HEART RATE ESTIMATION USING RPPG

A Project Report

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In

Department of Computer Science and Engineering

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DECLARATION

The Project Report entitled "HEART RATE ESTIMATION USING RPPG" is a record of bonafide work of BELLAM.KEERTHANA (2010030017), M. NISSIE (2010030095), M. SRAVANI CHOWDARY (2010030104), P. MOUNIKA REDDY (2010030485), submitted in partial fulfillment for the award of B.Tech in the Department of Computer Science and Engineering to the K L University, Hyderabad. The results embodied in this report have not been copied from any other Departments/ University/ Institute.

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CERTIFICATE

This is to certify that the Project Report entitled "VEHICLE ROUTING USING TABU SEARCH" is a record of bonafide work of BELLAM KEERTHANA (2010030017), M. NISSIE (2010030095), M. SRAVANI CHOWDARY (2010030104), P. MOUNIKA REDDY (2010030485), submitted in partial fulfillment for the award of B.Tech in CSE to the K L University,Hyderabad is a record of bonafide work carried out under our guidance and supervision.

The results embodied in this report have not been copied from any other departments/University/Institute.

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Signature of the HOD

Signature of the External Examiner

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First and foremost, we thank the lord almighty for all his grace & mercy showered upon us, for completing this project successfully.

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We wholeheartedly thank all the teaching and non-teaching staff of our department without whom we won't have made this project a reality. We would like to extend our sincere thanks especially to our parent, our family members and friends who have supported us to make this project a grand success

ABSTRACT

With the event of technology, new techniques are rapidly developing for the center rate measurement process, which is important, especially in hospitals. vital sign estimation is of great importance in determining an individual's mental and state. In some cases, it's impractical to use many medical devices like the finger pulse oximeter with PPG technology because of the patient's delicate health conditions. Remote photoplethysmography (rPPG) monitors vital sign without requiring physical contact, which allows for a good sort of applications. Deep learning-based rPPG has demonstrated superior performance over the normal approaches in a very controlled context. However, the lighting situation in indoor spaces is often complex, with uneven light distribution and frequent variations in illumination.

Remote monitoring of elderly people or patients in home isolation is an important a part of modern telemedicine. the basic idea relies on capturing minute changes in colour during a cycle of the physical body, involving the inflow and outflow of blood from the center to other body parts.

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CHAPTER 1

INTRODUCTION

Telemedicine as a remote clinical service for diagnostic and medical monitoring is an expanding public health unit. In particular, the COVID-19 pandemic has identified this as a priority. For all new issues in a telehealth session, the patient's face is an essential source of well-being information, as this is what is most visible to the healthcare professional. As a result, it would be advantageous to determine the patient's condition directly from the face. Heart rate (HR) is an essential parameter for cardiovascular activity.

The visual estimation of HR, the estimation of HR based on a video sequence or the direct feeding of a camera, has recently received a lot of attention. In comparison to contact methods, visual HR methods provide accurate measurements with inexpensive measuring devices (such as web cameras). This is particularly important for patients with acute skin conditions. Heart rate is an important indicator of human functioning and psychoemotional health. Remote photoplethysmography is useful in situations where conventional cardiac frequency estimation approaches such as electrocardiogram and photoplethysmography require physical contact with the subject is impractical. The acquisition of the rPPG signal is useful for estimating physiological signals such as heart rate (HR) and heart rate variation (HRV), which are important parameters for health care remotely. With the development of the computational vision algorithm, remote measurement of heart rate by remote photoplethysmography (rPPG) was proposed. Remote photoplethysmography (rPPG) monitors the heart rate without physical contact, which makes many applications possible. Deep learning rPPG has surpassed conventional approaches in a controlled environment.

CHAPTER 2

LITERATURE SURVEY

PAPER-01

This paper was published by IEEE Xplore. The authors are Benjamin, Kossack, eric, anna Hilsman, Preterist. This paper presents a model-based approach to measuring the vital signs from RGB video files that specialize in the guts rate. We use the plane-orthogonal- to-skin (POS) remote photoplethysmography (rPPG) transformation performed individually at five well-defined regions of interest (ROI) within the face. We extract the centre rate information by a correlation of the various rPPGNet signals in these ROIs and a magnitude-based reliability calculation. This increases the robustness of the centre rate extraction from videos. our model-based method is entirely automatic and doesn't require large amounts of knowledge for training or time-consuming training sessions: our approach will be applied immediately. The ubfc-rppg dataset is employed during this research model. our model-based method is entirely automatic and doesn't require large amounts of knowledge for training or time-consuming training sessions; our approach may be applied immediately.

