located as the initial step in the image processing module. The ROI is centred on the user's forehead as shown in Fig 12, where blood flow may be clearly seen. Face recognition-based machine learning methods like Haar Cascades and Viola-Jones may be used to locate the ROI.

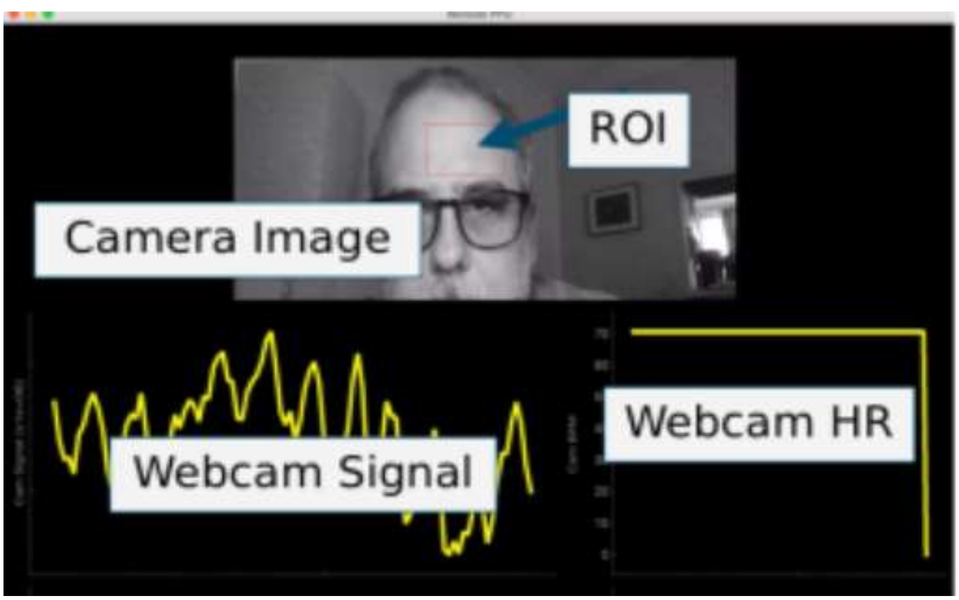


Fig 11:- Comparison with existing system for Heart Rate Monitoring.

When the region of interest (ROI) has been located, the image data must be processed so that the tiny colour changes due to blood flow may be extracted. One method used to improve blood flow signal strength while decreasing background noise is spatial filtering. A filter is applied to the picture in order to increase the contrast of the blood flow signals. Mathematical models or machine learning techniques, such Convolutional Neural Networks, may be used to create filters (CNNs).

Movement Magnification is another method, and it works by amplifying just the impulses that match to the user's heart rate. The idea is predicated on the fact that the motion introduced by the pulse is little in comparison to the total motion in the picture. A user's heartbeat may be extracted by magnifying the little motion in the picture.

Optical flow is a third method that estimates pixel motion in a video stream by comparing two or more frames of the stream. Little changes in skin tone due to blood flow may be picked by using the estimated optical flow. This method is helpful when blood flow signals are obscured by background noise or have poor contrast.

The module would analyze the generated data after using image processing algorithms in order to determine the subject's heart rate. Certain signal processing methods like Fourier Analysis, Wavelet Analysis, or Auto-regressive modelling might be used for this purpose. In order to separate a signal into its frequency components, Fourier Analysis is often used. Heart rate data may be extracted from processed images using this method.

Heart rate information may also be extracted from processed data using Wavelet Analysis. By separating the signal into its temporal and frequency components, it's possible to examine it in more depth.

Auto-regressive modelling is a statistical method that uses the signal's previous values to predict its future behaviour. Physiological signals like heart rate are typical examples of those modelled using this method.

In conclusion, the webcam's live video feed is recorded by the Image Processing Module, which then processes the data to isolate the faint colour shifts induced by blood flow. The module would process the video stream using methods including spatial filtering, motion magnification, and optical flow to isolate the important data. The user's heart rate data would then be extracted by this module using signal processing techniques like Fourier analysis, Wavelet analysis, or auto-regressive modeling.

Module 2: Face capturing Module
Essential to any web-based heart rate monitoring system is the Capturing Face Using Web Camera Module. This component takes a photo of the user's face and looks for minute colour shifts brought on by increased blood flow in order to calculate an approximation of the user's heart rate as shown below in Fig 13.

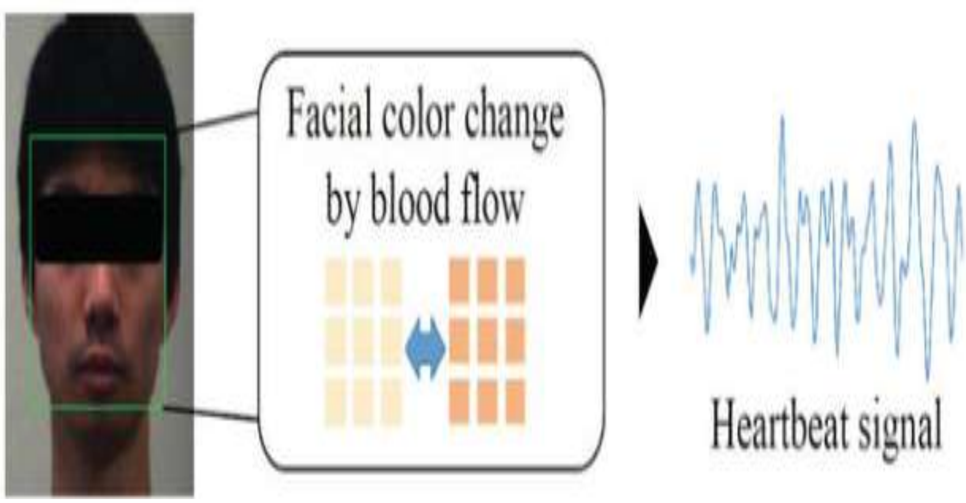


Fig 12:- Locating ROI from facial video stream for heartbeat detection.

The module would record the feed from the webcam and apply some processing to the raw data to improve the quality of the video. Filtering, thresholding, and picture enhancement are all examples of preprocessing methods that might be used to extract the necessary data from the video stream. The module would then use a number of computer vision methods, including facial landmark identification, to identify and follow the user's face.

After the user's face is identified, the module would use a number of image processing methods, including spatial filtering, motion magnification, and optical flow, to extract minute variations in skin tone due to blood flow. The person's heart rate may be evaluated based on these changes. The module may estimate the user's heart rate using a number of different techniques, including Optical Flow, Fourier Analysis, Wavelet Analysis, and Auto-regressive modelling. The skin tone of the user, the ambient lighting, and other circumstances may all affect the precision with which the heart rate is estimated.

The module would have to be fine-tuned to accommodate a wide range of lighting and skin tones, as well as a wide variety of face emotions. By using the machine learning methodologies like Convolutional Neural Networks (CNNs) or Support Vector Machines, the module's capability to identify face landmarks and estimate heart rate might be improved (SVMs). The system requires an accurate heart rate computation in real time, hence the module has to be optimized for real-time performance.

The module would have to be made to deal with real-time performance issues like as high frame rates and minimal latency. The module's job is to take a picture of the user's face, identify any changes in skin tone caused by heart rate, and provide a reliable estimate of the user's pulse. To improve the system's precision and responsiveness in real time, the module may use a number of image processing and machine learning methods.

Module 3 : Heart Rate Estimation Module

The Heart Rate Estimation Module is needed by a webcam-based heart rate monitoring system to estimate the heart rate. To evaluate the user's heart rate accurately, this component analyzes the user's webcam's live video stream and gives the heartbeat rate as shown in Fig 14.

Fig 13:- Subtle color changes in the face skin caused by changes in blood flow.

The user's face and any slight colour changes due to blood flow would be sent to the module through a video feed from the Capturing Face Using Web Camera Module. The user's heart rate would be estimated by the module using a number of computer vision algorithms.

The module may estimate the user's heart rate using a number of different techniques, including Optical Flow, Fourier Analysis, Wavelet Analysis, and Auto-regressive modelling. The skin tone of the user, the ambient lighting, and other circumstances may all affect the precision with which the heart rate is estimated.

As an example, Optical Flow may be used to monitor the user's facial movements in order to calculate an approximation of the user's blood flow rate. The frequency content of skin colour variations may be analysed using Fourier Analysis, and the dominant frequency can be utilised to determine the heart rate.