PAPER-02

This paper is published by the center for machine vision and signal the analysis university of Oulu. The author is zitong Yu, Xiaobo. In this paper, they estimate heart rate using the techniques like network architecture,3dcnn based phys net, rnn based phys net. MAHNOB-HCL dataset is used. they implemented end to end framework with Spatio-temporal networks which can recover rppg signals from raw facial videos fast and efficiently. Phys net can recover rppg signals with accurate time location of each pulse weak, which allows measuring not only the average hrv level features that enable potential applications in remote a detection and emotion recognition. There was one drawback in implementing these techniques that facial expression analysis for multimode emotional recognition has not been found.

PAPER-03

This paper is published by IEEE Xplore. The authors are ze yanghoafei hang, Feng leu.Remote photoplethysmography (rPPG) monitors rate without requiring physical contact, which allows for a large kind of applications. Deep learning based Rppg has demonstrated superior performance over the normal approaches during a controlled context. However, the lighting situation in indoor spaces is often complex, with uneven light distribution and frequent variations in illumination. It lacks a good comparison of various methods under different illuminations using the identical dataset. during this paper, they present a public dataset, namely the

BH-rPPG dataset, which contains data from twelve subjects under three illuminations: low, medium, and high illumination. We also provide the bottom truth pulse measured by an oximeter. We evaluate the performance of three deep learning-based methods to it of 4 traditional methods using two public datasets: the UBFC-rPPG dataset and therefore the BH-rPPG dataset. The experimental results demonstrate that traditional methods are generally more proof against fluctuating illuminations. We found that the rPPGNet achieves the bottom MAE among deep learning-based methods under medium illumination, whereas the CHROM achieves 1.5 beats per minute (BPM), outperforming the rPPGNet by 60%. These findings suggest that while developing deep learning-based pulse rate estimation algorithms, illumination variation should be taken under consideration. This work is a benchmark for rPPG performance evaluation, and it opens a pathway for future investigation into deep learning-based rPPG under illumination variations

PAPER-O4

This paper is published by the school of information science and technology, northwest university. The authors have panned Zhang, bin li, jin ye Peng, Wei Jiang. UBFC-RPPG AND COFACE datasets are used. The proposed method aims to reconstruct rPPG from RGB facial videos by designing a 3D spatiotemporal convolutional network with multi-hierarchical fusion. the proposed network includes four modules: low-level face feature generation (LFFG), 3D Spatio-temporal stack convolution (STSC), MHFF, and signal predictor (SP). Dataset Our dataset contained a total of 300 VIS videos with a frame rate of 30 fps from 300 objects at the age of 18-26 years. The length of each video was 1 min with a pixel resolution of 1920×1080. These videos were collected by an Honor v30 mobile phone in a well-lit environment. Physiological signals were collected by BIOPAC MP160, including the average HR, respiratory rate, SpO2, ECG signal, and blood volume pulse (BVP) wave of each subject. The physiological signal sampling rate was 1000 Hz. The BF -RPPG database contained 42 videos from 42 subjects. The videos were recorded using a simple low-cost webcam (Logitech C920 HD Pro) at 30 fps with a resolution of 640×480 pixels in an uncompressed 8-bit RGB format. A CMS5OE transmissive pulse oximeter was used to obtain the ground truth PPG waveform and PPG HRs. During the recording, the subject sat in front of the camera with his/her face visible. All experiments were conducted indoors with varying amounts of sunlight and indoor illumination. The OHFA dataset [26] contained 160 videos with high compression rates from 40 subjects (12 women and 28 men); each of the subjects contributed four one-minute videos: two videos in 20 well-lit conditions, and the other two captured under natural light. The videos were recorded with a Logitech HD C525 with a resolution of 640 480 pixels and an image frequency of 20 frames per second. Each subject wore a contact PPG sensor to obtain the BVP data.

PAPER-05

This paper is published by IEEE Xplore. The authors are ze yanghoafei hang, Feng leu.