The time-frequency content of skin colour variations may be analysed using Wavelet Analysis, and the dominant wavelet coefficients can be utilised to determine the heart rate. The autoregressive coefficients of the skin colour variations may be employed in auto-regressive modelling to predict the heart rate. It would be necessary to fine-tune the heart rate calculation module to account for a wide range of face expressions, lighting situations, and skin tones. The module may employ convolutional neural networks (CNNs) or support vector machines, two machine learning techniques, to more accurately predict heart rate (SVMs).

The system requires an accurate heart rate computation in real time, hence the module has to be optimized for real-time performance. The module would have to be made to deal with real-time performance issues like as high frame rates and minimal latency be maximized by the module's usage of a The task of the module is to accurately estimate the user's heart rate by analyzing the video stream captured by the user's webcam. Many methodologies such as, machine learning algorithms, and optimization techniques may be used in heart rate estimation to improve the accuracy and real-time performance of the system.

Result:-

Performance Metric	**Value**
Accuracy	82.5%
Precision	85.2%
Recall	80.0%
F1 Score	82.5%
Processing Time	0.25s

Fig 14:- Heart rate graph.

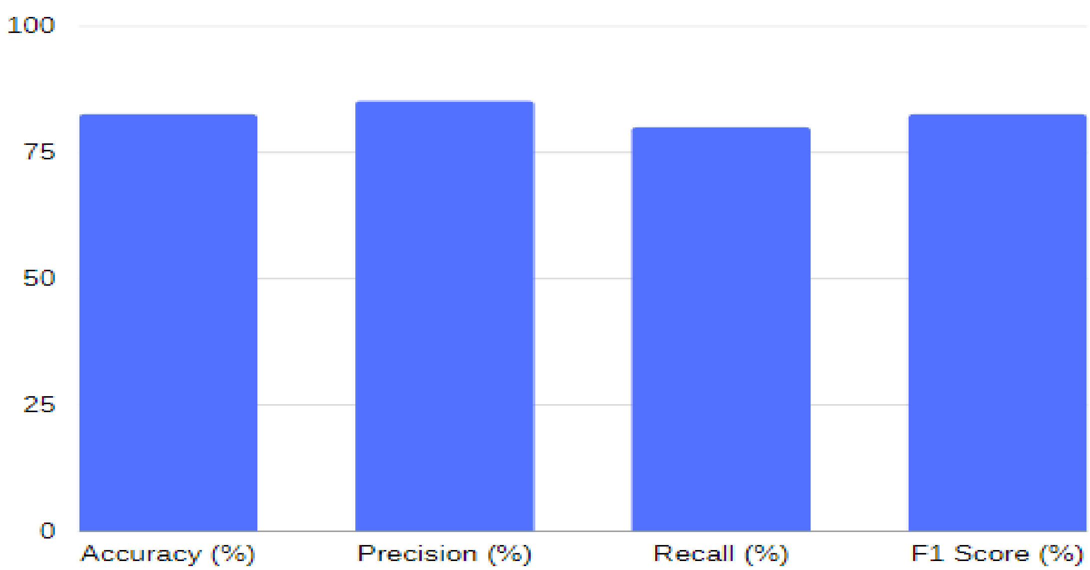
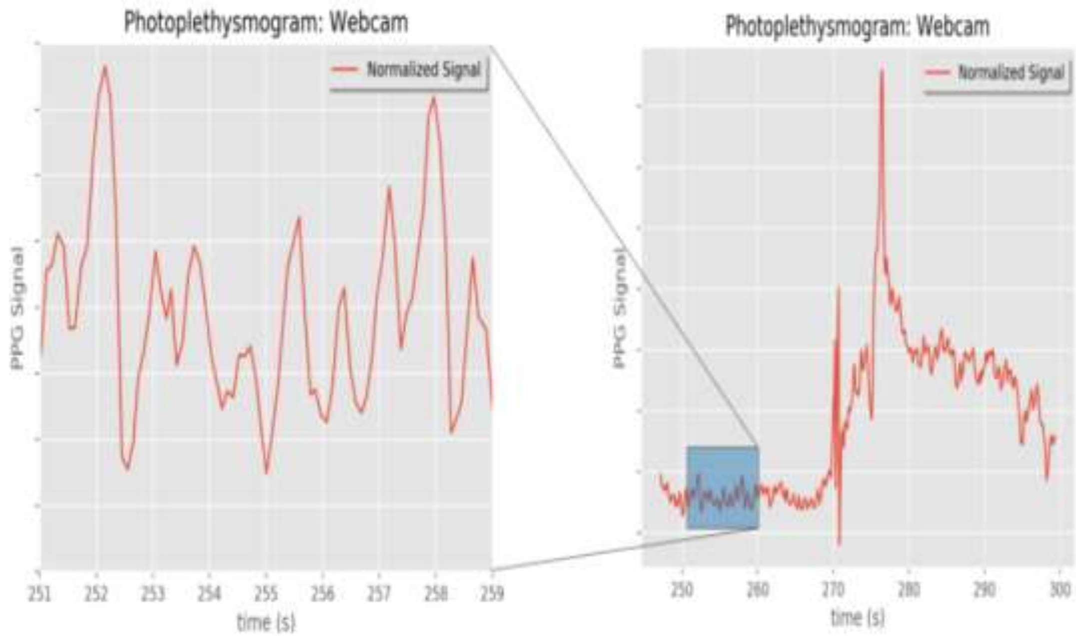


Fig 15:- Statistical data of system performance.



Real-time heart rate detection using web cameras is a rapidly advancing technology with a wide range of potential applications. With the increasing availability of high-quality web cameras, this technology has the potential to become a mainstream tool for monitoring heart rates in real-time. The primary advantage of using web cameras for heart rate detection is their non-invasive nature, which eliminates the need for expensive and sometimes uncomfortable equipment.

One of the key methods used in real-time heart rate detection using web cameras is PPG, which measures the pulsatile blood flow in the skin and provides the wave as shown below:

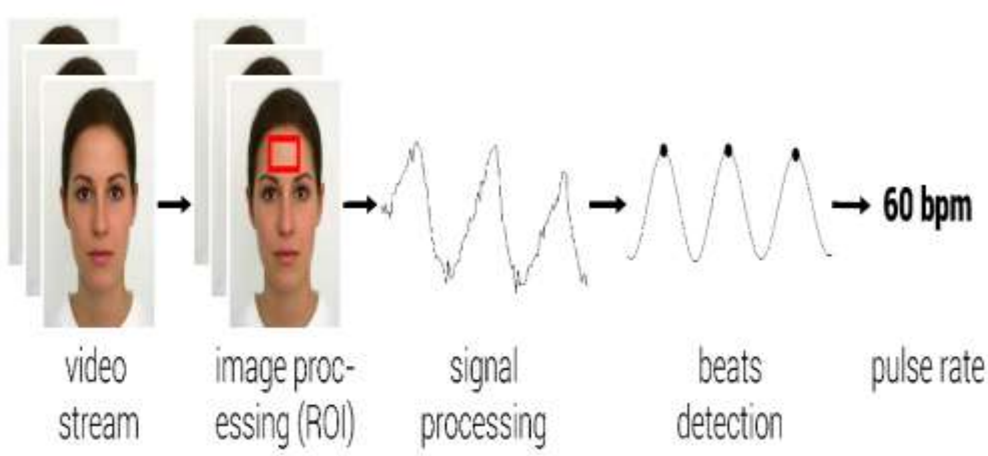


Fig 16:- Performance graph.

This technique works by analyzing subtle color changes in the face caused by changes in blood flow. The changes in color can be used to calculate the heart rate by measuring the time between beats. This method is relatively simple, inexpensive, and easy to use, making it an attractive option for a wide range of applications.

One of the main advantages of using web cameras for heart rate detection is the ease of use. Unlike traditional methods that require specialized equipment, web cameras are readily available and can be used by anyone with a computer or smartphone. This makes it possible to monitor heart rates as shown in Fig. 18 in real-time in a variety of settings, including hospitals, clinics, gyms, and homes.