Remote photoplethysmography (rPPG) monitors rate without requiring physical contact, which allows for a large kind of applications. Deep learning based Rppg has demonstrated superior performance over the normal approaches during a controlled context. However, the lighting situation in indoor spaces is often complex, with uneven light distribution and frequent variations in illumination. It lacks a good comparison of various methods under different illuminations using the identical dataset. during this paper, they present a public dataset, namely the BH-rPPG dataset, which contains data from twelve subjects under three illuminations: low, medium, and high illumination. We also provide the bottom truth pulse measured by an oximeter. We evaluate the performance of three deep learning-based methods to it of 4 traditional methods using two public datasets: the UBFC-rPPG dataset and therefore the BH-rPPG dataset. The experimental results demonstrate that traditional methods are generally more proof against fluctuating illuminations. We found that the rPPGNet achieves the bottom MAE among deep learning-based methods under medium illumination, whereas the CHROM achieves 1.5 beats per minute (BPM), outperforming the rPPGNet by 60%. These findings suggest that while developing deep learning-based pulse rate estimation algorithms, illumination variation should be taken under consideration. This work is a benchmark for rPPG performance evaluation, and it opens a pathway for future investigation into deep learning-based rPPG under illumination variations.

PAPER-06

Remote sensing of important signs has been developed to enhance the measurement environment by employing a camera without a skin-contact sensor. The camera-based method is predicated on two concepts, namely color, and motion. The color-based method, remote photoplethysmography (RPPG), measures the colour variation of the face generated by the reflectance of blood. during this article, the proposed method is that the fusion method for estimation of pulse rate using rppg. First, the face was detected and tracked from the consequence frame of the facial video. Then, photoplethysmography signals were extracted from the face by RPPG. These signals were wont to minimize noise and maximize cardiac components. Finally, the center rate was estimated from the combined signal within the frequency domain. Thus, this study employed the only shot detector with ResNet trained by the broader FACE dataset as mentioned within the article that they conducted several experiments. This paper mainly focuses to beat the noise of illumination variance and motion artifacts in RPP.
Title: super-high resolution for video-based vital sign estimation with a semi-blind
source separation method. This article states that selecting an appropriate resolution supported a given shooting distance also plays a vital role to boost the standard of rPPG measurements. Remote photoplethysmography (rPPG), a non-contact technique to estimate heart rates (HR) from video recordings, has attracted much attention from researchers in recent years. it's well-known that rPPG signals may be extracted
from low-resolution videos.

PAPER-07

This article was published by IEEE. The authors of this text are Xuesong Nau,Shiguang Shan, Hu Han. during this paper, they propose an end-to-end Rhythm Net for remote HR estimation from the face. In Rhythmed, they used spatial-temporal representation encoding the HR signals from multiple ROI volumes on their input. Then the spatial-temporal representations are fed into a convolutional network for HR estimation. they also take under consideration the connection of adjacent HR measurements from a video sequence via the Gated Recurrent Unit (GRU) and achieve efficient HR measurement. additionally, they build a large-scale multi-modal HR database (named VIPL-HR 1), which contains 2,378 visible radiation videos (VIS) and 752 near-infrared (NIR) videos of 107 subjects. The VIPL-HR database contains various variations like head movements, illumination variations, and acquisition device changes, replicating a less- constrained scenario for HR estimation. The proposed approach outperforms the state-of-the-art methods on both the public-domain and VIPL-HR databases.

PAPER-08

This paper is published by IEEE on 30 March 2020. Remote photoplethysmography (rPPG) could be a reasonably noncontact technique to live rate (HR) from facial videos. because the demand for long-term health monitoring grows, rPPG attracts much attention from researchers. However, the performance of conventional rPPG methods is well degenerated because of noise interference. Recently, some deep learning-based rPPG methods are introduced and that they revealed good performance against noise. during this article, we propose a replacement rPPG method with convolutional neural networks (CNNs) to create a mapping between a spatiotemporal HR feature image to its corresponding HR value. The feature map is made in a very time-delayed way with noise- contaminated pulse signals extracted from existing rPPG methods. The CNN
model is trained using transfer learning where images built from synthetic rPPG
signals are taken to coach the model first so as to come up with initials for the sensible one. The synthetic rPPG signals are interpolated from blood volume pulses or electrocardiograms through a modified Akima cubic Hermite interpolation. The proposed method is tested in both within-database and cross- database configurations on public databases. The results demonstrate that our method achieves overall the most effective performance compared to another typical rPPG methods. The mean absolute error reaches 5.98 beats per minute and also the mean error rate percentage is 7.97% within the cross-database testing on the MAHNOB-HCI data set. Besides, some key factors affect the performance of this method.