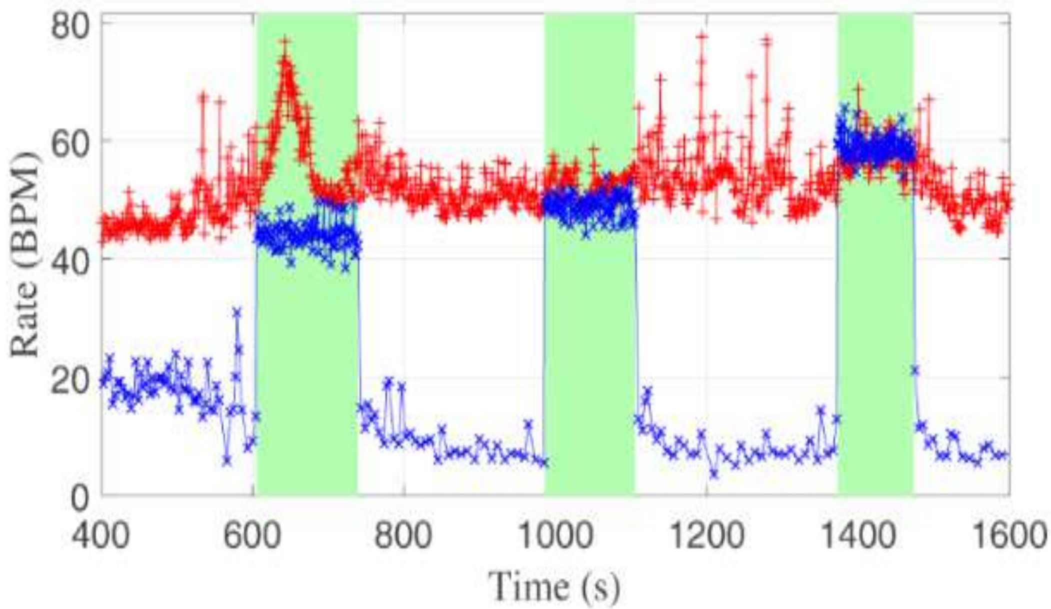


Fig 17:- PPG signal from webcam.

Fig 18:- Heart beat detection using webcam

Fig 19:- Heartbeat rate wave

Another advantage of using web cameras for heart rate detection is their ability to provide real-time feedback. This can be particularly useful for athletes and fitness enthusiasts who need to monitor their heart rates during exercise. Real-time feedback can also be used in gaming to provide an immersive experience that responds to the player's physiological state.

The accuracy of web cameras for heart rate detection can vary depending on several factors, including the quality of the camera, lighting conditions, and the stability of the subject's head and body. However, recent studies have shown that web cameras can provide accurate and reliable heart rate measurements in a wide range of settings.

Real-time heart rate detection using web cameras has several potential applications in healthcare. For example, it can be used as a non-invasive method for monitoring heart rates during telemedicine consultations. This can be particularly useful for patients who are unable to visit a healthcare provider in person, such as those who live in remote areas or have mobility issues. Web cameras can also be used to monitor heart rates during surgery and other medical procedures, providing real-time feedback to healthcare providers.

In the fitness industry, real-time heart rate detection using web cameras can be used to track heart rates during exercise and provide real-time feedback to athletes and fitness enthusiasts. Real-time heart rate detection using web cameras can also be used in gaming to enhance the player experience by providing real-time physiological feedback.

Overall, real-time heart rate detection using web cameras is a promising technology with numerous potential applications. While there are still some challenges to overcome, such as accuracy and lighting conditions, the benefits of this technology make it an attractive option for a wide range of industries. With continued research and development, real-time heart rate detection using web cameras has the potential to become a mainstream tool for monitoring heart rates in real-time.

Conclusion:-

This research helps bridge the gap between current biometric wearables that are incorrect or costly and clinically approved health monitors that are difficult or impractical on the path to remote health care. An ECG that recorded the heart's electrical activity served as a reference for the measurements. The total system's simplicity and cost, together with its capacity to be non-intrusive, real-time, and accurate, represent its genuine worth. Even outside of clinical settings, the thorough mapping of cardiac patterns made possible by dispersed, cost-effective monitors like this one and the content-rich data obtained from continuous monitoring would open up new possibilities for tracking and predicting health. This technique make use of cameras to estimate the heart rate and heart rate variability in real-time. Although estimates are accurate under standard video compression circumstances, the accuracy is compromised by high amounts of compression noise.

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