PAPER 9

The authors of this paper are Zitong Yu1, Wei Peng1, Xiaobai Li1, Xiaopeng Hong, and GuoyingZhao. during this paper, the guts rate was estimated by highly compressed facial videos. They proposed an end-to-end deep learning-based propose a two-stage, end-to-end method using hidden rPPG information enhancement and a spotlight network, which is that the first try and counter video compression loss and recover rPPG signals from highly compressed videos. The tactic includes two parts:

1) a Spatio-Temporal Video Enhancement Network (STEVEN) for video enhancement, and

2) an rPPG network (rPPGNet) for rPPG signal recovery. The rPPG Net can work on its own for robust rPPG measurement, and therefore the STVEN network is added and jointly trained to further boost the performance, especially on highly compressed videos. Comprehensive experiments are performed on two benchmark datasets to indicate that,

i) the proposed method not only achieves superior performance on compressed videos with high-quality videos pair,

ii) it also generalizes well on novel data with only compressed videos available, which suggests the promising potential for real-world applications. Two datasets are used – OBF and MAHNOB-HCI.

PAPER-10

This paper was published on 5 December 2020 by Elsevier. The authors are Gee-Sern JisonHsu and ArulMurugan Ambika path. during this paper, their approach is one amongst the pioneering works that propose a deep learning framework with TFRs as input for solving the guts rate estimation from facial videos. additionally, they need developed a rate database, named the heart beat from Face (PFF), and used it together with the present PURE database to coach the CNN. The PFF database is released for research purposes with this paper. they need evaluated the proposed framework on the MAHNOB-HCI database and also the VIPL-HR database and compared its performance thereupon of other contemporary approaches to demonstrate its efficacy. develop a unique deep learning framework for real-time estimation of heart rates by using an RGB camera. This approach consists of the subsequent four steps. we start Step 1 by detecting the face and facial landmarks within the video to spot the specified facial Region of Interest (ROIs). In Step 2, extract the sequence of the mean of the green-channeled video from the facial ROIs, and explore three-stage sequential filtering, including illumination rectification, trend removal, and signal amplification. In Step 3, the Short-Time Fourier Transform (STFT) is used to convert the 1D filtered signal into the corresponding 2D Time-Frequency Representation (TFR) for characterizing the frequencies over short time intervals. The 2D TFR allows the formulation of the guts rate estimation as a video-based supervised learning problem, which may be solved by exploring a deep Convolutional Neural Network (CNN), as is dispensed in Step 4. The approach is one in all the pioneering works that propose a deep learning framework with TFRs as input for solving the guts rate estimation from facial videos.

CHAPTER 3

HARDWARE AND SOFTWARE REQUIREMENTS

3.1 Hardware requirements

- Hardware requirements for insurance on internet will be same for both parties which are as follows:
- Processor: Dual Core
- RAM: 2 GB
- Hard DisK:320 GB

3.2 Software requirements

Operating System: Windows10 Ultimate which supports networking.

Python development toolkit.

- Python IDLE

Libraries

- Anaconda – Jupyter Notebook
- NumPy
- Pandas
- Matplotlib
- Sklearn
- Seaborn
- Python tool kit 3.7.1 and 3.8.0

CHAPTER 4

FUNCTIONAL AND NON-FUNCTIONAL REQUIREMENTS

4.1 Functional Requirements:

This section provides a requirement overview of the system.

Various functional modules that can be implemented by the system will be

Description:

The system can predict the best optimal path or route.

Take the feedback and suggestions within a period of time and improve it,

strike for better communication.

4.2 Non-Functional Requirements:

Following Non-Functional Requirements will be there in the insurance to the internet:

(i) Secure access to consumers' confidential data.

(ii) 24X7 availability.

(iii) Better component design to get better performance at peak time.

(iv) The flexible service-based architecture will be highly desirable for future extensions. Non-FunctionalRequirements define system properties and constraints.

Various other Non-Functional Requirements are:

- **Maintainability**

  This is maintainable as the system will ease with which a product can be maintained to correct defects or their cause

- **Reusability**

  The proposed system can be reused for other applications which follow the same functionalities

- **Compatibility**

  The system can be said to be compatible as it is in versatile in nature and can work with any other algorithm

CHAPTER 5

IMPLEMENTATION

5.1.1 Matplotlib-

Matplotlib is one in every of the foremost standard Python packages used for information visual image. Matplotlib is meant to be as usable as MATLAB, with the flexibility to use Python and therefore the advantage of being free and ASCII text file.

5.1.2 Numpy-

NumPy could be a highly regarded Python library for giant multi-dimensional array and matrix process, with the assistance of an outsized assortment of high-level mathematical functions. it's terribly helpful for elementary scientific computations in Machine Learning.

5.1.3- Opencv – python

OpenCV could be a standard Python library for period laptop vision. OpenCV could be a useful gizmo for image process and activity laptop vision tasks. it's associate degree ASCII text file library which will be wont to perform tasks like vital sign estimation, face detection, objection and pursuit, landmark detection.

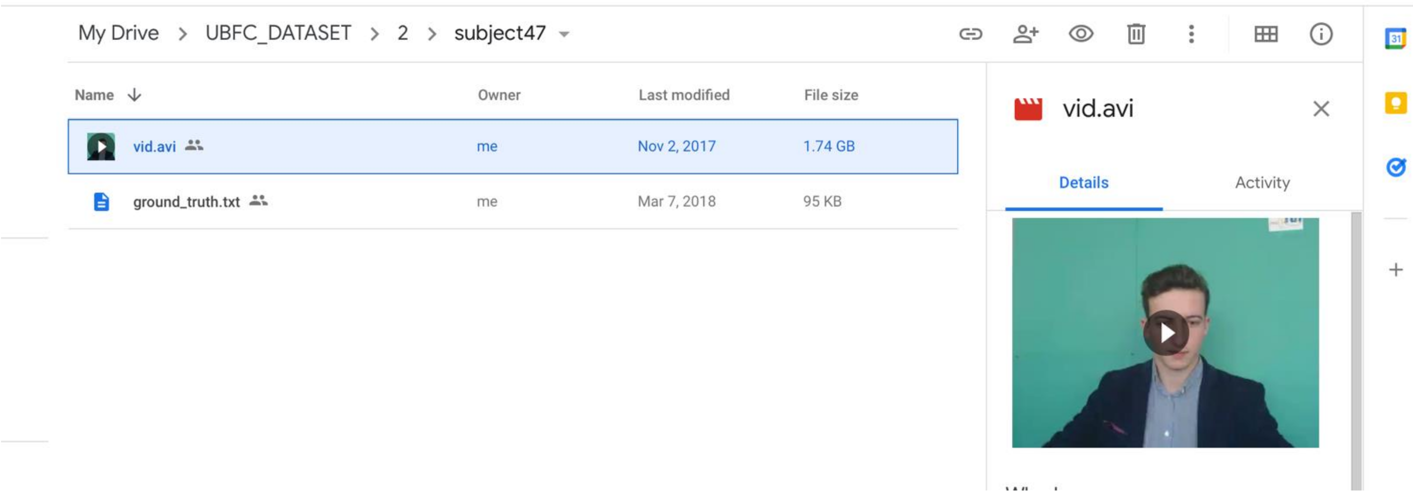
Fig 5.1 Packages installation

5.2 Dataset

UBFC

UBFC-rPPG (stands for Univ. Bourgogne Franche-Comté Remote PhotoPlethysmoGraphy) comprising of two datasets which are focused specifically for rPPG analysis.

The UBFC-RPPG database was created for video acquisition with a simple low cost webcam (Logitech C920 HD Pro) at 30fps with a resolution of 640x480 in uncompressed 8-bit RGB format. A CMS50E transmissive pulse oximeter was used to obtain the ground truth PPG data comprising of the PPG waveform as well as the PPG heart rates. During the recording, the subject sits in front of the camera (about 1m away from the camera) with his/her face visible. All experiments are conducted indoors with a varying amount of sunlight and indoor illumination.



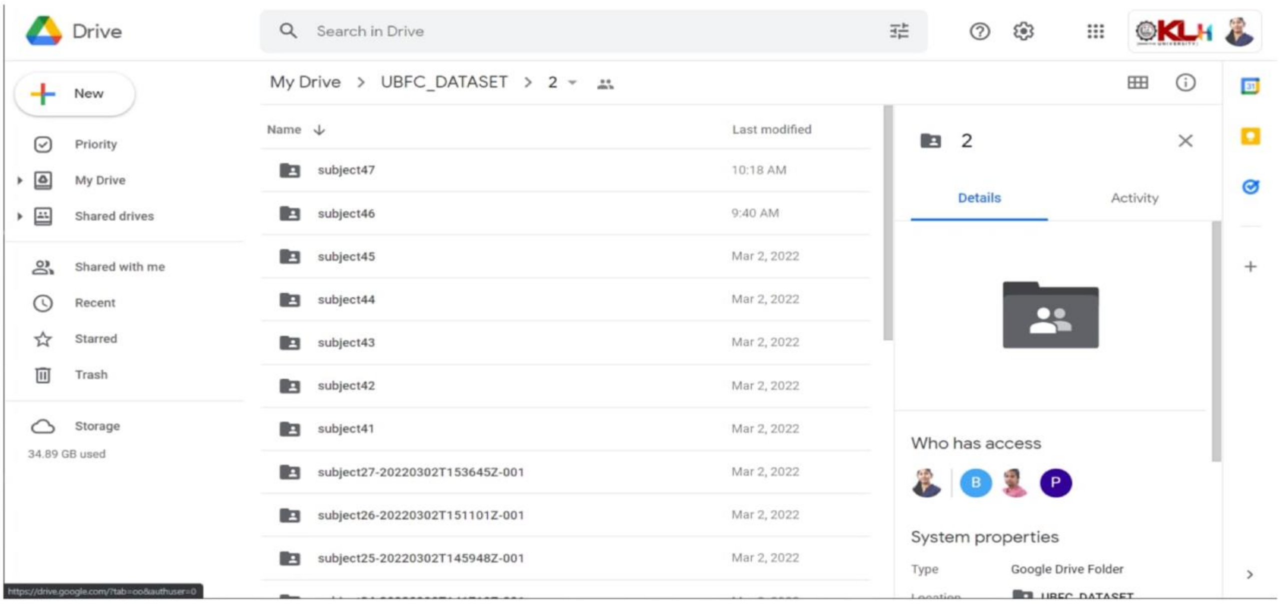


Fig 5.2 dataset

5.2 Data pre-processing

After reading we tend to found that the UBFC dataset is that the best-suited dataset for our project. and when downloading the dataset Then we've got applied feature engineering to the dataset to clean the information, feature scaling, information pre-processing, and like more things. Then we have a tendency to had to divide our dataset into two-part, here the primary half consists of the freelance feature and dependent feature. Independent feature, we have a tendency to thought-about the worth, and also the freelance feature considers the remainder of the column. Then we have a tendency to had to divide the dataset into two-part, within the 1st half, we have a tendency to trained the dataset, and in additionally second half take a look at the dataset. the information is that the most significant facet of a deep learning assignment, to that special attention ought to be paid. Indeed, the information can heavily have an effect on the findings looking on wherever we have a tendency to found them, however they're given if they're consistent, if there's associate degree outlier, and so on. several queries should be self-addressed at this stage to confirm that the educational formula is economical and proper. To obtain, clean, and convert the information, several sub-steps square measure needed. we are going to undergo these steps to know however they have been utilized in my project and why they are useful for the machine learning section. Age and floor parameters were handled for his or her missing values. the target attribute is additionally born aloof from the coaching dataset. Pandas' library is employed for this purpose. For applied mathematics image of the dataset, the min, max, variance, and mean of the target attribute was found.

5.3 Model Implementation

Analyzing information is for extracting correct estimation from basic info provided. when doing that we have a tendency to had to coach our model with the clean dataset. the model elite is stevn-rppg as this has been tried to be one in every of the simplest deep learning models.

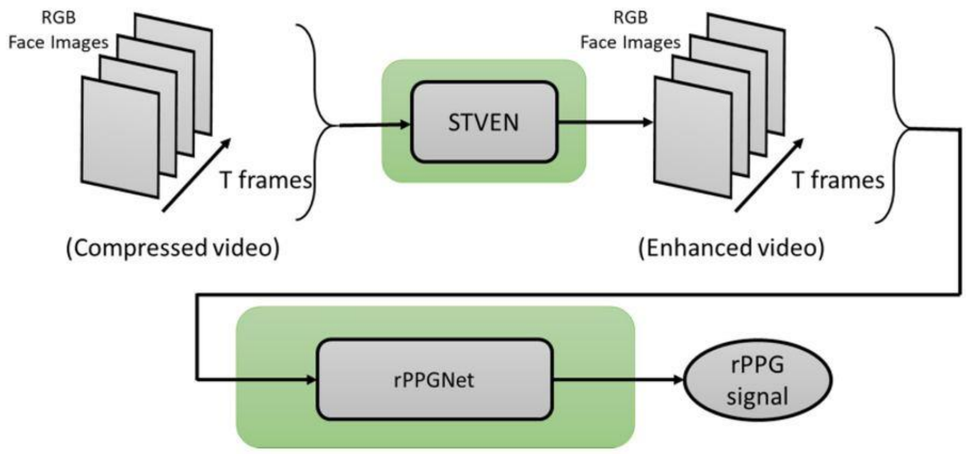


Fig 5.3 Model

5.4 Flow Chart

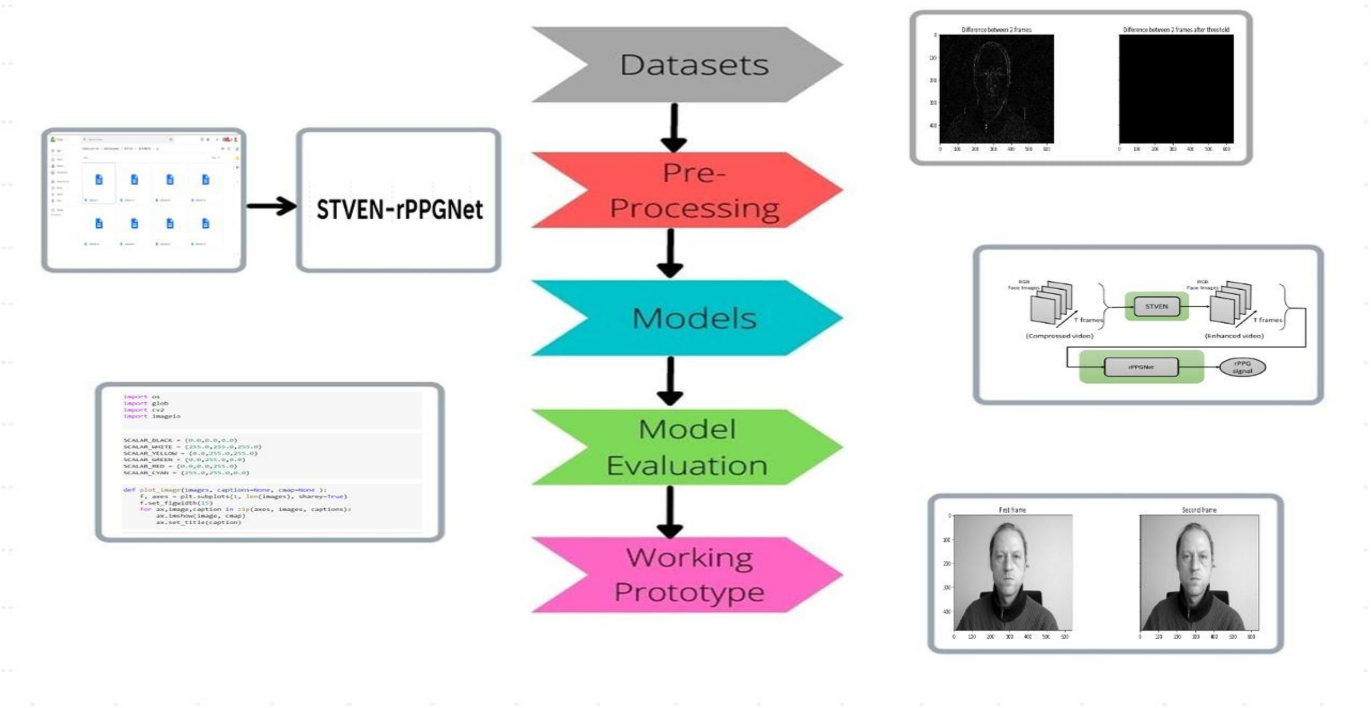


Fig 5.4: Flow Chart

CHAPTER 6

RESULTS AND DISCUSSION

we applied the deep learning method to the datasets collected in connection with our project's heart rate estimate. After many discussions with our teammates, we found that in-depth learning methods yield more precise results in predicting heart rate. This deep learning approach considers low resolution input video clips for heart rate measurement.

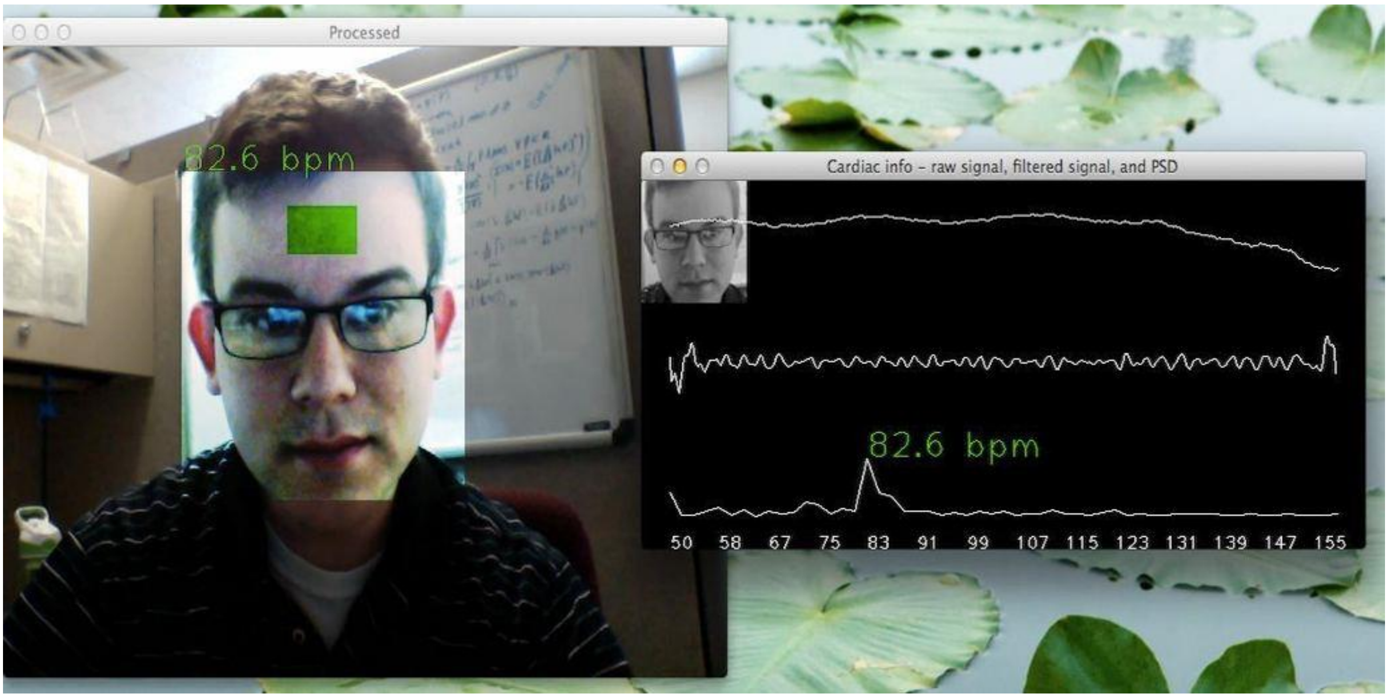


Fig 6.1 Result

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 CONCLUSION

Remote heart rate estimating consists of measuring the heart rate without physical contact with patients. During the pandemic period, telehealth and remote health monitoring have become increasingly important and people widely expect that this will have a permanent effect on healthcare systems.

According to the information from literature studies, we can say that deep learning-based methods generally give more correct and faster results than traditional methods.

7.2 FUTURE WORK

With further research and inevitable technological advances, remote health monitoring technology will undoubtedly play a vital role in many aspects. The utilization of contactless HR monitoring introduces benefits that existing contact-based PPG methods lack. In this section, we describe a few potential applications enabled by remote monitoring of physiological signals.

CHAPTER 8

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